Doctoral theses at NTNU, 2021:130

Ellika Taveres-Cachat

Advanced Building Envelopes

Opportunities, challenges, and future outlooks in building performance simulation

NTNU
Norwegian University of Science and Technology

Doctoral thesis

Ellika Taveres-Cachat

Doctoral theses at NTNU, 2021:130

NTNU
Norwegian University of
Science and Technology
Thesis for the degree of
Philosophiae Doctor
Faculty of Architecture and Design
Department of Architecture and Technology

ISBN 978-82-326-5194-8 (printed ver.)
ISBN 978-82-326-5707-0 (electronic ver.)
ISSN 1503-8181 (printed ver.)
ISSN 2703-8084 (electronic ver.)

NTNU
Norwegian University of
Science and Technology

NTNU

Ellika Taveres-Cachat

Advanced Building Envelopes

Opportunities, challenges, and future outlooks in building performance simulation

Thesis for the degree of Philosophiae Doctor

Trondheim, July 2021

Norwegian University of Science and Technology
Faculty of Architecture and Design
Department of Architecture and Technology

NTNU
Norwegian University of
Science and Technology

NTNU
Norwegian University of Science and Technology

Thesis for the degree of Philosophiae Doctor

Faculty of Architecture and Design
Department of Architecture and Technology

ISBN 978-82-326-5194-8 (printed ver.)
ISBN 978-82-326-5707-0 (electronic ver.)
ISSN 1503-8181 (printed ver.)
ISSN 2703-8084 (electronic ver.)

Doctoral theses at NTNU, 2021:130

PRINTED IN NORWAY
NO - 1598

NORDIC SWAN ECOLABEL
Printed matter
2041 0731

Printed by Skipnes Kommunikasjon AS

Preface

I grew up surrounded by some of the world's highest mountains, with icy peaks and sugar-coated domes stretching as far as the eye could see. As a child, I stared endlessly at these mountains, wondering if I would be able to see my house from the top of the Mont-Blanc, picturing the mirror image of where I stood now in my window corner with my father's binoculars. What I did not know then was that the highest mountains I would climb in the next two decades would only exist in my head. Doing a PhD is not dissimilar to going on a mountaineering expedition. You set out full of hope and excitement about the unknown. You have a route planned and a goal in mind. And it starts off great, before you know it you've climbed the first peak: the Dunning-Kruger effect inspired top known as idiot mountain. You stand tall for about a minute, and then comes the big tumble. The slippery slope of knowledge building into the so-called "valley of doom" where the air is thick with imposter syndrome. But you have to keep moving. You can't get stuck here in reviewer-number-two limbo and questions about why you didn't cite this "well-known" paper you've never heard of, or why you didn't do your experiments in a completely different way.

The truth is that your PhD journey is filled with smaller peaks, ones that were not on your map but that are much more satisfying. I would be lying if I did not say that I've felt despair, defeat, and exhaustion in the last four years. But more importantly, I also felt joy, hope, mastery, trust, and kinship. My expedition was never a solo trip, and for this I would like to thank all the people who cheered me on and helped me reach the finish line.

I would like to thank my supervisor, Dr Francesco Goia, for encouraging me to be ambitious, for believing in me, and for teaching me how to recognize and develop good research. And most of all, I would like to thank my parents, Jean-Elisabeth and Patrick Taveres-Cachat, for raising a girl that was never afraid to climb mountains.

Summary

Energy use in buildings is one of the most significant contributors to greenhouse gas emissions worldwide. As a result, there has been a strong motivation to transition the built environment towards more sustainable, healthy, energy-efficient, and aesthetically pleasing designs. One of the key focus areas for achieving this goal has been to develop new building envelope concepts and systems based on holistic design principles that support high indoor environmental quality while reducing energy use in buildings. In this thesis, such envelopes are referred to as Advanced Building Envelopes (ABEs). These are envelopes that aim to successfully balance competing performance aspects through the use of innovative material properties, complex control strategies or designs determined using novel design methodologies. Despite the potential of ABEs and the growing interest for them, these technologies still see a relatively low uptake in real-world projects. This situation is partly due to the complexity of modelling and simulating their design and operation and as a result, the non-triviality of predicting and characterizing their performance in most monolithic building performance simulation (BPS) tools. In recent years, researchers have pointed to the promising prospects offered by new modelling and simulation approaches such as i) performance-based design and ii) co-simulation to overcome current building simulation barriers. This thesis investigates these topics and relies on a conceptual modelling approach named the fit-for-purpose approach. This approach aims to tailor the model's complexity to the outputs' requirements or the information needed to abstract the physical object.

The work presented in this thesis first focuses on the methods that can improve modelling and simulation approaches. As a part of this analysis, it starts by presenting the development of a characterization framework that allows identifying key common properties of advanced building envelopes. This framework's output allows modellers to define conceptual modelling strategies that can be translated into fit-for-purpose modelling approaches. The second research activity focused on simulation methods

provides a complete overview of the application of co-simulation and evaluates the theoretical potential of this method.

The following chapters of this thesis present the results of simulation-based research activities using the parametric software grasshopper and the Ladybug tools and the case study of the design of an external louvred shading system with integrated photovoltaics. The studies presented in this thesis are used to illustrate the potential and added-value of using innovative approaches combining parametric scripting, co-simulation, and numerical optimization. The robustness of these approaches is then assessed experimentally using a full-scale validation of the case study's co-simulated performance. Finally, this thesis investigates critical aspects relating to the use of numerical optimization in building design. The result of this activity is the establishment of a conceptual definition for what is established as problem formulation and creates a new set of guidelines to help users verify the validity of their approaches.

The findings highlight that new building simulation approaches are promising despite the lack of standardization and guidance available in the field. There is immense potential considering new developments in terms of technologies and the tools used to model and simulate buildings. However, the flexibility of these tools and their nature somewhat requires users to develop inter-disciplinary skills that span architecture, engineering and data science.

Contents

Acronyms

ABE	Advanced Building Envelope
AEC	Architecture, Engineering, and Construction
BIPV	Building Integrated Photovoltaic
BIPV/T	Building Integrated Photovoltaic/Thermal
BES	Building Energy Simulation
BEM	Building Energy Modelling
BIEC	Building Integrated Energy Conversion
BIM	Building Information Modelling
BPS	Building Performance Simulation
cDA	Continuous Daylight Autonomy
DSM	Demand Side Management
EA	Evolutionary Algorithm
EP	Energy Performance
GA	Genetic Algorithm
HVAC	Heating Cooling Air Conditioning
IEA	International Energy Agency
IEQ	Indoor Environmental Quality
DA	Daylight Autonomy
LM	Load Management
MOO	Multi-Objective Optimization
nZEB	Nearly-Zero Energy Building
PV	Photovoltaic
PVSD	Photovoltaic Shading Device
WWR	Widow to Wall Ratio
ZEB	Zero-Emission Building
ZEN	Zero-Emission Neighborhood

1 Introduction

1.1 Context

In order to minimize its contribution to climate change, the building sector is implementing increasingly stringent carbon emission reduction policies [1,2]. These new demands require architecture, engineering, and construction (AEC) practitioners to go beyond the passive principles of the “energy conservation approach” [3], and actively take advantage of current advances in technology for building materials and systems in designs. This push for innovation has led to numerous sustainable building concepts such as nearly-Zero Energy Buildings (nZEB) and Zero-Emission Buildings (ZEB), which are now part of most national policies in the EU [4–6]. The central idea of (n)ZEBs is to implement holistic building design principles that reduce energy use, improve energy flexibility and harvest available renewable energy. In short, buildings are no longer mere consumers, but active players and prosumers. This shift requires combining four different strategies. These are: i) to minimize heat losses through building envelope components, ii) to implement efficient building systems with low energy consumption, iii) to harness renewable energy sources (RES), and iv) to implement technologies that allow the building envelope to adapt to the climatic environment or the needs of the users. The success of this approach is thoroughly documented by the findings of the IEA ECBS Annex 44 [7] and the Cost Action TU1043 – Adaptive Facades Network [8]. Both of these research groups highlighted that the buildings that will perform the best are the ones that can balance high architectural quality, improve energy flexibility, and have an increased level of responsiveness to their environment and users.

This work’s natural continuation has focused on transitioning building envelopes towards new concepts and advanced multi-purpose systems with integrated technologies. These new envelope systems have had many names such as *responsive*, *adaptive*, *multi-functional*, or *dynamic* building envelopes. The common trait of these developments is that building envelope components are becoming increasingly complex. This is because they integrate new functions enabled by technology to be higher-performing in sometimes multiple physical domains. For reasons of clarity, in this thesis, we decide to regroup all of these types of systems under an umbrella term we define as Advanced Building Envelopes or ABEs. More precisely, we describe ABEs as high performing systems that can balance competing aspects of building design such as low energy use, high indoor environmental quality, and integrate renewable energy harvesting technologies to reduce carbon emissions.

Interestingly, despite the growing popularity and advances in this field, the real-world uptake of ABEs is still limited. One of the main reasons for this is that modelling and simulating their complex behavior is not a trivial task. Until now, building envelopes have been mainly optimized towards one single criterion such as reducing heat loss or optimizing heat gains. ABEs, on the other hand, strive towards designs that can satisfy multiple performance targets in several physical domains (e.g. thermal, airflow, electrical, daylight, acoustic), and which must be developed in synergy with building systems and occupant needs. This results in the necessity to use and develop more advanced simulation tools and methods to tackle the diversity and complexity of ABEs and evaluate their holistic performance in operation.

1.2 Aim, audience, and structure of the thesis

The work presented in this thesis is an extended summary of the overall research activity carried out during this thesis and which was built on five peer-reviewed scientific journal publications. As such, this thesis' goal is to provide a comprehensive synopsis of the development of the research that both binds the individual published works and provides a meta-perspective of their different research questions, results, and conclusions. Regarding the topic of this thesis, the overarching aim is to contribute to developing new knowledge about the possibilities to use new approaches and methods in building performance simulation to explore, improve, and assess the potential of advanced building envelopes. This thesis is expected to reach a diverse audience in the field of building design due to the multi-disciplinarity relevance of the work carried out. For instance, the methodological elements developed and the findings of the studies may be relevant to individuals working with computer-aided tools - whether this is from an architecture or an engineering perspective - but also to people working in research and development of specific building technologies. Some of the more general investigations, such as ones regarding the use of co-simulation or optimization parameters are expected to reach a large audience as the knowledge developed is relevant to all types of simulations.

The growing user-base of building simulation tools is the fruit of significant efforts in the last decade to expand the field in terms of popularity, accessibility and modelling capabilities. The different research activities presented in this thesis utilize these developments to define and test new methodologies. The work spans the entire development of a simulation procedure from the early development of a modelling strategy to the evaluation of the robustness of simulation results. The thesis structure follows the developmental process and details the different steps and reflections in ten chapters. This first chapter provides a short introduction to advanced building envelopes and the aims of the thesis. The second chapter provides a more detailed theoretical background for the research. It contains a state of the art of current advanced building envelope technologies and presents the specific modelling challenges associated with using monolithic building performance simulation software. Furthermore, the chapter provides a foundation for the hypothesis that more advanced simulation strategies can improve the design, modelling, and performance prediction of advanced building envelopes. The knowledge gap outlined from the theoretical background as well as the main research questions that are addressed in this thesis are presented in Chapter 3. Chapter 4 explains the research strategy developed in this thesis and the different methods used.

The four following chapters, Chapters 5, 6, 7 & 8, respectively answer the four research questions outlined in Chapter 3. These sections also follow a natural logic starting from the first considerations of model development (Chapter 5), to the method used in the simulation (Chapter 6), and then the application and validation of the developed method (Chapter 7) to the final interrogations about the sensitivity and robustness of the approach (Chapter 8). The two final chapters, Chapter 9 and 10, present the discussion and limitations of the work carried out in the thesis as well as the conclusion and personal reflections on the work, its meaning, and its implications.

Note that the use of pronouns in this thesis is established with the following rules. When the research was developed as a team or speaking about a generally accepted method in the field, the pronoun “we” is used. Whenever personal thoughts, opinions or lessons learned are expressed, the pronoun “I” is used.

2 Background and theory

2.1 The importance of building envelopes for building performance

According to the International Energy Agency, the quality and performance of building envelopes hold a key stake in meeting sustainability and carbon emissions targets [9]. Building envelopes have always been critical architectural elements, but they are also essential climatic barriers, potential platforms for renewable energy harvesting, and security, structural integrity, and fire protection functions (Figure 2-1). This multitude of roles puts them in a unique position and is the source of many design challenges.

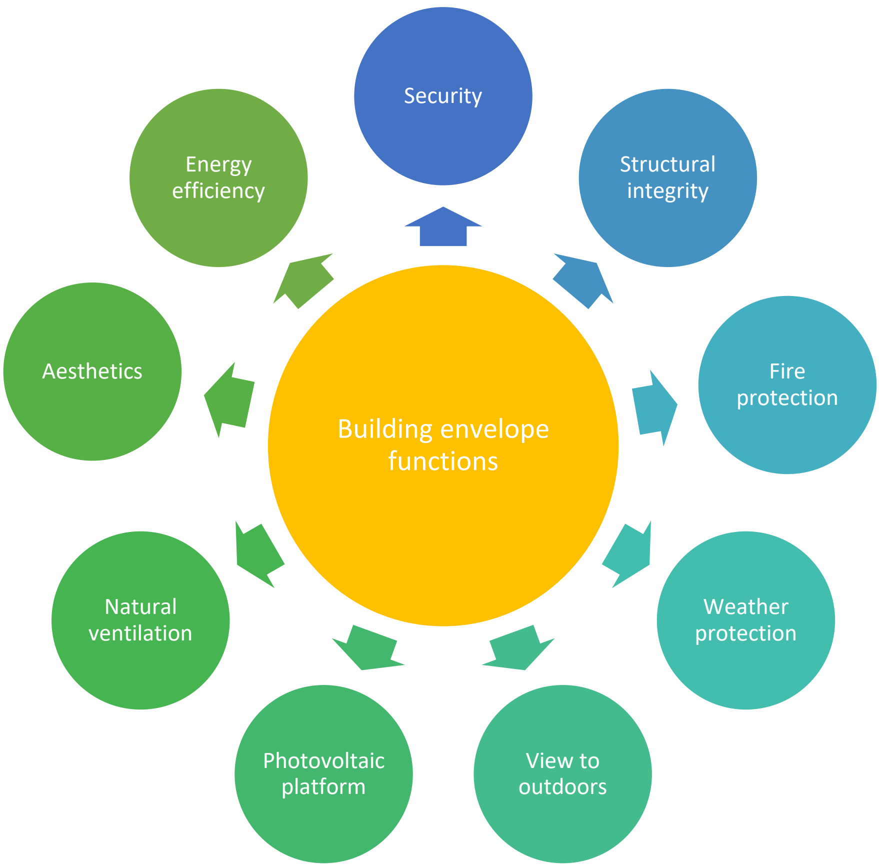


Figure 2-1 The roles of the building envelope adapted from [9]

Historically, because of the poor performance of building envelopes and their limited technological advancement, most of the effort and attention in the design was focused on implementing passive design strategies to reduce energy use following an energy conservation approach [10]. These measures concentrated on limiting energy demand for space heating and reducing heat loss through building shape optimization [11], solar passive strategies, increased insulation thickness, improved airtightness or using highly insulated windows [12,13]. This conventional approach is still currently reflected in most energy regulations and standards in which the compliance of the envelope construction is decided based on minimum requirements. However, these measures may not be indicative of the final building performance [14] and can present several limitations depending on the climatic context [15]. In the worst cases, it can even lead to situations in which the functions of different building envelope elements compete with one another [16]. Perino et al. [17], showed that a building envelope designed with the sole aim of reducing heat transfer led to higher HVAC energy use and lighting loads to compensate for lower daylighting and overheating. Thus, the risk of using the energy conservation approach for the design of building envelopes, is that it may increase cost and effort in order to achieve smaller and smaller incremental performance improvements, following the “law of diminishing returns” [18].

Due to this approach’s observed limitations, new high-performing building concepts such as zero-emission buildings (ZEB) have shifted towards holistic approaches to building design [19–21]. In this context, research on ZEBs reinforced the finding that building envelope could significantly improve building performance and reach higher sustainability targets. Specifically, improving its design provided opportunities to reduce greenhouse gas emissions, costs, and overall energy use while maximizing indoor environmental quality [17,22]. The potential benefits expanded when innovative technologies, including renewable energy harvesting solutions, were considered [23]. Many research efforts have followed to develop new innovative envelope systems that could utilize technological advancements in building materials and systems to balance the complex requirements of buildings. These include both static and dynamic systems and are referred to as Advanced Building Envelopes or ABEs in this thesis.

2.2 Advanced Building Envelopes

Definition developed in this thesis

In this thesis, we define advanced building envelopes as integrated envelope systems and technologies that ensure high building performance by interacting with several interrelated physical domains. They aim to successfully balance competing performance aspects through advanced design methods, advanced material properties and components, or advanced integrated control strategies. In doing so, ABEs can assume different appearances and be realized with different systems and technologies (Figure 2-2).

The design approach of using ABEs is particularly interesting for reducing carbon emissions and energy use during the building operation by improving energy management strategies. ABEs can provide energy savings and higher indoor comfort levels without negatively impacting the energy demand from building services like HVAC or artificial lighting [24–33]. Additionally, combining and integrating technologies in building envelope components is also interesting as it can lead to lower life cycle costs and reduced carbon emissions compared to add-on systems [34–36].

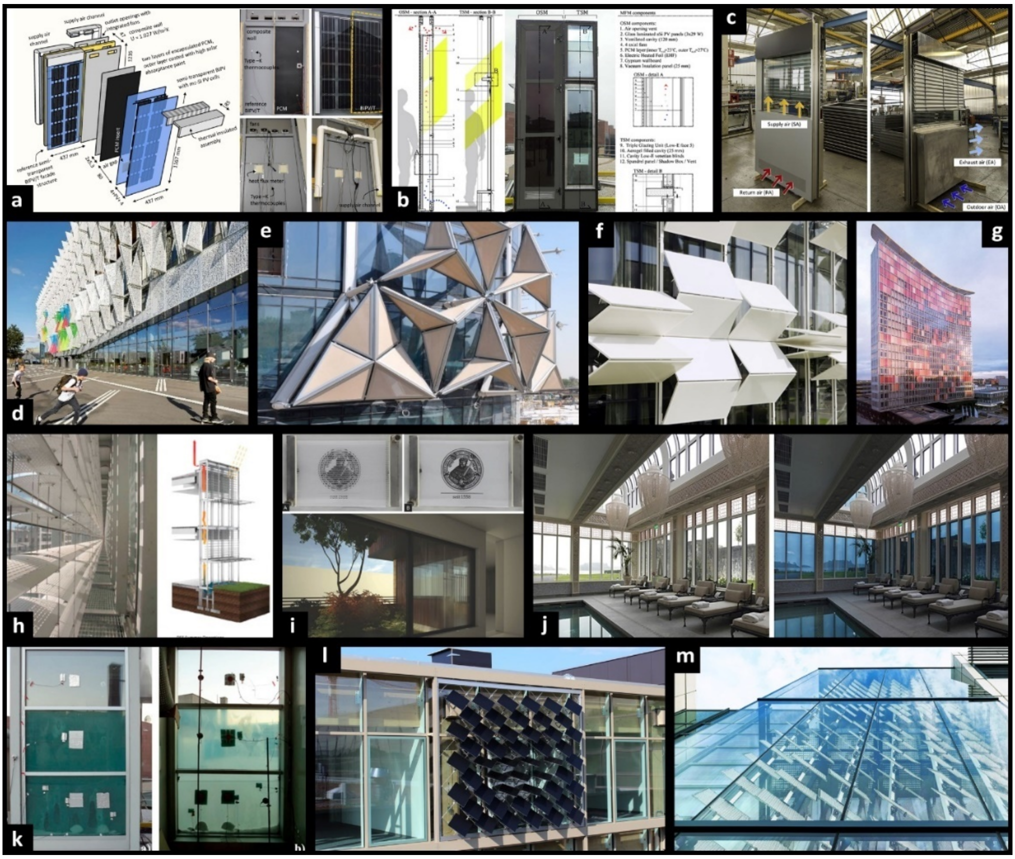


Figure 2-2 Examples of advanced building envelopes at research, prototype/demonstration, and commercial stage: multifunctional systems with integrated components such as solar (thermal) systems, HVAC units, ventilation systems, heat storage (a: [37]*; b:* [38]*; c:* [39]*), kinetic facades (d, e:* [40]*; f:* [41]*;); double skin facades and systems with heat carrier fluids (g:* [41]*; h:* [42]*; i:* [43]*), smart glazing systems (j:* [44]*; k:* [45]*); solar facades with integrated dynamic, multifunctional PV and shading devices (l* [46]*; m:* [47]*).*

ABEs regroup a large variety of components such as innovative window technologies [48–51], exterior shading systems [52–56], or walls and roofs systems [57–62]. Sadineni et al. [13] provide an exhaustive review of innovative envelope-integrated components and highlight for every type of technology, the advantages and expected benefits compared to standard building components. Some specific examples of technologies and physical domains they interact with are also shown in Figure 2-3.

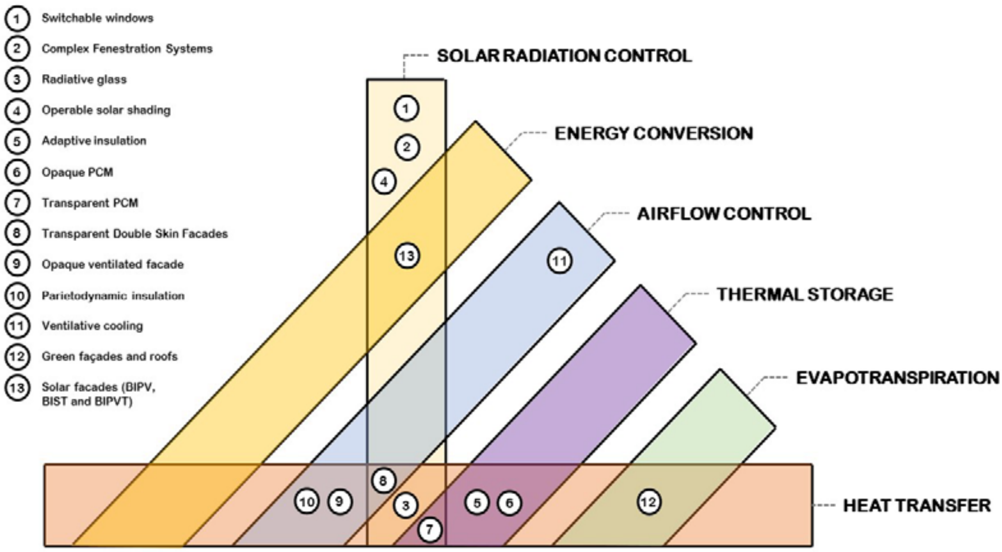


Figure 2-3 Interrelated physical domains/mechanisms influenced by advanced building envelope technologies. Original figure in [63].

ABE design principles

The design of ABEs is leveraged by developments in software and in technologies. The most significant change in design strategies has been the shift from one-size-fits-all solutions to a building-tailored approach aiming to deliver a context-oriented, synergic and efficient building envelope design. This change has been supported by a series of developments in simulation tools. In particular, methods based on parametric design and numerical optimization have shown to be promising developments [64]. These provide the possibility to assess free form façades and components with complex geometries (e.g. complex shading elements [65–68]), but also the ability to manage multi-scale [69,70] and multi-physical domain interactions in software [57]. Optimization algorithms and performance-based approaches have also contributed to modernizing building design methods [64].

The advancement of ABEs has also benefited from the development of integrated innovative building envelope technologies which, among others, include:

- Building-integrated renewable energy conversion systems such as solar thermal collectors, building-integrated photovoltaics or solar thermal and photovoltaic hybrid systems [71],
- Decentralized integrated HVAC elements [72],
- Materials and systems capable of actively and selectively managing the energy and mass transfer between the building and its external environment. This includes systems that can reversibly modulate their thermo-optical properties and operating strategies according to transient boundary conditions and performance requirements [26].

An overview of market-available technologies which represent different types of ABEs is presented in Table 2-1.

Table 2-1 Examples of advanced facade technologies and associated benefits adapted from [73]. *O = optical, T= thermal, A= airflow, E= electrical*

Type of ABE	Product example	Physical domains	Technical benefits and opportunities
Advanced translucent fenestration systems	External, transparent insulation system	O, T	Advanced translucent fenestration systems [61] transmit high amounts of diffuse daylight and solar heat while maintaining good "nighttime" insulation properties. ATFS include aerogel glazing and fenestration systems with capillary inlays between the panes. The latter has insets that allow for a better diffusion of light in rooms, while reducing convection and heat radiation
	Double/triple glazing with translucent cavity insulation	O, T	
	Dual glazing with aerogel cavity insulation	O, T	
Hybrid double skin window	Hybrid double skin window	O, T, A	Hybrid double skin façades [74] demonstrate considerable advantages in comparison to regular building façades. The extra air layer in the cavity provides improved acoustic insulation, solar control, and additional thermal insulation in cold climates. The cavity can be ventilated naturally or mechanically, and e.g., be coupled to ventilation systems. The double skin facade can also make use of several other technologies such as PV-cells or phase change materials (PCM). Phase change materials (PCM) reduce thermal fluctuations by storing and releasing energy at specific temperatures and act like thermal mass. Common types of material used in PCMS can be paraffin-based (dispersed or powdered wax mixture), salt hydrates and biobased materials.
	Translucent PCM window	O, T, A	
	DSF w/ PV Natural ventilation	O, T, A, E	
	DSF w/ integrated shading systems	O, T, A	
	DSF w/ natural ventilation	O, T, A	
Switchable glazing	Electrochromic windows	O, T, E	Switchable glazing systems [48,51] use glass panes that can change their light and heat transmission properties in response to voltage, light or temperature. The glass color can cover a large range of translucence
	Polymer dispersed liquid crystals	O, T, E	

	Thermochromic windows	O, T	and typically have multiple intermediate states. The main technologies currently manufactured in glazing components include electrochromic, thermochromic, thermotropic and polymer dispersed liquid crystal glazing systems.
Advanced solar shading and daylighting systems	Facade integrated screens or louvres	O, T	Advanced solar shading and daylighting systems [75] are developing towards facade integrated and window cavity integrated shading systems. This is because integrated systems are more discreet and offer improved architectural aesthetics. Additionally, when the system is integrated in a fenestration cavity, it will be less vulnerable to degradations due to wind and weathering.
	Folding shutters	O, T	
	Motorized, window cavity integrated venetian blind	O, T	
	Sunshade blades or passive louvre with integrated PV	O, T, E	
Building integrated energy conversion	Integrated solar thermal collectors	T	BIEC are technologies integrated in glazing components that enable the building to harvest or convert energy from renewable sources such as solar irradiation [60]. The energy can be converted to thermal energy or electricity and be directly or indirectly connected to other building systems.
	Integrated photovoltaics	E	
	Integrated photovoltaic-thermal	T, E	

2.3 Challenges of performance prediction of ABEs in whole building simulation tools

The use of building performance simulation (BPS) plays a critical role in modelling ABEs because of the considerable number of inputs to process, and the overall higher complexity of the systems. BPS is currently one of the most suitable tools for informed decision-making in building design, energy use prediction, building energy system sizing, fault detection and integration of renewable energy in buildings [68,76,77]. However, modelling and simulating ABE's multi-physical performance and intricate design are non-trivial tasks. This difficulty is reportedly one reason why ABEs still have a relatively low real-world uptake despite their potential advantages [78,79]. Research shows that there are two main barriers to the uptake of ABEs:

1. The first issue relates to a lack of knowledge about how to benchmark or systematically characterize ABEs compared to traditional envelopes.
2. The second difficulty is tied to the reduced possibilities to model and simulate ABEs in whole building monolithic legacy simulation tools.

Characterization challenges

Some of the most significant work on advanced building envelopes was carried out by the International Energy Agency (IEA EBC) in Annex 44 "*Integrating Environmentally Responsive Elements in Buildings*" [80]. The conclusion of this work outlined that responsive buildings show great promise as a concept. Still, their successful implementation is hindered by the lack of information about the technologies, their integration process, and their expected performance [81]. This research was also able to determine that there was not enough knowledge available about the methods required to design, develop, and integrate the systems to allow buildings to become more responsive. Another difficulty of implementing advanced (responsive) technologies, in the case of ABEs, is that it is not possible to capture their entire performance and impact using the traditional performance metrics for building envelopes (e.g. thermal transmittance values) [78]. This is a critical issue given that the gap between in-design and real-life performance in buildings can be significant in low energy designs [82,83]. There is also no reason to believe these discrepancies will not grow even larger when increasingly complex integrated building technologies are introduced. As a result, it is then clear that ABEs require new knowledge and methodologies to better understand, characterize, and predict their behavior. This is especially important with regard to evaluating their *integrated performance,* meaning their effect on whole building performance and the interplay with the other parameters of a building, as was highlighted by the IEA Annex 44.

Limitations of monolithic tools

To understand why predicting the performance of ABEs in BPS is a difficult task, it is important to first understand how whole building simulation tools are built. Most (whole building) BPS tools are monolithic legacy tools. This means that they were designed to simulate one (or a selected few) physical domains at a time. These domains may enable thermal simulations, daylighting simulations, airflow simulations, or simulate building services (Figure 2-4). In the past decade, BPS tools' capabilities have substantially improved as they have benefited from continuous development in active communities, and gradually incorporated new modelling possibilities, options, and added features [84–88]. However, these tools still suffer from several limitations due to their code structures or the equations they implement [64].

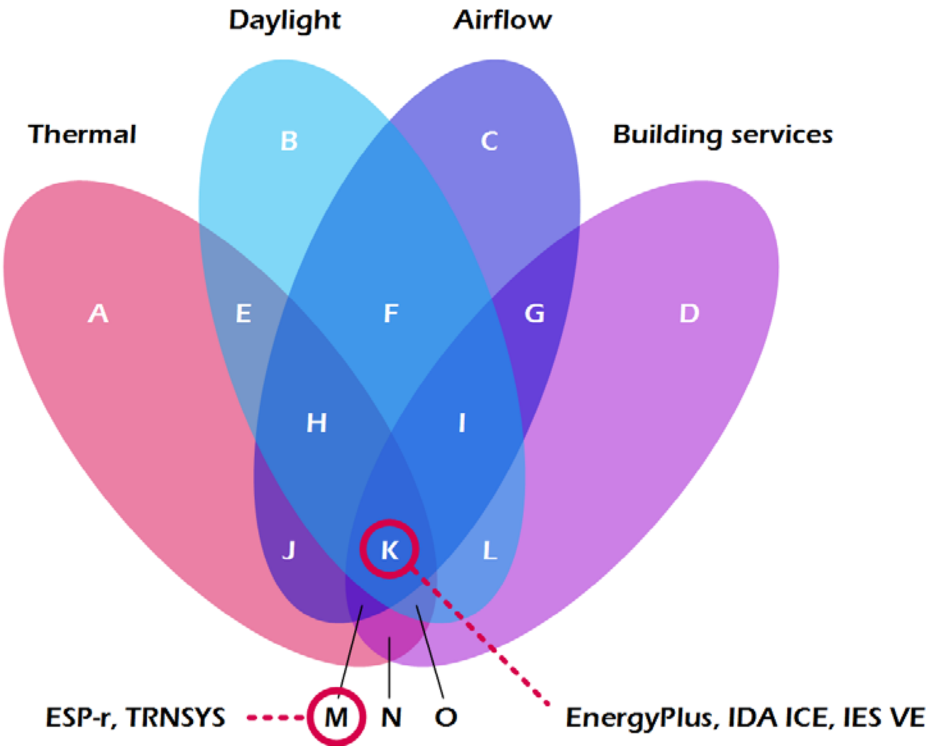


Figure 2-4 Monolithic Building Performance Simulation tool capabilities – original figure in [86].

Monolithic legacy tools typically have large codebases, which are difficult and costly to update and maintain. The combination of these tools' structure and the growing demand for advanced multi-domain simulations makes it difficult for them to keep up with the pace and the diversity of developments in building envelope materials and systems. This has resulted in a situation in which, currently, there is a gap between innovation in envelope technologies, and our capacity to model the systems as integrated parts of a whole building using monolithic software [86,89]. While ABEs can more easily be modelled as individual components in specialized software, this approach does not resolve the issue of assessing their integrated performance i.e. evaluating their impact on the whole building performance. This is an issue because it is expected that most of the added-values of ABEs lie in how they interact with and serve the building, not in their standalone behavior.

In the case of ABEs, the simulations required to predict the systems' performance are particularly complex. The models must allow for increasingly dynamic evaluations across multiple physical domains, with more advanced material properties, designs and control strategies. Loonen et al. [64] provide a complete overview of the main challenges of modelling and simulating advanced building technologies like ABEs. In addition to the rigidities in the structure of the tools due to their original intended purpose, they highlight the limited to non-existent capabilities to integrate a BPS tool with other software types or with dedicated models of specific technologies.

Additionally, most whole-building simulation tools only allow for a limited number of control strategies for ABE systems. This particular issue limits the possibility to account for stochastic user behavior or advanced control strategies based on climatic triggers, building states, or external factors such as energy prices [90]. The resulting situation is that there is currently no single whole building simulation tool able to accurately model all of the physical phenomena required in the performance assessment of ABEs [78,86,88,91]. Table 2-2 provides examples of the requirements in BPS to model specific types of properties common to ABEs.

Table 2-2 Fundamental properties and functions of ABEs and associated requirements in BPS.

Fundamental properties	Requirement in BPS
Multi-physical modelling (i.e. considering heat, moisture, light, energy, air, sound) of the interactions between the envelope, the indoor environment, and building services [64]	Requires solving the differential equations of different physical domains in a coupled way with an appropriate spatial and temporal resolution
Flexibility to integrate models of emerging technologies which may not be directly available in specific BPS tools [64]	Requires the possibility to develop or integrate dedicated models of advanced technologies into whole building simulation tools to consider coupled interactions with the rest of the building
Possibility to model time-varying facade properties that are controlled by boundary conditions (e.g. passive adaptive building envelope technologies such as phase change materials [92] or thermochromic materials [93]) or an input signal (e.g. active smart glazing [28])	Requires the possibility to simulate the dynamic operation of facade adaptation across multiple physical domains in coordination with the operation of building services or using specialized control-oriented software [94]
Possibility to simulate interactions between ABE systems and building occupants (for dynamic and/or controllable technologies).	Requires the possibility to integrate dedicated models replicating the stochastic nature of human behavior and interaction with advanced building envelope elements [95,96]
Possibility to integrate performance-based generative design and architectural form-finding workflows, for example, for systems with complex and kinetic geometries [97].	Requires the possibility to couple flexible design tools with input interfaces of BPS software.
Greater need for sensitivity and uncertainty analysis tools for model validation and calibration schemes to understand the influence of ABE design parameters on relevant building performance indicators [98], or conversely, of changing scenarios on design parameters [99]	Requires integrating approaches and models for global and local sensitivity analysis in BPS tools
Possibility to use numerical optimization tools to explore larger solution spaces [100] based on ABE design elements or properties	Requires coupling inputs and outputs of models and simulations to external algorithms and automatize the processes for simulation launching, output collection, and data analysis

Workarounds and modular approaches to simulation

To overcome the limitations of monolithic simulation tools, modellers have turned to several different strategies. Some of the most used workarounds, for example, to model dynamic properties of ABEs are described in [86]. Other approaches have been for modellers to develop their own codes in a different environment and connect these to a simulation engine (for example, to model phase change material in [92], or heat exchange parameters of integrated solar thermal systems in [101]). An increasingly promising solution originally developed to model HVAC systems [102] is to use modular approaches to building simulation. This method is known as co-simulation and consists of connecting multiple, specialized simulation engines. Each sub-model is simulated by a dedicated engine specialized for the task or the physical domain considered. The co-simulation approach allows the different engines to exchange data at different time steps during the simulation run-time. Applying this method requires a certain level of expertise. Its benefits are not widely documented for building envelope modelling, so its application for this topic is still limited.

2.4 The fit-for-purpose approach

The difficulty of choosing the right modelling approach for an ABE, which will accurately capture the desired properties of the technologies for the given context, is compounded by the fact that there can be many modelling approaches to choose from. But as model complexity grows and the number of inputs is large, it becomes increasingly important to ensure that the modelling approach selected fits the desired assessment's purpose. This is especially relevant when one aims to develop their own model and needs to define the level of detail used or pick between several approaches in modular simulation schemes. Robinson [103] discusses the difficulty of knowing what the best model to develop is, and the process of deciding what should and should not be included. The author describes conceptual modelling as the process of determining what to model, or as they define it, establishing "*a non-software specific description of the computer simulation model (that will be, is or has been developed), describing the* *objectives, inputs, outputs, content, assumptions and simplifications of the model”*. In describing this process, Robinson makes several key points. The first one is that the conceptual modelling approach is separate from the software. Second, it underlines the importance of knowing the outputs of the model. This means that it is impossible to create an appropriate model without understanding its purpose. Knowing the purpose of the model, the objectives, the inputs and the outputs is essential to defining the model’s content. This comes down to understanding the scope (what to model) and the level of detail (how to model it) that one should use.

The fit-for-purpose methodology [104] is a method similar to the recommendations made by Robinson. It encourages considering the needs of the model before deciding on a modelling environment or simulation software. An illustration of this methodology, applied to the modelling of solar building envelopes (SBE), a sub-category of ABEs, is provided in Figure 2-5. The main physical domains (Thermal, Electrical, Airflow, Daylight) and their control aspects are the elements that will be decisive in developing the conceptual model of the technology investigated. This defines “what is needed”. Then, the “how” is determined by the capabilities of existing simulation tools or models. In theory, the intersection of the “what”, the “how”, the constraints, and the available knowledge will define the most fit-for-purpose modelling strategy and simulation constraints, and the available knowledge will define the most fit-for-purpose modelling strategy and simulation.

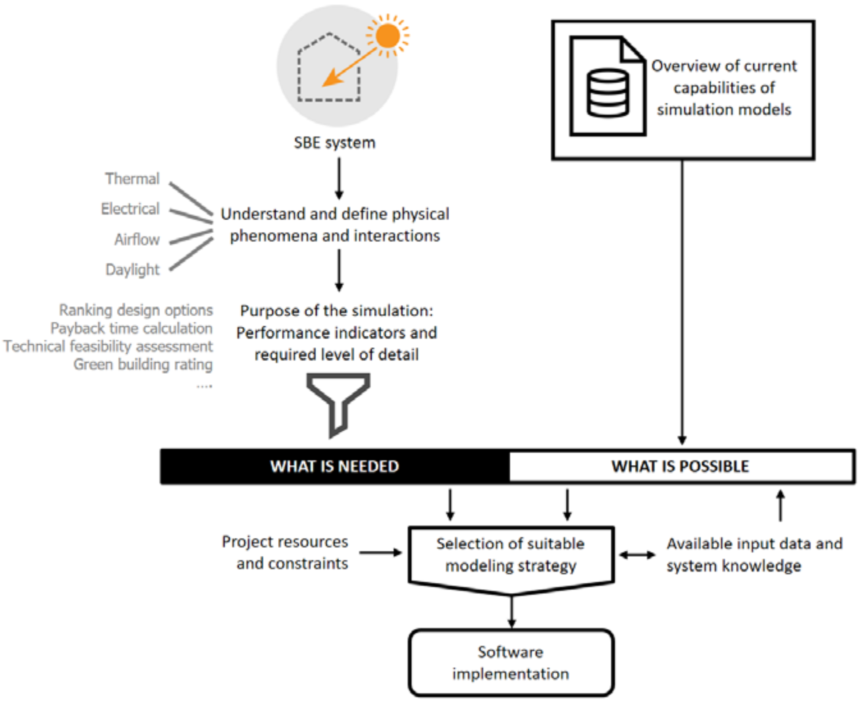


Figure 2-5 The fit-for-purpose methodology applied to solar building envelope design. Original illustration in [230]

3 Knowledge gap and research questions

3.1 Knowledge gap

As the building sector embraces a more digital path and integrates new technologies and building materials, there is an increasing need to develop and strengthen building simulation approaches. In the context of ABEs, this includes methods that can help improve our understanding of the technologies and how to model and simulate their performance more accurately. This task is currently challenging because of the multi-disciplinarity, complexity, and diversity of ABEs, which monolithic simulation tools cannot always tackle. The literature suggests that a potentially viable path to overcoming current limitations is to use more advanced simulation strategies based on co-simulation, parametric design, and numerical optimization. However, the challenges of modelling ABEs are not reduced to software issues. They also stem from the difficulty of setting up an appropriate modelling strategy depending on the system being modelled. Additionally, the information available to build reliable models and carry out robust simulations may be very fragmented, case-specific, or require different workarounds.

More specifically, the modelling and simulation approach may vary depending on:

a. The type of technology

b. The modelling skills of the person carrying out the simulations

c. The method of simulation required (mono- or co-simulation)

d. The possibilities in the BPS software selected and the type of model(s), its (their) precision and structure

e. The inter-model compatibility in co-simulation

f. The input that is available and which key output parameters to use (purpose of the simulation)

g. The meaningfulness of the outputs of the simulation and limitations of the tool itself

Overall, the knowledge gap identified in the literature is multi-faceted and can be summarized with the following propositions:

- There is a lack of methods that can systematically characterize such a diverse group of technologies as advanced building envelopes and do so in a way that the models can be built following a fit-for-purpose approach.
- Monolithic simulation tools present several limitations when it comes to modelling ABEs. This creates a need to explore new simulation approaches and investigate how and to what extent these can help overcome some of the limitations.
- Methods based on parametric design and optimization have shown to be promising as a way of creating more freedom in façade designs, but their potential and robustness are not yet fully explored.
- There is little knowledge about how to systematically analyze the opportunities, challenges, and limitations that modelers face when using new approaches, particularly when using co-simulation or numerical optimization.

3.2 Research questions and contributions of knowledge

This thesis aims to close this knowledge gap by investigating how combining a fit-for-purpose methodology and new modular simulation tools and techniques can be used to model ABEs. It also aims to improve the design and performance of ABEs by facilitating the handling of multi-criteria decision-making and multi-physical performance assessment considering performance tradeoffs (i.e. between energy use, occupant comfort, material efficiency, costs etc.).

This results in the following research questions:

1. What are the main characteristics of ABEs that must be considered to ensure a suitable design and modelling approach in the early design phase?

2. What are the opportunities, challenges, and tradeoffs associated with using co-simulation to improve and to evaluate the performance of ABEs?
3. What are the benefits of using modelling approaches based on a combination of parametric design, co-simulation and numerical optimization for ABEs?
4. What are important decisions modelers need to make when using numerical optimization to improve performance and what is their impact on the result?

The answers to these research questions are given using the work developed in five peer-reviewed scientific journal articles, as shown in Figure 3-1.

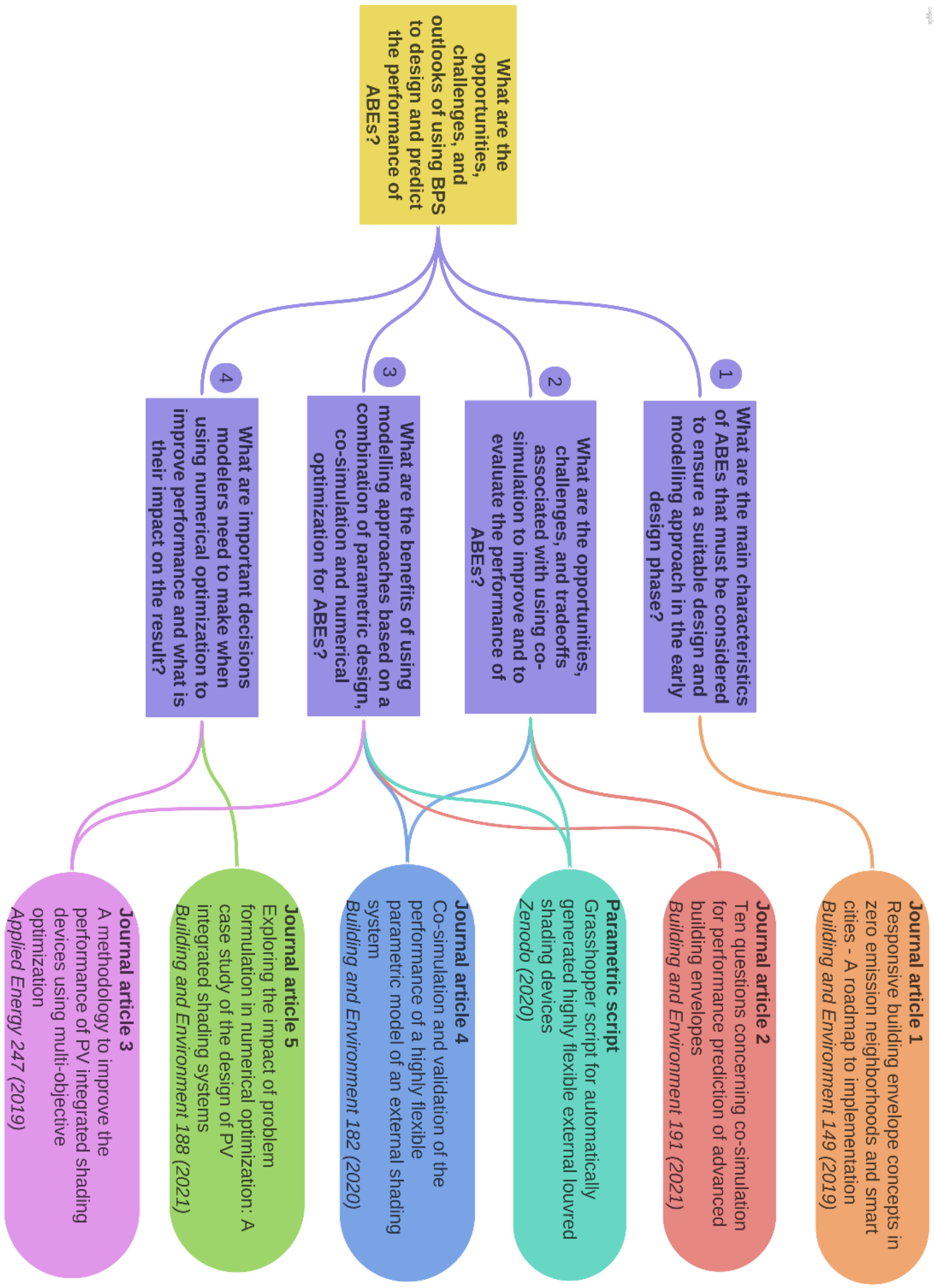


Figure 3-1 Organization of the research questions in the thesis and answers in the journal publication contributions.

The journal article contributions are listed as follows:

Journal article I

Responsive building envelope concepts in zero emission neighborhoods and smart cities - A roadmap to implementation

E Taveres-Cachat, S Grynning, J Thomsen, S Selkowitz

Building and Environment 149, Pages 446-457 (2019)

Journal article II

Ten questions concerning co-simulation for performance prediction of advanced building envelopes

E Taveres-Cachat, F Favoino, R Loonen, F Goia

Building and Environment 191, 107570 (2021)

Journal article III

A methodology to improve the performance of PV integrated shading devices using multi-objective optimization

E Taveres-Cachat, G Lobaccaro, F Goia, G Chaudhary

Applied Energy 247, Pages 731-744 (2019)

Journal article IV

Co-simulation and validation of the performance of a highly flexible parametric model of an external shading system

E Taveres-Cachat, F Goia

Building and Environment 182, 107111 (2020)

Journal article V

Exploring the impact of problem formulation in numerical optimization: A case study of the design of PV integrated shading systems

E Taveres-Cachat, F Goia

Building and Environment 188, 107422 (2021)

The value and impact of these contributions include:

- The first development of a framework to help characterize and implement advanced building envelopes with a scope that can be adapted to different urban scales in early phase planning and serve the fit-for-purpose modelling approach.
- The first comprehensive publication about the opportunities, challenges, and outlooks of applying co-simulation for performance prediction of advanced building envelopes.
- A modelling methodology based on parametric design, co-simulation and numerical optimization to model and simulate the integrated performance of a photovoltaic shading device.
- The first validation with a full-scale experimental analysis of a co-simulated parametric modelling approach developed in Rhino/Grasshopper and describing the coupled thermal and daylighting performance of multiple configurations of an external shading device.
- An open for download validated highly flexible script allowing to model and simulate the thermal and daylighting performance of an external louvred shading device in the Grasshopper/Rhinoceros environment.
- The establishment of the concept of problem formulation in numerical optimization and an exploratory study of its impact on optimization results. This work includes guidelines for parameter settings in genetic algorithms which were not previously available for architectural or building design applications, as well as one of the first a systematic analysis providing key insights about optimization result robustness.

4 Research design and methods

In this thesis, several methods are employed to design an overall research strategy. The work developed during my PhD followed an iterative learning procedure. The angle chosen to lead the investigation became more and more refined as both the software used evolved through new releases, and my own skill level as a parametric design user and modeller increased. This section explains the thought process leading up to this extended summary's final shape and highlights how the different methods used allowed answering the research questions investigated. This chapter thus describes a general approach. More details about the specific methods and the justification for each one of them can be found in each journal publication.

The thesis's starting point required understanding what types of technologies make up the heterogenic group of building components called "advanced building envelopes" and why their atypical properties made them challenging. This knowledge was gathered through narrative literature reviews [105] covering both the technologies available on the market and the current models used in building simulation tools to model different physical domains (light, heat, moisture etc.) [73]. These findings highlighted the complexity of modelling ABEs and the divide between what is possible with the standard approaches implemented in simulation tools, and what is needed to model ABEs in terms of flexibility and physical representations.

4.1 Regarding research question 1

The first research question about how to systematically characterize these technologies emerged as a necessary step to improve modelling approaches. This work initiated as a narrative literature review [105] focused on identifying previous characterization efforts for advanced technologies. This review's results were then critically analyzed to map which parts of the issue had been addressed in different studies. This analysis then made it possible to identify the remaining research gaps from the perspective of building performance simulation and strategies for energy management planning in zero-emission neighborhoods. The result of this work was an entirely new framework created as a step-by-step characterization guide, and which was published as the first journal article developed during this thesis. Its main added-value for building simulation was that it was built to support the fit-for-purpose modelling approach, which had been identified as a crucial element for modelling ABEs. In the concluding remarks and reflections following the completion of this work, it also became evident that modelling advanced building envelopes required more than just flexible approaches to abstract their innovative properties. They also needed more accurate multi-physical modelling than a typical wall or window would. Previous studies in the literature had been pointing to co-simulation, a technique used in many different industries, including building HVAC systems for almost 20 years as a means of overcoming this issue. Investigating its application for advanced building envelopes then became the core of the second research question in this thesis.

4.2 Regarding research question 2

The materials used to answer the second research question were developed in this thesis's second journal publication. These were based on knowledge acquired through several previous narrative literature reviews and the personal experience in BPS software of the different authors that contributed to the publication. Part of the knowledge presented in this section of the thesis also stems from personal reflections about how different methods and platforms that were not explicitly developed for co-simulation or advanced building envelopes could support their development. The "Ten Questions" format of the publication is a particular one that requires authors to find well-defined topics and formulate ten questions and answers relating to the most pressing research needs in the area [106]. The goal of these publications is to be visionary, authoritative and address many stakeholders. As a result, the method used to develop this research was anchored in story-telling and creating a series of questions that would lead the reader through a critical reflection on the topic. As such, part of the emphasis was put on future developments of co-simulation schemes focusing on the integration into digital workflows and efforts to digitalize the building industry through integration with BIM and digital twins.

4.3 Regarding research question 3

The next step in this thesis's methodological development was to use the previously gathered knowledge to investigate how using new simulation approaches and the implementation of performance-based design in a case study. The need to use a case study is justified because it is not possible to provide a complete and detailed answer to the research question for every possible type of ABE. However, by selecting one type of ABE technology that illustrates some of the main challenges, it was possible to explore a smaller problem in-depth and extract general knowledge and conclusions relevant to many ABE systems.

This part of the knowledge development process was particularly iterative and relied on parametric scripting and thinking [107–109], numerical optimization based on genetic algorithms [110,111], and co-simulation using building performance simulation [112]. More details about the specific approaches used are given in the third journal publication listed as part of the thesis contributions. Parametric scripting is very similar to computer programming in that that users have a toolbox of object types, functions, and logic tools, but the scripting flow is free and unique to each person. This means that there are many different ways to script (program) an operation, and the choice depends on the user's skill level and how they choose to process information. For this reason, the methodology developed to model, simulate, and optimize the technology selected as a case study was a continuous effort that gradually improved and became more complex as time went by. Using numerical optimization methods was also a natural step in the development of the case study. Building design or energy systems typically requires finding a balance between multiple, and sometimes antagonistic measures; which is why they are often referred to as multi-objective optimization problems by nature. The final design of the model presented uses a combination of the previous methodologies discussed: the fit-for-purpose approach, parametric design, co-simulation and numerical optimization. The study's goal was to demonstrate how these methods could create performance-based design workflows useful for early design investigation.

This modelling approach's reliability and accuracy were also investigated using experimental analysis in a full-scale test facility and model validation [113,114]. This step was essential to understand the extent to which simulation results from new modelling approaches compared with the system's real performance. For this chapter of the thesis, the methods used were experimental analysis and modelling techniques related to automated model calibration and model verification using statistical quantities [115,116]. The fourth journal publication listed in the thesis's contributions provides in-depth details about how the different methods were applied and justifications for the choices of the metrics used. The script used for the validation was also shared on an open-source file repository [117].

4.4 Regarding research question 4

The methods used in the fifth journal article listed in this extended summary and which aims to answer the final research question are based on a critical literature review [118] and a simulation-based investigation. The literature analysis about the necessary steps and decisions that lead up to an optimization procedure was analyzed and classified under an activity defined as problem formulation. Two main categories of decisions and possible investigations one can carry out were established and named "soft" and "hard" problem formulation. The simulation-based investigation's goal was to explore problem formulation and focus on the impact of modellers' choices. To do this, a different analysis of the case study previously presented is carried out and used to provide insight to readers about how their modelling choices may impact their simulation results.

5 Design considerations for advanced building envelopes in early design phase

Advanced building envelopes are expected to play an important role in the conception of zero-emission buildings and neighborhoods. The most promising aspect of these envelopes is that they can implement different technologies with innovative properties. For example, these systems can provide an optimized balance between various energy flows crossing the façade. Other types of goals could be to adjust their properties to enhance the user's experience of the indoor environment or actively participate in managing the building's operative requirements and the available renewable energy resources. However, the lack of knowledge about how to systematically characterize ABEs, given the breadth of technical systems, leads to difficulties in comparing the systems to one another (or to conventional solutions) or evaluating them holistically.

In this chapter, the classification framework developed in the first journal article of this thesis is presented [119]. This framework was designed as a six-step procedure that can either be used to find a suitable ABE solution based on criteria or to characterize a given solution using the selected criteria. The following section first provides a brief background for developing a characterization framework and presents the main knowledge gaps identified in the analysis of the existing literature. The proposed framework is then presented as a detailed walkthrough of the procedure to follow in each step.

5.1 Background for the characterization framework

Advanced building envelopes are anchored in multi-disciplinary, whole building performance principles. As mentioned in Chapter 2, ABEs also make up a heterogeneous group of technologies and systems, which may present differences on multiple levels. The lack of knowledge surrounding ABEs and methods to characterize them systematically was also one of the reported challenges of implementing ABEs in real-world projects according to the IEA Annex 44 [3]. Following the IEA's findings in Annex 44 and their first proposal for a classification in [120], other authors have also attempted proposed extended classification to enrich the field. These efforts include single technology classifications, such as it is suggested in [121] and [122], and holistic approaches such as the one presented in [123]. All of these existing classification systems have many strengths and address important knowledge gaps. However, they mostly adopt different focus areas or approaches that fall short of capturing relevant elements considered in this thesis. This is discussed more in detail in the first journal article, which this thesis builds on [119]. For instance, the standalone classification frameworks do not consider different triggers for the responses such as user needs or controls anchored in demand side management strategies.

The work presented in the next section builds upon the reviewed existing classification. However, it attempts to fill in the gaps identified by introducing the missing elements required to characterize RBE clusters. The result is an extended classification which should be seen as a roadmap to implementing ABEs in ZENs and smart sustainable cities. This roadmap can be useful in early- and later planning stages and provides sufficient flexibility to be applicable to existing and future envelope technologies.

As a result, conventional performance characterization methods are not sufficient to capture the entire performance of ABEs. The difficulty of modelling these complex systems' behaviour adds to the existing challenge of closing the gap between in-design performance and real-life performance in buildings - as these discrepancies are likely to grow larger in low energy buildings or when increasingly complex building technologies are introduced [82,124]. Thus, advanced building envelopes require new knowledge to help understand, characterize, and predict the behavior on multiple levels and, in the perspective of zero-emission neighborhoods, different scales of systems.

The framework developed and presented in this thesis is built as a six-step procedure, as shown in Figure 5-1. The five first steps allow to gradually map a specific ABE system's characteristics or outline criteria used to assess possible design strategies and solutions relevant to a particular project. The final step, Step 6, relates to the identification of the technological solutions and verifying that the responsive system performance is in line with the defined purpose. Compared to previous existing propositions in the literature, the added-value of the framework is that it is built in a way that it is precise yet flexible enough to characterize a broad range of technologies. It also considers several triggers for responses, in addition to being scalable to different system sizes (building, a cluster of buildings, or a neighborhood). The following section provides a step-by-step walkthrough of the framework and details about the different procedures that need to be undertaken in each one of them.

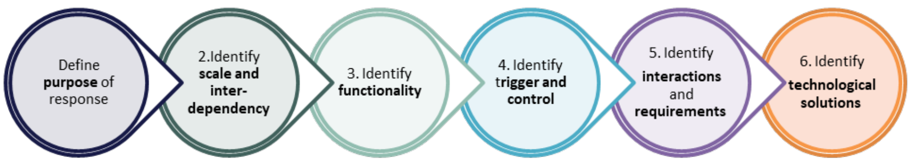


Figure 5-1 The six steps of the early phase design framework proposed. Original figure in [119].

5.2 Presentation of the six steps in the framework

Step 1: Defining the purpose and objectives of the response.

The first step of the framework is to define the purpose of the advanced building envelope technology as part of the building design strategy and, if applicable, in the neighborhood. There are three main categories of purpose: energy performance, user needs, and demand-side management. Figure 5-2 illustrates how advanced building envelopes can be integrated at different scales nested into each other. Each purpose is further described by a set of specific objectives, which work towards specific target actions and associated functionalities to achieve the given purpose. A key takeaway from this first step is to consider whether these are contradictory or compete in any measure. If so, different approaches to balance the system's goals in its design will need to be considered to either determine a hierarchy of importance or a solution based on compromise (as done, for example, in [125]).

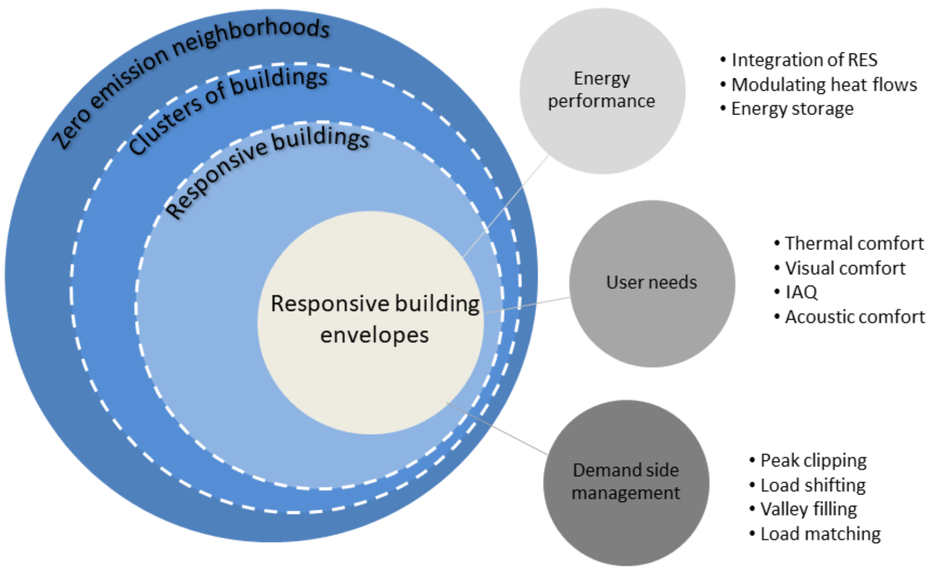


Figure 5-2 The purpose of advanced building envelopes with different scales of design. Adapted from the original figure published in [119].

Step 2: Identifying the scale and interdependencies in potential responses.

As mentioned previously, there are different possible scales of action or impact, depending on the type and the purpose of the advanced building envelope. When considering a larger scale of impact, it is important to understand how smaller groups of buildings can function alone or as a synergetic cluster. The idea is to design groups of buildings as interconnected nodes that share information or thermal and electrical energy. The collection of all the nodes form one large entity connected to the grid as an IoT system maintained by a primary manager (Figure 5-3).

The secondary networks are smaller clusters of buildings that can exchange resources in different optimized patterns or at different time intervals. This distributed configuration is useful to create multiple levels (named secondary information networks in Figure 5-3) of management within a neighborhood.

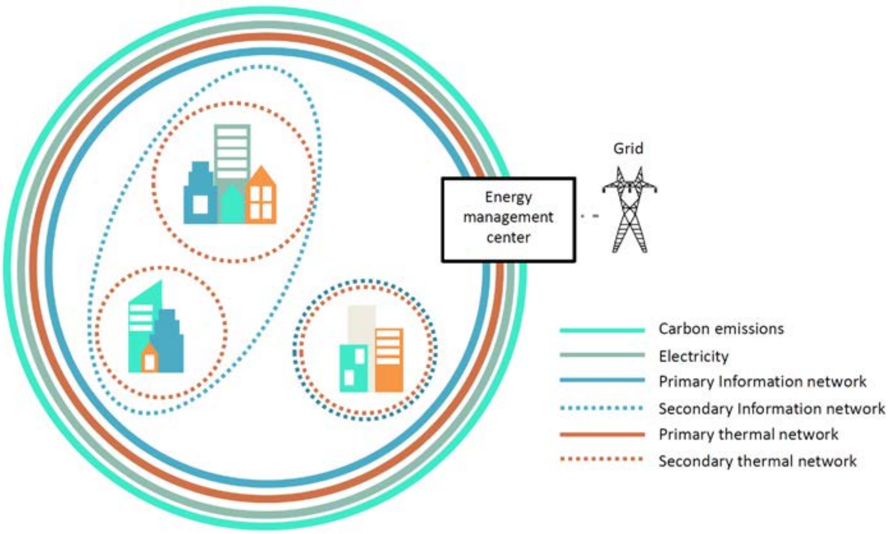


Figure 5-3 Scales of exchange within networks of buildings. Original figure in [119].

The complexity of the responsive cluster requires an underlying network of information flow to be established between the buildings. This is so that energy use can be managed in real-time conditions or even ahead of time. Orchestrating such a flow of information and energy requires careful consideration. Some advanced building envelope systems may have very different time-scales in terms of control or varying degrees of influence on the whole building performance. For example, some technologies may respond to stimuli within seconds or minutes (i.e. window opening, daylighting control, natural ventilation systems etc.) but may only impact a zone. Other systems may have much slower response times and possibly influence energy parameters at larger scales (i.e. thermal energy storage availability, battery charging status etc.).

Step 3: identifying the functionality of the advanced building envelope system.

The functionalities of advanced envelopes are linked to the purpose defined in step 1 and specific objectives. Table 5-1 provides an overview of possible functionalities associated with these objectives.

Table 5-1 Functionalities of advanced building envelopes

Purpose	Objective	Functionality	Description
Building energy performance	Intelligent energy management to reduce energy use	Recovery and conservation of available energy	Reduce energy use by modulating heat flows to maintain an optimum energy balance by promoting (admitting ingoing energy flows), preventing (protecting the indoor space from undesirable energy flows) and reducing energy flow through the envelope.
		Energy buffering	Peak clipping by using solutions to reduce the magnitude of the impact of an energy flow.
	Increase self-sufficiency	Energy storage	Load shifting by storing energy within the building.
		Renewable energy integration	Optimize energy conversion at building scale by changing system configuration to maximize renewable energy harvesting.
User comfort	Ensure the health and wellness of users Increase productivity	Indoor air quality	Reduce pollutant concentration in indoor spaces.
		Thermal comfort	Prevent discomfort due to drafts and vertical temperature gradients. Prevent overheating. Maintain comfortable operative temperatures.
		Visual comfort	Limit risk of glare Provide satisfactory levels of daylighting on work planes. Provide spaces with comfortable color temperatures. Provide satisfying color rendering.

Demand side management	Intelligent energy management to increase grid-friendliness	Reduce peak loads	Manage energy flows and energy sharing of electrical and thermal energy in clusters of buildings via use of smart control technologies.
			Control of high efficiency renewable energy conversion systems to reduce peak loads and optimize conversion parameters in building clusters.
		Peak load shifting Valley filling	Control of energy storage systems for surplus energy storage and distribution within cluster.
		Strategic conservation Strategic load growth Flexible load shape	Use of optimization and model predictive control to set up grid energy consumption/resell strategies based on given parameters (energy source, carbon intensity of energy, energy cost…).

The functionality of the advanced building envelope systems developed to improve building energy performance and user comfort is defined as an extension of the classification [126]. At these levels, the critical functionalities are solar energy harvesting, solar energy conversion, and energy storage. This comes naturally since solar energy management is a well-known factor in designing zero-emission buildings. Figure 5-4 shows an adapted illustration from the work of Looman [123] with the inclusion of the additional functionalities for energy conversion and dynamic features like “magnify/modulate” and possible triggers for dynamic, advanced building envelopes.

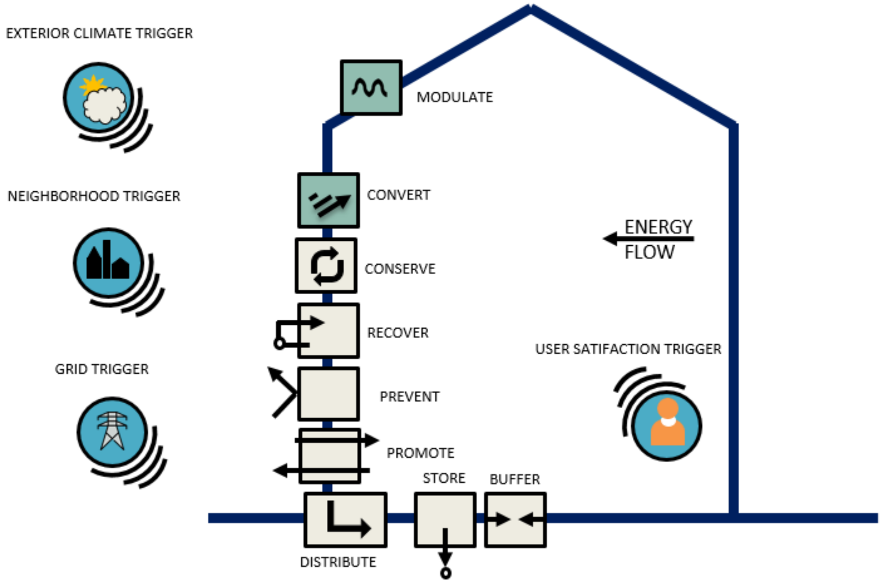


Figure 5-4 Envelope functionalities and triggers. Original print in [123].

When considering a higher level of energy management, demand side management becomes an important topic by considering grid or building-to-building interactions. Demand side management (DSM) functionalities can improve grid-friendliness and play a critical part in reaching zero-emission targets. DSM is the planning, implementation, and monitoring of grid interaction designed to produce changes in the building or neighborhood's load shape. It is achieved by changing peak energy consumption demands and modulating time-related energy use patterns. The functionalities of DSM revolve around the six strategies shown in Figure 5-5.

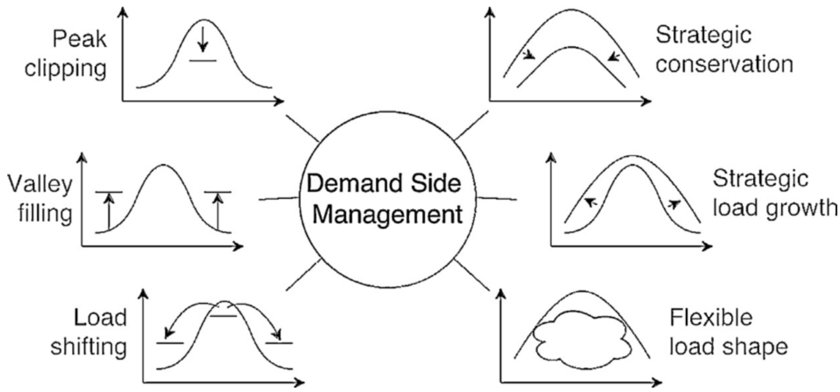


Figure 5-5 Strategies for demand side management reprinted from [127].

Step 4: Identifying triggers and controls for responsive advanced building envelopes.

In this section we distinguish single building related triggers and neighborhood related triggers. At a single building scale, control triggers are typically based on local external climate parameters (e.g. incoming solar radiation, wind speed or outdoor temperatures), local indoor climate conditions (e.g. operative temperatures or lighting levels) or user requests (e.g. personal preferences or changes in building schedules). In these cases, the aim is most often to optimize conditions in one zone or a single building. For this reason, the control strategies typically have shorter time horizons (seconds, minutes or hours). These controls may be intrinsic or extrinsic (e.g. opening windows, activating solar shading, activating artificial lighting or natural ventilation). The variation in the types of triggers and control strategies underlines the fact that advanced building envelopes can range from relatively simple systems to very complex ones. Here, it is important to note that "more complex" does not mean "better performing", and one of the outcomes of this step is to evaluate what kind of technologies are suitable for the project.

At a neighborhood scale, the triggers also include energy management within multiple buildings with control strategies that aim to fulfil optimization goals with longer time horizons (hours, days, weeks, seasons). Although DSM-related triggers are possible to implement at a single building scale, these are constrained by the building's energy flexibility in question. Neighborhoods are made up of different types of buildings and constructions, which, in theory, creates more flexibility for energy management due to the range of uses of the buildings. Triggers for neighborhood energy management can be based on the current or predicted energy use of the building cluster, grid energy prices, or the purchased energy's carbon intensity.

Within these trigger categories, we define three types of values: fixed, scheduled and real-time. Fixed triggers are mostly used for passive design (e.g. average annual ambient temperatures, sun angles or annual average internal load). As their name suggests, scheduled triggers are based on schedules or diurnal cycles (for example, sun paths or fixed events). Real-time triggers are direct stimuli from feedback-based values of parameters measured by sensors (e.g. CO2 levels, operative temperature, or occupancy detection). The responsiveness of a building component or system is tied to the control strategy, which is either intrinsic or extrinsic. Intrinsic and extrinsic behaviors are described [86] as: *"Intrinsic indicates that the adaptive mechanism is automatically triggered by a stimulus (surface temperature, solar radiation, etc.). Extrinsic refers to the presence of an external decision-making component that triggers the adaptive mechanisms according to a feedback rule".*

The possibility for responsive building envelopes to be sensitive to different triggers is a large part of their robustness. Table 5-2 presents the trigger categories and types, along with the associated type of control of the response.

Table 5-2 Typology of responses for advanced building envelope components (adapted from [98]). N.A. stands for "non applicable".

		Type of control		
		Passive	Active - Extrinsic	Cognitive - Intrinsic
Trigger category	**Type**			
Exterior local climatic	Fixed value			
	Scheduled value			
	Real-time value			
Interior local climatic	Fixed value			
	Scheduled value			
	Real-time value			
User demand	Fixed value			N.A.
	Scheduled value			N.A.
	Real-time value			N.A.
Neighborhood management	Fixed value			N.A.
	Scheduled value			N.A.
	Real-time value			N.A.

Step 5: Identifying interactions and requirements - The building users.

Responsive facades with automated controls play an important role in balancing different indoor environmental quality parameters such as glare discomfort, operative temperature, daylighting levels, air quality, privacy, and view to the outdoors. However, user interaction and satisfaction are two primary factors that shouldn't be disregarded in the implementation and operation of dynamic automated building systems. User well-being and acceptance are directly correlated to the perception occupants' have of controlling their environments [128], and as such, the possibility to overrule systems is an important aspect [129]. When planning the responses of advanced building envelopes, it is important to consider different control types for the systems depending on the type of system, the trigger, and the response characteristics (scale of response and timeline associated). An overview of different response typologies is given in Table 5-3 with a short description of the control details. An important consideration in this step is that not all advanced building envelope systems are built to interact with occupants. For example, systems that respond to objectives of load management (LM) or energy performance (EP) strategies may have no interaction with users. These systems may rely on intelligent/learning controls such as model predictive controls (MPC) to respond in the most efficient way possible to different triggers and requirements. Automated system with intelligent controls aimed at improving IEQ and support EP strategies refers to systems that can utilize previous and predicted user behavior to determine their current state or actions, meaning that users indirectly influence them. These controls are seen as an essential attribute to reconcile user needs, and the responsive systems' energy-saving potential, two objectives that may sometimes be antagonistic. Control strategies that users can overrule are considered semi-direct interactions and include controls defined by sensors, reinforcement learning controls, or schedule-based controls. The override can be temporary, meaning the system will resume to its normal function after a certain amount of time, or independent in time until it is reset. Finally, some systems allow for direct manual control from the users, enabling occupants to have a higher level of interaction with the system and a perception of control. In these cases, the controls' user interface must be carefully designed to be easily understood and must be physically accessible to users. In past times that might have meant a nearby wall switch; today, it might be based on an app on a cell phone.

*Table 5-3 Typology of user interactions with responsive systems. (*Model Predictive Control)*

Users' perception of control	Trigger	Level of user interaction	Type of control	Description
Less	**LM EP**	None	Automated w/ no impact on users	Systems with goals independent of users' needs and which do not affect the users' environment
	LM EP IEQ		Automated w/ impact on users	Systems with goals independent of users' needs but which may affect the users' environment
	EP IEQ	Indirect	Automated w/ MPC *	Systems with intelligent control based on past and predicted user behavior
	EP IEQ	Semi-direct	Automated w/ short term manual override	Automated systems with scheduled-based controls that can be overruled in real-time for a short period of time before resuming original control
	EP IEQ		Automated w/ manual override and MPC*	Systems with intelligent control based on past and predicted behavior. Can be overruled in real-time
More	**EP IEQ**		Automated w/manual override	Automated systems with schedule or sensor-based controls that can be overruled in real-time
	IEQ	Direct	Manual	Systems with no automated control

Step 6: selecting an advanced building envelope technology.

The final step of the characterization process is to select a technology that fits the requirements outlined in the first five steps. This task is simplified if different advanced building envelope components have been characterized and catalogued previously. Then, one could also apply the framework in reverse order. An example of the application of this framework is detailed in the first journal paper contribution of this thesis [119].

5.3 Elements of response to the first research question

Advanced building envelopes are innovative integrated systems that aim to increase buildings' sustainability by providing flexible and efficient energy management solutions while safeguarding healthy and comfortable indoor environments. The development of these technologies has increasingly relied on building performance simulation (BPS) tools to uncover complex interrelationships. These systems operate at the cross-section of architecture, engineering, and data science. They often involve transient multi-physical parameters and advanced material properties. Using frameworks to characterize advanced building envelopes and breaking down their properties to understand the key elements of their behaviors, is a helpful step in developing a fit-for-purpose modelling approach. Obtaining a systematic breakdown of the properties that will need to be modelled is also helpful to select the simulation environment(s) that will be used to perform the simulation. As mentioned previously, the complexity of advanced building envelopes is sometimes a barrier to their real-world implementation, in part due to the limitations in the modelling possibilities offered by monolithic legacy simulation tools. What this framework can allow a modeller to do, is to determine whether the technology can be modelled within existing simulation tool, perhaps using workarounds, or whether to use a more advanced simulation approach based on co-simulation, for example.

6 Co-simulation for performance prediction of advanced building envelopes

The previous chapter of this thesis presented a framework that allows identifying the key characteristics of an ABE. Some of these characteristics can be described in different physical domains and may require detailed models to satisfactorily abstract these properties. As mentioned in section 2.3, this task is not always easy to achieve using whole building monolithic simulation software. Such tools do not necessarily capture all the physical domains with the same depth. In this chapter, co-simulation is discussed as a promising approach to overcoming these limitations. The work presented here is a shorter version of the full evaluation of the opportunities and challenges of using co-simulation developed in the second journal article listed in this thesis [130]. The first section of this chapter starts by detailing the fundamentals of co-simulation and describing different implementation strategies used in the AEC industry. Then two following sections respectively discuss the advantages of co-simulation for ABEs in design and operation and the current barriers to the practice that were identified through this research. Finally, the last section of this chapter presents new outlooks regarding how different trends in information and communication technology (ICT) and simulation could facilitate the use of co-simulation and increase its accessibility in the near future.

6.1 Co-simulation in building simulation

In building simulation, the term co-simulation refers to approaches in which different models representing a part of the overall system's governing physical relationships (e.g. thermal models, airflow models, daylighting models, etc.) are coupled. Each model is run in a separate simulation tool or unit, in a way that they can exchange simulation data during runtime and replicate the behavior of the system seen as a whole. The need to use co-simulation often arises from combining specialized, domain-specific models that are not available in the same simulation environment. Some of the advantages of co-simulation reported by Trcka in [102] are that they allow combining heterogeneous simulation approaches and effectively use the tools that are best suited to model a given sub-system. This provides the possibility to carry out rapid testing of software prototypes and facilitates parallel-shared development in distributed teams, including the option to preserve intellectual property (IP) rights. Finally, co-simulation enables multi-scale simulations that reconstruct the interactions between different sub-systems and modeling each of them with an appropriate resolution or level-of-detail. The difference between integrated (monolithic) simulation tools and co-simulation approaches is illustrated in Figure 6-1.

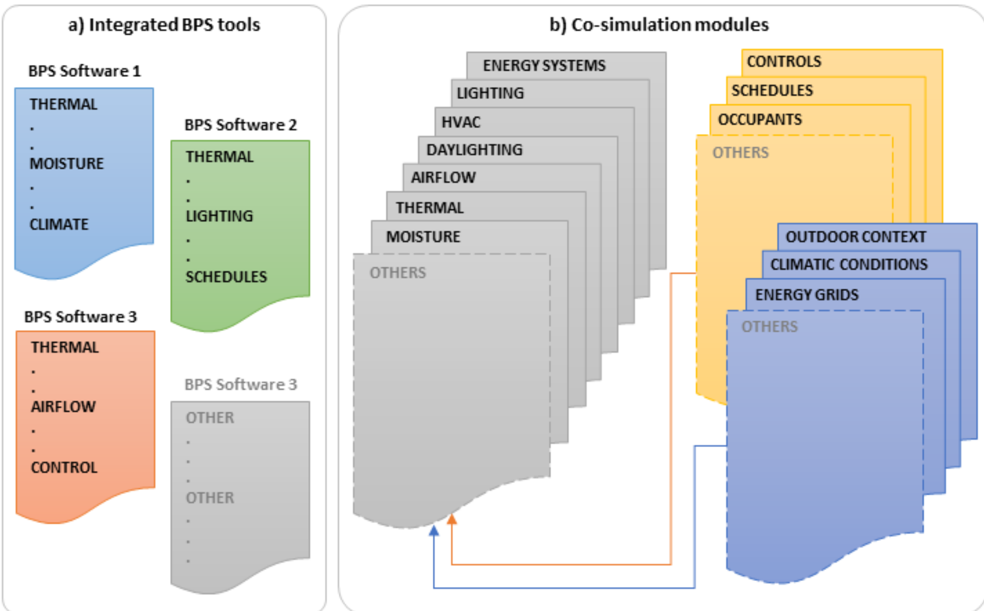


Figure 6-1 Illustration of the difference between integrated BPS tools and co-simulation modules. Original print in the second journal article listed in this thesis under reference [130].

Setting up a co-simulation approach requires specifying a number of parameters that will define different aspects of the data exchange, and which should be tailored to the task one wants to execute. The first elements to consider are the **coupling variables**, which are the parameters that will be exchanged during the simulation runtime. The recommendation is to, as much as possible, use physical quantities that can be measured and not abstracted data [102]. This is because it simplifies model verification tasks if these quantities can be measured in the real world. The second element to consider is the **coupling strategy**, which defines how the coupling will take place. In practice, there are two main strategies which are referred to as sequential and bi-directional. The difference between the two is that there is no possibility to include feedback in a sequential strategy, unlike in a bi-directional coupling approach. Bi-directional coupling is then further broken down into loose and strong coupling. Strong coupling involves an iterative process in which solvers need to meet predefined convergence criteria before moving to the next time step. In loose coupling, data is exchanged after each calculation time step is completed (i.e. each model uses the other model results in the previous time step). The most suitable strategy depends on the variability in boundary conditions and the simulation time step chosen [131,132].

The third element to consider is the **coupling technique** which can be one of the three following options: *one-to-one coupling*, co-simulation through a *middleware,* or co-simulation through *a standard interface*. Widely used applications of o*ne-to-one coupling* are, for example, implemented in the TRNSYS type 155, which connects the TRNSYS environment to Matlab. Other examples include the built-in connection between ESP-r and Radiance for coupled building energy and daylighting simulations [133], or the coupling between TRNSYS and ESP-r that made modeling of novel integrated energy systems possible [134]. *Middleware coupling approaches* are more flexible and modular since they can connect multiple (more than two) instances. The middleware task is to manage the simulation process, including the data exchange and reduce post-processing. Notable examples of platforms used in a middleware approach include the BCVTB [135] or RabbitMQ [136,137]. Finally, the so-called standard interface approach allows for direct coupling with any compatible software tool that can export a model as a functional mock-up unit (FMU). The functional mock-up interface (FMI) is a widely used standard for coupling software with several applications in the BPS domain.

The last parameter that must be specified is the **coupling frequency.** This is a critical element to consider as research has shown that it can significantly affect the co-simulation's stability and accuracy. The frequency of the data exchange can either be implemented at each time step of the simulation, or in a multi-rate approach meaning that it can use a different fixed time step or a variable time step.

When developing co-simulation strategies, all the considerations mentioned above are addressed simultaneously. This is particularly important for advanced envelope systems that exhibit complex multi-physical behavior, or that may be influenced by highly variable boundary conditions.

6.2 Advantages of co-simulation for advanced building envelopes

Co-simulation is particularly relevant in the design phase of advanced building envelopes. This is because it allows tailoring each part of a model and sub-model to the information available at that point in time, the level of modelling abstraction required, and the output desired for each physical domain. Commonly used co-simulation approaches for multi-domain evaluations of ABEs are, for example, the coupling of detailed daylighting simulations with thermal simulation engines. This approach provides a more accurate estimate of the amount of light (or heat) entering a zone, and provides insight into how the building envelope interacts with solar radiation depending on its design. For this particular case, the information obtained can be directly reused, for example, to calculate the dynamic HVAC loads. Alternatively, it could be used to evaluate indoor comfort parameters, including the risk of glare, with a much higher level of accuracy and all within the same simulation run. As a result, any design modification's impact can be estimated directly, and with a holistic approach.

However, the use of co-simulation for ABEs is not limited to design stages and is also a valuable tool to improve their operation. As discussed in Chapter 5, some advanced building envelopes are characterized by their ability to tune their properties or change their performance targets according to a triggering event. These triggers can originate from different sources such as outdoor climatic conditions, user-issued requirements, or from varyingly complex rule-based control logic [119]. In these cases, the successful simulation of the operation of an ABE not only relies on the appropriate (fit-for-purpose) modelling of its multi-physical behavior but also on the proper modelling of the triggering event itself. In many of the traditional approaches to building simulation, the possibilities to model triggers are quite limited. In co-simulation, because it's possible to link the models, one can develop a dedicated model for the triggering event and connect it as part of the control. This is particularly relevant for ABEs, considering that the systems may require modelling interactions with users, which is achieved using different methods [138].

Co-simulation approaches are also the only possibility to evaluate tradeoffs in multi-domain controls that combine different sources of information for the control logic. This is the case, for instance, in scenarios where energy performance requirements must interplay with user requirements and indoor environmental quality performance. This means that a control response for an ABE can be defined during a simulation run, based on the simultaneous evaluation of (i) a triggering event (for example, based on boundary conditions), (ii) th current state of the building given by the solver of the transport and energy conservation equations, and (iii) a pre-set control algorithm. As a result, co-simulation can allow obtaining more accurate performance evaluations of advanced envelopes and develop studies that focus on the control action itself and its optimization.

6.3 Current barriers to co-simulation

Despite the opportunities that a co-simulation approach may offer to overcome the challenges of legacy simulation tools, the process of developing them remains a complicated task. This section describes some of the main barriers to the wide-spread use of co-simulation and the elements that limit its accessibility.

Absence of guidelines and shared knowledge

The first issue discussed in this chapter is the absence of guidelines as to how or when to implement co-simulation approaches. As mentioned in section 6.1, four important elements define co-simulation approaches (the definition of the coupling variables, the coupling strategy, the coupling technique, and the coupling frequency). The choice of these elements influences the stability, accuracy, efficiency and ease of implementation of the approach chosen. Because there are very few guidelines on defining these parameters and setting up successful approaches, the accessibility of co-simulation is restricted to expert simulation users who have tacit knowledge of the software, their codes, and the mathematical and physical models used. This aspect is further reinforced by the fact that there is not yet an established culture for sharing or reusing co-simulation schemes. The result of this is that modellers capable of co-simulation often create custom-made approaches for each task and are likely to reinvent the wheel, sometimes unknowingly. While sharing knowledge and models would be a helpful step towards developing a larger user base for co-simulation, this task would require enormous effort because of the impossibility to create one-size-fits-all approaches given the nature of building simulation tools.

Lack of standardization of simulation tool structures and data

The second barrier to co-simulation concerns the lack of standardized approaches. Part of this issue is inherited from the monolithic structure of whole building simulation tools, which was developed with the exact opposite strategy of what co-simulation aims to achieve and which was to have standalone tools. The result of this is that the most widely used tools in building simulation, although developed to calculate the same final outputs, use different algorithms, different programming languages, different physical or mathematical models, and different methods to process data. And most importantly, none of these tools was initially built with the foresight to allow users to extract data at different steps of the calculation process, or includes any modularity.

In recent years, many of these tools have evolved to become more flexible as the demand for simulation has slowly changed. For example, some tools, such as EnergyPlus, have gradually switched to higher-level programming languages and evolved from Fortran to C+ and new to Python. Another notable change has been the integration in some BPS tools with modules such as the LBNL software Therm and Window libraries or the possibility of using the backwards raytracing software Radiance for daylighting studies. However, some issue regarding the exchange of data still remain. For example, these are tied to the physical and mathematical models used in the tools. Even if data can be extracted at different time steps, it is not guaranteed that the physical quantity needed as an input in one tool is available or exists as an output in the other tool. This is simply because the models may use different calculation methods or different levels of granularity in the calculations. A simple example of this can be seen when trying to extract inter-layer temperatures in walls, which are not calculated in all engines but are important to model phase change materials, among others.

Difficulty of benchmarking or verifying co-simulation approaches

Benchmarking and validation of simulation models and tools is an important step in the verification process of the accuracy and robustness of the results obtained in BPS. Conventional simulation tools are validated through numerous benchmarking procedures using standard data sets and problems such as the BesTest cases and the ANSI/ASHRAE Std-140 [139]. However, when it comes to co-simulation, the lack of standardization and guidelines previously described also makes it challenging to establish validation procedures based on a comprehensive set of standard applications. Given that individual tools are validated, one way to check the validity of a co-simulation approach could be to use a verification process [140]. This would allow to test and confirm that the data, algorithms, and numerical methods implemented are correctly executed when integrated into a single dataflow structure.

6.4 Future perspectives of co-simulation in BPS

The use of co-simulation is currently leveraged by developments within BPS tools, the emergence of new platforms, and the growing integration of simulation and building information modelling (BIM).

In terms of integration within BPS tools, the perspectives of increased use of co-simulation in the future are supported by the fact that simulation tools are continuously evolving to satisfy changing requirements. Existing whole building simulation tools have been gradually integrating co-simulation capabilities by adding possibilities to connect their interface to other engines (as mentioned previously, to Radiance [141], or to OpenFOAM [142] which allows carrying out computational fluid dynamic (CFD) simulations). Additionally, multiple whole building simulation tools are compatible with external programs that support more detailed control strategies or specific models, such as the Matlab -based tool Simulink. One expansion that is worth mentioning is the development by the US Department of Energy (DOE) of the Spawn of EnergyPlus (known as SPAOE or Spawn) [143,144]. Spawn reuses many of the capabilities of the EnergyPlus software [145], but the HVAC systems and controls are handled by the equation-based language Modelica [146,147].

That said, new developments within building simulation tools are not the only drivers for co-simulation. Over the past decade, many efforts have also been put into the development of platforms for co-simulation, such as the middleware known as the Building Control Virtual Test Bed (BCVTB) [148]. The BCVTB is a software environment that allows expert users to couple different simulation tools for distributed simulation or real-time simulations connected to a control system [149]. An example of a co-simulation approach based on middleware is given in Figure 6-2.

Another promising development for expanding the use of co-simulation is the previously mentioned development of the Functional Mock-up Interface (FMI) standard. The FMI is an interface standard that allows co-simulating two or more simulation programs and, for example, to create modular workflows [150]. The core of the FMI standard is maintained by the Modelica Association project [151] who’s aim is to simplify operations related to the creation, the storage, the exchange and the use (or reuse) of system models in collaboration with other software or hardware-in-the-loop simulation [152].

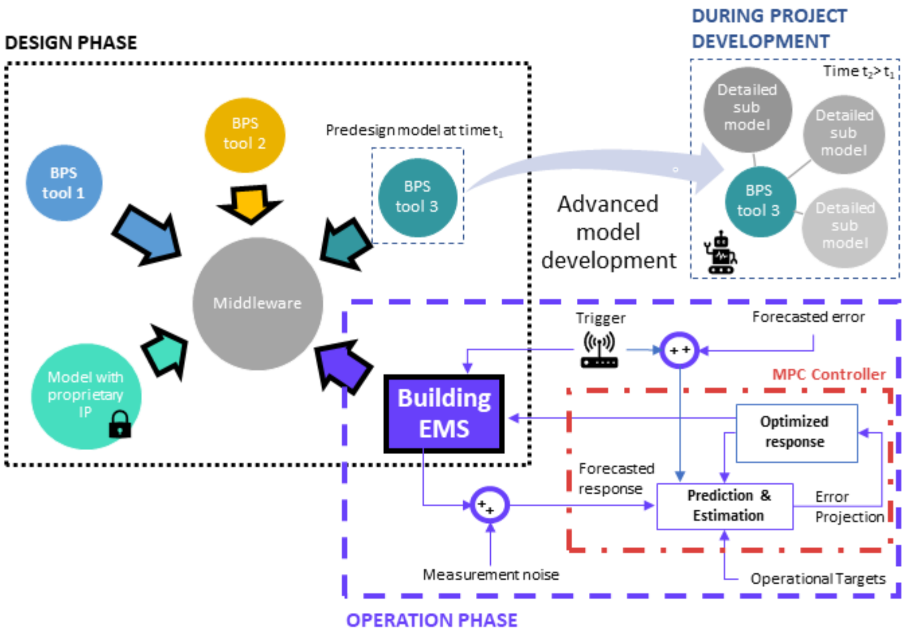


Figure 6-2 Example of a co-simulation framework based on a middleware approach. The figure also illustrates the possible development of models during project time and building operation.

The perspective of an increased use of co-simulation can also be seen in the development of new tools that are contributing to bridging the gap between the fields of architecture, data science, and engineering. For example, parametric design tools are growing in popularity and present several opportunities to integrate co-simulated modelling approaches. In particular, for building energy simulation and environmental analysis, the development of the Ladybug Tools [153] has created new opportunities to connect parametric building designs with an interface to EnergyPlus (including Open Studio), Radiance, Window, Therm, and OpenFOAM. Additionally, Grasshopper offers possibilities for structural engineering analysis, optimization approaches and more.

Finally, co-simulation could also provide one of the missing links between BPS and BIM. BPS and building energy modelling (BEM) tools process many inputs and outputs relating to geometric design, material properties, energy use and more. Specific performance simulation tools are already compatible with architectural software and derive several inputs from building information models (BIM) through industry foundation class (IFC) files. If co-simulation environments are connected to these models, the information could be further integrated into a multi-domain workflow spanning the entire development of an advanced building envelope, for example. Information processed through co-simulation can be directly linked to other workflows, such as greenhouse gas emission calculations from buildings materials or associated with building operation [154]. Similarly, information connected to cost can be dynamically assessed as a parameter of the model. Platforms supporting multi-domain integration and dynamic data exchange between disciplines are then a critical extension of co-simulation workflows. These can, for example, allow visualizing effects of variable inputs on multi-disciplinary key performance indicators, including a direct 3D visualization in BIM tools. Considering that co-simulation also provides the option to protect the IP of separate parts of the model, private actors can contribute through co-simulation to drive innovation and expand the application of their products as well. Overall, developments connected to co-simulation, digital twins and nDBIM are putting pressure on the industry to increase interoperability. As a result, new open-source data management platforms such as the Speckle server [155] are helping move the industry forward into a more digital form.

6.5 Elements of response to the second research question

Advanced building envelopes require a holistic performance assessment, and co-simulation approaches provide a number of advantages in that regard. Contrary to monolithic simulation tools, co-simulation approaches allow coupling different models that describe parts of the governing physical relationships in the system and leverage fit-for-purpose modelling approaches. These approaches are also essential to run what-if analysis or perform rapid prototyping and robustness checks. When designing advanced building envelopes, co-simulation supports innovative, performance-driven design approaches and allows users to model non-trivial behaviors and control strategies. Unfortunately, co-simulation approaches can still rapidly become complicated processes. With time and as co-simulation receives more attention, it is expected that the purely technical issue relating to IT languages, programs and routines to exchange data will be resolved. The more substantial challenges of co-simulation, which stem from a lack of standardization and knowledge, will require a more considerable effort from expert BPS users to share and disseminate specific guidelines for co-simulation. This includes recommendations about how to approach co-simulation tasks and how to select the suitable tools and engines.

If the current barriers to co-simulation are overcome, this approach to modelling and predicting the performance of systems and building could become a multi-user and multi-scale modular dynamic workflow. This would provide opportunities for the different stakeholders to exchange model data with a better understanding of design relationships and implications, and without compromising the IP of the individual simulation tools. In the field of advanced building envelopes, co-simulation approaches benefit from improved possibilities for batching simulation-runs to reduce computational overhead, and from the development of parametric design multi-interfaces to validated simulation tools, as well as the integration of optimization algorithms for single and multi-objective studies in whole building simulation tools. Finally, co-simulation for ABEs also benefits from other developments in ICT which are supporting methods based on data-driven design and can be used in coordination with parallel assessments based on model predictive control strategies thanks to advances in cloud and distributed computing and better solutions for data storage and management.

7 Application of advanced simulation methods for performance prediction

The two previous chapters highlighted the advantages of developing a fit for purpose modelling approach – aided by detailed characterization - and taking advantage of co-simulation possibilities. This chapter discusses how parametric scripting can be used together with these methods to create performance-based design approaches. These approaches are bottom-up design strategies. This means evaluation is not carried out from a perspective of setting inputs and evaluating a resulting performance, but from starting from the desired performance and defining how to optimize the input parameters to reach this goal.

The work presented in this chapter builds on the methodologies and results developed in the third [125] and fifth [156] journal articles which this thesis summarizes. The first section of this chapter aims to provide background about parametric design benefits, particularly when coupled with optimization. A case study of an advanced building envelope is then presented and used to illustrate how these methods can change the system's performance. In particular, the study investigates different parametrization degrees by considering the impact of adding variable properties. The core assumption behind the study presented in this chapter is that solar energy can be exploited in building facades in different forms, and that parametric design, co-simulation and other computational methods can help generate and explore new designs. The final three sections of this chapter show the co-simulated approach's validation developed with full-scale experimental results. These sections summarize some of the work undertaken in the fourth journal article listed in this thesis and discuss the methodology's strengths and weaknesses as a whole.

7.1 The value of parametric design and optimization

Low energy buildings are based on a design approach in which a combination of key parameters is optimized to reduce energy use without compromising the indoor environmental quality. This optimal balance is often achieved using computer-aided design tools. It can be applied to designing a building component, a control strategy, or the building's entire architectonic expression. Parametric analysis, coupled to global and local sensitivity analysis is one of the main strategies used to find optimal designs in BPS. The name “parametric analysis” comes from parametric equations in mathematics. However, in this context, it refers to the idea that a model’s outputs are controlled by a function containing specific inputs defined as value ranges. As a result, we say the problem is *parametrized* [157]. Recently, parametric analysis has become increasingly accessible through parametric software, such as the Grasshopper plug-in for Rhinoceros [158], which allows exploring larger solution spaces in the early design phase when changes can still be made to the building. When coupled to building performance simulation, parametric design establishes an explicit dynamic linkage between the geometric definitions of the building elements, the system parameters, and the performance of the whole building [159,160].

As buildings become more complex and innovative solutions are introduced, automated numerical optimization methods, stemming from the field of mathematics, have gained popularity as an alternative to full-factorial parametric analysis. These approaches allow searching large design spaces more efficiently and solving complex problems defined by parameters that may have antagonistic or nonlinear effects on the building performance. The latter is particularly relevant to building envelope design, or shading control problems, as these often require balancing competing parameters. For example, a classic optimization problem in building envelope design would be to define an optimal window-to-wall ratio (WWR) to obtain a satisfactory daylight level in a zone without increasing mechanical cooling loads. Numerical optimization and parametric analysis can also be used to understand the influence of different parameters on several key performance indicators and to carry out “what if” analysis [99,159,161]. These studies are well-suited to design stages in which the pace of design iteration is fast, and there are still a number of unknowns, but the cost of changing design choices is still relatively low.

In the literature, optimization approaches for building envelopes are used to investigate advanced control strategies or complex envelope geometries [162–165]. They are also used to support the development of free form facades or shading elements [65] or to carry out kinetic façade studies [67,166,167]. Finally, developing performance-based design workflows and integrating them into one parametric script, supports interdisciplinary studies. These studies combine architectural aspects like building morphology and façade design with engineering fields looking at optimizing energy demand or renewable energy use, and consider microclimates effects or carbon emissions [69,168,169].

7.2 Presentation of the case study

Building integrated photovoltaic and thermal applications such as Photovoltaic Shading Devices (PVSDs) combine the benefits of shading systems with renewable solar energy harvesting strategies. This is because the light that is blocked from entering the space is converted into electricity or heat. These advanced fenestrations components make up a complex boundary between the inside- and the outside of a building, the dynamics of which strongly affect the visual and thermal quality of the indoor environment (as well as the energy converted by the system). For this reason, implementing PVSDs requires additional design considerations in order to find the correct balance between competing uses of solar energy. For example, the transmission of large amounts of solar radiation through glazed elements has both benefits and drawbacks. Good daylighting increases productivity in workspaces by improving visual comfort [170] and solar gains contribute to lowering energy use for space heating and electric lighting. However, too much direct solar radiation can also lead to overheating and glare issues for the user [12,171,172]. But if too much solar radiation is blocked out, even though the photovoltaic material will convert more energy, the heating and artificial lighting demand will increase as a result and negate some of the original benefits. Therefore, modulating sunlight using PVSDs is a complex yet essential measure to keep thermal and visual conditions pleasant. It is reported to be particularly useful in office buildings' perimeter spaces where direct sunlight is undesirable [173]. Two examples of PVSD systems are shown in Figure 7-1.

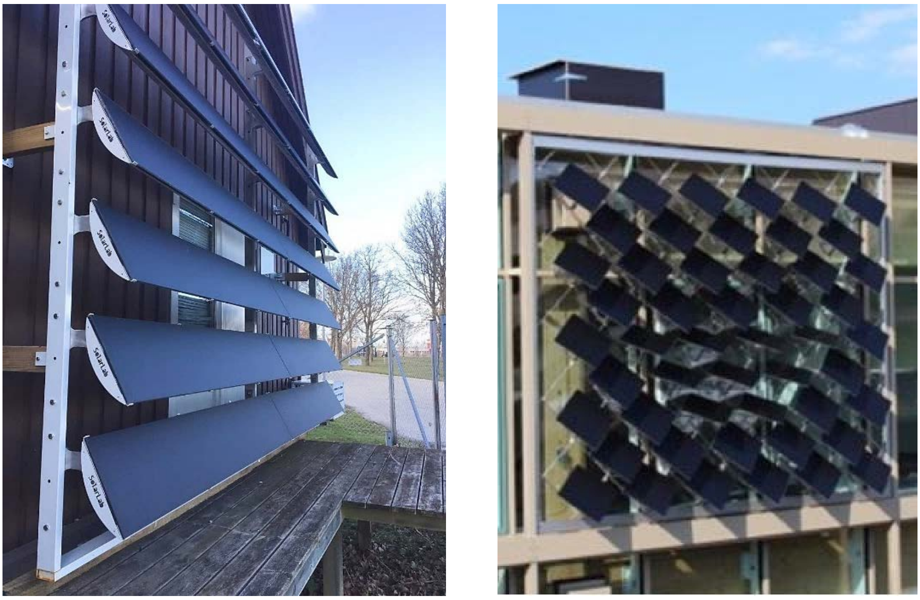


Figure 7-1 Left: Fixed PV integrated shading device from SolarLab (private photo); Right: The Adaptive Solar Façade developed by ETH Zurich, dynamic PV integrated shading device [174].

Existing studies have evaluated the potential of PVSDs and highlighted that when the systems are well-designed, they may be more advantageous than both traditional shading devices and unshaded windows in terms of energy use [52,56,175,176]. Optimal use of PVSDs has also shown to prevent overheating in summers while allowing sunlight to enter during the winter, which translates into ideal high-quality indoor environments [177,178]. Previous research efforts aiming to find optimal balances of solar energy through PV integrated [179] and non-PV integrated shading devices have focused on specific topics such as visual comfort [171,180], energy use for space conditioning [181], artificial lighting loads [29], and energy conversion [53]. The findings have led to the consensus that the "optimal" shading system depends on a large number of variables related to the building's features (e.g. building category, the efficiency of the building systems, efficiency of the building envelope etc.) [182]; to its location (i.e. weather, solar angles, orientation etc.) [183,184]; to the type of shading device [52]; and to the configuration of the shading device itself (i.e. size of blinds, blind angle control strategy etc.) [185–189]. The complexity associated with designing optimal PVSDs and the large number of input parameters required to ensure high performance are too numerous to use any simplistic approach or "rule of thumb". Instead, a promising approach to PVSD design is to use advanced building simulation tools coupled to input-flexible methodologies, such as parametric scripting and numerical optimization, to design systems with high performance.

The geometry of the system developed in this thesis is modelled on an existing external louvred shading system [190]. Although the existing system does not have photovoltaic material, the parametric script created in this study was designed to integrate solar energy harvesting capabilities through the addition of thin-film photovoltaic material on the upper surface of the louvres. Additionally, the model of the system was defined in a way that it could overcome the limitations of traditionally rigid horizontal blind systems (equally spaced louvres, equally tilted) to allow for non-conventional configurations, including variable inter-louvre spacing, individual louvre tilt angles and variable material on the top of the louvres (light-reflecting or thin-film photovoltaic covering). These modifications created a shading device that was no longer a simple shield from sunlight, but that could instead, be designed to balance competing parameters such as daylight levels in the zone, energy use for heating, cooling and artificial lighting, in addition to renewable energy conversion using the photovoltaic material. This approach adds functionalities to the system and ensures that almost all solar energy available and impinging on the system’s surface is effectively used in one way or another.

Using the previously presented framework to characterize advanced building envelopes, the technology used in this case study has the following attributes:

- **Technological solution**: Optimized highly flexible PVSD.

- **User interaction and requirements**: Indirect. The system affects users through its impact on daylight, but there is no interaction possible as it is fixed and does not move.
- **Trigger**: Here, the triggers don't lead to a dynamic behavior but inform the optimized design of the system. These are annual exterior climatic conditions and interior environmental quality.
- **Control**: None (fixed system).
- **Envelope functionality**: Prevention and conversion. The PVSD prevents situations with too high solar gains and converts solar radiation into electricity.
- **Scale and strategy**: Single building – Peak clipping. The scale considered here is a single zone which can be a room or a small building. In terms of demand side management, its main contribution is to clip peaks by reducing peak cooling demands and by balancing out part of its energy consumption through photovoltaic conversion.
- **Response functionality**: Renewable energy integration.
- **Purpose**: Building energy performance and indoor environmental quality

These attributes are also summarized in Figure 7-2.

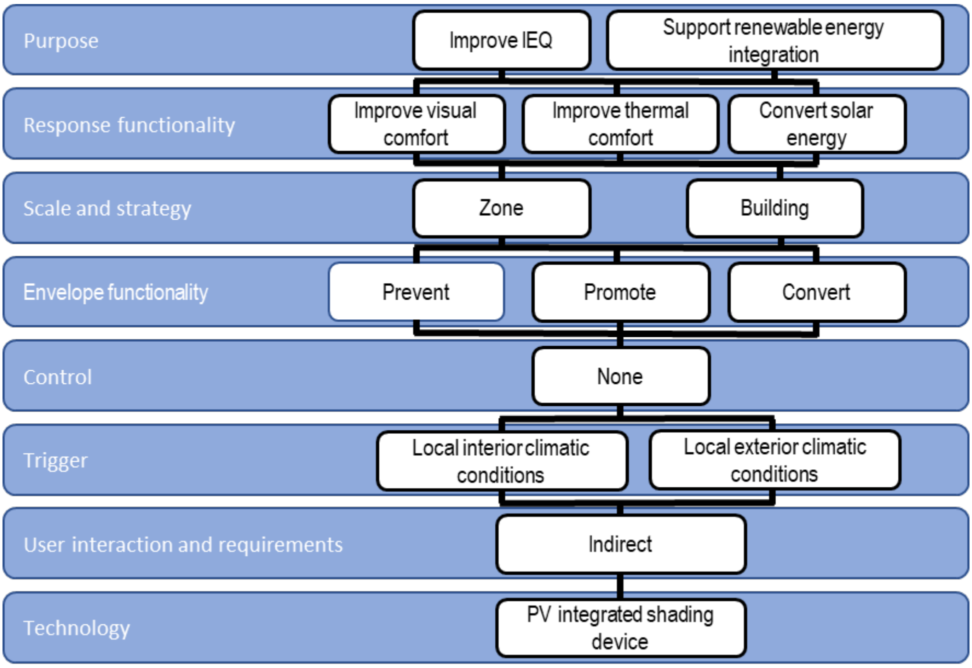


Figure 7-2 Characterization of the PVSD technology according to section 5.

In the optics of applying a fit-for-purpose modelling approach, the characterization is used to outline the following requirements for the model:

- The system **requires detailed and integrated modelling of indoor environmental quality,** including **daylighting and thermal comfort** to balance its roles of prevention and promotion of solar radiation entering the room.
- The model **requires modelling photovoltaic material** to convert solar radiation into energy.
- The system **does not require modelling grid interactions** or battery functionalities because it only considers building scale.
- The system does not require modelling user behavior or user interactions.
- The system's geometry has to be **defined in a way that it can be optimized** according to the interior and exterior climatic conditions.

Based on these properties, a modelling approach using parametric scripting, co-simulation of thermal and daylighting models, solar radiation analysis and numerical optimization of the system's geometry appears to satisfy most of the technical requirements.

7.3 Development of a parametric scripting approach

The analysis presented in this section summarises different research activities that aimed to demonstrate how parametric scripting, co-simulation and optimization could be combined to create a performance-driven envelope design for the case study previously defined. The modelling approach described in this section was an iterative process in which the degree of "parametrization" or freedom of the system's defining parameters gradually increased, which in turn also increased the complexity of the system.

This work's specific objectives were first to evaluate the ability of these combined approaches to capture the multi-faceted performance of a complex shading element such as a PVSD. The second goal of the study was to assess the potential of using a bottom-up, performance-based approach to balance competing uses of solar energy in a Nordic climate and achieve a high performing system in terms of energy use, energy conversion and daylighting. The third and final goal was to understand the extent to which increasing the freedom in the system's definition could impact the overall performance of the system.

Description of the modelling approach used

The entire modelling methodology described in this section was developed using the parametric design software Grasshopper [158] in the Rhinoceros environment [191]. The evaluation of the performance of the system was carried out using the Ladybug tools plug-in [153], which includes Honeybee, Ladybug, Butterfly and Dragonfly [192]. More details about the performance evaluation are provided later in this section.

The system used in this study is an external louvred shading device with the possibility to have photovoltaic material on the upper surface of the louvres. Because the system is modelled using a custom-developed script instead of the existing component for external shading devices available in Honeybee, its definition is much more flexible. The modeller can specify the number of louvres in the system, and each individual louvre can be controlled in terms of its vertical position in front of the window or its tilt angle. In more advanced versions of this script, the modeller can further choose to customize the louvres in terms of their individual width and thickness and select different material properties on the upper surface of each louvre. It is important to note that the system considered here is a fixed system. This means that it is assumed the geometry does not change once it is defined at the start of the simulation.

In this study, three different versions of the script with increasing degrees of parametrization are used. These are a reference model used in a classic parametric analysis, an optimized base model, and an optimized flexible model with a larger number of input parameters.

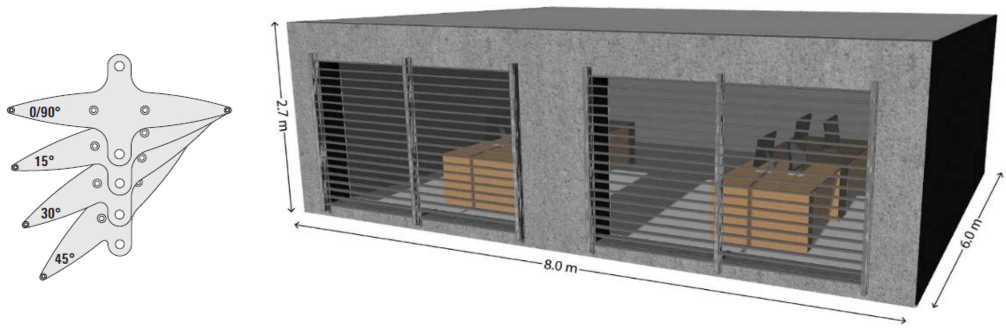


Figure 7-3 Illustration of the standard building used for the evaluation and the external photovoltaic shading system's louvre tilt angles.

The parametric analysis (PA) is used to create a reference case when comparing the different problem formulations' results. It included three different possible louvre sizes, four tilt-angles, and seven different densities of louvres. In this model, all of the louvres are identical in their shape, are evenly spaced and have the same tilt angle. In total, the parametric analysis can generate 84 possible designs from these parameter combinations. Both the base and the flexible model accommodate individually optimized louvres, meaning they are no longer evenly spaced or evenly tilted. The main differences between the base and the flexible model can be summarized as follows. In the base model, the louvres had a fixed width of 105 mm, whereas, in the flexible model, the louvres' width could be controlled for each one of them separately. The vertical distribution of the louvres was also scripted with different approaches in the two models. In the base model, the louvres could only move vertically within precalculated height intervals centered around a start position determined by the configuration with equally spaced louvres. In the flexible model, the number of louvres was controlled by the algorithm. This means the louvres' vertical distribution was also much freer, and the only constraint to avoid louvres overlapping was to respect a safety interspace recalculated for each case. Finally, in the base model, every louvre was considered to have PV material on its upper surface and otherwise, be built of aluminium. The reflectance of these materials was, however, only considered in the daylighting simulation. This means that they had a constant reflectance equal to 0.2 for the thermal model. This was not the case for the flexible model. Not only were reflectances carried over in the thermal model, but the coating of the louvres could also be selected to be photovoltaic or light-reflecting. The advantage of using light-reflecting material is that it allows investigating whether some of the louvres in the shading device can be used to redirect light into the zone instead of convert energy. Systems that have both photovoltaic and light reflecting louvres are referred to as hybrid systems [193]. Details about the differences between the three scripts are recapitulated in Table 7-1.

Table 7-1 Overview of the different parameters in the different models of the PVSD.

Parameter	Parametric analysis model	Base model	Flexible model
Number of louvres	[10:16]	Predefined for each case	[10:22] louvres
Tilt angle	[0;15;30;45] ° from horizontal but same angle for all louvres	[0;15;30;45] ° from horizontal	[0;15;30;45] ° from horizontal
Louvre coating reflectance	Photovoltaic R=0.10 for PV material in both thermal and daylighting simulations	Always photovoltaic R=0.10 in daylighting simulation R= 0.2 (default) in thermal simulation	Reflective or photovoltaic R=0.10 for PV material in both thermal and daylighting simulations R=0.65 for reflective material in both daylighting and thermal simulations
Louvre size	[100:200] mm with a 50 mm step but all louvres have the same width	105 mm	[100:200] mm with a 10 mm step
Vertical distribution of louvres	Equally spaced louvres, no vertical movement	Limited freedom - within a predefined fixed interval based on number of louvres	Extended freedom - within a recalculated interval

Description of the performance evaluation

The evaluation of the performance of the PVSD used a co-simulation approach based on the simultaneous evaluation of energy use (including heating, cooling and artificial lighting), daylighting in the zone, and the estimated amount of energy converted by the photovoltaic material on the upper surface of the louvres.

This study mainly used Honeybee, one of the Ladybug Tools' packages, which provides an interface to the simulation engines EnergyPlus for energy simulations and to Radiance (via Daysim) for the daylighting analysis. EnergyPlus is a widely used validated whole building energy simulation software developed by the Department of Energy in the United-States [145]. Radiance is a validated backwards ray-tracing software developed by Greg Ward and the Lawrence Berkeley National Laboratory and is widely used for daylighting and advanced light transmission studies.

The performance of the system was evaluated using the three following metrics:

- The total net electrical energy demand per year in kWh/m^2 or E_{TOT}, calculated as:

$$E_{TOT} = E_H + E_c + E_L - E_{PV}\ [kWh/m^2]$$

Where E_H is the heating energy demand, E_C the cooling energy demand and E_L the energy demand for artificial lighting. Note that the energy demand for artificial lighting is tied to the daylight availability via a proportional control strategy and a minimum dimming of 20% when the illuminance is below the threshold as described below:

$$E_L = \max(1 - \frac{measured\ illuminance}{500\ lux\ threshold}, 0.2) \times installed\ power\ [kWh/m^2]$$

- **The energy converted by the PV surfaces** located on the upper surface of the louvres in kWh/m^2 or $\mathbf{E_{PV}}$, calculated as:

$$E_{PV} = \frac{\text{Radiation received} \times \text{cell efficiency} \times \text{area of } PV\ material}{Floor\ area}\ [kWh/m^2]$$

The calculation of E_{PV} is carried out using a detailed radiation analysis on each louvre to account for self-shading between louvres. These quantities are then converted into an equivalent amount of electricity, assuming that 95% of the louvres' top surface has photovoltaic material, and 95% of this defined area is a photovoltaic cell. The PV cell's efficiency is set to 15% accounting for all the system losses assuming a thin-film solar cell.

- **The continuous daylight autonomy** or **cDA** expressed as a percentage of hours during working hours where the illuminance level on a work plan located 0.8 m over the floor level is at least 500 lux.

The continuous daylight autonomy (or cDA) calculates the number of working hours a year a given surface in a room receives an amount of light above a set threshold [171]. Hours during which the threshold is satisfied receive full percentage points. Hours during which the daylighting levels are below the threshold are awarded a proportional fraction of a percentage point. The reason for choosing to evaluate the performance of the system with the cDA was because it is well-suited for office buildings and defines a softer transition between compliance and non-compliance situations [194].

Description of the co-simulation

In this script, the co-simulation aspect concerned the connection between the detailed daylighting simulation results from Daysim and the control of the artificial lighting. The daylighting simulation calculates the average cDA in the room and the amount of light on a sensor surface in the zone. Depending on the latter quantity, the time and type of day (this information is controlled by the occupancy schedule), the script generates a schedule to dim the light. In this way, the building can save energy by reducing its use of electrical energy for lighting. Following this logic, it would also be possible to create control strategies for a dynamic louvre system which could adjust its tilt-angles or position based on the amount of light in the room and the energy demand.

Description of the optimization procedure

For this study, the parameters used as inputs and their ranges for the optimization are those presented in.

The three objectives set in the optimization were to minimize the total annual net electrical energy use (E_{TOT} [KWh/m^2.year]), to maximize the amount of energy converted into electricity by the PV cells (E_{PV} [KWh/m^2 year), and to maximize the daylighting level in the zone measured as the continuous daylight autonomy (cDA [%]).

The PV output was selected as an objective despite the fact that it is directly connected to the net energy demand calculation. The impact of this choice is discussed in Chapter 0. The reason for using this output as an objective was to include designs that support maximizing the return on investment associated with using PV material and because of the high environmental footprint of PV material [195,196]. Figure 7-4 also presents a complete overview of the application of the methodology on the case study presented in this thesis; and highlights the different inputs, outputs and processing of the data within the Grasshopper environment.

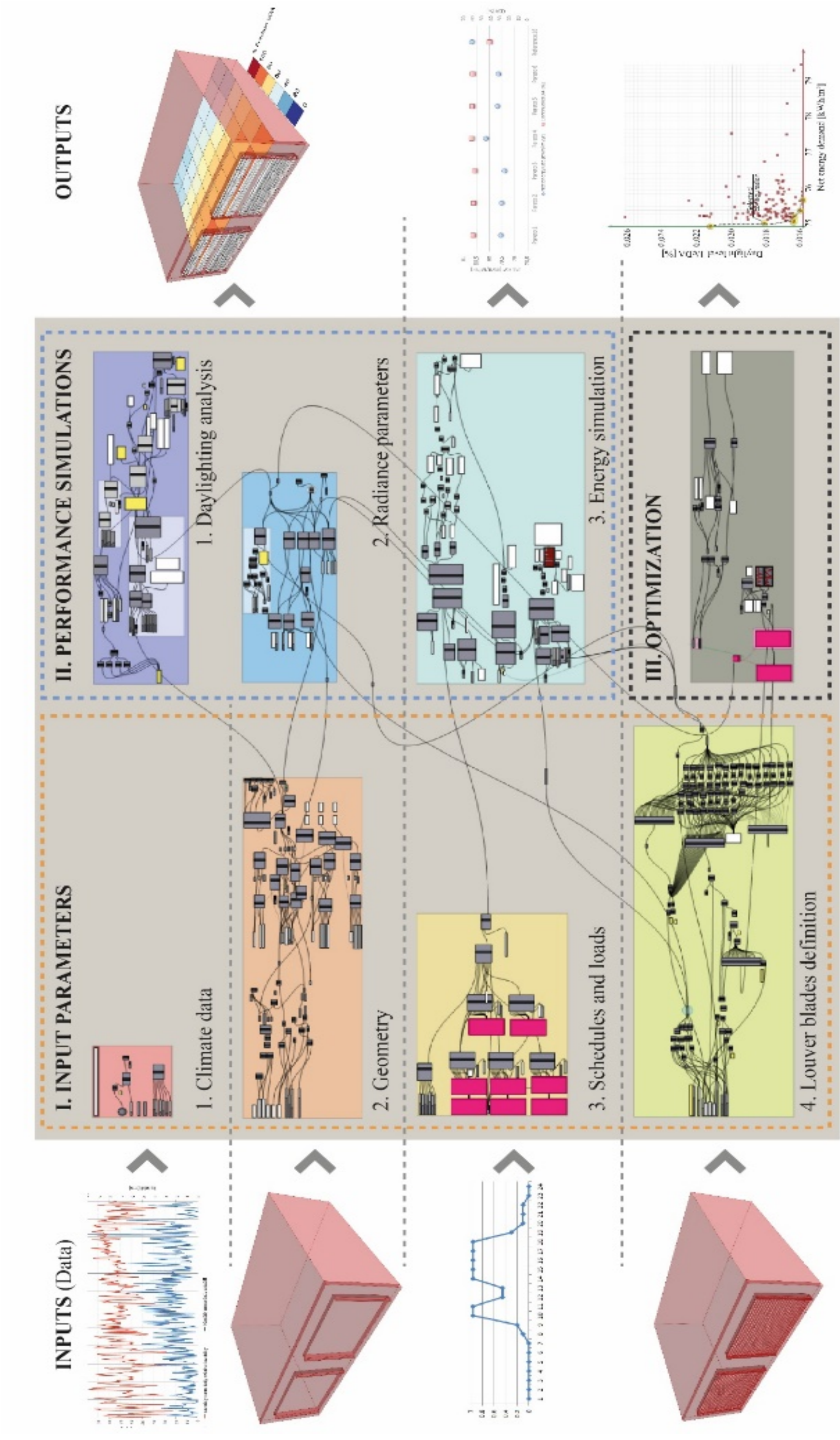


Figure 7-4 Overview of the script structure developed in grasshopper.

7.4 Results of the application of the methodology

The first set of results presented in Figure 7-5 show the outputs of the parametric analysis. Since there are three performance criteria (E_{TOT}, cDA, and E_{PV}), the results are shown with a 2D projection for each set of axis. Five configurations are selected from these results to be used for further analysis and to be able to compare with the results of the versions of the script using optimization. The five solutions are selected according to the following criteria: the solutions with the lowest E_{TOT} (PA 1), the solutions with the highest cDA (PA 2), the solution with the highest E_{PV} (PA 3), the solution with the lowest E_{TOT} and a cDA ≥ 50% (PA 4), and an intermediate solution that provides a good balance of all three criteria (PA 5). The performance of each one of these solutions is detailed in Table 7-2.

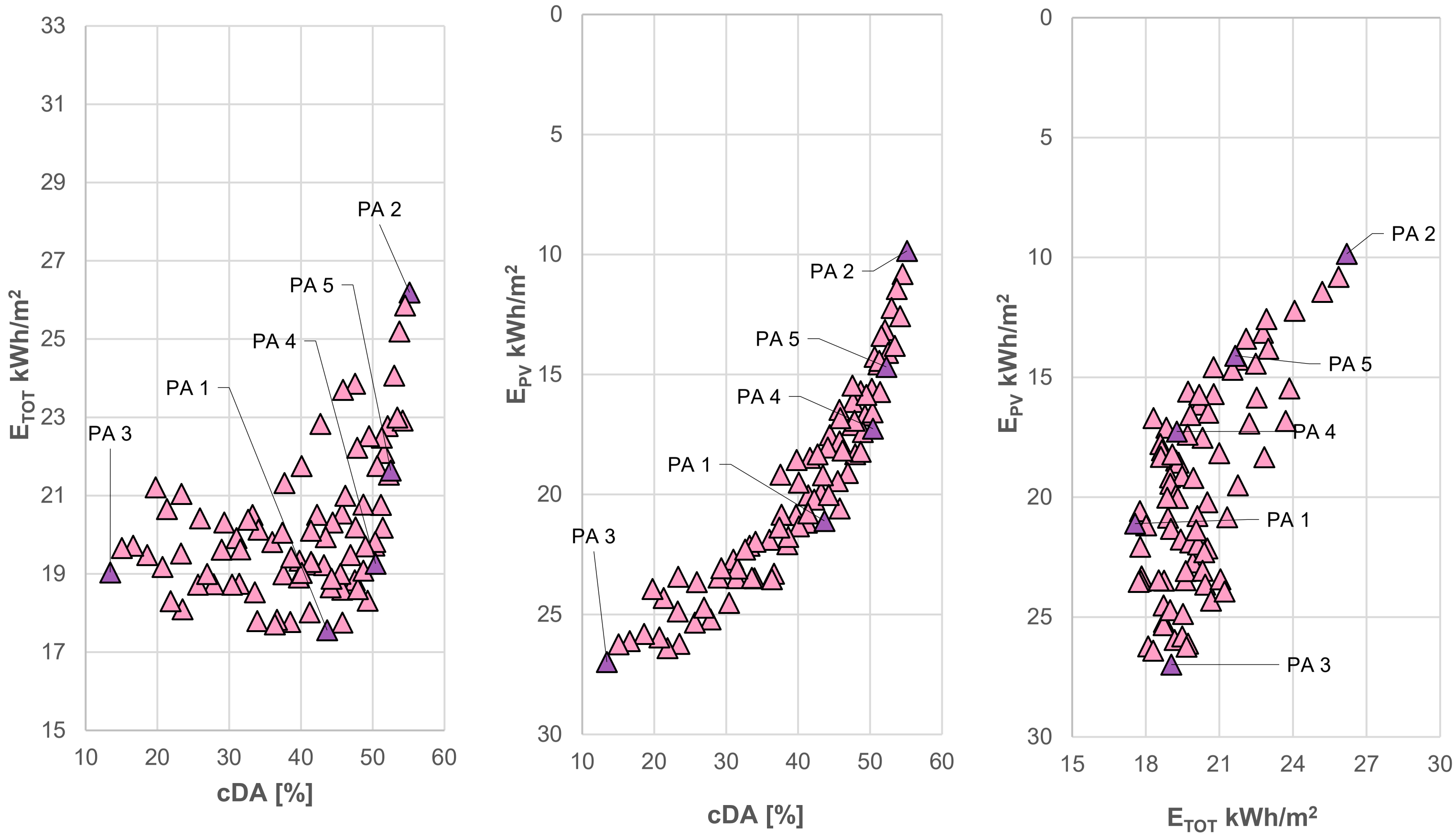
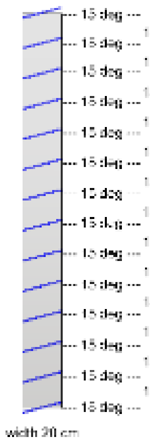
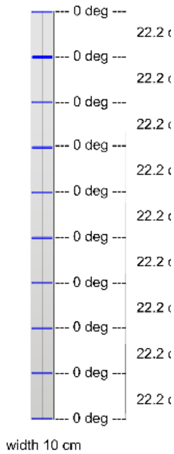
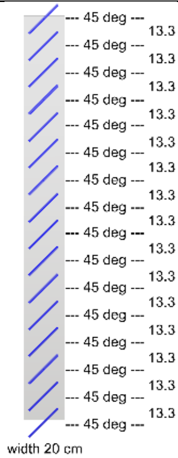
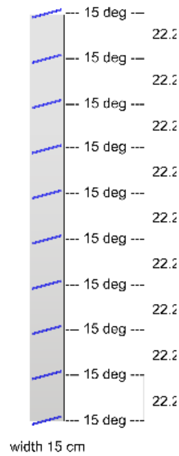
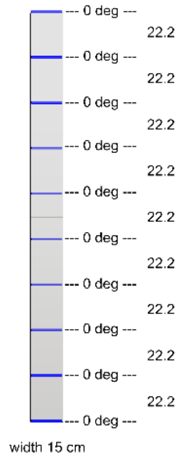


Figure 7-5 Overview of the results of the parametric analysis

Table 7-2 Overview of five selected solutions from the parametric analysis.

	PA 1 Lowest E_{TOT}	PA 2 Highest cDA	PA 3 Highest E_{PV}	PA 4 Lowest E_{TOT} with cDA≥50%	PA 5 Intermediate solution
E_{TOT} (kWh/m²)	17.6	26.2	19.0	19.3	21.6
cDA in %	44	55	13	50	53
E_{PV} (kWh/m²)	21.1	9.9	27.0	17.3	14.1
Number of louvres	11	10	16	10	10
Angle (°)	15	0	45	15	0
Louvre width (mm)	200	100	200	150	150
Visual					

The results of multi-objective optimizations with three objectives form what is called a 3D Pareto fronts (also called Pareto frontier). Pareto fronts are made up of non-dominated solutions which represent the best set of compromises for antagonistic goals. In Pareto visualizations, there is no ranking of the best solutions, and the modeller can observe the performance of all Pareto solutions. It is then up to them to select a solution from the Pareto front using a set of criteria if this is desirable. Figure 7-6, Figure 7-7, and Figure 7-8 show the projection of the results made up of the Pareto fronts for each optimization runs with the addition of the five solutions selected in the parametric analysis. Note that because these are projections of 3D plots onto 2D plots, not all solutions exhibit Pareto traits depending on the set of objectives selected, even if they are all Pareto solutions in reality. For the optimization with the base model, since the number of louvres is not a parameter that can be changed by the algorithm, two different simulation runs were considered. The first one had a system with 10 louvres, and the second one had 13 louvres. These points are referred to as “BASE 10 louvres” and “BASE 13 louvres” on the charts below. The flexible optimization results are listed under “FLEX”.

From these graphs, it is possible to see that the parametric analysis solutions follow the general shape of the projected Pareto fronts. It is also interesting to note that the Pareto solutions of the base optimization at times only marginally outperform the solutions from the parametric analysis. On the other hand, the Pareto solutions of the optimization with the flexible script consistently outperformed both the base model results and the parametric analysis for all three objectives considered. Most noticeably, the solution from the flexible script with the lowest E_{TOT} and a cDA value above 50%, reduced energy use by 15% compared to the best solution from the parametric analysis with this same criteria. Additionally, the Pareto solutions of the flexible script have the added-value that they cover a much larger range of performances. This means that the solution space they outline was higher performing and provided a wider range of high performing options. The parametric scripting approach had thus more value when the degree of parametrization was high. With regard to the specific objectives of the study defined at the beginning of this section, it is possible to make the following conclusions:

- The modelling methodology developed on a combination of parametric design, co-simulation and optimization was able to capture the complex behavior of PVSDs and showcase the performance tradeoffs inherent to the system's nature.
- Using a bottom-up approach allowed improving the performance of the system considering all three objectives simultaneously.
- Finally, increasing the degree of parametrization in the system also increased the system's performance and allowed obtaining solutions that also covered a broader range of performance goals.

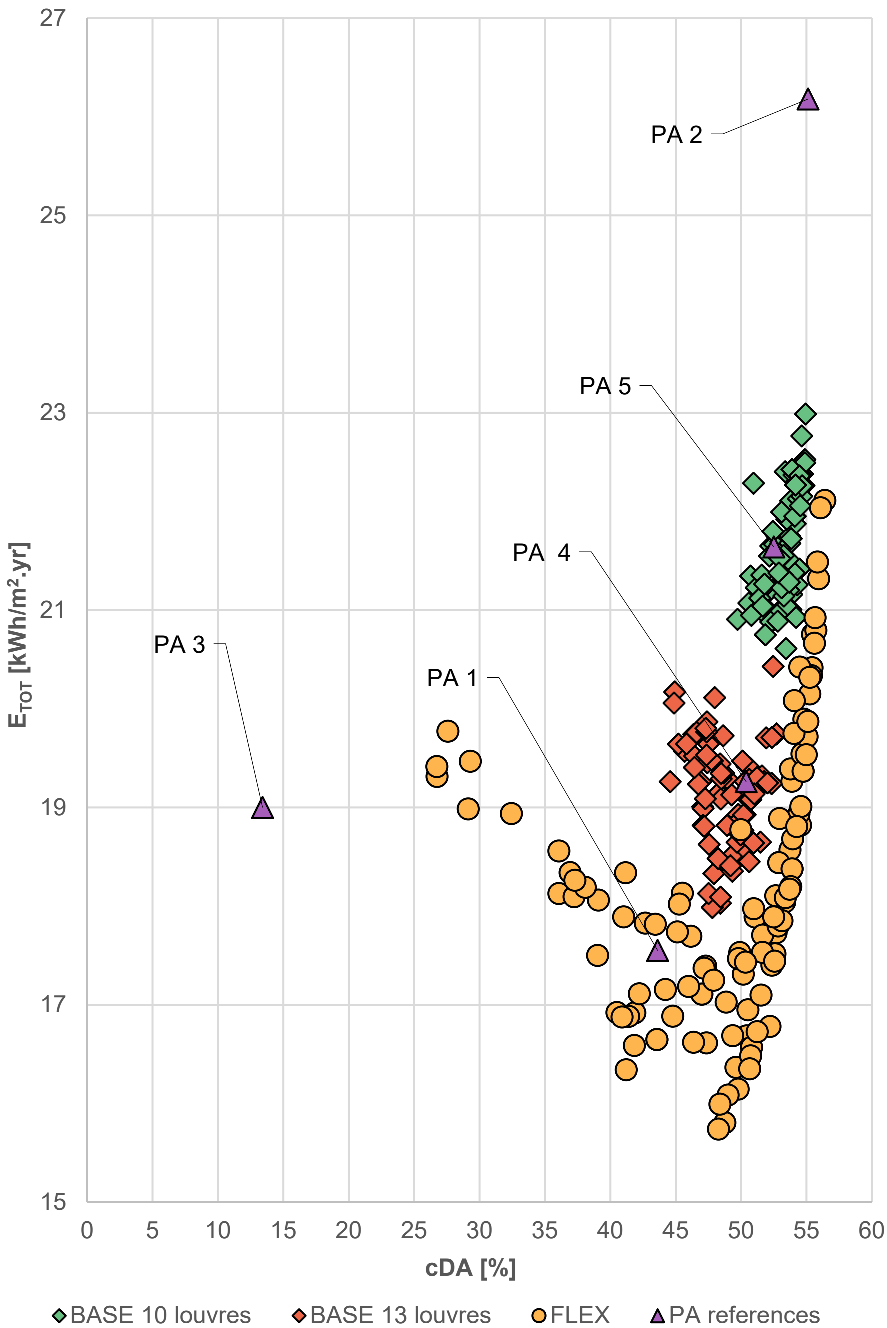


Figure 7-6 Results of the different scripts for the objectives continuous daylight autonomy and net total annual energy

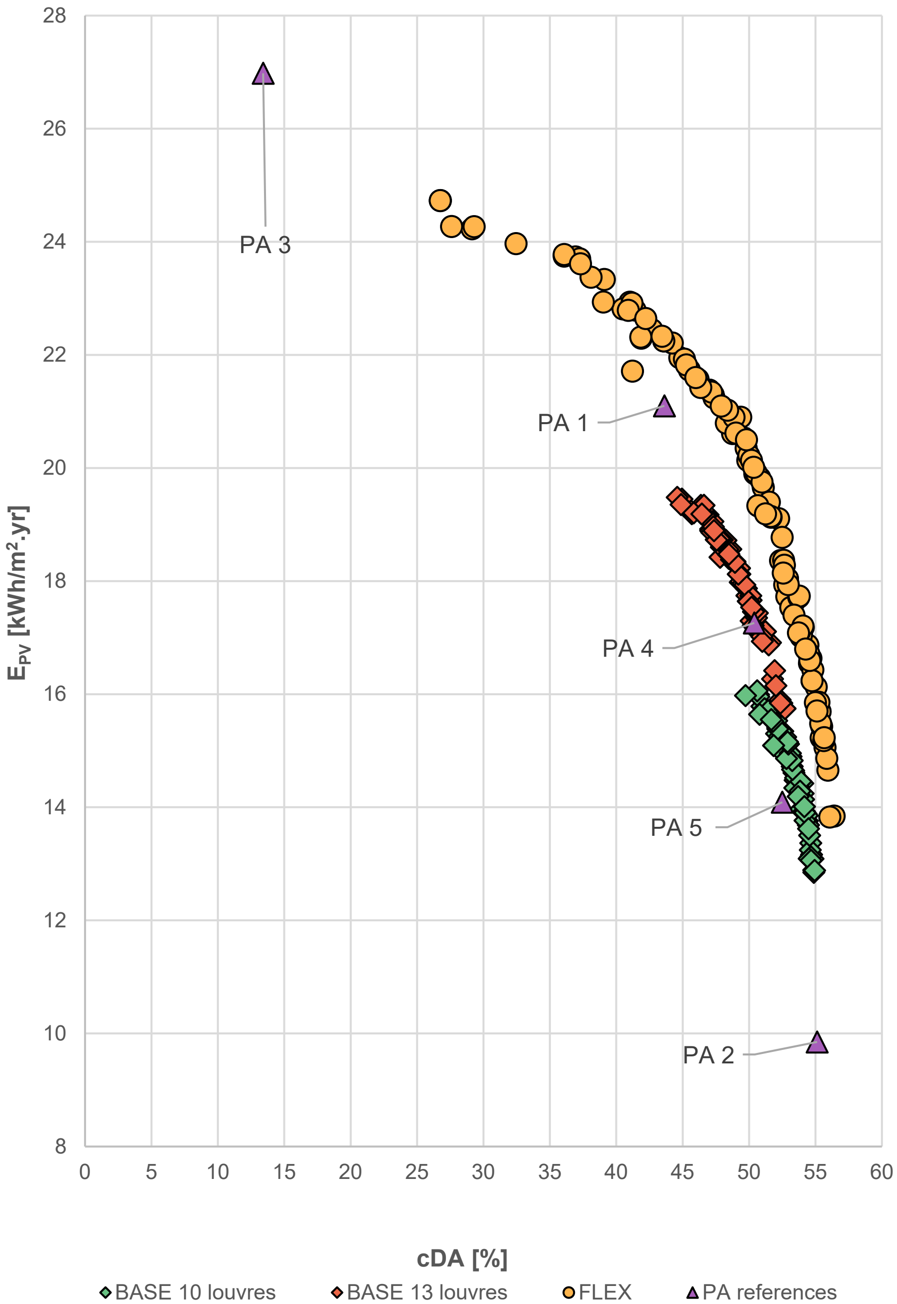


Figure 7-7 Results of the different scripts for continuous daylight autonomy and yearly energy conversion by photovoltaic surfaces.

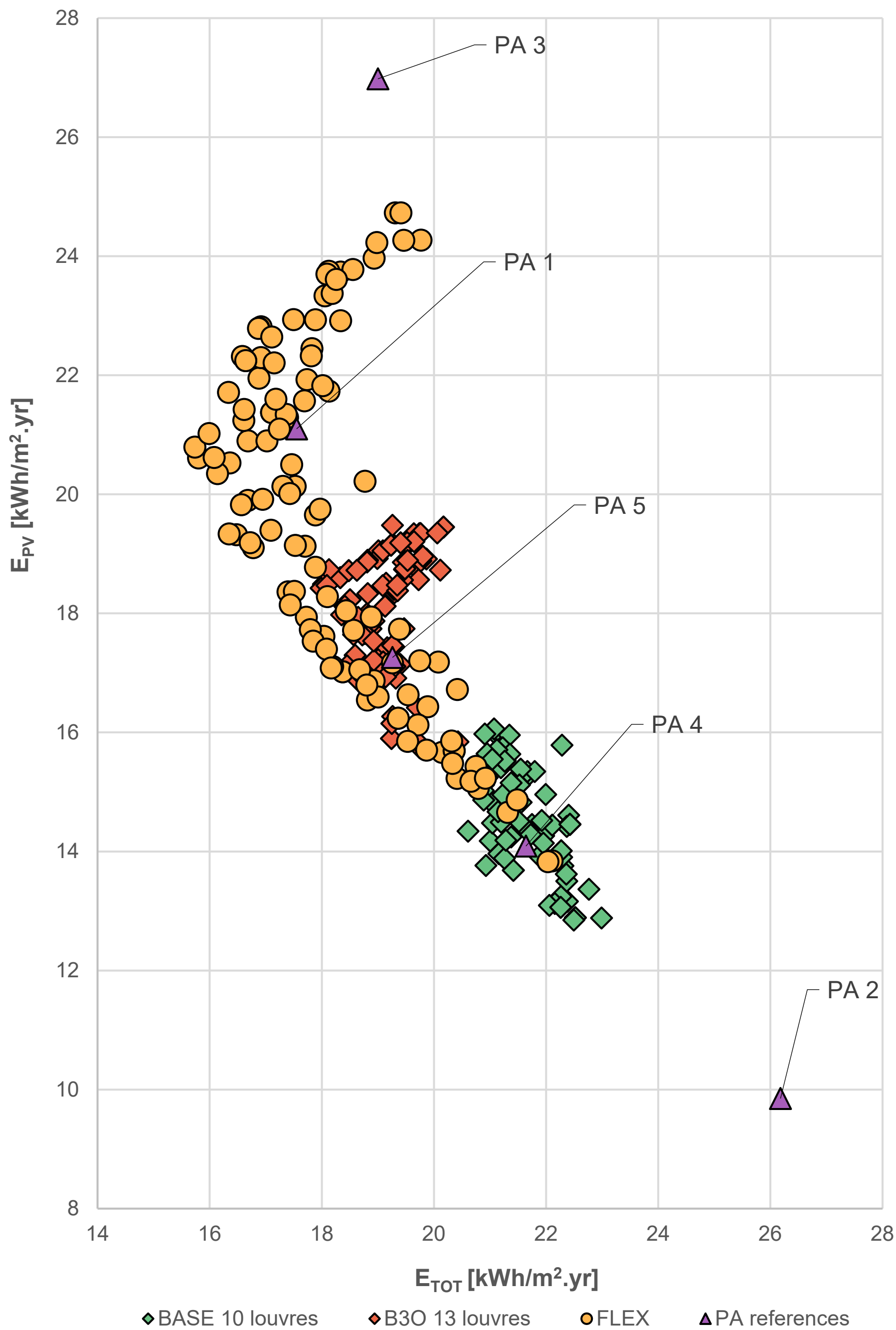


Figure 7-8 Results of the different scripts for the objectives net total annual energy and annual energy converted by photovoltaic surfaces.

7.5 Validation of the co-simulated approach

After investigating the potential of improving the performance of the PVSD with advanced building simulation tools, it is important to verify whether the theoretical improvements obtained through simulation correspond to real-world performance changes. This step is crucial in building performance simulation. The validation of models and modelling approaches plays an important part in ensuring that simulation results are accurate, reliable, and robust. It is also an important step in product development by allowing us to characterize different advanced building envelope solutions and comparing them with baselines. Finally, validation initiatives provide useful insight into the relationship between actual versus simulated performance and how to improve models to reduce this gap.

Scope of the validation procedure

This section of the thesis presents the full-scale validation of the co-simulated modelling approach previously described in section 7.3. The validation was carried out as a full-scale experimental analysis using SINTEF's test cell laboratory in Trondheim [197]. There were two main goals for this activity. The first one was to contribute to ongoing multi-physical validation efforts of models for shading systems. This work was specifically relevant for systems which cannot be modelled with existing predefined modules in simulation tools, or scenarios in which using bidirectional scattering surface distribution (BSDF) descriptions is not desirable. For example, this is the case when exploring free form facades or when using optimization algorithms where creating a new BSDF for each simulation run creates too much computational overhead. The second goal of the study was to verify the accuracy of the physical quantities calculated by the separate simulation engines and so, by extension, the co-simulation's accuracy.

The experimental data for this research activity was collected in a full-scale test laboratory which was equipped with a series of different configurations of an external louvred shading device similar to the one studied in the previous section. The experiments started in the second week of June and lasted until the first week of August 2019. During this period, the data collected comprised weather data, which allowed recreating outdoor boundary conditions, and several parameters inside the test cell relating to the indoor temperature and the illuminance levels in the test chamber (Table 7-3). Simulation results from the model were then compared to the measurement data to validate the thermal and the daylighting results obtained with each simulation engine Pictures of the façade and the inside of the test cell during the experiments are shown in Figure 7-9.

Table 7-3 Quantities measured in the test cell during the experiments.

Quantity measured in cell	Uncertainty on measure
Air temperature at 1 and 2 m height	±0.5 °C
Illuminance on a surface at 0.9 m height (desk surface) and 3 m height (ceiling surface). Note that the sensor on the desk were set to have a measurement range 0 to 1000 lux while the one on the ceiling were set to have a measurement range 0 to 500 lux	±5% of the maximum value in the range

Figure 7-9 Facade of the test cell facility and a picture of the test chamber used.

Description of the experimental activities

Five different configurations of the shading system corresponding to five cases were investigated in addition to a reference case with no shading system. As can be seen in

Table 7-4, the configurations varied from homogenous louvre distributions with two different colors of louvres (blue or white) to heterogenous, eclectic configurations that were defined by an optimization algorithm (case 13 modified A and B). These separate studies aimed at testing key aspects of the robustness of the modelling approach, such as the effect of the density and regularity of the shading device configuration or the system's architectural expression. A vertical cross-section of the different shading system configurations is shown in Figure 7-10.

Table 7-4 Summary of the cases investigated in the experimental study.

Case name	Case description
0	No shading device
16	16 blue louvres equally spaced and tilted at 15° from horizontal
13	13 blue louvres equally spaced and tilted at 15° from horizontal
13 modified A	13 blue louvres with heterogenous spacing and tilt angles
13 modified B	13 blue louvres with heterogenous spacing and tilt angles
13 white	13 white louvres equally spaced and tilted at 15° from horizontal

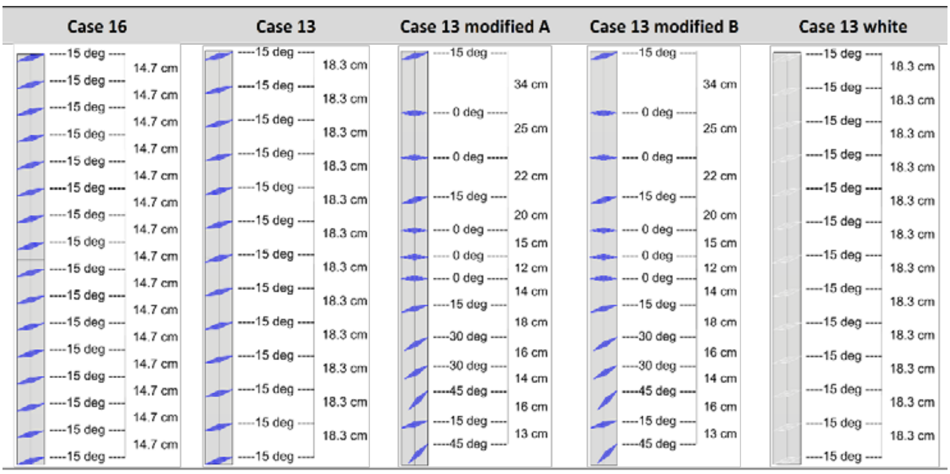


Figure 7-10 Profile of the different configurations investigated with individual louvre tilt angle and spacing.

To validate models, they must first be calibrated with existing measurement data to reduce errors connected to uncertainty on the base model's input data. This study used two calibration methods: automated calibration for the thermal model and hand calibration for the daylighting model. The reason for this choice was that the statistical mathematical indicators typically used in automated calibration procedures are challenging to use for models in which the output is liable to rapid changes, such is the case with daylighting models. Additionally, the illuminance sensors used in the experimental activity saturated during many hours in the first calibration, which means that a calibration method based on statistical errors alone could be misleading in this case due to cancellation effects between time steps. Hence, it was chosen to use an approach based on hand calibration and graphical assessment to calibrate the daylighting model.

The accuracy of the thermal and daylighting models for each case was evaluated numerically for the calibration and the validation using three indicators: the root mean square error (RMSE) given in the unit of measurement of the parameter selected, the mean bias error (MBE) in %, and the coefficient of variation of the root mean square error (CV RMSE) in %. The definition of these three quantities is provided below:

- The RMSE was calculated according to the following formula where N is the total number of values, m is the measured value and s is the simulated value:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(m_i - s_i)^2}{N}}$$

- the MBE or mean bias error is a non-dimensional metric that estimates the bias between the measured and the simulated data at each time step. This metric provides an indication of the overall positive or negative bias of the model over the period of time considered, but positive and negative errors can compensate each other because of how it is calculated:

$$MBE\ (\%) = \frac{\sum_{i=1}^{N}(m_i - s_i)}{\sum_{i=1}^{N} m_i}$$

With m_i being the measured value at time step i, s_i the simulated value at time *step i.*

- the CV RMSE or coefficient of variation of the root mean square error in %. This value estimates the accuracy of a model with regard to the value of the offset of the error between measured and simulated data. It is calculated in a similar way to the RMSE, but using $\overline{m}$ – the average of the measured value during the considered time period, as follows:

$$CV\ RMSE\ (\%) = \frac{\sqrt{\left(\frac{\sum_{i=1}^{N}(m_i - s_i)^2}{N}\right)}}{\overline{m}}$$

Finally, it is important to underline that three specific measures were implemented to avoid overfitting the data for each calibration and validation procedure. First, the data sets used in the calibration of each case are completely independent of the data sets used to test the model in the validation. Second, for each period considered and, as much as possible, the days selected for the validation period were chosen to be a series of days with a large range of boundary conditions, i.e. containing one fully sunny day, one slightly cloudy and one cloudier day. And finally third, there was always a 24-hour period in between the end of the datasets used for one configuration and the beginning of the dataset of the next configuration investigated. This method was followed for each set of measurements to avoid any dependency on the data collected in terms of the order of the cases investigated.

7.6 Results of the validation

The results for the calibration and validation of the chamber's base model without the shading device (case 0) are presented in Table 7-5.

The results show that the accuracy of the thermal model in the calibration and validation phases is almost identical with low RMSE, CV RMSE and MBE values. These values indicate that the distance between the measured and simulated data points was small, and the level of accuracy of the model is well within the acceptable error of building performance simulation tools. For the daylighting model, the shape of the illuminance dome received by the two surfaces in the chamber matched the measured illuminances both during the calibration and the validation periods. However, during both these periods, the sensors saturate and make it impossible to verify the model's accuracy in terms of peak illuminance levels. Nonetheless, the overall values given by the RMSE, CV RMSE and MBE are satisfactory given the sensors' accuracy.

Table 7-5 Results of the calibration and validation of the model for case 0 (no shading)

Model	Quantity	Calibration period	Validation period
Thermal	RMSE	0.5 °C	0.6 °C
	CV RMSE	2%	2%
	MBE	-2%	-2%
Daylighting on desk	RMSE	41 lux	71 lux
	CV RMSE	8%	14%
	MBE	0%	-3%
Daylighting on ceiling	RMSE	36 lux	35 lux
	CV RMSE	17%	15%
	MBE	-10%	-8%

Table 7-6 shows the validation results of the model with the different configurations of the shading devices. Note that prior to this validation, a small secondary calibration of the blue louvres' reflectance was carried out. From this table, it is possible to see that the thermal simulation yielded results that were also within the simulation engine's uncertainty for all the cases investigated (RMSE ≤ 0.6 °C, 0 ≤ MBE ≤ 1%, CV RMSE≤ 5%).

The daylighting model predicting the illuminance on the desk and on the ceiling in the simulation had higher values for the RMSE, MBE and CV RMSE. This indicates that the model was less accurate at predicting the daylighting levels than it was for predicting the indoor air temperature.

Table 7-6 Result of the calibration and validation of the shading configurations investigated.

		Second calibration †	**Validation**				
Model	Quantity	Case 16	Case 16	Case 13	Case 13 mod. A	Case 13 mod. B	Case 13 white
Thermal	RMSE	0.2 °C	0.2 °C	0.3 °C	0.2 °C	0.3 °C	0.2 °C
	CV RMSE	5%	5%	5%	5%	5%	1%
	MBE	0%	0%	1%	0%	0%	0%
Daylighting on desk	RMSE	42 lux	58 lux	74 lux	52 lux	72 lux	82 lux
	CV RMSE	18%	22%	25%	16%	19 %	35%
	MBE	2%	10%	5%	-2%	0%	1%
Daylighting on ceiling	RMSE	57 lux	46 lux	58 lux	40 lux	39 lux	25 lux
	CV RMSE	35%	27%	41%	29%	26 %	11%
	MBE	24%	17%	-27%	-18%	-13%	1%

† Calibration of the optical properties (reflectance) of the shading device system

Figure 7-12 shows an example of the graphical outputs of the validation for case 13 modified A. In this case, it is possible to see that the data match was quite satisfactory in terms of the illuminance profiles' general shape. For comparison, Figure 7-13, shows the graphical results for case 13, where larger discrepancies appear.

It is assumed that one of the sources of error in the daylighting model stems from the calculation of sun positions in Daysim [198], which is a known issue with the software. To understand the magnitude of the error this infers, we compare the values obtained in the simulations with those of the measurements using two daylighting metrics: the daylight autonomy (DA) [199] and the continuous daylight autonomy (cDA) [200]. The metrics are computed using two different illuminance thresholds and a standard occupancy profile (7 AM to 6 PM with all days considered weekdays). The results of this analysis are shown in Figure 7-14.

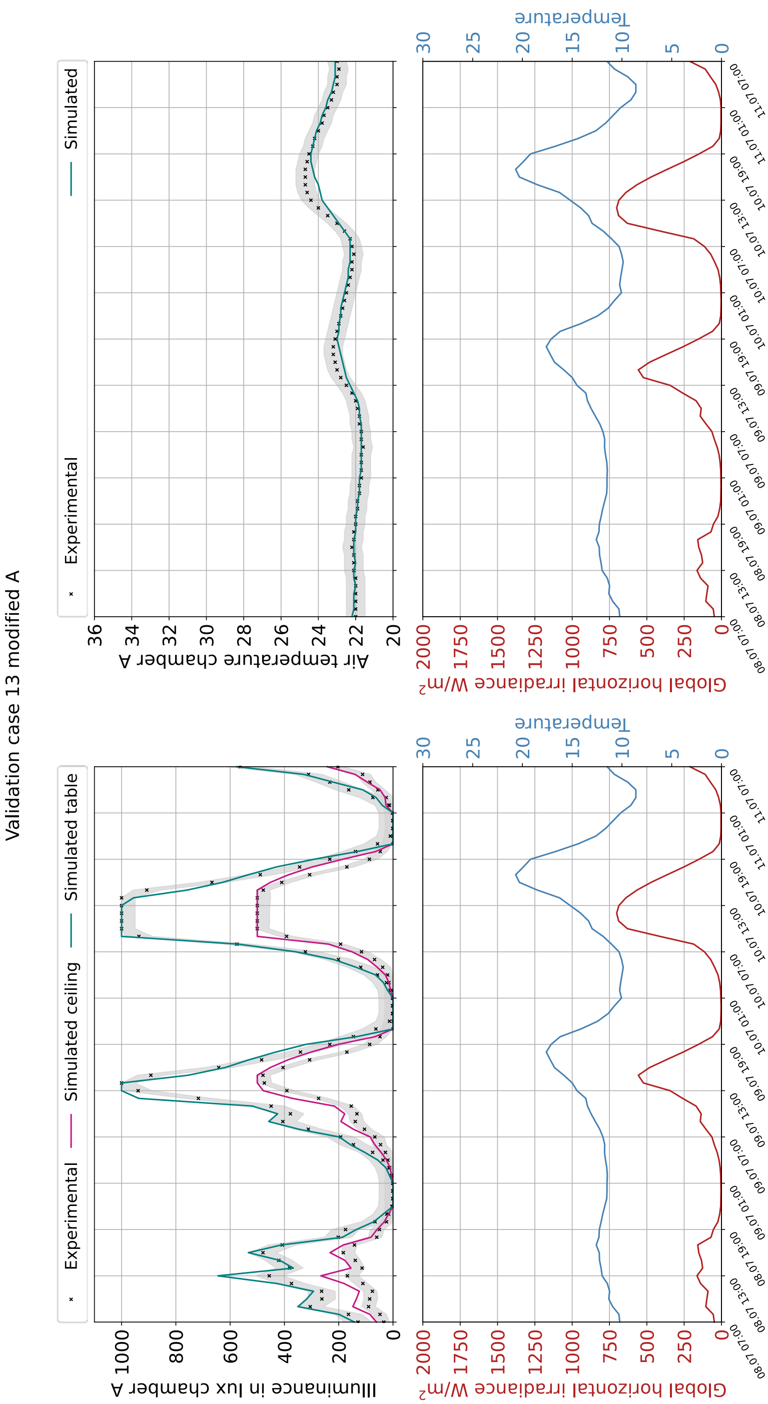


Figure 7-11 Validation of case 13 modified A. The grey hue around the experimental points corresponds to the uncertainty on the measurements. The two lower quadrants provide the outdoor boundary conditions at the time of the experiments.

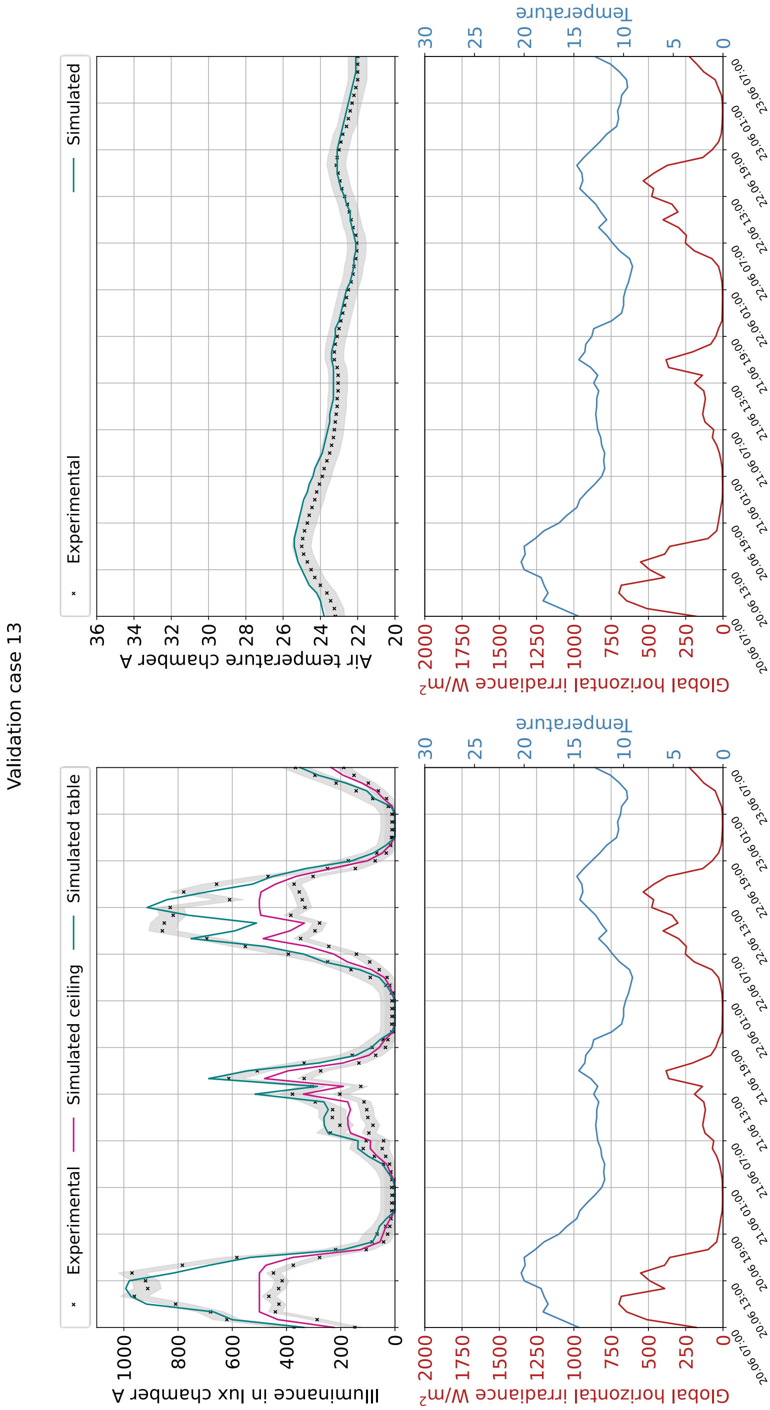


Figure 7-12 Results of the validation for case 13. The grey hue around the experimental values represents the uncertainty on the measurement. The two lower quadrants provide the outdoor boundary conditions at the time of the experiments.

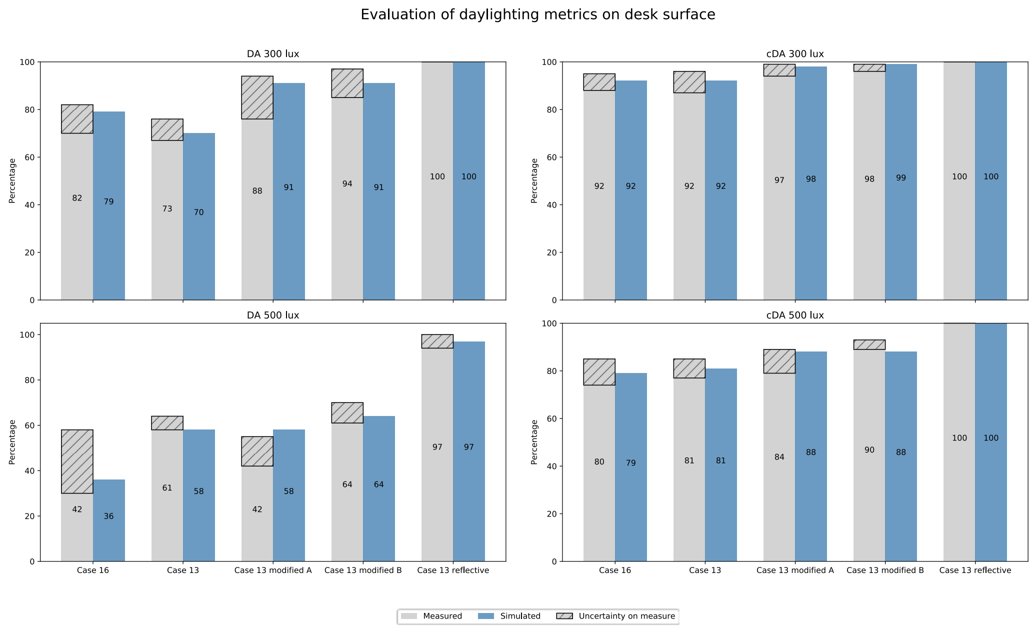


Figure 7-13 Evaluation of two daylighting metrics on the desk surface compared to experimental data.

Although these values only provide a snapshot of the expected accuracy due to the limited analysis period, it is possible to see that most of the modelled cases yielded values within the uncertainty ranges of the measured values when using an illuminance threshold of 300 lux. With the higher threshold of 500 lux, it appears that the models for the modified configurations were less accurate, but the differences reported are still within the 20% uncertainty range of climate-based daylighting metrics [201].

7.7 Elements of response to the third research question

This chapter showed how parametric design, co-simulation, and numerical optimization could be used together to define and efficiently search a larger solution space to design a photovoltaic shading device.

The first investigation in this chapter illustrated the added-value of performance-based design approaches. It showed that using such a methodology allowed increasing the performance of a photovoltaic shading device with regard to all three given objectives in the study. The gain in performance was also shown to be larger when the model was increasingly flexible. Finally, using the most flexible parametric scripting approach and numerical optimization allowed obtaining better performing Pareto solutions and a broader set of solutions with a larger range of performances.

The second study in this chapter presented the results of the full-scale experimental validation of the co-simulated modelling approach used throughout this thesis. The results of this study showed that for all five cases considered, the results of the simulation were in good agreement with the measurements. As a result, it was possible to validate all the results of the simulations. The thermal model that estimated the indoor air temperature was highly accurate, while the daylighting model used to predict indoor illuminance levels was found to be less reliable. This finding indicates that the daylighting model used would most likely not be appropriate to evaluate the risk of glare, for example, since the simulations were not able to completely capture every peak when the incoming radiation varied abruptly. However, the simplified shading model implemented in the Honeybee legacy model did show sufficient accuracy for work plane illuminance studies, even when the shading devices took on non-traditional setups and resemble more free form configurations. The quantities calculated by each separate simulation engine used in the co-simulation approach proved to be accurate enough to characterize the system and could be used to define more advanced control strategies. For example, they could be used to define a dynamic schedule for the shading device's configurations and increase its responsiveness to boundary conditions.

The use of optimization algorithms for architectural and building design applications has, in particular, increased drastically in the past five years. While in the computer science field, optimization algorithms and optimization theory have been explored in-depth (considering the diversity of algorithms developed, the mathematical methods behind them, their characteristics, appropriateness or ability to solve specific problems), there is very little comparable work on these topics in the field of buildings. While the interest for them is warranted, their extensive application to all types of problems requires critical scrutiny. In the next chapter of this thesis, the application of optimization algorithms for design in the AEC field is analyzed more in detail with a critical analysis of the robustness of the methods used.

8 Numerical optimization uses in building design

In the previous chapters, we have focused on investigating how new modelling approaches based on parametric design, co-simulation and numerical optimization could improve the performance prediction of an advanced building envelope and its actual performance. However, despite the growing popularity of numerical optimization, few studies have investigated the quality and the robustness of the optimizations performed. While developing the work presented in this thesis, it was also found there were very few guidelines or best-practice reviews available in the literature to help modellers set up optimization problems. The work presented in this chapter is based on the research published in the fifth journal article of this thesis [156] and which was one of the first contributions to establishing better practices. This first section of this chapter starts by presenting the main challenges of using optimization, both in terms of the mathematical aspects and on more fundamental levels. Then, based on an in-depth investigation of the use of optimization in the AEC field and a cross-field literature review, we present a conceptual development we define as problem formulation. We then use a case study to outline the major decisions modellers need to make to create robust optimization studies and investigate the impact of different problem formulation on optimization results. By creating examples of how to critically analyze optimization results, we can provide a baseline for more robust uses of optimization algorithms and support their use in a more informed manner.

8.1 Challenges of optimization approaches

Optimization of building design or energy systems typically requires finding a balance between multiple, and sometimes antagonistic measures. This is why buildings are often referred to as multi-objective optimization problems by nature. The use of numerical optimization has been increasingly popular. It has led to better environmental performance than traditional paths to building design rooted in rules of thumb, best practice, and sensitivity analysis. The growing availability of optimization algorithms for building design has also created the temptation to apply them across the board, and with much less rigor than in mathematics, their original field of application. In architectural optimization, the procedure is not so focused on finding true minima or maxima, representing the best possible solution, as much as it is used to find an *improved* solution.

Currently, modelers still face difficult choices in finding algorithms that satisfy their needs, and often face tradeoffs such as accuracy vs simplicity, capability vs usability, flexibility vs visualization, or efficiency vs cost [202]. This is despite there being many optimization algorithms available [203–205]. According to Machairas et al. [203], this creates several issues and weaknesses in optimization studies because "*the understanding of optimization method's strengths and weaknesses is crucial in order for them to be used effectively in related design problems".*

In the literature, most of the efforts to improve optimization outcomes have focused on creating benchmarks studies for algorithms [100,202,206–209] and developing new optimization methods [210,211]. These studies are useful as they address one important aspect of the optimization, which is related to the fundamental question that is "is this the correct algorithm for the type of problem considered?". This challenge is rooted in the "No Free lunch Theorems" [194] also known as the concept of "no free lunch in optimization". These theorems "*establish that for any algorithm, any elevated performance over one class of problems is offset by performance over another class*" [194]. In practice, this means no single algorithm is best suited to all types of problems and instead, different algorithms perform better for different types of problems. However, selecting an appropriate algorithm is not the only challenge of applying optimization. In 1980, when the use of optimization in the AEC (architecture, engineering and construction) field was in its infancy, Radford and Gero stated that the main disadvantage of using optimization was *"the difficulty of formulating meaningful quantifiable objectives in a discipline characterized by multiple and ill-defined* *objectives."* [212]. Not much has changed since then. Almost 40 years later, a survey of architectural design optimization users found that formulating objectives was still one of the largest challenges in their practice [213]. This finding was supported by another survey [214], which highlighted the need to establish better methods and tools to improve our understanding of the underlying workings of optimization procedures. In this survey, practitioners from the AEC also said they wished to control better the processes in terms of defining parameters in the optimization. Overall, it appears that a recurring issue in numerical optimization has to do with the fact that users struggle to have enough insight into how the optimization algorithms they use work, what parameter settings should be used and how to formulate objective functions.

Best- practice recommendations encourage modelers to run sensitivity analysis on their optimization problems and run them multiple times [69,210]. But oftentimes, for computationally slow simulations based on physical-mathematical models such as raytracing or computational fluid dynamics, there is little time available, and modelers must make a number of assumptions or use default settings. This means they may not have time to consider how their problem's phrasing will impact the search or even the result.

8.2 General definition of problem formulation

In this thesis, we define the concept of problem formulation as the way an optimization problem is set up in terms of the nature and number of parameters being optimized, the choice of the nature and number of objectives, and the parameter settings selected for the type of algorithm used. Problem formulation investigations thus consider the dimension of the solution space where the optimization takes place, and how it will be searched for solutions. It can then be broken down into two different aspects, which we distinguish as "soft" and "hard" problem formulation.

"Soft" problem formulation includes:

- The size of the design space defined by the number of variables used as input parameters in the optimization.
- Objective settings which relate to the number of objectives in the optimization, whether they are formulated independently or as a combination to create a single objective.

"Hard" problem formulation includes:

- The physical-mathematical complexity of the model used. This relates to the level of abstraction used to model the object of the optimization.
- The choice of the algorithm itself and the mathematical equations implemented in it. This also includes parameter tuning within the algorithm, such as investigating the effect of population size, number of generations, crossover rates and mutation rates in genetic algorithms, for example.

8.3 Soft problem formulation

Lobo et al. [215] mentioned that part of a challenge of defining optimization procedures is that they should be based on problem difficulty, but "*problem difficulty is very hard to estimate for real-world problems, […]".* Soft problem formulation studies, as we define them, can prove to be useful in overcoming this difficulty as they provide more insight into a specific optimization problem. They can be used, for example, to investigate tradeoffs between model complexity, output performance and computational effort by varying the size of the solution space. These studies can also investigate how the solution space is searched depending on the choice or formulation of the objective functions.

Previous studies we consider to be soft problem formulation investigations typically include works that considered changing the number of objectives used, or different combinations of the same objectives. This is the case, for example, when two-step approaches are used, such as in [216]. These are methods in which an optimization problem is first used to determine high performing solutions based on one set of general parameters, and later refined with a second optimization focused on another set of parameters. Some authors also recommend considering whether there was a need for multiple objectives at all and whether some objectives are better formulated as constraints to the problem [217]. However, we also found that sometimes problem formulation issues are discovered when authors discuss their results. This can be seen in a study by Li et al. [218], who analyzed the relevance of the objectives used in their investigation after looking at their results, and concluded that the objective functions they had borrowed from a different field were not completely adapted to their own problem.

Practical investigation of soft problem formulation

In the case study presented earlier in section 7, two types of investigations of soft problem formulation were carried out. The first one consisted of investigating the effect of changing the size of the solution space by increasing the flexibility of the design. The goal of that study was to evaluate the cost-benefit relationship between adding flexibility to the system design and increasing the optimization's length and complexity versus simplifying the task of the algorithm by reducing the solution space. The conclusion was that the larger solution space yielded higher performing solutions and that the optimization had the most value for that case. The same case study can also be used to investigate the impact of how the number and nature of the objectives selected direct the search of the algorithm within the solution space. In the original case study, the optimization is defined using three objectives: the annual net energy demand E_{TOT} [kWh/m^2], the continuous daylight autonomy cDA [%], and the annual energy converted by the PV material E_{PV} [kWh/m^2].

To investigate the impact of soft problem formulation more in-depth, the same optimization problem with the most flexible model was run twice more to create two new scenarios to investigate the impact of the formulation of the objectives. The first one used two objectives which were to minimize E_{TOT} and maximize the cDA. The second one had only one objective, which was to minimize E_{TOT}. The logic behind the definition of these cases is that the calculation of E_{TOT} already contains the quantity E_{PV} and that energy use for artificial lighting E_L, is related to the cDA through the lighting control. Figure 8-1, Figure 8-2, and Figure 8-3 contain the summary of these new optimization runs as 2D-projections in a similar fashion to the results previously presented in Chapter 7. Note that to provide a bigger picture of the single-objective optimization, the next six dominated solutions were plotted in addition to the best solution that emerged from the optimization.

A short reminder of the cases investigated is shown in Table 8-1. For more details about the cases, we refer to section 7.3.

Table 8-1 Short description of the cases investigated for soft problem formulation.

Case name	Description
PA references	Configurations with 10 to 16 louvres with homogenous tilt angles and louvre-sizes
Base 10 (13) louvres	Configurations determined by optimization with fixed numbers of louvres and sizes but individual tilt angles. The vertical position of the louvres is in a fixed interval centered on the starting position
Flex 3 Obj **Flex 2 Obj** **Flex 1 Obj**	Configurations determined by optimized with variable numbers of louvres, sizes, and individual tilt angles. The vertical position of the louvres is recalculated dynamically to avoid collisions but provide a larger amount of flexibility. Louvres can also have different reflectance. 3 Obj = minimize $E_{TOT,}$ maximize E_{PV} and the cDA 2 Obj = minimize E_{TOT} and maximize the cDA 1 Obj = minimize E_{TOT}

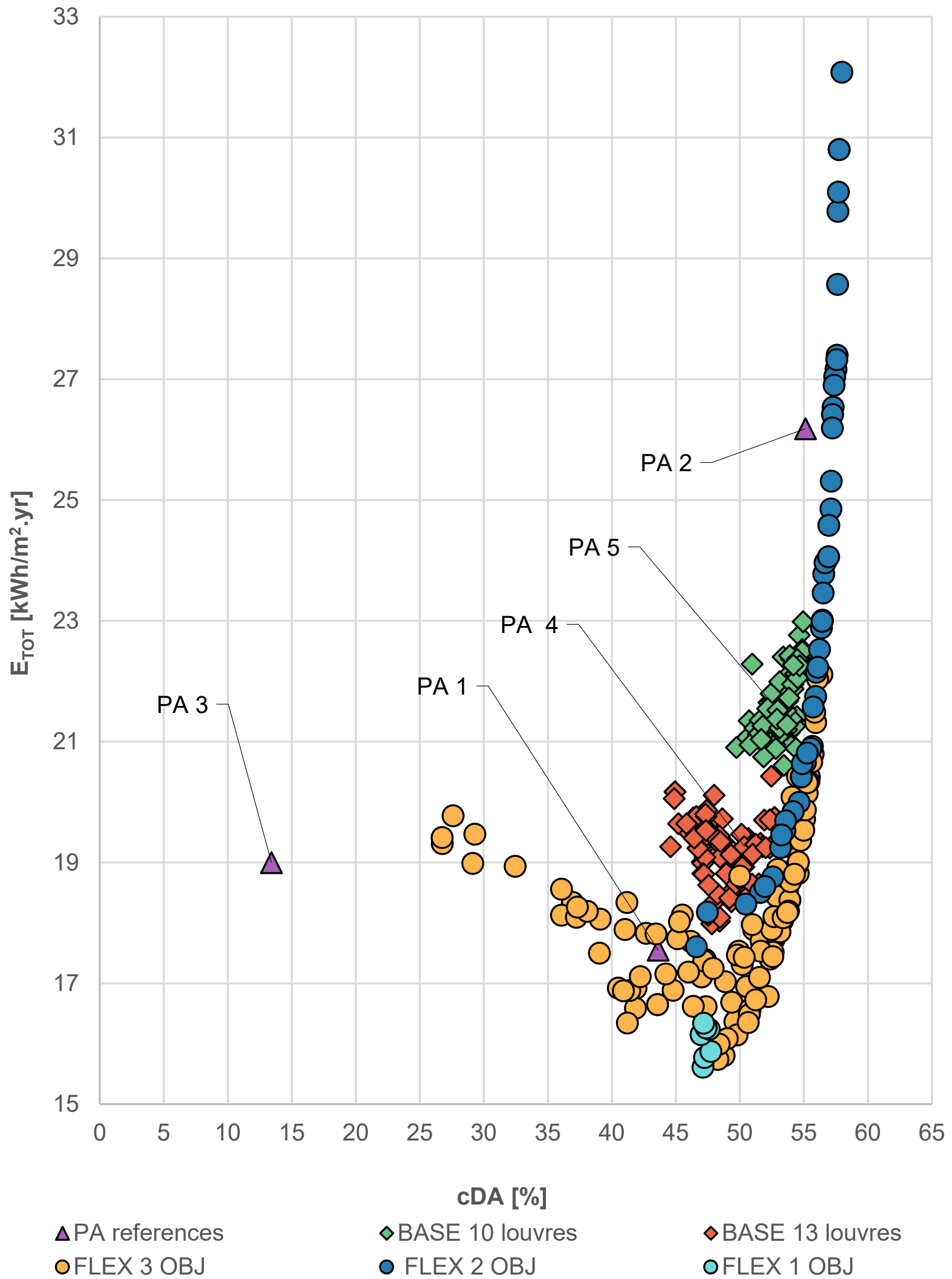


Figure 8-1 Summary plot of the problem formulation investigation with a 2D projection of the fitness of the Pareto front solutions and selected results from the parametric analysis for the tradeoffs cDA versus E_{TOT}.

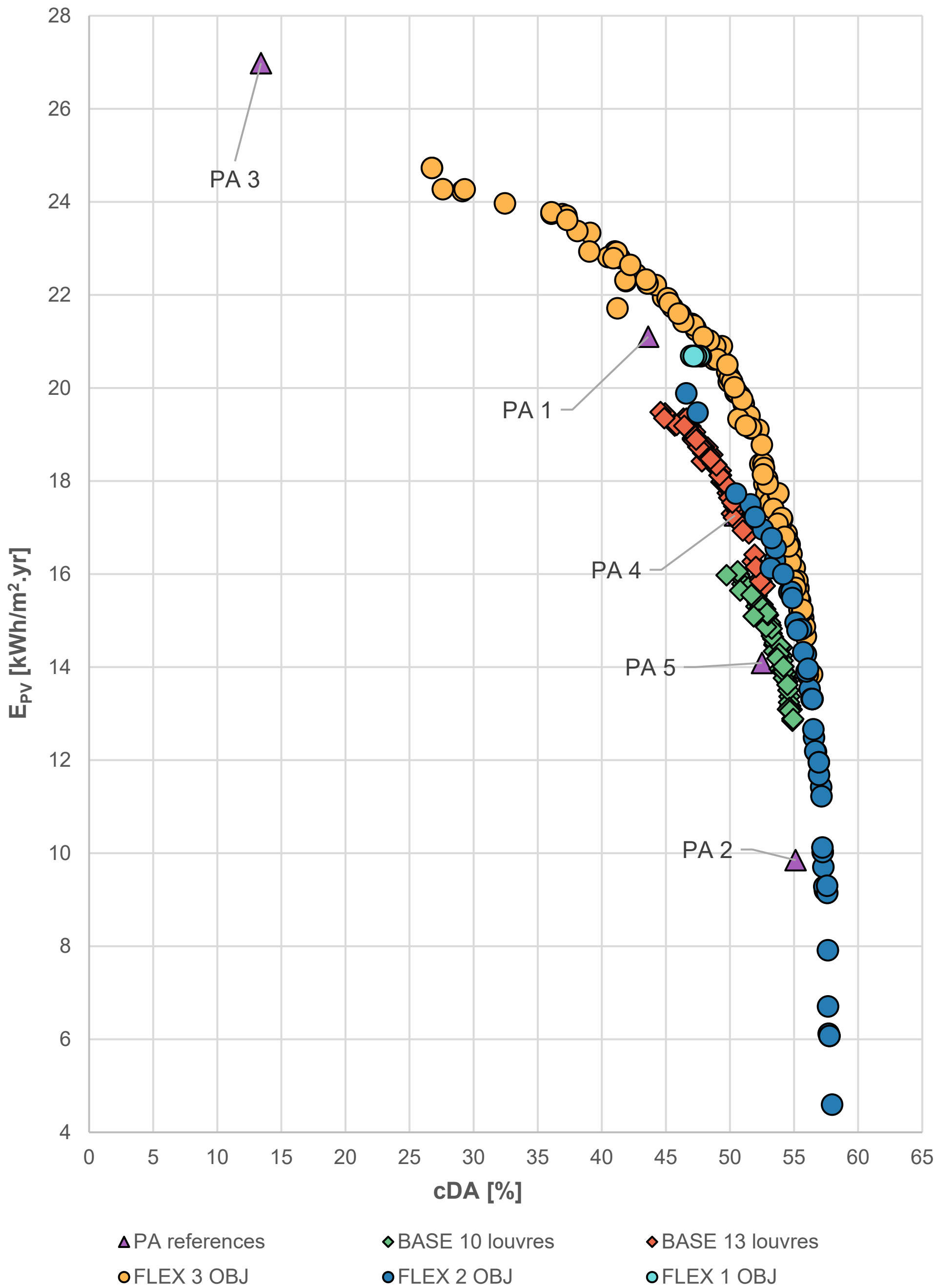


Figure 8-2 Summary plot of the problem formulation investigation with a 2D projection of the fitness of the Pareto front solutions and selected results from the parametric analysis for the tradeoffs cDA versus E_{PV}.

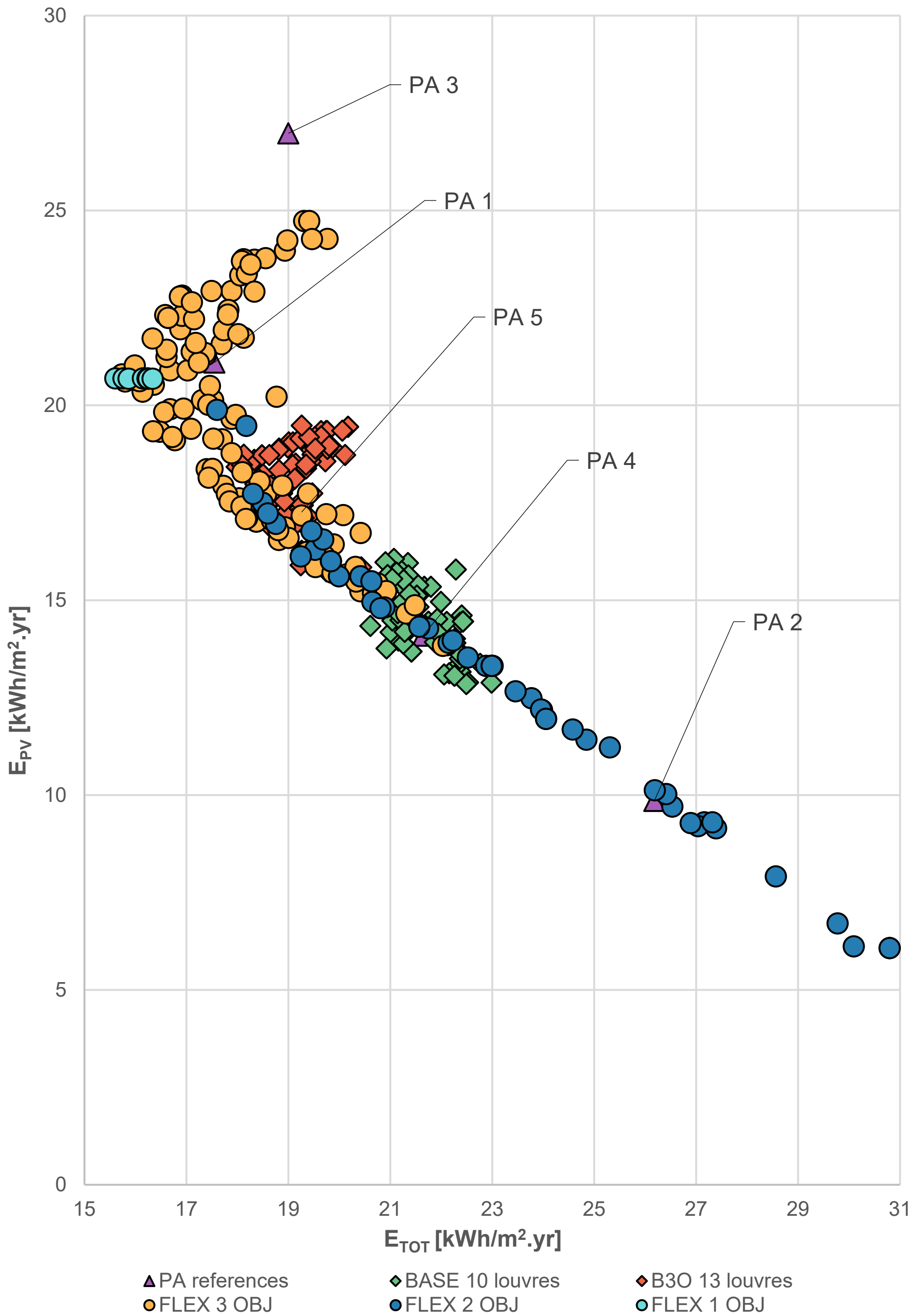


Figure 8-3 Summary plot of the problem formulation investigation with a 2D projection of the fitness of the Pareto front solutions and selected results from the parametric analysis for the tradeoffs E_{TOT} versus E_{PV}.

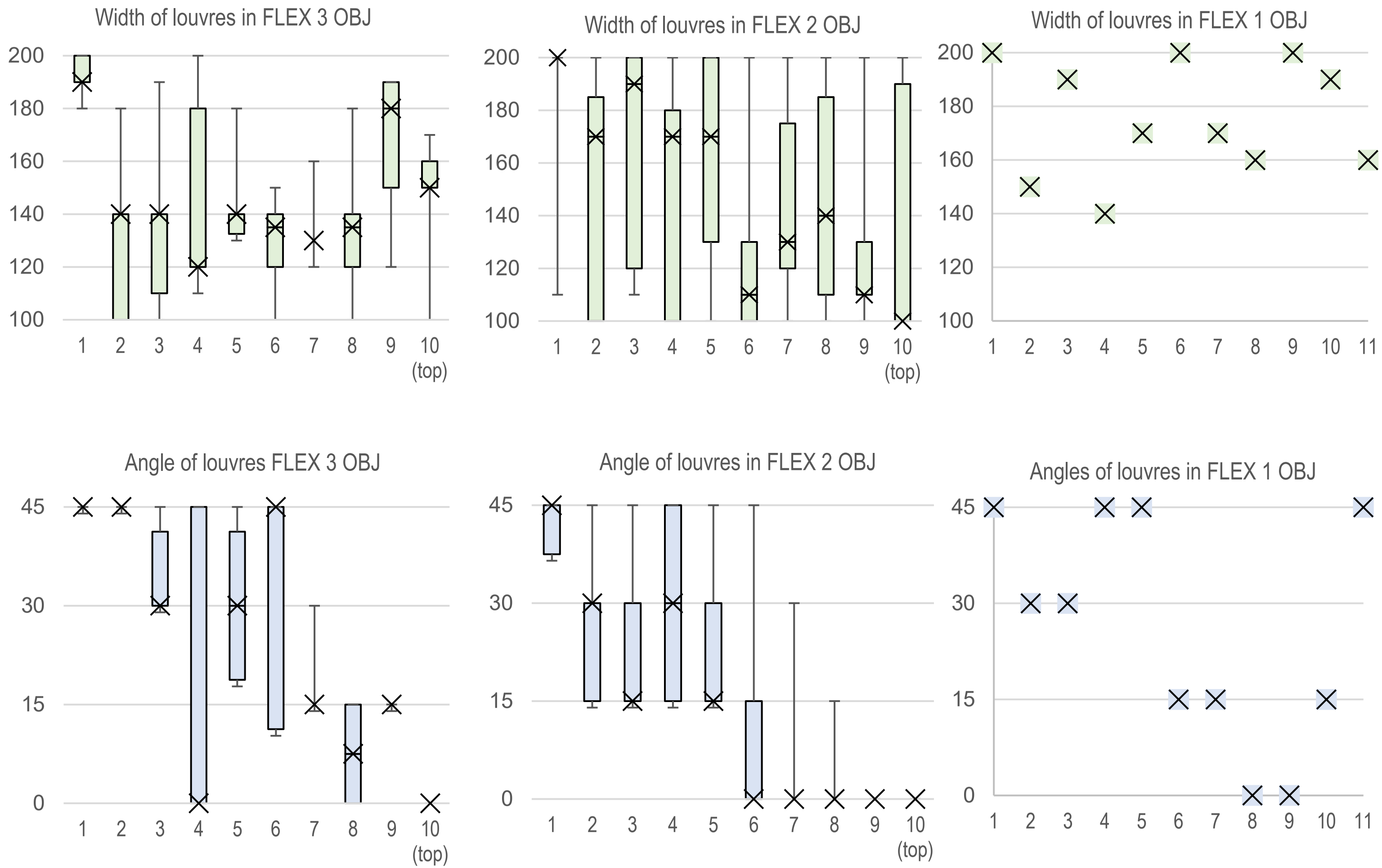
From these figures, it is possible to obtain the following insight into the optimization problem:

- The combination of the solutions from the flexible models formed a complete Pareto front that outperformed any other solution from the optimization runs with the base model or the parametric analysis. This confirms that the model's degree of flexibility was the most important feature and weighed more than the number or nature of the objectives.
- When using the flexible model, having three objectives allowed obtaining a larger amount of Pareto solutions in the middle of the Pareto front, meaning they represented better-balanced solutions in terms of performance tradeoffs. The only case where it was not more advantageous to use three objectives was if good daylight was a priority in the design. In this case, the optimization with two objectives found solutions that provided much higher performance.
- Using E_{PV} and E_{TOT} as objectives lead to a degenerate Pareto front. This was not clearly visible in the three objective optimizations with the base model using 10 louvres, but obvious when using the flexible model or when the base model had 13 louvres. The polynomial V-shape of the curve indicates that there were multiple solutions with the same E_{TOT} but different values of E_{PV}. This highlights that a balance could be found between letting light into the zone and increasing daylight, versus using it for electricity and compensating for the added heating and artificial lighting load.

The results of the investigation of soft problem formulation can also be examined further to increase the robustness of the design selected. One way to do this is to look at the statistical variation of the value of the parameters of Pareto solutions.

Figure 8-4 shows these values for all three optimization runs with the flexible model. Note that the results are presented for Pareto solutions with 10 louvres, and for which all of the louvres had PV material. This represents the majority of Pareto solutions except for the flexible model with one objective where the best solution had 11 louvres. This particular finding also provides insight into the problem formulation, and that the flexible model could have been simplified not to have reflective material and not allow more than 11 louvres.

Studying the statistical distributions of parameter values allowed visualizing Pareto design trends for high performing PVSDs. In this specific investigation, we can see that the louvres at the bottom part of the window are typically wider, sit tighter together, and are tilted at higher angles. The louvres in the higher parts of the window are gradually narrower, more spaced, and inch towards a horizontal position. This design's assumed effect is that it creates openings for sunlight at the top of the window while it favors energy conversion on the lower part of the shading system.


Width of louvres in FLEX 3 OBJ
200
180
160
140
120
100
1 2 3 4 5 6 7 8 9 10
(top)
Width of louvres in FLEX 2 OBJ
200
180
160
140
120
100
1 2 3 4 5 6 7 8 9 10
(top)
Width of louvres in FLEX 1 OBJ
200
180
160
140
120
100
1 2 3 4 5 6 7 8 9 10 11
Angle of louvres FLEX 3 OBJ
45
30
15
0
1 2 3 4 5 6 7 8 9 10
(top)
Angle of louvres in FLEX 2 OBJ
45
30
15
0
1 2 3 4 5 6 7 8 9 10
(top)
Angles of louvres in FLEX 1 OBJ
45
30
15
0
1 2 3 4 5 6 7 8 9 10 11

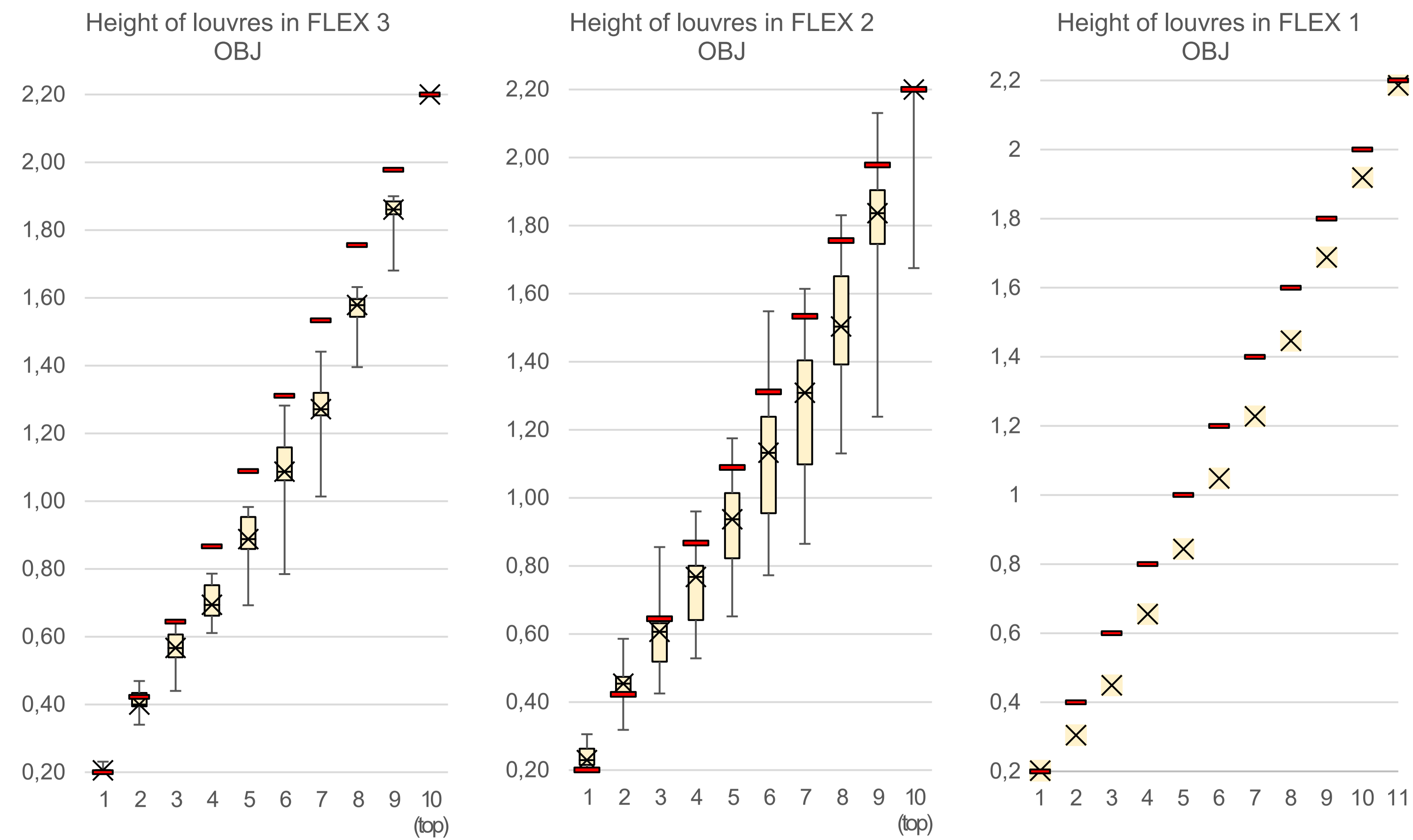


Figure 8-4 Statistical distribution of the louvre widths, angles, and heights among Pareto solutions with the flexible model.

Hard problem formulation

While soft problem formulation is anchored in a perspective of design and performance of a system, hard problem formulation in optimization refers to more hard-science aspects of optimization. In such studies, the level of complexity of the models used to abstract reality is examined. The choice of the model may then relate to the Fit-for-purpose strategy implemented and, for example, whether one needs to use co-simulation or not. In these studies, different algorithms are also examined with the goal of assessing the speed of convergence and the quality of the solutions found. In these benchmarks, users can test different stopping criteria defined for the problem they want to investigate [206,210,211].

However, hard problem formulation studies do not only evaluate the models and the type of optimization algorithm implemented, but they may also go deeper into evaluating the parameters used by the algorithm itself. For example, the performance of genetic algorithms (GAs), both in terms of quality of the solutions and speed of convergence, is affected by parameter value settings. Although these algorithms are the most widely used in the AEC field [89,186] and were introduced in 1975 [111], guidelines for selecting these parameters are often not clearly communicated in the literature of building design optimization.

To understand what the different parameters of GAs represent, it is important first to understand their main mechanisms. The particularities of GAs are that they are metaheuristic, population-based algorithms that use principles similar to those found in evolutionary biology to solve problems. The way GAs solve optimization problems is to start by generating a random population (set) of individuals (solutions). Then, a loop starts where each iteration represents what is called a generation. In this loop, the algorithm assesses the fitness of the current population, that is the performance of each one of the individuals considering the objectives that are set. The goal of this process is to select the best performing individuals based on their fitness value, and pair them so they can undergo a mating procedure in which they become “parents” to a new solution called their offspring. The selection process follows the general rule of "the better the individual is; the higher its chance of being a parent" [219]. By selecting the "best" solutions at each generation, the algorithm aims at increasing the fitness of the global population. The creation of offspring depends on several settings decided by the programmer and on a genetic operator called the *crossover rate,* which decides the contribution of each parent to the genotype of the offspring. To avoid premature convergence, in which the algorithm would "get stuck" around a local minima or maxima, the breeding of new individuals is also regulated with a second genetic operator called the *mutation rate.* This operator's role is to add diversity to the population at each new generation by introducing random modifications in the genotype of the offspring. The loop of an optimization problem runs until a stopping criterion is reached, which could be a given number of generations, for example, or when a given fitness is obtained. Hence, the main settings for these algorithms, which can be evaluated in hard problem formulation studies, are the population size, the number of generations, the crossover rate, and the mutation rate.

Research in the field of computer science has shown that the optimal parameter values in a genetic algorithm vary from problem to problem. There is an intuitive and accepted belief that population sizing, for example, should be set proportionally to the problem's size and difficulty [215,220]. When it comes to mutation and crossover operators, the ideal strategy is to strike a good balance between maintaining the fittest solutions in each new generation and introducing diversity. Previous studies were able to outline trends such as the fact that if the number of parameters in the optimization problem is low, the impact of the operator values is less, but this was no longer true when the problems became more complex [221]. This aspect is connected to the soft problem formulation previously detailed and the size of the solution space. It appears quite intuitive that under a given time constraint, the larger the solution space, the more efficient the algorithm must be. Many authors agree that high mutation and crossover values are more efficient in small populations, but that *too high* mutation rates will lead to a random search problem [222]. As a result, in problems with large populations, and thus many input parameters, lower mutation rates were preferred. Many studies also agree on the superiority of approaches in which these parameters are not static, but either follow a predefined variation [219] or are self-adapting [223–225]. However, these approaches are not yet standard in building optimization studies. Table 8-2 provides an overview of guidelines from a cross-field literature review for parameter settings in optimizations using GAs.

Table 8-2 Overview of guidelines and recommendations in the literature for parameter settings of genetic algorithms.

Source	Parameter setting	Value	Condition
Li et al. (2017) [205]	Population size	<50	Number of parameters <16
	Mutation rate	0.1	Number of parameters <21
	Crossover rate	0.5	Number of parameters <21
	Maximum generation	<1000	Number of parameters <21
Hamdy et al. (2016) [209]	Population size	2 to 4 times the number of parameters.	1400 - 1800 simulation in total
De Jong (1975) [226]	Population size	50 to 100	
	Mutation rate	0.001	
	Crossover rate	0.6	
Grefenstette (1986) [222]	Mutation rate	Maximum 0.01 otherwise, the problem becomes a random search regardless of other parameters. Values above 0.05 are typically harmful.	
	Settings for small populations (20 to 60 individuals)	High crossover rate and low mutation rate High crossover and high mutation.	

Mühlenbein et al. (1993) [227]	GA parameters	The mutation rate is given by 1/N. Mutation rates are more important in small populations to introduce diversity and avoid premature convergence Crossover rates depend on population size and are more important in large populations.	N is the number of parameters or the size of the problem

The findings from the literature about the relationships between population size, mutation probability and crossover rates can be summarized as such: problems with undersized populations can lead to poor solutions. Larger populations provided better solutions as there is an increased chance that a good solution, or an optimal, is present within the population. This can be addressed by following the recommendation of Hamdy et al. [209] and respecting a population size that is at least twice the number of parameters considered. Optimizations with smaller populations (20 to 60 individuals) should be combined with higher mutation rates to increase diversity and avoid premature convergence. Conversely, problems with large populations should have low mutation rates and higher crossover rates to behold better solutions from its already diverse population.

In the case study that was used in the work presented in this thesis, hard aspects of problem formulation were not investigated in detail. However, the variability of the settings used for the evolutionary algorithm implemented can be seen in Table 8-3. In this case, it is also interesting to note that in the flexible version of the script that was used, the number of parameters is hard to estimate as they were not independent. In these kinds of problems, parameter settings become even more challenging.

Table 8-3 Parameter settings used in the case study.

Case study name	Nb. of parameters	Population size	Nb. of generations	Elitism	Mutation	Crossover probability
BASE	2 per louvre	80	25	0.5	Rate 0.5 Probability 0.1	0.8
FLEX 1 OBJ	4 per louvre	100	100	0.5	Rate 0.5 Probability 0.06	0.8
FLEX 2 OBJ	4 per louvre	100	100	0.5	Rate 0.5 Probability 0.06	0.8
FLEX 3 OBJ	4 per louvre	100	100	0.5	Rate 0.5 Probability 0.06	0.8

NB: In the version of the evolutionary algorithm SPEA2 implemented in Octopus, the mutation parameter defining "the probability of a gene of undergoing mutation" is defined by the product of the mutation probability and the mutation rate as defined in Octopus.

8.4 Elements of response to the fourth research question

Investigating soft and hard problem formulation can contribute to increasing the robustness of optimization procedures in the AEC field. Additionally, these investigations can be used to gain insight into optimization problems and lead to performance-based design but also *performance-informed* design [213]. In the case study used to illustrate an investigation of soft problem formulation, the procedure allowed increasing the performance of the system. The results indicated that using the most flexible script, which had the largest amount of parameters, provided better solutions regardless of the formulation of the objectives. However, among the optimization runs with the flexible script, the investigation with three objectives provided the best set of tradeoffs, except in a case where very high levels of daylight are required. The assessment of the impact of soft problem formulation also allowed gaining a much deeper understanding of the phenotype of high performing solutions and of the dynamics in the different tradeoffs of the performance of a PVSD. This finding suggests that optimizations could be used in place of parametric analysis when the solution spaces are very large.

Hard aspects of problem formulation were reviewed with a particular focus on genetic algorithms. Despite the increasing popularity of optimization in the AEC field, there are still few guidelines available to researchers on the topic of parameter settings. It is hoped that with time, the guidelines coming from different fields and presented in this thesis, can be further enriched and also extend to different types of algorithms which may be more suited to carry out computationally demanding simulations.

9 Discussion and limitations

This thesis investigated how different building performance approaches can support the development of advanced building envelopes. The main knowledge gap it addressed relates to the difficulty of assessing the performance of new technologies due to their level of complexity.

The thesis anchors itself in the fit-for-purpose modelling approach, which is necessary when the system considered is too complex to be fully modelled in detail. The fit-for-purpose approach was not originally developed for building simulations but is a general modelling approach that recommends identifying which parts of the model to include to capture the physical object's behavior correctly, and with what level of detail.

This topic inspired **the first research question** addressed in Chapter 5 and which was "What are the main characteristics of ABEs that must be considered to ensure a suitable design and modelling approach in the early design phase?". The central answer to this question was a six-step framework to characterize advanced building envelopes and outline a strategy for modelling and simulating a specific solution. As part of this task, four key questions that modellers should ask themselves stood out. The first one was the purpose of the technology. The second one concerned the nature of the trigger(s) to consider as impacting the design or the control of the system. The third one concerned the type of control if there is one and whether it required modelling occupants. Finally, the last question concerned the scale of the technology's effects and whether this was a single zone, the entire building or if, for example, it was necessary to model a neighborhood response.

A different type of outcome of this framework is that it can also help establish whether a modeller should consider co-simulation to improve the modelling and simulation approach's accuracy. This topic was the subject of ***the second research question*** "*What are the opportunities, challenges, and tradeoffs associated with using co-simulation to improve and to evaluate the performance of ABEs?".* Chapter 6 dealt with this question and the topic of co-simulation by gathering state-of-the-art knowledge about this topic and proposing a critical assessment of its application to the modelling of ABEs. This chapter's main findings were that co-simulation allows overcoming many of the documented limitations of monolithic simulation tools and is particularly relevant for advanced building envelopes. Unfortunately, it is still not standardized enough to be easily implemented despite it being a promising approach. Most of the aspects described in this thesis and the journal publication on this topic focused on advanced building envelopes. However, many of the elements discussed apply to the use of co-simulation for building simulation in general. One of these is that co-simulation requires expertise in simulation tools and models, so it is currently mainly used in research, rather than in everyday consulting. There are, however, many ongoing developments in the data science and building information modelling fields, including a growing interest in digital twins, which may increase the accessibility of co-simulation. These developments are favourable for the uptake of digital tools and may lead to the cross-disciplinary platforms needed for the AEC industry to embrace a more digital future.

The third research question, "What are the benefits of using modelling approaches based on a combination of parametric design, co-simulation and numerical optimization for advanced building envelopes?" invited to a hands-on investigation detailed in Chapter 7. The particular case study selected to answer the question was the design of a parametrically scripted photovoltaic integrated shading device (PVSD). The developed methodology evaluated whether using a bottom-up approach could improve the system's efficiency by better balancing partially antagonistic goals. The system's overall performance was formulated through three objectives: to reduce net energy use, increase daylighting in the zone, and maximize the amount of renewable energy converted by the photovoltaic material. The approach's benefits were analyzed by comparing the outcomes of three different models with different complexity levels. First, a traditional parametric analysis (used as a reference and that did not require parametric scripting), then an optimized base parametric model, and finally, an optimized highly flexible parametric model. The study results showed that the parametric modelling approach allowed evaluating a larger number of solutions and efficiently compared to the reference. However, to find solutions that more significantly outperformed reference configurations, the degree of freedom in the model needed to be increased, and the system defined with more variables. Another benefit of the approach was that it led to solutions that could simultaneously improve all three objectives. In practice, this means one can outline a design "sweet spot" using this methodology and then explore it more in detail.

The reliability of the modelling approach was also verified through a full-scale experimental validation. This step was necessary to estimate the accuracy of the quantities simulated by the different simulation engines used in the co-simulation. It was also a way to assess the approach's limitations, which mostly concerned the daylight simulations. For instance, it showed that the co-simulation approach was good enough to evaluate illuminance levels when using climate-based daylighting metrics. However, it was not accurate enough to assess the risk of glare.

The fourth research question highlighted the variability of model outcomes by specifically investigating their sensitivity to numerical optimization parameters. The question was posed as "*What are important decisions modelers need to make when using numerical optimization to improve performance and what is their impact on the result?*". The main answers to this question are presented in Chapter 8 as an evaluation of the impact of problem formulation. The first take-away from this study is that the field of optimization is highly technical. However, to transfer applications to buildings, some of these complexities are overlooked. The literature unequivocally agrees that modellers need to have a good understanding of both the optimization algorithms and the problems they apply them to in order to have robust results. This is sometimes expressed as the need to understand the difficulty of the problem they want to solve. In reality, there are few guidelines in the field of buildings regarding how to do this, and very few studies share the details of their methodologies. The work presented in this chapter of the thesis tried to address this lack of guidelines for problems by defining soft and hard problem formulation. The decisions that rest with modelers were thus for soft problem formulation ones that concerned the nature of the objectives, their number or how many parameters are worth including in the optimization. For hard problem formulation, these were: what algorithm to use, what parameter settings to use, and which level of complexity should the model have. Cross-disciplinary research reviews provided a basis for parameter settings for genetic algorithm applications but will need to be enriched in the future to cover more algorithms.

One of the most interesting findings of investigating soft problem formulation was that it allowed obtaining a different view on how to use optimization in building design. Optimization in buildings is not only a way to define the highest performing design (given the specific assumptions in the problem), but it is arguably a handy tool to obtain insight into the problem itself. When applied to the case study used throughout this thesis, investigating different objectives settings, for example, highlighted that using all three objectives explicitly could provide better tradeoffs in the performance. This was, despite two of them being redundant. It also allowed understanding better how the algorithm was searching in the solution space. Statistically plotting parameter variations in the Pareto solutions was also interesting to check the robustness of the algorithm's solutions. Although these studies are time-consuming, they provide much more knowledge of the problems at hand and allow tackling changes that may happen later in the project.

The limitations of this work due to its scope should also be mentioned. These mainly concern the fact that the detailed modelling methods and validation in the presented work were mainly destined to the early-phase design of a fixed PVSD. These analyses were also only carried out using a single simulation tool. They could be extended to cover different types of technologies and different types of simulation environments to improve their validity. Furthermore, parametric scripting is a very free activity, and the choices made along the way are likely to have influenced the results. This also means that potentially many different scripting approaches could prove to be more efficient or more accurate than the ones developed in this thesis.

Another important element is that the impact of the technology on the building's net energy use and indoor comfort were not evaluated in a framework that considered occupant behavior or occupant preferences specifically. For this reason, there was also no consideration of any advanced modelling of user behavior or dynamic operation. As a result, the case study that is used in this thesis is also modelled using standard ranges for indoor comfort. In reality, these ranges are continuously questioned, and in recent years, many studies focused on defining and assessing more realistic human comfort ranges. This topic has become a field of its own, and covering it in-depth was impossible due to time and scope limitations. Finally, the simulation work presented is mainly carried out with a single type of optimization algorithm. Recent work in the optimization field has shown that the type of algorithm used, genetic algorithms are not as superior in building optimization problems as initially thought. Comparing several algorithms would have provided more depth to the analysis carried out in this work. This may also have impacted the results and the conclusions, particularly given the speed of development in the field and the constant progress and integration of new tools.

10 Conclusions and personal reflections

The work presented in this thesis spans the entire development of a modelling approach of an ABE, starting with the initial characterization and development of a fit-for-purpose modelling approach, and ending with the verification of the robustness of an optimized solution. On a meta-level, this research is one of many efforts to improve building energy efficiency in the built environment by generating new methods, knowledge, and developing solutions to achieve climate-related goals. Part of the research developed focused on a "low-tech" and relatively low-cost case study. It demonstrated its potential to improve indoor comfort, reduce energy use and support renewable energy conversion. Because of the system's simplicity regarding its components and function, its market-appeal is likely to be consequent. One path to continuing this research could be to use the methods developed in this thesis to create a commercially viable system and implement it as part of carbon emission reduction strategies.

From a scientific point of view, the research activities presented in this thesis have potential scientific impacts in different building simulation fields. The characterization framework presented stemmed from a critical analysis of the literature and identified the weaknesses of existing classifications. In this thesis, its value was to create a unified characterization tool for an extremely heterogeneous group of technologies. However, this work's potential impact goes beyond this particular application, and the research's potential audience could extend to urban planners, architects, and policymakers. Part of this work's vision was to create a tool with a new angle to zero-emission neighborhood design. The idea was to explore if it was possible to design building envelopes based on their requirements and those of a neighborhood. In this perspective, the total building envelope area available in a neighborhood becomes a canvas in different integrated renewable energy technologies are used to support the energy autonomy of the built environment as a whole.

The research activity on the topic of co-simulation was the first publication to provide a comprehensive review of this technique. Although the application in this thesis is focused on building envelopes, the findings are very much applicable to simulation in general. By publishing this paper as part of the ambitious "Ten questions" initiative, knowledge about co-simulation could reach a more "mainstream" audience and attract attention to the topic across different research fields. The focus on ongoing developments in research is also an important element of the publication as this might inspire new effort (possibly coming from other fields) to help solve the remaining challenges.

The simulation-based investigations in this thesis have the most impact among groups interested in parametric design for building performance. The most important contributions of this activity were the validation of the co-simulated modelling approach and the script's sharing as an open-access file. The script's full development was a procedure that took approximately one year when one starts from a blank canvas. Sharing scripts creates much value for people working with these tools because it can help teach parametric thinking and show people how to use different plug-ins or techniques.

Finally, the fifth research article which investigated the use of optimization was developed out of the realization that the knowledge available in the literature for the field of architectural optimization was scarce. The target audience of this publication is simulation users interested in using optimization in general, but users interested in genetic algorithms will also benefit from the substantial literature review focused on parameter settings. This work is an important contribution to the field but will need to be completed with more studies that will help solidify the guidelines that it started to establish.

As we shift our expectations of buildings from simple consumers to active entities that interact with their environment and are able to interplay with other buildings or infrastructure to stabilize the grid, building design is also changing. Advanced building envelopes are one of the many technologies used to achieve these new goals. Focusing on building skins' design and performance is an exciting approach because it becomes the merging point of two previously distinct fields: architecture and engineering. As an engineering student, I heard many jokes about architects, and there has always been a love-hate relationship as far as I can see between the two fields. But now, more than ever, the lines are blurred. Architects are venturing into more advanced daylighting simulation, evaluating energy use, and designing renewable energy conversion systems. On the other hand, engineers are using more design tools and making baby steps into a more creative process.

Central to this overlapping of disciplines lay parametric design tools and the possibility of using numerical optimization and building simulation. The development of these tools has, in many ways, made simulation accessible to a broader base of users. While they may take over some of the more repetitive tasks of architects, and allow the use of optimization to define building shapes or massing plans, I do not believe that these tools will ever replace architects or engineers. This is because these tools do not have human judgement, and they are precisely this: tools.

Recently, Dr Christoph Waibel on the ETH energy blog [211] discussed how smart grids will change the future of how architects design buildings. In this article, the author suggests that despite the ever-growing complexity of buildings, the solution to tackle this is not to add engineering or computer science to architecture curriculums but to have better tools. I believe this may be a bit optimistic. The accessibility and ease of use of new tools such as those used in this thesis are partly misleading. Because these tools make things look seamless, they sometimes hide the complexity of the simulations they involve. In reality, these approaches are no more foolproof than any other modelling task. This is not all bad, but most people who work with programming or simulation will tell you that a large part of the work we do is debugging. And a lot of this work requires understanding how the simulation engines work and where or how the inputs are used.

Buildings are complex eco-systems with highly non-linear behavior, and each building is unique in its way. And this isn't easy to simplify while maintaining some degree of accuracy. Building models' inputs can also contain thousands of variables with many known knowns, known unknowns, and unknown unknowns. One of the consequences of this is, for example, that optimization for building design cannot be used to define absolute best performing solutions on reproducible problems as it is used for well-structured, known problems in the field of mathematics. Another consequence is that there is a growing need to include uncertainty in our models. When building simulation was used as a benchmark, the simulation's accuracy was not as much a central question as to when we use it to make policy, design cities or deliver contractual documents based on real performance.

A very interesting manifesto article published in Nature [212] about modelling and uncertainty, and the dangers of politicizing results from models predicting COVID-19 trends makes several compelling arguments on this topic. Among other things, they highlight the importance of considering sensitivity, for example, for all uncertain parameters. The authors also discuss the importance of complexity versus accuracy (the foundation of the fit-for-purpose approach). They point out that we should treat most models the same way we consider some of the most used models: weather forecasting models. We tend to accept uncertainty around these, yet they are used by many different people, from pilots to hikers, and for decisions of variable gravity. This is an excellent point because, at the end of the day, we are all still bound by the famous rule of modelling and simulation that is "garbage in, garbage out". And the awareness of the consequences of our assumptions needs to be passed down simultaneously as we develop more tools and new models. The right way to do this is likely to build interdisciplinary teams and knowledge and train people to bridge these gaps in teams. This ability is perhaps the most important skill I have acquired during my work as a PhD candidate.

References

[1] The European Parliament and the Council of the European Union, Directive 2012/27/EU on energy efficiency, amending directives 2009/125/EC and 2010/30EU and repealing Directives 2004/8/EC and 2006/32/EC, Off. J. Eur. Union. (2012).

[2] P. Van Berkel, K. Kruit, F. Van de Poll, F. Rooijers, J. Vendrik, Zero carbon buildings 2050 - background report, (2020).

[3] IEA–ECBCS Annex 44, Integrating environmentally responsive elements in buildings, state of the art review, in: M. Perino (Ed.), 2007.

[4] J. Kurnitski, nZEB definitions in Europe EPBD recast – Nearly zero energy buildings nZEB, (2014).

[5] D. D'Agostino, P. Zangheri, B. Cuniberti, D. Paci, P. Bertoldi, Synthesis Report on the National Plans for NZEBs, JRC Science Hub, 2016. https://doi.org/10.2790/659611.

[6] I. Davis, D. Carriero, O. Dzioubinski, S. Foster, S. Held, L. Jachia, A. Piwowarska, G. Roll, A. Vasilyev, I. Atamuradova, M. Banjac, A. Bäuml, R. Bernhardt, G. Prata Dias, L. De Francesco, A. Freyre, K. Gura, J. Hogeling, V. Jalalyan, A. Karapetyan, N. Laure, A. Leskoviku, R. Meyer, M.-M. Nahod, M. Kumar Patel, S. Robu, H. Schramm, A. Solujić, D. Yordanova, Mapping of Existing Energy Efficiency Standards and Technologies in Buildings in the UNECE Region, (2018) 130. http://www.unece.org/housing/eestandardsinbuildings.html.

[7] IEA, IEA Annex 44. Integrating Environmentally Responsive Elements in Buildings. State-of-the-art Review. Vol.1. State-of-the-Art Report, 2008. http://www.annex44.civil.aau.dk/puplications/Technical Reports/State-of-the-Art Vol 1.pdf.

[8] Cost Action TU1403, (n.d.). http://tu1403.eu/ (accessed November 1, 2019).

[9] IEA, Transition to Sustainable Buildings - Strategies and opportunities to 2050, 2013. https://doi.org/10.1787/9789264202955-en.

[10] IEA, Technology Roadmap - Energy Efficient Building Envelopes, 2013. https://webstore.iea.org/technology-roadmap-energy-efficient-building-envelopes.

[11] A. Okeil, A holistic approach to energy efficient building forms, Energy Build. 42 (2010) 1437–1444. https://doi.org/https://doi.org/10.1016/j.enbuild.2010.03.013.

[12] E. Gratia, A. De Herde, Design of low energy office buildings, Energy Build. 35 (2003) 473–491. https://doi.org/10.1016/S0378-7788(02)00160-3.

[13] S.B. Sadineni, S. Madala, R.F. Boehm, Passive building energy savings: A review of building envelope components, Renew. Sustain. Energy Rev. 15 (2011) 3617–3631. https://doi.org/10.1016/j.rser.2011.07.014.

[14] F. Favoino, R.C.G.M. Loonen, M. Doya, F. Goia, C. Bedon, F. Babich, Building

performance simulation and characterisation of adaptive facades – Adaptive Facade Network, 2018. http://tu1403.eu/wp-content/uploads/Vol-3-2_for-web-Open-Access_9789463661119.pdf.
[15] S.J. Hayter, P. a Torcellini, R.R. Hayter, The energy design process for designing and construcitng high-performance buildings, CLIMA 2000 World Congr. (2001) 15–18.
[16] D.H.W. Li, L. Yang, J.C. Lam, Zero energy buildings and sustainable development implications - A review, Energy. 54 (2013) 1–10. https://doi.org/https://doi.org/10.1016/j.energy.2013.01.070.
[17] M. Perino, V. Serra, Switching from static to adaptable and dynamic building envelopes: A paradigm shift for the energy efficiency in buildings, J. Facade Des. Eng. 3 (2015) 143–163. https://doi.org/10.3233/fde-150039.
[18] R.W. Shepard, The law of diminishing returns, Lect. Notes Econ. Math. Syst. (1974) 287–318.
[19] K. Voss, I. Sartori, A. Napolitano, S. Geier, H. Gonzalves, M. Hall, J. Widén, J. a Candanedo, A.J. Marszal, Load Matching and Grid Interaction of Net Zero Energy Building, Proc. Build. Simul. 2011. 6 (2011) 14–16. http://www.bounceinteractive.com/bs2011/bs2011/pdf/P_1787.pdf.
[20] S.M. Fufa, R. Dahl Schlanbusch, K. Sørnes, M. Inman, I. Andresen, A Norwegian ZEB Definition Guideline, 2016. https://doi.org/10.13140/RG.2.2.26443.80162.
[21] P.A. Torcellini, D.B. Crawley, Understanding zero-energy buildings, ASHRAE J. 48 (2006).
[22] Q. Jin, M. Overend, Sensitivity of façade performance on early-stage design variables, Energy Build. 77 (2014) 457–466. https://doi.org/10.1016/j.enbuild.2014.03.038.
[23] D. Chwieduk, Towards sustainable-energy buildings, Appl. Energy. 76 (2003) 211–217. https://doi.org/10.1016/S0306-2619(03)00059-X.
[24] F. Favoino, M. Overend, A simulation framework for the evaluation of next generation Responsive Building Envelope technologies, Energy Procedia. 78 (2015) 2602–2607. https://doi.org/10.1016/j.egypro.2015.11.302.
[25] W.N. Hien, W. Liping, A.N. Chandra, A.R. Pandey, W. Xiaolin, Effects of double glazed facade on energy consumption, thermal comfort and condensation for a typical office building in Singapore, Energy Build. 37 (2005) 563–572. https://doi.org/10.1016/j.enbuild.2004.08.004.
[26] F. Favoino, F. Goia, M. Perino, V. Serra, Experimental assessment of the energy performance of an advanced responsive multifunctional façade module, Energy Build. 68 (2014) 647–659. https://doi.org/10.1016/j.enbuild.2013.08.066.
[27] F. Favoino, Q. Jin, M. Overend, Design and control optimisation of adaptive insulation systems for office buildings. Part 1: Adaptive technologies and simulation framework, Energy. 127 (2017) 301–309. https://doi.org/10.1016/j.energy.2017.03.083.
[28] F. Favoino, F. Fiorito, A. Cannavale, G. Ranzi, M. Overend, Optimal control and

performance of photovoltachromic switchable glazing for building integration in temperate climates, Appl. Energy. 178 (2016) 943–961. https://doi.org/10.1016/j.apenergy.2016.06.107.

[29] F. Goia, M. Haase, M. Perino, Optimizing the configuration of a façade module for office buildings by means of integrated thermal and lighting simulations in a total energy perspective, Appl. Energy. 108 (2013) 515–527. https://doi.org/10.1016/j.apenergy.2013.02.063.

[30] A. Aldawoud, Conventional fixed shading devices in comparison to an electrochromic glazing system in hot, dry climate, Energy Build. 59 (2013) 104–110. https://doi.org/10.1016/j.enbuild.2012.12.031.

[31] P.F. Tavares, A.R. Gaspar, A.G. Martins, F. Frontini, Evaluation of electrochromic windows impact in the energy performance of buildings in mediterranean climates, Energy Policy. 67 (2014) 68–81. https://doi.org/10.1016/j.enpol.2013.07.038.

[32] F. Favoino, M. Overend, Q. Jin, The optimal thermo-optical properties and energy saving potential of adaptive glazing technologies, Appl. Energy. 156 (2015) 1–15. https://doi.org/10.1016/j.apenergy.2015.05.065.

[33] A. De Gracia, L. Navarro, A. Castell, Á. Ruiz-Pardo, S. Álvarez, L.F. Cabeza, Thermal analysis of a ventilated facade with PCM for cooling applications, Energy Build. 65 (2013) 508–515. https://doi.org/10.1016/j.enbuild.2013.06.032.

[34] R.S. Kamel, A.S. Fung, Modeling, simulation and feasibility analysis of residential BIPV/T+ASHP system in cold climate—Canada, Energy Build. 82 (2014) 758–770. https://doi.org/10.1016/j.enbuild.2014.07.081.

[35] O.B. Kazanci, M. Skrupskelis, P. Sevela, G.K. Pavlov, B.W. Olesen, Sustainable heating, cooling and ventilation of a plus-energy house via photovoltaic/thermal panels, Energy Build. 83 (2014) 122–129. https://doi.org/10.1016/j.enbuild.2013.12.064.

[36] H. Gholami, H.N. Røstvik, D. Müller-Eie, Holistic economic analysis of building integrated photovoltaics (BIPV) system: Case studies evaluation, Energy Build. 203 (2019). https://doi.org/10.1016/j.enbuild.2019.109461.

[37] C. Arkar, T. Žižak, S. Domjan, S. Medved, Dynamic parametric models for the holistic evaluation of semi-transparent photovoltaic/thermal façade with latent storage inserts, Appl. Energy. 280 (2020) 115994. https://doi.org/10.1016/j.apenergy.2020.115994.

[38] F. Favoino, F. Goia, M. Perino, V. Serra, Experimental analysis of the energy performance of an ACTive, RESponsive and Solar (ACTRESS) façade module, Sol. Energy. (2016). https://doi.org/10.1016/j.solener.2016.03.044.

[39] P. Bonato, M. D'Antoni, R. Fedrizzi, Modelling and simulation-based analysis of a façade-integrated decentralized ventilation unit, J. Build. Eng. 29 (2020) 101183. https://doi.org/10.1016/j.jobe.2020.101183.

[40] A. Tabadkani, M. Valinejad Shoubi, F. Soflaei, S. Banihashemi, Integrated parametric design of adaptive facades for user's visual comfort, Autom.

Constr. 106 (2019) 102857. https://doi.org/10.1016/j.autcon.2019.102857.
[41] A. Tabadkani, A. Roetzel, H.X. Li, A. Tsangrassoulis, Design approaches and typologies of adaptive facades: A review, Autom. Constr. 121 (2021) 103450. https://doi.org/10.1016/j.autcon.2020.103450.
[42] A. Ghaffarianhoseini, A. Ghaffarianhoseini, U. Berardi, J. Tookey, D.H.W. Li, S. Kariminia, Exploring the advantages and challenges of double-skin façades (DSFs), Renew. Sustain. Energy Rev. 60 (2016) 1052–1065. https://doi.org/10.1016/j.rser.2016.01.130.
[43] B.P. Heiz, Z. Pan, G. Lautenschläger, C. Sirtl, M. Kraus, L. Wondraczek, Ultrathin Fluidic Laminates for Large-Area Façade Integration and Smart Windows, Adv. Sci. 4 (2017) 1600362.
[44] M. Casini, Active dynamic windows for buildings: A review, Renew. Energy. 119 (2018) 923–934. https://doi.org/10.1016/j.renene.2017.12.049.
[45] L. Bianco, Y. Cascone, F. Goia, M. Perino, V. Serra, Responsive glazing systems: Characterisation methods and winter performance, Sol. Energy. (2017). https://doi.org/10.1016/j.solener.2017.06.029.
[46] P. Jayathissa, M. Luzzatto, J. Schmidli, J. Hofer, Z. Nagy, A. Schlueter, Optimising building net energy demand with dynamic BIPV shading, Appl. Energy. 202 (2017) 726–735. https://doi.org/10.1016/j.apenergy.2017.05.083.
[47] A. Varela Souto, R. Loonen, Lumiduct, (2018).
[48] E. Cuce, S.B. Riffat, A state-of-the-art review on innovative glazing technologies, Renew. Sustain. Energy Rev. 41 (2015) 695–714. https://doi.org/10.1016/j.rser.2014.08.084.
[49] E. Cuce, P.M. Cuce, C.J. Wood, S.B. Riffat, Toward aerogel based thermal superinsulation in buildings: A comprehensive review, Renew. Sustain. Energy Rev. 34 (2014) 273–299. https://doi.org/10.1016/j.rser.2014.03.017.
[50] G. Quesada, D. Rousse, Y. Dutil, M. Badache, S. Hallé, A comprehensive review of solar facades. Transparent and translucent solar facades, Renew. Sustain. Energy Rev. 16 (2012) 2643–2651.
[51] R. Baetens, B.P. Jelle, A. Gustavsen, Properties, requirements and possibilities of smart windows for dynamic daylight and solar energy control in buildings: A state-of-the-art review, Sol. Energy Mater. Sol. Cells. 94 (2010) 87–105. https://doi.org/10.1016/j.solmat.2009.08.021.
[52] M. Mandalaki, K. Zervas, T. Tsoutsos, A. Vazakas, Assessment of fixed shading devices with integrated PV for efficient energy use, Sol. Energy. 86 (2012) 2561–2575. https://doi.org/10.1016/j.solener.2012.05.026.
[53] S.-H. Yoo, E.-T. Lee, Efficiency characteristic of building integrated photovoltaics as a shading device, Build. Environ. 37 (2002) 615–623. https://doi.org/10.1016/S0360-1323(01)00071-3.
[54] S. Kang, T. Hwang, J.T. Kim, Theoretical analysis of the blinds integrated photovoltaic modules, Energy Build. 46 (2012) 86–91. https://doi.org/10.1016/j.enbuild.2011.10.042.
[55] M. Mandalaki, S. Papantoniou, T. Tsoutsos, Assessment of energy production

from photovoltaic modules integrated in typical shading devices, Sustain. Cities Soc. 10 (2014) 222–231. https://doi.org/10.1016/j.scs.2013.09.001.
[56] X. Zhang, Building Perormance Evaluation of Integrated Transparent Photovoltaic Blind System by a Virtual Testbed, 2014.
[57] R.C.G.M. Loonen, M. Trčka, D. Cóstola, J.L.M. Hensen, Climate adaptive building shells: State-of-the-art and future challenges, Renew. Sustain. Energy Rev. 25 (2013) 483–493. https://doi.org/10.1016/j.rser.2013.04.016.
[58] T.N. Anderson, M. Duke, G.L. Morrison, J.K. Carson, Performance of a building integrated photovoltaic/thermal (BIPVT) solar collector, Sol. Energy. 83 (2009) 445–455. https://doi.org/10.1016/j.solener.2008.08.013.
[59] H. Manz, T. Frank, Thermal simulation of buildings with double-skin façades, Energy Build. 37 (2005) 1114–1121. https://doi.org/10.1016/j.enbuild.2005.06.014.
[60] T. Yang, A.K. Athienitis, A review of research and developments of building-integrated photovoltaic/thermal (BIPV/T) systems, Renew. Sustain. Energy Rev. 66 (2016) 886–912. https://doi.org/10.1016/j.rser.2016.07.011.
[61] I.L. Wong, P.C. Eames, R.S. Perera, A review of transparent insulation systems and the evaluation of payback period for building applications, Sol. Energy. 81 (2007) 1058–1071. https://doi.org/10.1016/j.solener.2007.04.004.
[62] C. Maurer, T. Baumann, M. Hermann, P. Di Lauro, S. Pavan, L. Michel, T.E. Kuhn, Heating and cooling in high-rise buildings using facade-integrated transparent solar thermal collector systems, J. Build. Perform. Simul. 6 (2013) 449–457. https://doi.org/10.1080/19401493.2013.766263.
[63] E. Taveres-Cachat, F. Favoino, R. Loonen, F. Goia, Ten questions concerning co-simulation for performance prediction of advanced building envelopes, Build. Environ. (2021).
[64] R.C.G.M. Loonen, F. Favoino, J.L.M. Hensen, M. Overend, Review of current status, requirements and opportunities for building performance simulation of adaptive facades†, J. Build. Perform. Simul. 10 (2017) 205–223. https://doi.org/10.1080/19401493.2016.1152303.
[65] A. Kirimtat, O. Krejcar, B. Ekici, M. Fatih Tasgetiren, Multi-objective energy and daylight optimization of amorphous shading devices in buildings, Sol. Energy. 185 (2019) 100–111. https://doi.org/10.1016/j.solener.2019.04.048.
[66] S.M. Hosseini, M. Mohammadi, A. Rosemann, T. Schröder, J. Lichtenberg, A morphological approach for kinetic façade design process to improve visual and thermal comfort: Review, Build. Environ. 153 (2019) 186–204. https://doi.org/10.1016/j.buildenv.2019.02.040.
[67] A.H.A. Mahmoud, Y. Elghazi, Parametric-based designs for kinetic facades to optimize daylight performance: Comparing rotation and translation kinetic motion for hexagonal facade patterns, Sol. Energy. 126 (2016) 111–127. https://doi.org/10.1016/j.solener.2015.12.039.
[68] R.C.G.M. Loonen, S. Singaravel, M. Trčka, D. Cóstola, J.L.M. Hensen, Simulation-based support for product development of innovative building

envelope components, Autom. Constr. 45 (2014) 86–95.
[69] C. Waibel, R. Evins, J. Carmeliet, Co-simulation and optimization of building geometry and multi-energy systems: Interdependencies in energy supply, energy demand and solar potentials, Appl. Energy. 242 (2019) 1661–1682. https://doi.org/10.1016/j.apenergy.2019.03.177.
[70] H. Taleb, M.A. Musleh, Applying urban parametric design optimisation processes to a hot climate: Case study of the UAE, Sustain. Cities Soc. 14 (2015) 236–253. https://doi.org/10.1016/j.scs.2014.09.001.
[71] C.M. Lai, S. Hokoi, Solar façades: A review, Build. Environ. 91 (2015) 152–165. https://doi.org/10.1016/j.buildenv.2015.01.007.
[72] A. Prieto, T. Klein, U. Knaack, T. Auer, Main perceived barriers for the development of building service integrated facades: Results from an exploratory expert survey, J. Build. Eng. 13 (2017) 96–106. https://doi.org/10.1016/j.jobe.2017.07.008.
[73] E. Taveres-Cachat, S. Grynning, O. Almås, F. Goia, Advanced transparent facades: market available products and associated challenges in building performance simulation, in: Energy Procedia, Elsevier, Trondheim, 2017.
[74] A. Ghaffarian Hoseini, A. Ghaffarian Hoseini, U. Berardi, J. Tookey, D.H.W. Li, S. Kariminia, Exploring the advantages and challenges of double-skin facades (DSFs), Renew. Sustain. Energy Rev. 60 (2016) 1052–1065. https://doi.org/10.1016/j.rser.2016.01.130.
[75] M. Konstantoglou, A. Tsangrassoulis, Dynamic operation of daylighting and shading systems: A literature review, Renew. Sustain. Energy Rev. 60 (2016) 268–283. https://doi.org/10.1016/j.rser.2015.12.246.
[76] S. Attia, M. Hamdy, W. O'Brien, S. Carlucci, Assessing gaps and needs for integrating building performance optimization tools in net zero energy buildings design, Energy Build. 60 (2013) 110–124. https://doi.org/10.1016/j.enbuild.2013.01.016.
[77] S. Attia, E. Gratia, A. De Herde, J.L.M. Hensen, Simulation-based decision support tool for early stages of zero-energy building design, Energy Build. 49 (2012) 2–15. https://doi.org/10.1016/j.enbuild.2012.01.028.
[78] S. Attia, S. Bilir, T. Safy, C. Struck, R. Loonen, F. Goia, Current trends and future challenges in the performance assessment of adaptive façade systems, Energy Build. 179 (2018) 165–182. https://doi.org/10.1016/j.enbuild.2018.09.017.
[79] S. Envelope, S. For, Report on barriers for new solar envelope systems Report on barriers for new solar envelope systems, (n.d.). https://doi.org/10.18777/ieashc-task56-2018-0001.
[80] IEA, IEA Annex 44. Integrating Environmentally Responsive Elements in Buildings. State-of-the-art Review. Vol.2 A. Responsive Building Elements, 2008. http://www.annex44.civil.aau.dk/puplications/Technical Reports/State-of-the-Art of RBE Vol2A.pdf.
[81] P.K. Heiselberg, Expert Guide Part 1 Responsive Building Concepts, 2010.
[82] J. Thomsen, L. Gullbrekken, S. Grynning, J. Holme, Evaluering av boliger med

lavt energibehov (EBLE), 2017.

[83] J. Liang, Y. Qiu, M. Hu, Mind the energy performance gap: Evidence from green commercial buildings, Resour. Conserv. Recycl. 141 (2019) 364–377. https://doi.org/10.1016/j.resconrec.2018.10.021.

[84] D.B. Crawley, J.W. Hand, M. Kummert, B.T. Griffith, Contrasting the capabilities of building energy performance simulation programs, Build. Environ. 43 (2008) 661–673. https://doi.org/10.1016/j.buildenv.2006.10.027.

[85] J.A. Clarke, J.L.M. Hensen, Integrated building performance simulation: Progress, prospects and requirements, Build. Environ. 91 (2015) 294–306. https://doi.org/10.1016/j.buildenv.2015.04.002.

[86] R.C.G.M. Loonen, F. Favoino, J.L.M. Hensen, M. Overend, Review of current status, requirements and opportunities for building performance simulation of adaptive facades, J. Build. Perform. Simul. 2 (2017) 205–223. http://dx.doi.org/10.1080/19401493.2016.1152303%5Cnhttp://www.tandfonline.com/doi/full/10.1080/19401493.2016.1152303.

[87] L. Mazzarella, M. Pasini, Building Energy Simulation and Object-Oriented Modelling: Review and Reflections Upon Achieved Results and Further Developments, in: Elev. Int. IBPSA Conf., Glasgow, UK, 2009: pp. 638–645.

[88] J.A. Clarke, J.L.M. Hensen, Integrated building performance simulation: Progress, prospects and requirements, Build. Environ. 91 (2015) 294–306. https://doi.org/10.1016/j.buildenv.2015.04.002.

[89] E. Taveres-Cachat, S. Grynning, O. Almas, F. Goia, Advanced transparent facades: Market available products and associated challenges in building performance simulation, in: Energy Procedia, 2017. https://doi.org/10.1016/j.egypro.2017.09.685.

[90] B. Dong, K.P. Lam, A real-time model predictive control for building heating and cooling systems based on the occupancy behavior pattern detection and local weather forecasting, Build. Simul. 7 (2014) 89–106. https://doi.org/10.1007/s12273-013-0142-7.

[91] R. Brahme, Z.O. Neill, W. Sisson, K. Otto, Net-Zero energy buildings – challenges and workarounds United Technologies Research Centre , East Hartford , CT Robust Systems and Strategy , LLC, Energy. (2009) 9–16. http://www.ibpsa.org/proceedings/BS2009/BS09_0009_16.pdf.

[92] F. Goia, M. Perino, M. Haase, A numerical model to evaluate the thermal behaviour of PCM glazing system configurations, Energy Build. 54 (2012) 141–153. https://doi.org/10.1016/j.enbuild.2012.07.036.

[93] L. Giovannini, F. Favoino, A. Pellegrino, V.R.M. Lo Verso, V. Serra, M. Zinzi, Thermochromic glazing performance: From component experimental characterisation to whole building performance evaluation, Appl. Energy. 251 (2019) 113335. https://doi.org/10.1016/j.apenergy.2019.113335.

[94] C. Gehbauer, D.H. Blum, T. Wang, E.S. Lee, An assessment of the load modifying potential of model predictive controlled dynamic facades within the California context, Energy Build. 210 (2020) 109762.

https://doi.org/10.1016/j.enbuild.2020.109762.
[95] H.B. Gunay, W. O'Brien, I. Beausoleil-Morrison, A critical review of observation studies, modeling, and simulation of adaptive occupant behaviors in offices, Build. Environ. 70 (2013) 31–47. https://doi.org/10.1016/j.buildenv.2013.07.020.
[96] A. Luna-Navarro, R. Loonen, M. Juaristi, A. Monge-Barrio, S. Attia, M. Overend, Occupant-Facade interaction: a review and classification scheme, Build. Environ. 177 (2020) 106880. https://doi.org/10.1016/j.buildenv.2020.106880.
[97] E. Taveres-Cachat, F. Goia, Co-simulation and validation of the performance of a highly flexible parametric model of an external shading system, Build. Environ. 182 (2020). https://doi.org/10.1016/j.buildenv.2020.107111.
[98] T. Wei, A review of sensitivity analysis methods in building energy analysis, Renew. Sustain. Energy Rev. 20 (2013) 411–419. https://doi.org/10.1016/j.rser.2012.12.014.
[99] C.J. Hopfe, J.L.M. Hensen, Uncertainty analysis in building performance simulation for design support, Energy Build. 43 (2011) 2798–2805. https://doi.org/10.1016/j.enbuild.2011.06.034.
[100] R. Evins, A review of computational optimisation methods applied to sustainable building design, Renew. Sustain. Energy Rev. 22 (2013) 230–245. https://doi.org/10.1016/j.rser.2013.02.004.
[101] C. Maurer, T.E. Kuhn, Transparent solar thermal façade collectors : New Trnsys Type and first validation results, (2011). https://doi.org/10.13140/2.1.4373.1847.
[102] M. Trčka, Co-simulation for performance prediction of innovative integrated mechanical energy systems in buildings, 2008. http://www.bwk.tue.nl/bps/hensen/team/past/Trcka.pdf%5Cnfile:///Users/ilinca/Desktop/Dropbox/Papers2/Articles/2008/2008_Trčka.pdf%5Cnpapers2://publication/uuid/AA1C2492-3E96-4ED6-A575-1B31C20F80B4.
[103] S. Robinson, Choosing the right model: Conceptual modeling for simulation, Proc. - Winter Simul. Conf. (2011) 1423–1435. https://doi.org/10.1109/WSC.2011.6147862.
[104] I. Gaetani, P.J. Hoes, J.L.M. Hensen, Occupant behavior in building energy simulation: Towards a fit-for-purpose modeling strategy, Energy Build. 121 (2015) 188–204. https://doi.org/10.1016/j.enbuild.2016.03.038.
[105] C. Hart, Doing a literature review : releasing the research imagination, 2nd editio, SAGE Publications Ltd, Los Angeles, California (USA), 2018.
[106] B. Blocken, New initiative: "Ten questions" paper series in building & environment, Build. Environ. 94 (2015) 325–326. https://doi.org/10.1016/j.buildenv.2015.08.012.
[107] R. Oxman, Thinking difference: Theories and models of parametric design thinking, Des. Stud. 52 (2017) 4–39. https://doi.org/10.1016/j.destud.2017.06.001.
[108] S. Bhooshan, Parametric design thinking: A case-study of practice-embedded

architectural research, Des. Stud. 52 (2017) 115–143. https://doi.org/10.1016/j.destud.2017.05.003.
[109] D. Karle, B.M. Kelly, Parametric Thinking, ACADIA Reg. 2011 Parametr. SPC. (2011) 109–113.
[110] L. Davis, Handbook of genetic algorithms, Van Nostrand Reinhold, New York, 1991.
[111] J. Holland, Adaptation in natural and artificial systems : an introductory analysis with application to biology, MIT Press Cambridge, MA, USA. (1975).
[112] J.A. Clarke, Energy simulation in building design, Routeledge, Glasgow, UK, 2007.
[113] R. Judkoff, J. Neymark, Model validation and testing: The methodological foundation of ASHRAE Standard 140, ASHRAE Trans. 112 PART 2 (2006) 367–376.
[114] R.D. Judkoff, J. Neymark, I. Beausoleil-morrison, D.B. Crawley, D.E. Knebel, S.J. Rees, G.N. Walton, B.A. Wilcox, B.P. Dougherty, J.F. Hogan, F.E. Jakob, S.D. Kennedy, D.E. Knebel, K.W. Peterson, Standard method of test for the evaluation of building energy analysis computer programs, ASHRAE Stand. 8400 (2011).
[115] T. Yang, Y. Pan, J. Mao, Y. Wang, Z. Huang, An automated optimization method for calibrating building energy simulation models with measured data: Orientation and a case study, Appl. Energy. 179 (2016) 1220–1231. https://doi.org/10.1016/j.apenergy.2016.07.084.
[116] G. Ramos Ruiz, C. Fernández Bandera, T. Gómez-Acebo Temes, A. Sánchez-Ostiz Gutierrez, Genetic algorithm for building envelope calibration, Appl. Energy. 168 (2016) 691–705. https://doi.org/10.1016/j.apenergy.2016.01.075.
[117] E. Taveres-Cachat, Grasshopper script for automatically generated highly flexible external louvred shading devices, (2020). https://doi.org/10.5281/zenodo.3929432.
[118] M.J. Grant, A. Booth, A typology of reviews: An analysis of 14 review types and associated methodologies, Health Info. Libr. J. 26 (2009) 91–108. https://doi.org/10.1111/j.1471-1842.2009.00848.x.
[119] E. Taveres-Cachat, S. Grynning, J. Thomsen, S. Selkowitz, Responsive building envelope concepts in zero emission neighborhoods and smart cities - A roadmap to implementation, Build. Environ. 149 (2019) 446–457. https://doi.org/10.1016/j.buildenv.2018.12.045.
[120] Perino M. et al., Annex 44 - Responsive building Elements: state of the art Review. Vol. 2A, Iea Shc/Ecbs. (2008) 197.
[121] R. Loonen, J.M. Rico-Martinez, F. Favoino, M. Brzezicki, C. Menezo, G. La Ferla, L. Aelenei, Design for facade adaptability - Towards a unified and systematic characterization, in: Proc. 10 Th Conf. Adv. Build. Ski., Bern, Switzerland, 2015: pp. 1284–1294.
[122] B. BASARIR, M.C. ALTUN, A Classification Approach for Adaptive Façades, in: I. Istanbul (Ed.), Istanbul , Turkey, 2017.

[123] R. Looman, Climate-responsive design: A framework for an energy concept design-decision support tool for architects using principles of climate-responsive design, 2017. https://doi.org/10.7480/abe.2017.1.

[124] S. Mallory-Hill, M. Gorgolewski, Mind the Gap: Studying Actual Versus Predicted Performance of Green Buildings in Canada, in: Preiser W., Hardy A., Schramm U. Build. Perform. Eval., Springer, Cham, 2017. https://doi.org/https://doi.org/10.1007/978-3-319-56862-1_20.

[125] E. Taveres-Cachat, G. Lobaccaro, F. Goia, G. Chaudhary, A methodology to improve the performance of PV integrated shading devices using multi-objective optimization, Appl. Energy. (2019). https://doi.org/10.1016/j.apenergy.2019.04.033.

[126] R. Looman, Climate-responsive design A framework for an energy concept design-decision support tool for architects using principles of climate-responsive design, Delft University of Technology, Faculty of Architecture and the Built Environment, 2017.

[127] C.W. Gellings, The concept of demand-side management for electric utilities, Proc. IEEE. 73 (1985) 1468–1470. https://doi.org/10.1109/PROC.1985.13318.

[128] S. STEVENS, Intelligent Facades: Occupant Control and Satisfaction, Int. J. Sol. Energy. 21 (2001) 147–160. https://doi.org/10.1080/01425910108914369.

[129] L.G. Bakker, E.C.M. Hoes-van Oeffelen, R.C.G.M. Loonen, J.L.M. Hensen, User satisfaction and interaction with automated dynamic facades: A pilot study, Build. Environ. 78 (2014) 44–52. https://doi.org/10.1016/j.buildenv.2014.04.007.

[130] E. Taveres-Cachat, R.C.G.M. Loonen, F. Favoino, F. Goia, Ten questions concerning co-simulation for performance prediction of advanced building envelopes, (2020).

[131] M. Janák, Whole Building Energy Simulation With Complex External Shading Devices, in: Eighth Int. IBPSA Conf., Eindhoven, The Netherlands, 2003: pp. 571–576.

[132] J. Hensen, Modelling coupled heat and airflow : Ping-pong versus onions, in: Proc. 16th Conf. Implement. Results Vent. Res., Coventry, UK, 1995.

[133] M. Janak, Coupling Building Energy and Lighting Simulation, Fifth Int. IBPSA Conf. Sept. 8 – 10. (1997) 313 – 319.

[134] I. Beausoleil-Morrison, F. Macdonald, M. Kummert, T. McDowell, R. Jost, Co-simulation between ESP-r and TRNSYS, J. Build. Perform. Simul. 7 (2014) 133--151. http://dx.doi.org/10.1080/19401493.2013.794864.

[135] M. Wetter, Co-simulation of building energy and control systems with the Building Controls Virtual Test Bed, J. Build. Perform. Simul. 4 (2011) 185–203. https://doi.org/http://dx.doi.org/10.1080/19401493.2010.518631.

[136] V. Zavrel, Building energy modelling to support the commissioning of holistic data centre operation, Technische Universiteit Eindhoven, 2018.

[137] D. Le-Phuoc, H.Q. Nguyen-Mau, J.X. Parreira, M. Hauswirth, A middleware framework for scalable management of linked streams, J. Web Semant. 16

(2012) 42–51. https://doi.org/10.1016/j.websem.2012.06.003.
[138] T. Hong, H. Sun, Y. Chen, S.C. Taylor-Lange, D. Yan, An occupant behavior modeling tool for co-simulation, Energy Build. 117 (2016) 272–281. https://doi.org/10.1016/j.enbuild.2015.10.033.
[139] R. Judkoff, J. Neymark, J. Neymark, TWENTY YEARS ON !: UPDATING THE IEA BESTEST BUILDING THERMAL FABRIC TEST CASES FOR ASHRAE STANDARD 140 National Renewable Energy Laboratory , Golden , Colorado , U . S ., (2011) 63–70.
[140] M. Trčka, J.L.M. Hensen, M. Wetter, Co-simulation for performance prediction of integrated building and HVAC systems - An analysis of solution characteristics using a two-body system, Simul. Model. Pract. Theory. 18 (2010) 957–970. https://doi.org/10.1016/j.simpat.2010.02.011.
[141] G. Ward, R. Shakespeare, Rendering with RADIANCE. The Art and Science of Lighting Visualization, Morgan Kaufmann Publishers, 1998.
[142] OpenFOAM, (n.d.). https://www.openfoam.com/ (accessed September 9, 2020).
[143] M. Wetter, T.S. Nouidui, D. Lorenzetti, E.A. Lee, A. Roth, PROTOTYPING THE NEXT GENERATION ENERGYPLUS SIMULATION ENGINE Lawrence Berkeley National Laboratory , Berkeley , CA University of California at Berkeley , Berkeley , CA US Department of Energy , Washington , DC, Build. Simul. Conf. (2015) 403–410.
[144] Spawn of EnergyPlus, (n.d.). https://lbl-srg.github.io/soep/ (accessed September 9, 2020).
[145] D.B. Crawley, L.K. Lawrie, F.C. Winkelmann, W.F. Buhl, Y.J. Huang, C.O. Pedersen, R.K. Strand, R.J. Liesen, D.E. Fisher, M.J. Witte, J. Glazer, EnergyPlus: Creating a new-generation building energy simulation program, Energy Build. 33 (2001) 319–331. https://doi.org/10.1016/S0378-7788(00)00114-6.
[146] M. Wetter, M. Bonvini, T.S. Nouidui, Equation-based languages - A new paradigm for building energy modeling, simulation and optimization, Energy Build. 117 (2016) 290–300. https://doi.org/10.1016/j.enbuild.2015.10.017.
[147] M. Wetter, W. Zuo, T.S. Nouidui, X. Pang, Modelica Buildings library, J. Build. Perform. Simul. 7 (2014) 253–270. https://doi.org/10.1080/19401493.2013.765506.
[148] Building Control Virtual Test Bed, (n.d.). https://simulationresearch.lbl.gov/bcvtb (accessed September 9, 2020).
[149] X. Pang, M. Wetter, P. Bhattacharya, P. Haves, A framework for simulation-based real-time whole building performance assessment, Build. Environ. 54 (2012) 100–108. https://doi.org/10.1016/j.buildenv.2012.02.003.
[150] M. Mitterhofer, G.F. Schneider, S. Stratbücker, K. Sedlbauer, An FMI-enabled methodology for modular building performance simulation based on Semantic Web Technologies, Build. Environ. 125 (2017) 49–59. https://doi.org/10.1016/j.buildenv.2017.08.021.
[151] Modelica, (n.d.). https://modelica.org (accessed September 9, 2020).

[152] FMI standard, (n.d.).
[153] M. Sadeghipour Roudsari, M. Pak, Ladybug: a parametric environmental plugin for grasshopper to help designers create an environmentally-conscious design, in: 13th Conf. Int. Build. Simul. Assoc. IBPSA, IBPSA, Chambery, France, 2013. http://www.ibpsa.org/proceedings/BS2013/p_2499.pdf.
[154] C. Cavalliere, G. Habert, G. Raffaele, D. Osso, A. Hollberg, Continuous BIM-based assessment of embodied environmental impacts throughout the design process, J. Clean. Prod. 211 (2019) 941–952. https://doi.org/10.1016/j.jclepro.2018.11.247.
[155] Speckle, (n.d.). https://speckle.systems/ (accessed September 9, 2020).
[156] E. Taveres-Cachat, F. Goia, Exploring the impact of problem formulation in numerical optimization: a case study of the design of PV integrated shading systems, (2020).
[157] Meriem Webster, Definition of parametrisation, (n.d.).
[158] D. Rutten, Grasshopper - Algorithmic modeling for Rhino version 0.9.0076, (2017). http://www.grasshopper3d.com/ (accessed October 9, 2017).
[159] J. Nembrini, S. Samberger, G. Labelle, Parametric scripting for early design performance simulation, Energy Build. 68 (2014) 786–798. https://doi.org/10.1016/j.enbuild.2013.09.044.
[160] V. Granadeiro, J.P. Duarte, J.R. Correia, V.M.S. Leal, Building envelope shape design in early stages of the design process: Integrating architectural design systems and energy simulation, Autom. Constr. 32 (2013) 196–209. https://doi.org/10.1016/j.autcon.2012.12.003.
[161] J.C. Lam, S.A.M.C.M. Hui, Sensitivity Analysis of Energy Performance of Office Buildings, 31 (1996) 27–39.
[162] D.A. Chi, D. Moreno, J. Navarro, Design optimisation of perforated solar façades in order to balance daylighting with thermal performance, Build. Environ. 125 (2017) 383–400. https://doi.org/10.1016/j.buildenv.2017.09.007.
[163] M. Manzan, A. Clarich, FAST energy and daylight optimization of an office with fixed and movable shading devices, Build. Environ. 113 (2017) 175–184. https://doi.org/10.1016/j.buildenv.2016.09.035.
[164] A. Eltaweel, Y. Su, Controlling venetian blinds based on parametric design; via implementing Grasshopper's plugins: A case study of an office building in Cairo, Energy Build. 139 (2017) 31–43. https://doi.org/10.1016/j.enbuild.2016.12.075.
[165] A.G. Kheybari, S. Hoffmann, Exploring the Potential of The Dynamic Facade : Simulating Daylight and Energy Performance of Complex Fenestration Systems (Venetian Blinds), (2018).
[166] S.M. Hosseini, M. Mohammadi, A. Rosemann, T. Schröder, J. Lichtenberg, A morphological approach for kinetic façade design process to improve visual and thermal comfort: Review, Build. Environ. 153 (2019) 186–204. https://doi.org/10.1016/j.buildenv.2019.02.040.
[167] A. Tabadkani, M. Valinejad Shoubi, F. Soflaei, S. Banihashemi, Integrated

parametric design of adaptive facades for user's visual comfort, Autom. Constr. 106 (2019) 102857. https://doi.org/10.1016/j.autcon.2019.102857.
[168] G. Lobaccaro, A.H. Wiberg, G. Ceci, M. Manni, N. Lolli, U. Berardi, Parametric design to minimize the embodied GHG emissions in a ZEB, Energy Build. 167 (2018) 106–123. https://doi.org/10.1016/j.enbuild.2018.02.025.
[169] H. Samuelson, S. Claussnitzer, A. Goyal, Y. Chen, A. Romo-Castillo, Parametric energy simulation in early design: High-rise residential buildings in urban contexts, Build. Environ. 101 (2016) 19–31. https://doi.org/10.1016/j.buildenv.2016.02.018.
[170] R.P. Leslie, Capturing the daylight dividend in buildings: Why and how?, Build. Environ. 38 (2003) 381–385. https://doi.org/10.1016/S0360-1323(02)00118-X.
[171] J.A. Jakubiec, C.F. Reinhart, The 'adaptive zone'-A concept for assessing discomfort glare throughout daylit spaces, Light. Res. Technol. 44 (2012) 149–170. https://doi.org/10.1177/1477153511420097.
[172] B.S. Matusiak, Glare from a translucent façade, evaluation with an experimental method, Sol. Energy. 97 (2013) 230–237. https://doi.org/10.1016/j.solener.2013.08.009.
[173] A. Tzempelikos, A.K. Athienitis, The impact of shading design and control on building cooling and lighting demand, Sol. Energy. 81 (2007) 369–382. https://doi.org/10.1016/j.solener.2006.06.015.
[174] B. Svetozarevic, M. Begle, P. Jayathissa, S. Caranovic, R.F. Shepherd, Z. Nagy, I. Hischier, J. Hofer, A. Schlueter, Dynamic photovoltaic building envelopes for adaptive energy and comfort management, Nat. Energy. 4 (2019) 671–682. https://doi.org/10.1038/s41560-019-0424-0.
[175] H.H. Alzoubi, A.H. Al-Zoubi, Assessment of building facade performance in terms of daylighting and the associated energy consumption in architectural spaces: Vertical and horizontal shading devices for southern exposure facades, Energy Convers. Manag. 51 (2010) 1592–1599. https://doi.org/10.1016/j.enconman.2009.08.039.
[176] A.I. Palmero-Marrero, A.C. Oliveira, Effect of louver shading devices on building energy requirements, Appl. Energy. 87 (2010) 2040–2049. https://doi.org/10.1016/j.apenergy.2009.11.020.
[177] J.J. Kim, S.K. Jung, Y.S. Choi, J.T. Kim, Optimization of photovoltaic integrated shading devices, Indoor Built Environ. 19 (2010) 114–122. https://doi.org/10.1177/1420326X09358139.
[178] M.H. Oh, K.H. Lee, J.H. Yoon, Automated control strategies of inside slat-type blind considering visual comfort and building energy performance, Energy Build. 55 (2012) 728–737. https://doi.org/10.1016/j.enbuild.2012.09.019.
[179] X. Zhang, S.K. Lau, S.S.Y. Lau, Y. Zhao, Photovoltaic integrated shading devices (PVSDs): A review, Sol. Energy. 170 (2018) 947–968. https://doi.org/10.1016/j.solener.2018.05.067.
[180] E.S. Lee, S.E. Selkowitz, D.L. Dibartolomeo, J.H. Klems, R.D. Clear, K. Konis, R. Hitchcock, M. Yazdanian, R. Mitchell, M. Konstantoglou, High Performance

Building Façade Solutions PIER Final Project Report, 2009.

[181] P. Jayathissa, J. Zarb, M. Luzzatto, J. Hofer, A. Schlueter, Sensitivity of Building Properties and Use Types for the Application of Adaptive Photovoltaic Shading Systems, Energy Procedia. 122 (2017) 139–144. https://doi.org/10.1016/j.egypro.2017.07.319.

[182] S.H. Yoo, H. Manz, Available remodeling simulation for a BIPV as a shading device, Sol. Energy Mater. Sol. Cells. 95 (2011) 394–397. https://doi.org/10.1016/j.solmat.2010.02.015.

[183] Y. Ibraheem, P. Piroozfar, E.R.P. Farr, Integrated Façade System for office buildings in hot and arid climates : A comparative analysis, in: M. Dastbaz, C. Gorse, A. Moncaster (Eds.), Build. Inf. Model. Build. Performance, Des. Smart Constr., 1st ed., Springer, 2017: pp. 273–288. https://doi.org/10.1007/978-3-319-50346-2_19.

[184] W. Bahr, Optimal Design Parameters of the Blinds Integrated Photovoltaic Modules Based on Energy Efficiency and Visual Comfort, in: Cent. Eur. Towar. Sustain. Build. 2013, Prague, Czech Republic, 2013: pp. 1–10.

[185] M. Mandalaki, T. Tsoutsos, N. Papamanolis, Integrated PV in shading systems for Mediterranean countries: Balance between energy production and visual comfort, Energy Build. 77 (2014) 445–456. https://doi.org/10.1016/j.enbuild.2014.03.046.

[186] G. Datta, Effect of fixed horizontal louver shading devices on thermal perfomance of building by TRNSYS simulation, Renew. Energy. 23 (2001) 497–507. https://doi.org/10.1016/S0960-1481(00)00131-2.

[187] S. Grynning, N. Lolli, S. Wågø, B. Risholt, Solar Shading in Low Energy Office Buildings - Design Strategy and User Perception, J. Daylighting. 4 (2017) 1–14. https://doi.org/10.15627/jd.2017.1.

[188] S. Hoffmann, E.S. Lee, A. McNeil, L. Fernandes, D. Vidanovic, A. Thanachareonkit, Balancing daylight, glare, and energy-efficiency goals: An evaluation of exterior coplanar shading systems using complex fenestration modeling tools, Energy Build. 112 (2016) 279–298. https://doi.org/10.1016/j.enbuild.2015.12.009.

[189] T. Hwang, S. Kang, J.T. Kim, Optimization of the building integrated photovoltaic system in office buildings - Focus on the orientation, inclined angle and installed area, Energy Build. 46 (2012) 92–104. https://doi.org/10.1016/j.enbuild.2011.10.041.

[190] Schueco Large Louvre Blades ALB - passive, (n.d.). https://www.schueco.com/web2/us/architects/products/sun_shading_systems/large_louver_systems/alb_passive (accessed April 21, 2017).

[191] McNeel Robert and Associates, "Rhinoceros Version 5.0," 2015, (n.d.). https://www.rhino3d.com/.

[192] Ladybug tools, (n.d.). https://www.ladybug.tools/ (accessed May 30, 2018).

[193] E. Taveres-Cachat, F. Goia, Investigating the performance of a hybrid PV integrated shading device using multi-objective optimization, in: J. Phys. Conf.

Ser., Institute of Physics Publishing, 2019. https://doi.org/10.1088/1742-6596/1343/1/012086.
[194] C.F. Reinhart, J. Mardaljevic, Z. Rogers, C.F. Reinhart, J. Mardaljevic, Z.R. Dynamic, C.F. Reinhart, J. Mardaljevic, Z. Rogers, Dynamic Daylight Performance Metrics for Sustainable Building Design, LEUKOS - J. Illum. Eng. Soc. North Am. 3 (2006) 7–31. https://doi.org/10.1582/LEUKOS.2006.03.01.001.
[195] H.C. Kim, V. Fthenakis, J. Choi, D.E. Turney, Life Cycle Greenhouse Gas Emissions of Thin-film Photovoltaic Electricity Systematic Review and Harmonization, 16 (2012). https://doi.org/10.1111/j.1530-9290.2011.00423.x.
[196] M. Marwede, A. Reller, Estimation of Life Cycle Material Costs of Cadmium Telluride – and Copper Indium Gallium Diselenide – Photovoltaic Absorber Materials based on Life Cycle Material Flows, 18 (2014) 254–267. https://doi.org/10.1111/jiec.12108.
[197] F. Goia, C. Schlemminger, A. Gustavsen, The ZEB Test Cell Laboratory. A facility for characterization of building envelope systems under real outdoor conditions, Energy Procedia. 132 (2017) 531–536. https://doi.org/10.1016/j.egypro.2017.09.718.
[198] S. Subramaniam, R. Mistrick, A More Accurate Approach for calculating Illuminance with Daylight Coefficients, Illum. Eng. Soc. Annu. Conf. 2017. (2018) 18. http://sarith.in/papers/2017-IES.pdf.
[199] C.F. Reinhart, O. Walkenhorst, Validation of dynamic RADIANCE-based daylight simulations for a test office with external blinds, Energy Build. 33 (2001) 683–697. https://doi.org/10.1016/S0378-7788(01)00058-5.
[200] Z. Rogers, D. Goldman, Daylighting metric development using daylight autonomy calculations in the sensor placement optimization tool, Archit. Energy Corp. (2006) 1–52.
[201] E. Brembilla, D.A. Chi, C.J. Hopfe, J. Mardaljevic, Evaluation of climate-based daylighting techniques for complex fenestration and shading systems, Energy Build. 203 (2019). https://doi.org/10.1016/j.enbuild.2019.109454.
[202] A.T. Nguyen, S. Reiter, P. Rigo, A review on simulation-based optimization methods applied to building performance analysis, Appl. Energy. 113 (2014) 1043–1058. https://doi.org/10.1016/j.apenergy.2013.08.061.
[203] V. Machairas, A. Tsangrassoulis, K. Axarli, Algorithms for optimization of building design: A review, Renew. Sustain. Energy Rev. 31 (2014) 101–112. https://doi.org/10.1016/j.rser.2013.11.036.
[204] Y. Huang, J. Niu, Optimal building envelope design based on simulated performance: History, current status and new potentials, Energy Build. 117 (2016) 387–398. https://doi.org/10.1016/j.enbuild.2015.09.025.
[205] T. Li, G. Shao, W. Zuo, S. Huang, Genetic Algorithm for Building Optimization - State-of-the- Art Survey, in: Proc. 9th Int. Conf. Mach. Learn. Comput., Association for Computing Machinery, Singapore, Singapore, 2017: pp. 205–210. https://doi.org/https://doi.org/10.1145/3055635.3056591.

[206] T. Wortmann, Genetic evolution vs . function approximation : Benchmarking algorithms for architectural design optimization, J. Comput. Des. Eng. 6 (2019) 414–428. https://doi.org/10.1016/j.jcde.2018.09.001.

[207] F. Kheiri, A review on optimization methods applied in energy-efficient building geometry and envelope design, Renew. Sustain. Energy Rev. 92 (2018) 897–920. https://doi.org/10.1016/j.rser.2018.04.080.

[208] M. Wetter, J. Wright, A comparison of deterministic and probabilistic optimization algorithms for nonsmooth simulation-based optimization, Build. Environ. 39 (2004) 989–999. https://doi.org/10.1016/j.buildenv.2004.01.022.

[209] M. Hamdy, A.-T. Nguyen, J.L.M. Hensen, A performance comparison of multi-objective optimization algorithms for solving nearly-zero-energy-building design problems, Energy Build. 121 (2016) 57–71. https://doi.org/10.1016/j.enbuild.2016.03.035.

[210] C. Cubukcuoglu, B. Ekici, M.F. Tasgetiren, S. Sariyildiz, OPTIMUS: Self-Adaptive Differential Evolution with Ensemble of Mutation Strategies for Grasshopper Algorithmic Modeling, Algorithms. 12 (2019) 141. https://doi.org/10.3390/a12070141.

[211] T. Wortmann, A. Costa, G. Nannicini, T. Schroepfer, Advantages of surrogate models for architectural design optimization, (2015) 471–481. https://doi.org/10.1017/S0890060415000451.

[212] A.D. Radford, J.S. Gero, On optimization in computer aided architectural design, Build. Environ. 15 (1980) 73–80. https://doi.org/10.1016/0360-1323(80)90011-6.

[213] T. Wortmann, Architectural Design Optimization—Results from a User Survey, KnE Soc. Sci. 2019 (2019) 473–483. https://doi.org/10.18502/kss.v3i27.5550.

[214] J.M. Cichocka, W.N. Browne, E.R. Ramirez, E.B.T.-I.C. on C.-A.A.D.R. in A. Rodriguez, OPTIMIZATION IN THE ARCHITECTURAL PRACTICE An International Survey, Caadria. (2017) 387–397. http://papers.cumincad.org/data/works/att/caadria2017_155.pdf.

[215] F.G. Lobo, C.F. Lima, Adaptive Population Sizing Schemes in Genetic Algorithms, in: Springer Berlin (Ed.), Param. Setting Evol. Algorithms. Stud. Comput. Intell., Heidelberg, Germany, 2007. https://doi.org/https://doi.org/10.1007/978-3-540-69432-8_9.

[216] D. Hou, G. Liu, Q. Zhang, L. Wang, R. Dang, Integrated Building Envelope Design Process Combining Parametric Modelling and Multi-Objective Optimization, Trans. Tianjin Univ. 23 (2017) 138–146. https://doi.org/10.1007/s12209-016-0022-1.

[217] T. Wortmann, T. Fischer, Does architectural design optimization require multiple objectives ? A critical analysis, RE Anthr. Proc. 25th Int. Conf. Assoc. Comput. Archit. Des. Res. Asia. 1 (2020) 365–374.

[218] H. Li, S. Wang, R. Tang, Robust optimal design of zero/low energy buildings considering uncertainties and the impacts of objective functions, Appl. Energy. 254 (2019) 113683. https://doi.org/10.1016/j.apenergy.2019.113683.

[219] A. Hassanat, K. Almohammadi, E. Alkafaween, E. Abunawas, Choosing Mutation and Crossover Ratios for Genetic Algorithms — A Review with a New Dynamic Approach, (2019). https://doi.org/10.3390/info10120390.
[220] F.G. Lobo, D.E. Goldberg, The parameter-less genetic algorithm in practice, Inf. Sci. (Ny). 167 (2004) 217–232. https://doi.org/10.1016/j.ins.2003.03.029.
[221] N.R. Siriwardene, B.J.C. Perera, Selection of genetic algorithm operators for urban drainage model parameter optimisation, 44 (2006) 415–429. https://doi.org/10.1016/j.mcm.2006.01.002.
[222] J.J. Grefenstette, Genetic Algorithms, IEEE Trans. Syst. Man. Cybern. 16 (1986) 122–128.
[223] M. Srinivas, L.M. Patnaik, Adaptive Probabilities of Crossover and Mutation in Genetic Algorithms, 24 (1994) 656–667.
[224] W. Lin, Adapting Crossover and Mutation Rates in Genetic Algorithms . Adapting Crossover and Mutation Rates * in Genetic Algorithms, (2003).
[225] V.P. Patil, D.. Pawar, The optimal crossover or mutation rates in genetic algorithm: a review, Appl. Eng. Technol. 5 (2015) 38–41.
[226] K.A. De Jong, An analysis of the behavior of a class of genetic adaptive systems, University of Michigan, Ann Arbor, Michigan, USA, 1975.
[227] H. Mülhenbein, D. Schlierkamp-Voosen, Analysis of Selection , Mutation and Recombination in Genetic Algorithms, in: Lect. Notes Comput. Sci., Evolution and Biocomputation, 1995: pp. 142–168. https://doi.org/10.1007/3-540-59046-3.
[228] C. Waibel, How smart grids will change the way architects have to design buildings, (2020).
[229] A. Saltelli, G. Bammer, I. Bruno, E. Charters, M. Di Fiore, E. Didier, W.N. Espeland, J. Kay, S. Lo Piano, D. Mayo, R.P. Jr, T. Portaluri, T.M. Porter, A. Puy, J.R. Ravetz, E. Reinert, D. Sarewitz, P.B. Stark, A. Stirling, J. Van Der Sluijs, P. Vineis, Five ways to ensure that models serve society: a manifesto, Nature. 582 (2020) 482–484.
[230] E. Taveres-Cachat, R.C.G.M. Loonen, J. Eisenlohr, F. Goia, C. Maurer, Report on simulation models of solar envelope components envelope components, 2019. https://doi.org/10.18777/ieashc-task56-2019-0002.

A1 Paper I

Responsive building envelope concepts in zero emission neighborhoods and smart cities-A roadmap to implementation

E Taveres-Cachat, S Grynning, J Thomsen, S Selkowitz

Building and Environment Volume 149, Pages 446-457, (2019)

Building and Environment 149 (2019) 446–457

Contents lists available at ScienceDirect

Building and Environment

journal homepage: www.elsevier.com/locate/buildenv

Responsive building envelope concepts in zero emission neighborhoods and smart cities - A roadmap to implementation

Ellika Taveres-Cachat[a,b], Steinar Grynning[a,*], Judith Thomsen[a], Stephen Selkowitz[c]

[a] SINTEF Building and Infrastructure, Department for Architecture, Building Materials and Construction, Høgskoleringen 7b, 7491, Trondheim, Norway
[b] NTNU, Department for Architecture and Technology, Alfred Getz Vei 3, Sentralbygg 1, 7491, Trondheim, Norway
[c] Lawrence Berkeley National Laboratory, Building Technology and Urban Systems Division, Bldg. 90-3111, Berkeley, CA, 94720, USA

ARTICLE INFO

Keywords:
Building envelopes
Smart cities
Responsive
Façade
Zero emission neighborhoods

ABSTRACT

Designing a zero emission neighborhood (ZEN) from an energy point of view, has the benefit of distributing loads over time by creating a mosaic of buildings which individually may not have a zero emission balance, but reach it as an ensemble. Responsive building envelopes (RBEs) are expected to play an important role in the design of ZENs and future smart sustainable cities. RBEs are useful to optimize the balance between several energy flows at single- and multi building scale, as well as to actively manage both on-site renewable- and purchased energy in addition to improving user experience and indoor comfort by providing an interactive interface with the outdoors. This article provides a review of the potential and the requirements associated with using RBEs to manage complex interactions between buildings, clusters of buildings and utility grids. A six-step pathway for the implementation of RBEs in ZEN-like projects are proposed. The six steps are related to identifying; purpose of response, scale and interdependency, functionality, trigger and control, interactions and finally to identifying technical solutions. The proposed process emphasizes the importance of defining specific information such as the responsive goal hierarchies, the scale of the responses in relation to their purpose, and the importance of the aesthetic expression to foster positive user experience.

1. Introduction: from zero emission buildings to neighborhoods and the role of building envelopes

Zero energy and zero emission building design revolve around two main strategies [1–3] that are to reduce energy use and to harvest renewable energy to compensate for the energy used [4,5]. Reducing energy use is achieved through installing highly efficient energy recovery systems [6] and increasing the performance of building envelopes by using passive design solutions such as building shape optimization [7], improving envelope insulation and airtightness, and using highly insulating windows [8,9]. However, as pointed out by Loonen et al. [10], this static building design approach can be flawed despite allowing to meet sustainability goals. This is because it is most often based on structuring building envelopes as a sequence of independent solutions, which creates the risk of the final design becoming a sub-optimized assembly of competing solutions [11] with limited grid friendliness in terms of load matching of renewable energy flows [12,13]. Furthermore, this approach also largely favors energy savings over user satisfaction and comfort [14] which is against recommendations in research [15]. Instead, zero energy building design should consider alternative solutions that offer higher system flexibility [10,16,17], or that are optimized to reduce the effect of competing parameters [18–20], and which could provide better overall building performance and potentially surpass the traditionally defined limits of cost-optimal façade design [9].

"Responsive building design" and design using "responsive building envelopes" (RBEs) (also known as smart, climate-adaptive, or intelligent) is one of these flexible alternative approaches, and has been a popular topic in literature for decades [21,22]. In the field of building envelope design, RBEs are often found under the names responsive, dynamic, adaptive, kinetic, advanced, or multifunctional building elements. Despite the minor semantic differences introduced, most RBE technologies can be described as an extension of the definition for "climate adaptive building shells" (CABS) given in Ref. [10]. The core concept is the result of architects and engineers being inspired to design buildings that could express similar responses to the ones found in plants, or that could imitate human physiological responses like sweating or shivering [10,23–27]. In order to replicate such functionalities in buildings, RBEs rely on integrated technologies that are designed to enable the building to respond to a range of triggers (stimuli),

* Corresponding author.
E-mail address: steinar.grynning@sintef.no (S. Grynning).

https://doi.org/10.1016/j.buildenv.2018.12.045
Received 11 September 2018; Received in revised form 19 December 2018; Accepted 20 December 2018
Available online 21 December 2018

using a combination of passive, active, and/or cognitive control strategies. This design approach is particularly interesting given that building envelopes have a significant impact on the performance of buildings [28]. By incorporating more advanced control strategies and renewable energy harvesting systems (RES), it is possible to improve the overall performance of the building in terms of energy management (purchased and renewably harvested), occupant comfort, and operational costs. Such concepts becomes even more powerful when applied to a cluster of buildings as distributing energy flows currently are more advantageous at aggregated levels [29]. In fact, implementing a range of RBEs in a cluster of different typologies of buildings allows diversifying the functionalities and types of systems or controls used. This can be combined to efficiently harvest larger amounts of renewable energy, but also increase possibilities for storing and distributing energy within networks of different sizes, and on different time scales. A cluster of buildings equipped with RBEs can be designed to resemble a mosaic of buildings, which individually may not have a zero emission balance, but reach it as a group [30]. Hence, introducing clusters of responsive buildings could be used as a mean of reducing carbon emissions in urban forms, and can be integrated into sustainability strategies for zero emission neighborhoods (ZEN) and smart sustainable cities [31]. However, there is still very little material or guidance available in literature regarding the challenges associated with scaling up the use of RBE technologies from the design of a single building to designing an entire neighborhood, and how synergies between networks of RBEs could help in achieving zero emission neighborhood or smart sustainable cities goals.

The aim of this article is to begin bridging this gap by investigating how the existing work on responsive building envelopes and systems can be extended to designing a network of responsive buildings and to explore the potential role of RBEs in the design of smart sustainable cities and zero emission neighborhoods. This task requires defining the specificities of RBE technologies and characterizing their potential scales of application in clusters of buildings along with identifying the opportunities and challenges that come with the change of scale. The outcomes of this work are presented as a roadmap for architects and engineers to help them define strategies for implementing RBEs in large-scale projects and aim to provide an understanding of the complexity of the challenges associated with RBE networks.

The remainder of this paper is organized as follows: section 2 presents the state of the art of the topics which are essential to include when evaluating the opportunities and challenges associated with implementing RBEs in neighborhoods. Section 3 details the existing classifications for RBEs at single building scale, and outlines the elements which have yet to be addressed in the context of a neighborhood project. In section 4, the resulting proposal for a pathway to implementing RBEs at neighborhood scale is presented in the form of a roadmap, with a description of the different additional elements that need to be accounted for as result of the change of scale. The issues this roadmap does not cover are presented and discussed in section 5, and the conclusion are drawn in section 6.

2. State of the art: responsive building envelopes in neighborhoods and smart cities

Smart sustainable cities are described by the authors of [32] as the interlinking of sustainability awareness, urban growth and technological developments in urban planning. Hence, urban forms such as smart sustainable cities and zero emission neighborhoods, inherently require a strong presence of ICT and IoT (Internet of Things) integrated in the urban domain to manage the complex set of relations between clusters of buildings and services [33]. Currently, there are still many gaps in the research field of smart sustainable cities, particularly regarding how to connect smart city concepts and real urban development. There are also need for approaches for integrating smart ICT technologies in design concepts of sustainable urban forms [33]. As argued by Ref. [34], it is also crucial that design frameworks for sustainability in cities have interdisciplinary and transdisciplinary approaches to be successful. This finding also applies to the subfield of energy and carbon emission management in smart cities, where the models used are limited to certain aspects [35], and should be combined with research on micro-grids and demand-response strategies so as to be able to include district energy networks. With this in mind, the following section highlights the different disciplines and aspects that a framework for implementing RBEs in zero emission neighborhoods must include.

2.1. Carbon emissions

RBEs have a large potential for reducing carbon emissions as they allow acting on both energy harvesting and energy management. In this paper, a neighborhood is "*a group of interconnected buildings with associated infrastructure, located within a confined geographical area. A zero emission neighborhood aims to reduce its direct and indirect greenhouse gas emissions towards zero over the analysis period. The area has a defined physical boundary to external grids (electricity and heat, and if included, water, sewage, waste, mobility and ICT). However, the system boundary for analysis of energy facilities serving the neighborhood is not necessarily the same as the geographical area*" [31]. In ZENs and in most buildings, facades take on many roles. From an energy point of view, facades are designed to minimize total life cycle costs, have high energy efficiency and can integrate technologies allowing to power the neighborhood with a high share of renewable energy, as well as manage energy flows in single buildings and in conjunction with the surrounding energy systems. These roles must be fulfilled without sacrificing occupant comfort, the aspects of which are discussed in section 2.3.

At single building scale, responsive building envelopes can improve energy management by reducing overall energy use and harvest renewable energy by converting it to electricity or by storing it as thermal energy in the building mass. For example, RBEs using glazed components with controllable optical and physical properties have shown to provide significant energy demand reductions compared to traditional facades [36–38]. The same effects can be expected when connecting buildings together in a cluster, with the additional benefit of reducing risks of system redundancy in installed renewable energy conversion systems or HVAC compared to having many independent buildings. The diversity of building typologies in a neighborhood provides the opportunity to consider a broader range of RBE systems, and these can be designed in a way that their functionalities are beneficial to the building they are installed on, and other buildings in the neighborhood [39]. Bigger RBE installations also contribute to harvesting and storing larger amounts of electrical and thermal energy, which can be used to modify load shapes of buildings (the daily and seasonal electricity demand by time-of-day, day-of-week, and season). This can be done either directly [40–43] or indirectly by taking advantage of the coupling between the building envelope and its effect on the technical systems used for space conditioning, as well as contribute to increasing energy flexibility potential. Scaling the use of this strategy up to a cluster of buildings, introduces the capacity to change the total load shape of the neighborhood and implement different strategies for demand side management (DSM) [44]. DSM is a central element for reducing operational costs or carbon intensity of purchased energy, and allows timing grid interactions so that electricity is purchased at strategic moments and in accordance with climatic parameters, as well as the current and forecasted needs of the neighborhood [45,46].

2.2. Architecture

Zero emission buildings have a variety of architectural expressions and concepts [47]. The aesthetic expression of responsive elements is critical to explore as a technical solution given that what is perceived as attractive will also be easier to choose for architects, building -owners and –investors [48]. Responsive building design can present interesting new architectural features in building due to the introduced dynamic aspects. A building envelope can then be thought as having multiple configurations, depending on the time of the day, the season and the use, which may result in a certain architectural quality [49]. This aspect should be incorporate to strengthen the most common design strategies for zero emission buildings [50,51]. These strategies include the use of a climate adapted building form (in cold climates this often results in a compact building to reduce heat loss) in combination with informed design and placement of glazing elements (with or without solar shading systems) for optimal solar energy management, the reduction embodied emissions with strategic material choices, the implementation integrated HVAC system, and the integration of solar energy harvesting systems. The last element will highly influence the design of the building since the performance of solar based RES systems is very much dependent on their orientation [47]. However, when changing the scale of design from single building to multi-building, and because of the realities of city planning and the complexity of existing urban context such as street orientations or shading from adjacent buildings, design guidelines must be versatile. This is especially true when creating new smart sustainable urban environments with increased interactions between buildings and the people living in the neighborhood.

2.3. User comfort and acceptance

Responsive systems can also be used to improve and personalize thermal comfort [52,53]. Research indicates that offering occupants control over their indoor climate leads to fewer health issues, higher comfort, and improved mental productivity [54,55]. Furthermore, new European directives and standards recognize the importance of maintaining occupant's comfort when improving energy and environmental performance of buildings, a trend that is likely to stay. However, while it is recognized that buildings should be designed to meet their users' needs, their performance will to a large degree be dependent on the occupant's behavior and attitude. This is demonstrated by e.g. Refs. [56–62] which all highlighted differences between actual and predicted performance in a vast number of buildings. It appears that the occupant's attitude to energy use is often ambivalent, and even though many regard energy saving as positive, they are not willing to sacrifice personal comfort [61]. Research also indicates that users are often insufficiently informed about the technologies they interact with, or know little about how their own behavior affects the resulting energy use in the building [14,63]. In general, occupants are pleased with living or working in energy-efficient buildings, but feel frustrated when they cannot interact in a simple way to regulate temperature, ventilation systems [64–66] or automatic shading systems [67,68]. A combination of user control and intelligent controls with robust and intuitive design seems to be a promising solution to solving these issues [69]. User-acceptance strategies must be paired with automation strategies (e.g. using "smart controllers and software) to avoid competing control strategies. User parameters and behaviors should be carefully considered when changing the scale of design from single building scale to multi-building scale as the role of users in smart cities is often misunderstood or overly simplified [70].

2.4. Characterization of performance

According to the International Energy Agency (IEA ECBCS) in Annex 44 *Integrating Environmentally Responsive Elements in Buildings* [71], responsive buildings show great promise as a concept. However, successful implementation in occupied buildings is often being made difficult [72] by the lack of information available about the technologies, their integration process and their expected performance. There is also little understanding of the new challenges RBEs introduce since the physical parameters needed to describe them are inherently more complex than those of most non-responsive types. Characterization of building envelope components have traditionally been based on static parameters such as annual single value thermal transmittance values (U-values) and solar heat gain coefficients (g-values). However these are not typically used for characterizing advanced facades due to the dynamic nature of RBEs [52,73,74] and their multi-domain impacts [75]. Instead, more holistic approaches are preferred including net energy use, and user thermal or visual comfort [41,76].

The gap between in-design performance and real-life performance in buildings with more traditional technologies can be substantial [61] and these discrepancies are likely to grow larger when increasingly complex technologies are introduced. As a result, several research efforts following the one of the IEA have proposed methods for classifying responsive building elements and improve the understanding of these technologies at single-building scale. These classifications are reviewed in the following section.

3. Existing classification systems for adaptive and responsive building envelopes

3.1. Single technology classification schemes

Many suggestions of frameworks to classify dynamic, adaptive or responsive building elements have been proposed [77]. Three of the most recent proposals for a unified characterization of stand-alone responsive building envelope technologies were reviewed and used to define some of the key parameters for the proposed final framework. These proposals are described in the following paragraphs.

The first classification system this framework builds upon, is the work that was carried out in IEA ECBCS Annex 44 [22,71,78,79]. The Annex 44 was a considerable effort to map environmentally responsive technologies and resulted in a classification system with a given technology as a starting point. The proposed characterization scheme is flexible in that it can be applied to any given technology like a mask to map out its *responsiveness*. Despite this strength, the scope of this work was limited to RBEs in the context of climate triggers only. The work did not cover technologies with user-defined controls, schedule controls, advanced ICT controls or AI (artificial intelligence) controls; all of which are required to characterize newer technologies and neighborhood scale implementations, and hence the framework as such cannot be used as is in the scope of this paper.

The second classification reviewed is proposed by Loonen et al. [77] as part of the work carried out in EU COST Action TU1403. This work review existing taxonomies for adaptive facades, and results in a new framework where the purpose of the adaptive façade is the starting point. The characterization matrix proposed does not separate the type of stimuli (indoor and outdoor climate variables, user's experience etc.), but distinguishes two fundamental types of control "extrinsic" and "intrinsic" (see section 4.4 for definitions). Although this classification is one of the most comprehensive, it is not perfectly suited to the context of planning ZENs. Firstly, the solutions are not scalable to neighborhoods meaning the potential for load management (electrical and thermal energy) at multi-building level is not explicitly discussed. Secondly, the existing classification is designed to characterize a given responsive technology solution as a standalone. In order to implement RBEs at a neighborhood scale, the purpose of the technology has to be put in relation to the needs of the whole network. This aspect is deemed critical by the ZEN research center which insists that neighborhood interaction should facilitate the transition to a decarbonized energy system and reduction of power and heat capacity requirements [27]. Further discussions on neighborhood interactions are provided in section 3.3.

In the third classification, Basarir et al. [80] describe a framework for adaptive facades based on the previously mentioned definition of climate adaptive building shells (CABS) [10]. The authors point out that the criteria used in RBE classifications are ambiguous and make it difficult to use for comparison. This classification uses the "element of adaptation” (façade, component, element, material) and the “agent of adaptation” e.g. the stimulus, as the two starting elements to define the mechanisms of the adaptation. A strength of this work is that the architectural features of RBEs are described in much more detail than in the two previous classifications and it includes the level of architectural visibility, the effect of the adaptation and performance with regard to human experience. The limitation of this classification, seen in a neighborhood context, is that it is most suited for RBEs that rely on moveable parts as it provides much higher levels of detail for systems that require physical movement. This means that e.g., an electrochromic window does not have a full explicit and thus, the classification leaves out technologies that should be considered in ZENs or smart sustainable city projects.

3.2. Holistic building perspective of responsive systems

Looman [81] describes a comprehensive framework with a holistic approach to climate responsive design. In his work, he proposes seven basic response functions relevant for the building level: conserve, recover, prevent, promote, distribute, store and buffer. This approach allows a clear definition of concepts for architecture and the purpose of different climate responsive features. The resulting characterization addresses the role of different technologies in climate responsive design. However, for the task of using RBEs to design neighborhoods, there is a need for a clearer link between the suggested functionalities of the system and their purpose, as well as more clarification about the different control strategies and timeframes. Finally, the characterization proposed only addresses the role of different technologies in climate responsive design and architecture. It leaves out most user related aspects as well as advanced control strategies and neighborhood related requirements.

3.3. The knowledge gap in a neighborhood perspective

The existing classification systems have many strengths but they mostly adopt different areas of focus and/or approaches, which fall short of fulfilling the interdisciplinary approach required in a neighborhood perspective described in section 2. The work presented in the next section builds upon the reviewed existing classification but attempts to fill in the gaps identified by introducing the missing elements required to characterize RBE clusters. The result is an extended classification which should be seen as a roadmap to implementing RBEs in the design of ZENs and smart sustainable cities. This roadmap can be useful in both early- and later planning stages, and provides sufficient flexibility to be applicable to existing and future envelope technologies.

4. Results – defining a roadmap for implementing responsive building envelopes in zero emission neighborhoods

4.1. A strategy for responsive building envelope implementation at neighborhood scale

Defining a strategy for integrating different responsive building technologies in building envelopes is a key process in planning the energy concept of zero emission neighborhoods. As there are many technologies and solutions to choose from, a systematic breakdown of the properties and requirements of the responsive technologies is necessary to have a portfolio of solutions that can pave the way towards a zero emission goal for the neighborhood. The approach developed in this work is based on the work presented in Ref. [77], but incorporates energy load management and renewable energy harvesting within the cluster of buildings, as well as the interactions with a larger grid system (see Fig. 1).

In order to do this, a strategy to define performance goals is proposed in a six-step procedure as shown in Fig. 2. The initial five steps build the foundation for decision-makers to be able to assess possible design strategies and solutions that are relevant for the particular project. Step 5 includes the identification of interactions between the building users and the responsive system, and presents the definition of the criteria and building design requirements. Step six consists of the identification of technological solutions and verification that the system performance is in line with the defined purpose.

4.2. Defining the purpose and objective of the response

Given the large variety of responsive technologies and RBE systems, the first step is to define the purpose of the response as part of the building design strategy in the neighborhood. RBE functionalities as an element in the design of a ZEN, and the different response scales (single building, cluster of buildings and neighborhood) of the technologies are nested into each other (Fig. 2) (the scales of responses are described in section 4.3).

The main categories of purpose for RBEs are defined as energy performance, user needs, and demand side management as shown in Fig. 4. It is important to note that these purposes are not mutually exclusive as a single system could (and should) have more than one purpose. These purposes can sometimes also present competing parameters because of the nature of the RBE, in which case it advised to develop more advanced design strategies to balancing competing aspects [82]. In this framework, each purpose is described by a set of specific objectives, with target actions and associated functionalities to achieve the given purpose (see section 4.4 for more detail).

4.3. Identifying the scale and interdependencies of the response

Planning ZENs around responsive buildings requires looking at different scales of action and understanding how smaller groups of buildings can function alone, and together with others in a cluster. The idea is to design groups of buildings as interconnected nodes that share resources such as information, thermal and electrical energy. The nodes are connected to the grid through a main energy management center or part of an intelligent operation center (IOC), which regulates interactions based on the set goal using specific strategies and/or “learning responses” (Fig. 5). IOCs process a large variety of information as described in Ref. [83]. However for the specific scope of this paper, only energy management information is considered here.

The building nodes can form smaller secondary networks, which exchange resources in different patterns or timescales. Buildings can e.g. exchange thermal energy surplus directly without intermittent storage. This distributed configuration is useful to create multiple levels (named secondary information networks in Fig. 3) of management within a neighborhood. The complexity of the responsive cluster requires a network for information flow between the buildings, so that energy use can be managed both in real-time conditions and ahead of time. The type of information exchanged includes for example live schedules, live and forecasted energy use profiles, live and forecasted energy prices, and live and forecasted weather data. This information is useful to define the parameters relevant to the dynamic energy flexibility index status of the different buildings. Since RBEs should be designed as an integrated part of the buildings, their operations are designed in coordination with the technical systems in the building, the inner structural elements of the buildings (such as thermal mass enabling), and with regard to their impact on the user environment.

Due to the diversity of systems and features in responsive building envelopes, it is paramount to identify the different scales of the associated responses as well as time related parameters. The responses may have shorter or longer timeframes, and may have varying degrees of influence over the whole building. Some technologies may respond to stimuli within seconds or minutes (i.e. window opening, daylighting control, natural ventilation systems etc.) others will have much slower response times (i.e. thermal energy storage and release, set point change management etc.).

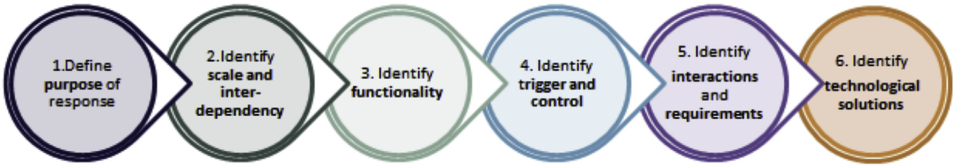


Fig. 1. The six-step performance goal strategy.

4.4. Identifying the functionality of the response

The functionalities of responsive envelopes are linked to objectives aimed at being fulfilled. This can relate to a larger scale of the neighborhood as well as on building level as shown in Table 1.

4.4.1. Building and neighborhood functionality

In a ZEN context the ability to modify the electrical energy demand after the anticipated load-curve shape is crucial. At neighborhood scale, this can be achieved by changing the profile of the total energy requirements of each building according to a strategy aimed at e.g. lowering costs, limiting grid interactions or reducing the carbon footprint. Demand side management (DSM) functionalities can allow for improved grid-friendliness. As described in section 2, DSM is the planning, implementation, and monitoring of grid interaction designed to produce changes in the neighborhoods load shape by changing the energy use magnitude and time related patterns. The functionalities of DSM revolve around the six strategies shown in Fig. 6. E.g.; a properly designed (and controlled) solar shading device can reduce peak cooling demands (peak clipping) in warm periods, thermal storage (thermal mass) in the envelope can shift heating and cooling loads and BIPV (with proper storage) can contribute to a more flexible load shape.

4.4.2. Envelope functionality

As previously mentioned, the framework presented by Loomans in Ref. [81] lacks the ability to have a neighborhood perspective. Therefore, in this work, two new RBE functionalities have been added (modulate and convert) to the ones already described by Looman. Additional types of the triggers for RBEs have also been made explicit to include grid related demands, neighborhood demands and user demands, all of which emphasizes the importance of considering response times in RBE functionalities. Fig. 5 shows Looman's illustration with the inclusion of the functionalities conversion and magnify/modulate as well as the identified triggers (as described in 4.5).

4.5. Types of response and triggers for responsive building envelopes

4.5.1. Single building related triggers

The types of triggers for response at a building level differ from the ones at a larger cluster- or neighborhood level both in terms of scale and time horizons. At the scale of single buildings located within a ZEN, triggers categories are local external climate (e.g., incoming solar radiation, wind speed or outdoor temperature), indoor climate (e.g. operative temperature or lighting level) or user requests (e.g. personal preference or change in building schedule). At single building level, the control mechanisms used are for short term responses (seconds, minutes or hours), and the *responsiveness* of the building is directly connected to the nature of the control strategy. These can be intrinsic (e.g. phase change materials, thermal mass, thermotropic glazing, photochromic glazing) or extrinsic (e.g. opening windows, activating solar shading, activating artificial lighting or natural ventilation). Intrinsic and extrinsic behaviors are described in Refs. [10,52]: *"Intrinsic indicates that the adaptive mechanism is automatically triggered by a stimulus (surface temperature, solar radiation, etc.). Extrinsic refers to the presence of an external decision-making component that trigger the adaptive mechanisms according to a feedback rule".* In essence, intrinsic or cognitive controls refer to embedded properties in the material or assembly, which are typically only triggered by climatic (indoor and outdoor climate) stimuli. Extrinsic controls offer a much larger range of actions and can include strategies such as fixed control, schedules, ruled based control, model predictive control and direct real time user control. These technologies are able to respond to all 4 categories of triggers described Fig. 5 (climatic, grid, neighborhood, and user). However, because of the above mentioned differences in nature of the control mechanisms, technologies with the lowest degree of artificial control (i.e. intrinsic) will provide smaller ranges of maneuver in terms of real-time DSM

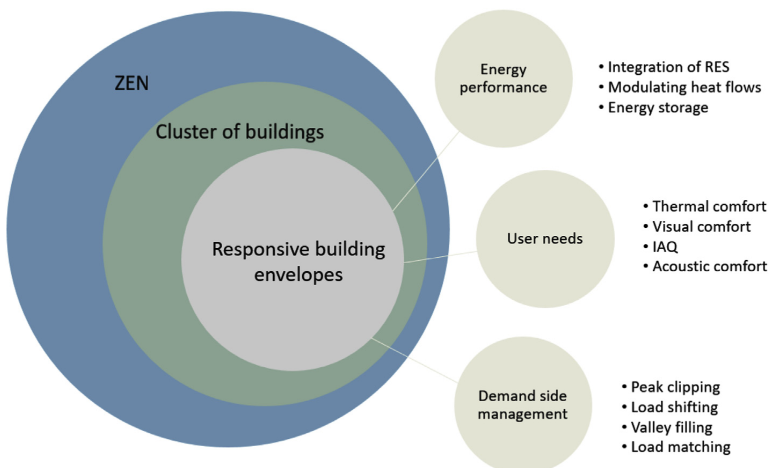


Fig. 2. Responsive building envelope design in a Zero Emission Neighborhoods context.

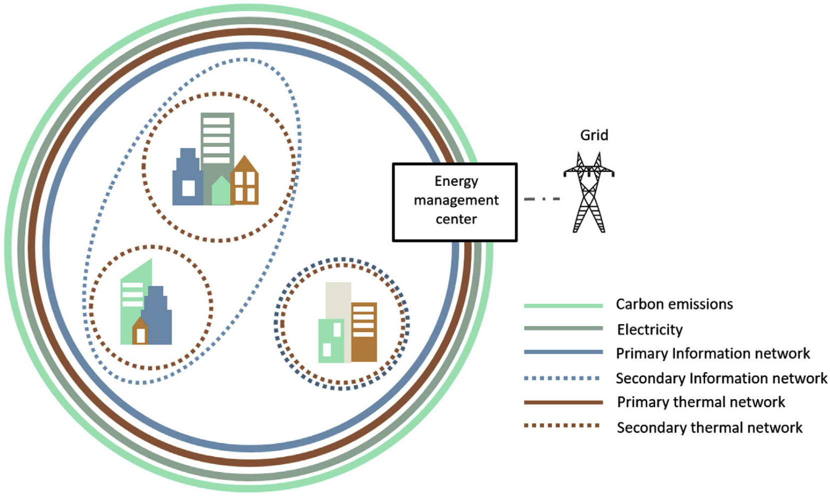


Fig. 3. Scales of exchange between clusters of buildings within the larger scale of the neighborhood. The interactions between RES and buildings are described in detail in section 4.4.2.

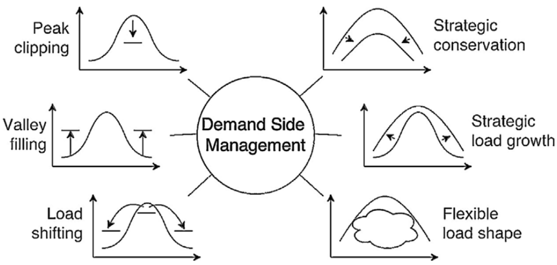


Fig. 4. Strategies for demand side management (from Ref. [44]).

options and will require the building to rely more heavily on both electrical and thermal storage options to improve energy management.

Triggers types can also be broken down further into different subgroups for each category, which are fixed, scheduled and real-time. Fixed triggers are mostly used for passive design (e.g. average annual ambient temperatures, sun angles or annual average internal load). Envelope designs based on fixed triggers encompass for example fixed shading systems. Scheduled are based on diurnal cycles whereas real-time stimuli are direct (real-time) feedback parameters measured by sensors (e.g. CO_2 levels, operative temperature or presence). These designs englobe systems for natural ventilation systems by use of double skin facades for example.

4.5.2. Neighborhood related triggers

Neighborhoods comprise different types of buildings and

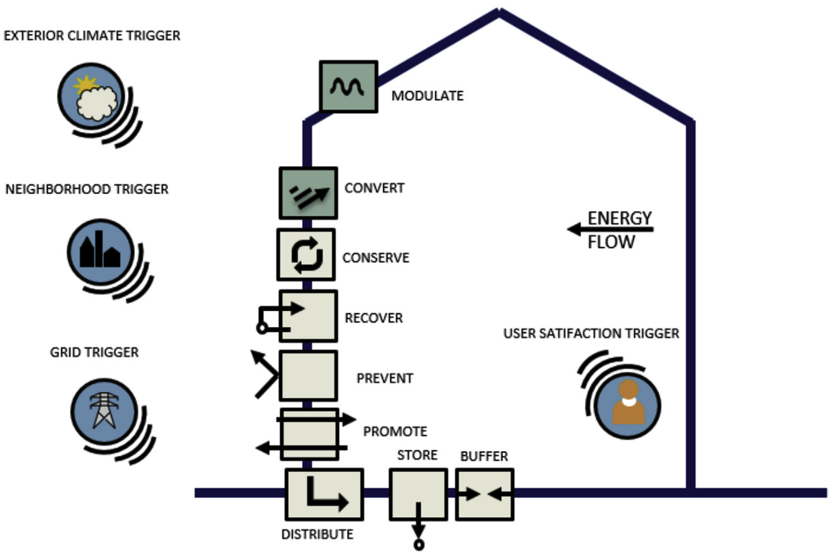


Fig. 5. Triggers and functionalities. Adopted (and refined) from Ref. [81].

Table 1
Functionalities of responsive building envelopes.

Purpose	Objective	Functionality	Description
Building energy performance	Intelligent energy management to reduce energy use	Recovery and conservation of available energy	Reduce energy use by modulating heat flows to maintain an optimum energy balance by promoting (admitting ingoing energy flows), preventing (protecting the indoor space from undesirable energy flows) and reducing energy flow through the envelope
		Energy buffering	Peak clipping by using solutions to reduce the magnitude of the impact of an energy flow
	Increase self-sufficiency	Energy storage	Load shifting by storing energy within the building
		Renewable energy integration	Optimize energy conversion at building scale by changing system configuration to maximize renewable energy harvesting
User comfort	Ensure health and wellness of users	Indoor air quality	Reduce pollutant concentration in indoor spaces
	Increase productivity	Thermal comfort	Prevent discomfort due to drafts and vertical temperature gradients Prevent overheating Maintain comfortable operative temperatures
		Visual comfort	Limit risk of glare Provide sufficient levels of daylighting Provide spaces with comfortable color temperatures Provide satisfying color rendering View to the outdoors
		Acoustic comfort	Reduce exposure to sources of aural discomfort Maintain privacy
Demand side management	Intelligent energy management to increase grid-friendliness	Reduce peak loads	Manage energy flows and energy sharing of electrical and thermal energy in clusters of buildings via use of smart control technologies Control of high efficiency renewable energy systems to reduce peak loads and optimize conversion parameters in building clusters
		Peak load shifting Valley filling	Control of energy storage systems for surplus energy storage and distribution within cluster
		Strategic conservation and load growth Flexible load shape	Use of model predictive control to set up grid energy consumption/resell strategies based on given parameters (energy source, carbon intensity of energy, energy cost …)

constructions and it is important to realize that not all buildings can offer the same flexibility in operation [45]. The varying degrees of responsiveness imply that not all elements of the building should include complicated technologies. Some of the design features can be static design features and will allow the building to respond to predictable changes in the building's operation (typically; schedules, or climate sensors for shading systems control) and allow to prevent a drop in performance. However, the more advanced responsive components allow the building or cluster of buildings to respond to unexpected changes and allow for a more diverse range of response. This typically requires using technologies with pro-active features based on anticipation (i.e. building systems or model predictive control [84,85]). The result is that a responsive building can react to exploit the modifications in its environment, and take advantage of the changes instead of merely sustaining them, overall continuously striving to operate at optimal conditions on multiple levels.

At a cluster- or neighborhood level, the stimuli are linked to extrinsic control strategies (e.g. DSM), and typically aim to fulfill optimization goals with longer time horizons (hours, days, weeks or months). These controls may be based on the current or predicted energy use of the building cluster, grid energy prices and/or carbon intensity of the energy. The responses can be similar to those for weather triggers but should mainly involve components, which preferably do not directly affect the occupants, as they cannot exert any direct control over the responses. The possibilities for responsive building envelopes to act on different types of triggers makes up a large part of their robustness. Table 2 provides a matrix of the trigger categories and type with the associated type of control of the response.

4.6. Interactions and requirements - the building users

Responsive facades with extrinsic controls play an important role in balancing different parameters of indoor environmental quality such as glare discomfort, operative temperature, daylighting levels, air quality, privacy and view to the outdoors. However, user interaction and satisfaction are two primary factors that must not be disregarded in the implementation and operation of automated building systems. User well-being and acceptance is directly correlated to the perception of

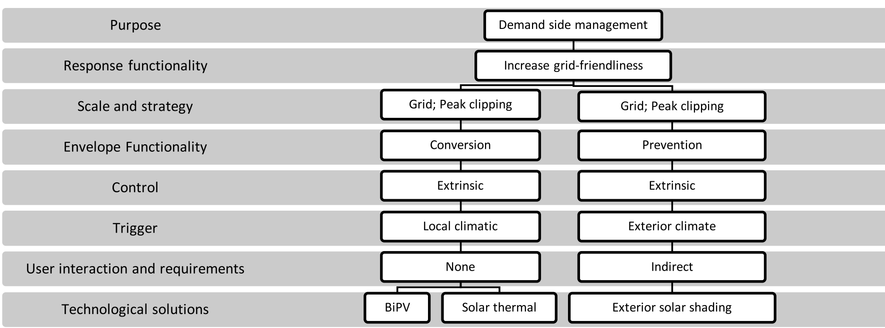


Fig. 6. Example of pathways to achieve good demand side management.

Table 2
Typology of responsive components for single buildings (adapted from Ref. [56]). Showing combinations of control and related trigger categories with sub-categories.

	Trigger category	Type	Type of control		
			Passive – Non-responsive	Active - Extrinsic	Cognitive - Intrinsic
Single building scale control strategies and related trigger types	Local climatic	Fixed value			
		Scheduled value			
		Real time value			
	User demand	Fixed value			Not Applicable
		Scheduled value			N.A.
		Real time value			N.A.
	Neighborhood management	Fixed value			N.A.
		Scheduled value			N.A.
		Real time value			N.A.

Table 3
Typology of user interactions with responsive systems. (*Model Predictive Control).

Users perception of control

Trigger	Level of user interaction	Type of control	Description
LM EP	None	Automated w/ no impact on users RBC, P, PI, PID	Systems with goals independent of user needs and which do not affect the user's environment
LM EP IEQ		Automated w/ impact on users RBC, P, PI, PID	Systems with goals independent of user needs but which may affect the user's environment
EP IEQ	Indirect	Automated w/ MPC *	Systems with intelligent control based on user past and predicted user behavior
EP IEQ	Semi-direct	Automated w/ short term manual override RBC, P, PI, PID	Automated systems with scheduled-based controls that can be overruled in real time for a short period of time before resuming original control
EP IEQ		Automated w/ manual override, RLC and MPC*	Systems with intelligent control based on past and predicted behavior. Can be overruled in real time
EP IEQ		Automated w/manual override	Automated systems with schedule or sensor-based controls that can be overruled in real time
IEQ	Direct	Manual	Systems with no automated control

and exercised personal control the occupants have over the systems [86] and the possibility to overrule systems is primordial to ensure user satisfaction [87]. When planning responsive buildings, it is important to consider different types of control for the systems depending on the type of system, the trigger and the response characteristics (scale of response and timeline associated). An overview of different response typologies is given in Table 3 with a short description of the control details.

Not all responsive systems should be designed to interact directly with occupants. For example, systems that respond to objectives of load management (LM) or some energy performance (EP) strategies may have no need for interaction with users. The larger part of these systems use rule based or reactive rule base controls (RBC), proportional response, PI or PID. These systems may implement advanced controls such as model predictive controls (MPC) or reinforced learning controls (RLC) in order to be most efficient in their responses and adjust to user patterns [83]. Other systems may be fully automated and user independent in their primary objectives, but affect the indoor environmental quality (IEQ) to a certain extent. Automated system with intelligent controls aimed at improving IEQ and support EP strategies are based on previous and predicted user behavior to determine their current state or actions, meaning that users indirectly influence them. These MPC/RLC are seen as an essential attribute to reconcile user needs and the energy saving potential of the responsive systems, two objectives that may sometimes compete. Control strategies that can be overruled by users are considered as semi-direct interactions and include controls driven by sensors, MPC/RLC or schedule based rules. The override function can be temporary, meaning the system will resume to its normal function after a certain amount of time, or independent in time until it is reset. Finally, some systems allow for direct manual control from the users, which allow occupants to have direct interaction with the system a perception of control. In these cases, it is essential that the user interface for the controls is easily understood. It must also be physically accessible to users. In past times that might have meant a nearby wall switch; today it might be based on an app on a cell phone. Spaces occupied by many people may have special challenges since the desires of different occupants may vary widely.

4.7. Choice of potential technological solution

4.7.1. The performance goal procedure exemplified

The aim of the step-by-step procedure presented is to provide a foundation for the evaluation of technologies that could be effective and serve a desired purpose. In the next section, two examples of application are presented (see Figs. 6 and 7).

A Top-down example is shown in Figs. 6 and 7. A dwelling is to be placed within a zero-emission neighborhood. In this neighborhood, power is scarce during periods of the day. Hence, the first purpose is chosen; to ensure a well-functioning demand side management system, with the reduction of peak-loads as the primary objective. A limitation in the grid calls for a strategy relating to peak-power reduction (Fig. 6). This, in term lead to the need for an extrinsic (grid-based) control. Solar radiation- and power is abundant, so on-site solar conversion and cooling prevention during peak solar hours are chosen as key functionalities. User comfort is chosen as the second purpose (Fig. 7). The building owner wants large windows facing south to provide view. Preventing overheating as well as glare becomes key response functionalities in the envelope. Both energy optimization (peak clipping) and comfort optimization are the governing purposes, and extrinsic control seems pertinent. Ultimately, this gives two distinct performance goal definition pathways (illustrated in Figs. 6 and 7). To achieve a purpose, several pathways may be chosen. The aim should be to identify one or more technological solution that can provide several, or all of the, response functionalities under each purpose. In this case, an exterior solar shading should be paired with building integrated solar energy conversion (BIPV and solar thermal). Figs. 6 and 7 shows that

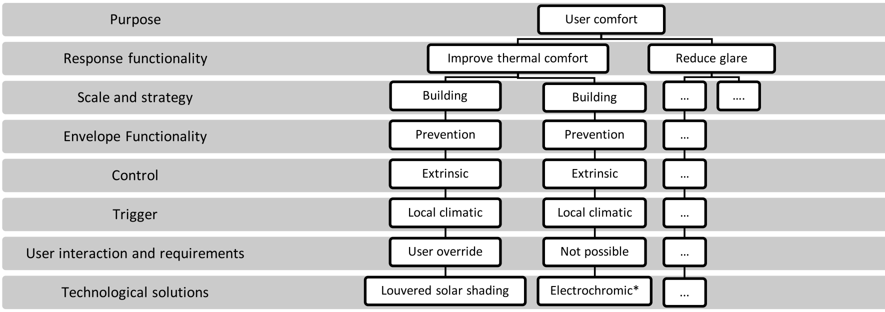


Fig. 7. Example of pathways to achieve desirable user comfort.

both grid demand and user comfort purposes can be addressed. Even though the functionality has different goals and the scale and strategy differs, a common denominator is that the local climate is a governing trigger. However, user interaction and requirements differs, pointing to the need to strike the proper balance at this level. This could include the design of control systems and strategies of the solar shading where users have the possibility to override an automatic system. It is imperative that users are informed of how manual override affect the energy performance. It should be noted that these examples are meant to illustrate a decision process. If using this in a real design-process, it is imperative that documentation of choices are provided.

4.7.2. Classification of technologies – the reversed pathway

The procedure can be used as both a top-down and a bottom-up tool to either determine or characterize a potential choice of technological solution. Starting with a technology the pathway scheme can be used to identify a technology's inherent functionality in a responsive building framework. By doing this, it can be used to map out and make a matrix of functionalities, possible control algorithms, triggers and finally which purposes the existing technologies are suited for. Although evident for this case, following the examples given in Figs. 6 and 7 in reverse, one can see that exterior solar shading enhances comfort as well as contribute to demands side management purposes.

5. Discussion

One of the major barriers preventing a large-scale uptake of RBEs is the lack of understanding of their behavior and the difficulties associated with predicting their performance in building simulation tools. Reliable methods for performance assessment are needed to improve system design and to carry out cost benefit analysis of the systems along with code compliance assessments. In the current state of simulation tools available, modelling and simulating responsive building elements is not a straightforward task. This is because of the complexity of the interplay of the different physical aspects, the difficulty of measuring performance in relation to the purpose and because as for most models, it requires identifying tradeoffs between the input in the structure of the model and the needed accuracy of the simulation results.

Modelling responsive buildings is further made complicated because RBEs by nature are more sensitive to weather data than non-responsive buildings, and this is particularly true for buildings with responsive behavior controlled by climatic stimuli. Obtaining reliable local weather data is a common issue in the field building performance simulation. It may require extensive post-processing of weather-data from weather stations far away or even setting up weather stations in the vicinity in order to have meaningful weather data inputs. The availability of high quality local solar data is especially scarce and data handling is cumbersome [88,89]. Additionally, RBEs require a lot of work regarding the choice of which technologies will be controlled by users and to what extent users may impact their function. The choice of user-technology interaction (see Table 3) affect the complexity of the control strategy and may require to model users with elaborate approaches. The process of selecting a modelling approach should be done according to the fit for purpose methodology in order to avoid unnecessary complexity [90]. Additionally, it is always useful to model not only the "final" solution but to parametrize key designs features or operating assumptions to estimate the sensitivity of output to these values. These issues are compounded when the focus includes performance measures for occupant comfort, energy and carbon goals, and grid impacts too.

The following subsections discuss two different approaches that can be adopted to tackle some of the discussed issues, and allow a smoother transition from a single building-to a neighborhood level model and simulation.

5.1. Neighborhood level characterization

5.1.1. Modelling and simulating urban clusters with simplified models

One way of dealing with the complexity required to model clusters of buildings has been to use lumped capacitance models and grey box modelling approaches [35]. These approaches are much less input intensive than traditional integrated whole building simulations models in widely used software such as EnergyPlus, TRNSYS, ESP-r or IDA ICE, which require large amounts of data and information related to the geometry of the building, the thermal properties of the envelope, HVAC system performance and so on. The suitability of such models to predict energy needs and thermal behavior has been recently investigated in Ref. [70]. This method of using simple components and grey box modelling approaches has also proven to be useful to model clusters of buildings as demonstrated in Refs. [70,91,92].

Many of the issues discussed in Ref. [35] for modelling urban areas apply to the scope of neighborhoods too. For instance modelling larger scales of urban areas requires identifying the tradeoffs between model accuracy and model complexity. This leading to the necessity to model key characteristics of elements and using these as inputs for meta-scale simulations where faster run-times are a requirement. This is in particular relevant in the case of RBEs as the requirements for the model are more advanced [52]. Information can be extracted from more detailed simulations such as the ones presented in the following section and reused as inputs for the larger scale models.

5.1.2. Co-simulation of several entities

Simulating and connecting multiple models of different systems or buildings is possible via co-simulation, but at the scale of a neighborhood the approach required is beyond the level of modelling used in industry and might even be beyond what regular co-simulation allows. Model based design (MBD) approaches are new and currently only used in research but this could help solving such issues if used in industry. MBD allow using a common simulation test bed to connect and share mixtures of models of computation (i.e. models in different BPS software). MBD supports designing and analyzing non-conventional energy and control strategies with a faster implementation of models for equipment, building systems and control algorithms at different levels. In the context of zero emission neighborhoods, it could permit the use of simulation models in combination with nonlinear programming algorithms. These are interesting because they can limit numerical noise in cost functions such as energy use, or carbon intensity during operation. This enables solving control problems, potentially involving state trajectory constraints or control functions with a large number of independent parameters. Other possibilities are to manage load prediction data-driven demand response schemes, analysis of the operation of building systems while allowing reusing models during operation for functional testing, verification of energy minimizing control sequences, fault detection and diagnostics. These features come in addition to options for modelling HVAC systems, multi-zone heat transfer and airflows, single zone computational fluid dynamics coupled to thermal parameters as well as electrical systems.

The framework presented in this work assumes that solutions are put in place so that most problems can be solved at any given level (material, system, building, or neighborhood) and that issues with the scalability of the selected solution can be handled in the modelling. In reality it is likely that modelling a system at different scales will present several pros and cons and require sophisticated tools for decisions making. These parameters, together with the skill of the modeler and the simulation tool used, could shape the modelling approach and the choice of system implemented.

6. Concluding remarks and further work

A roadmap to help architects and building designers identify pathways for implementation of RBE solutions in zero emission neighborhoods (ZENs) and smart sustainable cities is presented. Because neighborhoods consist of a combination of buildings of different types, e.g. new, existing, retrofitted, they can accommodate a large variety of RBEs with different functionalities and purposes. In the context of ZENs, the overarching goal should be to achieve a zero balance of greenhouse gas (GHG) emissions over a defined period of time, but this goal may be broader in the context of a smart sustainable city. For the scope of this work, three main purposes were selected: demand-side management-, energy performance- and user comfort. The resulting framework proposes a bidirectional pathway approach, which can be used to map out functionalities and concepts for responsive building envelopes.

Future research should aim at developing performance indicators for the facades of the future. Indicators should provide a comprehensive, yet easily understandable, description of how the buildings and their envelopes perform related to a defined series of purposes. The performance goals approach proposed in this paper is a step towards the development of such indicators but falls short of providing concrete benchmarks of responsiveness. The use of validated simulation tools for detailed analyses should be used as a steppingstone towards the development of simplified tools useable for a broader audience outside the research communities. The definition of control strategies and definition of triggers will require more attention in the continuation of this work, including the development of new approaches like Model predictive control (MPC), Model based design (MBD) and co-simulation for RBEs. This will become especially interesting when looking at it from a neighborhood perspective where grid optimization based on e.g. power abundancy, energy prices etc. can be implemented. Future work should also focus on identifying user needs in relation to RBEs in more detail. Looking ahead at the future of occupants and building controls, one must account for the rapidly growing capabilities of the Internet of Things (IoT) using low cost sensors, cell phone based apps, and cloud computing. It must address the rapid deployment of home automation-based control solutions, e.g. "Siri/Alexa, please close the shades in the living room when the sun sets and open the shades in the kitchen when I arrive". As homeowners become accustomed to these smart technologies, they more readily accept complex systems in offices and commercial buildings.

Finally, the coupling between the façade and technical installations should be further developed to avoid the previously described dangers of sub-optimization when only parts of the bigger picture are addressed. RBEs should be thoroughly planned with regard to their goals, modes of action, control typologies and impacts on the different aspects of building operation as well as user experience. This analysis should be done early in the building design phase and accompanied by appropriate modelling efforts in building performance simulation tools to ensure that the system meets the defined goals. The modelling and simulation of RBE and RSEs in coordination with energy systems must also account for the differences between assumed behaviors and the reality of imperfect control and fuzzy user behavior. This issue is tightly connected with the challenges of data and model availability, which were existing a single building scale and pertain at neighborhood scale too, due to the need to communicate large amounts of simulation with varying temporal and spatial scales.

Acknowledgements

The authors gratefully acknowledge the support from the Research Council of Norway and several partners through the Research Center on Zero Emission Neighbourhoods in Smart Cities (FME ZEN) under grant No. 257660. This paper is also supported by the SkinTech project funded by the Research Council of Norway under grant No. 255252 and the industrial partners in the project.

References

[1] T.H. Dokka, T. Kristjansdottir, B. Time, S. Mellegård, A Zero Emission Concept Analysis of a Single Family House, (2013).
[2] T.H. Dokka, T. Kristjansdottir, B. Time, S. Mellegård, A Zero Emission Concept Analysis of an Office Building, (2013).
[3] D.H.W. Li, L. Yang, J.C. Lam, Zero energy buildings and sustainable development implications - a review, Energy 54 (2013) 1–10, https://doi.org/10.1016/j.energy.2013.01.070.
[4] P.A. Torcellini, D.B. Crawley, Understanding zero-energy buildings, ASHRAE J. 48 (2006).
[5] I. Sartori, A. Napolitano, K. Voss, Net zero energy buildings: a consistent definition framework, Energy Build. 48 (2012) 220–232, https://doi.org/10.1016/j.enbuild.2012.01.032.
[6] M. Justo Alonso, P. Liu, H.M. Mathisen, G. Ge, C. Simonson, Review of heat/energy recovery exchangers for use in ZEBs in cold climate countries, Build. Environ. 84 (2015) 228–237, https://doi.org/10.1016/j.buildenv.2014.11.014.
[7] A. Okeil, A holistic approach to energy efficient building forms, Energy Build. 42 (2010) 1437–1444 https://doi.org/10.1016/j.enbuild.2010.03.013.
[8] E. Gratia, A. De Herde, Design of low energy office buildings, Energy Build. 35 (2003) 473–491, https://doi.org/10.1016/S0378-7788(02)00160-3.
[9] S.B. Sadineni, S. Madala, R.F. Boehm, Passive building energy savings: a review of building envelope components, Renew. Sustain. Energy Rev. 15 (2011) 3617–3631, https://doi.org/10.1016/j.rser.2011.07.014.
[10] R.C.G.M. Loonen, M. Trčka, D. Cóstola, J.L.M. Hensen, Climate adaptive building shells: state-of-the-art and future challenges, Renew. Sustain. Energy Rev. 25 (2013) 483–493, https://doi.org/10.1016/j.rser.2013.04.016.
[11] D.H.W. Li, L. Yang, J.C. Lam, Zero energy buildings and sustainable development implications - a review, Energy 54 (2013) 1–10 https://doi.org/10.1016/j.energy.2013.01.070.
[12] J. Salom, A.J. Marszal, J. Wid??n, J. Candanedo, K.B. Lindberg, Analysis of load match and grid interaction indicators in net zero energy buildings with simulated and monitored data, Appl. Energy 136 (2014) 119–131, https://doi.org/10.1016/j.apenergy.2014.09.018.
[13] K.B. Lindberg, D. Fischer, G. Doorman, M. Korpås, I. Sartori, Cost-optimal energy system design in Zero Energy Buildings with resulting grid impact: a case study of a German multi-family house, Energy Build. 127 (2016) 830–845, https://doi.org/10.1016/j.enbuild.2016.05.063.
[14] J. Thomsen, T. Berker, Å. Lappegard Hauge, K. Denizou, S. Wågø, S. Jerkø, The interaction between building and users in passive and zero-energy housing and offices, Smart Sustain. Built Environ. 2 (2013) 43–59, https://doi.org/10.1108/20466091311325845.
[15] R.J. Cole, Z. Brown, Reconciling human and automated intelligence in the provision of occupant comfort, Intell. Build. Int. 1 (2009) 39–55, https://doi.org/10.3763/inbi.2009.0007.
[16] B. De Boer, G.J. Ruijg, L. Bakker, W. Kornaat, L. Zonneveldt, S. Kurvers, N. Alders, a Raue, J.L.M. Hensen, R.C.G.M. Loonen, M. Trcka, Energy saving potential of

climate adaptive building shells-Inverse modelling of optimal thermal and visual behaviour, International Adaptive Architecture Conference, Building Centre, London, March 2011.
[17] F. Favoino, F. Goia, M. Perino, V. Serra, Experimental assessment of the energy performance of an advanced responsive multifunctional façade module, Energy Build. 68 (2014) 647–659, https://doi.org/10.1016/j.enbuild.2013.08.066.
[18] K. Bøe, Balancing Solar Energy Use with Competing Parameters in a Fixed Louvre PV-integrated Shading System, Norwegian University of Science and Technology, NTNU, 2017.
[19] E. Taveres-Cachat, K. Bøe, G. Lobaccaro, F. Goia, S. Grynning, Balancing competing parameters in search of optimal configurations for a fix louvre blade system with integrated PV, Energy Procedia, 2017, https://doi.org/10.1016/j.egypro.2017.07.357.
[20] S. Hoffmann, E.S. Lee, A. McNeil, L. Fernandes, D. Vidanovic, A. Thanachareonkit, Balancing daylight, glare, and energy-efficiency goals: an evaluation of exterior coplanar shading systems using complex fenestration modeling tools, Energy Build. 112 (2016) 279–298, https://doi.org/10.1016/j.enbuild.2015.12.009.
[21] W. M, J. Harris, Intelligent skins, Vasa, (2002), p. 171 http://medcontent.metapress.com/index/A65RM03P4874243N.pdf.
[22] M. Perino, et al., Annex 44 - Responsive Building Elements: State of the Art Review 2A Iea Shc/Ecbs, 2008, p. 197.
[23] K.R. Wiebe, Biomimetic Design of the Building Envelope: Biological Climate Adaptations and Thermal Controls in the Sonoran Desert, University of Southern California, 2009.
[24] R.C.G.M. Loonen, Bio-inspired adaptive building skins, in: F. Pacheco Torgal, J.A. Labrincha, M. V Diamanti, C.-P. Yu, H.K. Lee (Eds.), Biotechnol. Biomimetics Civ. Eng, Springer International Publishing, Cham, 2015, pp. 115–134, , https://doi.org/10.1007/978-3-319-09287-4_5.
[25] M. López, R. Rubio, S. Martín, B. Croxford, R. Jackson, Active materials for adaptive architectural envelopes based on plant adaptation principles, J. Facade Des. Eng. 3 (2015) 27–38, https://doi.org/10.3233/FDE-150026.
[26] L. Badarnah, Y. Nachman Farchi, U. Knaack, Solutions from Nature for Building Envelope Thermoregulation, vol. 138, 2010, pp. 251–262, , https://doi.org/10.2495/DN100221 Delft, the Netherlands.
[27] M. Addington, Contingent behaviours, Architect. Des 79 (2009) 12–17, https://doi.org/10.1002/ad.882.
[28] IEA, Transition to Sustainable Buildings - Strategies and Opportunities to 2050, (2013), https://doi.org/10.1787/9789264202955-en.
[29] H. Lund, A. Marszal, P. Heiselberg, Zero energy buildings and mismatch compensation factors, Energy Build. 43 (2011) 1646–1654, https://doi.org/10.1016/j.enbuild.2011.03.006.
[30] K. Sornes, I. Sartori, E. Fredriksen, F. Martinsson, A. Romero, F. Rodriguez, P. Schneuwly, ZenN Nearly Zero Energy Neighborhoods - Final Report on Common Definition for NZEB Renovation vols. 1–89, (2014) www.zenn-fp7.eu.
[31] ZEN, Zero Emission Neighborhoods in Smart Cities (ZEN), (n.d.). http://fmezen.no/what-is-a-zen/(accessed March 13, 2018).
[32] M. Höjer, S. Wangel, Smart sustainable cities:definitions and challenges, in: L. Hilty, B. Aebischer (Eds.), ICT Innov. Sustain. Adv. Intell. Syst. Comput, vol. 310, Springer, Cham, 2015, https://doi.org/10.1007/978-3-319-09228-7_20.
[33] S.E. Bibri, J. Krogstie, Smart sustainable cities of the future: an extensive interdisciplinary literature review, Sustain. Cities Soc. 31 (2017) 183–212, https://doi.org/10.1016/j.scs.2017.02.016.
[34] S.E. Bibri, A foundational framework for smart sustainable city development: theoretical, disciplinary, and discursive dimensions and their synergies, Sustain. Cities Soc. 38 (2018) 758–794, https://doi.org/10.1016/j.scs.2017.12.032.
[35] M.J. Jiménez, H. Madsen, K.K. Andersen, Identification of the main thermal characteristics of building components using MATLAB, Build. Environ. 43 (2008) 170–180, https://doi.org/10.1016/j.buildenv.2006.10.030.
[36] F. Favoino, M. Overend, A simulation framework for the evaluation of next generation Responsive Building Envelope technologies, Energy Procedia 78 (2015) 2602–2607, https://doi.org/10.1016/j.egypro.2015.11.302.
[37] W.N. Hien, W. Liping, A.N. Chandra, A.R. Pandey, W. Xiaolin, Effects of double glazed facade on energy consumption, thermal comfort and condensation for a typical office building in Singapore, Energy Build. 37 (2005) 563–572, https://doi.org/10.1016/j.enbuild.2004.08.004.
[38] F. Goia, Y. Cascone, The impact of an ideal dynamic building envelope on the energy performance of low energy office buildings, Energy Procedia, 2014, pp. 185–192.
[39] P. Jayathissa, J. Zarb, M. Luzzatto, J. Hofer, A. Schlueter, Sensitivity of building properties and use types for the application of adaptive photovoltaic shading systems, Energy Procedia 122 (2017) 139–144, https://doi.org/10.1016/j.egypro.2017.07.319.
[40] F. Favoino, Q. Jin, M. Overend, Design and control optimisation of adaptive insulation systems for office buildings. Part 1: adaptive technologies and simulation framework, Energy 127 (2017) 301–309, https://doi.org/10.1016/j.energy.2017.03.083.
[41] L. Sun, L. Lu, H. Yang, Optimum design of shading-type building-integrated photovoltaic claddings with different surface azimuth angles, Appl. Energy 90 (2012) 233–240, https://doi.org/10.1016/j.apenergy.2011.01.062.
[42] S.K. Jung, Optimal Control Methods for PV-integrated Shading Devices, University of Michigan, 2014, https://doi.org/10.1192/bjp.205.1.76a.
[43] N. Nord, L.H. Qvistgaard, G. Cao, Identifying key design parameters of the integrated energy system for a residential Zero Emission Building in Norway, Renew. Energy 87 (2016) 1076–1087, https://doi.org/10.1016/j.renene.2015.08.022.
[44] C.W. Gellings, The concept of demand-side management for electric utilities, Proc. IEEE 73 (1985) 1468–1470, https://doi.org/10.1109/PROC.1985.13318.
[45] L. Gelazanskas, K.A.A. Gamage, Demand side management in smart grid: a review and proposals for future direction, Sustain. Cities Soc. 11 (2014) 22–30, https://doi.org/10.1016/j.scs.2013.11.001.
[46] Z. Ma, J.D. Billanes, B.N. Jørgensen, Aggregation potentials for buildings-Business models of demand response and virtual power plants, Energies 10 (2017), https://doi.org/10.3390/en10101646.
[47] A. Gunnarshaug Lien, Is there a ZEB architecture? in: N.L. Eik-Nes, A.G. Hestnes (Eds.), Zero Emiss, Build., 2017.
[48] N. Tractinsky, A.S. Katz, D. Ikar, What is beautiful is usable, Interact. Comput. 13 (2000) 127–145, https://doi.org/10.1016/S0953-5438(00)00031-X.
[49] M. Meagher, Designing for change: the poetic potential of responsive architecture, Front. Archit. Res. 4 (2015) 159–165, https://doi.org/10.1016/j.foar.2015.03.002.
[50] S.M. Fufa, R. Dahl Schlanbusch, K. Sørnes, M. Inman, I. Andresen, A Norwegian ZEB Definition Guideline, (2016), https://doi.org/10.13140/RG.2.2.26443.80162.
[51] The research center for Zero Emission Buildings in Norway, (n.d.). http://www.zeb.no/index.php/en/(accessed April 24, 2017).
[52] R.C.G.M. Loonen, F. Favoino, J.L.M. Hensen, M. Overend, Review of current status, requirements and opportunities for building performance simulation of adaptive facades, J. Build. Perform. Simul. 2 (2017) 205–223 https://doi.org/10.1080/19401493.2016.1152303%5Cnhttp://www.tandfonline.com/doi/full/10.1080/19401493.2016.1152303.
[53] F. Favoino, M. Overend, Q. Jin, The optimal thermo-optical properties and energy saving potential of adaptive glazing technologies, Appl. Energy 156 (2015) 1–15, https://doi.org/10.1016/j.apenergy.2015.05.065.
[54] P. Antoniadou, A.M. Papadopoulos, Occupants' thermal comfort: state of the art and the prospects of personalized assessment in office buildings, Energy Build. 153 (2017) 136–149, https://doi.org/10.1016/j.enbuild.2017.08.001.
[55] A. Boerstra, Personal control in future thermal comfort standards, Adapt. To Chang. New Think, (2010), pp. 9–11 http://www.seedengr.com/documents/Personalcontrolinfuturethermalcomfortstandards.pdf.
[56] K. Gram-Hanssen, A. Rhiger Hansen, Forskjellen Mellom Målt Og Beregnet Energiforbrug Til Oppvarmning Av Parcelhuse, (2016).
[57] K. Gram-Hanssen, Efficient technologies or user behaviour, which is the more important when reducing households' energy consumption? Energy Effic 6 (2013) 447–457, https://doi.org/10.1007/s12053-012-9184-4.
[58] K. Gram-Hanssen, S. Georg, Energy performance gaps: promises, people, practices, Build. Res. Inf. 46 (2018) 1–9, https://doi.org/10.1080/09613218.2017.1356127.
[59] C. Eon, G.M. Morrison, J. Byrne, The influence of design and everyday practices on individual heating and cooling behaviour in residential homes, Energy Effic (2017) 1–21, https://doi.org/10.1007/s12053-017-9563-y.
[60] S. Goodhew, Sustainable Construction Processes: a Resource Text, John Wiley & Sons, 2016.
[61] J. Thomsen, L. Gullbrekken, S. Grynning, J. Holme, Evaluering Av Boliger Med Lavt Energibehov, EBLE, 2017.
[62] T.S. Larsen, H.N. Knudsen, A.M. Kanstrup, E.T. Christiansen, K. Gram-Henssen, M. Mosgaard, H. Brohus, P. Heiselberg, J. Rose, Occupants Influence on the Energy Consumption of Danish Domestic Buildings, (2010).
[63] A. Hinge, O. Tanjea, M. Bobker, Sustainability in commercial building: bridging the gap from design to operations, Green Build. Insid. (2008).
[64] A. Leaman, B. Bordass, Are users more tolerant of "green" buildings? Build. Res. Inf. 35 (2007) 662–673, https://doi.org/10.1080/09613210701529518.
[65] R.J. De Dear, G.S. Brager, J. Reardon, F. Nicol, D. Ph, Developing an adaptive model of thermal comfort and preference, Design (1998) 4106.
[66] F. Nicol, S. Roaf, Post-occupancy evaluation and field studies of thermal comfort, Build. Res. Inf. 33 (2005) 338–346, https://doi.org/10.1080/09613210500161885.
[67] S. Grynning, N. Lolli, S. Wågø, B. Risholt, Solar shading in low energy office buildings - design strategy and user perception, J. Daylighting. 4 (2017) 1–14, https://doi.org/10.15627/jd.2017.1.
[68] C. Reinhart, K. Voss, Monitoring manual control of electric lighting and blinds, Light. Res. Technol. 35 (2003) 243–258, https://doi.org/10.1191/1365782803li064oa.
[69] S. Karjalainen, Should we design buildings that are less sensitive to occupant behaviour? A simulation study of effects of behaviour and design on office energy consumption, Energy Effic 9 (2016) 1257–1270, https://doi.org/10.1007/s12053-015-9422-7.
[70] J. Vivian, A. Zarrella, G. Emmi, M. De Carli, An evaluation of the suitability of lumped-capacitance models in calculating energy needs and thermal behaviour of buildings, Energy Build. 150 (2017) 447–465, https://doi.org/10.1016/j.enbuild.2017.06.021.
[71] IEA, IEA Annex 44. Integrating environmentally responsive elements in buildings. State-of-the-art review 2 A (2008) Responsive Building Elements http://www.annex44.civil.aau.dk/puplications/Technical Reports/State-of-the-Art of RBE Vol2A.pdf.
[72] P.K. Heiselberg, Expert Guide Part 1 Responsive Building Concepts, (2010).
[73] C. Maurer, T.E. Kuhn, Variable g value of transparent facade collectors, Energy Build. 51 (2012) 177–184, https://doi.org/10.1016/j.enbuild.2012.05.011.
[74] P.C. Tabares-Velasco, C. Christensen, M. Bianchi, Verification and validation of EnergyPlus phase change material model for opaque wall assemblies, Build. Environ. 54 (2012) 186–196, https://doi.org/10.1016/j.buildenv.2012.02.019.
[75] P.A.B. James, M.F. Jentsch, A.S. Bahaj, Quantifying the added value of BiPV as a shading solution in atria, Sol. Energy 83 (2009) 220–231, https://doi.org/10.1016/j.solener.2008.07.016.
[76] W. Bahr, A comprehensive assessment methodology of the building integrated photovoltaic blind system, Energy Build. 82 (2014) 703–708, https://doi.org/10.1016/j.enbuild.2014.07.065.
[77] R. Loonen, J.M. Rico-Martinez, F. Favoino, M. Brzezicki, C. Menezo, G. La Ferla,

L. Aelenei, Design for facade adaptability - towards a unified and systematic characterization, Proc. 10 Th Conf. Adv. Build. Ski, Bern, Switzerland, 2015, pp. 1284–1294.
[78] IEA, Expert Guide Part 2 Responsive Building Elements, (2009).
[79] A. van der Aa, P. Heiselberg, M. Perino, Designing with responsive components, IEA-ECBCS Annex 44 integr, Environ. Responsive Elem. Build. (2011), https://doi.org/10.1017/CBO9781107415324.004 IEA-ECBCS annex 44 Integrating Environmrntally Res.
[80] B. Basarir, M.C. Altun, A classification approach for adaptive façades, ICBEST Istanbul, Istanbul, Turkey, 2017.
[81] R. Looman, Climate-responsive Design a Framework for an Energy Concept Design-decision Support Tool for Architects Using Principles of Climate-responsive Design, Delft University of Technology, Faculty of Architecture and the Built Environment, 2017.
[82] E. Taveres-Cachat, K. Bøe, G. Lobaccaro, F. Goia, S. Grynning, Balancing competing parameters in search of optimal configurations for a fix louvre blade system with integrated PV, Energy Procedia, Elsevier, 2017.
[83] L. Yang, Z. Nagy, P. Goffin, A. Schlueter, Reinforcement learning for optimal control of low exergy buildings, Appl. Energy 156 (2015) 577–586, https://doi.org/10.1016/j.apenergy.2015.07.050.
[84] B. Dong, K.P. Lam, A real-time model predictive control for building heating and cooling systems based on the occupancy behavior pattern detection and local weather forecasting, Build. Simul. 7 (2014) 89–106, https://doi.org/10.1007/s12273-013-0142-7.
[85] E.R. Stephens, D.B. Smith, A. Mahanti, Game theoretic model predictive control for distributed energy demand-side management, IEEE Trans. Smart Grid 6 (2015) 1394–1402, https://doi.org/10.1109/TSG.2014.2377292.
[86] S. STEVENS, Intelligent facades: occupant control and satisfaction, Int. J. Sol. Energy 21 (2001) 147–160, https://doi.org/10.1080/01425910108914369.
[87] L.G. Bakker, E.C.M. Hoes-van Oeffelen, R.C.G.M. Loonen, J.L.M. Hensen, User satisfaction and interaction with automated dynamic facades: a pilot study, Build. Environ. 78 (2014) 44–52, https://doi.org/10.1016/j.buildenv.2014.04.007.
[88] K. Yaman, G. Arslan, The impact of hourly solar radiation model on building energy analysis in different climatic regions of Turkey, Build. Simul. 11 (2018) 483–495, https://doi.org/10.1007/s12273-017-0420-x.
[89] R. Urraca, A.M. Gracia-Amillo, T. Huld, F.J. Martinez-de-Pison, J. Trentmann, A.V. Lindfors, A. Riihelä, A. Sanz-Garcia, Quality control of global solar radiation data with satellite-based products, Sol. Energy 158 (2017) 49–62, https://doi.org/10.1016/j.solener.2017.09.032.
[90] I. Gaetani, P. Hoes, J. Hensen, M. L, Occupant behavior in building energy simulation: towards a fit-for-purpose modeling strategy, Energy Build. 121 (2016) 188–204 https://doi.org/10.1016/j.enbuild.2016.03.038.
[91] E. Georges, B. Cornélusse, D. Ernst, V. Lemort, S. Mathieu, Residential heat pump as flexible load for direct control service with parametrized duration and rebound effect, Appl. Energy 187 (2017) 140–153, https://doi.org/10.1016/j.apenergy.2016.11.012.
[92] D. Patteeuw, K. Bruninx, A. Arteconi, E. Delarue, W. D'haeseleer, L. Helsen, Integrated modeling of active demand response with electric heating systems coupled to thermal energy storage systems, Appl. Energy 151 (2015) 306–319, https://doi.org/10.1016/j.apenergy.2015.04.014.

A2 Paper II

Ten questions concerning co-simulation for performance prediction of advanced building envelopes

E Taveres-Cachat, F Favoino, R Loonen, F Goia

Building and Environment Volume 191, 107570, (2021)

Building and Environment 191 (2021) 107570

Contents lists available at ScienceDirect

Building and Environment

journal homepage: http://www.elsevier.com/locate/buildenv

Ten questions concerning co-simulation for performance prediction of advanced building envelopes

Ellika Taveres-Cachat [a,b], Fabio Favoino [c], Roel Loonen [d], Francesco Goia [a,*]

[a] Department of Architecture and Technology, Norwegian University of Science and Technology, Sentralbygg 1 Gløshaugen, 7034, Trondheim, Norway
[b] Sintef Community, Høgskoleringen 4b, 7034, Trondheim, Norway
[c] Technology Energy Building Environment (TEBE) Research Group, Department of Energy, Politecnico di Torino, Corso Duca Degli Abruzzi 24, 10129, Turin, Italy
[d] Department of the Built Environment, Eindhoven University of Technology, Eindhoven, the Netherlands

ARTICLE INFO

Keywords:
Building performance simulation
Adaptive facades
Advanced control strategies
Multi-physical model
Integrated analysis
Modular modeling

ABSTRACT

Advanced building envelopes (ABEs) are innovative integrated systems that aim to increase the sustainability of buildings by providing flexible and efficient energy management solutions while safeguarding healthy and comfortable indoor environments. These building envelopes operate at the cross-section of architecture, engineering and data science, often involving transient multi-physical parameters and advanced material properties. The development of ABEs has increasingly relied on building performance simulation (BPS) tools to improve the understanding and management of their complex interrelationships. However, this complexity has sometimes shown to constitute barriers for their real-world implementation, in part caused by the limitations of monolithic legacy BPS tools. One of the most promising alternatives to overcoming these difficulties has been to use co-simulation. Co-simulation allows modelers to use multiple sub-models and link them to enable simultaneous data exchange during simulation runtime. This approach provides added possibilities for implementing advanced control strategies, integrating innovative data-driven inputs, and creating collaborative interdisciplinary and evolutive workflows for building envelopes at different stages and scales in projects.

This article provides a critical overview of the possibilities that co-simulation approaches offer to improve performance assessments of advanced building envelopes. This article also presents current barriers to co-simulation and discusses critical elements to overcome them. Ongoing trends in BPS and information and communication technologies are highlighted, emphasizing how they transform the field and create new opportunities for modelers working in research and industry.

1. Introduction

In order to minimize its contribution to climate change, the building sector is targeting increasingly stringent carbon emission reduction measures throughout the entire life cycle of buildings [1–4]. These policy developments place new demands on building design – and in particular building envelope design. They require going beyond the simplistic passive principles of the *"energy conservation approach"* [5] and actively exploit current technological developments in building materials and systems. As a result, significant research and innovation efforts have been deployed to develop novel building envelope systems and new design blueprints that could allow balancing these targets with the complex requirements of buildings. However, the transition from traditional building envelope designs to ones integrating innovative technologies is not seamless. Part of the reason for this is that most of the simulation tools used to evaluate envelope performance are legacy software [6,7]. This means that they originate from a time when the requirements for building envelopes and their properties were much different from today's [8]. As a result, modelers face several challenges to accurately and reliably assess the performance of new envelope technologies in legacy building performance simulation (BPS) tools. A promising approach to overcoming these limitations is to use more progressive simulation methods such as co-simulation.

This paper aims to share the critical insights of experts in building simulation on how co-simulation can be used to improve the performance prediction of innovative building envelopes. The material compiled in this work is a balanced blend of highlights from articles available in the literature, personal experiences, and a shared vision of future frameworks for co-simulation. The ten questions answered here

* Corresponding author.
E-mail addresses: francesco.goia@ntnu.no, francegoia@gmail.com (F. Goia).

https://doi.org/10.1016/j.buildenv.2020.107570
Received 13 October 2020; Received in revised form 18 December 2020; Accepted 27 December 2020
Available online 2 January 2021

Acronyms

ABE	Advanced building envelope
AF	Adaptive Facade
API	Application programming interface
BPS	Building performance simulation
EMS	Energy management system
GHG	Greenhouse gas
HVAC	Heating, ventilation, and air conditioning
ICT	Information and communication technology
MPC	Model predictive control
ODE	Ordinary differential equation
PDE	Partial differential equation

are chosen to lead the reader through a critical reflection on the challenges of using BPS for complex envelope systems, and the reasons why co-simulation may provide an interesting alternative. Readers unfamiliar with co-simulation will be warned of the many traps and difficulties that come with this approach, while experienced users may recognize challenges they have themselves faced. Readers will also find helpful recommendations based on the fit-for-purpose method to limit some of the potential issues in co-simulation and ensure that the approach developed is most relevant for the intended investigation. The added value of co-simulation for building envelope design, despite its challenges, is emphasized by highlighting its potential contribution in a bigger picture where it is integrated from design to commissioning as a dynamic layer in a larger project workflow. The reader will also find up-to-date information about the latest developments that support the uptake of co-simulation in its many forms in the field of building envelopes. Finally, it is worth mentioning that most of the challenges, opportunities and limitations of using co-simulation approaches to study and develop ABEs are also relevant for different building systems. For this reason, the answers to the ten questions proposed in this paper highlight topics and research priorities that could extend to the field of building simulation in general.

2. Ten questions concerning co-simulation for performance prediction of advanced building envelopes

2.1. *Question 1: What are advanced building envelopes?*

Advanced Building Envelopes (ABEs) are integrated envelope systems and technologies that can ensure high building performance across a wide range of physical domains (Fig. 1). ABEs aim to successfully balance competing performance aspects using a combination of advanced material properties, advanced components, and advanced integrated control strategies; or by having designs based on advanced design methodologies.

Designing such building envelopes, first requires shifting the focus from one-size-fits-all solutions to case-specific ones that aim at delivering a context-oriented, synergic and efficient envelope design. This is possible thanks to a series of developments in the capabilities of design and simulation tools (supporting, for example, free-form façades and geometrically complex shading elements [9–12]) and an improved ability to manage intricate interactions between different scales (material, building [13], or urban scale [14]) considering different physical domains [15]. These tools are also compatible with optimization, allowing to improve further the design and operation of innovative envelope technologies [7]. Overall, this approach is powerful in that it transforms a traditionally rigid building envelope design into a performance-oriented flexible design process that enables new functions, new behaviors, and new performance goals supported by the integration of innovative technologies.

Depending on the setting and the type of integrated technology, advanced building envelopes are also sometimes known as Responsive [5,16] or Adaptive building elements [17]. Alternatively, they may also be referred to in the literature as kinetic, smart, switchable, or multi-functional envelopes.

ABEs can assume different appearances and can be realized with different systems (Fig. 2). The main types of technologies used to design ABEs are: i) building-integrated solar energy conversion systems [18] (solar thermal, photovoltaic and hybrid systems); ii) decentralized integrated HVAC elements [19]; iii) components based on materials or systems capable of actively and selectively managing the energy and mass transfer through building envelopes, by reversibly modulating their thermo-optical properties and operating strategies according to transient boundary conditions and performance requirements [20], also

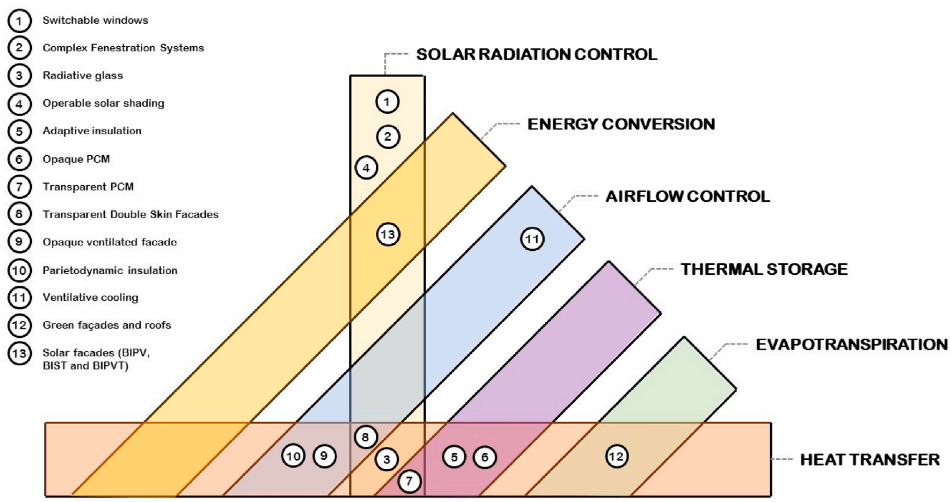


Fig. 1. Interrelated Physical domains/mechanisms influenced by advanced façade technologies (after [19]).

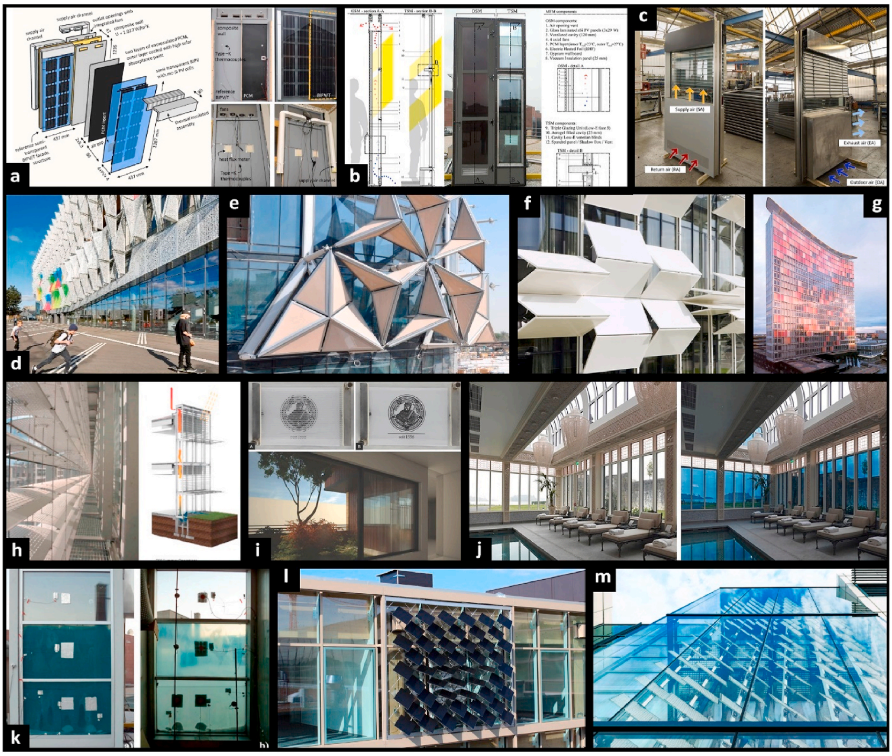


Fig. 2. *Examples of advanced building envelopes at research, prototype/demonstration, and commercial stage: multifunctional systems with integrated components such as solar (thermal) systems, HVAC units, ventilation systems, heat storage (a:* [21]*; b:* [22]*; c:* [23]*), kinetic facades (d, e:* [24]*; f:* [25]*;); double skin facades and systems with heat carrier fluids (g:* [25]*; h:* [26]*; i:* [27]*), smart glazing systems (j:* electrochromic [28]*; k:* thermochromic [29]*); solar facades with integrated dynamic, multifunctional PV and shading devices (l* [30]*; m:* [31]*).*

known as Adaptive Facades (AF).

Practical examples of ABEs may be: double skin facades or advanced integrated façades [32]; switchable glazing technologies such as electrochromic, liquid crystal, thermochromic glazing etc. [33]; operable solar shading [34–36] and complex fenestration systems [37]; wall integrated phase change materials [38]; and dynamic insulation [39] and multifunctional facades [40].

The multi-physicality of these components is illustrated in Fig. 1, where specific examples of technologies are placed according to their influence on the different domains they interact with [15]. These interactions may include more than one domain and may be static or dynamic, depending on whether the physical properties are variable and controllable. However, the intrinsic complexity of ABEs that initially sets them apart from traditional building envelopes and makes them attractive, also makes it challenging to predict their performance in BPS tools and ensure suitable design choices.

2.2. Question 2: What are the challenges of predicting the performance of advanced building envelopes?

The complex nature of ABEs calls for a holistic performance assessment in order to capture the full extent of their benefits. According to the literature, BPS plays a vital role in supporting decision making in design, product development, manufacturing, and operations of ABEs [41]. It is also crucial for verifying certification schemes and compliance with regulations [42]. However, modelling and simulating ABEs is not trivial. Simulating the operation of ABEs requires modelling phenomena that typically cannot efficiently be described in monolithic simulation software. This is because ABEs have many different prerequisites compared to a simulation-based analysis of conventional building envelopes, as discussed in Table 1.

As a result, using legacy monolithic simulation software presents several challenges. These are due to rigidities in the structure of the tools, limitations due to their intended purpose, and limited to nonexistent integration options with other types of software (solving a different set of differential equations) nor with specific models (e.g. models of novel technologies developed in different tools and codes). The original issue comes from the fact that monolithic legacy tools were mainly developed to abstract the physical reality of one single domain. This means they were only built to solve the differential equations for one (or a selected few) physical domain at once (Fig. 3.a). Today, these tools continue to evolve to improve their accuracy and integrate new capabilities, which includes the addition of specific modules for the simulation of more advanced building systems. However, their large codebases render it difficult and costly to update and maintain them continuously. It is expected that in the long run, their current monolithic form will hinder them from keeping up with the pace and diversity of new material and envelope technology developments. The alternative to keep using these tools is to implement them as part of co-simulation approaches in which multiple specialized simulation engines and scripts are interconnected and exchange data (Fig. 3.b). These approaches are more suited to the modelling and simulation of complex systems and have the potential to facilitate the design and delivery of higher-performing buildings. Additionally, co-simulation could reduce redundant modelling activities (i.e. building multiple models of the same building or technology) and provide more accurate, multifaceted

Table 1
Main prerequisites for modelling ABE properties and associated requirements in terms of simulation capabilities.

Prerequisite	Requirement in BPS
Multi-physical modelling (i.e. considering heat, moisture, light, energy, air, sound) of the interactions between the envelope, the indoor environment, and building services [43]	It requires solving the differential equations of different physical domains in a coupled way with an appropriate spatial and temporal resolution
Flexibility to **integrate models of emerging technologies** which may not be directly available in a specific BPS tool [43]	It requires the possibility to develop or integrate dedicated models of advanced technologies into whole building simulation tools to consider coupled interactions with the rest of the building
Possibility to model **time-varying facade properties** that are controlled by boundary conditions (e.g. passive adaptive building envelope technologies such as phase change [44] or thermochromic materials [45]) or an input signal (e.g. active smart glazing [46])	It requires the possibility to simulate the dynamic operation of facade adaptation across multiple physical domains in coordination with the operation of building services or using specialized control-oriented software [47]
Possibility to simulate **interactions between ABE systems and building occupants** (for dynamic and/or controllable technologies)	It requires the possibility to integrate dedicated models replicating the stochastic nature of human behavior and interaction with advanced building envelope elements [48,49]
Possibility to **integrate performance-based generative design and architectural form-finding workflows**, for example for systems with complex and kinetic geometries [50], in BPS tools	It requires the possibility to couple flexible design tools with input interfaces of BPS tools
Greater need for **sensitivity and uncertainty analysis tools** for model validation and calibration to understand the influence of ABE design parameters on relevant building performance indicators [51], or conversely, of changing scenarios on design parameters [52]	It requires integrating approaches and models for global and local sensitivity analysis in BPS tools
Possibility to use **numerical optimization tools** to explore larger solution spaces [53] based on ABE design elements or properties	It requires coupling inputs and outputs of models and simulations to external algorithms and automatize the processes for simulation launching, output collection, and data analysis

and integrated building performance evaluations.

2.3. *Question 3: What is meant by co-simulation in building performance simulation?*

Co-simulation has been defined in computer science as the combination of theory and techniques to enable the global simulation of a coupled system via the composition of multiple simulators [54]. The motivation for co-simulation is often found in the necessity of combining specialized domain-specific models that are developed in different software environments. According to Ref. [55], the advantages of co-simulation include the possibility to:

- Combine heterogeneous simulation approaches and tools that are best suited for the sub-system modeled;
- Perform rapid testing of software prototypes;
- Facilitate parallel-shared developments in distributed teams, including the option to preserve intellectual property (IP) rights;
- Enable multi-scale simulations to address the interactions between different sub-systems by modeling each of them with an appropriate level-of-detail.

In building simulation, the term co-simulation is usually used to describe approaches allowing to couple different models, each describing only one part of the governing physical relationships in the overall system (e.g. thermal models, airflow models, daylighting models etc.). Each model is run in a separate simulation tool or unit, in a way that they can exchange simulation data during runtime, and replicate the behavior of the system seen as a whole.

In this process, several decisions need to be made to establish a successful co-simulation strategy. The following considerations have an impact on the stability, accuracy, efficiency and ease of implementation, and are therefore essential when developing successful co-simulation strategies.

Coupling variables: The simulation user should decide which state variables will be exchanged during simulation runtime. It is advised that these coupling variables should represent as much as possible physical quantities as opposed to derived or abstracted data [55]. In this way, model verification and validation are easier to perform because the variables could be measured in the real world. Moreover, selecting

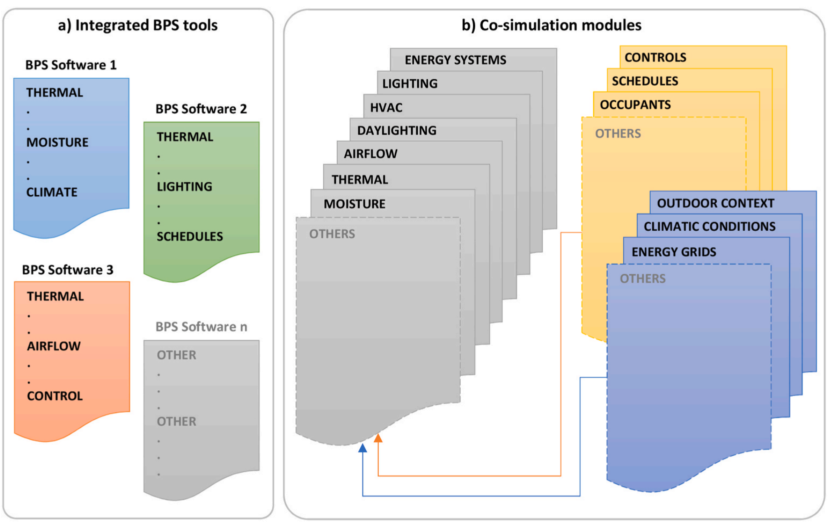


Fig. 3. Illustration of the difference between integrated BPS tools and co-simulation modules.

variables that are available in multiple domain simulators increases the modularity and opportunities for future extension.

Coupling strategies: Different methods exist for coupling multiple simulation models with one another. A first distinction can be made between sequential and bi-directional coupling strategies. In sequential coupling strategies, there is no possibility for feedback. This is, for example, the case when daylight simulations are pre-calculated, with outcomes being fed to the thermal model that is invoked afterwards [54]. Bi-directional coupling strategies, on the other hand, do allow for feedback, which is accomplished through runtime exchange of coupled data. Within this category, a further distinction can be made between strong and loose coupling. Strong coupling involves an iterative process in which solvers need to meet predefined convergence criteria before moving to the next time step. In loose coupling, on the other hand, data is exchanged after each calculation time step is completed (i.e. each model uses the results of the other model in the previous time step). The most suitable strategy depends on the level of variability in boundary conditions and the simulation time step that is chosen [56,57].

Coupling techniques: *One-to-one coupling* refers to dedicated implementations that connect two simulators. Examples of this type of coupling include TRNSYS type 155 which links the TRNSYS environment to Matlab, the built-in connection between ESP-r and Radiance for coupled building energy and daylighting simulations [58], or the coupling between TRNSYS and ESP-r that was developed to enable modeling of novel integrated energy systems [59]. Co-simulation approaches based on *middleware* are much more flexible and modular, as they couple any number of simulation programs, instead of two simulators directly. The task of the middleware is to orchestrate the simulation process, manage data exchange between the simulators and facilitate post-processing. Notable examples of middleware for co-simulation include BCVTB [60] or RabbitMQ [61,62]. The third technique for co-simulation is to use a so-called *standard interface approach*. This technique allows for direct coupling with any software tool that has the same interface implemented. The functional mock-up interface (FMI) is a widely used standard for coupling software with many applications in the BPS domain.

Coupling frequency: Different coupling frequencies can be chosen depending on the type of simulation task performed. Research has shown that the coupling frequency can significantly affect the stability and accuracy of the co-simulation. This frequency should, therefore, be carefully chosen. For building energy systems, this often means that the coupling frequency should match the thermal time constant of the system investigated [63]. It should also be mentioned that the data exchange can either take place at every time step of the simulation or in a multi-rate approach with either fixed or variable time steps. Multi-rate approaches are often used when coupling CFD with BES in which the mismatch in simulation time between the two solvers favors asynchronously calling each of them.

All the considerations mentioned above must be simultaneously addressed when developing co-simulation strategies. This is especially the case for systems that exhibit complex behavior or that are exposed to highly variable boundary conditions. In this context, ABEs are a textbook example of systems that benefit from co-simulation. The reason for this is that ABEs are characterized by several performance requirements in different physical domains. Co-simulation involving multiple BPS tools also plays a vital role in providing a more accurate characterization of the integrated performance of ABEs, given that these systems do not have fixed designs or operation strategies and are defined on a case-by-case basis.

2.4. Question 4: How can co-simulation improve performance prediction of advanced building envelopes in multiple domains?

The main advantage of using co-simulation in the design phase of an ABE is that it allows tailoring each part of a model (or sub-model) to the current information available, the level of abstraction required, and to the desired output from each physical domain. Another asset of this approach is that the information exchanged between the models is both more precise and more relevant to the purpose of the simulation. Commonly used co-simulation approaches for multi-domain evaluations of ABEs are, for example, the coupling of detailed daylighting simulations with thermal simulation engines. This approach can provide more accurate estimates of the amount of light (or heat) entering a zone and result in a deeper understanding of how the building envelope interacts with solar radiation through its design. The outputted information can be immediately reused to calculate the dynamic HVAC loads or to evaluate indoor comfort parameters with a much higher level of accuracy and all within the same simulation run. This results in a direct and holistic estimation of the impact of any design modification in the system.

Co-simulation approaches also provide several other advantages for facade design compared to their traditional counterparts. First, they can be used to create dynamically evolving workflows with interlinked models that actively interact and update as new information arises during the project, as well as include sensitivity and uncertainty analysis [64]. This is a critical added value, as it avoids having multiple - and sometimes redundant - models using potentially suboptimal descriptions of non-trivial behaviors. Second, the plug and play properties provide the flexibility to use models that describe multiple physical phenomena with variable levels of detail, as well as models with different code structures or programming languages.

Ultimately, the additional information obtained through co-simulation about the behavior of ABEs is valuable for improving the design of the systems, conducting what-if analysis, and generally provides more in-depth insights about the dynamics of the envelope and its interaction with the rest of the building or occupants. All these elements not only improve the performance of ABEs in their design, but they also allow predicting their performance and quantifying their benefits more accurately. However, the use of co-simulation is not limited to the design phase of ABEs and plays an extensive role in modelling control-response behaviors.

2.5. Question 5: How can co-simulation improve the operation of advanced building envelopes?

Advanced building envelopes, particularly adaptive facades, are often characterized by their ability to tune their properties or change their performance targets following a triggering event. These triggers can originate from different sources such as natural (climatic) mechanisms, user-issued requirements, or from varyingly complex rule-based controls [16]. Successfully simulating the operation of an ABE is therefore often contingent on modelling detailed control sequences and different types of triggers based on the simultaneous analysis of the multi-physical behavior of the ABE system and its response.

In co-simulation, the modelling of a triggering event for a system can be developed in a dedicated tool and then linked to the separate simulation engines involved. Additionally, because the different tools can exchange information at different time steps, control sequences can be dynamically created and fed in during the same simulation loop. This means that a control response for an ABE can be defined during the simulation run, based on the simultaneous evaluation of (i) a triggering event (for example, based on boundary conditions), (ii) the current state of the building given by the solver of the transport and energy conservation equations, and (iii) a pre-set control algorithm. This allows for a much wider variety and complexity of control options compared to the relatively simple rule-based controls that legacy BPS tools offer. In fact, both the modelling of the triggering event and the response can be described with a higher degree of freedom in co-simulation [65].

The added flexibility given by combining performance simulation engines with dedicated algorithms that replicate triggering events is furthermore alluring for two reasons. First, it allows obtaining a more accurate performance evaluation of a distinct solution using a specific control action. Second, it enhances the possibility to focus the study on the control action itself, which is something that current building simulation tools do not fully support. Another clear advantage of co-simulation approaches is that they also allow considering occupant behavior and occupant related triggers, where the interactions between the envelope and the occupants can be modeled using many different methodologies [66]. Co-simulation approaches are also the only possibility to evaluate trade-offs in multi-domain controls that combine different sources of information for the control logic. For example, they are useful in scenarios where energy performance requirements must interplay with user requirements and indoor environmental quality performance.

Finally, co-simulation can be used in parallel to hardware-in-the-loop simulations with actual controller components in real-time simulations using the techniques and tools discussed in section 2.9. This approach is particularly relevant for ABEs since many of these systems are characterized by dynamic behaviors. Hence, there are obvious benefits to actively tuning their responses to real-time triggers. These responses can be based on different control strategies, where threshold values or rule-based algorithms are the simplest ones, and the most complex ones are based on a real-time search of the ABE's best performance through model predictive control (MPC) [47,67,68]. In MPC, a model (often a reduced-order model or a data-driven model) of the system is used to continuously search for the optimal operating state of a system considering real-time boundary conditions (or other real-time inputs). MPC is a relatively common control strategy in many processes and industries, but just recently appeared in the built environment (e.g. Ref. [69]). Only a few studies and applications are available when it comes to ABEs (e.g. Refs. [46,47]). Because of the intrinsic complexity and multi-domain characteristics of many ABEs, MPC is, in theory, ideal to ensure the most significant improvement in the operation of advanced building envelopes. However, there is still a long way to go before such advanced control methods become standard solutions for ABEs. Nonetheless, this application of co-simulation will, without doubt, constitute a hot topic in research and developments in this field in the coming years. It is expected to impact methods and techniques for control-oriented model construction, algorithms for optimization, and platforms for dataflow integration.

Overall, co-simulation approaches have the potential to solve several of the challenges that modelers face when using monolithic software. Additionally, they offer sophisticated possibilities for optimal and real-time dynamic control of ABEs. However, they are still in no way a silver bullet. In practice, there are still several barriers that prevent the widespread use of co-simulation approaches for ABEs and limit its implementation to studies carried out by experts with intimate knowledge of simulation engines.

2.6. Question 6: What are the current barriers and challenges to co-simulation of advanced building envelopes?

The main barriers to co-simulation approaches stem from two tightly interrelated issues, namely a standardization gap and a knowledge gap.

Standardization gap

The standardization gap points to the lack of systematic and homogeneous interfaces for data exchange between different software tools or simulation engines. This gap ends up manifesting itself at several different levels in co-simulation approaches, affecting not only the data being exchanged but also how the exchange happens, with many negative ramifications.

The issue initially stems from the fact that legacy BPS tools have been developed independently, each one with a different organizational structure. Because the engines were also intended to be monolithic, their coding structure did not anticipate the possibility to exchange data with one another. This makes them neither flexible nor modular. Only very recently have releases of BPS software started to address this by offering more access to the solvers, including the possibility to feed in or extract data during runtime. However, despite recently increased integration between BPS tools and generic programming languages, substantial difficulties for co-simulation due to an absence of standardization persist.

Standardization issues in co-simulation mainly concern the nature of the data, the information it contains, and the way data is extracted and provided to the different simulation tools and scripts. The solvers used in different BPS software may differ greatly, and the accessibility of data may also vary. This means that, for example, a data point (let that be a variable, an input or an output) that is accessible in one tool may not necessarily be accessible in another tool. This issue is deeply rooted in the fact that BPS tools have different levels of detail in their sub-routines and do not process inputs the same way.

Another consequence of the lack of standardization concerns the limited number of reusable methodologies for carrying out co-simulation. Combining different simulation engines is still a complex task with no generic one-size-fits-all approaches, and the end product is often tailor-made for the application and the BPS tools used. This issue is only made worse by the fact that there is not yet an established culture to promote sharing of models. This often results in a duplication of efforts in research.

Finally, the lack of standards hinders the establishment of a shared benchmarking procedure for co-simulation approaches. While conventional BPS tools undergo validation and comparison based on reference simulation cases (e.g. when it comes to thermal behavior, using the BESTEST cases), the nature of co-simulation makes it difficult to have a comprehensive set of standard applications. In respect to this topic, it is expected that single engines can be validated for individual domains using existing standards. However, co-simulation approaches should instead rely primarily on a verification process [70] - i.e. to test and confirm that the algorithms and numerical methods implemented are correctly executed when integrated into a single dataflow structure.

Knowledge gap

The knowledge gap is tightly related to the standardization gap. Today, co-simulation is mostly reserved for a somewhat limited group of experienced BPS users due to the lack of easily accessible and shared documentation. Successful execution of co-simulation requires robust knowledge of the physico-mathematical models and algorithms implemented in BPS tools, as well as programming skills. Additionally, a deep understanding of possible workarounds and "backdoors" to overcome the rigidity of the current simulation tools is also a prerequisite for today's implementation of co-simulation approaches.

Currently, there is limited widely available know-how to tackle the technical challenges of correctly defining data exchange parameters in co-simulation. Data exchange protocols in co-simulation depend on three elements: the timing of the exchange (i.e. inter or intra time step), the frequency of the exchange, and the nature of the data exchanged. All of these aspects are to be set up with care to ensure that the different numerical solvers implemented in the linked engines are stable, that they converge, and that they lead to meaningful numerical solutions. This is particularly true for strong coupling approaches where systems of ODE or PDE need to be resolved numerically and simultaneously in different engines - which can prove to be a delicate procedure. However, other desynchronized or loosely coupled strategies are less impacted by these challenges. Hence, it is often advised to investigate whether a strong coupling strategy can be modified to an equivalent, more loosely connected approach without leading to a major loss in accuracy or significance of the outputs. The reason why these challenges persist is that the practical implementations to overcome them are almost always case-dependent (i.e. the standardization gap). They might differ based on the internal routine of one or another simulation engine but almost always depend on the tool used as well as the level of complexity necessary to describe the ABE co-simulation task. As a result, creating guidelines is a laborious task and users are often left on their own to set-up their co-simulation approaches. Another aspect that can be considered part of the knowledge gap relates to the fact that the value proposition of using co-simulation is sometimes unclear. While the use of simulation-based design is becoming more widespread, the use of advanced dedicated workflows is still reserved for high profile projects. In these projects, the requirement to provide a fully holistic characterization of the ABE is a cornerstone of the design process. Consequently, the value and the reasons to use co-simulation may not always be known to all the stakeholders in a less ambitious project. There is still limited knowledge transfer between modellers, designers, consultants, developers, contractors, and policymakers that could highlight the benefits of using co-simulation or of developing multi-factorial performance assessments. Overcoming this would support a more general adoption of integrated simulation approaches as well as it would support a greater uptake of efficient building envelope solutions. This may also allow overcoming barriers to ABEs due to a lack of widely accepted performance metrics to communicate their benefits.

With time and as co-simulation receives more attention, it is expected that the purely technical issue relating to IT languages, programs and routines to exchange data will be resolved in the coming years. However, the more substantial challenges of co-simulation which stem from a lack of standardization and knowledge require a larger effort from expert BPS users to share and disseminate specific guidelines and knowledge about co-simulation. This includes recommendations about how to approach co-simulation tasks and how to select the suitable tools and engines.

2.7. Question 7: Which important elements should one take into consideration before selecting a co-simulation approach and a suitable set of software tools?

The decision whether to use a co-simulation approach when modelling an ABE is a complex choice the modeler should make primarily based on the purpose of the simulation and their knowledge and skills. It is important to remember that co-simulation often requires significant efforts before any meaningful result can be extracted due to the discussed lack of standardization. In research and development, the time and effort required to develop new simulation approaches is often accepted as part of the task. However, this may not always be the case in professional practices where the stakes are different. In most cases, it is worth verifying whether something that may seem to require a completely new co-simulation workflow might be solved with some minor trade-offs using functions or documented workarounds in conventional BPS tools.

The first recommendation to successfully using co-simulation is to follow a fit-for-purpose approach [71,72]. The fit-for-purpose method supports starting any modelling task with the development of a software agnostic conceptual model with a comprehensive analysis of the goal of the simulation. The point is to ensure that each model used has the right inputs, and provides the correct outputs, with a minimum modelling and computational effort. Then, special care should be given to the selection of the basic simulation environment(s) that will make up the multi-domain representation (e.g. the thermal energy simulation, the optical behavior, the fluid dynamics, etc.). These decisions should be based on the experience of the modelers since it may require them to have intricate knowledge of the different software and models implemented. In particular, it is recommended that one carefully considers the modularity of the algorithms used and the accessibility of the different variables in the physical-mathematical models.

Additionally, as much as possible, one should consider using sequential simulations rather than ones that require the synchronized solving of differential equations. This is to increase the robustness of the coupled simulation environments and avoid stability or convergence issues, due to using different time steps in the simulation engines, for example. Co-simulation can still be difficult even for experienced modellers, however recent developments in BPS have been trying to facilitate the process. This can be seen through native integration of other modules or by allowing external code to be called directly within simulation engines to create more advanced modelling and simulation workflows.

2.8. Question 8: How can co-simulation be integrated into multi-disciplinary design workflows of advanced building envelopes?

BPS and, in particular, building energy modelling (BEM) software process many inputs and outputs relating to geometric design, material properties, energy use and more. Some performance simulation tools are already compatible with architectural software and derive inputs from building information models (BIM) through industry foundation class (IFC) imports. This connection allows developing performance-based design approaches for ABEs with immediate 3D visual feedback. However, in a perspective of co-simulation, this information can be further integrated into a multi-domain workflow spanning the entire development of an ABE (Fig. 4). In such workflows, information processed through co-simulation can be directly linked to, for example, cost or GHG emission from materials and building operations [73]. In such workflows, it is also possible to consider peak loads and equipment sizing calculations when ABE systems are tightly integrated with HVAC services, hence detailing the calculation to fully assess the potentials given by the holistic approach in the design of the building envelope and building service.

Platforms supporting multi-domain integration and dynamic data exchange between disciplines are a key extension of co-simulation workflows. These can, for example, allow visualizing effects of variable inputs on multi-disciplinary key performance indicators. Considering that co-simulation also provides the option to protect the IP of separate parts of the model, private actors can contribute through co-simulation to drive innovation and expand the application of their products. This prospect is also an important step to integrating new technologies directly into projects with the option to assess their benefits in the same simulation loop. For building envelope design, this approach is most powerful, as envelopes also define the architectural expression of the building and impact many stakeholders.

The inclusion of an interconnected building simulation layer in digital twins is also a way to ensure proper commissioning and follow-up on actual building performance results during operation. As previously discussed, co-simulation schemes can support parallel hardware-in-the-loop simulations, which provides the possibility to troubleshoot any deviations between expected and actual operations as well as resolve issues that may otherwise go undetected [74,75].

Currently, there are two paths to integrating building performance simulation into larger BIM workflows. The first one is to use BIM-based simulation tools that can directly reuse building data created by architects and different parties through standard data schemes such as industry foundation class (IFC) and green building extensible markup language format files (gbXML) [76]. The second path is to use BIM to BEM translators, for example, based on the ModelicaBIM library [77] and object-oriented physical modelling (OOPM) [78], or in the ModelicaBEM framework [79]. A complete overview of the current possibilities to implement BIM in BPS tools is provided in Refs. [80,81].

Finally, new open-source data management platforms such as the Speckle server [82] are emerging and challenging traditional workflows of building design in the industry. Speckle is a platform for automation and interoperability that connects different modelling tools from the architecture, engineering and construction industry. It is built to allow multiple users to visualize specific data across disciplines of simulation. Moreover, Speckle lives in the cloud and allows users to manage who has access to projects, coordinate and collaborate by streaming project data between people and extend the platform to create custom third-party applications and workflows. Currently, Speckle connects to the BIM modelling software Revit, to the Rhinoceros and Grasshopper environments as well as Dynamo and others.

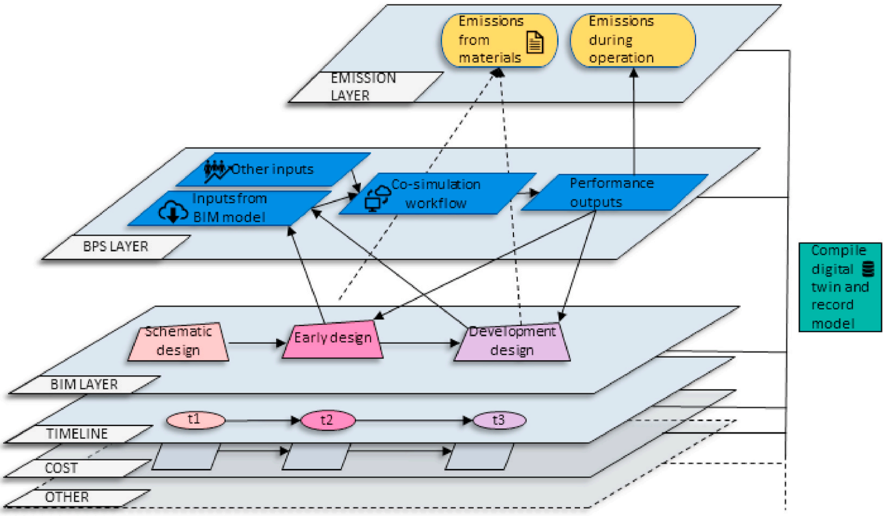


Fig. 4. Example of a multi-layer workflow integrating a co-simulation layer.

2.9. Question 9: Which recent developments in BPS provide added possibilities for co-simulation of ABEs?

BPS tools have benefited from many advancements in the past decade. For co-simulation, these changes pertain to two main categories: the integration of co-simulation options within existing software and the development of new tools with added flexibility for co-simulation. In the latter category, we distinguish tools and platforms that are more engineering-oriented and those that are more architecture-oriented. We also note that while these changes affect building performance simulation capabilities in general, they can be particularly interesting to improve the performance of ABEs themselves and the quality of the performance prediction.

Developments within existing whole building performance simulation tools

Several recent developments in software include inbuilt connections in simulation tool interfaces to different specialized engines. These are, for example, the integration of the backwards ray-tracing algorithm Radiance or the possibility to use computational fluid dynamic calculations with OpenFOAM [83]. BPS tools are also increasingly integrating inbuilt connections to the LBNL software Window [84] and THERM [85]. The possibility to directly couple BPS tools to Matlab-based block diagram environments, such as Simulink, also provides options for multi-domain simulations, model-based design, and optimization.

More specifically, the DOE simulation software EnergyPlus has, in recent years, substantially improved its ability to implement co-simulation [86]. In its 9.3 version release, the developers' of EnergyPlus have announced the introduction of a Python plug-in that can allow users to write their own scripts and connect to the EMS system. Version 9.3 also provides a new API that allows calling EnergyPlus as a library, where either a compiled C program or a Python script can be used. This API exposes functional, runtime, and data exchange capabilities in the software. Finally, one of the most significant developments tied to the EnergyPlus software is the creation of the Spawn of EnergyPlus, also referred to as Spawn or SPAOE [87,88]. Spawn does not aim to replace EnergyPlus but provides a version of the software which allows reusing modules for lighting, the building envelope, and load definition. The difference with the monolithic version of EnergyPlus is that the HVAC systems and controls are handled by the equation-based language Modelica [89,90]. Spawn can be coupled to platforms made for co-simulation and Functional Mock-up Units, both of which are described in the next paragraph. Note that for users, both Spawn and EnergyPlus work with the Open Studio interface [91], which means the interface for both software are identical and compatible with Open Studio measures.

Development of external tools and platforms supporting co-simulation

The second category of development in BPS supporting co-simulation is the emergence of tools and (co)simulation platforms that aim at facilitating co-simulation between existing tools. Currently, the only platform or middleware for co-simulation in building performance simulation is the Building Control Virtual Test Bed (BCVTB) [92]. BCVTB is a software environment that allows expert users to couple different simulation tools for distributed simulation or real-time simulation connected to a control system [93] (Fig. 5). The BCVTB connects to many whole building simulation tools, to Functional mock-up Units (FMUs), Dymola [94], and Matlab-based tools such as Simulink. Importantly, for co-simulation of multi-physical phenomena, the BCVTB connects to simulation software such as Radiance, which can allow using detailed daylighting simulations [95].

One of the most advanced approaches for co-simulation is driven by the development of the Functional Mock-up Interface (FMI) standard. Whereas co-simulation using the BCVTB is a method based on middleware (Fig. 5), the FMI is an interface standard that allows co-simulating two or more simulation programs in a co-simulation environment and, for example, to create modular workflows [96]. The core of the FMI standard is maintained by the Modelica Association project [97]. Its aim is to simplify operations related to the creation, the storage, the exchange and the use (or reuse) of system models in collaboration with other software or hardware-in-the-loop simulation and considering different applications such as cyber-physical systems [98]. The FMI standard defines the structure of the inputs and returns of Functional Mock-up Units (FMU) that different software must be packaged into to allow for co-simulation. The data exchange between the FMU is orchestrated by a master algorithm which controls data exchange between slave programs. The sub-systems are solved by their individual solvers but exchange data at discrete points in time. The approach of using the FMI standard for the performance prediction of ABEs is particularly interesting for systems that require advanced controls. The advantage of the FMI approach versus the BCVTB middleware approach

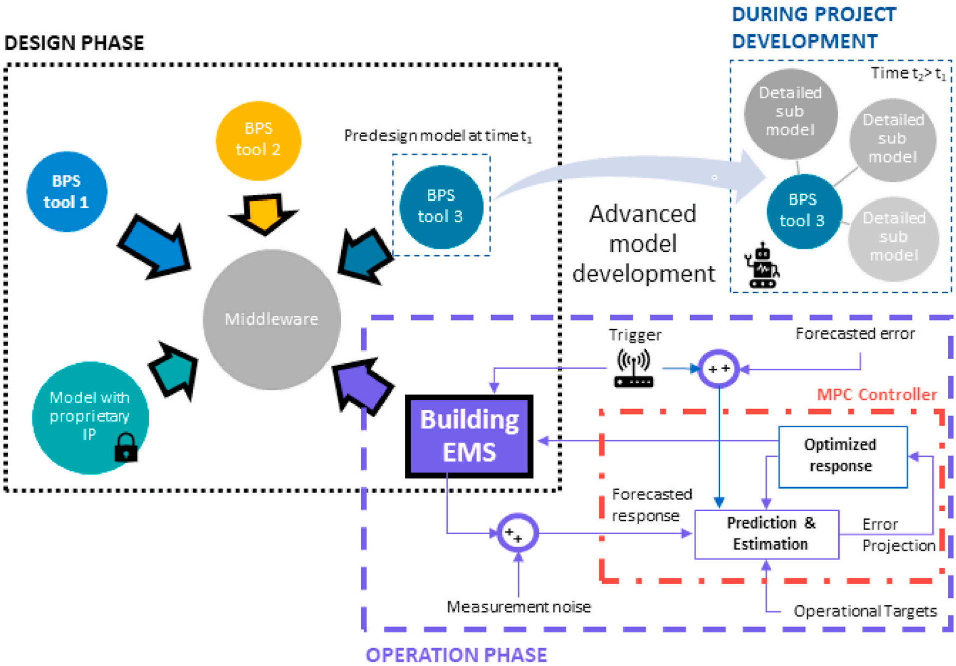


Fig. 5. Example of a co-simulation framework based on a middleware approach. The figure also illustrates the possible development of models during project time and building operation.

is that the FMI provides a more streamlined method for co-simulation. However, the FMI and the BCVTB both support hardware-in-the-loop (HIL) simulation, which is a significant added value for better control design of ABEs and can be used in parallel to co-simulation schemes.

As previously presented, the successful design of ABE solutions needs to address performance considerations at multiple spatial scales, ranging from materials, components and system assemblies to whole-building integration aspects [99]. The focus of these analyses can change over time as more information becomes available when the design process evolves. Co-simulation strategies, and especially structures, tools, and platforms enabling co-simulation should facilitate smooth transitions across these spatial scales as this can benefit from the hierarchic modeling paradigm [100]. Here, the term hierarchy refers to the use of agreed-upon input-output definitions that allow for multiple interchangeable sub-models and which encapsulate descriptions of the relevant physical interrelationships with different levels of detail relating to, e.g. fenestration systems [100] or façade-integrated HVAC systems [101]. It should be acknowledged that such multi-layered simulations reinforce the need for systematic approaches for collection, storage, sharing, and analyses of both simulation input and output data [102]. For example, a novel approach has recently been proposed by Mitterhofer et al. [103] to preserve the integrity of input data in co-simulation. To ensure consistency in simulation output and performance metrics across model resolutions and spatial scales, it is expected that explicit approaches such as the ones presented, in general terms for co-simulation, by Bleil de Souza and Tucker [104] and Mahdavi and Wolosiuk [105] will help to guarantee an error-free simulation process and to quantify the quality of the co-simulation infrastructure.

Finally, a simpler approach to co-simulation can be achieved through parametric scripting platforms such as Grasshopper in the Rhinoceros 3D modelling environment [106]. Parametric design has become an increasingly popular topic in architecture in the last decade and presents many opportunities for integrating loosely coupled co-simulation approaches. In particular, the development of The Ladybug Tools [107] - which provide interfaces to EnergyPlus (including Open Studio), Radiance, Window, Therm, and OpenFOAM - support performance-based design approaches for advanced building envelopes. Additionally, Grasshopper offers possibilities for structural engineering analysis, optimization approaches and more. The entire list of plug-ins is available at Food4Rhino [108]. The added value of coupling geometric design parameters directly to simulation software is also an important function that can help with the design of free-form facades, kinetic facades, or any type of architecturally responsive façade. The Grasshopper environment is compatible with scripts written in Python and C#, which also provides users with the freedom of writing components.

2.10. *Question 10: Which recent developments in ICT provide added possibilities for co-simulation?*

Many advances in ICT can be exploited to enhance the adoption and performance of co-simulation workflows. Distributed and cloud computing, are two of the developments which are expected to help leverage co-simulation the most. The option to divide the different computational tasks over more than one machine (distributed computing), and to outsource the computational tasks to external shared servers (cloud computing) are structurally compatible with co-simulation - especially when models with very different requirements in terms of computational power are combined. The application of distributed and cloud computing to co-simulation tasks can help to overcome these bottlenecks by dispatching sequential sub-routines across different resources. These computational techniques rely on the implementation of dedicated infrastructure that can allow timely communication between the distributed nodes in the computing system, or between the local machine and the computational system in the cloud. External server or distributed machines can execute a task from a list of commands, and computationally heavy tasks can be streamlined to an even higher degree by allocating these parts of the overall simulation process to machines, servers, or supercomputers with a higher computational capacity. These approaches can be found in the literature, for example, batching of daylighting simulation as executable Radiance files [109].

These developments, together with improved solutions for collecting, storing and managing data have made it possible to develop the previously discussed trends of data-driven design and model predictive control. Indeed, as the market of smart home sensors and the IoT (internet of things) grows, an unprecedented amount of data is recorded, with a remarkable level of granularity. This data covers indoor temperatures, daylighting level, relative humidity, CO_2 levels, – all of which are important indicators for comfort - as well as local weather data and sub-hourly energy use. This information can be exploited during operation to improve the performance of ABEs, both for real-time control but also for anticipated control like MPC. These approaches can use weather data or behavioral data collected with IoT devices can deliver tailored control sequences based on data analytics and machine learning. Effective implementation of MPC-based strategies for ABEs' optimal performance management will depend on a list of future development that spans from dedicated control-oriented modelling, algorithms for optimal control, and dedicated integration platforms (e.g. Ref. [110]).

Edge computing (local execution of computational tasks) can be an efficient solution to support co-simulation when combined with cloud computing, for example, to address real-time simulation targeting optimal control of ABEs. While computationally expensive optimization processes are impossible to run in real-time on controller embedded in ABEs, even if based on a simplified model representation of the ABEs, these are possible if executed in the cloud. In the long run, it is possible to imagine synergic management of ABEs where cloud computing supports identifying the optimal values for a series of performance requirements (for example in the form of heat gain, or fresh air supply). In contrast, edge computing takes care of translating such performance requirements into process variables and communicating them to different actuators in the envelope.

3. Conclusions

Advanced building envelopes (ABEs) are integrated envelope systems and technologies that ensure high-performance in multiple physical domains to efficiently balance competing aspects through advanced design, advanced material properties and components, and when appropriate, advanced control strategies. ABEs demand a holistic performance assessment in building performance simulation to capture the full extent of their benefits efficiently. This task often requires modelling details or physical phenomena that cannot efficiently be carried out in monolithic simulation software tools. Interdisciplinary approaches like co-simulation, which allows coupling different models that describe parts of the governing physical relationships in the system (e.g. thermal models, daylighting models, etc.), provide a valuable alternative.

In co-simulation, each sub-model describing the ABE is run in a separate simulation tool or unit and connected in a way that key information is exchanged during runtime to replicate the behavior of the whole system. This approach provides solid grounds for what-if analysis and robustness checks of systems as well as it supports the innovative, performance-driven design of envelope systems with non-trivial behaviors and controls. However, it is not a fool-proof process and still suffers from several barriers that relate to a lack of standardization and of widely available knowledge about how to implement it correctly. Conducting a successful co-simulation requires that users consider different elements before selecting the software that will be used. Adopting a fit-for-purpose approach will avoid overcomplicating tasks and models and improve the robustness of modelling strategies. This approach recommends selecting a tool based on the purpose of the simulation, the knowledge and skill level of the modeler, the structure and the characteristics of the information exchanged by the different simulation units, and the type of co-simulation which will be used to evaluate the performance of the whole system.

Ideally, a co-simulation scheme can become a multi-user and multi-scale modular dynamic workflow describing a building envelope, and that evolves as information becomes increasingly available in the project. This provides opportunities for the different stakeholders to exchange model data with a better understanding of design relationships and implications, without compromising the IP of the individual simulation tools. Co-simulation for predicting the behavior of ABEs is further supported by several recent trends and development in BPS tools. These range from the development of model libraries for simulation and equation-based modelling, the development of new generation computational tools for building and community energy systems, to the development of a standard interface for co-simulation. Additionally, co-simulation approaches for ABEs benefit from improved possibilities for batching simulation-runs to reduce computational overhead, the development of parametric design multi-interfaces to validated simulation tools, and the integration of optimization algorithms for single and multi-objective studies in whole building simulation tools. Finally, co-simulation for ABEs also benefits from other developments in ICT which are supporting methods based on data-driven design and can be used in coordination with parallel assessments based on model predictive control strategies thanks to advances in cloud computing, data storage, and data management.

While focusing our analysis on the specific, yet broad topic of simulation-based performance prediction of advanced building envelopes, many of the presented challenges, flaws, potentials, and possibilities are relevant for larger sets of other complex modelling and simulation tasks such as the simulation of building clusters and neighborhoods and interactions with thermal and electrical grids. The identified key-questions and the answers we provided in this paper can be used to drive both a more conscious implementation of co-simulation, as well as to stimulate research and development efforts that can enable a more robust and user-friendly implementation of multi-domain, integrated performance simulation.

Description of expertise of the authors on the topic

Ms. Ellika Taveres-Cachat is a doctoral candidate working with performance-based design of building facades based on parametric design, numerical optimization as well as integrated energy and daylighting building simulation.

Dr. Fabio Favoino is an assistant professor of building physics in the Technology Energy Building Environment research group at Politecnico di Torino. His research, teaching and professional activity focus on performance-based evaluation and optimization methods for high performance building envelope systems and materials, adaptive facades, and facade control strategies integrated with building systems.

Dr. Roel Loonen is an assistant professor of the Building Performance group at the Eindhoven University of Technology. His research and teaching focus on the development and application of modeling and simulation strategies to provide decision support for designing buildings that combine high indoor quality with low or no impact on the environment.

Dr. Francesco Goia is a professor of building physics at the Norwegian University of Science and Technology (NTNU). His research activity focuses primarily on ideation and assessment of strategies, materials and technologies for building integrated envelope systems characterized by dynamic behavior, distributed intelligence, and embedded solar energy exploitation devices.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The research presented in this work is the fruit of a collaboration between three research groups from three European Universities working with the topics of advanced building envelopes and co-simulation. The funding of the work was provided through individual national research grants as indicated here below:

•the "SkinTech" and in the "ReInVent Windows" projects funded by the Research Council of Norway and the industrial partners in the project under grants No. 255252 and No. 262198.

•Italian Ministry of Economic Development (MiSE) and Italian National Agency for New Technologies, Energy and Sustainable Economic Development (ENEA) for Italian project funding, which enabled to develop further the research and experience related to this work (Activity 18 -PTR_19_21_ENEA_PRG_4 2019–2022)

The authors would also like to gratefully acknowledge the COST Action TU1403 "Adaptive Facades Network" for providing excellent research networking and the foundation for this collaboration.

References

[1] P. Van Berkel, K. Kruit, F. Van de Poll, F. Rooijers, J. Vendrik, Zero Carbon Buildings 2050 - Background Report, 2020.
[2] D. D'Agostino, P. Zangheri, B. Cuniberti, D. Paci, P. Bertoldi, Synthesis report on the national plans for NZEBs, JRC Science Hub, https://doi.org/10.2790/659611, 2016.
[3] I. Davis, D. Carriero, O. Dzioubinski, S. Foster, S. Held, L. Jachia, A. Piwowarska, G. Roll, A. Vasilyev, I. Atamuradova, M. Banjac, A. Bäuml, R. Bernhardt, G. Prata Dias, L. De Francesco, A. Freyre, K. Gura, J. Hogeling, V. Jalalyan, A. Karapetyan, N. Laure, A. Leskoviku, R. Meyer, M.-M. Nahod, M. Kumar Patel, S. Robu, H. Schramm, A. Solujić, D. Yordanova, Mapping of Existing Energy Efficiency Standards and Technologies in Buildings in the UNECE Region, 2018, p. 130.
[4] E. Comission, Proposal for a Directive of the European Parliament and of the Council Amending Directive 2010/31/EU on the Energy Performance of Buildings, Brussels, Belgium, 2016.
[5] M. Perino (Ed.), IEA–ECBCS Annex 44, Integrating Environmentally Responsive Elements in Buildings, State of the Art Review, 2007.
[6] D.B. Crawley, J.W. Hand, M. Kummert, B.T. Griffith, Contrasting the capabilities of building energy performance simulation programs, Build. Environ. 43 (2008) 661–673, https://doi.org/10.1016/j.buildenv.2006.10.027.
[7] R.C.G.M. Loonen, F. Favoino, J.L.M. Hensen, M. Overend, Review of current status, requirements and opportunities for building performance simulation of adaptive facades, J. Build. Perform. Simul. 2 (2017) 205–223.
[8] J.M. Ayres, E. Stamper, Historical development of building energy calculations, Build. Eng. (1995) 841–849.
[9] A. Kirimtat, O. Krejcar, B. Ekici, M. Fatih Tasgetiren, Multi-objective energy and daylight optimization of amorphous shading devices in buildings, Sol. Energy 185 (2019) 100–111, https://doi.org/10.1016/j.solener.2019.04.048.
[10] S.M. Hosseini, M. Mohammadi, A. Rosemann, T. Schröder, J. Lichtenberg, A morphological approach for kinetic façade design process to improve visual and thermal comfort: Review, Build. Environ. 153 (2019) 186–204, https://doi.org/10.1016/j.buildenv.2019.02.040.
[11] A.H.A. Mahmoud, Y. Elghazi, Parametric-based designs for kinetic facades to optimize daylight performance: comparing rotation and translation kinetic motion for hexagonal facade patterns, Sol. Energy 126 (2016) 111–127, https://doi.org/10.1016/j.solener.2015.12.039.
[12] R.C.G.M. Loonen, S. Singaravel, M. Trčka, D. Cóstola, J.L.M. Hensen, Simulation-based support for product development of innovative building envelope components, Autom. ConStruct. 45 (2014) 86–95.
[13] H. Taleb, M.A. Musleh, Applying urban parametric design optimisation processes to a hot climate: case study of the UAE, Sustain. Cities Soc. 14 (2015) 236–253, https://doi.org/10.1016/j.scs.2014.09.001.
[14] C. Waibel, R. Evins, J. Carmeliet, Co-simulation and optimization of building geometry and multi-energy systems: interdependencies in energy supply, energy demand and solar potentials, Appl. Energy 242 (2019) 1661–1682, https://doi.org/10.1016/j.apenergy.2019.03.177.
[15] R.C.G.M. Loonen, M. Trčka, D. Cóstola, J.L.M. Hensen, Climate adaptive building shells: state-of-the-art and future challenges, Renew. Sustain. Energy Rev. 25 (2013) 483–493, https://doi.org/10.1016/j.rser.2013.04.016.
[16] E. Taveres-Cachat, S. Grynning, J. Thomsen, S. Selkowitz, Responsive building envelope concepts in zero emission neighborhoods and smart cities - a roadmap to implementation, Build. Environ. 149 (2019) 446–457, https://doi.org/10.1016/j.buildenv.2018.12.045.
[17] F. Favoino, R.C.G.M. Loonen, M. Doya, F. Goia, C. Bedon, F. Babich, Building Performance Simulation and Characterisation of Adaptive Facades – Adaptive Facade Network, 2018.
[18] C.M. Lai, S. Hokoi, Solar façades: a review, Build. Environ. 91 (2015) 152–165, https://doi.org/10.1016/j.buildenv.2015.01.007.
[19] A. Prieto, T. Klein, U. Knaack, T. Auer, Main perceived barriers for the development of building service integrated facades: results from an exploratory expert survey, J. Build. Eng. 13 (2017) 96–106, https://doi.org/10.1016/j.jobe.2017.07.008.
[20] F. Favoino, M. Overend, Q. Jin, The optimal thermo-optical properties and energy saving potential of adaptive glazing technologies, Appl. Energy 156 (2015) 1–15, https://doi.org/10.1016/j.apenergy.2015.05.065.
[21] C. Arkar, T. Žižak, S. Domjan, S. Medved, Dynamic parametric models for the holistic evaluation of semi-transparent photovoltaic/thermal façade with latent storage inserts, Appl. Energy 280 (2020), https://doi.org/10.1016/j.apenergy.2020.115994, 115994.
[22] F. Favoino, F. Goia, M. Perino, V. Serra, Experimental analysis of the energy performance of an ACTive, RESponsive and Solar (ACTRESS) façade module, Sol. Energy 133 (2016) 226–248, https://doi.org/10.1016/j.solener.2016.03.044.
[23] P. Bonato, M. D'Antoni, R. Fedrizzi, Modelling and simulation-based analysis of a façade-integrated decentralized ventilation unit, J. Build. Eng. 29 (2020), https://doi.org/10.1016/j.jobe.2020.101183, 101183.
[24] A. Tabadkani, M. Valinejad Shoubi, F. Soflaei, S. Banihashemi, Integrated parametric design of adaptive facades for user's visual comfort, Autom. ConStruct. 106 (2019), https://doi.org/10.1016/j.autcon.2019.102857, 102857.
[25] A. Tabadkani, A. Roetzel, H.X. Li, A. Tsangrassoulis, Design approaches and typologies of adaptive facades: a review, Autom. ConStruct. 121 (2021), https://doi.org/10.1016/j.autcon.2020.103450, 103450.
[26] A. Ghaffarianhoseini, A. Ghaffarianhoseini, U. Berardi, J. Tookey, D.H.W. Li, S. Kariminia, Exploring the advantages and challenges of double-skin façades (DSFs), Renew. Sustain. Energy Rev. 60 (2016) 1052–1065, https://doi.org/10.1016/j.rser.2016.01.130.
[27] B.P. Heiz, Z. Pan, G. Lautenschläger, C. Sirtl, M. Kraus, L. Wondraczek, Ultrathin fluidic laminates for large-area façade integration and smart windows, Adv. Sci. 4 (2017), 1600362.
[28] M. Casini, Active dynamic windows for buildings: a review, Renew. Energy 119 (2018) 923–934, https://doi.org/10.1016/j.renene.2017.12.049.
[29] L. Bianco, Y. Cascone, F. Goia, M. Perino, V. Serra, Responsive glazing systems: characterisation methods and winter performance, Sol. Energy 155 (2017) 372–387, https://doi.org/10.1016/j.solener.2017.06.029.
[30] P. Jayathissa, M. Luzzatto, J. Schmidli, J. Hofer, Z. Nagy, A. Schlueter, Optimising building net energy demand with dynamic BIPV shading, Appl. Energy 202 (2017) 726–735, https://doi.org/10.1016/j.apenergy.2017.05.083.
[31] A. Varela Souto, R. Loonen, Lumiduct. https://task56.iea-shc.org/product?ProductID=29, 2018. (Accessed 15 December 2020).
[32] D. Saelens, J. Carmeliet, H. Hens, Energy performance assessment of multiple-skin facades, HVAC R Res. 9 (2003) 167–185, https://doi.org/10.1080/10789669.2003.10391063.
[33] R. Baetens, B.P. Jelle, A. Gustavsen, Properties, requirements and possibilities of smart windows for dynamic daylight and solar energy control in buildings: a state-of-the-art review, Sol. Energy Mater. Sol. Cells 94 (2010) 87–105, https://doi.org/10.1016/j.solmat.2009.08.021.
[34] M.V. Nielsen, S. Svendsen, L.B. Jensen, Quantifying the potential of automated dynamic solar shading in office buildings through integrated simulations of energy and daylight, Sol. Energy 85 (2011) 757–768, https://doi.org/10.1016/j.solener.2011.01.010.
[35] S.M. Al-Masrani, K.M. Al-Obaidi, Dynamic shading systems: a review of design parameters, platforms and evaluation strategies, Autom. ConStruct. 102 (2019) 195–216, https://doi.org/10.1016/j.autcon.2019.01.014.
[36] M. Konstantoglou, A. Tsangrassoulis, Dynamic operation of daylighting and shading systems: a literature review, Renew. Sustain. Energy Rev. 60 (2016) 268–283, https://doi.org/10.1016/j.rser.2015.12.246.
[37] Y. Sun, Y. Wu, R. Wilson, A review of thermal and optical characterisation of complex window systems and their building performance prediction, Appl. Energy 222 (2018) 729–747, https://doi.org/10.1016/j.apenergy.2018.03.144.
[38] F. Kuznik, D. David, K. Johannes, J.-J. Roux, A review on phase change materials integrated in building walls, Renew. Sustain. Energy Rev. 15 (2011) 379–391, https://doi.org/10.1016/j.rser.2010.08.019.
[39] F. Favoino, Q. Jin, M. Overend, Design and control optimisation of adaptive insulation systems for office buildings. Part 1: adaptive technologies and simulation framework, Energy 127 (2017) 301–309, https://doi.org/10.1016/j.energy.2017.03.083.
[40] F. Favoino, F. Goia, M. Perino, V. Serra, Experimental assessment of the energy performance of an advanced responsive multifunctional façade module, Energy Build. 68 (2014) 647–659, https://doi.org/10.1016/j.enbuild.2013.08.066.
[41] R.C.G.M. Loonen, M.L. de Klijn-Chevalerias, J.L.M. Hensen, Opportunities and pitfalls of using building performance simulation in explorative R&D contexts, J. Build. Perform. Simul. 12 (2019) 272–288, https://doi.org/10.1080/19401493.2018.1561754.
[42] J.A. Clarke, J.L.M. Hensen, Integrated building performance simulation: progress, prospects and requirements, Build. Environ. 91 (2015) 294–306, https://doi.org/10.1016/j.buildenv.2015.04.002.
[43] R.C.G.M. Loonen, F. Favoino, J.L.M. Hensen, M. Overend, Review of current status, requirements and opportunities for building performance simulation of adaptive facades†, J. Build. Perform. Simul. 10 (2017) 205–223, https://doi.org/10.1080/19401493.2016.1152303.
[44] F. Goia, M. Perino, M. Haase, A numerical model to evaluate the thermal behaviour of PCM glazing system configurations, Energy Build. 54 (2012) 141–153, https://doi.org/10.1016/j.enbuild.2012.07.036.
[45] L. Giovannini, F. Favoino, A. Pellegrino, V.R.M. Lo Verso, V. Serra, M. Zinzi, Thermochromic glazing performance: from component experimental characterisation to whole building performance evaluation, Appl. Energy 251 (2019), https://doi.org/10.1016/j.apenergy.2019.113335, 113335.

[46] F. Favoino, F. Fiorito, A. Cannavale, G. Ranzi, M. Overend, Optimal control and performance of photovoltachromic switchable glazing for building integration in temperate climates, Appl. Energy 178 (2016) 943–961, https://doi.org/10.1016/j.apenergy.2016.06.107.
[47] C. Gehbauer, D.H. Blum, T. Wang, E.S. Lee, An assessment of the load modifying potential of model predictive controlled dynamic facades within the California context, Energy Build. 210 (2020), https://doi.org/10.1016/j.enbuild.2020.109762, 109762.
[48] H.B. Gunay, W. O'Brien, I. Beausoleil-Morrison, A critical review of observation studies, modeling, and simulation of adaptive occupant behaviors in offices, Build. Environ. 70 (2013) 31–47, https://doi.org/10.1016/j.buildenv.2013.07.020.
[49] A. Luna-Navarro, R. Loonen, M. Juaristi, A. Monge-Barrio, S. Attia, M. Overend, Occupant-Facade interaction: a review and classification scheme, Build. Environ. 177 (2020), https://doi.org/10.1016/j.buildenv.2020.106880, 106880.
[50] E. Taveres-Cachat, F. Goia, Co-simulation and validation of the performance of a highly flexible parametric model of an external shading system, Build. Environ. 182 (2020), https://doi.org/10.1016/j.buildenv.2020.107111.
[51] W. Tian, A review of sensitivity analysis methods in building energy analysis, Renew. Sustain. Energy Rev. 20 (2013) 411–419, https://doi.org/10.1016/j.rser.2012.12.014.
[52] C.J. Hopfe, J.L.M. Hensen, Uncertainty analysis in building performance simulation for design support, Energy Build. 43 (2011) 2798–2805, https://doi.org/10.1016/j.enbuild.2011.06.034.
[53] R. Evins, A review of computational optimisation methods applied to sustainable building design, Renew. Sustain. Energy Rev. 22 (2013) 230–245, https://doi.org/10.1016/j.rser.2013.02.004.
[54] C. Gomes, C. Thule, D. Broman, P.G. Larsen, H. Vangheluwe, Co-simulation: a survey, ACM comput, Far E. Surv. 51 (2018) 1–33, https://doi.org/10.1145/3179993.
[55] M. Trčka, Co-simulation for Performance Prediction of Innovative Integrated Mechanical Energy Systems in Buildings, 2008.
[56] M. Janák, Whole Building Energy Simulation with Complex External Shading Devices, in: Eighth Int. IBPSA Conf., Eindhoven, The Netherlands, 2003, pp. 571–576.
[57] J. Hensen, Modelling Coupled Heat and Airflow : Ping-Pong versus Onions, in: Proc. 16th Conf. Implement. Results Vent, Res., Coventry, UK, 1995.
[58] M. Janak, Coupling building energy and lighting simulation, Fifth Int. IBPSA Conf. Sept. 8 (– 10) (1997) 313–319.
[59] I. Beausoleil-Morrison, F. Macdonald, M. Kummert, T. McDowell, R. Jost, Co-simulation between ESP-r and TRNSYS, J. Build. Perform. Simul. 7 (2014) 133–151.
[60] M. Wetter, Co-simulation of building energy and control systems with the building controls virtual test bed, J. Build. Perform. Simul. 4 (2011) 185–203, https://doi.org/10.1080/19401493.2010.518631.
[61] V. Zavrel, Building Energy Modelling to Support the Commissioning of Holistic Data Centre Operation, Technische Universiteit Eindhoven, 2018.
[62] D. Le-Phuoc, H.Q. Nguyen-Mau, J.X. Parreira, M. Hauswirth, A middleware framework for scalable management of linked streams, J. Web Semant. 16 (2012) 42–51, https://doi.org/10.1016/j.websem.2012.06.003.
[63] M. Trčka, J.L.M. Hensen, M. Wetter, Co-simulation for performance prediction of integrated building and HVAC systems - an analysis of solution characteristics using a two-body system, Simulat. Model. Pract. Theor. 18 (2010) 957–970.
[64] J. Nembrini, S. Samberger, G. Labelle, Parametric scripting for early design performance simulation, Energy Build. 68 (2014) 786–798, https://doi.org/10.1016/j.enbuild.2013.09.044.
[65] C. Anastasiadi, A.I. Dounis, Co-simulation of fuzzy control in buildings and the HVAC system using BCVTB, Adv. Build. Energy Res. 12 (2018) 195–216, https://doi.org/10.1080/17512549.2017.1279077.
[66] T. Hong, H. Sun, Y. Chen, S.C. Taylor-Lange, D. Yan, An occupant behavior modeling tool for co-simulation, Energy Build. 117 (2016) 272–281, https://doi.org/10.1016/j.enbuild.2015.10.033.
[67] J. Arroyo, I. Cupeiro, D. Blum, K. Arendt, D. Kim, E.P. Oll, J. Oravec, M. Wetter, D.L. Vrabie, L. Helsen, Annual Reviews in Control All you need to know about model predictive control for buildings ' n Drgo n. https://doi.org/10.1016/j.arcontrol.2020.09.001, 2020.
[68] H. David, C. Gehbauer, D.H. Blum, T. Wang, E.S. Lee, Integrated dynamic facade control with an agent-based architecture for commercial buildings energy technologies area, Berkeley, California, USA, https://doi.org/10.20357/B7CP4S, 2020.
[69] R. De Coninck, L. Helsen, Practical implementation and evaluation of model predictive control for an office building in Brussels, Energy Build. 111 (2016) 290–298, https://doi.org/10.1016/j.enbuild.2015.11.014.
[70] M. Trčka, J.L.M. Hensen, M. Wetter, Co-simulation for performance prediction of integrated building and HVAC systems - an analysis of solution characteristics using a two-body system, Simulat. Model. Pract. Theor. 18 (2010) 957–970, https://doi.org/10.1016/j.simpat.2010.02.011.
[71] S. Robinson, Choosing the right model: conceptual modeling for simulation, Proc. 2011 Winter Simul. Conf. (2011) 1423–1435.
[72] I. Gaetani, P. Hoes, J. Hensen, L M, Occupant behavior in building energy simulation: towards a fit-for-purpose modeling strategy, Energy Build. 121 (2016) 188–204, https://doi.org/10.1016/j.enbuild.2016.03.038.
[73] C. Cavalliere, G. Habert, G. Raffaele, D. Osso, A. Hollberg, Continuous BIM-based assessment of embodied environmental impacts throughout the design process, J. Clean. Prod. 211 (2019) 941–952, https://doi.org/10.1016/j.jclepro.2018.11.247.
[74] J. Fitzgerald, P.G. Larsen, K. Pierce, Multi-modelling and Co-simulation in the engineering of cyber-physical systems: towards the digital twin, in: M.H. ter Beek, A. Fantechi, L. Semini (Eds.), From Softw. Eng. To Form. Methods Tools, Back Essays Dedic. to Stefania Gnes. Occas. Her 65th Birthd., 2019, pp. 40–55, https://doi.org/10.1007/978-3-030-30985-5_4. Springer International Publishing, Cham.
[75] A. Jain, D. Nong, T.X. Nghiem, R. Mangharam, Digital twins for efficient modeling and control of buildings an integrated solution with SCADA systems, Build. Perform. Model. Conf. SimBuild, Co-Organized by ASHRAE IBPSA-USA Chicago, IL, Sept. 26-28 (2018) 799–806.
[76] BuildingSMART, List of Software Compatible with IFC and BCF Formats, 2020.
[77] J.B. Kim, W. Jeong, M.J. Clayton, J.S. Haberl, W. Yan, Developing a physical BIM library for building thermal energy simulation, Autom. ConStruct. 50 (2015) 16–28, https://doi.org/10.1016/j.autcon.2014.10.011.
[78] M. Wetter, Modelica-based modelling and simulation to support research and development in building energy and control systems, J. Build. Perform. Simul. 2 (2009) 143–161, https://doi.org/10.1080/19401490902818259.
[79] W.S. Jeong, J.B. Kim, M.J. Clayton, J.S. Haberl, W. Yan, A framework to integrate object-oriented physical modelling with building information modelling for building thermal simulation, J. Build. Perform. Simul. 9 (2016) 50–69, https://doi.org/10.1080/19401493.2014.993709.
[80] M. Wetter, C. Van Treeck, New generation computational tools for building and community energy systems annex 60 final report. https://doi.org/10.4103/0973-1229.86137, 2017.
[81] G.B. Ozturk, Interoperability in building information modeling for AECO/FM industry, Autom. ConStruct. 113 (2020), https://doi.org/10.1016/j.autcon.2020.103122, 103122.
[82] Speckle, (n.d.).
[83] OpenFOAM, (n.d.).
[84] C. Curcija, S. Vidanovic, R. Hart, J. Jonsson, R. Powles, R. Mitchell, WINDOW Technical Documentation, Lawrence Berkeley National Laboratory, CA (USA), 2018.
[85] Lawrence Berkeley National Laboratory, THERM, (n.d.).
[86] D.B. Crawley, L.K. Lawrie, F.C. Winkelmann, W.F. Buhl, Y.J. Huang, C. O. Pedersen, R.K. Strand, R.J. Liesen, D.E. Fisher, M.J. Witte, J. Glazer, EnergyPlus: creating a new-generation building energy simulation program, Energy Build. 33 (2001) 319–331, https://doi.org/10.1016/S0378-7788(00)00114-6.
[87] M. Wetter, T.S. Nouidui, D. Lorenzetti, E.A. Lee, A. Roth, PROTOTYPING the NEXT GENERATION ENERGYPLUS SIMULATION ENGINE Lawrence Berkeley National Laboratory, CA University of California at Berkeley, Berkeley, 2015, pp. 403–410. Berkeley , CA US Department of Energy , Washington , DC, Build. Simul. Conf.
[88] Spawn of EnergyPlus, (n.d.).
[89] M. Wetter, M. Bonvini, T.S. Nouidui, Equation-based languages - a new paradigm for building energy modeling, simulation and optimization, Energy Build. 117 (2016) 290–300, https://doi.org/10.1016/j.enbuild.2015.10.017.
[90] M. Wetter, W. Zuo, T.S. Nouidui, X. Pang, Modelica buildings library, J. Build. Perform. Simul. 7 (2014) 253–270, https://doi.org/10.1080/19401493.2013.765506.
[91] OpenStudio, (n.d.).
[92] Building Control Virtual Test Bed, (n.d.).
[93] X. Pang, M. Wetter, P. Bhattacharya, P. Haves, A framework for simulation-based real-time whole building performance assessment, Build. Environ 54 (2012) 100–108, https://doi.org/10.1016/j.buildenv.2012.02.003.
[94] Dassault Systèmes, Dymola Systems Engineering, (n.d.).
[95] E. Shen, J. Hu, M. Patel, Energy and visual comfort analysis of lighting and daylight control strategies, Build. Environ. 78 (2014) 155–170, https://doi.org/10.1016/j.buildenv.2014.04.028.
[96] M. Mitterhofer, G.F. Schneider, S. Stratbücker, K. Sedlbauer, An FMI-enabled methodology for modular building performance simulation based on Semantic Web Technologies, Build. Environ. 125 (2017) 49–59, https://doi.org/10.1016/j.buildenv.2017.08.021.
[97] Modelica, (n.d.).
[98] FMI Standard, (n.d.).
[99] S. Attia, S. Bilir, T. Safy, C. Struck, R. Loonen, F. Goia, Current Trends and Future Challenges in the Performance Assessment of Adaptive Façade Systems, Energy Build, 2018, https://doi.org/10.1016/j.enbuild.2018.09.017.
[100] C. Kohler, P. Lyons, R.G. Hart, C.D. Curcija, A Comparison of the Latest Window Modeling Methods in EnergyPlus Lawrence Berkeley National Laboratory, United States of America Peter Lyons & Associates, Kaleen , Australia, Build. Simul, 2019, pp. 4902–4909.
[101] B. Bueno, M. Street, T. Pflug, C. Braesch, A co-simulation modelling approach for the assessment of a ventilated double-skin complex fenestration system coupled with a compact fan-coil unit, Energy Build. 151 (2017) 18–27, https://doi.org/10.1016/j.enbuild.2017.04.029.
[102] J.A. Clarke, J.W. Hand, N. Kelly, A. Malik, A. Samuel, P.A. Strachan, P.G. Tuohy, A data model for integrated building performance simulation, First Build. Simul. Optim. Conf. (2012) 340–347.
[103] M. Mitterhofer, G.F. Schneider, S. Stratbücker, S. Steiger, Semantics for assembling modular components in a scalable building performance simulation, J. Build. Perform. Simul. 12 (2019) 145–159, https://doi.org/10.1080/19401493.2018.1492020.
[104] C. Bleil de Souza, S. Tucker, Thermal simulation software outputs: a conceptual data model of information presentation for building design decision-making, J. Build. Perform. Simul. 9 (2016) 227–254, https://doi.org/10.1080/19401493.2015.1030450.

[105] A. Mahdavi, D. Wolosiuk, A Building Performance Indicator Ontology : Structure and Applications Ardeshir Mahdavi, Dawid Wolosiuk TU Wien, Vienna, 2019, pp. 77–82. Austria Ontological schema for building performance indicators.
[106] McNeel Robert, Associates, Rhinoceros Version 5.0, 2015.
[107] M. Sadeghipour Roudsari, M. Pak, Ladybug: a Parametric Environmental Plugin for Grasshopper to Help Designers Create an Environmentally-Conscious Design, in: 13th Conf. Int. Build. Simul. Assoc. IBPSA, IBPSA, Chambery, France, 2013.
[108] Food 4 Rhino, (n.d.).
[109] A. Wagdy, F. Fathy, A parametric approach for achieving optimum daylighting performance through solar screens in desert climates, J. Build. Eng. 3 (2015), https://doi.org/10.1016/j.jobe.2015.07.007.
[110] D. Blum, F. Jorissen, S. Huang, Y. Chen, J. Arroyo, K. Benne, Y. Li, V. Gavan, L. Rivalin, L. Helsen, D. Vrabie, M. Wetter, M. Sofos, Prototyping the BOPTEST Framework for Simulation-Based Testing of Advanced Control Strategies in Buildings, 2019.

A3 Paper III

A methodology to improve the performance of PV integrated shading devices using multi-objective optimization

E Taveres-Cachat, G Lobaccaro, F Goia, G Chaudhary

Applied Energy Volume 247, Pages 731-744, (2019)

Applied Energy 247 (2019) 731–744

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

A methodology to improve the performance of PV integrated shading devices using multi-objective optimization

Ellika Taveres-Cachat[a,b], Gabriele Lobaccaro[a], Francesco Goia[a,*], Gaurav Chaudhary[a]

[a] Department of Architecture and Technology, Faculty of Architecture and Design, Norwegian University of Science and Technology NTNU, Trondheim, Norway
[b] SINTEF Building and Infrastructure, Høgskoleringen 7b, 7491 Trondheim, Norway

HIGHLIGHTS

- A parametric design methodology for PV shading devices (PVSD) is presented.
- Multi-objective optimization is used to balance competing uses of solar energy through the PVSD.
- Total solar energy exploitation can be enhanced through an optimized PVSD system.

ARTICLE INFO

Keywords:
Building integrated photovoltaic shading device
Multi-objective optimization
Solar building envelope
Passive solar energy technologies
Daylighting
Parametric design

ABSTRACT

Solar energy can be exploited efficiently in building façades using building integrated photovoltaics (BIPV). This study presents a methodology to optimize the design of fixed, parametrically modelled PV integrated shading devices (PVSDs) based on multi-objective optimization (MOO) coupled with integrated thermal, electric, and lighting simulations. The goal of this work is to gain insight into the potential benefits of using optimization algorithms for PVSD design. This task is carried out by evaluating the extent to which competing solar energy uses can be balanced with regard to thermal, visual and electrical parameters; and investigating whether existing simulation tools successfully characterize the complexity associated with PVSDs.

The methodology developed is used to design and assess the performance of different optimized configurations of a fixed exterior louvre PVSD installed on the southern face of an office building in a Nordic climate. The parameters used for the optimization were the number of louvre-blades as well as their individual tilt angle and position along the vertical axis. This allowed the introduction of a higher degree of eclecticism through the optimization process compared to standard shading systems. The three objectives of the optimization were the total net energy demand, the energy converted by the PV material, and the daylighting level in the zone measured as the continuous daylight autonomy. The results highlighted that configurations with smaller louvres counts were preferable for the specific case study and that optimization increased the performance of the PVSD compared to a reference case. The results of the study also demonstrated that the application of the proposed methodology was able to improve the exploitation of solar energy through a multi-domain façade, and thereby that advanced simulation tools, in this case, allowed overcoming the limitations of more standardized façade configurations. Based on these findings, it is assumed that methodologies like the one developed in this article can be a starting point to stimulate successful discussion and foster fruitful collaboration between researchers, stakeholders, and façade manufacturers, resulting in the development of innovative technological solar integrated façade solutions.

1. Introduction

1.1. Context of the research activity

The European Union has pledged to cut CO_2 emissions associated with energy use in buildings by one fifth by 2020, a decision which has resulted in a set of policies to make all new buildings nearly net-zero energy and improve the performance of the existing building stock. In this push for a less carbon-intensive built environment, building integrated photovoltaics (BIPV) and building integrated photovoltaic/thermal (BIPVT) systems have emerged as one of the most relevant technological solutions to mitigate CO_2 emissions and support the use

* Corresponding author.
E-mail address: francesco.goia@ntnu.no (F. Goia).

https://doi.org/10.1016/j.apenergy.2019.04.033
Received 31 August 2018; Received in revised form 22 March 2019; Accepted 9 April 2019
Available online 02 May 2019

Applied Energy 247 (2019) 731–744

Nomenclature

cDA	continuous daylight autonomy [%]
E_C	annual cooling energy demand [kWh/m^2]
E_H	annual heating energy demand [kWh/m^2]
E_L	annual lighting energy demand [kWh/m^2]
E_{PV}	annual PV-converted energy [kWh/m^2]
E_{TOT}	annual net energy demand [kWh/m^2]

Acronyms

BIPV	building integrated photovoltaic
BIPV/T	building integrated photovoltaic/thermal
CIGS	copper indium gallium selenide
MOO	multi-objective optimization
PV	photovoltaic
PVSD	photovoltaic shading device

of renewable energy conversion in new and existing buildings [1–4]. In fact, the demand for photovoltaics (PV) conversion technologies is expected to grow in the coming years given that electricity consumption is globally surging [5], and in the EU 27 alone, BIPV systems are projected to provide over 20% of the energy needs by 2030 [6].

The first BIPV solutions emerged in the 1980s, but at the time, high costs and complex technical applications obstructed their market uptake [7]. It wasn't until the 1990s when increased monetary and research investments to support BIPV as a key application were made [8–10], that a renewed interest in the technology spurred rapid growth in the solar industry. Nowadays, the rising popularity of BIPV application can be attributed to their suitability for newly developed zero-energy and zero-carbon building design [11,12], as well as their ability to help reach benchmarks defined by building energy labels. Despite the progress made from a technology point of view, implementing BIPV/BIPVT in shading systems still remains non-trivial from a technical standpoint and often requires balancing different uses of solar energy (i.e. passive solar heating vs. solar gain leading to cooling load, daylighting vs. PV-conversion). There is, therefore, a need to establish robust methodologies to support the design and development of new BIPVT systems with optimized behaviors and increased cost efficiency.

1.2. Balancing competing roles of solar energy through building integrated PV

Building integrated photovoltaic and thermal applications such as Photovoltaic Shading Devices (PVSDs) combine the benefits of shading systems with renewable solar energy harvesting strategies since the light that is refrained from entering the space is converted to electricity (Fig. 1). These advanced fenestrations components make up a complex boundary between the outside- and the inside space of a building, the dynamics of which strongly affect the visual and thermal quality of the indoor environment and the energy converted by the system. For this reason, implementing PVSDs requires additional design considerations in order to find the correct balance between the competing roles of solar energy. For example, the transmission of large amounts of solar radiation through glazed elements has both benefits and drawbacks. Good daylighting increases productivity in workspaces by improving visual comfort [13] and solar gains contribute to lowering energy use for space heating and electric lighting. However, too much direct solar radiation can also lead to overheating and glare issues for the user [14–16]. But if too much solar radiation is blocked out, despite the fact that the photovoltaic material will convert more energy, the heating and artificial lighting demand will increase as a result and negate some of the original benefits. Therefore, modulating sunlight using PVSDs is a complex, yet essential measure to keep thermal and visual conditions pleasant, and is reported to be particularly useful in perimeter spaces of office buildings where direct sunlight is undesirable [17].

Existing studies have evaluated the potential of PVSDs and highlighted that when the systems are well-designed, they may be more advantageous than both traditional shading devices and unshaded windows in terms of energy use [18–21]. Optimal use of PVSDs has also shown to prevent overheating in summers while allowing the penetration of maximum daylight during winter, which translates into ideal high-quality indoor environments [22,23]. Previous research efforts aiming to find optimal balances of solar energy through PV integrated [24] and non-PV integrated shading devices have focused on specific topics such as visual comfort [14,25], energy use for space conditioning [26], artificial lighting loads [27], and energy conversion [28]. The findings have led to the consensus that the "optimal" shading system depends on a large number of variables related to the building's features (e.g. building category, efficiency of the building systems, efficiency of the building envelope, etc.) [29]; to its location (i.e. weather, solar angles, orientation, etc.) [30,31]; to the type of shading device [20]; and to the configuration of the shading device itself (i.e. size of blinds, blind angle control strategy, etc.) [32–36]. The complexity associated with designing optimal PVSDs and the large number of input parameters required to ensure high performance, are thus too numerous to use any kind of simplistic approach or "rule of thumb". Instead, a promising approach to PVSD design is to use advanced building simulation tools coupled with input-flexible methodologies to design systems with optimal performance.

1.3. Using advanced simulation tools with multi-objective optimization (MOO)

Accurate simulation of shading devices requires integrated energy simulation tools that can efficiently couple the thermal and optical domains of the models [37,38]. When some of the parameters in the models are variable, these simulation tools can be coupled with optimization approaches based on single- or multi-objective optimization

Fig. 1. A PVSD product from SOLARLAB at the BIPV demo site of the Danish Technological Institute in Høje-Taastrup (Denmark).

(MOO) [39–41], which is particularly useful to balance competing design parameters in high-performance buildings (e.g. low energy buildings) [42]. Of these two methods, single objective optimization is more frequently used because of its simplicity, but most real-life design challenges involve several design criteria or antagonistic goals which makes MOO a more valuable approach to managing tradeoffs [43,44].

Conventional louvre blade shading system geometries (i.e. symmetrically built, homogenous tilt angles) are not usually originally fully optimized to balance uses of solar energy and instead offer a "one size fits all" solution. This makes MOO a potentially interesting method to explore the extent to which PVSD performance could be improved by changing some of the parameters of the system such as the shape, orientation, or inclination angle of the louvres (e.g. [39,45–47]); while at the same time limit performance degradation due to environmental causes such as self-shading [48,49]. The advantage of using an optimization algorithm versus, for example, conducting a parametric analysis, is that it allows investigating a larger space of solutions.

1.4. Aims and innovative aspects of the paper

This study aims at developing a design methodology based on MOO with a twofold goal: first, to evaluate the extent to which several it is possible to balance competing uses of solar energy in PVSDs; second, to investigate whether existing simulation tools coupled with MOO are able to address the complexity associated with designing and modelling systems for optimal use of solar energy.

The methodology developed is novel in that it introduces the possibility to design PVSDs and by extension BIPV systems by exploring a larger space of design solutions with a bottom-up approach where the environmental context and the goal of the system define its geometry. This process leads to out-of-the box solutions to complex design problems that require meeting multiple challenges simultaneously (i.e. balance competing uses of solar energy, responding to facade control strategies, energy performance targets, material emission thresholds, etc.). The focus of the study will then not be on the specific final solutions yielded by the optimization, but the process itself as a mean of improving design methods and gaining insight on possibilities for balancing solar parameters. In the larger scheme of things, the ambition of the proposed approach is to have enough impact to create a starting point for stimulating successful discussion and fostering fruitful collaboration between researchers, stakeholders, and façade manufacturers, resulting in the development of innovative, technological solar integrated façade solutions.

This remainder of this work is organized as follows: Section 2 presents the proposed design methodology developed to generate and assess optimal configurations, including the overall research strategy, the case study used to demonstrate the methodology, and the assumptions made for the different parameters. This section also provides a detailed overview of the process of the optimization and the different simulation and modelling tools used, in addition to presenting the method used to determine the reference cases used in the analysis. The results and discussion of the application of the methodology to the case study are presented in Section 3 and a critical assessment of the study is presented in Section 4. Finally, Section 5 summarizes the conclusions and implications of this study for future work.

2. Methods and materials

2.1. Overall research strategy

This work is part of a wider research initiative about PVSD applications lead by the authors. The initial study available in Ref. [50] focused on design solutions defined by a simple preliminary parametric analysis of a similar PVSD's impact on the heating and cooling demand of a building. The methodology presented in this paper is a step up from the existing work in that it uses MOO and a fully parametric PVSD model to evaluate both daylighting and energy-related parameters while being flexible enough to accommodate any shading device design for commercial or residential projects.

The overall research goal is to develop a methodology that aspires to overcome the difficulty of balancing solar energy in building envelopes, and in particular for PVSDs, as discussed in Section 1.2. The idea is to break away from the limitations of the more traditional designs with symmetrical features, and attempt to balance competing uses for solar energy in PVSDs by letting the system adopt any of the resulting configurations created from the combination of parametrically defined geometrical inputs.

2.2. Description of the case study

The reference building and the blades system were modelled in the *Rhinoceros* environment [51] using *Grasshopper* [52], a visual programming language for parametric modelling; while *Ladybug* [53], a *Radiance*-based plug-in for *Grasshopper*, was used to conduct grid-based solar irradiation and daylighting analyses. The energy calculations are provided by *Honeybee* [53] which use the *EnergyPlus* engine [54]. EnergyPlus is a whole building energy simulation program based on the best features and capabilities of BLAST and DOE-2.1, developed under the auspices of the US Department of Energy and is widely used both in research and industry.

The geometry of the reference building is given by the Bestest Case 600, which is a 48 m^2 rectangular room (6 m × 8 m × 2.7 m) with two large south facing windows (3 m × 2 m). The PVSD system is based on the design of an existing non-PV integrated shading system with 105 mm wide louvres that can be tilted between 0 and 45° in 15° increments. In the model, both windows are equipped with the PVSD system, with a center blade to windowpane distance of 16 cm. All of the parameters in the model can be controlled parametrically to accommodate any change in the building geometry, building loads and schedules or in the PVSD configuration.

The simulations for this study were run over the period of one year with climate data for the location of Oslo, Norway (*EnergyPlus* weather file (.epw), Typical Meteorological Year – TMY). Table 1 shows the mean monthly dry bulb temperatures, heating degree days for a set point temperature of 21 °C, and the average monthly global solar radiation for the selected location.

The internal loads and schedules were set according to the Norwegian Standards NS 3031:2016 and NS3701:2012 using the standardized values for the office-building category. A proportional response artificial lighting control strategy was also implemented to ensure a minimum illuminance level of 500 lx on the work plane at a height of 80 cm above ground. The properties of the building envelope and the technical systems are listed in Table 2.

Table 1
Average monthly weather data extracted from the .epw file for Oslo, Norway.

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Average dry bulb temperature	−3.8	−0.9	0.9	4.6	11.9	14.7	17.5	16.5	11.1	6.7	1.8	−1.6
Average monthly global radiation (W/m^2)	12	31	77	77	202	207	208	155	92	46	15	6
Heating degree days	676	594	530	416	194	112	44	59	216	351	498	608

Table 2
Thermal properties of the building model and building equipment.

Component	Value	Unit	Note
U-value external wall	0.18	W/(m² K)	Under the maximum value from NS3031
U-value roof	0.10	W/(m² K)	Slightly above the recommended value from NS3701
U-value external floor	0.10	W/(m² K)	Slightly above the recommended value from NS3701
U-value window (3 panes)	0.8	W/(m² K)	Maximum value according to NS3701
g Value	0.54	–	N/A
Air tightness	0.6	h − 1	Maximum value according to NS3701
HVAC system	Ideal air load	–	Honeybee setting with no air economizer
Internal load lighting	9.6	W/m²	During occupation hours, dimming function to maintain 500 lx on work plane at 0.8 m from floor
Maximum Internal load occupants	382	W	Variable according to schedules defined in NS3031
Maximum internal load equipment	21	W/m²	Variable according to schedules defined in NS3031
COP heating system	3	–	Heat pump
COP cooling system	5	–	Heat pump
Set points (heating-cooling)	21–26	°C	Set back to 19° for heating outside occupation hours
Occupation hours	7–18	–	Weekdays

Custom *Radiance* materials were defined in a Radiance library for Honeybee to take into account the optical properties of the room's surfaces and characteristics of the shading system (Table 3). The values were set to be conservative and in compliance with the recommendations from the Illuminating Engineering Society found in standard IES-LM-83. The window used in the simulation is a triple pane window with a low-E coating (total U-value = 0.8 W/m^{2}K), with a 16 mm gap and 90% Argon gas. The light-transmission was defined as 60% (65% transmissivity) and the reflectance as 21%, following calculation from NS-EN 410:2011. A moderate assumption of 65% solar reflection was made for the frame of the shading device and for all the non-PV-coated surfaces of the louvre blades. The PV material used, CIGS (copper indium gallium selenide), was assumed to have a reflection of 10%.

2.3. Description of the numerical model's objectives and settings

The proposed methodology was built around integrated whole building energy (*EnergyPlus* based plug-ins *Honeybee* [53]), and daylight simulations (Ladybug is Radiance based). Fig. 2 provides an overview of the complexity of the workflow developed and the three main sections of the model script: Part I) Inputs parameters, climatic reference, occupancy schedules, energy loads, geometry data of the buildings and louvres, Part II) Performance simulation in which energy and daylight simulations are conducted, and Part III) Optimization process using MOO.

In this study, the input parameters that the optimization algorithm can modify are the individual tilt angle and the vertical distribution of the louvre-blades (Table 4). The way the model is scripted, the blades can freely distribute along the vertical axis z with the only constraint being that the interspace between the blades must be of at least 5 cm to avoid the geometry of the blades overlapping. Naturally, as the number of louvre blades increases, this constraint reduces the number of possible configurations by diminishing the interval of possible z coordinate values each blade can adopt.

The three objectives set in the optimization were to minimize the total annual net energy electricity use (E_{TOT} [kWh/m^2 year), maximize the amount of energy converted into electricity by the PV cells (E_{PV} [kWh/m^2 year), and maximize the daylighting level in the zone measured as the continuous daylight autonomy (cDA [%]). The annual total net energy use (E_{TOT} [kWh/m^2 year]) is the sum of the electrical energy use for heating (E_H [kWh/m^2] year), cooling (E_C [kWh/m^{2}year]), and artificial lighting (E_L [kWh/m^2]) discounted for the energy converted by the PV cells (E_{PV} [kWh/m^{2}year]). The PV output was chosen as an objective despite its influence being partially accounted for in the calculation of the net energy demand. This choice was motivated by the wish to support maximizing the return on investment associated with using PV material and because of the high environmental footprint of PV material [55,56]. To account for self-shading of the PVSD from blade to blade, the energy converted by the PV material is determined using a detailed radiation analysis of the light impinging on each blade. Solar radiation is converted to electricity assuming that 95% of the blades area is covered with PV material, and 95% of this defined area is a photovoltaic cell. The PV conversion rate is set to 15% accounting for all the system losses. The metric used for daylight, the continuous daylight autonomy (or cDA) calculates the number of working hours a year a specific surface in a room receives an amount of light over a given threshold [14]. Hours with illuminance values above the set limit receive full percentage points, while hours with daylighting levels below the threshold are awarded a proportional fraction of a percentage point. The cDA was chosen as the daylight measuring metric as opposed to the daylight autonomy because of its suitability for office buildings with regard to larger ranges of user-preferred illuminances, and the possibility for a softer transition between compliance and non-compliance situations [57].

For this case study, the threshold was set to a minimum of 500 lx received on a work plane modelled as a point located 0.8 m above the floor level and 2 m inwards on the center line one of the windows. The settings used for the *Radiance* daylighting analysis are given in Table 5. The main contributor to simulation time (apart from complex geometry) is the number of ambient bounces (ab) which is a numerical parameter representing the maximum number of diffuse bounces a ray of light will go through before being considered fully dissipated.

The value of the ab parameters for the daylighting analysis was selected after conducting a sensitivity analysis of its impact on the cDA and simulation runtime. The results of this analysis (Table 6) demonstrated that the differences in the calculated cDA were marginal (at most 2% of the value) when the number of ambient bounces varied from 3 to 6 bounces and the quality was kept constant. The additional computational time required for the daylight analysis, on the other hand, was significant and judged unacceptable for a preliminary analysis when the quality setting was set to a higher value. Given the scope of this methodology, it was deemed acceptable to use a slightly simplified and conservative daylighting calculation with a number of ambient bounces set to 3 and the "low quality" *Radiance* setting in *Grasshopper* to reduce computational time. Note that for this study

Table 3
Optical properties of the surfaces used in the case study.

Material name	Material type	RGB reflectance	Transmissivity
Generic Ceiling_70	Plastic, opaque	0.7, 0.7, 0.7	–
Generic Floor_20	Plastic, opaque	0.2, 0.2, 0.2	–
Generic IntWall_50	Plastic, opaque	0.5, 0.5, 0.5	–
Generic Furniture_50	Plastic, opaque	0.5, 0.5, 0.5	–
Triple Pane Argon90	Glass, transparent	–	0.65, 0.65, 0.65
Aluminium_65	Opaque	0.65, 0.65,0.65	–
CIGS_10	Opaque	0.1, 0.1, 0.1	–

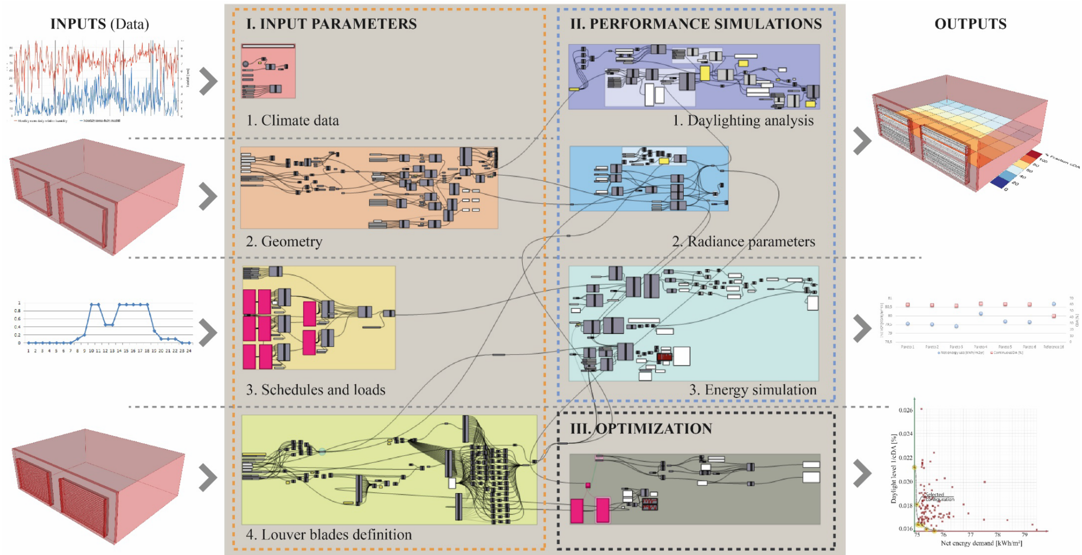


Fig. 2. Visualization of the workflow developed in the Grasshopper environment.

relied on a workstation with 11 CPU allocated to the daylight simulation. The computer used has 24 GB RAM and a 3.46 GHz processor. On average, each complete run of optimization as described in the next section took 10 days to run with the listed settings.

2.4. Description of the optimization process

The optimization process was carried out using the genetic MOO algorithm Octopus and the logic flow given in Fig. 3. Genetic algorithms use principles similar to those displayed in evolutionary processes in Nature to find one or a set of good solutions to a problem according to given objectives. In order to do that, the problem must be modelled in a parametric manner where a number of variable inputs (i.e. in this work the tilt angles of the louvre blades and their disposition along the z-axis) are used to generate changes in the measured outputs of the model (i.e. E_{TOT}, E_{PV}, cDA). The outputs are evaluated by the algorithm according to a fitness function that allows quantifying the performance of a set of solutions

The basic procedure a genetic algorithm follows is to start by building a random initial population of solutions and to assess the fitness of that population. Then, a loop starts where each iteration represents what is called a generation. The loop consists in selecting the best-fit individuals from the population to use for reproduction, then breeding new individuals followed by evaluating the fitness of the new offspring and finally, replacing part of the population with the fittest offspring. To ensure that the genetic algorithm is assessing a large enough space of solutions (possibilities) and is able to discover new alternatives, the breeding of new individuals is based on *genetic operators* such as crossover- and mutation rates, as well as a crossover- and mutation *probability*. This loop could in theory run endlessly unless a defined end criterion is reached. For this study, the end criterion was

Table 5
Radiance setting for the daylighting simulation.

Ambient bounces	Ambient divisions	Ambient sampling	Ambient accuracy	Ambient resolution
3	1000	100	0.1	300

Table 6
Sensitivity analysis of the number of ambient bounces and quality setting for the Radiance daylighting analysis for a set configuration with 16 louvre blades.

Number of ambient bounces	Low-quality setting cDA [%]	Medium quality setting cDA [%]
3	50	50
4	51	52
5	51	53
6	51	53

chosen to be 18 generations with 100 individuals each. More information about genetic algorithms can be found in Refs. [58,59].

The number of solutions generated is chosen as a compromise between computational time and having a meaningful number of cases for the algorithm to be able to find Pareto-optimal solutions. These solutions form what is called the Pareto front when plotted- which in our case is a 3-dimensional plot. All the points on the Pareto front represent non-dominated solutions meaning that they embody the best compromise (tradeoff) of performance with regard to competing objectives. All the other points generated in the optimization process are called dominated solutions as there is always at least one other solution that outperforms them.

Table 4
Description of the parameters for the optimization process.

Variable	Range of values	Unit
Angle of louvre blades	0; 15; 30; 45	Degrees from a horizontal plane
Z coordinate of the center point of each individual blade	[0.20; 1.20]	Meters

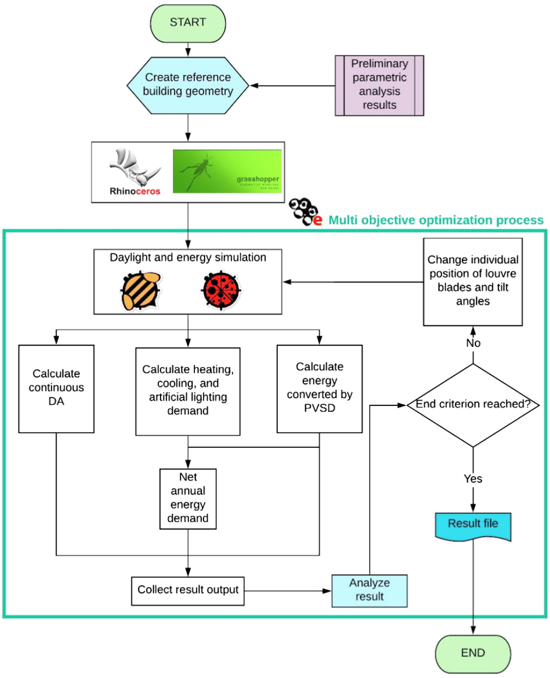


Fig. 3. Flowchart summary of the design methodology.

2.5. Reference cases for MOO performance verification

While MOO is a tool often used to evaluate how different parameters can be tuned to improve the overall performance of a system, the results of the optimization must be put in context using a reference configuration in order to be able to quantify the improvement the optimization brings about. For this study, the preliminary groundwork was done using a parametric analysis which allowed characterizing the performance of more standard PVSD configurations (i.e. with equally spaced- and homogenously tilted blades). The study was done in the same software environments with the same assumptions as described previously, only without the optimization process.

3. Results and discussion

3.1. Selection of reference cases

The results from the parametric analysis are presented below in Fig. 4. The procedure followed for this preliminary analysis resembles the logic described for the MOO study, but the system is constrained to having homogenously tilted louvre-blades with even spacing. This means that the number of configurations is limited by the possible tilt angles of the blades and the number of case studies investigated. For this study, four cases with four tilt angles and one configuration with no shading system present were investigated, which resulted in 17 configurations in total. The goal of this procedure was to obtain a picture of the performance of possible reference cases that could serve as a point of comparison for the results of the optimization.

The results of the preliminary parametric analysis (Fig. 4) were in line with the anticipated effect of the shading system: the cooling load was reduced significantly (up to 60%) while the heating and artificial lighting loads increased compared to a case with an unshaded window. Interestingly, even as a non-optimized design, implementing the PVSD system reduced the total net energy use by 1/3 thanks to the conversion of solar energy. The results also outlined a trend in some cases where increasing tilt angles provided smaller solar gains, which as mentioned previously reduced the cooling demand in the zone, but only up until a certain point where the artificial lighting demand became so large as a result of the loss of daylight, that it created excess heat and required

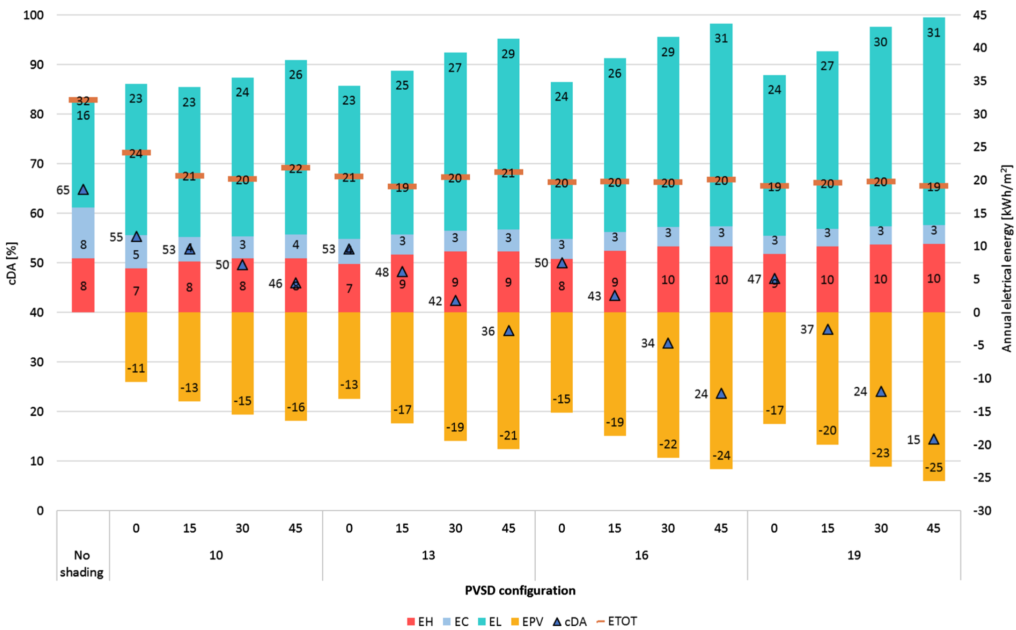


Fig. 4. Results of the preliminary parametric analysis of the PVSD. The best performing configuration for each case is selected and later used as a benchmark to evaluate the performance of the optimization results.

additional cooling. The existence of this trend highlights what appears to be a "sweet spot" in which the parameters were balanced in a way that the total net energy use was minimized before it increased again. This finding supported the idea that optimization could be useful to exploit this "sweet spot" further.

Based on the results of the parametric analysis, it was chosen to use a reference configuration with a tilt angle of 15° for the configurations with 10 and 13 louvre blades, and 0° for configurations with 16 and 19 louvres. For 10 and 13 louvres, this choice is based on the fact that an angle of 15° provides more energy conversion than a 0° tilt angle, smaller values of net energy use and only reduces daylighting levels by a small amount. For the cases with 16 and 19 louvres, a 0° tilt angle provides significantly more daylight and a very similar value for the net energy use as a 15° tilt angle despite the PV conversion being less meaningful.

3.2. Results of the multi-objective optimization

3.2.1. Global results of the optimization

The 2D Pareto fronts for each combination of 2 objectives are shown in Figs. 5–7. While the Pareto front was clearly defined for the tradeoff between the cDA value and the PV conversion (Fig. 5) and for the cDA vs net energy use (Fig. 6), there is no clear relationship for the tradeoffs between energy use and PV conversion (Fig. 7). This finding supported the idea that the optimization problem is non-trivial and the relationship between the objectives is complex. An important observation from these plots is that for each case study (10, 13, 16 and 19 louvres) there are Pareto points from the optimizations that performed better than the references with regard to at least two objectives simultaneously. This indicates that the optimization was consistently able to improve the performance of the systems and validates the assumption behind the study, which is that optimization can be used to improve the design of PVSDs. However, it is also worth noting that some of the results from the parametric analysis, and thus the references used, are very close to the Pareto points meaning that there is little room for improvement especially with regard to daylight levels. The implications of this observation are discussed later in this section.

For the rest of this section, the references from Section 3.1 were used as a benchmark to evaluate the performance of five selected Pareto points for each case study. The Pareto points used from here on in the analysis were picked as according to two criteria: (i) solutions that best balanced the cDA value and the net energy use (ii) solutions within that first selection with highest energy conversion including solutions that improved all three objectives when they existed.

3.2.2. Case specific results

In this section, 5 Pareto points in each case study were chosen to be investigated more in depth and selected on the basis of prioritizing the cDA and the net energy use. This choice followed the reasoning that these parameters represent direct costs and user comfort variables, whereas the PV conversion is seen as secondary in addition to being partially accounted for in the net energy use. Fig. 8 shows the performance in terms of daylight availability and energy use for the five Pareto points from each case study along with the reference used for comparison. From this graph, one can identify early on the range of the effect the optimization had on different cases. For example, for a case with 10 or 13 louvres, both daylight and total energy demand parameters were possible to improve. However, for a case with 16 or 19 louvres, only one of the two objectives was possible to improve with the given number of generations in the optimization. Note that in this section, all of the percentages described are relative changes in the value of the parameters.

The performance of each Pareto point was then analyzed in more detail to understand how the optimization changed the balance of the different parameters measured. These results are presented in Figs. 9–12. The analysis of the optimization for the 10 louvres case showed that the algorithm was able to create PVSD configurations that could outperform the reference case with regard to all three objectives simultaneously while maintaining cDA values above 50%. The cDA was, however, only possible to improve by 3% while E_{TOT} could be reduced by almost 6% and E_{PV} could be improved by up to 10%. This last finding is interesting given that this value was achieved for configurations that were not predominantly selected to perform well with regard to PV conversion alone, yet still provided a significant improvement compared to the reference. Overall, the cDA was the parameter with the least potential for improvement, this is likely because the values were relatively high and possibly close to the upper threshold of what can be achieved in a Nordic climate.

In the case of a PVSD with 13 louvres, the simultaneous improvement for all three objectives was also possible, but only for one of the Pareto points (Pareto point 5). The four other Pareto points are only able to improve two of the three objectives at a time. Because of the point selection being focused on daylighting levels and net energy use, the Pareto points shown in the analysis are solutions that mainly improved these objectives, and this was done at the expense of a reduced E_{PV} value compared to the reference. Despite the fact that only one solution could improve the performance on all fronts, the results show the optimization of the 13 louvres configuration provided the most potential for increasing the cDA compared to the reference configuration. Pareto point 1–4 all improved the cDA, with Pareto point 2 achieving a 7% increase in the cDA. In terms of E_{TOT}, the case with 13 louvres only showed moderate possibilities to reduce net energy use through the optimization, the maximum reduction being 3% in Pareto point 5. Other Pareto points, which were not selected for this analysis, showed cDA levels similar to the 13 louvres 0° tilt case but performed no better in comparison to the latter in terms of E_{TOT} despite showing increased E_{PV} values.

For the 16 louvres case, there were no optimized configurations that could improve all three parameters simultaneously and no configuration with a cDA above 50% and improved the reference case. This was assumed to be in part because the reference case used was already high performing in terms of the daylighting level in the zone. However, the performance of both the net energy use and the energy converted by the PV were possible to improve through the optimization. The optimization of the 16 louvres cases was the study that yielded the most potential for reducing the net energy use compared to the reference and the highest increase in PV conversion. Pareto points 1–3 all maintained a cDA at 49% while reducing energy use by up to nearly 7% and increased the amount of energy converted by PV by almost 20% for Pareto point 3. Pareto point 1 represented the solutions that showed the smallest relative loss in daylight (−1.8%) in comparison to the reference, while still reducing the net energy use by almost 3% and increasing the amount of energy converted by the PV by more than 14%.

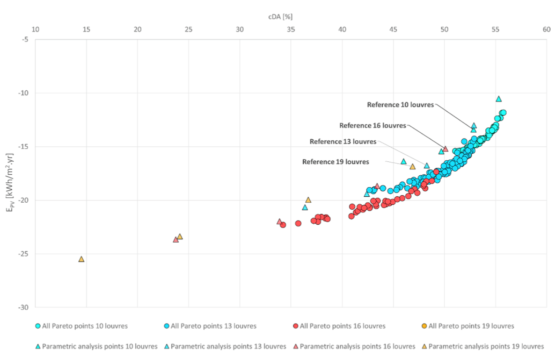


Fig. 5. Visualization of the Pareto points from the optimization study with regard to PV conversion and cDA.

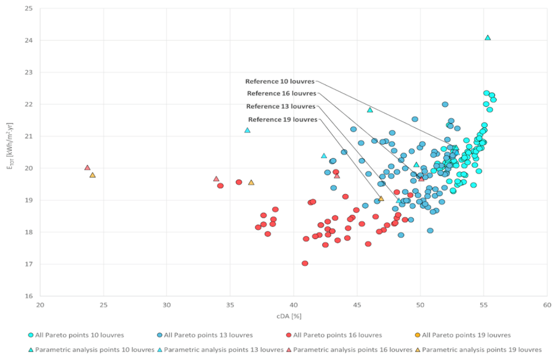


Fig. 6. Visualization of the Pareto points from the optimization study with regard to energy use and the cDA.

Fig. 7. Visualization of the Pareto points from the optimization study with regard to energy use and PV conversion.

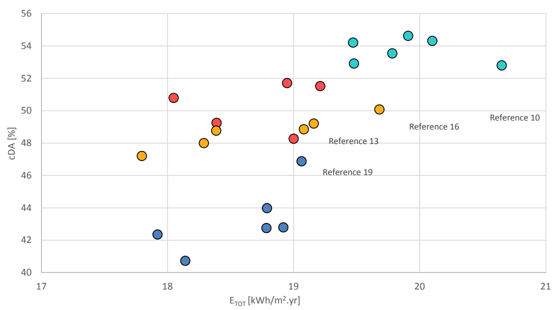


Fig. 8. Visualization of the performance of the selected Pareto points for each case study in terms of cDA and net energy use compared to the references determined in the parametric analysis.

Pareto points 4 and 5 provided the largest reductions in net energy use (7–10% relative reduction) which goes in hand with the fact that they also had the largest increase in PV conversion (relatively 22–23% more energy converted) but the lowest cDA values (48% and 47%). Finally, it is interesting to note that there was very little difference in the net energy use between 13 and 16 louvres, which seems to indicate that 13 louvres was a better option as since it provided better cDA with fewer louvres and the same E_{TOT}.

For the case with 19 louvres, it was not possible to improve the cDA through optimization compared to the reference with a 0° tilt angle, and the smallest loss in cDA (6%) was found for Pareto point 5. The variation in E_{TOT} was limited with at most a 6% reduction in net energy use (Pareto point 1). Naturally, the E_{PV} was the parameter, which had the highest potential for improvement and could be increased up to 23% for Pareto point 1. These results were in line with what could be expected of a system with a high number of louvres blades when compared to a reference that prioritized daylighting over energy conversion. A large number of blades provides a higher amount of area with PV material and thus, higher ratios of energy converted. However, the high density of the blades also reduced the daylighting levels drastically, especially when tilted as they obstruct the windows to a large extent. Furthermore, due to the non-overlapping condition, the range of movement of the blades was highly constrained and reduced the possibility to space out the blades even more in key sections of the window. Globally, the detailed energy profile shows that the use of energy was similar for all of the Pareto points, the main difference compared to the reference case being an increased E_L compensated for with a higher E_{PV}.

For all of the Pareto configurations, the analysis of the cDA grid showed that daylighting levels were very similar to the reference cases, with only slight improvements for all of the cases, especially towards the back of the room (Figs. 13–16). In terms of the distribution of the louvre blades, the optimized configurations showed a common trend where the louvres were more spaced in the upper half of the window than in the lower half. The blade angles also tended to gradually increase towards 45° in the lower half of the window, and in particular for the louvres below the plan of the daylighting grid (located 80 cm above the floor level). This maximized conversion in the area where the louvres had the least impact on daylight penetration. On the other hand, as can be seen by the different sun angles, from a visual comfort point of view, these optimized cases may present risks of glare during the winter if no additional protection is provided to users and depending on the layout of the furniture in the room.

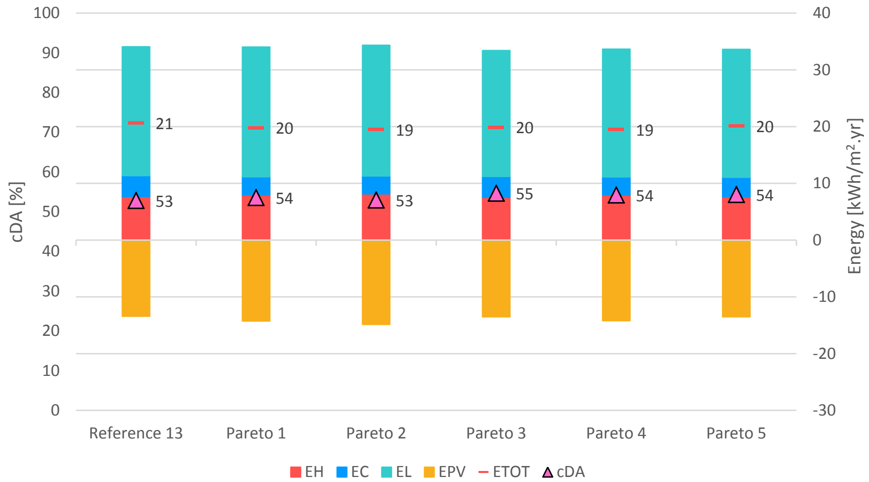
A side-by-side rendering of a configuration with 10 louvres is shown in Fig. 17 as a way to observe the impact of the shading system on the view of the outdoors. Based on this rendering, it is expected that a configuration with few louvres does not significantly obstruct the view, even in its Pareto optimized form. This is because the louvres with the highest angle (and therefore which obstruct the view the most) are mostly located below seated eye level, and still allow a partial view of the outdoors. This rendering provides a promising preliminary response to concerns of user acceptance and esthetics of an optimized fixed PVSD, although these should be evaluated more in depth.

4. Critical assessment of the methodology

4.1. Limitation of the model

The results of the study support the assumption that it is possible to improve the performance of PVSDs by using optimization. The methodology developed in this study is subject to the same issues most optimization problems have, that is the necessity to include enough parameter flexibility to make sure an optimum is not disregarded but without over or under constraining the problem. For this study, the desire to include daylight simulations in the optimization provided a limitation in terms of speed of the process. The algorithms used in *Radiance* require large amounts of computational power, thus if the optimization runtimes are too long, the methodology will be unattractive to a consultant or an architect. It is therefore important to find a certain equilibrium between the accuracy and effort required. When this is reached, the optimization can provide a different set of solutions and may improve the overall performance of the building with possibly only small additional costs. For this study, the simulation took an average of 10 days to run but this time could be decreased substantially if cloud computing was used for example.

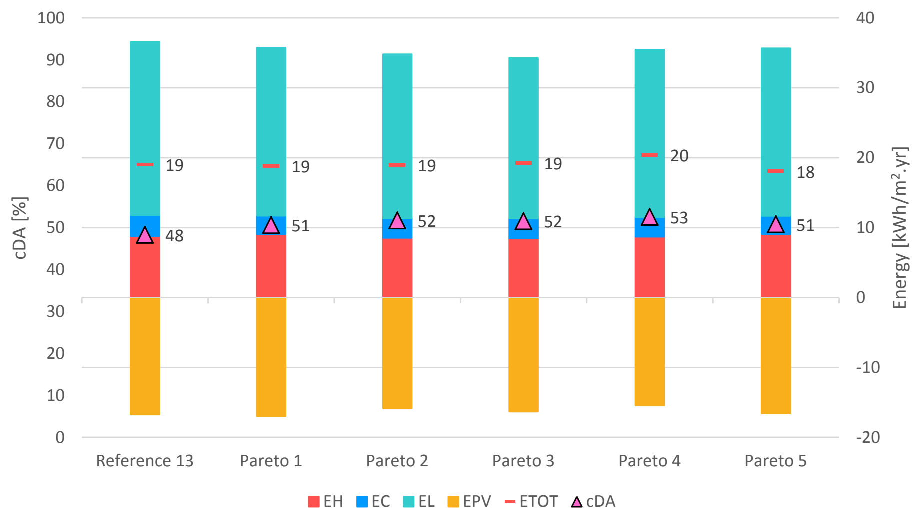
Overall the results of the optimization only provided a small increase in performance. This is suspected to be due to a combination of



	Pareto 1	Pareto 2	Pareto 3	Pareto 4	Pareto 5
Improvement cDA	1.4 %	0.2 %	3.5 %	2.7 %	2.9 %
Improvement E_{TOT}	4.2 %	5.7 %	3.6 %	5.7 %	2.7 %
Improvement E_{PV}	6.3 %	10.8 %	0.8 %	5.9 %	0.9 %

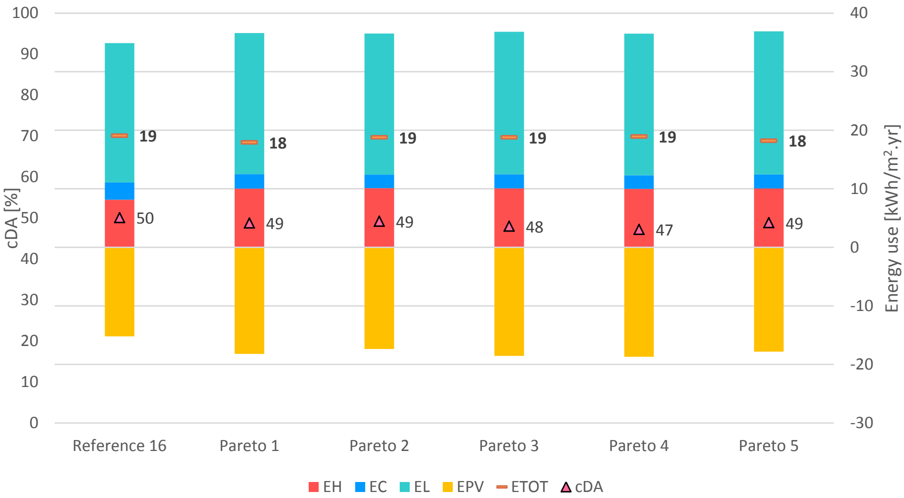
Fig. 9. Performance of the 5 selected Pareto points for the 10 louvres case with a comparison to the reference configuration in terms of cDA and E_{TOT}.

the following points. First, the limitations inherent to the model to avoid configurations with overlapping louvres (i.e. non-physically possible configurations) reduce the possibility to fully optimize the system. Second, if the objectives had been weighted with a hierarchy of importance, the range of improvement could be very different and one could potentially improve the performance of the PVSD with regard to one dominating parameter. In this case study, the optimized solutions chosen from the Pareto front were picked with the equal priority of improving both the daylight levels in the room and the total net energy demand. This means that a large number of Pareto points which



	Pareto 1	Pareto 2	Pareto 3	Pareto 4	Pareto 5
Improvement cDA	4.8 %	7.1 %	6.2 %	8.8 %	2.0 %
Improvement E_{TOT}	1.2 %	0.3 %	1.7 %	-7.2 %	3.2 %
Improvement E_{PV}	1.4 %	-5.4 %	-7.0 %	-7.8 %	3.2 %

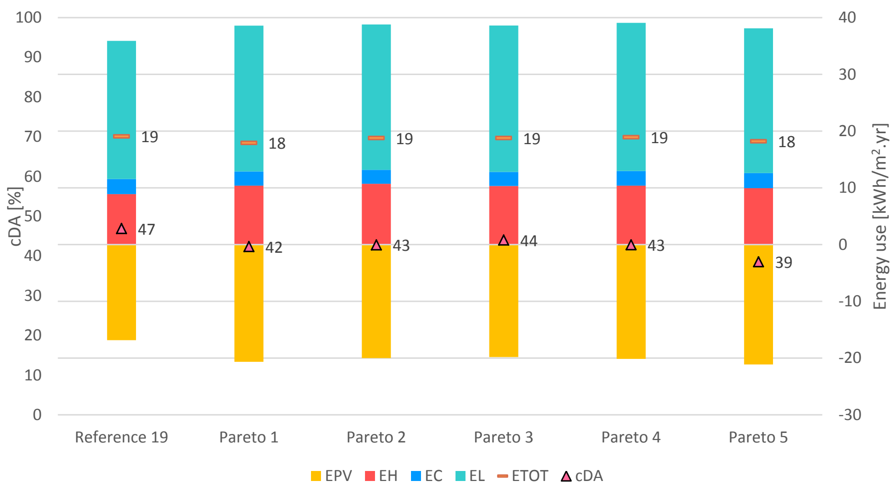
Fig. 10. Performance of the 5 selected Pareto points for the 13 louvres case with a comparison to the reference configuration in terms of cDA and E_{TOT}.



	Pareto 1	Pareto 2	Pareto 3	Pareto 4	Pareto 5
Improvement cDA	-2.7 %	-1.8 %	-4.2 %	-5.8 %	-2.5 %
Improvement E_{TOT}	6.7 %	2.7 %	7.2 %	9.7 %	3.1 %
Improvement E_{PV}	19.8 %	14.2 %	21.9 %	23.0 %	17.2 %

Fig. 11. Performance of the 5 selected Pareto points for the 16 louvres case with a comparison to the reference configuration in terms of cDA and E_{TOT}.

substantially improved a single parameter were not selected in the evaluation. Third, it is reasonable to assume that the results obtained were influenced by the climatic context in which the building was set (heating dominated climate) and the technical assumptions about the building properties and operation. As pointed out earlier, the building had a low energy demand by nature and was operated with ideal building systems with high COPs, while the PV conversion efficiency was relatively low. In a building with a poorer thermal envelope, the PVSD could have a more significant impact on the net energy demand. One can also wonder if in a non-heating dominated climate or in locations closer to the equator, which receive more sunlight, the results of the optimization would lead to very different configurations, as the dynamics of the balance in the objectives will be changed and the cooling demand becomes more important. Additionally, the



	Pareto 1	Pareto 2	Pareto 3	Pareto 4	Pareto 5
Improvement cDA	-9.6 %	-8.8 %	-6.2 %	-8.7 %	-17.9 %
Improvement E_{TOT}	6.0 %	1.5 %	1.4 %	0.8 %	4.5 %
Improvement E_{PV}	22.7 %	18.8 %	17.7 %	19.7 %	25.4 %

Fig. 12. Performance of the 5 selected Pareto points for the 19 louvres case with a comparison to the reference configuration in terms of cDA and E_{TOT}.

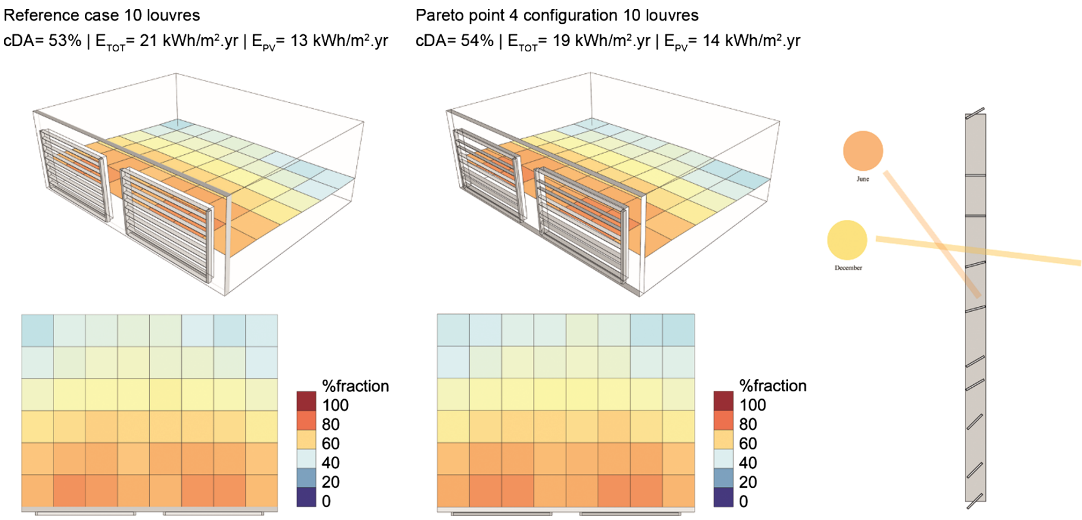


Fig. 13. Louvre system with 10 blades. Visual distribution of the cDA (perspective and top view) for the reference configuration and for selected best solution from the Pareto front, together with the cross section of the louvre system of the optimized solution.

characteristics of the building in terms of internal loads, also affect the outcome of the optimization since different loads would change the energy use profile of the building It is also worth noting that some of the results from the parametric analysis, and thus the references used were very close to the Pareto points and might be Pareto configurations themselves with regard to daylight levels, which makes the task of improving these parameters more difficult. Finally, it's possible that the results of the simulation were somewhat linked to the choice of metrics used, the minimums set for the daylighting standard, and the choice of the reference configuration. For this study, the cDA was judged as the most appropriate metric, but a metric with a harder cutoff, such as the Daylight Autonomy, may have yielded different results. It is also questionable whether a threshold of 300 lx should have been used instead of 500 lx.

4.2. Evaluation of the robustness of the optimized solutions

In this study, the approach of using optimization to help design a shading system was investigated, but this approach is incomplete without a critical assessment of the outputs of the algorithm. Despite their indisputable ability to process larger amounts of data than any human brain could, optimization algorithms are not aimed at replacing designers or provide a human-centered architectural assessment of the solutions they identify as high performing. For this reason and due to the fact that the simulation could in theory run endlessly if no end criterion was provided, the final step of the approach in the proposed methodology is to evaluate the best performing solutions from a designer point of view. This requires assessing the performance according to the objectives of the study and additionally, to consider whether these solutions are (i) obviously possible to improve with small

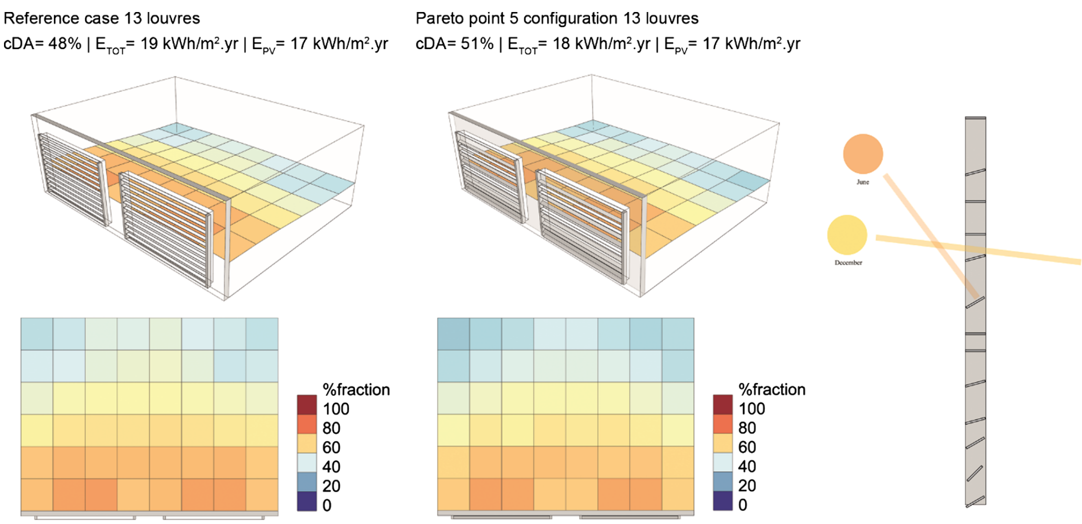


Fig. 14. Louvre system with 13 blades. Visual distribution of the cDA (perspective and top view) for the reference configuration and for selected best solution from the Pareto front, together with the cross section of the louvre system of the optimized solution.

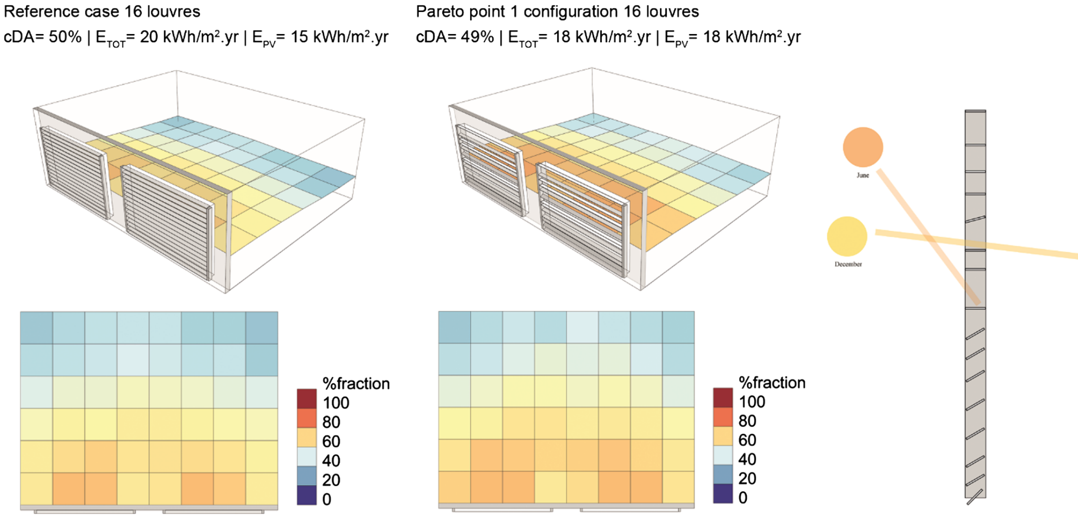


Fig. 15. Louvre system with 16 blades. Visual distribution of the cDA (perspective and top view) for the reference configuration and for selected best solution from the Pareto front, together with the cross section of the louvre system of the optimized solution.

changes, (ii) possible to manufacture as a real shading system, and (iii) architecturally pleasing. For this final step, the two final configurations selected with 10 and 13 louvres were assessed and modified slightly to fit these requirements. In the configuration with 10 louvres, the modifications made were to shift 1 and then 2 louvres in the upper part of the window from a 15 to a 0° tilt to improve the daylight penetration as well as increase the aesthetics of the system. This resulted in no detectable change in the cDA but increased E_{TOT}, signifying that the configuration yielded by the optimization was indeed a non-trivial result of a complex balancing of the parameters. The same test was run on a configuration with 13 louvres with the same results, i.e. the cDA could only be slightly improved but not without increasing E_{TOT}. These findings indicate that the results of the optimization are sufficiently advanced and likely to outperform any "manual" optimization. If this had not been the case, it would be an indication that the optimization had not run long enough and a larger number of generations would be necessary.

5. Conclusion

In this article, a design methodology aiming to improve the performance of a PVSD using multi-objective optimization was developed and demonstrated with the case study of an office building located in a Nordic climate. The findings of the analysis were compared to defined reference cases and demonstrated that the application of the proposed methodology could improve the exploitation of solar energy through a multi-domain façade. The results also supported the assumption that advanced simulation tools can be used in some cases to overcome the limitations of more standardized façade configurations. In particular, it was found that the increase in performance of the system was more

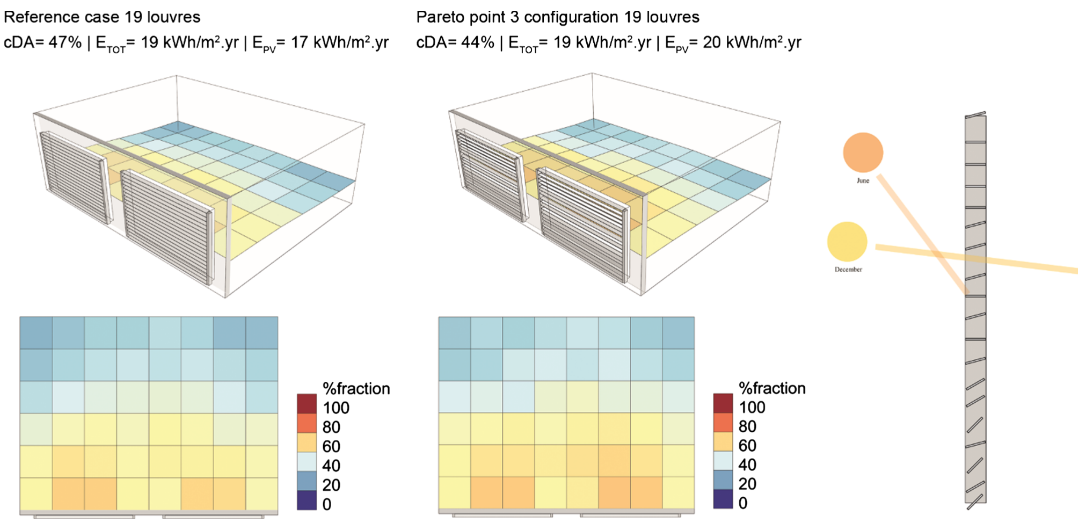


Fig. 16. Louvre system with 19 blades. Visual distribution of the cDA (perspective and top view) for the reference configuration and for selected best solution from the Pareto front, together with the cross section of the louvre system of the optimized solution.

Fig. 17. Side-by-side rendering of the reference case (a) with 10 louvres and the Pareto optimized configuration (b).

significant for configurations with fewer louvres as it allowed the louvres to move vertically in a larger space than when the louvres were more numerous. This finding was also confirmed by the observation that optimized configurations with fewer louvres were most likely to yield results which improved all three of the objectives simultaneously, something the configurations with higher counts of louvres could not achieve. In fact, above a given number of louvres, it appeared that one could only improve two parameters at a time with clear tradeoffs.

Overall, in this study, only a relatively small increase in the global performance of the PVSD could be achieved with the use of optimization. This is believed to be a consequence of the limitations in the structure of the script used to build the methodological framework and the boundary conditions chosen for the study. The analysis of the detailed energy profile of the Pareto configurations resulting from the optimization showed that the total net energy demand was similar for all of the Pareto configurations regardless of the number of louvres (about 19 kWh/m^2). The main difference in the energy demand profiles between the final configurations was that as the number of louvres grew, so did the amount of energy required for artificial lighting, but this was in turn compensated for with a larger amount of energy converted by the PV. As one would expect, in terms of daylight, the configurations with 10 louvres provided the highest cDA and hence, the optimization could only improve it by another relative 3% compared to the reference case, approaching the upper limit of what is achievable in the chosen climate. The total energy demand E_{TOT} could be reduced by nearly 6% and the energy converted by the PV E_{PV} could be improved by up to 10% for the same 10 louvres case. For cases with 13 louvres, the simultaneous improvement for all three objectives was also possible but in a relatively smaller range of values than for 10 louvres. However, when focusing on only two objectives, the cDA could be improved by 7% relatively to the reference case, which made 13 louvres the case with the most potential for improving daylighting via optimization. The case with 16 louvres was not able to provide configurations with a cDA above 50%, but the net energy demand and the PV conversion could be improved by almost 7% and 20% respectively compared to the reference configuration. The configuration with 19 louvres also proved difficult to improve the cDA without sacrificing the net energy demand, and the configuration with the best tradeoffs reduced the cDA by 6% but improved the net energy use by about 1.5% and provided close to 18% more converted energy.

Future work on the optimization methodology presented in this paper could consist of removing some of the constraints in the model, which were put in place to avoid overlapping configurations. A system which would allow the louvre blades to freely distribute but avoid collisions through a different control is likely to provide better results. However, this would require a longer optimization or a larger amount of computational power than what was used in this study. Additionally, the degree of flexibility in the system could be further increased by introducing the possibility to let the optimization algorithm pick the number of louvre-blades in the PVSD, their size, and whether to have PV material on each blade individually or to have a reflective coating instead. Further, the study would be enriched by a multi-climate analysis, under the assumption that the current study is bound by the limited amount of solar energy available during a large portion of the year. The methodology could also be improved with cross-validation of its outputs with data from experimental setups of the system in full-scale laboratories. This future part of the work would allow verifying the in-situ performance of the shading system in different locations, and it would help to determine real system losses due to self-shading of the blades and the effect of temperature on the PV cells. Additionally, these setups could be used to better understand user acceptance of such systems and risk of glare or visual discomfort because of the irregular obstruction of the glazed surface.

Acknowledgements

This paper is part of research activities developed in the SkinTech project funded by the Research Council of Norway under grant No. 255252/E20 and the industrial partners in the project. The authors would like to acknowledge previous work in the project carried out by Kristian Bøe and Martin Fischer in their respective Master's thesis, which contributed to the development of preliminary versions of the proposed methodology. The authors would also like to thank the IEA Task 56 for creating a platform for rich scientific exchange as well as discussion about current and future research prospects in the field of solar building envelopes.

References

[1] Assouline D, Mohajeri N, Scartezzini JL. Quantifying rooftop photovoltaic solar energy potential: a machine learning approach. Sol Energy 2017;141:278–96. https://doi.org/10.1016/j.solener.2016.11.045.
[2] Buonomano A, Calise F, Palombo A, Vicidomini M. BIPVT systems for residential applications: an energy and economic analysis for European climates. Appl Energy 2016;184:1411–31. https://doi.org/10.1016/j.apenergy.2016.02.145.
[3] Strzalka A, Alam N, Duminil E, Coors V, Eicker U. Large scale integration of photovoltaics in cities. Appl Energy 2012;93:413–21. https://doi.org/10.1016/j.apenergy.2011.12.033.
[4] Shafiei S, Salim RA. Non-renewable and renewable energy consumption and CO_2 emissions in OECD countries: a comparative analysis. Energy Policy 2014;66:547–56. https://doi.org/10.1016/j.enpol.2013.10.064.
[5] Allouhi A, El Fouih Y, Kousksou T, Jamil A, Zeraouli Y, Mourad Y. Energy consumption and efficiency in buildings: current status and future trends. J Clean Prod 2015;109:118–30. https://doi.org/10.1016/j.jclepro.2015.05.139.
[6] Defaix PR, van Sark WGJHM, Worrell E, de Visser E. Technical potential for photovoltaics on buildings in the EU-27. Sol Energy 2012;86:2644–53. https://doi.org/10.1016/j.solener.2012.06.007.
[7] Ekoe A, Akata AM, Njomo D, Agrawal B. Assessment of Building Integrated Photovoltaic (BIPV) for sustainable energy performance in tropical regions of Cameroon. Renew Sustain Energy Rev 2017;80:1138–52. https://doi.org/10.1016/j.rser.2017.05.155.
[8] James PAB, Jentsch MF, Bahaj AS. Quantifying the added value of BiPV as a shading solution in atria. Sol Energy 2009;83:220–31. https://doi.org/10.1016/j.solener.2008.07.016.
[9] Biyik E, Araz M, Hepbasli A, Shahrestani M, Yao R, Shao L, et al. A key review of building integrated photovoltaic (BIPV) systems. Eng Sci Technol an Int J 2017;20:833–58. https://doi.org/10.1016/j.jestch.2017.01.009.
[10] Yang T, Athienitis AK. A review of research and developments of building-integrated photovoltaic/thermal (BIPV/T) systems. Renew Sustain Energy Rev

2016;66:886–912. https://doi.org/10.1016/j.rser.2016.07.011.
[11] Jakica N. State-of-the-art review of solar design tools and methods for assessing daylighting and solar potential for building-integrated photovoltaics. Renew Sustain Energy Rev 2018;81:1296–328. https://doi.org/10.1016/j.rser.2017.05.080.
[12] Maturi L, Adami J. Building Integrated Photovoltaic (BIPV) in Trentino Alto Adige. Springer; 2018.
[13] Leslie RP. Capturing the daylight dividend in buildings: why and how? Build Environ 2003;38:381–5. https://doi.org/10.1016/S0360-1323(02)00118-X.
[14] Jakubiec JA, Reinhart CF. The 'adaptive zone'-a concept for assessing discomfort glare throughout daylit spaces. Light Res Technol 2012;44:149–70. https://doi.org/10.1177/1477153511420097.
[15] Matusiak BS. Glare from a translucent façade, evaluation with an experimental method. Sol Energy 2013;97:230–7. https://doi.org/10.1016/j.solener.2013.08.009.
[16] Gratia E, De Herde A. Design of low energy office buildings. Energy Build 2003;35:473–91. https://doi.org/10.1016/S0378-7788(02)00160-3.
[17] Tzempelikos A, Athienitis AK. The impact of shading design and control on building cooling and lighting demand. Sol Energy 2007;81:369–82. https://doi.org/10.1016/j.solener.2006.06.015.
[18] Zhang X. Building performance evaluation of integrated transparent photovoltaic blind system by a virtual testbed; 2014.
[19] Alzoubi HH, Al-Zoubi AH. Assessment of building facade performance in terms of daylighting and the associated energy consumption in architectural spaces: Vertical and horizontal shading devices for southern exposure facades. Energy Convers Manag 2010;51:1592–9. https://doi.org/10.1016/j.enconman.2009.08.039.
[20] Mandalaki M, Zervas K, Tsoutsos T, Vazakas A. Assessment of fixed shading devices with integrated PV for efficient energy use. Sol Energy 2012;86:2561–75. https://doi.org/10.1016/j.solener.2012.05.026.
[21] Palmero-Marrero AI, Oliveira AC. Effect of louver shading devices on building energy requirements. Appl Energy 2010;87:2040–9. https://doi.org/10.1016/j.apenergy.2009.11.020.
[22] Kim JJ, Jung SK, Choi YS, Kim JT. Optimization of photovoltaic integrated shading devices. Indoor Built Environ 2010;19:114–22. https://doi.org/10.1177/1420326X09358139.
[23] Oh MH, Lee KH, Yoon JH. Automated control strategies of inside slat-type blind considering visual comfort and building energy performance. Energy Build 2012;55:728–37. https://doi.org/10.1016/j.enbuild.2012.09.019.
[24] Zhang X, Lau SK, Lau SSY, Zhao Y. Photovoltaic integrated shading devices (PVSDs): a review. Sol Energy 2018;170:947–68. https://doi.org/10.1016/j.solener.2018.05.067.
[25] Lee ES, Selkowitz SE, Dibartolomeo DL, Klems JH, Clear RD, Konis K, et al. High performance building façade solutions PIER final project report. Berkeley, CA (United States): Lawrence Berkeley National Lab. (LBNL); 2009.
[26] Jayathissa P, Zarb J, Luzzatto M, Hofer J, Schlueter A. Sensitivity of building properties and use types for the application of adaptive photovoltaic shading systems. Energy Procedia 2017;122:139–44. https://doi.org/10.1016/j.egypro.2017.07.319.
[27] Goia F, Haase M, Perino M. Optimizing the configuration of a façade module for office buildings by means of integrated thermal and lighting simulations in a total energy perspective. Appl Energy 2013;108:515–27. https://doi.org/10.1016/j.apenergy.2013.02.063.
[28] Yoo S-H, Lee E-T. Efficiency characteristic of building integrated photovoltaics as a shading device. Build Environ 2002;37:615–23. https://doi.org/10.1016/S0360-1323(01)00071-3.
[29] Yoo SH, Manz H. Available remodeling simulation for a BIPV as a shading device. Sol Energy Mater Sol Cells 2011;95:394–7. https://doi.org/10.1016/j.solmat.2010.02.015.
[30] Ibraheem Y, Piroozfar P, Farr ERP. Integrated façade system for office buildings in hot and arid climates: a comparative analysis. In: Dastbaz M, Gorse C, Moncaster A, editors. Build inf model build performance, des smart constr. 1st ed.Springer; 2017. p. 273–88https://doi.org/10.1007/978-3-319-50346-2_19.
[31] Bahr W. Optimal design parameters of the blinds integrated photovoltaic modules based on energy efficiency and visual comfort. Cent Eur towar sustain build, Prague, Czech Republic. 2013. p. 1–10.
[32] Mandalaki M, Tsoutsos T, Papamanolis N. Integrated PV in shading systems for Mediterranean countries: balance between energy production and visual comfort. Energy Build 2014;77:445–56. https://doi.org/10.1016/j.enbuild.2014.03.046.
[33] Datta G. Effect of fixed horizontal louver shading devices on thermal performance of building by TRNSYS simulation. Renew Energy 2001;23:497–507. https://doi.org/10.1016/S0960-1481(00)00131-2.
[34] Grynning S, Lolli N, Wågø S, Risholt B. Solar shading in low energy office buildings – design strategy and user perception. J Daylight 2017;4:1–14. https://doi.org/10.15627/jd.2017.1.
[35] Hoffmann S, Lee ES, McNeil A, Fernandes L, Vidanovic D, Thanachareonkit A. Balancing daylight, glare, and energy-efficiency goals: an evaluation of exterior coplanar shading systems using complex fenestration modeling tools. Energy Build 2016;112:279–98. https://doi.org/10.1016/j.enbuild.2015.12.009.
[36] Hwang T, Kang S, Kim JT. Optimization of the building integrated photovoltaic system in office buildings – focus on the orientation, inclined angle and installed area. Energy Build 2012;46:92–104. https://doi.org/10.1016/j.enbuild.2011.10.041.
[37] Loonen RCGM, Favoino F, Hensen JLM, Overend M. Review of current status, requirements and opportunities for building performance simulation of adaptive facades. J Build Perform Simul 2017;2:205–23.
[38] Bustamante W, Uribe D, Vera S, Molina G. An integrated thermal and lighting simulation tool to support the design process of complex fenestration systems for office buildings. Appl Energy 2017;198:36–48. https://doi.org/10.1016/j.apenergy.2017.04.046.
[39] Khoroshiltseva M, Slanzi D, Poli I. A Pareto-based multi-objective optimization algorithm to design energy-efficient shading devices. Appl Energy 2016;184:1400–10. https://doi.org/10.1016/j.apenergy.2016.05.015.
[40] Manzan M, Clarich A. FAST energy and daylight optimization of an office with fixed and movable shading devices. Build Environ 2017;113:175–84. https://doi.org/10.1016/j.buildenv.2016.09.035.
[41] Manzan M. Genetic optimization of external fixed shading devices. Energy Build 2014;72:431–40. https://doi.org/10.1016/j.enbuild.2014.01.007.
[42] Hamdy M, Nguyen A-T, Hensen JLM. A performance comparison of multi-objective optimization algorithms for solving nearly-zero-energy-building design problems. Energy Build 2016;121:57–71. https://doi.org/10.1016/j.enbuild.2016.03.035.
[43] Zhang A, Bokel R, van den Dobbelsteen A, Sun Y, Huang Q, Zhang Q. Optimization of thermal and daylight performance of school buildings based on a multi-objective genetic algorithm in the cold climate of China. Energy Build 2017;139:371–84. https://doi.org/10.1016/j.enbuild.2017.01.048.
[44] Lu Y, Wang S, Yan C, Huang Z. Robust optimal design of renewable energy system in nearly/net zero energy buildings under uncertainties. Appl Energy 2017;187:62–71. https://doi.org/10.1016/j.apenergy.2016.11.042.
[45] Sun L, Lu L, Yang H. Optimum design of shading-type building-integrated photovoltaic claddings with different surface azimuth angles. Appl Energy 2012;90:233–40. https://doi.org/10.1016/j.apenergy.2011.01.062.
[46] Méndez Echenagucia T, Capozzoli A, Cascone Y, Sassone M. The early design stage of a building envelope: multi-objective search through heating, cooling and lighting energy performance analysis. Appl Energy 2015;154:577–91. https://doi.org/10.1016/j.apenergy.2015.04.090.
[47] Jayathissa P, Luzzatto M, Schmidli J, Hofer J, Nagy Z, Schlueter A. Optimising building net energy demand with dynamic BIPV shading. Appl Energy 2017;202:726–35. https://doi.org/10.1016/j.apenergy.2017.05.083.
[48] Mulcué-Nieto LF, Mora-López L. Methodology to establish the permitted maximum losses due to shading and orientation in photovoltaic applications in buildings. Appl Energy 2015;137:37–45. https://doi.org/10.1016/j.apenergy.2014.09.088.
[49] Lee JB, Park JW, Yoon JH, Baek NC, Kim DK, Shin UC. An empirical study of performance characteristics of BIPV (Building Integrated Photovoltaic) system for the realization of zero energy building. Energy 2014;66:25–34. https://doi.org/10.1016/j.energy.2013.08.012.
[50] Taveres-Cachat E, Bøe K, Lobaccaro G, Goia F, Grynning S. Balancing competing parameters in search of optimal configurations for a fix louvre blade system with integrated PV. Energy Procedia 2017;122. https://doi.org/10.1016/j.egypro.2017.07.357.
[51] McNeel Robert and Associates. Rhinoceros version 5.0; 2015. https://www.rhino3d.com/.
[52] Rutten D. Grasshopper – algorithmic modeling for Rhino version 0.9.0076; 2017. http://www.grasshopper3d.com/ [accessed October 9, 2017].
[53] Ladybug tools; n.d. https://www.ladybug.tools/ [accessed May 30, 2018].
[54] Crawley DB, Lawrie LK, Winkelmann FC, Buhl WF, Huang YJ, Pedersen CO, et al. EnergyPlus: creating a new-generation building energy simulation program. Energy Build 2001;33:319–31. https://doi.org/10.1016/S0378-7788(00)00114-6.
[55] Kim HC, Fthenakis V, Choi J, Turney DE. Life cycle greenhouse gas emissions of thin-film photovoltaic electricity systematic. Rev Harmoniz 2012;16. https://doi.org/10.1111/j.1530-9290.2011.00423.x.
[56] Marwede M, Reller A. Estimation of life cycle material costs of cadmium telluride – and copper indium gallium diselenide – photovoltaic absorber materials based on life cycle material flows. J. Ind. Ecol. 2014;18:254–67. https://doi.org/10.1111/jiec.12108.
[57] Reinhart CF, Mardaljevic J, Rogers Z, Reinhart CF, Mardaljevic J, Dynamic ZR, et al. Dynamic daylight performance metrics for sustainable building design. LEUKOS – J Illum Eng Soc North Am 2006;3:7–31. https://doi.org/10.1582/LEUKOS.2006.03.01.001.
[58] Davis L. Handbook of genetic algorithms. New York: Van Nostrand Reinhold; 1991.
[59] Vierlinger R. Multi objective design interface. TU Wien; 2013https://doi.org/10.13140/RG.2.1.3401.0324.

A4 Paper IV

Co-simulation and validation of the performance of a highly flexible parametric model of an external shading system

E Taveres-Cachat, F Goia

Building and Environment Volume 182, 107111, (2020)

Building and Environment 182 (2020) 107111

Contents lists available at ScienceDirect

Building and Environment

journal homepage: http://www.elsevier.com/locate/buildenv

Co-simulation and validation of the performance of a highly flexible parametric model of an external shading system

Ellika Taveres-Cachat [a,b], Francesco Goia [a,*]

[a] Norwegian University of Science and Technology, Department for Architecture and Technology, Trondheim, Norway
[b] SINTEF Community, Department for Architecture, Building Materials and Construction, Trondheim, Norway

ARTICLE INFO

Keywords:
Parametric design
Louvred shading system
Experimental validation
Full-scale test
Automated calibration
Daylighting analysis
Thermal model

ABSTRACT

The article presents a validation study of a modelling approach implemented in a numerical script for external louvred shading systems based on an experimental analysis in a full-scale test facility. The model developed to abstract the system was entirely parametric and used co-simulation to predict the indoor air temperature and illuminance levels in two points of the test cell.

The calibration of the model of the test facility was carried out using a combination of two methods: automated calibration based on multi-objective optimization with a genetic algorithm and manual calibration. In total, six different configurations of the external shading system with varying complexity were investigated to validate the script. Its performance was assessed using three metrics: the root mean square error, the coefficient of variation of the root mean square error, and the normalized mean bias error.

The results showed that the thermal environment was simulated with consistent accuracy for all the cases investigated, predicting air temperatures with an error well within the tolerance of building performance simulation tools and the experimental uncertainty. The daylighting model satisfactorily captured the different dynamics of illuminance peaks and dips, replicating the variations between different configurations, but with a lower degree of accuracy than for the thermal simulations.

1. Introduction

1.1. Parametric scripting and co-simulation in building performance simulation

Parametric software allow the exploration of a larger solution space in early design stages when changes are still relatively easy to implement and less costly. These tools rely on an explicit dynamic linkage between geometric definitions of the buildings elements, system parameters, and whole-building performance [1,2]. Because these tools can simultaneously be used as interfaces to different building simulation engines, they can help increase the interoperability of simulation tools by supporting co-simulation frameworks. Co-simulation is a method used in building performance simulation which allows coupling different models that describe parts of the building (i.e. thermal models, daylighting models etc.), each of which is run in a different simulation tool in a way that they can exchange simulation data during run-time [3]. Co-simulation is specifically interesting for the study of geometrically complex shading systems or façade elements that simultaneously affect multiple parameters of indoor comfort (thermal and visual) and energy use, and which still suffer from simulation deficiencies in building simulation [4]. The development of new simulation approaches is thus useful as it can help investigate advanced control strategies or complex geometries [5–8] as well as support the development of design approaches such as free form facades and shading elements [9].

Previous studies using parametric design coupled to optimization algorithms have underlined the greater amount of flexibility and control over design problems they obtained and the increased ability to manage complex interactions between micro- and macrosystems [10–12]. This method has also been used to define more advanced control strategies, for example in kinetic façade studies [13–15], by dynamically connecting shading system properties such as size and movements to daylighting strategies and occupant visual and thermal comfort. Developing performance-based design workflows and integrating them into one parametric script can further help create interdisciplinary studies that combine architectural aspects like building morphology and façade design with engineering fields looking at energy demand, renewable energy availability, microclimate effects, and carbon

* Corresponding author.
E-mail address: francesco.goia@ntnu.no (F. Goia).

https://doi.org/10.1016/j.buildenv.2020.107111
Received 10 April 2020; Received in revised form 3 July 2020; Accepted 4 July 2020
Available online 24 July 2020

emissions to define optimal designs [16–18].

1.2. Model validation

Building performance simulation and co-simulation are powerful tools to assess and predict the quality of building designs in terms of energy use, operational costs, indoor climate and more. To ensure that this approach is viable, simulations results must also be validated to safeguard their accuracy, reliability, and robustness. When it comes to shading systems, experimental validation is important because it can help improve existing models in software [19–24] and help develop new modelling approaches for complex or novel façade- and shading elements [24–28]. It also allows comparing more accurately different solutions with baselines, characterizing the performance of novel components, and understanding the relationships between actual versus simulated performance - which in turn drives product development.

Model validation of façade components is used to verify both thermal and daylighting models [29–34]. Commonly, models are calibrated before they are validated using existing measurement data to overcome limitations and uncertainties connected to input data. This can be done using global or local sensitivity analysis, manual calibration methods, and more recently automated techniques for model calibration. Different procedures and approaches for automated calibration can be found in the literature [35–40], most of which typically use mathematical and statistical key performance indicators like the Root Mean Square Error (RMSE), the Normalized Mean Bias Error (NMBE), or the Coefficient of Variation of the Root Mean Square Error (CV RMSE). The impact of the choice of the indicator or combination of indicators used in the calibration on the accuracy of the model is investigated and discussed in Ref. [41].

2. Innovative aspects of the study and outputs

The work in this article presents the co-simulated performance of a highly flexible parametric model of an external louvred shading system, the results of which are validated using experimental data from a full-scale laboratory to ensure its robustness. The geometric definition of the model used for this study was developed using the parametric design tool Rhinoceros v5 by McNeel & Associates [42] and its visual programming editor Grasshopper [43]. The model developed is built in an entirely parametric way and allows for a high degree of freedom in the geometric definition of the individual louvres to support free form search studies. Among other parameters, it allows defining the number of louvres in the system, their individual width, spacing, and angle as well as their appearance. The model is also set up in a way that the material and geometric input parameters can be used in optimization studies and ensures that the distribution of the louvres does not contain any geometric collisions by dynamically defining individual vertical distribution constraints based on adjacent louvre sizes and tilt angles. Because Grasshopper is compatible with a large number of plug-ins including the Ladybug tools [44] and sub-packages Ladybug, Honeybee, Honeybee [+], Butterfly, and Dragonfly [45], the model can be connected to validated building energy performance simulation engines such as EnergyPlus [46] and the backwards ray-tracing engine Radiance [47]. In this study, co-simulation was used to describe both the thermal model and the daylighting model of the system simultaneously by connecting geometric outputs to Honeybee daylighting analysis via Honeybee_context and to energy simulations by connecting to the EnergyPlus module in Honeybee. It is important to note that the geometry of the shading system was not created using the component for integrated shading systems nor was it implemented as a BSDFs, but it was modelled as a "Honeybee_context" shading element in the Honeybee legacy plug-in. Special care was given to ensure that its reflectance was considered both in the daylighting and in the thermal simulations as this is not a default setting. The model and its degree of flexibility are described in the appendix with a link allowing to download the model from a data repository for further use.

The experimental data used to validate the model was collected in a full-scale test laboratory which was equipped with a series of different versions of the shading system and collected weather data, temperature data, and illuminance data, offering the possibility of a full characterization of the system investigated. The experimental campaign started in the second week of June 2019 and lasted until the first week of August 2019 in the location of Trondheim (Norway), in total providing two months of data and a range of varying boundary conditions. These separate studies aimed at testing key aspects of the robustness of the modelling approach, such as the effect of the density and regularity of the shading device configuration, or the architectural expression of the system.

The main output of this work is thus a modelling workflow, which can be used for the co-simulated performance of external louvred shading systems characterized by a high degree of flexibility. It aims at contributing to exploring applications of parametric design and ongoing multi-physical validation efforts of models for shading systems, specifically for systems which cannot be modelled with existing predefined modules inside whole building simulation tools. This approach is also useful to provide an assessment of the accuracy of using parametric shading device models for studies in which using a more detailed model of a fenestration system, such as a bidirectional scattering surface distribution (BSDF) description, is either not possible or not convenient. For example, if one is interested in exploring free form facades or using optimization algorithms, creating a new BSDF for each simulation run may lead to too much computational overhead.

The remainder of this article is set up with the following structure: in section 3, the methodology for the study is laid out and describes the parametric modelling assumptions, the test facility used, and the procedure for the calibration and the validation. The results of both the calibration and the validation are presented in section 4, with a separation between the results obtained for the test facility without the shading system and those obtained with the shading system. Section 5 of this article contains the discussion of the validation results obtained, as well as the limitations of the study. Finally, the conclusions of the study are presented in section 6.

3. Methodology

3.1. Description of the building performance simulation model

For the experimental assessment presented in this study, the input of the model was set up to generate an external fixed louvred shading system with 155 mm wide louvres with variable tilt angles. The system modelled and studied is based on an existing passive louvre system [48] which was modified in its set up to accommodate a much larger degree of freedom, with a variable number of louvres that can be vertically distributed in any chosen way. Each louvre can individually be tilted using interchangeable brackets from 0° (horizontal) to 45° in 15° increments (Fig. 1). An early modelling approach of this system is also described in a previous study available in Ref. [49].

The modelling approach developed in this work was used to generate the studied louvred shading system in front of a test chamber identical to the one used to validate the model experimentally. The properties and characteristics of the test chamber and the surrounding guard volume are described in section 3.2. The chamber itself is a rectangular volume modelled as a single zone surrounded by three volumes which were merged into a second zone and formed the guard room around the chamber.

While the test chamber was modelled as unconditioned for reasons discussed in section 3.2, the guard room zone was conditioned with an ideal system with scheduled heating and cooling setpoint temperatures. These dynamically scheduled setpoints were defined to match the measured surface temperatures of the test cell chamber wall (measured on the side of the guard volume). The interior convection coefficients on

Fig. 1. Attachment of a blue louvre (left) and brackets for the four different angles the louvres can be tilted at (0, 15, 30, and 45° from horizontal) (right).

these surfaces were increased to fictionally high values to ensure that the temperatures of the surfaces of the test chamber (facing the guard room) were identical to the air temperature of the guard room, and thus, recreating the boundary conditions which were measured during the experiments.

For the daylighting model, two analysis surfaces were created inside the model of the chamber to replicate the measurement points of illuminance on a desk and on the ceiling. The simulated illuminance measured in the model was calculated as the average illuminance on a 10 cm × 10 cm surface centred around the position of the sensor. The desk sensor was placed at 1.30 m from the window (desk height 0.8 m) and the ceiling sensor was located at 3 m height in the middle of the room.

To characterize the effect of the shading system on the air temperature and illuminance levels in the chamber, six different cases corresponding to six different configurations were investigated (Table 1). These configurations differed from one another in the number of louvres considered in the system, the tilt angle of each louvre, the interspace between the louvres, and the colour of the louvres which was either dark blue (colours RAL 5000) or pure white (RAL 9010). The latter was used to investigate the effect of the appearance of the shading system. It is important to note that the cases with 13 modified louvres are configurations that aim to be more complex than the previous cases by having louvres that are no longer equally spaced and have several different tilt angles. This means that the shading system no longer forms a regular patterned shadow in front of the window. These configurations are interesting to investigate to understand how well the modelling approach applied to an odd geometry is translated into inputs for the different simulation engines. The choice of these configurations was based on previous work described in Ref. [50]. A vertical cross-section of the different shading system configurations is shown in Table 2.

3.2. Description of the experimental facility

The experimental campaign aiming to measure the effect of different configurations of the studied external louvred shading system was carried out between June and August 2019 using one of the test chambers from the ZEB TestCell facility located in Trondheim, Norway. The test chamber is a rectangular room (with internal dimensions 2.5 m × 4.4 m - floor area 11 m^2) with a height of 3.3 m. The interior walls, floor and ceiling are built of insulating polyurethane sandwich panels with a white aluminium casing. All the opaque surfaces in the test cell are white except for the floor which had an additional layer of 2 cm woodchip boards and the interior surface of the façade which had a similar light

Table 1
Summary of the cases investigated in the experimental study.

Case name	Case description	Calibration period and properties modified	Validation period
0	No shading device	Thermal properties of the test chamber with automated calibration (see Table 6) Optical properties of the surfaces in the chamber with manual calibration (see Table 7) Duration: 2 days: August 3rd 7 a.m. to August 5th 7 a.m.	Duration 2 days: August 5th 8 a.m. to August 7th 8 a.m.
16	16 blue louvres equally spaced and tilted at 15° from horizontal	Sensitivity analysis only affecting the reflectance value of the louvres 3 days: June 16th 7 a.m. to June 19th 7 a.m.	3 days: June 13th 7 a.m. to June 16th 7 a.m.
13	13 blue louvres equally spaced and tilted at 15° from horizontal	No calibration	3 days: June 20th 7 a.m. to June 23rd 7 a.m.
13 modified A	13 blue louvres with heterogenous spacing and tilt angles	No calibration	3 days: July 8th 7 a.m. to July 11th 7 a.m.
13 modified B	13 blue louvres with heterogenous spacing and tilt angles	No calibration	3 days: July 19th 7 a.m. to July 21st 7 a.m.
13 white	13 white louvres equally spaced and tilted at 15° from horizontal	No calibration	3 days: July 29th 7 a.m. to August 2nd 7 a.m.

Table 2
Vertical cross-sections of the facade with the different shading configurations, including individual louvre tilt angles and interspaces.

Case 16	Case 13	Case 13 modified A	Case 13 modified B	Case 13 white
15 deg	15 deg	15 deg	15 deg	15 deg
14.7 cm	18.3 cm	34 cm	34 cm	18.3 cm
15 deg	15 deg	0 deg	0 deg	15 deg
14.7 cm	18.3 cm	25 cm	25 cm	18.3 cm
15 deg	15 deg	0 deg	0 deg	15 deg
14.7 cm	18.3 cm	22 cm	22 cm	18.3 cm
15 deg	15 deg	15 deg	15 deg	15 deg
14.7 cm	18.3 cm	20 cm	20 cm	18.3 cm
15 deg	15 deg	0 deg	0 deg	15 deg
14.7 cm	18.3 cm	15 cm	15 cm	18.3 cm
15 deg	15 deg	0 deg	0 deg	15 deg
14.7 cm	18.3 cm	12 cm	12 cm	18.3 cm
15 deg	15 deg	0 deg	0 deg	15 deg
14.7 cm	18.3 cm	14 cm	14 cm	18.3 cm
15 deg	15 deg	15 deg	15 deg	15 deg
14.7 cm	18.3 cm	18 cm	18 cm	18.3 cm
15 deg	15 deg	30 deg	30 deg	15 deg
14.7 cm	18.3 cm	16 cm	16 cm	18.3 cm
15 deg	15 deg	30 deg	30 deg	15 deg
14.7 cm	18.3 cm	14 cm	14 cm	18.3 cm
15 deg	15 deg	45 deg	45 deg	15 deg
14.7 cm	18.3 cm	16 cm	16 cm	18.3 cm
15 deg	15 deg	15 deg	15 deg	15 deg
14.7 cm	18.3 cm	13 cm	13 cm	18.3 cm
15 deg	15 deg	45 deg	45 deg	15 deg
14.7 cm				
15 deg				
14.7 cm				
15 deg				
14.7 cm				
15 deg				

brown colour at the time of the experiments. The south-facing façade element is built of insulated timber frame with a 2.2 m × 2 m triple pane window with argon gas (Fig. 2). More details about the window are provided in Table 3. A more exhaustive description of the whole test cell facility in Ref. [51].

For this study, although the test chamber is equipped with a full HVAC system to condition the indoor volume, the chamber was left unconditioned while the surrounding guard volume was conditioned. The reasons for this choice were plural. First, keeping the volume unconditioned created larger temperature fluctuations which could be measured more accurately than a smaller temperature signal. Second, if the volume were conditioned with an HVAC system and setpoints, the measurements would have to be done on the amount of energy delivered to condition the room. This would have required many more assumptions regarding the modelling of the HVAC system itself, and would have added significant uncertainty to the results of the model. The nature of the data recorded during the experimental campaign is summarized in Table 4 and Table 5.

It is important to note that the sensors measuring the illuminance level in the chamber were set with two different ranges (see Table 5). This choice was as a compromise between limiting the time the sensors would saturate and obtaining accurate readings. Because this study did not assess the risk of glare, the goal of these measurements was only to investigate whether the space with the shading system would receive a minimum threshold value of illuminance.

Table 3
Characteristics of the window of the test cell.

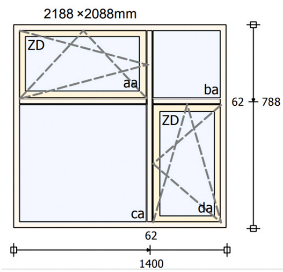


Fig. 2. Facade of the test cell facility and a picture of the test chamber used.

Table 4
Quantities measured inside the test chamber during the experimental campaign.

Quantities measured in cells	Uncertainty on measure
Air temperature at 1 and 2 m height	±0.5 °C
Illuminance on a surface at 0.8 m height (desk surface) and 3 m height (ceiling surface). Note that the sensor on the desk was set to have a measurement range of 0–1000 lux while the one on the ceiling was set to have a measurement range of 0–500 lux (sensor manufacturer S + S Regeltechnik)	±5% of the maximum value in the range

During the time of the experiments, weather data was collected by a weather station to create an EPW weather data file for the corresponding analysis period. Because the pyranometer of the weather station only recorded global irradiance, the Engerer2 code described in Ref. [52] was used to obtain the fractions of diffuse and direct radiation (W/m^2). This algorithm was selected because it is validated, and its developers found that it performed particularly well with hourly radiation data in cold climates in latitudes close to the ones of Trondheim.

Table 5
Quantities measured in the guard volume and by the weather station during the experimental campaign.

Quantities measured in guard volume and by weather station	Uncertainty on measure
Air temperature in guard volume in multiple points	±0.5 °C
Surface temperatures in multiple points on the chamber walls on the side of the guard volume	±0.5 °C
Global horizontal irradiance (thermopile)	II class pyranometer
Exterior dry bulb temperature	±0.15 °C + 0,1%$_{measured}$
Exterior air relative humidity	±1.5%$_{rh}$ +1.5%$_{measured}$
Wind speed and wind direction (ultrasonic sensor)	accuracy speed: ±3%; accuracy direction: ±2 deg.
Dew point temperature	±0.15 °C + 0.1%$_{measured}$
Atmospheric pressure (piezoresistive sensor)	±50 Pa

Table 6
Parameters used for the calibration of the thermal model.

Parameter used for calibration of thermal model	Nominal value	Value range given as input	Final value
U-value of the façade including window frame construction and thermal bridge	Wall construction 0.18 W/m^{2}K Frame construction 1.45 W/m^{2}K Total thermal bridge 0.34 W/K Total equivalent to 0.52 W/m^{2}K	Total value between [0.52:0.60] W/m^{2}k	0.52 W/m^{2}k
Thermal mass surface equivalent	Significant amount of equipment in room with high thermal mass	[5.0:15.0] m^2 of material equivalent to 1 cm of concrete	15 m^2
Internal load	Estimated to 10 W, only due to measuring equipment in room	[10:15] W	10 W
Infiltration to the outdoor	Estimated from previous reports between 0.10 and 0.15 h^{-1} excluding infiltration due to cables exiting through window frame	[0.1: 0.3] h^{-1}	0.3 h^{-1}
U-value of the internal walls of the cell	0.23 W/m^{2}K without considering thermal bridges/ up to 0.40 W/m^{2}K including geometrical thermal bridges	[0.23:0.40] W/m^{2}K	0.40 W/m^{2}K
g value of the glazing assembly	0.38 from manufacturer	[0.33:0.38]	0.33
U value of glazing	0.62 W/m^{2}K from manufacturer	[0.62:0.68] W/m^{2}K	0.68 W/m^{2}K

3.3. *Description of the procedure for the calibration of the thermal and daylighting models*

The calibration period defined for case 0 spanned a two-day period during which no shading system was installed on the test cell facility. The calibration itself was done using the multi-objective optimization plug-in Octopus [53] with the following procedure. First, a small number of parameters were selected on the basis that they had the most uncertainty due to lacking documentation or because previous sensitivity studies [54] had determined them to have the most impact on the heat balance of the test chamber. These parameters were then provided as input to the algorithm with a range of values they could take. Second, the objectives of the optimization were defined by a fitness function

Table 7
Parameters used for the calibration of the daylighting model.

Parameters used for the calibration of the daylighting model	Nominal value	Value range given as input	Final value
Reflectance of internal walls	White surface	[0.70:0.85]	0.80
Reflectance of floor	Chip board	[0.30:0.40]	0.30
Reflectance ceiling	White surface with many obstacles (ducts and light fixtures)	[0.70:0.85]	0.80
Reflectance of blue louvres	0.066 from RAL 5000 paint reference	[0.05:0.10]	0.07
Reflectance of white louvres	0.85 from RAL 9010 paint reference	[0.80:0.90]	0.85

which aimed at minimizing the root mean square error (RMSE) between the measured and the simulated air temperature in the chamber at each hour, as well as reducing the maximum hourly error for each day (peak error). To avoid overfitting the model, the range of the input parameters used by the Octopus algorithm was contained, at most, within a ±10% interval of the assumed or known value except for the g-value for which a value 15% lower than what was provided by the window manufacturer was set as the lower boundary. This assumption was based on the findings of [55], which showed that the discrepancies between measured and announced g-values of double glazed units could reach up to 23% during a summer period in the same location as the experiments described in our study.

For the daylighting model of the cell without the shading system, a similar procedure was followed, but using a manual calibration on the same two days used for the automated thermal calibration. This was because the saturation point of the sensors was reached for many hours during the day when the chamber had no shading. A second daylighting calibration, this time only focusing on the reflectance values of the shading system, was carried out over another set of two days when the test chamber was set up with the case study called case 16. In this case, a light hand calibration was used on one parameter only.

In the fitness function for the optimization, the RMSE (Eq. (1)) was calculated according to the following formula where N is the total number of values, *m* is the measured value and *s* is the simulated value, both at time step *i*:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(m_i - s_i)^2}{N}} \quad \text{(Eq. 1)}$$

The accuracy of the thermal and daylighting models for each case was evaluated using two additional metrics: the CV RMSE or coefficient of variation of the root mean square error in % (Eq. (2)) and the NMBE or normalized mean bias error (Eq. (3)).

The CV RMSE is calculated similarly to the RMSE but uses $\overline{m}$ the average of measured value during the considered period, as follows:

$$CV\ RMSE\ (\%) = \frac{\sqrt{\left(\frac{\sum_{i=1}^{N}(m_i - s_i)^2}{N}\right)}}{\overline{m}} \quad \text{Eq. 2}$$

The NMBE is calculated according to the following formula:

$$NMBE\ (\%) = \frac{\sum_{i=1}^{N}(s_i - m_i)}{N \times \overline{m}} \quad \text{Eq. 3}$$

3.4. *Description of the procedure for the validation of the thermal and daylighting models*

For each calibration and validation procedure, two completely independent data sets were used each time to ensure that the model results were reliable. For the cases with the shading system (case 16, 13, 13 modified A, 13 modified B, and 13 white), the model was also run with new datasets representing a simulation period of three consecutive days starting at 7 a.m. on the first day and ending at 7 a.m. on the last day. For each period considered, as much as possible, the days selected for the validation period were chosen to be a series of days containing one fully sunny day, one slightly cloudy day, and one cloudy day. The choice of the starting times for the analysis, that is 7 a.m., was selected to create consistency. Each time the shading configurations were changed during the experiments, the switch was done in the early morning at approximately 7 or 8 a.m. and required about 40 minutes to execute. It was assumed that it would take about 24 h before the data recorded was no longer influenced by the louver switching intervention, and so the data recorded on these switching days was discarded until the next day at 7 a.m. This method was followed for each set of measurements to avoid any dependency of the data collected on the order of the cases investigated.

To assess whether the model could be validated or not, the same metrics used during the calibration were calculated for the new set of results (RMSE, CV RMSE and NMBE). Additionally, a graphical assessment was used to understand whether the simulated values also matched visually with the measured data. This was specifically important for the daylighting model because illuminance values can vary very rapidly and, in theory, a model giving statistically accurate values could fail to capture the dynamics of the measured data and suffer from a cancellation effect between time steps.

4. Results

4.1. Results of the calibration and validation of the simulation model without a shading device

The results for the calibration and validation of the thermal model of the chamber without the shading device (case 0) are presented in Table 6. For the daylighting model, the hand calibration of the model yielded the values given in Table 7.

The results of the simulated values for the illuminance levels and air temperature in the chamber given by the calibrated model are compared against the measured values in Fig. 3 and the accuracy of the calibrated model is estimated in Table 8. The outdoor boundary conditions (outdoor air temperature and global horizontal irradiance) are provided below each graph to compare the results of the model and the measurements to the variations of intensity of the environmental signal. From Fig. 3 and Table 8, it possible to see that the simulated temperature was almost always within the uncertainty interval of the measured value (±0.5 °C) and yielded an RMSE of 0.5 °C. The CV RMSE was +2% and the NMBE was 2%, which indicates that the distance between the measured and simulated data points was small, and the level of accuracy of the model is well within the acceptable error of building performance simulation tools. Overall, the evolution of the indoor air temperature in the chamber without the shading system followed the same trend as the outdoor air temperature, but had a small delay of approximately one to two hours in the peaks due to the inertial effect of the test cell.

For the daylighting, the model with the selected parameters recreated the correct shape of the signal for solar irradiation entering the chamber, and captured the small dips in daylight levels measured both

Table 8
Metrics to estimate the accuracy of the model after calibration and validation.

Model	Quantity	Calibration period (August 3rd 7 a.m. to August 5th 7 a.m.)	Validation period (August 5th 8 a.m. to August 7th 8 a.m.)
Thermal	RMSE	0.5 °C	0.6 °C
	CV RMSE	2%	2%
	NMBE	2%	2%
Daylighting on desk	RMSE	41 lux	71 lux
	CV RMSE	8%	14%
	NMBE	0%	−3%
Daylighting on ceiling	RMSE	36 lux	35 lux
	CV RMSE	17%	15%
	NMBE	10%	8%

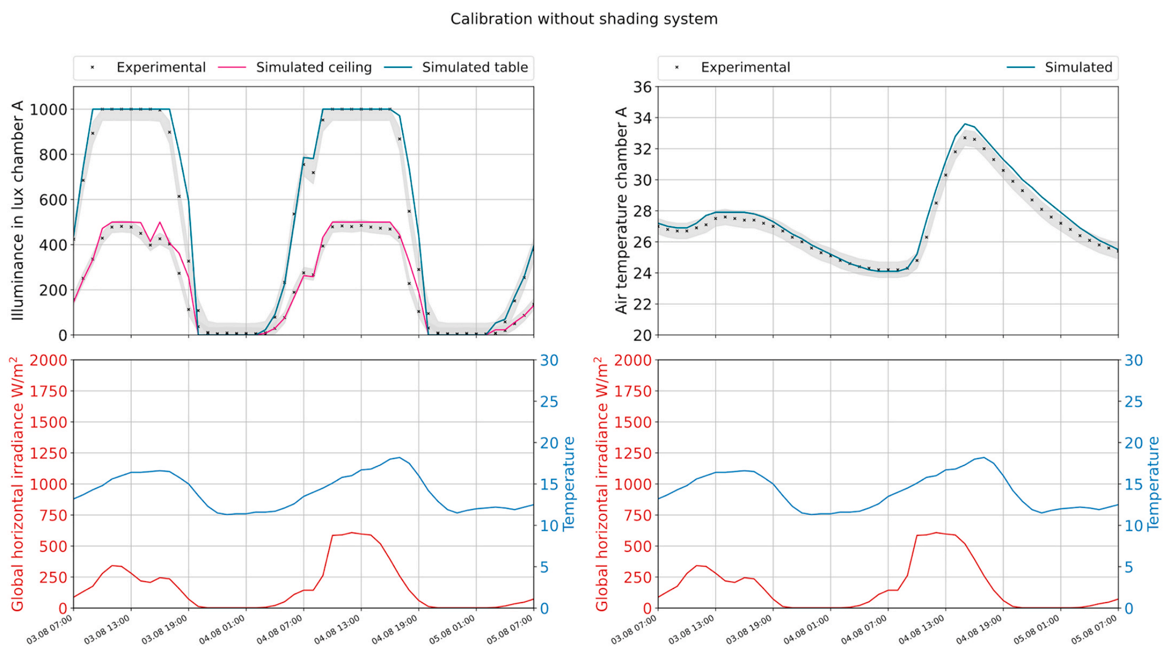


Fig. 3. Results of the calibration of the model for case 0 (no shading) during the period August 3rd 7 a.m. to August 5th 7 a.m.

on the ceiling and on the desk surfaces. Despite the boundary conditions depicting one fully sunny day and one slightly cloudier day, both illuminance sensors in the chamber saturated during the middle of the day and made it impossible to calibrate the model with peak illuminance levels. For the daylighting model the RMSE was calculated as 41 lux and 36 lux for the desk and the ceiling surface respectively, the CV RMSE as 8% and 17% and the NMBE as 0% and 10% again for the desk and ceiling surface respectively.

The model was then tested on a new independent data set representing two days in order to be validated. The results of the validation phase of this study are reported alongside those of the calibration period in Table 8 and show that the RMSE was 0.6 °C for the thermal model. As can be seen in Fig. 4, the air temperature simulated in the chamber was also almost always within the confidence interval of the measured value, only slightly above during the first day. For the validation period, the CV RMSE of the thermal model was calculated as 2% and the NMBE as 2%. These two values indicate good accordance between the measurements and the simulation results, but the positive bias shows that the model predicted a slightly higher air temperature than what was measured in-situ.

For the daylighting model, the shape of the illuminance dome received by the two surfaces in the chamber matched the measured illuminances as it did during the calibration period, but again it was not possible to compare peak illuminance levels because of the saturation points of the sensors. For the daylighting results, the RMSE was calculated as 71 lux and 35 lux for the desk and ceiling surface respectively, and the CV RMSE and NMBE were calculated as 14% and -3% for the desk, and 15% and 8% for the ceiling surface. Overall, the values given by the RMSE, CV RMSE, and NMBE for both models are considered close to the ones obtained during the calibration period given the accuracy of the sensors, and thus satisfactory in replicating the thermal and daylighting performance of the space under test.

4.2. Results of the calibration and validation of the model with the shading device

An overview of the results for all the cases is presented in Table 9 before being discussed individually in the following section. Table 9 also shows the results of the second part of the calibration associated with determining the reflectance value of the louvres using case 16. For each case, as previously, two separate graphs are plotted: one for the daylighting model and one for the thermal model with the specific corresponding measured boundary conditions reported below each graph.

The second calibration, which only changed the reflectance of the louvres was carried out manually over two days corresponding to June 17th 7 a.m. until June 19th 7 a.m. and provided an RMSE of 0.2 °C for the thermal model, a CV RMSE of 5%, and an NMBE of 0%. For the daylighting model, the RMSE was calculated to be 42 lux on the desk and 57 lux on the ceiling. The CV RMSEs were 18% and 35% for the desk and the ceiling respectively. Finally, the NMBEs were −2% on the desk and −24% on the ceiling. This calibration allowed determining a reflectance value of 0.07 for the blue louvres as reported earlier in Table 7 and the corresponding graphical results of the calibration are shown in Fig. 5.

To validate the model for case 16, a simulation was run on a new set of data corresponding to three days between June 12th at 7 a.m. and June 15th at 7 a.m. The results of the simulation are shown in Fig. 6. These show that the simulated temperature was always either within or very close to the value measured and within the uncertainty range. The trend formed by the simulated temperatures, although almost identical in its shape, was slightly delayed compared to the measured values and the discharge phase (i.e. the time after the temperature peak) did not seem as rapid as it did in the measurements. According to Table 9, the calculated RMSE for the thermal model of the case 16 was also 0.2 °C. The CV RMSE was determined as 5% and the NMBE, once again, showed a negligible bias with a value of 0%.

For the daylighting model, the model yielded an illuminance profile similar in its shape to the measured illuminance levels, this time without

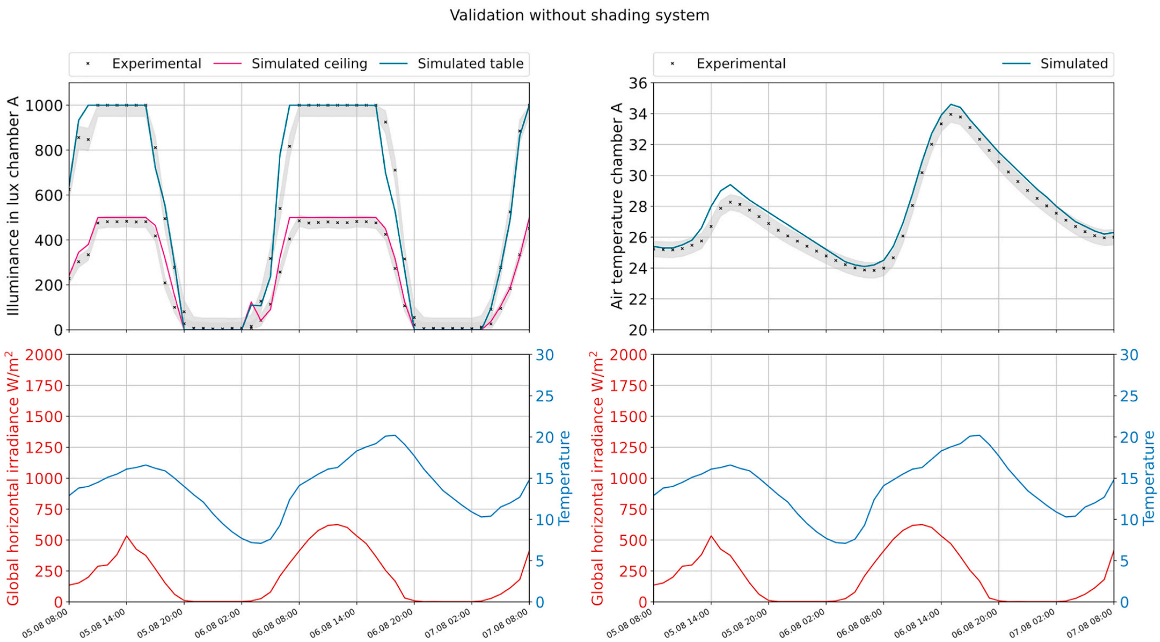


Fig. 4. Validation of the model for case 0 (no shading system) during the period August 5th 8 a.m. to August 7th 8 a.m.

Table 9
Metrics calculated to assess the accuracy of the model predictions for all cases investigated.

Engine/method	Model	Quantity	Second calibration[a]	Validation				
			Case 16	Case 16	Case 13	Case 13 mod. A	Case 13 mod. B	Case 13 white
EnergyPlus	Thermal	RMSE	0.2 °C	0.2 °C	0.3 °C	0.2 °C	0.3 °C	0.2 °C
		CV RMSE	5%	5%	5%	5%	5%	1%
		NMBE	0%	0%	−1%	0%	0%	0%
Daysim in Honeybee legacy	Daylighting on desk	RMSE	42 lux	58 lux	74 lux	52 lux	72 lux	82 lux
		CV RMSE	18%	22%	25%	16%	19%	35%
		NMBE	−2%	−10%	−5%	2%	0%	−1%
	Daylighting on ceiling	RMSE	57 lux	46 lux	58 lux	40 lux	39 lux	25 lux
		CV RMSE	35%	27%	41%	29%	26%	11%
		NMBE	−24%	−17%	27%	18%	13%	−1%

[a] Calibration of the optical properties (reflectance) of the shading device.

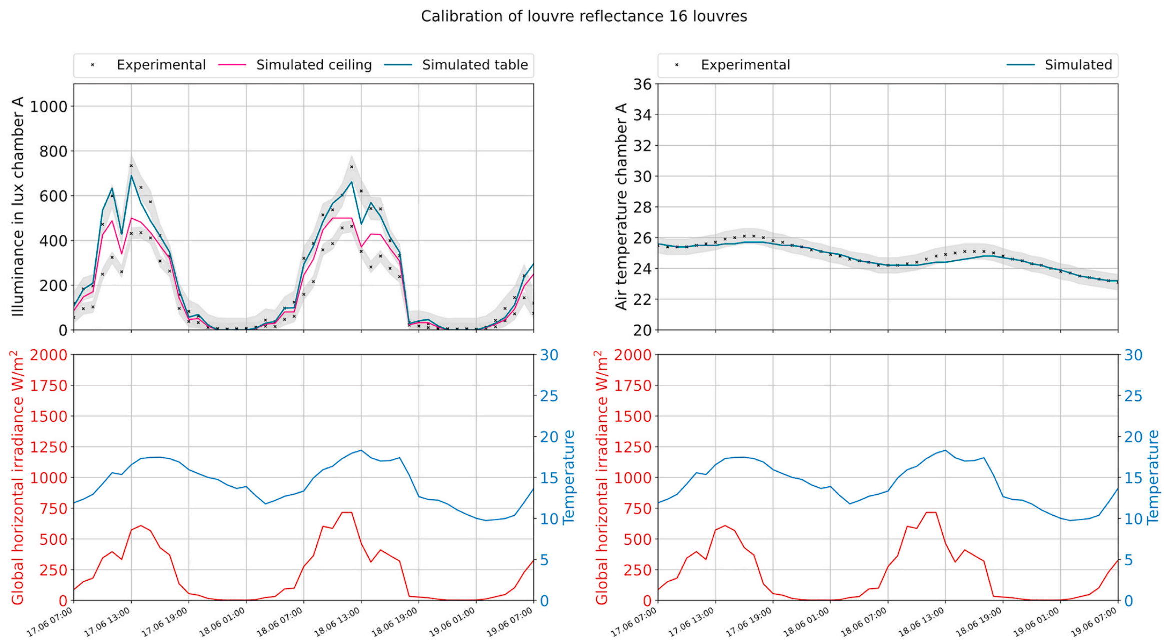


Fig. 5. Results of the calibration of the louvre reflectance using case 16 during the period June 17th 7 a.m. to June 19th 7 a.m. (16 equally spaced and tilted louvres).

the sensors saturating. The shape of the peaks was respected but the intensity was underestimated, especially on the last day of the validation. The RMSE, CV RMSE, and NMBE were 58 lux, 22%, −10% and 46 lux, 27%, −17% for the desk and the ceiling surface, respectively.

For the case 13, which had 13 louvres equally spaced and tilted at 15°, the thermal model was able to predict the air temperature inside the chamber within the uncertainty interval of the measured temperature as seen in Fig. 7. The simulation error was particularly small when the outdoor temperature and the global horizontal irradiance were lower. During this period, as shown in Table 9, the RMSE of the thermal model was 0.3 °C, the CV RMSE was 5%, and the NMBE -1%. All these values indicate that the model for case 13 maintained the same accuracy level as it had during the validation of the model without the shading system and with the shading system in case 16.

For the daylighting model, the simulated illuminance on the desk and ceiling followed quite closely the values obtained with the measurements. However, as in the previous case, the illuminance was often overestimated on the ceiling. On the third day, both simulated illuminance profiles match the recorded global irradiance but provided a poorer match to the measured values, especially on the desk. The RMSE for the daylighting model for case 13 was calculated as 74 lux for the desk and 58 lux for the ceiling. The CV RMSE and NMBE were calculated as 25%, −5% and 41%, 27% respectively for the two analysed surfaces. This indicated that the model was on average a less accurate in predicting illuminance on the ceiling in conditions where the illuminance profiles showed a large amount of variation during the day, and tended to overestimate the amount of light in the chamber.

For the 13 louvres modified cases, the louvres were set up in a way that their spacing was heterogeneous and the angles of each louvre could also be different from one another as shown previously in Table 2. The results for the first one of the modified cases, referred to as case 13 modified A, are shown in Fig. 8. For the thermal model, the predicted temperature was well within the uncertainty interval of the measured temperature during the days with lower outside temperature and weaker solar radiation. The RMSE of 0.2 °C indicates that the distance between the simulated and measured values was small (Table 9). The CV RMSE and NMBE which were −5% and 0% were in line with the previously determined accuracies.

For the daylighting model, the simulated values followed the trend of the measured values, but the daily profile shows a slight early dip in the

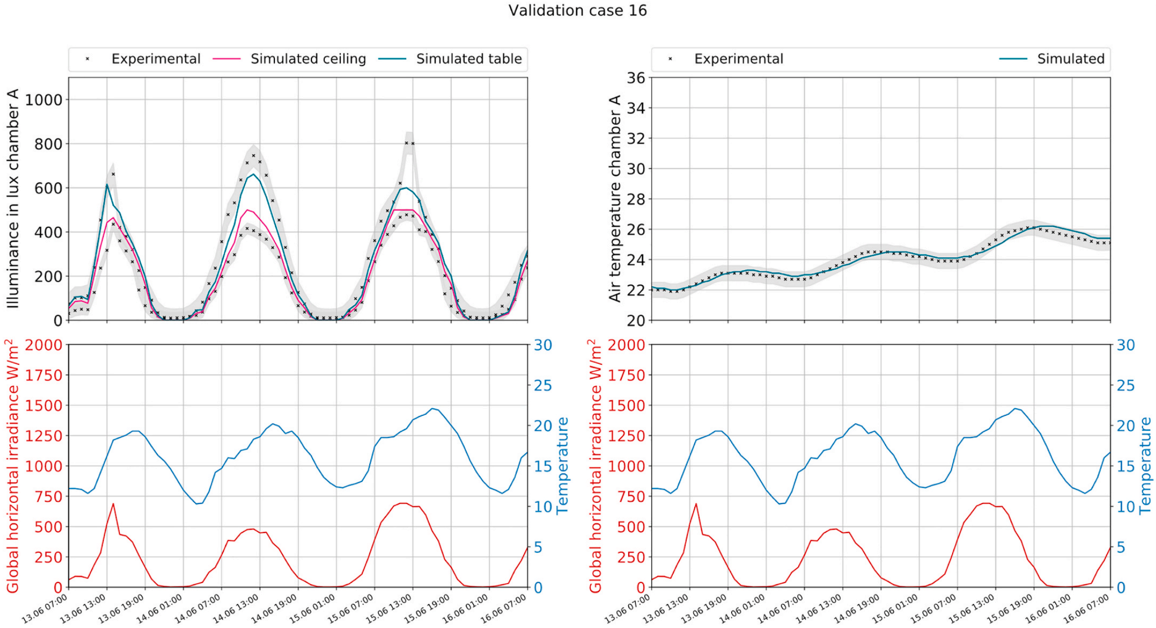


Fig. 6. Results of the validation for case 16 (16 equally spaced and tilted louvres).

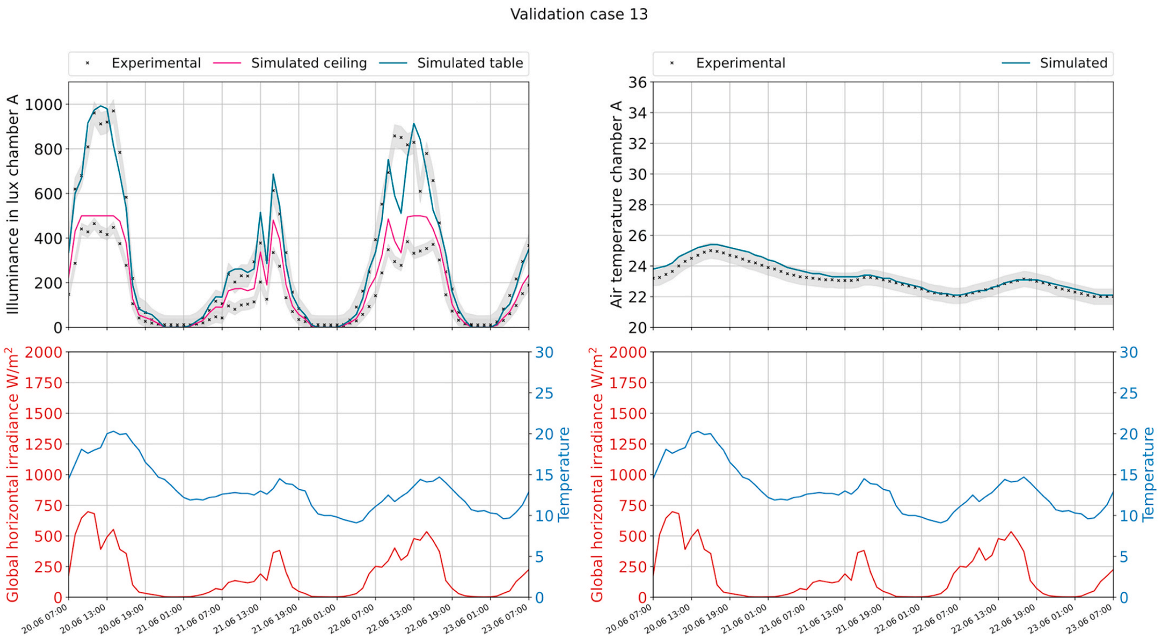


Fig. 7. Results of the validation for case 13 (13 louvres equally spaced and tilted).

illuminance a couple of hours before the measurements did on days with higher solar irradiation. The RMSE values (52 and 40 lux) for the two surfaces were like those of case 16 and smaller than in case 13. The CV RMSE values showed the model was consistent in its level of accuracy for the ceiling surface (16%) and slightly more accurate than previously on the desk with a CV RMSE of 29%. In terms of the NMBE, the illuminance on the desk was, on average, overestimated by 2% while the illuminance on the ceiling was overestimated on average by 18%.

For the second modified configuration (Fig. 9), referred to as case 13 modified B, the thermal model predicted the air temperature with an

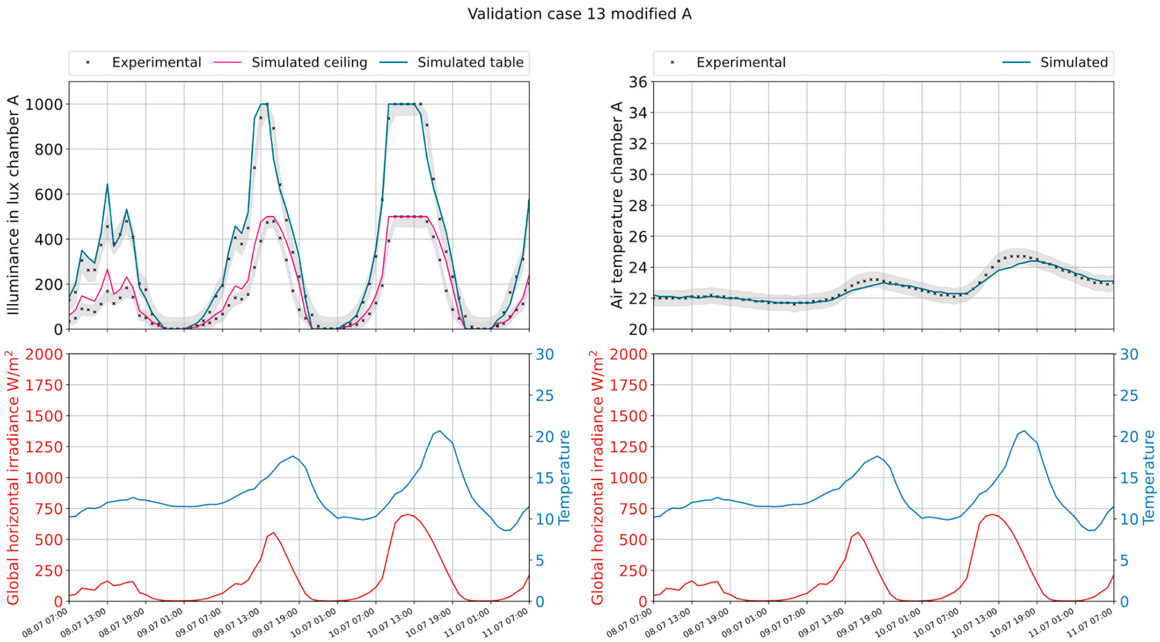


Fig. 8. Results of the validation for case 13 modified A (variable interspacing of the louvres and angles).

RMSE of 0.3 °C, the CV RMSE and NMBE were 5% and 0% respectively. These values are consistent with the previously reported values.

The simulated illuminance values show that the model was able to reproduce the variations of the measured values but was less accurate when the light was more variable as it was on the last day. The RMSE value of 72 lux on the desk is like the value obtained in the case 16, and the RMSE of 39 lux is the lowest value obtained for the blue louvres all configurations considered. The CV RMSE values were 19% on the desk and 26% on the ceiling. The NMBEs also indicate a more accurate model with 0% on the desk and 13% on the ceiling surface.

For the case with 13 white louvres, it was not possible to select three days with a large variation in the outdoor boundary conditions, and the

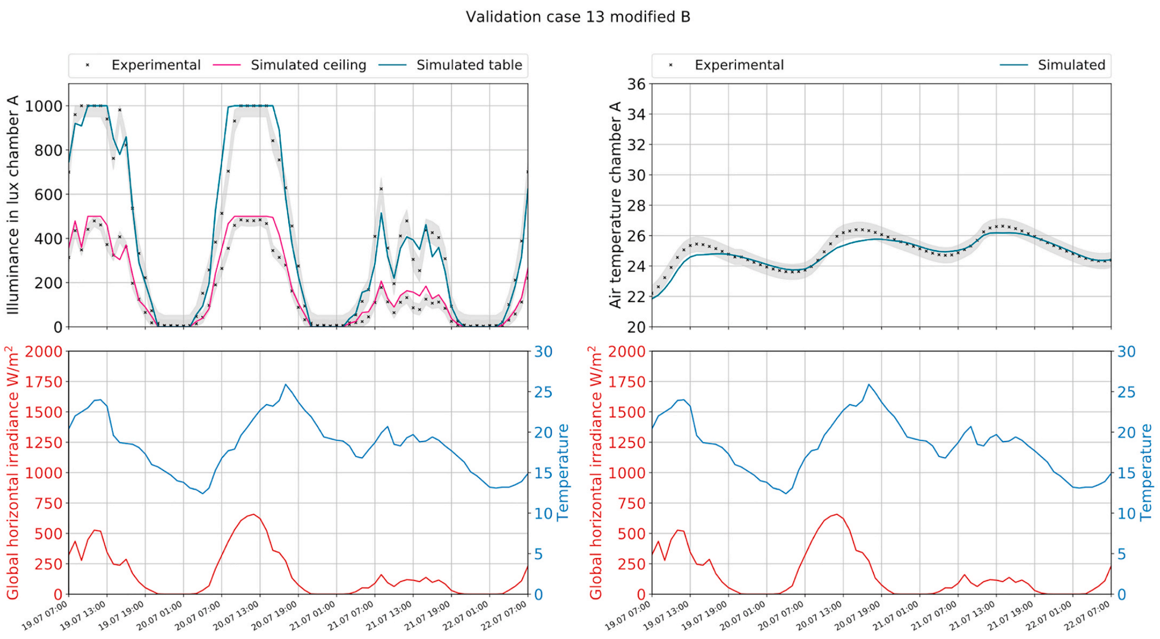


Fig. 9. Results of the validation for case 13 modified B (variable interspacing of the louvres and angles).

measurements were obtained during three mostly sunny days (Fig. 10). The results of the simulated temperature in the chamber were, once again, quite close to the measured values and within the uncertainty interval. However, the profile of the simulated temperature slightly underestimated the peak temperature. Overall the RMSE was 0.2 °C, which was identical to previous validation cases. Both the CV RMSE and NMBE reported in (Table 9) indicated that the model was as accurate as previously.

For the daylighting models, because the boundary conditions consisted of three very sunny days and due to the reflecting nature of the louvres, both sensors saturated during the day as previously during the first validation period. The global shape of the illuminance on the ceiling was in line with the measurements while the one for the desk showed a flawed trend in which the illuminance level on the desk dropped preemptively at the end of the day. As a result, the RMSE was as 82 lux on the desk surface while it was 25 lux on the ceiling. The CV RMSEs and NMBEs were 35%, −1% and 11%, −1% respectively, which makes this model one of the least accurate of the models investigated in predicting the illuminance on the desk and the most accurate on the ceiling.

5. Discussion

The approach chosen in this study was to use parametric design coupled to co-simulation to run both thermal energy and backwards ray-tracing daylighting simulations. The thermal model was calibrated using automated calibration, and yielded results that were within the uncertainty of the simulation engine for all cases investigated (RMSE $\leq$ 0.3 °C, 0 $\leq$ NMBE $\leq$ 1%). The CV RMSE was similar during validation and calibration (2%), and ranged from 1 to 5% for the cases with the shading system. This indicates that the thermal model was particularly accurate since, according to the authors of [41], calibrations with a CV RMSE below 3% provide the highest accuracy for the input parameters in energy or temperature simulations.

The daylighting model estimated the illuminance at two different heights in the test chamber and was calibrated using hand calibration. The illuminance on the ceiling was predicted in all cases with an RMSE between 25 and 58 lux, but the CV RMSE and NMBE indicated that the model mostly overestimated the amount of light reaching the ceiling sensor. The illuminance predicted on the desk had an RMSE between 53 lux and 74 lux, except for the case with white louvres where it was 82 lux. Considering that the model without a shading device during the validation had an RMSE of 71 lux, the accuracy of the simulated illuminance on the desk for the cases with the blue (low-reflectance) louvres was as good as when there wasn't a shading system, and slightly less when the system was white. The value of the CV RMSE on the desk was consistent for all the cases with shading devices, but was sometimes twice as much as when there was no shading system. This error could be due to the conditions during the calibration where the sensors saturated during the day, and may have provided a false sense of accuracy which was revealed when the shading system was present and the sensors no longer saturated. For the case with 16 louvres, it appeared that the model possibly underestimated the amount of light entering the room, which could be an issue tied to how the global solar radiation was split between its direct and diffuse components, or be due to how the Daysim software calculates sun positions. The latter is a weakness of the software discussed in Ref. [57]. For other cases, the main type of error in the model seemed to appear on sunny afternoons where the simulated illuminance dropped ahead of the measured one, and the models always underestimated the amount of light. This error could be due to how direct radiation was reflected into the room.

In order to provide a sense of the magnitude of the error related to using a simplified modelling approach such as is used in Daysim, two daylighting metrics, the daylighting autonomy (DA) [58] and the continuous daylighting autonomy (cDA) [59] were calculated on the desk surface based on the simulation results and the measurements. The calculations usied two different illuminance thresholds and a standard occupancy profile (7 a.m.–6 p.m. with all days considered weekdays). The results are shown in Fig. 11. Although these values only provide a

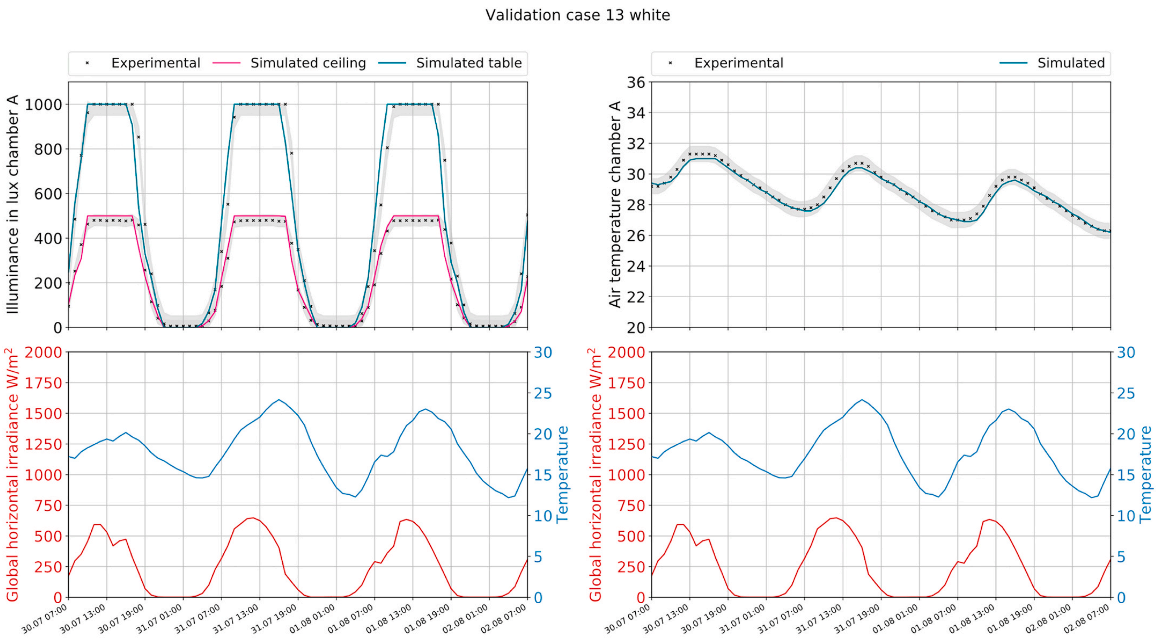


Fig. 10. Results of the validation for case 13 white louvres (equally spaced and tilted at 15°).

snapshot of the expected accuracy because of the limited analysis period, it is possible to see that most of the modelled cases yielded metric values within the uncertainty range of the measured values when using an illuminance threshold of 300 lux. With the higher threshold of 500 lux, it appears that the models for the modified configurations were less accurate, but the differences reported are still within the 20% uncertainty range of climate-based daylighting metrics [60].

Globally, the values outputted by the models showed that the accuracy of the simulations was below the maximum threshold defined in the ASHRAE guideline 14 [61] when it came to the thermal model, and within the uncertainty of the simulation engine. However, it is important to keep in mind that the maximum values provided in the standard are for annual simulations with hourly values. This may indicate that the values calculated over a shorter time only reflect the accuracy of the model for the type of boundary conditions measured at that time, i.e. summer conditions with high solar altitudes. Model calibration and validation are nonetheless, by nature, under constricted problems and many models using different parameter input values can theoretically yield similar results. To make sure that the model is accurate during other times of the year, it would be useful to verify the results during a different time with different boundary conditions, for example during the winter, spring, or fall.

Finally, the current model may suffer from certain limitations due to the modelling choices. For example, to avoid concave surfaces which may sometime lead to instability in the thermal engine, the oval-shaped surfaces of the louvres were not modelled as such but as diamond-shaped surfaces. This could impact how the radiation impinging on the louvres was reflected into the room. Additionally, because the louvres were modelled as context elements, the thermal model does not consider their temperature and whether they radiate heat towards the glazed surface behind them. This aspect was, however, considered quite minimal given the fact the glazing assembly had a low thermal transmittance with low e-coating and the airflow was not restricted around the shading system. For the daylighting model, the accuracy of the results was more inconsistent than for the thermal model, even though the illuminance profiles were well replicated by the model. Inaccuracies in the results could also be due to the fact that the daylighting model showed to be sensitive to shading masks from surrounding buildings and reflections. Unknowns of these parameters may be contributing to the deviations seen and possibly explain the discrepancies in the late afternoon hours of sunny days. Despite these limitations, the results altogether indicate that the simplified shading model implemented in the Honeybee legacy model has an acceptable level of accuracy for early design phases to model louvred shading devices, even when they start to take on non-traditional setups and resemble more free form configurations. However, the model may not be used for glare studies, as these are highly directional and work plan illuminance may not be enough.

6. Conclusion

In this study, a full-scale test facility was used to validate a highly flexible parametric co-simulation script for different configurations of an external louvred shading device. The simulations for the validation were carried out using a combination of thermal and ray-tracing simulation engines, which allowed assessing both daylighting and air temperature results. To ensure the robustness of the validation, six different cases corresponding to six different configurations were investigated. This approach aimed to understand whether the models could provide a consistent level of accuracy when specific properties of the system were modified such as the number of louvers, the homogeneity of the shadow created, and whether the model could accurately capture the effect of the appearance of the system. To further improve the robustness of this study, the calibration process is presented in detail including the specific precautions which were taken to avoid overfitting the data. First, the values of the parameters used for the calibration never deviated more than 10% from the nominal values. Second, the days selected for the

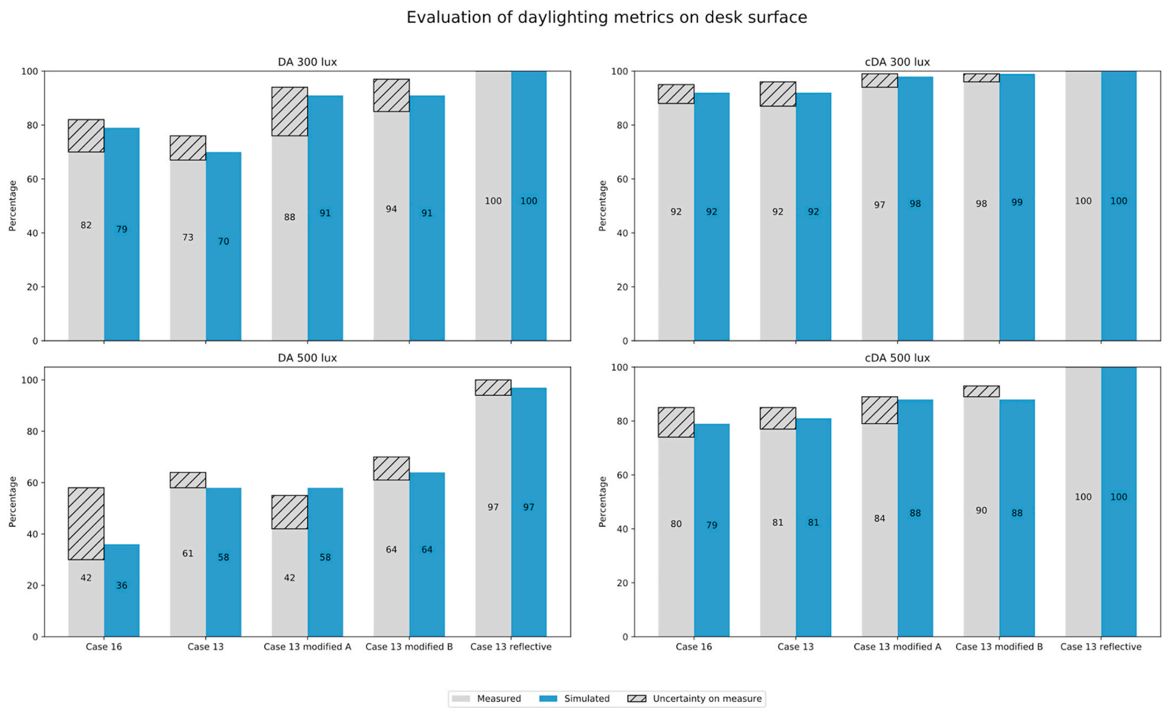


Fig. 11. Evaluation of two daylighting metrics on the desk surface compared to experimental data.

validations were specifically picked to cover different boundary conditions as much as possible.

The results of this study showed that for all six cases considered, the results of the simulation were in good agreement with the measurements and it was possible to validate all the models. The thermal models for the shading system were specifically reliable with an RMSE between 0.2 and 0.3 °C when the shading system was used. The models for the illuminance were slightly less accurate and more sensitive to surroundings (context elements) around the test chamber. Indeed, the results were not able to completely capture every peak when the incoming radiation varied abruptly, which would create difficulties estimating glare situations for example. However, for work plane illuminance studies, the general trends of the measurements were satisfactory with a maximal RMSE of 58 lux on the ceiling and 82 lux on the desk. The work presented in this article supports the idea that parametric scripting can be used in the early design phase to model complex shading elements which are not described with BSDFs with a certain level of accuracy, and that these models can successfully be coupled to multiple simulation engines to achieve co-simulation. Additionally, the approach was proven to be compatible with automated calibrations processes using optimization algorithms. By nature, parametric scripts allow modellers to access and control specific parameters which may not always be easy to isolate in the interface of whole building simulation tools, and these same parameters can be used as inputs for the calibration process. The ability to perform mathematical operations directly in the canvas of the parametric script also allows calculating key metrics that can be used as fitness functions (objectives) for the optimization component.

The output of this study is a robust grasshopper script which can be used and downloaded by users to model highly flexible external louvred shading systems considering a variable number of louvres, individually controlled tilt angles, material properties, and sizes. The script can be connected to daylighting studies and energy simulations as well as it can be implemented in optimization frameworks for more freeform search type studies for shading systems. Overall, the findings regarding the validation of the model are promising as façade design becomes more and more complex and the effect of non-conventional shading elements must be assessed considering the full spectrum of physical domains they interact with, that is light, air, and heat. As modern architecture evolves and façade elements gradually incorporate more and more functions, approaches such as the one described in this article are becoming more common for early design exploration and for this reason, validating models is of utmost importance to ensure the reliability and performance of advanced façade designs.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The work presented in this article was funded by the Research Council of Norway under grant number 255252/E20 for the SkinTech project. The authors would like to thank Schüco International, a partner of the SkinTech project for providing all the louvres and the brackets used in the experimental analysis. The authors would also like to thank Gaurav Chaudhary from the Norwegian University of Science and Technology for his assistance in creating of the.epw weather file, as well as Øystein Holmberget, Stig Roar Rudolfsen, Aleksandar Jankovic, and Alessandro Nocente from NTNU and SINTEF Community who provided extensive help to set up the shading system and the measurement equipment in the test chamber, working in scorching heat and pouring rain.

Appendix

Brief description of the script

The louvred shading device is generated from the base geometry of the blades which is a diamond-shaped surface defined by the thickness of the louvres and their width. The diamond-shape is then multiplied n-times, with n being the number of louvres, initially evenly distributed along the vertical axis of the window geometry. Then, the individual height of each louvre can be modified by providing a list of coordinates for the desired position of the louvres. The tilt angle of the louvres is also controlled either with a single slider input if the louvres are equally tilted or a list of angles. The diamond-shaped base surface of the louvres is then rotated following that angle from the horizontal position. The base shapes are finally extruded to match the required width of the window.

Each llouvre in the system can be further customized depending on the thickness, width and angle one wants to give it. To be able to freely distribute the llouvres in the vertical axis of the window, the script allows multiple types of input: one can either require evenly spaced and distributed llouvres, a list of input with inter-louvre distances, a list of coordinates or a genetic pool panel with variable values in given ranges. When using the latter, an additional part of the script is used to avoid geometric collisions between the louvres. To do so, a so-called “safety interval” is calculated around each louvre based on the size and the angle of adjacent llouvres. This is used to create what could be considered a “no llouvre zone” and can be increased with an additional safety distance of choice. The position of the louvres is then effectively controlled by two parameters instead of just one, the size of the zones where the louvres can be, which are separated above and below by “no louvre zones” and a second input which controls the exact position of the louvre in that zone.

Once the louvre geometries are created, the elements are connected to a Honeybee_context component with a radiance material description and then connected to the Honeybee_zone input of the Honeybee_annual_daylight component. For the thermal model, the geometries are connected to a different custom-made script which allows modifying the reflectance of the louvres by overwriting the default value of 0.2 in the IDF generated for EnergyPlus. This is done by generating text which should be connected in the additional strings input and redefines the Honeybee_context properties. In EnergyPlus, this includes defining the portion of the element which is glazed as a window to wall ration since context elements can be other surrounding building, the reflectance of the glazed part and the reflectance of the opaque part of the context. The geometries are also passed through a Honeybee_context component and connected as HB context on the Run EnergyPlus component.

The script can be found in open access and freely downloaded at the following web address:

https://zenodo.org/record/3929432#.Xv81XWgza9I and can be cited with the following DOI https://doi.org/10.5281/zenodo.3929432 https://doi.org/10.5281/zenodo.3929432.

References

[1] J. Nembrini, S. Samberger, G. Labelle, Parametric scripting for early design performance simulation, Energy Build 68 (2014) 786–798, https://doi.org/10.1016/j.enbuild.2013.09.044.
[2] V. Granadeiro, J.P. Duarte, J.R. Correia, V.M.S. Leal, Building envelope shape design in early stages of the design process: integrating architectural design systems and energy simulation, Autom. Constr. 32 (2013) 196–209, https://doi.org/10.1016/j.autcon.2012.12.003.
[3] M. Trcka, J. Hensen, Model and tool requirements for co-simulation of building performance, Proc. 15th IASTED Int. Conf. Appl. Simul. Model. (2006) 428–434, 2006.
[4] J.A. Clarke, J.L.M. Hensen, Integrated building performance simulation: progress, prospects and requirements, Build. Environ. 91 (2015) 294–306, https://doi.org/10.1016/j.buildenv.2015.04.002.

[5] D.A. Chi, D. Moreno, J. Navarro, Design optimisation of perforated solar façades in order to balance daylighting with thermal performance, Build. Environ. 125 (2017) 383–400, https://doi.org/10.1016/j.buildenv.2017.09.007.
[6] M. Manzan, A. Clarich, FAST energy and daylight optimization of an office with fixed and movable shading devices, Build. Environ. 113 (2017) 175–184, https://doi.org/10.1016/j.buildenv.2016.09.035.
[7] A. Eltaweel, Y. Su, Controlling Venetian blinds based on parametric design; via implementing Grasshopper's plugins: a case study of an office building in Cairo, Energy Build 139 (2017) 31–43, https://doi.org/10.1016/j.enbuild.2016.12.075.
[8] A.G. Kheybari, S. Hoffmann, Exploring the potential of the dynamic facade: simulating daylight and energy performance of complex fenestration systems (Venetian blinds), in: IBPSA (Ed.), BauSIM2018, 7th Ger. IBPSA Conf., IBPSA, Karlsruhe, Germany, n.d.: pp. 286–294.
[9] A. Kirimtat, O. Krejcar, B. Ekici, M.F. Tasgetiren, Multi-objective energy and daylight optimization of amorphous shading devices in buildings, Sol. Energy. 185 (2019) 100–111, https://doi.org/10.1016/j.solener.2019.04.048.
[10] H. Taleb, M.A. Musleh, Applying urban parametric design optimisation processes to a hot climate: case study of the UAE, Sustain. Cities Soc. 14 (2015) 236–253, https://doi.org/10.1016/j.scs.2014.09.001.
[11] A. Eltaweel, Y. Su, Parametric design and daylighting: a literature review, Renew. Sustain. Energy Rev. 73 (2017) 1086–1103, https://doi.org/10.1016/j.rser.2017.02.011.
[12] Y.K. Yi, Building facade multi-objective optimization for daylight and aesthetical perception, Build, Environ 156 (2019) 178–190, https://doi.org/10.1016/j.buildenv.2019.04.002.
[13] A.H.A. Mahmoud, Y. Elghazi, Parametric-based designs for kinetic facades to optimize daylight performance: comparing rotation and translation kinetic motion for hexagonal facade patterns, Sol. Energy. 126 (2016) 111–127, https://doi.org/10.1016/j.solener.2015.12.039.
[14] S.M. Hosseini, M. Mohammadi, A. Rosemann, T. Schröder, J. Lichtenberg, A morphological approach for kinetic façade design process to improve visual and thermal comfort: Review, Build. Environ. 153 (2019) 186–204, https://doi.org/10.1016/j.buildenv.2019.02.040.
[15] A. Tabadkani, M. Valinejad Shoubi, F. Soflaei, S. Banihashemi, Integrated parametric design of adaptive facades for user's visual comfort, Autom. Constr. 106 (2019) 102857, https://doi.org/10.1016/j.autcon.2019.102857.
[16] C. Waibel, R. Evins, J. Carmeliet, Co-simulation and optimization of building geometry and multi-energy systems: interdependencies in energy supply, energy demand and solar potentials, Appl. Energy. 242 (2019) 1661–1682, https://doi.org/10.1016/j.apenergy.2019.03.177.
[17] G. Lobaccaro, A.H. Wiberg, G. Ceci, M. Manni, N. Lolli, U. Berardi, Parametric design to minimize the embodied GHG emissions in a ZEB, Energy Build 167 (2018) 106–123, https://doi.org/10.1016/j.enbuild.2018.02.025.
[18] H. Samuelson, S. Claussnitzer, A. Goyal, Y. Chen, A. Romo-Castillo, Parametric energy simulation in early design: high-rise residential buildings in urban contexts, Build, Environ 101 (2016) 19–31, https://doi.org/10.1016/j.buildenv.2016.02.018.
[19] R. Hart, H. Goudey, D.C. Curcija, Experimental validation and model development for thermal transmittances of porous window screens and horizontal louvred blind systems, J. Build. Perform. Simul. 11 (2018) 190–204, https://doi.org/10.1080/19401493.2017.1323010.
[20] R. Hart, H. Goudey, D.C. Curcija, Experimental validation for thermal transmittances of window shading systems with perimeter gaps, J. Build. Perform. Simul. (2018) 1–13, https://doi.org/10.1080/19401493.2018.1436192, 0.
[21] I. Maestre, L. Pérez-Lombard, J. Foncubierta, P. Cubillas, Improving direct solar shading calculations within building energy simulation tools, J. Build. Perform. Simul. 6 (2013) 437–448, https://doi.org/10.1080/19401493.2012.745609.
[22] A.P. de A. Rocha, R.C.L.F. Oliveira, N. Mendes, Experimental validation and comparison of direct solar shading calculations within building energy simulation tools: polygon clipping and pixel counting techniques, Sol. Energy. 158 (2017) 462–473, https://doi.org/10.1016/j.solener.2017.10.011.
[23] H. Manz, P. Loutzenhiser, T. Frank, P.A. Strachan, R. Bundi, G. Maxwell, Series of experiments for empirical validation of solar gain modeling in building energy simulation codes-Experimental setup, test cell characterization, specifications and uncertainty analysis, Build. Environ. 41 (2006) 1784–1797, https://doi.org/10.1016/j.buildenv.2005.07.020.
[24] H. Simmler, B. Binder, Experimental and numerical determination of the total solar energy transmittance of glazing with Venetian blind shading, Build. Environ. 43 (2008) 197–204, https://doi.org/10.1016/j.buildenv.2006.10.011.
[25] C. Maurer, Theoretical and Experimental Analysis and Optimization of Semi-transparent Solar Thermal Façade Collectors, Karlsruher Instituts für Technologie (KIT), 2012, https://doi.org/10.13140/2.1.3979.9686.
[26] T. Wang, G. Ward, E.S. Lee, Efficient modeling of optically-complex, non-coplanar exterior shading: validation of matrix algebraic methods, Energy Build 174 (2018) 464–483, https://doi.org/10.1016/j.enbuild.2018.06.022.
[27] N. Jakica, A. Zanelli, F. Frontini, Experimental validation of optical simulation for complex building integrated photovoltaic system, in: Proc. 31st Eur. Photovolt. Sol. Energy Conf. Exhib. (EU PVSEC 2015), Hamburg, Germany, 2015, pp. 2890–2895, https://doi.org/10.16285/j.rsm.2012.01.048.
[28] C.A. Domínguez-Torres, A.L. León-Rodríguez, R. Suárez, A. Domínguez-Delgado, Numerical and experimental validation of the solar radiation transfer for an egg-crate shading device under Mediterranean climate conditions, Sol. Energy. 183 (2019) 755–767, https://doi.org/10.1016/j.solener.2019.03.054.
[29] L. Karlsen, P. Heiselberg, I. Bryn, H. Johra, Solar shading control strategy for office buildings in cold climate, Energy Build 118 (2016) 316–328, https://doi.org/10.1016/j.enbuild.2016.03.014.
[30] P.G. Loutzenhiser, H. Manz, C. Felsmann, P.A. Strachan, G.M. Maxwell, An empirical validation of modeling solar gain through a glazing unit with external and internal shading screens, Appl. Therm. Eng. 27 (2007) 528–538, https://doi.org/10.1016/j.applthermaleng.2006.06.016.
[31] M.C. Ho, C.M. Chiang, P.C. Chou, K.F. Chang, C.Y. Lee, Optimal sun-shading design for enhanced daylight illumination of subtropical classrooms, Energy Build 40 (2008) 1844–1855, https://doi.org/10.1016/j.enbuild.2008.04.012.
[32] S.J. Choi, D.S. Lee, J.H. Jo, Lighting and cooling energy assessment of multi-purpose control strategies for external movable shading devices by using shaded fraction, Energy Build 150 (2017) 328–338, https://doi.org/10.1016/j.enbuild.2017.06.030.
[33] I. Konstantzos, A. Tzempelikos, Y.C. Chan, Experimental and simulation analysis of daylight glare probability in offices with dynamic window shades, Build. Environ. 87 (2015) 244–254, https://doi.org/10.1016/j.buildenv.2015.02.007.
[34] C. Carletti, F. Sciurpi, L. Pierangioli, F. Asdrubali, A.L. Pisello, F. Bianchi, S. Sambuco, C. Guattari, Thermal and lighting effects of an external Venetian blind: experimental analysis in a full scale test room, Build. Environ. 106 (2016) 45–56, https://doi.org/10.1016/j.buildenv.2016.06.017.
[35] K. Sun, T. Hong, S.C. Taylor-Lange, M.A. Piette, A pattern-based automated approach to building energy model calibration, Appl. Energy. 165 (2016) 214–224, https://doi.org/10.1016/j.apenergy.2015.12.026.
[36] L.G.R. Santos, A. Afshari, L.K. Norford, J. Mao, Evaluating approaches for district-wide energy model calibration considering the Urban Heat Island effect, Appl. Energy. 215 (2018) 31–40, https://doi.org/10.1016/j.apenergy.2018.01.089.
[37] G. Ramos Ruiz, C. Fernández Bandera, T. Gómez-Acebo Temes, A. Sánchez-Ostiz Gutierrez, Genetic algorithm for building envelope calibration, Appl. Energy. 168 (2016) 691–705, https://doi.org/10.1016/j.apenergy.2016.01.075.
[38] T. Yang, Y. Pan, J. Mao, Y. Wang, Z. Huang, An automated optimization method for calibrating building energy simulation models with measured data: orientation and a case study, Appl. Energy. 179 (2016) 1220–1231, https://doi.org/10.1016/j.apenergy.2016.07.084.
[39] S. Asadi, E. Mostavi, D. Boussaa, M. Indaganti, Building energy model calibration using automated optimization-based algorithm, Energy Build 198 (2019) 106–114, https://doi.org/10.1016/j.enbuild.2019.06.001.
[40] G. Chaudhary, J. New, J. Sanyal, P. Im, Z. O'Neill, V. Garg, Evaluation of "Autotune" calibration against manual calibration of building energy models, Appl. Energy. 182 (2016) 115–134, https://doi.org/10.1016/j.apenergy.2016.08.073.
[41] S. Martínez, P. Eguía, E. Granada, M. Hamdy, A performance comparison of Multi-Objective Optimization-based approaches for calibrating white-box Building Energy Models, Energy Build 216 (2020) 109942, https://doi.org/10.1016/j.enbuild.2020.109942.
[42] McNeel Robert and Associates, "Rhinoceros Version 5.0," (n.d.), 2015, https://www.rhino3d.com/.
[43] D. Rutten, Grasshopper - Algorithmic Modeling for Rhino, 2017, version 0.9.0076. http://www.grasshopper3d.com/ (accessed October 9, 2017).
[44] M. Sadeghipour Roudsari, M. Pak, Ladybug: a parametric environmental plugin for grasshopper to help designers create an environmentally-conscious design, in: 13th Conf. Int. Build. Simul. Assoc. IBPSA, IBPSA, Chambery, France, 2013, in: http://www.ibpsa.org/proceedings/BS2013/p_2499.pdf.
[45] The Ladybug tools (n.d.), https://www.ladybug.tools/ (accessed March 6, 2019).
[46] E.D. Team, EnergyPlus engineering reference: the reference to EnergyPlus calculations, EnergyPlus (2016). Version 8.6. https://energyplus.net/.
[47] G. Ward Larson, R. Shakespeare, Rendering with RADIANCE. The Art and Science of Lighting Visualization, 1998.
[48] Schueco large louvre blades ALB - passive (n.d.), https://www.schueco.com/web2/us/architects/products/sun_shading_systems/large_louver_systems/alb_passive (accessed April 21, 2017).
[49] E. Taveres-Cachat, G. Lobaccaro, F. Goia, G. Chaudhary, A methodology to improve the performance of PV integrated shading devices using multi-objective optimization, Appl. Energy. (2019), https://doi.org/10.1016/j.apenergy.2019.04.033.
[50] E. Taveres-Cachat, K. Bøe, G. Lobaccaro, F. Goia, S. Grynning, Balancing competing parameters in search of optimal configurations for a fix louvre blade system with integrated PV, Energy Procedia 122 (2017) 607–612, https://doi.org/10.1016/j.egypro.2017.07.357.
[51] F. Goia, C. Schlemminger, A. Gustavsen, The ZEB Test Cell Laboratory. A facility for characterization of building envelope systems under real outdoor conditions, Energy Procedia 132 (2017) 531–536, https://doi.org/10.1016/j.egypro.2017.09.718.
[52] J.M. Bright, N.A. Engerer, Engerer2: global re-parameterisation, update, and validation of an irradiance separation model at different temporal resolutions, J. Renew. Sustain. Energy. 11 (2019), https://doi.org/10.1063/1.5097014.
[53] R. Vierlinger, Multi Objective Design Interface, TU Wien, 2013, https://doi.org/10.13140/RG.2.1.3401.0324.
[54] G. Cattarin, L. Pagliano, F. Causone, A. Kindinis, F. Goia, S. Carlucci, C. Schlemminger, Empirical validation and local sensitivity analysis of a lumped-parameter thermal model of an outdoor test cell, Build. Environ. 130 (2018) 151–161, https://doi.org/10.1016/j.buildenv.2017.12.029.
[55] F. Goia, M. Romeo, M. Perino, Simplified metrics for advanced window systems. Effects on the estimation of energy use for space heating and cooling, Energy Procedia 122 (2017) 613–618, https://doi.org/10.1016/j.egypro.2017.07.358.
[57] S. Subramaniam, R. Mistrick, A More Accurate Approach for Calculating Illuminance with Daylight Coefficients, 2018.
[58] C.F. Reinhart, O. Walkenhorst, Validation of dynamic RADIANCE-based daylight simulations for a test office with external blinds, Energy Build 33 (2001) 683–697, https://doi.org/10.1016/S0378-7788(01)00058-5.

[59] Z. Rogers, D. Goldman, Daylighting metric development using daylight autonomy calculations in the sensor placement optimization tool, Archit. Energy Corp. (2006) 1–52.
[60] E. Brembilla, D.A. Chi, C.J. Hopfe, J. Mardaljevic, Energy & Buildings Evaluation of Climate-Based Daylighting Techniques for Complex Fenestration and Shading Systems, 2019, p. 203, https://doi.org/10.1016/j.enbuild.2019.109454.
[61] American Society of Heating Refrigerating and Air-Conditioning Engineers, Ashrae, Guideline 14-2002: Measurement of Energy and Demand Savings, 2002.

A5 Paper V

Exploring the impact of problem formulation in numerical optimization: A case study of the design of PV integrated shading systems

E Taveres-Cachat, F Goia

Building and Environment Volume 188, 107422, (2021)

Building and Environment 188 (2021) 107422

Contents lists available at ScienceDirect

Building and Environment

journal homepage: http://www.elsevier.com/locate/buildenv

Exploring the impact of problem formulation in numerical optimization: A case study of the design of PV integrated shading systems

Ellika Taveres-Cachat [a,b], Francesco Goia [a,*]

[a] Norwegian University of Science and Technology. Department for Architecture and Technology. Trondheim, Norway
[b] SINTEF Community, Department for Architecture, Building Materials and Construction. Trondheim, Norway

ARTICLE INFO

Keywords:
Multi-objective optimization
Genetic algorithms
Genetic operators
Performance-based design
Shading devices

ABSTRACT

Optimization in buildings has been increasingly popular due to its growing availability and documented ability to improve the performance of building designs following specified targets. However, the quality and robustness of optimized solutions may be dependent on how the optimization problem is formulated, and few studies have investigated the impact of modelling choices or optimization strategies. This study presents a simulation-based investigation of the impact of problem formulation in building design optimization using the case study of a PV integrated shading device (PVSD) and an evolutionary algorithm. For this, we modify both the size of the solution space and how it is searched using three different approaches to define the objective function(s): single-objective optimization, bi-objective optimization, and tri-objective optimization. The results show that increasing the size of the solution space provided better designs compared to both a full factorial parametric analysis and an optimized but more rigid model, regardless of the nature and number of objectives. The findings support the idea that exploring the impact of problem formulation may be an important part of the process of optimization in buildings and allows obtaining more insight into the tradeoffs at play and the workings of a selected optimization study.

1. Introduction

The use of numerical optimization to design buildings and energy systems has become an increasingly popular topic in recent years with many algorithms available to researchers wishing to use optimization [1–5]. Nevertheless, this diversity of approaches also means that modellers still face difficult choices in setting up optimization problems that satisfy their needs and face tradeoffs such as accuracy vs simplicity, capability vs usability, flexibility vs visualization, or efficiency vs cost [4]. As pointed out by Machairas et al. [1] "*the understanding of optimization method's strengths and weaknesses is crucial in order for them to be used effectively in related design problems*".

Ideally, modellers should run sensitivity analysis before they start their optimization both to identify parameters and their value ranges [6,7], and to test the settings used in the algorithm selected [8]. However, often, for computationally slow simulations based on physico-mathematical models such as raytracing, there is little time available to run multiple analysis before time-expensive optimization runs, and modellers must make several assumptions. This means they may not have time to consider how the phrasing of their problem will impact their search.

While extensive work has been done on benchmarking different optimization algorithms for building design [9–11], to the knowledge of the authors, only a handful of studies [12–16] have considered the impact of the phrasing of the optimization problem on the resulting optimal designs. This results in a situation in which there are few guidelines available for researchers to understand what an adequate problem formulation is. By problem formulation, we mean how the optimization problem is set up in terms of the nature and number of parameters being optimized, the nature and number of objectives, and the settings selected for the type of algorithm used. These elements impact the dimension of the solution space and how it will be searched for solutions. We distinguish two aspects of problem formulation referred to as "soft" and "hard".

"Soft" problem formulation includes:

- The size of the solution space according to the number of variables used as parameters in the optimization
- The choice of the objectives both in terms of the number of objectives and whether they are formulated independently or as a combination

* Corresponding author.
E-mail address: francesco.goia@ntnu.no (F. Goia).

https://doi.org/10.1016/j.buildenv.2020.107422
Received 20 August 2020; Received in revised form 23 October 2020; Accepted 28 October 2020
Available online 4 November 2020

Nomenclature

cDA	Continuous Daylight Autonomy [%]
UDI	Useful Daylight Illuminance [%]
E_C	Annual cooling energy demand [kWh/m^2]
E_H	Annual heating energy demand [kWh/m^2]
E_L	Annual lighting energy demand [kWh/m^2]
E_{PV}	Annual PV-converted energy [kWh/m^2]
E_{TOT}	Annual net energy demand [kWh/m^2]

Acronyms

PV	Photovoltaic
PVSD	Photovoltaic Shading Device
GA	Genetic Algorithm
B3O	Base model with 3 objectives
F1O	Flexible model with 1 objective
F2O	Flexible model with 2 objectives
F3O	Flexible model with 3 objectives
PA	Parametric analysis

"Hard" problem formulation includes:

- The physico-mathematical complexity of the model used. This relates to the level of abstraction used to model the object of the optimization
- The choice of the algorithm itself and the mathematical equations implemented in it. This also includes parameter tuning within the algorithm, such as investigating the effect of population size, number of generations, crossover rates and mutation rates.

Both elements of problem formulation are important in building optimization. However, the impact of soft problem formulation has been investigated in a disproportionally lower number of studies compared to some of the aspects of hard problem formulation. For this reason, this study focuses on exploring the impact of soft problem formulation using the case study of the design of a fixed external louvred shading device with integrated PV (PVSD). PVSDs are "classic" optimization problems that must balance multiple competing objectives through different properties and geometric configurations. To ensure that our study is consistent and robust, following the concept of "No Free lunch Theorems" [17] or "no free lunch in optimization", we limit our investigation to search with an evolutionary algorithm implementing aspects of genetic algorithms. The NFL theorems "*establish that for any algorithm, any elevated performance over one class of problems is offset by performance over another class*" [17].

To explore the impact of problem formulation, we use two different models of a PVSD with different levels of flexibility in the design. We also use different optimization strategies in terms of the number and nature of the objectives set. This allows addressing the following research questions:

- What are the tradeoffs associated with increasing the size of the solutions space in the optimization of a shading device? This concerns the cost-benefit relationship between adding flexibility to the system design and possibly unnecessarily increasing the length and complexity of the optimization, versus simplifying the task of the algorithm by reducing the solution space
- How do the number and the nature of the objectives direct the search of the algorithm within the solution space?
- How do problem formulation studies help improve our understanding of optimization as a technique to explore interactions between physical parameters and building design targets?

The remainder of this article has the following structure: in section 2, we review guidelines for hard aspects of problem formulation given in the field of building design and data science. Previous works of shading device optimization are also reviewed in terms of problem formulation choices. In section 3, we present the methodology used in the study and the benchmark optimization problem used. Section 4 contains the results of the study and a discussion of the findings. The conclusions and future outlooks of the study are given in section 5.

2. Theoretical background

2.1. Building optimization problems

Radford & Gero [18] stated in 1980 that "*Design in architecture is a goal-directed activity in which decisions are taken about the physical form of buildings and their components in order to ensure their fitness for intended purposes. In order to take those decisions, the architect needs information on the relationship between his goals and the means at his disposal for achieving them.*" Since then, many studies have aimed at investigating these relationships in building design through optimization. A large number of these studies have focused on the building envelope and considered parameters related to its shape, orientation, and window to wall ratio as reviewed by Ref. [2,19]. Fewer studies considered optimizing daylighting parameters in buildings due to the associated algorithmic overheard, i.e. the computationally intensive task of running detailed daylighting simulations.

According to the literature, most of the studies in the building design optimization field have been carried out using genetic algorithms (GAs), which were first introduced by John Holland in 1975 [20]. This is because of the higher ability of GAs to solve building optimization problems [3,10]. However, their superiority to other algorithms for all problems has been questioned recently [9]. GAs are a subcategory of evolutionary algorithms, which are based on principles of evolution and biology. They are population-based algorithms, meaning that they search a solution space by creating increasingly better sets of solutions, one after the other. This is done using mechanisms of mating and a combination of two genetic operators, namely crossover and mutation. The performance of the algorithm both in terms of quality of the solutions and speed of convergence is affected by the value settings for some of these parameters. For GAs, these are mainly the population size, the number of generations, the crossover rate, and the mutation rate.

Despite GAs being more efficient than parametric analysis or random search when the solution space is large, the computational overhead associated with using GAs is sometimes prohibitive. For this reason, ideally, a GA should be set up to explore the design space without converging too early on a local optimal, but still, converge fast enough that unnecessary computational resource use is avoided. It should also be set up with a large enough solution space so that non-intuitive solutions can emerge from the process. To ensure maximum output value from an optimization, one should understand how problem formulation impacts the results. This means understanding the size of the problem space one wants to explore, the complexity of the problem, and selecting appropriate optimization settings accordingly.

2.2. "Soft" problem formulation in building design optimization

Only a few studies in the literature have considered the impact of different soft problem formulations on building design optimization problems.

Lu et al. [12] investigated the impact of using single versus multi-objective optimization for renewable energy systems considering two scenarios. They concluded that both optimizations outperformed the baselines but that while the single-objective optimization could find the optimal solution directly, the multi-objective optimization allowed obtaining more insight into the relationship between the parameters.

Li et al. [13] investigated the impact of using different combinations of objective functions for robust building envelope design of zero/low energy buildings in subtropical regions. Three objectives were considered following a review of design indicators in other fields. The authors found that one of the objectives turned out not to be appropriate for their building design problem. This indicates that exploring the formulation of the objectives was important to ensure the meaningfulness of the optimization.

Méndez Echenagucia et al. [14] used an integrated approach to obtain details about the relationship between building envelope configurations and energy efficiency in early design stages. Using GAs, they investigated several parameters of the building envelope in two different cases. They plotted the statistic distribution of the parameter values of Pareto solutions to highlight their variability. This was done to gain an understanding of which parameters had very small ranges of values and from this, deduce which parameters were useful to include in an optimization. Although the authors carried out this analysis after completing the optimization, they pointed out the fact that sensitivity analysis of parameter value ranges was a valuable step before using optimization. Indeed, reducing the range of values for each parameter narrows the solution space and helps focus the search of the algorithm.

Hou et al. [15] investigated the use of a two-step optimization approach, in which different variables were optimized at separate times. They found that compared to a traditional approach, the two-step method yielded solutions with less diversity in terms of parameter values, but these solutions were, in fact, closer to true optimum designs.

Delgarm et al. [16] studied a building design problem using three objectives which were first formulated in three separate single-objective runs and then combined in a tri-objective optimization. They found that, compared to a baseline, none of the single-objective optimizations could improve the performance of the building. For the tri-objective optimization, even though the algorithm couldn't find a solution that improved the performance considering all three objectives, selecting solutions that improved the performance of two objectives at a time was sufficient to improve the performance of the design compared to the baseline. For this reason, the authors inferred that multi-objective optimizations might be more interesting than single-objective optimizations.

2.3. General guidelines for "hard" problem formulation for GAs in the literature

Just like there is "no free lunch in optimization" regarding algorithm choices, optimal parameters in optimization problems also vary from problem to problem. However, there is an intuitive and accepted belief that in GAs, for example, some parameters can be set proportionally to the problem's size and difficulty [21]. Following the expressed scope of our study, we review guidelines and rules of thumb described in the literature to improve problem formulation for optimizations with GAs and allowing to define population sizes, number of simulations, and genetic operators.

Previous studies were able to outline trends such as the fact that if the number of parameters in the optimization problem is low, the impact of operator values is less, but this was no longer true when the problems became more complex [22]. Other studies have found that high mutation and crossover values are more efficient in small populations, but that too high mutation rates will lead to a random search problem [23]. In problems with large populations, low mutation rates were preferred. Many studies agree on the superiority of approaches in which these parameters are not static but either follow a predefined variation [24] or are even self-adapting [25]. However, these approaches are not yet standard in building optimization studies.

Magnier & Haghighat [26] point out that to reduce computational time, modellers tend to revert to two potentially harmful approaches: the first one is to simplify the models as much as possible, with the risk of oversimplifying the optimization problem; and the second one, is to select very small population sizes in the GA or only run a very small number of generations, which may lead to premature convergence and non-optimal solutions [23].

Two studies have proposed using parameter values based on benchmark problems and statistics from previous work [27,28]. This approach is promising but requires that knowledgeable optimization researchers be transparent in their work and provide a given level of certainty that the values are appropriate for the problem. In the literature, some guidelines related to hard aspects of problem formulation are provided, both for building design problems specifically and more general problems. These are reported and presented in Table 1. Note that some of these guidelines also introduce a dependency of the GA settings on the number of variables (parameters) in the problem.

The findings from the literature about the relationships between population size, mutation probability, and crossover rates can be summarized as such: problems with small population sizes can lead to inadequate solutions; larger populations provided better solutions as there is an increased chance that a good solution or an optimal is present within the population. This can, to some extent, be addressed by following the recommendation of Hamdy et al. [11] regarding population sizes. Optimizations with smaller populations (20–60 individuals) should be combined with higher mutation rates to increase diversity and avoid premature convergence. Conversely, problems with large populations should have low mutation rates and higher crossover rates to behold better solutions from their already diverse population.

To ensure that the optimization algorithm and the settings used are appropriate, it is also recommended in the literature that the optimization procedures be repeated a number of times. Waibel et al. [32] repeated the procedure three times while Cubukcuoglu et al. repeated it

Table 1
Overview of guidelines and recommendations in the literature for parameter settings of genetic algorithms.

Reference	Parameter setting	Value	Condition
Li et al. (2017) [29]	Population size	<50	Number of parameters <16
	Mutation rate	0.1	Number of parameters <21
	Crossover rate	0.5	Number of parameters <21
	Maximum generation	<1000	Number of parameters <21
Hamdy et al. (2016) [11]	Population size	2 to 4 times the number of parameters	1400 - 1800 simulation in total
De Jong (1975) [30]	Population size Mutation rate Crossover rate	50 to 100 0.001 0.6	
Grefenstette (1986) [23]	Mutation rate	Maximum 0.01 otherwise the problem becomes a random search regardless of other parameters. Values above 0.05 are typically harmful	
	Settings for small populations (20–60 individuals)	High crossover rate and low mutation rate Low crossover and high mutation rate	
Mühlenbein et al. (1993) [31]	GA parameters	The mutation rate is given by 1/N Mutation rates are more important in small populations to introduce diversity and avoid premature convergence Crossover rates depend on population size and are more important in large populations	N is the number of parameters or the size of the problem

five times [33].

2.4. Trends for problem formulation for optimization of shading devices in literature

An overview of soft and hard problem formulation details used in previous studies of optimal shading devices is presented in Table 2. This table provides insight on trends in problem formulation choices in studies based on evolutionary algorithms. It is possible to see that the variability of parameters used is large and that they are sometimes only partially communicated in the publications. Some disparities can also be noticed, for example, at an equal number of parameters, some authors ran up to six times the amount of simulations. Few studies used many parameters (<10), but these studies generally used the most simulation runs. In more recent years, there is also a general trend of running more simulations, likely because of the increase in the availability of computational power. It is also worth noting that there are no studies that investigated different numbers of parameters or objectives for the optimization of shading device design.

3. Methodology

3.1. Case study

This study is a simulation-based investigation of the impact of soft problem formulation on the design of external photovoltaic louvre shading systems (PVSD). The general approach used to augment PVSD performance is to investigate how the geometry can be modified to improve the ability of the system to balance competing parameters. These are daylight availability, solar gains, and electricity conversion on the surface of the louvres. In this study, the PVSD is modelled with the parametric software Rhinoceros [55] and the plug-in Grasshopper [56].

Table 2
Overview of previously published studies on the topic of optimization of shading devices. NC: not communicated in publication. Nb: number.

Reference	Object of optimization	Nb. of objectives	Algorithm name(s) or type	Nb. of parameters	Population size	Nb. of generations	Total nb. of simulations	Additional notes
Rapone et al. (2013) [34]	Ext. louvres	2	Self-developed in Matlab	5	40	15	600	
Gadelhak (2013) [35]	Light shelf Solar screen	1 1	SPEA2 in Octopus	6 3	NC NC	26 20		The authors indicated that the second study was not a completed full optimization
Manzan et al. (2014) [36]	Ext. louvres	1	ModeFrontier	4	16	100	1600	
Shan (2014) [37]	Fixed shading structure of variable depth	4	Self-developed	3	12	7	84	The authors ran the optimization several times
Gonzales et al. (2015) [38]	Ext. louvres	1	Galapagos	3	10	10	100	
Khoroshitlseva et al. (2016) [39]	Static shading device above window	4	Harmony search	12	30	50	1500	
Zani et al. (2016) [40]	Concrete static shading	4	SPEA2 in Octopus	4	NC	NC	1300	
Mahdavinejad et al. (2016) [41]	Fixed shading device	2	SPEA2 in Octopus	3	100	10	1000	
Manzan et al. (2017) [42]	Exterior louvres	1	ModeFrontier	3	16	100	1600	
Lavin et al. (2017) [43]	Perforated shading screens	1	Galapagos	4	10	10	100	
Vera et al. (2017) [44]	Ext. louvres	2	GenOpt	3	10	10	1000	
Toutou et al. (2018) [45]	Ext. horizontal shading device	2	SPEA2 in Octopus	7	50	6	300	
Sghiouri et al. (2018) [46]	Overhang shading devices	1	JEplus + EA (NSGA II)	4	150	8	1200	
Mangkuto et al. (2018) [47]	Light shelf	2	SPEA2 in Octopus	4	20	30	600	
Yun Kyu Yi (2019) [48]	Ext. louvres	3	NSGA II	4	40	100	4000	The authors ran tests using Matlab to define the parameters and the optimization problem converged before reaching 100 generations in every test run
Kirimtat et al. (2019) [49]	Amorphous shading device	2	NSGA II	25	100	50	5000	A second optimization was run in parallel using a surrogate modelling approach
Ho Jeong (2019) [50]	Surround-Type Shade	3	SPEA2 in Octopus	4	100	NC	NC	
Taveres-Cachat et al. (2019) [51]	PVSD	3	SPEA2 in Octopus	20 to 36	100	20	2000	Four different cases were investigated
Taveres-Cachat et al. (2019) [52]	PVSD	2	SPEA2 in Octopus	30 39 48 57	100 100 100 100	20 20 10 16	2000 2000 1000 1600	Four cases were investigated – computational time was an issue
Samadi et al. (2019) [53]	Ext. louvres	1	Galapagos	8	NC	17	NC	
Settino et al. (2020) [54]	PVSD	4	SPEA2 in Octopus	5	NC	NC	NC	

The performance simulation of the system is done using the environmental analysis plug-in Ladybug tools [57]. The optimization procedure used the plug-in Octopus [58]. The PVSD is scripted following a highly flexible parametric methodology previously described in Ref. [51] and validated in Ref. [59]. The validation procedure of this modelling approach was based on a full-scale experimental analysis of the thermal and the daylighting of several eclectic configurations of the external louvred shading device using a test cell. These configurations included several setups with unevenly spaced and individually tilted louvres and shading devices with two different reflectance values.

The reference building geometry used in this study is based on the Bestest case 600 [60] with an epw weather file for the location Oslo in Norway. The Bestest case 600 geometry is a 48 m^2 rectangular room (6 m × 8 m x 2.7 m) with two large south-facing windows (3 m × 2 m) that are equipped with the PVSD for this study. The building envelope properties, building operation schedules, and internal loads were defined to comply with the Norwegian technical standards NS3031 and NS3701 [61]. The HVAC parameters were modelled as ideal air loads and the energy source for the case study was assumed to be a heat pump (COP heating = 3, COP cooling = 5). More details are provided in Table 3.

The daylighting simulations were carried out using the Honeybee legacy plug-in based on Daysim. The daylighting level was measured using the continuous daylight autonomy (cDA) with a threshold of 500 lux on a work plan located 0.8 m above floor level. The radiance parameters for the daylighting simulations were set to the following: ambient bounce value of 3, ambient divisions value of 1000, ambient sampling value of 100, ambient accuracy value of 0.1, and an ambient resolution value of 300. For the details on these settings and the choice of the metric used, we refer to the full description of the methodology presented in Ref. [51].

The performance of the system was assessed using the following metrics:

- The total net energy demand in kWh/m^2 or E_{TOT}, calculated as:

$$E_{TOT} = E_H + E_c + E_L - E_{PV}\left[kWh/m^2\right]$$

where E_H is the heating energy demand, E_C the cooling energy demand and E_L the energy demand for artificial lighting.

- The continuous daylight autonomy or cDA expressed as a percentage of hours during working hours where the illuminance level on a work plan is above a threshold of 500 lux
- The energy converted by the PV surfaces in kWh/m^2 or E_{PV}, calculated as:

$$E_{PV} = \frac{\text{Radiation received on geometry} \times \text{cell efficiency} \times \text{area of louvre with } PV\ material}{Floor\ area}\left[kWh/m^2\right]$$

Note that the energy demand for artificial lighting is tied to the daylight availability via a proportional control strategy and a minimum dimming of 20% when the illuminance is below the threshold as described below:

$$E_L = \max\left(1 - \frac{measured\ illuminance}{500lux\ threshold}, 0.2\right) \times installed\ power$$

Table 3
Characteristics of the benchmark building used.

Component	Value	Note
U-value external wall	0.18 W/(m^{2}K)	Below the maximum value from NS3031
U-value roof	0.10 W/(m^{2}K)	Slightly above the recommended value from NS3701
U-value external floor	0.10 W/(m^{2}K)	Slightly above the recommended value from NS3701
U-value window (3 panes)	0.8 W/(m^{2}K)	Maximum value according to NS3701
g value	0.54	N/A
Air tightness	0.6 h^{-1}	Maximum value at 50Pa according to NS3701
HVAC system		Ideal air load
Mechanical ventilation	5.2 m^3/h per person 0.5 m^3/h. m^2	Ventilation load calculated for 4 people during occupation hours in addition to base flow rate for materials and VOC emissions
Internal load lighting	9.6 W/m^2	During occupation hours. Proportional artificial lighting control schedule to maintain 500 lx on work plane at 0.8 m from the floor
Maximum Internal load occupants	382 W	Variable according to schedules defined in NS3031
Maximum internal load equipment	21 W/m^2	Variable according to schedules defined in NS3031
COP heating system	3	Heat pump
COP cooling system	5	Heat pump
Setpoints (heating-cooling)	20–24	
Occupation hours	7–18	Weekdays

Table 4
Overview of the different parameters of in the base and flexible models of the PVSD.

Parameter	Parametric analysis model	Base model	Flexible model
Number of louvres	[10:16]	Predefined for each case	[10:22] louvres
Tilt angle	[0; 15; 30,45] ° from horizontal but same angle for all louvres	[0; 15; 30,45] ° from horizontal	[0; 15; 30,45] ° from horizontal
Louvre coating	Photovoltaic	Always photovoltaic	Reflective or photovoltaic
reflectance	R = 0.10 for PV material in both thermal and daylighting simulations	R = 0.10 in daylighting simulation R = 0.2 (default) in thermal simulation	R = 0.10 for PV material in both thermal and daylighting simulations R = 0.65 for reflective material in both daylighting and thermal simulations. Corresponds to aluminium
Louvre size	[100:200] mm with a 50 mm step but all louvres have the same width	105 mm	[100:200] mm with a 10 mm step
Vertical distribution of louvres	Equally spaced louvres, no vertical movement	Limited freedom - within a predefined fixed interval based on number of louvres	Extended freedom - within a recalculated interval

3.2. Description of the PVSD models

In this study, three different models are used to carry out the investigation: a reference model used in a parametric analysis, a base model, and a flexible model with a larger number of parameters. These are described in Table 4.

The parametric analysis is used to create a reference case when comparing the results of the different problem formulations. It included 3 different possible louvre sizes, 4 tilt-angles, and 7 different densities of louvres. This resulted in 84 possible combinations. The main differences between the base and the flexible model can be summarized as follows. In the base model, the louvres have a fixed width of 105 mm, whereas, in the flexible model, the width of the louvres could be controlled for each one of them separately. The vertical distribution of the louvres was also scripted with different approaches in the two models. In the base model, the louvres could only move vertically within precalculated height intervals centered around the positions of equally spaced louvres. In the flexible model, the number of louvres was controlled by the algorithm. This means the vertical distribution of the louvres was also much freer, and the only constraint to avoid louvres overlapping was to respect a safety interspace recalculated for each case.

Finally, in the base model, every louvre was considered to have PV material on its upper surface and otherwise be built of aluminium. The reflectance of these materials was, however, only considered in the daylighting simulation. This means that they had a constant reflectance equal to 0.2 for the thermal model. This was not the case for the flexible model, where not only were reflectances carried over in the thermal model, but the coating of the louvres could also be selected to be photovoltaic or light-reflecting. This allowed the creation of hybrid systems like the ones described in Ref. [52].

3.3. Impact of soft problem formulation

The problem formulation investigated in this study is used to evaluate three aspects.

First, we consider the impact of increasing the solution space by adding flexibility to the PVSD model. This is investigated using the characteristics of the different models described previously in section 3.2.

Second, we evaluate the impact of the strategy used in terms of objective formulation and the resulting relative performance of Pareto solutions obtained. This is done by comparing the results of multiple optimization runs in which three separate possible formulations of the objectives are used: single-objective optimization, bi-objective optimization, and tri-objective optimization. The different simulation procedures used in this study are reported in Table 5. It is worth highlighting that in all problems investigated, the elements that make up the objectives are always present, and the different objective functions simply consider them either explicitly or implicitly.

Third, we evaluate the impact of different problem formulations on the resulting phenotypes of optimal PVSD designs. For this, we analyze the statistical variability of the parameter values in Pareto solutions obtained with the different problem formulations. Studying the phenotypes of optimal solutions is interesting because, in building design, there may be more value in identifying robust *improved* designs rather than identifying a single *mathematical global optimal* solution to a problem.

3.4. Hard problem formulation settings

The optimizations were run using the same algorithm (Octopus). Octopus is a multi-objective optimization algorithm based on the evolutionary algorithm SPEA2 but implements a hypervolume indicator (HI) to overcome some of the weaknesses of the SPEA2 algorithm [62]. The size of the population, the number of generations, and the values of the genetic operators were kept constant between cases for each model version, but these numbers were adjusted between the base and the flexible model to reflect the increase in complexity of the problem. Increasing the size of the population allows having more genetic diversity in the solutions and maintain it for each generation (cf. section 2). The stopping criteria for each simulation run was defined by the total number of function evaluations. The details about the optimization settings are given in Table 6.

The simulations in this study were run on Dell computer Intel® Core™ i7-8700 @ 3.20 GHz and a 32 GB RAM, which can be considered a conventional business desktop designed for everyday commercial needs.

4. Results and discussion

4.1. Results of the parametric analysis

The first step of the study was to run a parametric analysis of the PVSD to create a reference; the results of the 84 possible combinations are presented in Fig. 1. The results of the parametric analysis were also used to run a simple analysis of variance (ANOVA) to check whether certain parameters could be eliminated due to not having any influence. The results showed that all parameters mattered equally and the P-value for all the parameters, that is the number of louvres, the tilt angle and the louvre size, was the same and equal to 0. This means that the ANOVA analysis could not identify inputs that could be eliminated to reduce the number of parameters based on the relationship between the inputs and the outputs.

Five reference configurations are selected among the results of the parametric analysis (PA) for the further analysis as baseline points with the following criteria: the solution which provided the highest cDA, the solution that provided the lowest E_{TOT}, the solutions that provided the

Table 5
Description of the 5 cases investigated with the optimization algorithm. NA: not applicable.

Case study name	Input parameter type	Objectives
PA - Initial parametric analysis for reference	Number of louvres Equally spaced louvres Single tilt angle for all louvres Single width for all louvres	N.A.
B3O- Base model with 3 objectives (fixed number of louvres)	Louvre tilt angles Vertical position of louvre	Maximize the cDA [%] Minimize E_{TOT} [kWh/m^2] Maximize E_{PV} [kWh/m^2]
F1O- Flexible model with 1 objective	Number of louvres Louvre tilt angles Vertical position of louvre Louvre size Louvre reflectance	Minimize E_{TOT} [kWh/m^2]
F2O- Flexible model with 2 objectives	Number of louvres Louvre tilt angles Vertical position of louvre Louvre size Louvre reflectance	Maximize the cDA [%] Minimize E_{TOT} [kWh/m^2]
F3O- Flexible model with 3 objectives	Number of louvres Louvre tilt angles Vertical position of louvre Louvre size Louvre reflectance	Maximize the cDA [%] Minimize E_{TOT} [kWh/m^2] Maximize E_{PV} [kWh/m^2]

Table 6
Overview of the genetic operator settings, population and generation settings used in the study.

Case study name	Number of parameters	Population size	Nb. generations	Elitism	Mutation	Crossover probability
B3O	2 per louvre	80	25	0.5	Rate 0.5 Probability 0.1	0.8
F10	4 per louvre	100	100	0.5	Rate 0.5 Probability 0.06	0.8
F20	4 per louvre	100	100	0.5	Rate 0.5 Probability 0.06	0.8
F30	4 per louvre	100	100	0.5	Rate 0.5 Probability 0.06	0.8

highest E_{PV}, the solution that provided the lowest E_{TOT} with a cDA above 50%, and the solution that provided the best balance. These solutions are highlighted in purple in Fig. 1, and their characteristics are detailed in Fig. 2.

4.2. Results of the investigation of soft problem formulation on the performance of the PVSD

The results of the different optimization runs are presented in Table 7. Because the base model uses a predefined number of louvres,

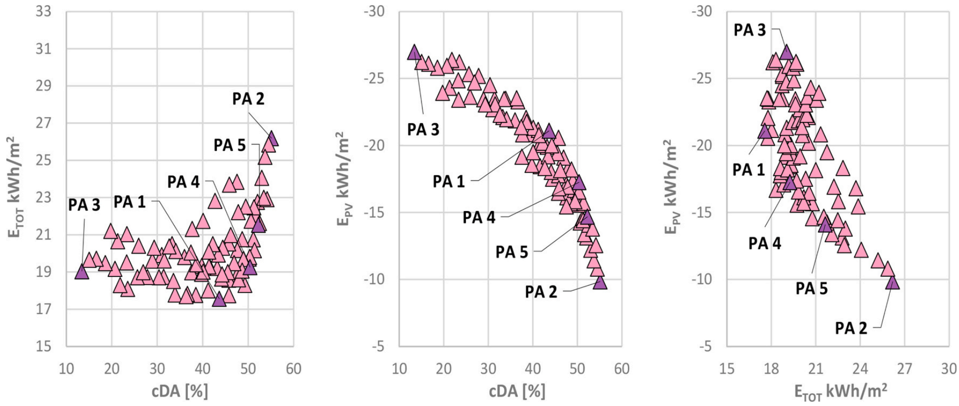


Fig. 1. Results of the parametric analysis projected in a 2D view. The points selected in purple are the points analyzed in Fig. 2. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Configuration code and description	PA 1 Lowest E_{TOT}	PA 2 Highest *cDA*	PA 3 Highest E_{PV}	PA 4 Lowest E_{TOT} with *cDA* ≥ 50%	PA 5 Intermediate solution
E_{TOT} [kWh/m²]	17.6	26.2	19.0	19.3	21.6
cDA [%]	44	55	13	50	53
E_{PV} [kWh/m²]	21.1	9.9	27.0	17.3	14.1
Number of louvres	11	10	16	10	10
Louvre tilt angle [°]	15	0	45	15	0
Louvre width [mm]	200	100	200	150	150

PVSD system section drawing and specifications

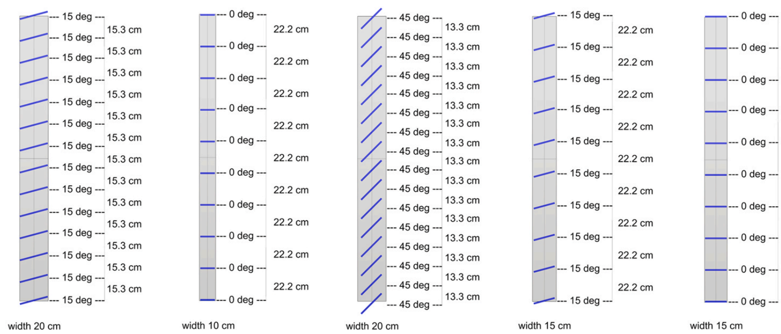


Fig. 2. Results of the parametric analysis of the PVSD.

Table 7
Simulation run-time and number of non-dominated solutions for all optimization cases.

Case	Average time per simulation	Nb. of non-dominated solutions	Total nb. of simulations
B3O – 10 louvres	Ca. 280 s	86	2000
B3O – 13 louvres	Ca. 280 s	95	2000
F3O	Ca. 280 s	110	10 000
F2O	Ca. 280 s	53	10 000
F1O	Ca. 280 s	1	10 000

two different simulation runs were used with 10 and 13 louvres. The number of louvres selected for these two cases is based on the findings of [51] and the results of the parametric analysis.

To compare the effect of having a different number of objectives, the Pareto points from the different simulation runs were combined in and plotted as 2D charts. To provide a bigger picture of the single-objective optimization, the nine dominated solutions were plotted in addition to the best solution that emerged from the optimization.

In Fig. 3, it is possible to see that the combination of the solutions from the flexible models formed a complete Pareto front that outperformed any solution obtained by the parametric analysis or by the base model optimization. The optimization with F3O provided the largest amount of Pareto solutions and provided the most solutions in the middle of the Pareto front, meaning they represent better-balanced solutions in terms of tradeoffs. Most noticeably, the solution with the lowest E_{TOT} and a cDA value above 50% reduced energy demand by 15% compared to the best solution from the parametric analysis with this same criteria. The results of the optimization with F2O were located at the top of the front meaning they provided better-performing solutions with regard to daylight than any other optimization run and a large number of solutions that improved both daylight and energy compared to the B3O and the PA. The results of F1O yielded solutions that visually seem to extend the Pareto front with a natural preference for reducing E_{TOT}, but the optimal solution performed no better than F3O.

The results of the optimization with B3O - 10 louvres allowed finding solutions that were intermediate between the results of the PA and F2O. They also outperformed PA 2 without increasing energy use. For the optimization with B3O - 13 louvres, the solutions given in the Pareto front provided some improvement compared to the results of the PA and were more oriented towards reducing E_{TOT} than B3O −10 louvre solutions.

When considering the cDA vs E_{PV} in Fig. 4, it is possible to see once

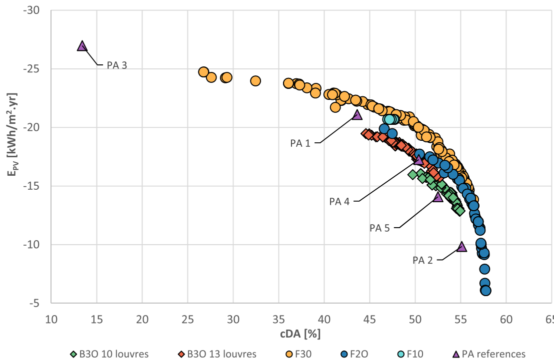


Fig. 4. Summary plot of all optimization runs with a 2D projection of the fitness of the Pareto front solutions and selected results from the parametric analysis for the tradeoffs energy converted by PV (E_{PV}) versus cDA. Note that E_{PV} is represented as negative to illustrate that this energy is discounted from the base energy demand.

more that the results from F3O performed uncontestably better than all the other models, providing many non-dominated solutions. The solutions of F2O, here again, prolong the Pareto front from F3O and perform better than all B3O results, as do the F1O results. In this case, the from the B3O −10 louvres were better compared to PA 5 and PA 2, but with if cutoff at cDA≥ 50% is used, then PA 4 provided a better solution. Interestingly, the results of B3O – 13 louvres are very similar to PA 4 and can only improve one or the other objective at a time. Note that in these figures E_{PV} is marked with a negative sign, this was to illustrate that it is energy discounted from the energy demand and differentiate it from E_{TOT} which is the net energy demand.

Fig. 5 shows the 2D plot of the Pareto points of all the models considering E_{TOT} and E_{PV}. An important observation that can be made about this plot is that it is not a Pareto front, which indicates that this was a degenerate Pareto problem when E_{TOT} and E_{PV} were used as objectives. The relationship between the objectives seems to have been linear for the problem set with the base model with 10 louvres, F2O and

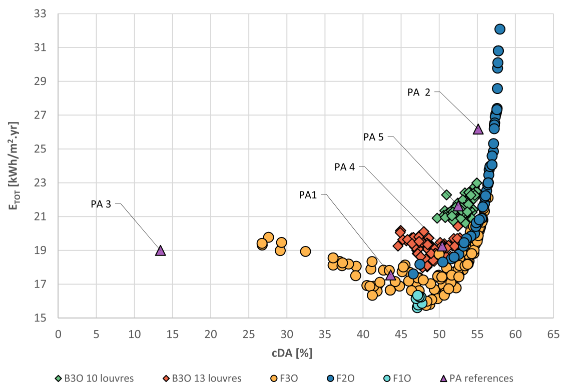


Fig. 3. Summary plot of all optimization runs with a 2D projection of the fitness of the Pareto front solutions and selected results from the parametric analysis for the tradeoffs cDA versus total net energy demand (E_{TOT}).

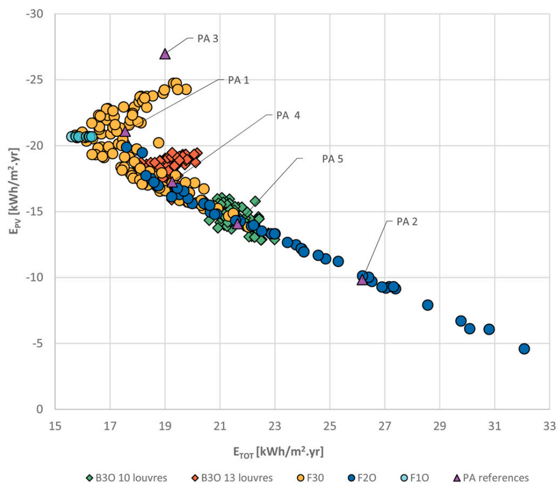


Fig. 5. Summary plot of all optimization runs with a 2D projection of the fitness of the Pareto front solutions and selected results from the parametric analysis for the tradeoffs energy converted by PV (E_{PV}) versus total net energy demand (E_{TOT}). Note that E_{PV} is represented as negative to illustrate that this energy is discounted from the base energy demand.

F1O. However, in solutions of F3O and B3O - 13 louvres, the relationship was not linear and had a polynomial V shape; with multiple solutions having the same E_{TOT} but different values of E_{PV}. This highlights that a balance could be found between letting light into the zone and increasing daylight, versus using it for electricity and compensating for the added heating and artificial lighting load. In this case, we can also see that only solutions from F3O and F1O could outperform PA 1, but the improvement was relatively significant. Here again, one may notice that the results of B3O – 10 louvres were always close to PA 5 while the results of B3O – 13 louvres resembled those of PA 4.

4.3. Results of the impact of soft problem formulation on the design of the PVSD and parameter values

For the rest of this section, the phenotypes of the Pareto points given by the flexible models only are investigated more in detail to understand how the problem formulation impacted the type of designs contained in Pareto solutions. The outcomes of this analysis are presented in Fig. 6 and Fig. 7. For the F2O optimization, all the Pareto solutions had 10 louvres except for two solutions. The F3O optimization had 45/110 Pareto points with 10 louvres, and the rest had 11. For the sake of comparability, the results presented below are calculated based on configurations with 10 louvres for F2O and F3O. The results of the best solution for the F1O optimization had 11 louvres, but the results are still shown in parallel for comparison. Note that regardless of the problem formulation, none of the Pareto solutions had louvres with light-reflecting material, meaning that the coating of the louvres was always PV material, and therefore this parameter variation is not presented. This, in addition to the fact that Pareto solutions all have 10 or 11 louvres, indicates that the problem formulation could have been improved and the solution space may have been possible to reduce. However, this problem can never be eliminated in optimization without taking the risk of exploring a solution space that is too small or excludes some solutions. It can only, at best, be minimized through problem formulation studies.

In the F3O optimization, the bottom louvre was almost always as large as possible. Narrower louvres followed and then slowly grew wider again for louvres at the top of the window in positions 9 and 10. The analysis of the width of the louvres in the optimization with F2O provides slightly different results. Multiple, large louvres appear at the bottom of the window, followed by gradually narrower louvres from just below mid-way up the window at louvre in position 6 and upwards. The results of the F1O optimization form a much more erratic pattern, and the only conclusion possible to make seems to be that the louvres in the solution were on average wider.

For the analysis of the tilt angle of the louvres, the F3O optimization provides a statistical trend in which the louvres at the lower part of the window were tilted as much as possible - except for louvre 4. The louvres at the top of the window were, on the other hand, horizontal. This trend is also visible for the F2O optimization, but the trend was more abrupt, and the upper louvres were consistently horizontal with no variability. For the F1O optimization, the angulation of the louvres followed a somewhat similar pattern, but the louvres were tilted at 15° rather than being horizontal.

The vertical distribution of the louvres shows a trend common to all three optimizations and previously outlined in Ref. [51]. This creates a design in which the louvres at the bottom part of the window are tightly spaced compared to a system with equally spaced louvres (reported in red on the figure), and then gradually space out more and more. Because the louvres at the top of the window were also horizontal, this created openings for the sunlight to enter and contribute to increasing the illuminance in the zone. The presence of this trend in the F1O optimization scenario, further shows that the tradeoffs associated with too low or too high solar gains – which in turn increased energy demand - were dealt with having a larger amount of light enter the room at the top of the window. It is also interesting to note that the position of the individual louvres in the F3O optimization only varied within a remarkably small interval compared to the F2O optimization, and in general, the variability of the parameters was contained within a smaller range. This is likely due to the additional constraint of the 3rd objective. This is also interesting since, to some extent, using E_{PV} as an objective created redundancy and acted in a similar way to weighting objectives.

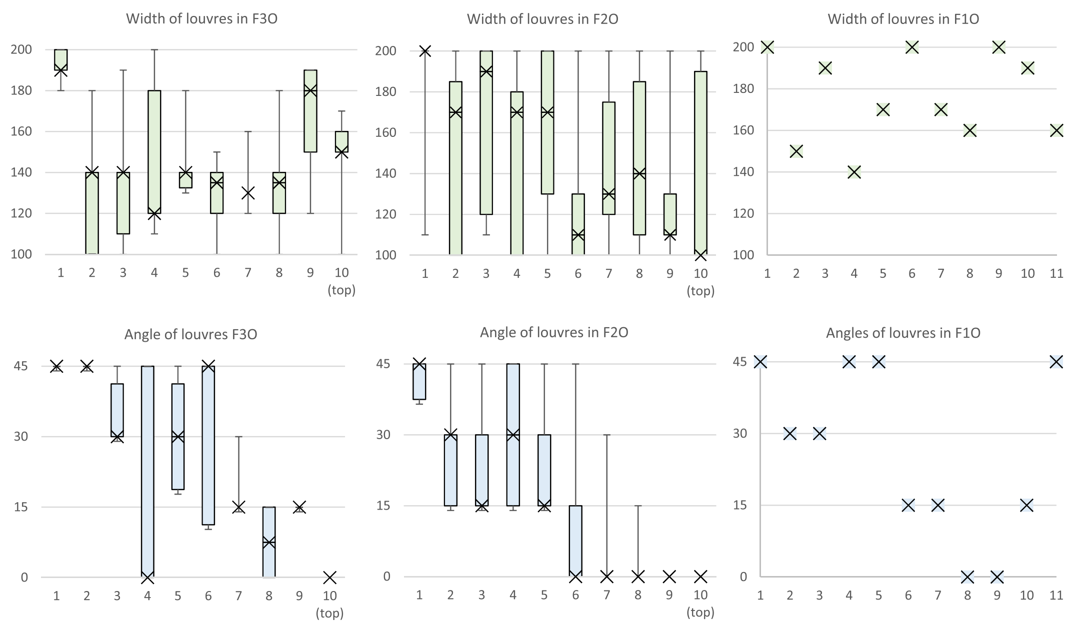


Fig. 6. Statistical analysis of the parameters making up the in Pareto solutions.

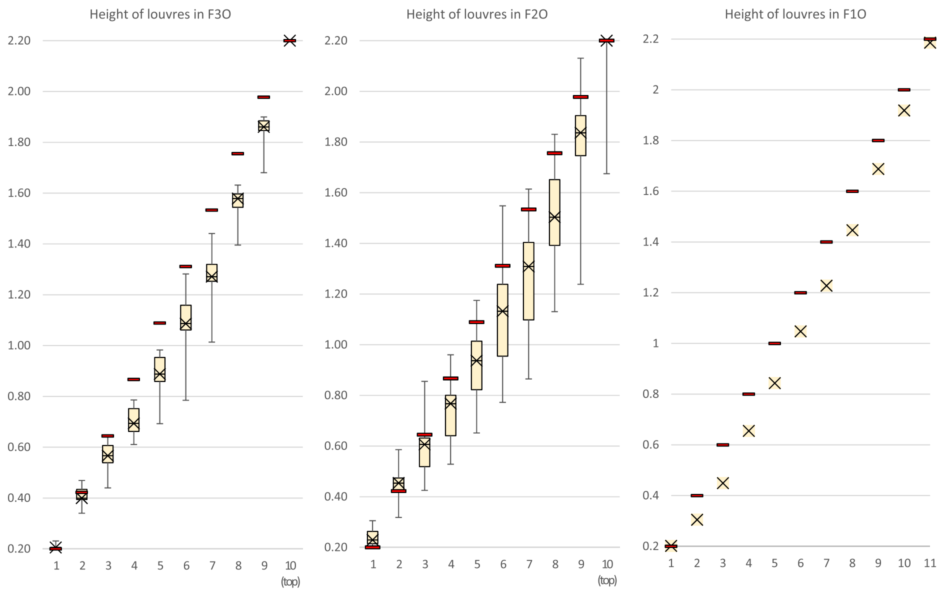


Fig. 7. Statistical analysis of the vertical distribution of the louvres in Pareto solutions. In red: height of equally spaced louvres as in the parametric analysis. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

4.4. Limitations and implications of the study

The focus of this study was to explore the impact of the aspects tied to soft problem formulation on optimization studies using a specific case technology. Because we did not simultaneously consider hard aspects of problem formulation, the results of the work presented here may be incomplete as these may influence each other and are dependent on the assumptions made in the benchmark problem used. Additionally, while it seems intuitive that the parameters used for soft aspects of problem formulation should be defined before selecting the algorithm and the parameters associated, the process may not be linear. This work did not either consider the option of using constraints in the optimization procedure, which could help narrow the search in some problems. Recently, there have been discussions in the literature regarding the formulation of objectives, the need for multi-objective searches, and whether using constraints instead of objectives may be more useful in some problem sets [63].

In a conventional optimization-based design process, where clear performance goals or statutory requirements are well defined, these constrains can be used to reduce the domain of the search and increase the efficiency of the optimization by simply giving the problem less freedom. In such a context, a well designed process can often benefit from a two-step approach, where a larger domain is initially investigated with a limited number of simulations (either through parametric searches or though optimization algorithms), and then a second round of simulations is carried out in a more limited area of the original domain which appeared to be more promising one according to the results of the first step. However, because of the nature of this study, which aimed at being exploratory and at investigating the impact of different choices and variables, we decided to avoid constraining the problems or using a succession of steps. The chosen approach might have made the use of the optimization procedure less efficient computationally speaking, but was consciously considered a better tradeoff in balancing the aims of the research and the resources available – a tradeoff that might be different when real building projects are involved.

Finally, although the specific findings of this study cannot be extended to any façade design beyond shading systems, the procedure described in this work contributes to fostering awareness about the impacts of problem formulation. The results outlined in this work shed light on several relationships between design parameter, decisions variables, and optimal PVSD design. Optimization may not always be used to find designs that correspond to a mathematical global optimal, but *near-optimal* designs should also be robust and understood by modellers. Optimization is also a tool that can allow gaining insight into design tradeoffs, in a similar way that parametric analysis is used, but it can be applied with a larger number of strategies and a more refined approach to investigate a more extensive solution space. Lobo et al. [21] mentioned that part of a challenge of defining optimization procedures is that they should be based on problem difficulty, but "*problem difficulty is very hard to estimate for real-world problems, […]*". Approaches such as the one described here aim at giving modellers a sense of the difficulty of the problem they wish to optimize.

5. Conclusions and future outlooks

This study investigated the soft aspects of problem formulation in GA optimization problems related to PV integrated external shading systems. These relate to two elements. The first one is the impact of changing the size of the solution space by increasing the number of parameters optimized by adding flexibility to the model. The second element concerns how the solution space is searched regarding the number and nature of the objectives, formulated either implicitly or explicitly. This was done by considering different combinations of objectives tied to daylight, total net energy demand, and energy converted by PV surfaces.

The model with more flexibility - which was obtained by allowing the louvres of the system to have variable sizes, and a higher degree of freedom in the geometric configuration – consistently outperformed both the base model and the results of a preliminary parametric analysis. This was true regardless of the number and nature of the objectives. On the other hand, the results of the base model could only bring on moderate improvement compared to the parametric analysis in most cases. When considering the impact of the objectives in the flexible model, the optimization with 2 objectives (daylight and net energy demand) provided more solutions with higher amounts of daylight, but this came at the cost of increasing energy demand. The optimization with 3 objectives provided the largest number of Pareto solutions, which was expected. However, it also yielded solutions that had better tradeoffs than any other optimization despite having a partially degenerate Pareto front and performed as well or better than the optimal solution yielded by the single-objective optimization.

Problem formulation also influenced the resulting statistical values for parameters in the different cases investigated. The optimization with 2 and 3 objectives in the flexible model allowed highlighting common trends that were hard to identify in the single-objective optimization. Certain elements did set apart the geometries, but these were typically in line with what may be expected when considering the shape of the Pareto fronts. Overall, it was found that multi-objective optimizations have more value for designers wishing to understand how the different tradeoffs in PVSD design play out and can allow identifying new types of designs based on the optimal trends.

Future work on the topic should investigate hard aspects of problem formulation, including choices relating to algorithms themselves but also levels of abstractions in models. As optimization studies become more popular, there is a need to gather more insight on problem formulation to help modellers use optimization more efficiently and uncover not only improved designs but also more robust ones. For studies with high computational overhead, there are also many benefits to be gained by developing options allowing to batch simulations and use cloud computing to overcome limitations associated with computational time.

Declaration of competing interest

None.

Acknowledgments

The work presented in this article was funded by the Norwegian Research Council under grant number 255252/E20 for the SkinTech project.

References

[1] V. Machairas, A. Tsangrassoulis, K. Axarli, Algorithms for optimization of building design: a review, Renew. Sustain. Energy Rev. 31 (2014) 101–112, https://doi.org/10.1016/j.rser.2013.11.036.
[2] F. Kheiri, A review on optimization methods applied in energy-efficient building geometry and envelope design, Renew. Sustain. Energy Rev. 92 (2018) 897–920, https://doi.org/10.1016/j.rser.2018.04.080.
[3] R. Evins, A review of computational optimisation methods applied to sustainable building design, Renew. Sustain. Energy Rev. 22 (2013) 230–245, https://doi.org/10.1016/j.rser.2013.02.004.
[4] A.T. Nguyen, S. Reiter, P. Rigo, A review on simulation-based optimization methods applied to building performance analysis, Appl. Energy 113 (2014) 1043–1058, https://doi.org/10.1016/j.apenergy.2013.08.061.
[5] B. Ekici, C. Cubukcuoglu, M. Turrin, I.S. Sariyildiz, Performative computational architecture using swarm and evolutionary optimisation: a review, Build. Environ. 147 (2019) 356–371, https://doi.org/10.1016/j.buildenv.2018.10.023.
[6] H. Li, S. Wang, H. Cheung, Sensitivity analysis of design parameters and optimal design for zero/low energy buildings in subtropical regions, Appl. Energy 228 (2018) 1280–1291, https://doi.org/10.1016/j.apenergy.2018.07.023.
[7] R. Evins, P. Pointer, R. Vaidyanathan, S. Burgess, A case study exploring regulated energy use in domestic buildings using design-of-experiments and multi-objective optimisation, Build. Environ. 54 (2012) 126–136, https://doi.org/10.1016/j.buildenv.2012.02.012.
[8] J. Wright, A. Alajmi, Efficient Genetic Algorithm sets for optimizing constrained building design problem, Int. J. Sustain. Built Environ. 5 (2016) 123–131, https://doi.org/10.1016/j.ijsbe.2016.04.001.
[9] T. Wortmann, Genetic evolution vs . function approximation : benchmarking algorithms for architectural design optimization, J. Comput. Des. Eng. 6 (2019) 414–428, https://doi.org/10.1016/j.jcde.2018.09.001.
[10] M. Wetter, J. Wright, A comparison of deterministic and probabilistic optimization algorithms for nonsmooth simulation-based optimization, Build. Environ. 39 (2004) 989–999, https://doi.org/10.1016/j.buildenv.2004.01.022.
[11] M. Hamdy, A.-T. Nguyen, J.L.M. Hensen, A performance comparison of multi-objective optimization algorithms for solving nearly-zero-energy-building design problems, Energy Build. 121 (2016) 57–71, https://doi.org/10.1016/j.enbuild.2016.03.035.
[12] Y. Lu, S. Wang, Y. Zhao, C. Yan, Renewable energy system optimization of low/zero energy buildings using single-objective and multi-objective optimization methods, Energy Build. 89 (2015) 61–75, https://doi.org/10.1016/j.enbuild.2014.12.032.
[13] H. Li, S. Wang, R. Tang, Robust optimal design of zero/low energy buildings considering uncertainties and the impacts of objective functions, Appl. Energy (2019) 306–2619, https://doi.org/10.1016/j.apenergy.2019.113683.
[14] T. Méndez Echenagucia, A. Capozzoli, Y. Cascone, M. Sassone, The early design stage of a building envelope: multi-objective search through heating, cooling and lighting energy performance analysis, Appl. Energy 154 (2015) 577–591, https://doi.org/10.1016/j.apenergy.2015.04.090.
[15] D. Hou, G. Liu, Q. Zhang, L. Wang, R. Dang, Integrated building envelope design process combining parametric modelling and multi-objective optimization, Trans. Tianjin Univ. 23 (2017) 138–146, https://doi.org/10.1007/s12209-016-0022-1.
[16] N. Delgarm, B. Sajadi, F. Kowsary, S. Delgarm, Multi-objective optimization of the building energy performance: a simulation-based approach by means of particle swarm optimization (PSO), Appl. Energy 170 (2016) 293–303, https://doi.org/10.1016/j.apenergy.2016.02.141.
[17] D.H. Wolpert, W.G. Macready, No free lunch theorems for optimization, IEEE Trans. Evol. Comput. 1 (1997) 67–82, https://doi.org/10.1109/4235.585893.
[18] A.D. Radford, J.S. Gero, On optimization in computer aided architectural design, Build. Environ. 15 (1980) 73–80, https://doi.org/10.1016/0360-1323(80)90011-6.
[19] S. Li, L. Liu, C. Peng, A review of performance-oriented architectural design and optimization in the context of Sustainability : dividends and challenges, Sustainability 12 (2020).
[20] J. Holland, Adaptation in Natural and Artificial Systems : an Introductory Analysis with Application to Biology, MIT Press Cambridge, MA, USA, 1975.
[21] F.G. Lobo, C.F. Lima, Adaptive population sizing schemes in genetic algorithms, in: Springer Berlin (Ed.), Param. Setting Evol. Algorithms. Stud. Comput. Intell., Heidelberg, Germany, 2007, https://doi.org/10.1007/978-3-540-69432-8_9.
[22] N.R. Siriwardene, B.J.C. Perera, Selection of genetic algorithm operators for urban drainage model parameter optimisation 44 (2006) 415–429, https://doi.org/10.1016/j.mcm.2006.01.002.
[23] J.J. Grefenstette, Genetic algorithms, IEEE Trans. Syst. Man. Cybern. 16 (1986) 122–128.
[24] A. Hassanat, K. Almohammadi, E. Alkafaween, E. Abunawas, Choosing mutation and crossover ratios for genetic algorithms — a review with a new dynamic approach. https://doi.org/10.3390/info10120390, 2019.
[25] V.P. Patil, D. Pawar, The optimal crossover or mutation rates in genetic algorithm: a review, Appl. Eng. Technol. 5 (2015) 38–41.
[26] L. Magnier, F. Haghighat, Multiobjective optimization of building design using TRNSYS simulations , genetic algorithm , and Artificial Neural Network, Build. Environ. 45 (2010) 739–746, https://doi.org/10.1016/j.buildenv.2009.08.016.
[27] S. Carlucci, G. Cattarin, F. Causone, L. Pagliano, Multi-objective optimization of a nearly zero-energy building based on thermal and visual discomfort minimization using a non-dominated sorting genetic algorithm (NSGA-II), Energy Build. 104 (2015) 378–394, https://doi.org/10.1016/j.enbuild.2015.06.064.
[28] X. Chen, H. Yang, W. Zhang, Simulation-based approach to optimize passively designed buildings : a case study on a typical architectural form in hot and humid climates, Renew. Sustain. Energy Rev. 82 (2018) 1712–1725, https://doi.org/10.1016/j.rser.2017.06.018.
[29] T. Li, G. Shao, W. Zuo, S. Huang, Genetic algorithm for building optimization - state-of-the- art survey, in: Proc. 9th Int. Conf. Mach. Learn. Comput., Association for Computing Machinery, Singapore, Singapore, 2017, pp. 205–210, https://doi.org/10.1145/3055635.3056591.
[30] K.A. De Jong, An Analysis of the Behavior of a Class of Genetic Adaptive Systems, University of Michigan, Ann Arbor, Michigan, USA, 1975.
[31] H. Mülhenbein, D. Schlierkamp-Voosen, Analysis of selection , mutation and recombination in genetic algorithms, in: Lect. Notes Comput. Sci., Evolution and Biocomputation, 1995, pp. 142–168, https://doi.org/10.1007/3-540-59046-3.
[32] C. Waibel, R. Evins, J. Carmeliet, Co-simulation and optimization of building geometry and multi-energy systems: interdependencies in energy supply, energy demand and solar potentials, Appl. Energy 242 (2019) 1661–1682, https://doi.org/10.1016/j.apenergy.2019.03.177.
[33] C. Cubukcuoglu, B. Ekici, M.F. Tasgetiren, S. Sariyildiz, OPTIMUS: self-adaptive differential evolution with ensemble of mutation strategies for grasshopper algorithmic modeling, Algorithms 12 (2019) 141, https://doi.org/10.3390/a12070141.
[34] G. Rapone, O. Saro, G. Zemella, Multi-objective optimisation of external shading devices for energy efficiency and visual comfort, Build. Simul. Appl. 2013-Janua (2013) 191–198.
[35] M. Gadelhak, Integrating computational and building performance simulation techniques for optimized facade designs, 31th, Int. ECAADe Conf. - Educ. Res. Comput. Aided Archit. Des. Eur. 2 (2013) 261–270.
[36] M. Manzan, Genetic optimization of external fixed shading devices, Energy Build. 72 (2014) 431–440, https://doi.org/10.1016/j.enbuild.2014.01.007.
[37] R. Shan, Optimization for heating, cooling and lighting load in building façade design, Energy Procedia 57 (2014) 1716–1725, https://doi.org/10.1016/j.egypro.2014.10.142.

[38] J. González, F. Fiorito, Daylight design of office buildings: optimisation of external solar shadings by using combined simulation methods, Buildings 5 (2015) 560–580, https://doi.org/10.3390/buildings5020560.
[39] M. Khoroshiltseva, D. Slanzi, I. Poli, A Pareto-based multi-objective optimization algorithm to design energy-efficient shading devices, Appl. Energy 184 (2016) 1400–1410, https://doi.org/10.1016/j.apenergy.2016.05.015.
[40] A. Zani, M. Andaloro, L. Deblasio, P. Ruttico, A.G. Mainini, Computational design and parametric optimization approach with genetic algorithms of an innovative concrete shading device system, in: Int. High-Performance Built Environ. Conf. - A Sustain. Built Environ. Conf. 2016 Ser. (SBE16), IHBE 2016, Procedia Engineering, 2017, pp. 1473–1483, https://doi.org/10.1016/j.proeng.2017.04.310.
[41] M. Mahdavinejad, S. Mohammadi, Parametric optimization of daylight and thermal performance through louvers in hot and dry climate of Tehran, J. Fund. Appl. Sci. 8 (2018) 1221, https://doi.org/10.4314/jfas.v8i3.32.
[42] M. Manzan, A. Clarich, FAST energy and daylight optimization of an office with fixed and movable shading devices, Build. Environ. 113 (2017) 175–184, https://doi.org/10.1016/j.buildenv.2016.09.035.
[43] C. Lavin, F. Fiorito, Optimization of an external perforated screen for improved daylighting and thermal performance of an office space, Procedia Eng 180 (2017) 571–581, https://doi.org/10.1016/j.proeng.2017.04.216.
[44] S. Vera, D. Uribe, W. Bustamante, G. Molina, Optimization of a fixed exterior complex fenestration system considering visual comfort and energy performance criteria, Build. Environ. 113 (2017) 163–174, https://doi.org/10.1016/j.buildenv.2016.07.027.
[45] A. Toutou, M. Fikry, W. Mohamed, The parametric based optimization framework daylighting and energy performance in residential buildings in hot arid zone, Alexandria Eng. J. 57 (2018) 3595–3608, https://doi.org/10.1016/j.aej.2018.04.006.
[46] H. Sghiouri, A. Mezrhab, M. Karkri, H. Naji, Shading devices optimization to enhance thermal comfort and energy performance of a residential building in Morocco, J. Build. Eng. 18 (2018) 292–302, https://doi.org/10.1016/j.jobe.2018.03.018.
[47] R.A. Mangkuto, F. Feradi, R. Eka, R.T. Atmodipoero, F. Favero, Optimisation of daylight admission based on modifications of light shelf design parameters, J. Build. Eng. 18 (2018) 195–209, https://doi.org/10.1016/j.jobe.2018.03.007.
[48] Y.K. Yi, Building facade multi-objective optimization for daylight and aesthetical perception, Build. Environ. 156 (2019) 178–190, https://doi.org/10.1016/j.buildenv.2019.04.002.
[49] A. Kirimtat, O. Krejcar, B. Ekici, M. Fatih Tasgetiren, Multi-objective energy and daylight optimization of amorphous shading devices in buildings, Sol. Energy 185 (2019) 100–111, https://doi.org/10.1016/j.solener.2019.04.048.
[50] H.J. Kim, C.S. Yang, H.J. Moon, A study on multi-objective parametric design tool for surround-type movable shading device, Sustain. Times 11 (2019), https://doi.org/10.3390/su11247096.
[51] E. Taveres-Cachat, G. Lobaccaro, F. Goia, G. Chaudhary, A methodology to improve the performance of PV integrated shading devices using multi-objective optimization, Appl. Energy (2019), https://doi.org/10.1016/j.apenergy.2019.04.033.
[52] E. Taveres-Cachat, F. Goia, Investigating the performance of a hybrid PV integrated shading device using multi-objective optimization, in: J. Phys. Conf. Ser, Institute of Physics Publishing, 2019, https://doi.org/10.1088/1742-6596/1343/1/012086.
[53] S. Samadi, E. Noorzai, L.O. Beltra, S. Abbasi, A computational approach for achieving optimum daylight inside buildings through automated kinetic shading systems, Front. Archit. Res. (2019), https://doi.org/10.1016/j.foar.2019.10.004.
[54] J. Settino, C. Carpino, S. Perrella, N. Arcuri, Multi-objective analysis of a fixed solar shading system in different climatic areas, Energies 13 (2020) 3249, https://doi.org/10.3390/en13123249.
[55] McNeel Robert, Associates, "Rhinoceros Version 5.0," 2015, (n.d.). https://www.rhino3d.com/.
[56] D. Rutten, Grasshopper - algorithmic modeling for rhino version 0.9.0076. http://www.grasshopper3d.com/, 2017 accessed October 9, 2017.
[57] M. Sadeghipour Roudsari, M. Pak, Ladybug: a parametric environmental plugin for grasshopper to help designers create an environmentally-conscious design, in: 13th Conf. Int. Build. Simul. Assoc. IBPSA, IBPSA, Chambery, France, 2013, in: http://www.ibpsa.org/proceedings/BS2013/p_2499.pdf.
[58] R. Vier, Octopus, (n.d.). http://www.grasshopper3d.com/group/octopus accessed October 9, 2017.
[59] E. Taveres-Cachat, F. Goia, Co-simulation and validation of the performance of a highly flexible parametric model of an external shading system, Build. Environ. 182 (2020), https://doi.org/10.1016/j.buildenv.2020.107111.
[60] R. Judkoff, J. Neymark, International Energy Agency building energy simulation test (BESTEST) and diagnostic method, Natl. Renew. Energy Lab. (1995) 296, https://doi.org/10.2172/90674.
[61] NS3031, Calculation of Energy Performance of Buildings Method and Data, Norway, 2016, 2016.
[62] R. Vierlinger, Multi objective design interface, Master thesis, Institute of Construction, Structural Dynamics and Building Technology, Faculty of Civil Engineering, Vienna University of Technology, 2013, https://doi.org/10.13140/RG.2.1.3401.0324.
[63] T. Wortmann, T. Fischer, Does architectural design optimization require multiple objectives ? A critical analysis, RE Anthr. Proc. 25th Int. Conf. Assoc. Comput. Archit. Des. Res. Asia. 1 (2020) 365–374.