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

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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

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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	50 to 100	
	Mutation rate	0.001	
	Crossover rate	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:

$$E_{PV} = \frac{\text{Radiation received on geometry} \times \text{cell efficiency} \times \text{area of louvre with } \mathit{PV\ material}}{\mathit{Floor\ area}}\left[kWh/m^2\right]$$

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:

$$E_L = \max\left(1 - \frac{\mathit{measured\ illuminance}}{500\mathit{lux\ threshold}}, 0.2\right) \times \mathit{installed\ power}$$

Table 3
Characteristics of the benchmark building used.

Component	Value	Note
U-value external wall	0.18 W/(m^2K)	Below the maximum value from NS3031
U-value roof	0.10 W/(m^2K)	Slightly above the recommended value from NS3701
U-value external floor	0.10 W/(m^2K)	Slightly above the recommended value from NS3701
U-value window (3 panes)	0.8 W/(m^2K)	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 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. 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,

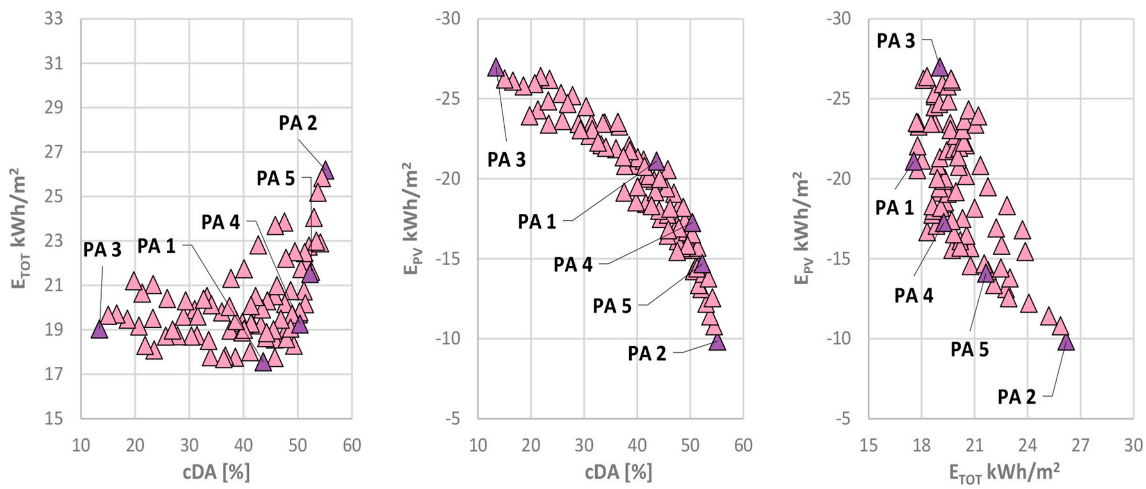

Fig. 1. Results of the parametric analysis projected in a 2D view. The points selected in purple are the points analyzed in Fig. 2. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

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					

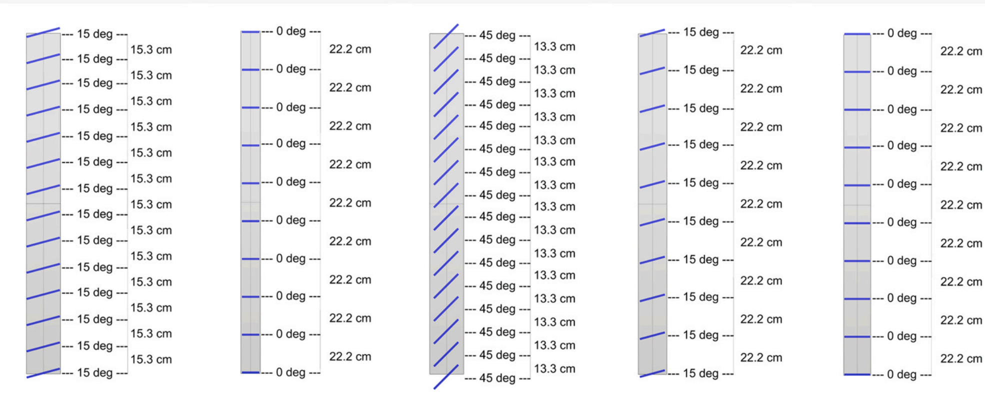

Fig. 2. Results of the parametric analysis of the PVSD.

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 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

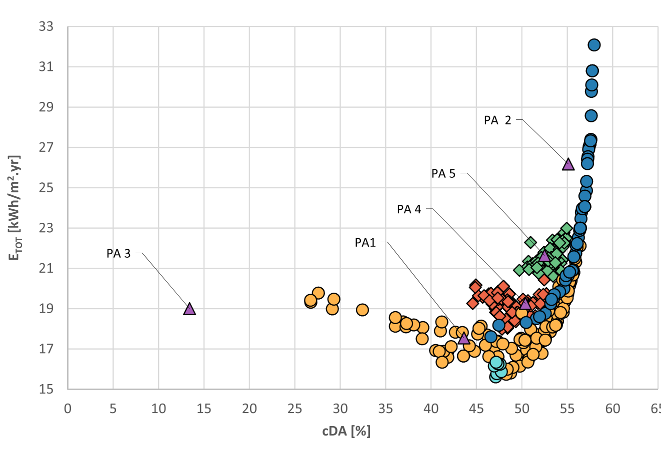

Fig. 3. Summary plot of all optimization runs with a 2D projection of the fitness of the Pareto front solutions and selected results from the parametric analysis for the tradeoffs cDA versus total net energy demand (E_{TOT}).

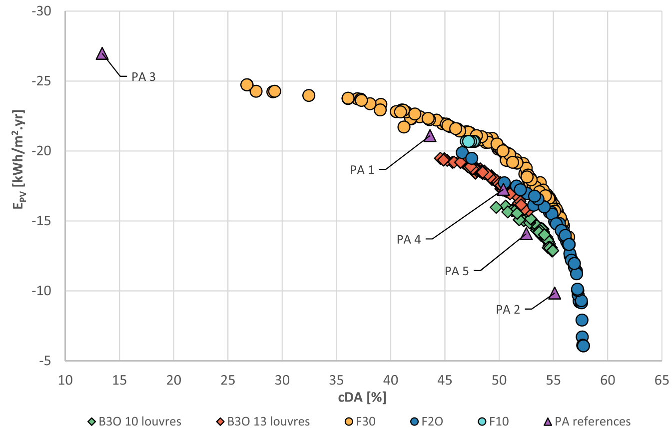

Fig. 4. Summary plot of all optimization runs with a 2D projection of the fitness of the Pareto front solutions and selected results from the parametric analysis for the tradeoffs energy converted by PV (E_{PV}) versus cDA. Note that E_{PV} is represented as negative to illustrate that this energy is discounted from the base energy demand.

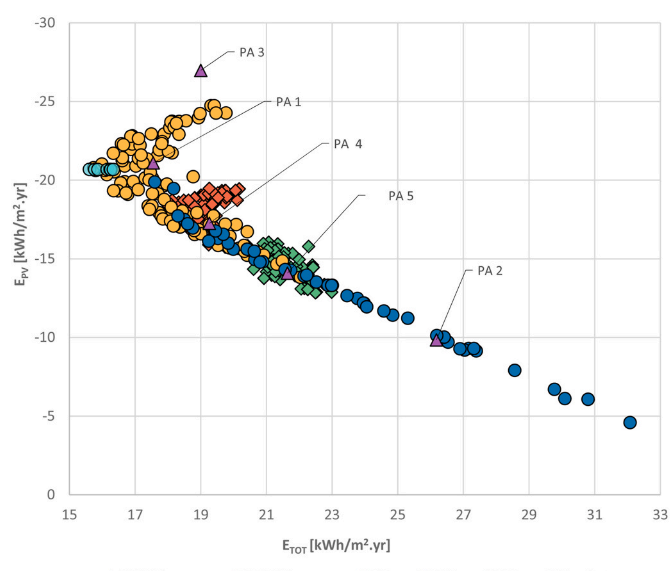

Fig. 5. Summary plot of all optimization runs with a 2D projection of the fitness of the Pareto front solutions and selected results from the parametric analysis for the tradeoffs energy converted by PV (E_{PV}) versus total net energy demand (E_{TOT}). Note that E_{PV} is represented as negative to 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.

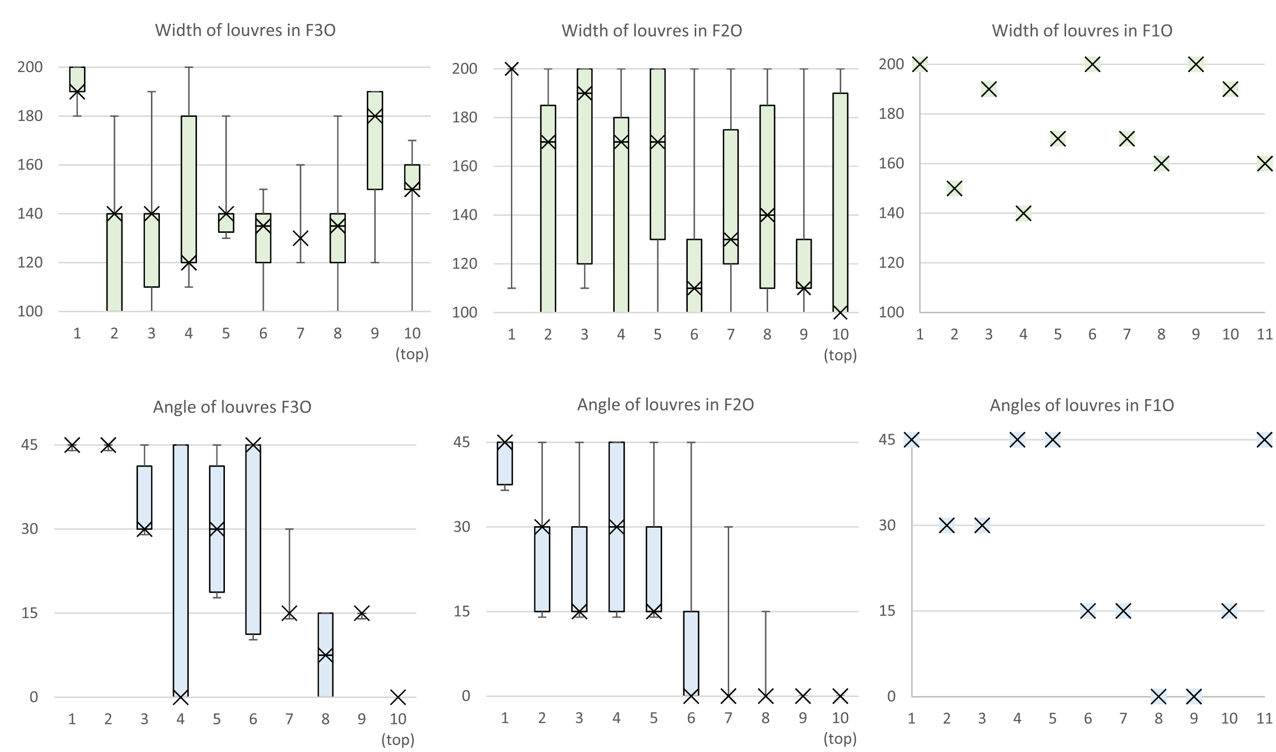

Fig. 6. Statistical analysis of the parameters making up the in Pareto solutions.

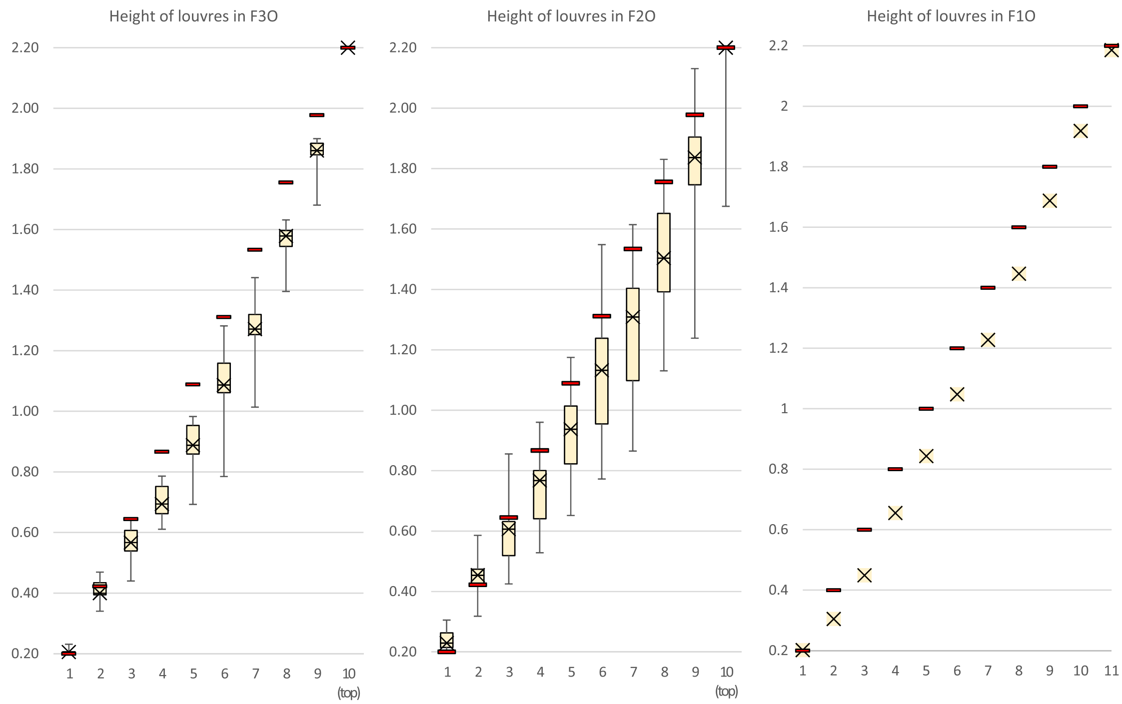

Fig. 7. Statistical analysis of the vertical distribution of the louvres in Pareto solutions. In red: height of equally spaced louvres as in the parametric analysis. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

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.

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