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Dimitri Pinel

Optimal Investment in the Energy System of Zero Emission Neighborhoods

A Study of the Methodology, Influencing Factors and Consequences for the Power System

Doctoral thesis

NTNU
Norwegian University of Science and Technology
Thesis for the Degree of Philosophiae Doctor
Faculty of Information Technology and Electrical Engineering
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Abstract

This thesis tackles the challenge of the optimal design of the energy systems of Zero Emission Neighborhoods (ZENs). ZENs are neighborhoods that aim to reach net-zero greenhouse gases emissions over their lifetime. This puts very specific and strong requirements on the energy system of such neighborhoods, making finding a cost-optimal solution difficult. This thesis studies the methods and influencing factors for the design of ZEN energy systems, the resulting ZENs energy system designs and the consequences of ZENs on the power system with a focus on Norway and Europe.

Other similar concepts have been studied and exist in the literature such as nearly zero energy buildings, and zero emission buildings, but they do not cover the specific challenges and opportunities that arise at the neighborhood level. A diverse body of literature also covers optimal investment in the energy system of neighborhoods or local energy systems, but a zero emission framework, or emissions in general, are not considered. This thesis addresses this gap in the literature. The research questions this thesis focuses on are: which methodology to use in order to efficiently obtain the cost-optimal design of ZEN energy systems, what impacts do definitions and policies have on these designs, what are the consequences on the European power system of the emergence of such neighborhoods and how to make short-term decisions on the operation of the neighborhood in order to reach the long-term zero emission goal.

To answer those research questions, several versions of a mixed integer linear program (MILP) have been developed (aggregated, non-aggregated, with refurbishment). Several modeling approaches and their consequences have also been explored (clustering, emission factors, zero emission percentage). This model has also been soft-linked to a European capacity expansion planning model to study the impact of ZENs at the European level.

The main results are the following. Certain technologies are recurrent in the energy systems of ZENs. In particular, photovoltaic (PV) panels are crucial to reaching the zero emission balance. Heat pumps (air or ground source depending on the conditions) are also recurrent. Other technologies, such as those based on biomass, are also often used but their type can vary. Around 2050, batteries and solid oxide fuel cells are expected to become major contributors to the ZEN due to their cost reduction and the benefits that their flexibility brings to the energy system. Allowing external compensation ensures a reduction of the cost of ZENs. The choice of emission factor is important, but annual average factors seem to be sufficient for the design of the energy system of ZENs in Norway. The scope of the emission cap-and-trade system does generally not affect the energy systems of ZENs but the reduction of the cap together with reducing cost towards 2050 changes the system designs. Grid tariffs also have no significant impact on the design of the ZEN energy systems but they change the operation and export patterns. Designing the energy system of ZENs to be net zero emission is not necessarily sufficient to achieve the zero emission target during their lifetime; considering the operation strategy is also crucial, especially in systems that do not only rely on PV for the compensations. At the European level, ZEN energy systems contribute to a reduction of the cost of the power system and affect the technology mix to a small extent, but due to the cap system they do not reduce the emissions.

This thesis focuses on ZENs in Norway and Europe, but some results can also apply to local energy communities and the rest of the world. For instance, ZENs are highly suited to testing the effect of grid tariffs on extreme prosumers. The technologies chosen for the ZENs are relevant in general to local energy systems trying to reduce their emissions and the methodology used can be applied to other cases.

This thesis contributes to the literature by specifically investigating the investment models for cost-optimal energy systems of ZENs and their consequences.

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List of Symbols

$t(\mathcal{T})$	Timestep in hour within year, $\in [0, 8759]$
$\kappa(\mathcal{K})$	Cluster representative (centroid)
$t_\kappa(\mathcal{T}_\kappa)$	Timestep within cluster κ, $\in [0, 23]$
$b(\mathcal{B})$	Building or building type
$i(\mathcal{I})$	Energy technology, $\mathcal{I} = \mathcal{F} \cup \mathcal{E} \cup \mathcal{HST} \cup \mathcal{EST}; \mathcal{I} = \mathcal{Q} \cup \mathcal{G}$
$f(\mathcal{F})$	Technology consuming fuel (gas, biomass, etc.)
$e(\mathcal{E})$	Technology consuming electricity
$hst(\mathcal{HST})$	Heat storage technology
$est(\mathcal{EST})$	Electricity storage technology
$q(\mathcal{Q})$	Technologies producing heat
$g(\mathcal{G})$	Technologies producing electricity
α_{CHP}	Heat-to-electricity ratio of the CHP
α_i	Part load limit as ratio of installed capacity
$\dot{Q}^{MaxPipe}_{b_1,b_2}$	Maximum heat flow in the heating grid pipe going from b_2 to b_1 [kWh]
$\dot{Q}^{max}_{st}$	Maximum charge/discharge rate of est/hst [kWh/h]
η_{est},η_{hst}	Efficiency of charge and discharge

η_{inv}	Efficiency of the inverter
η_i	Efficiency of i
$\phi^{CO_2,f}$	CO_2 factor of fuel type f [g/kWh]
$\phi_t^{CO_2,e}$	CO_2 factor of electricity at t [g/kWh]
σ_κ	Number of occurrences of cluster κ in the year
$\varepsilon_{r,D}^{tot}$	Discount factor for the duration of the study D with discount rate r
B_q^{DHW}	Binary parameter stating whether q can produce DHW
C^{HG}	Cost of investing in the heating grid [€]
$C_{i,b}^{maint}$	Annual maintenance cost of i in b [€/kWh]
$C_{i,b}^{var,disc}$,$C_{i,b}^{fix,disc}$	Variable/Fixed investment cost of i in b discounted to the beginning of the study including potential re-investments and salvage value [€/kWh]/[€]
C_{sl}	Cost of external carbon offsetting [€/gCO_2]
$COP_{hp,b,t}$	Coefficient of performance of heat pump hp
$E_{b,t}$	Electric load of b at t [kWh]
G^{stc}	Irradiance in standard test conditions: $1000W/m^2$
GC	Size of the neighborhood grid connection [kW]
$H_{b,t}^{SH}$,$H_{b,t}^{DHW}$	Heat (Space Heating/Domestic Hot Water) load of b at t [kWh]
IRR_t^{tilt}	Total irradiance on a tilted plane [W/m^2]
M	“Big M”, taking a large value
P^{grid}	Electricity grid tariff [€/kWh]
$P_{hp,b,t}^{input,max}$	Maximum Power consumption of hp at t based on manufacturer data and output temperature
P^{ret}	Retailer tariff on electricity [€/kWh]
P_f^{fuel}	Price of fuel of g [€/kWh]
P_t^{spot}	Spot price of electricity at t [€/kWh]

Q_{b_1,b_2}^{HGloss}	Heat loss in the heating grid in the pipe going from b_2 to b_1
T^{coef}	Temperature coefficient
T^{noct}	Normal operating cell temperature [°C]
T^{stc}	Ambient temperature in standard test conditions [°C]
T_t	Ambient temperature at t [°C]
X_i^{max}	Maximum investment in i [kW]
X_i^{min}	Minimum investment in i [kW]
$\overline{x_{i,b,t}}$	Maximum production from i [kWh]
b^{HG}	Binary for the investment in the Heating Grid
$b_{i,b}$	Binary for the investment in i in b
$d_{e,t,b}$	Electricity consumed by e in b at t [kWh]
e_{sl}	Emission compensated via external carbon offsetting [gCO_2]
$f_{f,t,b}$	Fuel consumed by f in b at t [kWh]
$g_{t,b}^{curt}$	Solar energy production curtailed [kWh]
$g_{g,t,b}^{dump}$	Electricity generated but dumped by g at t [kWh]
$g_{g,t,b}$	Electricity generated by g at t [kWh]
$g_{t,g,b}^{ch}$	Electricity generated by g used to charge the 'prod' batteries at t [kWh]
$g_{t,g,b}^{selfc}$	Electricity generated by g self consumed in the neighborhood at t [kWh]
$o_{i,t,b}$	Binary controlling if i in b is on or off at t
$q_{t,st,b}^{ch}$, $q_{t,st,b}^{dch}$	Energy charged/discharged from the neighborhood to the storage at t [kWh]
$q_{t,b}^{dump}$	Heat dumped at t in b [kWh]
$q_{b_1,b_2,t}^{HGtransfer}$	Heat transferred via the heating grid from b_1 to b_2 at t [kWh]
$q_{b,t}^{HGused}$	Heat taken from the heating grid by b at t [kWh]

$q_{q,t,b}$	Heat generated by q in b at t [kWh]
$v^{stor}_{t,st,b}$	Level of the storage st in building b at t [kWh]
$x_{i,b}$	Capacity of i in b
$y^{ch}_{t,est,b}$	Electricity charged from on-site production to est at t [kWh]
$y^{dch}_{t,est,b}$	Electricity discharged from est to the neighborhood at t [kWh]
$y^{exp}_{t,est,b}$	Electricity exported from the est to the grid at t [kWh]
$y^{imp}_{t,est,b}$	Electricity imported from the grid to est at t [kWh]
$y^{exp}_{t,g,b}$	Electricity exported by g to the grid at t [kWh]
y^{imp}_{t}, y^{exp}_{t}	Electricity imported from the grid to the neighborhood/exported at t [kWh]

List of Abbreviations

BAU Business As Usual

CCS Carbon Capture and Storage

CDM Clean Development Mechanism

CHP Combined Heat and Power Plant

COP Coefficient of Performance

DHW Domestic Hot Water

DSO Distribution System Operator

EU European Union

ETS Emission Trading System

GHG Greenhouse Gases

GIS Geographic Information System

GB Grid-side Battery, i.e "virtual" battery linked to the grid

HP Heat Pump

IPCC Intergovernmental Panel on Climate Change

LEC Local Energy Community

LP Linear Program

MILP Mixed Integer Linear Program

MPC Model Predictive Control

PV Photovoltaic

PB Production-side Battery, i.e “virtual” battery linked to the on-site production of electricity

SH Space Heating

SOFC Solid Oxide Fuel Cell

ToU Time of Use

ZEB Zero Emission Buildings or Zero Energy Buildings

ZEN Zero Emission Neighborhoods

ZENIT Zero Emission Neighborhoods Investment Tool - the model optimization developed to help design optimal ZEN energy systems

Preface

The work of this Thesis has been conducted at the Department of Electric Power Engineering of the Norwegian University of Science and Technology (NTNU) in Trondheim, Norway. A part of the work has also been conducted during an exchange semester in the Institute of Energy Systems, Energy Efficiency and Energy Economics at the Technical University Dortmund, Germany.

The project has been financed by the research center on Zero Emission Neighborhoods in smart cities (FME[1] ZEN). My main supervisor has been Professor Magnus Korpås with Associate Professor Karen B. Lindberg as my co-supervisor.

[1]Centres for Environment-friendly Energy Research
https://www.forskningsradet.no/en/about-the-research-council/programmes/fme/

Chapter 1

Introduction

Most nations still do not meet the ambitious greenhouse gas emission reduction targets that they set during the various United Nations climate change conferences, with potentially severe consequences on climate change. Reductions of greenhouse gas (GHG) emissions are needed in every aspect of society to reach these goals. Neighborhoods and the buildings that comprise them have an important role in this transition due to their high share of the total energy use. It is thus important to find ways to reduce the emissions in such neighborhoods. The emissions associated with neighborhoods are related to different parts of their life-cycle. In the construction phase, emissions are related to the machines and the embodied emissions of the material. In the operation phase, the emissions are related to the electricity and heat needs of the users. The emissions related to transport are also relevant in the case of neighborhoods. The last phase of the life-cycle, the deconstruction, also contributes to the total emissions. When it comes to emissions related to energy needs, one needs to think about where the energy comes from. For example, what are the emissions from the electricity imports from the grid and which technology is used to produce heat for the buildings? Local renewable electricity generation must also be considered. The concept of Zero Emission Neighborhood (ZEN) sets a target of net zero emissions of greenhouse gases during the lifetime of the neighborhood. In this context, the local generation of renewable energy also contributes to reaching the net zero emission target. This concept is connected to the more general concept of Local Energy Communities (LEC).

Selecting and sizing the energy system of a neighborhood and each of the buildings it comprises is not a trivial problem, especially when considering the need for net zero emissions. Indeed, the investment cost of each technology alone is not enough to provide a solution, as the fuel and maintenance cost can have a significant impact on the total cost of the system. Moreover, there needs to be a balance between demand and supply, and finding the correct mix of technology that allows us to best achieve this at a minimum cost while accounting for the technology-specific operational constraint and achieving net zero emission in the lifetime is complex. This thesis investigates how to design the energy system of neighborhoods in a way that makes them have net zero emissions by including local renewable energy; what are the consequences of different policy settings on those neighborhoods and on the power system; and how to ensure that the operation of the neighborhood will guarantee zero emissions at the end of its lifetime.

1.1 Scope and research questions

The focus of this thesis is to answer several questions linked to the energy system of ZENs in a local context and from a power system perspective. Four main research questions are raised:

Q1 How to obtain an optimal design for ZEN energy systems, i.e. energy systems ensuring net zero emission in their lifetime?

- **Q1.1** Which modeling decisions should be taken for obtaining those designs in reasonable computational time?

Q2 How to ensure that the operation of such derived ZENs is performed according to the original design in order to meet the net zero emission requirement?

Q3 What impacts do definitions and policies have on ZEN designs? In particular:

- **Q3.1** What impacts do climate and energy policy settings have on ZEN energy systems designs?
- **Q3.2** What impact does the definition of compensation have on ZEN energy system designs?

Q4 What impacts do ZENs developments across European countries have on the European power system?

This scope can be defined by two parts. The first focuses on the methodology of designing the energy system of ZENs while the second focuses more on the analysis of ZENs regarding policies or the European power system.

1.2 Contributions

The main contributions of the work presented in this thesis are:

- Methodologies based on a MILP optimization to design the energy (electrical and heating) system of ZENs for various cases: aggregated loads, disaggregated loads and including refurbishment, are presented. The complexity of the model can be tackled using temporal clustering. The performance of various clustering approaches in the context of ZEN energy systems' design has been compared.

- The impacts of regulations and zero emission definition on the design of ZEN energy systems are explored.

- A methodology linking models at different scales is presented and used to investigate the potential of ZENs as a resource to the European power system and the differences in ZEN energy system designs across Europe are studied.

- Demonstrate the need for specific short-term operation strategies to reach zero-emission requirements in the long-term and suggest potential operation approaches.

These contributions are developed in the different publications included as a part of this thesis.

1.3 Publications

The main publications presented in this thesis are:

Paper 1 D. Pinel, M. Korpås and K. B. Lindberg, "Cost Optimal Design of ZEN's Energy System: Model Presentation and Case Study on Evenstad". I: Advances in Energy System Optimization Proceeding of the 2nd International Symposium on Energy System Optimization. Springer, 2019, p. 145-163

Paper 2 D. Pinel, S. Bjarghov and M. Korpås, "Impact of Grid Tariffs Design on the Zero Emission Neighborhoods Energy System Investments," Proceedings of 2019 IEEE Milan PowerTech, Milan, Italy, 2019

Paper 3 D. Pinel, "Clustering methods assessment for investment in zero emission neighborhoods' energy system", International Journal of Electrical Power & Energy Systems, Volume 121, 2020, Article 106088

Paper 4 D. Pinel, M. Korpås, K. B. Lindberg, "Impact of the CO2 factor of electricity and the external CO2 compensation price on zero emission neighborhoods' energy system design", Building and Environment, Volume 187, 2021, Article 107418

Paper 5 D. Pinel, M. Korpås, "Enforcing Annual Emission Constraints in Short-Term Operation of Local Energy Systems", under review

Paper 6 S. Backe, D. Pinel, M. Askeland, K.B. Lindberg, M. Korpås, A. Tomasgard, "Emission reduction in the European power system: exploring the link between the EU ETS and net-zero emission neighbourhoods", under review

Paper 7 D. Pinel, M. Korpås, "Optimal investment in the energy system of Zero Emission Neighborhoods considering the refurbishment of the building stock." Proceedings of Applied Energy Symposium 2020 100% renewable, Pisa, Italy, 2020

Other publications related to the PhD work:

- S. Backe, D. Pinel, P. C. del Granado, M. Korpås A. Tomasgard and K. B. Lindberg, "Towards Zero Emission Neighbourhoods: Implications for the Power System," 2018 15th International Conference on the European Energy Market (EEM), Lodz, 2018, pp. 1-6
- S. Backe, Å. L. Sørensen, D. Pinel, J. Clauß and C. Lausselet, "Opportunities for local energy supply in Norway: A case study of a university campus site", IOP Conference Series: Earth and Environmental Science (EES) 2019 ;Volume 352:012039. p. 1-9
- S. Backe, D. Pinel, M. Askeland, K.B. Lindberg, M. Korpås, A. Tomasgard, "Zero emission neighbourhoods in the European energy system", report of the Research center for Zero Emission Neighborhoods in smart cities (FME ZEN), 2021

1.4 Structure of the thesis

The thesis starts with a description of the background elements necessary to understand the rest of the thesis (Chapter 2). The second part (Chapter 3) contains the methodological elements developed for accomplishing the work presented in this thesis. The main findings of the completed work are then presented in Chapter 4. The findings are further discussed in Chapter 5. Finally, Chapter 6 concludes the thesis and suggests avenues for future research.

The thesis is centered around seven articles (c.f. section 1.3) produced during the PhD that are presented at the end of the thesis. These papers are referred to in the different parts of the thesis.

Chapter 2

Background on ZENs and on the design of local energy systems

2.1 Emission reduction and Norway's role

After decades of warnings about the relation between climate change and human-related greenhouse gas emissions, these scientific findings have become widely accepted and more and more people are taking the issue seriously [1]. This is illustrated in Fig. 2.1.

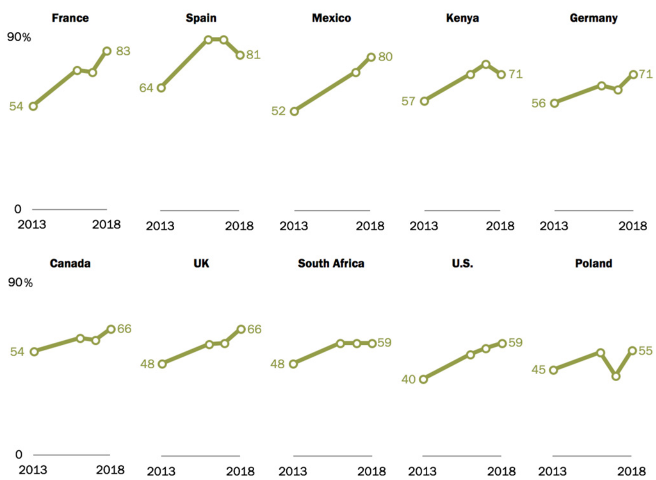


Figure 2.1: Evolution of concerns about climate change in various countries. Share of participants who responded that climate change is a major threat to their country. Source:[2]

The emissions of greenhouse gases come from all sectors of the economy and a breakdown of the emissions by sector was presented in the 2014 IPCC report (Fig. 2.2). A significant part of the emissions comes from the energy sector and buildings themselves account for 6.4% of the total. Both the total emissions and their breakdown are very different between countries of different levels of income. In high-income countries, energy and buildings together account for around half of the emissions.

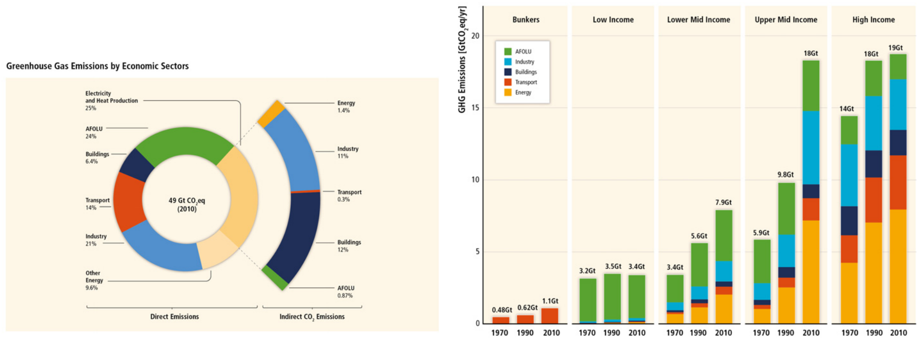


Figure 2.2: Greenhouse gas emissions by economic sector. Source: [3]

During the Paris climate summit, the participating countries have agreed on stricter emission reduction targets than the previous ones in order to limit the impact of climate change. However, there is still much that needs to be done in order to reach the emission reduction that the countries have agreed to.

The EU aims to be climate-neutral by 2050 and EU member states must develop national long-term strategies to achieve this goal. Norway has set a target of a 50% reduction of emissions from 1990 levels. Norway is an important oil producer but, on the other hand, has a green power system thanks to its abundant hydrologic resources. The country has pushed early for the adoption of electric vehicles by consumers and they now represent around 10% of the cars in Norway[1]. Multiple research projects are also being undertaken to enable the future low-carbon economy, such as the research center for Zero Emission Neighborhoods (ZENs)[2], the +CityxChange[3], or the Beyond project for instance. The emissions of Norway are primarily related to its industry and in particular oil production as well as oil consumption from vehicles (Fig. 2.3). The energy supply and heating of buildings are relatively small contributors.

[1] https://www.ssb.no/en/bilreg
[2] https://fmezen.no/
[3] https://cityxchange.eu/

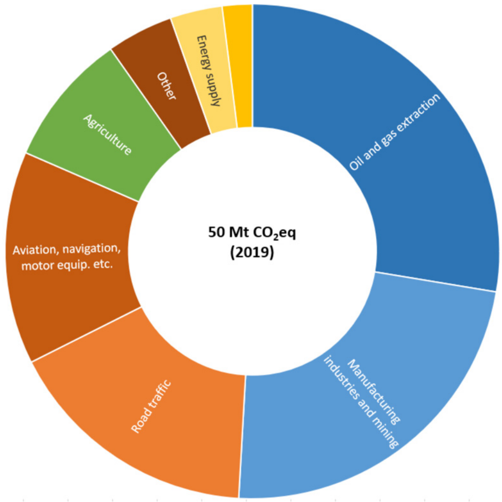


Figure 2.3: CO_2 emissions of Norway by sector.

2.2 Zero Emission Neighborhoods and Buildings

2.2.1 Nearly Zero Energy Buildings and Local Energy Communities concepts

The EU defines a framework for the building standards of its members through the directive on the energy performance of buildings (EPBD) introduced in 2002[4]. In particular, it requires member states to establish a methodology for the calculation of the energy performance of buildings and set minimum energy performance requirements. The EPBD recast in 2010[5] strengthened the directive and introduced the concept of nearly Zero Energy Buildings (nZEB). Such buildings need to reduce their energy consumption to a minimum and cover the remainder with renewable energy. More recently an emphasis has been put on the renovation of the existing building stock. In addition, the focus has been placed on energy communities in directives and in research projects financed by the EU. The EU provides two frameworks [4]: renewable energy communities and citizen energy communities. The +CityXchange[6] project is an example of EU-financed research and focuses on the concept of positive energy blocks and districts. The Renaissance project[7] looks

[4] https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A32002L0091
[5] https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32010L0031
[6] https://cityxchange.eu/
[7] https://www.renaissance-h2020.eu/about/

at enabling Local Energy Communities (LEC) across Europe. Furthermore, it is important to note the emphasis that is put on the empowerment of citizens and the will to support citizen initiatives and ways to involve them.

In Norway, the research center on Zero Emission Buildings has studied both zero emission and zero energy buildings. The research center concluded with a recommendation to move to the neighborhood level and led to the creation of the research center for ZEN in smart cities. Studying the neighborhood level allows to consider additional elements such as district heating and synergies between buildings.

2.2.2 Zero Emission Neighborhoods

The report "Definition, key performance indicators and assessment criteria" [5] from the research center for ZEN in smart cities, defines ZEN in the following way: "*In the ZEN research centre, a neighborhood is defined as 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 (GHG) emissions towards zero over the analysis period, in line with a chosen ambition level with respect to which life cycle modules and building and infrastructure elements to include. The neighborhood should focus the following, where the first four points have direct consequences for energy and emissions:*

- a - *Plan, design and operate buildings and associated infrastructure components towards zero life cycle GHG emissions.*
- b - *Become highly energy efficient and powered by a high share of new renewable energy in the neighborhood energy supply system.*
- c - *Manage energy flows (within and between buildings) and exchanges with the surrounding energy system in a smart and flexible way.*
- d - *Promote sustainable transport patterns and smart mobility systems.*
- e - *Plan, design and operate with respect to economic sustainability, by minimizing total life cycle costs.*
- f - *Plan and locate amenities in the neighborhood to provide good spatial qualities and stimulate sustainable behavior.*
- g - *Development of the area is characterized by innovative processes based on new forms of cooperation between the involved partners leading to innovative solutions.*"

The items of particular importance for this thesis are a, b, c and e. In the context of this thesis, we define ZENs as neighborhoods that aim at having net zero emissions of CO_2 during their lifetime through the appropriate cost-optimal design and operation of their energy system. This net zero requirement is called the zero emission balance, and can be represented as follows:

$$\sum Emissions = \sum Compensations \tag{2.1}$$

with $\sum Emissions = \sum$ Emissions from electricity imports + $\sum$ Emissions from fuel use. The emissions can also include embedded emissions in materials and emissions for construction and deconstruction. However, we do not consider those emissions in the analyses conducted in this thesis.

2.2.3 Compensation mechanism and CO_2 factors

The first definition of compensations is that exports of electricity from the ZEN towards the power system weighted by the proper emission factor count as compensations. The basis for this is that by exporting the surplus of locally produced electricity to the power system, the ZEN replaces some of the production from more carbon-intensive sources in the power system. The definition of a ZEN from the research center could be extended to include other types of compensations. A selection of possible extensions is presented and discussed in the following subsections. Paper 4 looks at the impact of extending the definition of compensation for the design of their energy system.

Carbon offset companies

Multiple "carbon offset companies" offer the possibility for private individuals and companies to offset their emissions of CO_2 by financing projects such as reforestation, preventing deforestation, or renewable energy in developing countries.

Table 2.1: Selection of Carbon Offset Companies and their Offers.

Company	Offset Price (€/$tonCO_2$)	Project Type
Compensate[1]	20	Forestry/Land use
Atmosfair[2]	23	Energy
Native Energy[3]	14	Land use, Energy, Water, Methane
Carbon Offset to Alleviate Poverty[4]	10	Forestry/Land use
My Climate[5]	24	Forestry/Land use, Energy, Water
Cool Effect[6]	3-12	Forestry/Land use, Energy, Wildlife

[1] www.compensate.com/
[2] www.atmosfair.de/en/
[3] www.nativeenergy.com/
[4] www.cotap.org/
[5] www.myclimate.org/
[6] www.cooleffect.org/

The projects that they offer can involve reforestation or protection against deforestation, in some cases in a close partnership with the local population, energy-related

Table 2.2: Other Compensation Options and their Estimated Carbon Prices.

Compensation Type	Compensation Price (€$/tonCO_2$)
EU ETS	20-30
CCS	18-250

such as solar, wind, energy efficiency, biomass and biogas (gathered under the label "Energy" in Table 2.1), methane destruction, related to wildlife preservation or to water quality and saving. Specific examples and details of projects can be found on the companies' websites. Some companies explicitly mention that they use mechanisms from the Kyoto Protocol. CDM projects (i.e. clean development mechanism projects, one type of mechanism of the Kyoto Protocol) are supposed to offer emission reductions that are additional to what would have normally occurred without them. The projects are often related to renewable and sustainable energy and energy efficiency. However, it has been found that around 80% of CDM projects are not likely to be additional ([6]). It is specified that, among CDM projects, those most likely to be additional are industrial gas and methane projects ([6]). The additionality of biomass power projects is dependent on local conditions ([6]). Project types that are frequently seen with carbon offset companies (Table 2.1), namely energy efficiency or generation and new cooking stove, are found to be respectively unlikely to be additional and have over-estimated emission reductions.

While it is possible to offset emissions via a carbon offsetting company, it is important to carefully choose the company and project.

EU Emission Trading System

The EU Emissions Trading System (EU ETS) could also be used to compensate emissions. The EU ETS is an emission trading system set up in the European Union and primarily impacts the power sector and aircraft operators. It sets a limit on the amount of emissions that can be emitted, then some allowances are given to companies while others are auctioned to the affected entities. Some of the allowances are given to companies that may choose to relocate their source of emissions to countries where they would not face such a policy if they had to pay the full cost. Allowances are given back to the EU according to the actual emissions of the company. If the company does not have sufficient allowances, these need to be purchased in the market; conversely entities in excess can bank allowances or offer them on the market.

More information about the EU ETS can be found in the EU ETS Handbook[8].

[8]https://ec.europa.eu/clima/sites/clima/files/docs/ets_

If neighborhoods were to buy allowances from the EU ETS and given that the cap on the emission is fixed, this would reduce the amount of available allowances on the market and potentially push more entities towards carbon-reduction measures. This could however be hindered by the use of more non-additional CDM projects.

In the last year, the CO_2 price on the EU ETS has been in the 20 to 30 $€/tonCO_2$ range.

Carbon Capture and Storage (CCS)

CCS is the process of capturing CO_2 from the combustion of fossil fuels, exhausts from industrial processes such as concrete and steel production, or from ambient air, transporting it and then storing it, typically in specific underground rock formations. This offers another possibility for compensating for emissions by paying for capturing emissions elsewhere. In 2005, the IPCC reported costs for CCS in different types of coal and gas plants in the range of 18 to 250 $€/tonCO_2$ ([7]). More recently, costs of avoided CO_2 emissions ranging from 5 to 155 $€/tonCO_2$, depending on the technology where CCS is used, were reported in the literature ([8]). Costs between 15 to 110 $€/tonCO_2$ are reported by the global CCS institute ([9]). One drawback of CCS is that it indirectly promotes energy from fossil sources whose concentrated emissions can be captured relatively easily. Extracting CO_2 from ambient air is also a technology being developed, but there is no certainty regarding it ever achieving the commercial stage.

CO_2 factors

In order to calculate the amount of emissions and assess the compensations, it is necessary to define the carbon intensity, also known as the emission factors of the different energy sources. The emissions from burning fuel can be obtained from several sources such as [3] or [10]. They correspond to the amount of CO_2 equivalent emissions from burning the fuel. Those factors can be used together with the plants' characteristics such as efficiency. When it comes to electricity, the emission factor is harder to define. Due to the nature of the power system, it is not realistic (although possible in theory [11]) to try to trace the origin of the electricity used at all times to a specific generator. This means that we need to define the emission factor of electricity on another basis. A common approach is to consider the average electricity generation of a bidding zone. Marginal emission factors, defined either as the emission factor of the marginal unit in the electricity market or as the emission factor from producing one more unit of power, can also be used when dealing with uncertain consumption and production. Paper 4 deals with the choice of CO_2 factor for electricity and its impact on the resulting ZEN's

handbook_en.pdf

energy system design.

In the ZEB research center, the emission factor of electricity has been extensively discussed. The discussion focused on the type of factor and the spatial scope that it should represent. In the research center, the choice was made to use emission factors based on a linear decarbonization of the European power system towards 2055, such as represented in Fig. 2.4. [12] presents some aspects of this discussion along with other interesting elements of the discussion around the definition of what Zero Emission Building means in the ZEB research center.

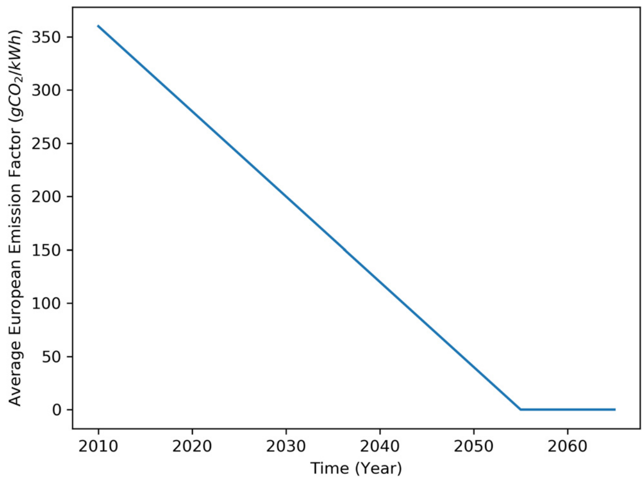


Figure 2.4: Scenario of a decarbonization of the European power system used for selecting the emission factor in the context of ZEBs [12].

2.3 Optimization

Optimization is a field of applied mathematics that aims to find the best solution to a given problem. It is often used for economic and technical decision-making situations. An optimization problem can be written in the form:

$$\begin{aligned} &\min f(\mathbf{x}) \\ &\text{s.t. } g_i(\mathbf{x}) \leq b_i, \qquad i = 1, ..., m \end{aligned}$$

x is a vector of variables. The optimization problem aims at finding **x** that minimizes (or maximizes) the objective function $f(\mathbf{x})$. A set of constraints expressed by $g_i(\mathbf{x})$ and b_i limits the solution space.

If all functions (f and g_i) are linear and all variables continuous, then the problem is a linear problem (LP). Those problems can usually be solved fairly quickly. If some of the variables can take integer values we define it as a mixed integer linear problem (MILP); these problems are harder to solve.

Two main algorithms exist to solve LP problems: the simplex and the interior points methods. The simplex method looks for a solution along the vertices, i.e. extreme points, of the feasible region. Starting from a basic solution, the method iteratively moves to an adjacent vertice in a direction that locally improves the objective function until no further improvement can be made [13]. The interior points method, in contrast, explores the feasible region from the inside. Affine scaling and path following are two examples of interior point methods.

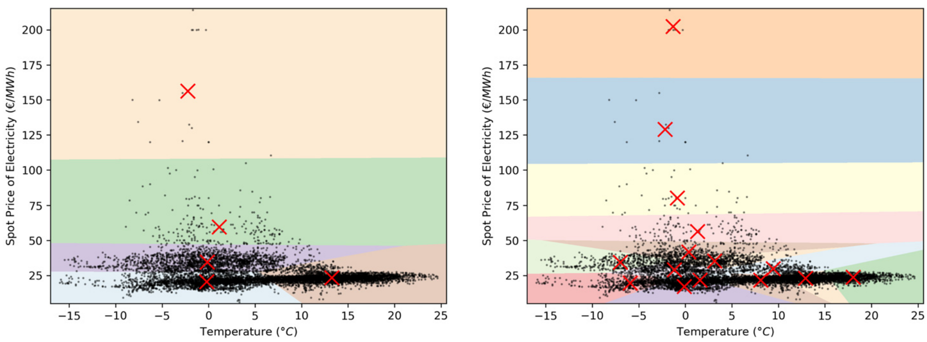
MILP problems cannot be solved with the same methods as LP problems because those take advantage of specific properties of linear problems that MILP problems do not have. Several other methods can be used instead but they can take a significant amount of time to reach an optimal solution. MILPs also have properties that can be used to find a solution. For example, solving a relaxed version of the problem (meaning the same problem without some constraints for example) gives an optimistic bound to the optimal solution, while finding a feasible solution to the original problem gives a pessimistic bound. The MIP gap or optimality gap is the difference between the pessimistic and optimistic bounds and can be used as a stop criterion to the optimization. Branch and Bound is a commonly used method to solve MILP problems. It involves decomposing the problems into subproblems, typically by fixing integer variables, and exploring the tree made by solving the problems with one more freed variable at a time. The solutions to the relaxed problems provide optimistic bounds and if a solution is found that is also feasible in the original problem, it provides a pessimistic bound. The tree can then be explored toward an optimal solution.

Other types of optimization models exist that should be mentioned. Among them, heuristics and metaheuristics are solution methods often used for complex problems. These methods differ from traditional optimization in that there is no guarantee of optimality or no information on the quality of the solution found. Such methods typically rely on exploring the feasible solution space by looking for an improvement to the current best solution in its proximity. This tends to only find local optimums. The metaheuristics, which are often inspired by behavior observed in nature, try to solve this by temporarily going towards less good solutions.

Stochastic and robust optimization are two approaches to dealing with uncertainties in the input data of the optimization.

2.4 Clustering

Clustering is the action of grouping multiple objects together based on their properties. In the context of optimization, it is often used to reduce the complexity of a problem by reducing the number of variables. The data are grouped based on the distance between datapoints; each group is called a cluster and inside each cluster, a cluster representative is calculated or chosen among the dataset. The cluster representative can be used instead of all the datapoints it represents.



(a) 5 Clusters **(b)** 15 Clusters

Figure 2.5: Example of clustering 2D data (hourly temperature in Oslo and spot price in NO1 in 2016) with 5 and 15 clusters. Each cluster is represented by a color and its representative is marked by a red cross.

Figure 2.5 shows an example of a clustering performed on a dataset containing hourly temperatures in Oslo and the spot price of electricity in NO1 in 2016 with 5 and 15 clusters. In total there are 8760 points that are grouped together by a k-means algorithm, which tries to minimize the distance between different points inside a cluster and the mean of those points. This form of clustering can reduce the complexity of a problem by significantly reducing the number of timesteps.

Two common clustering algorithms are the k-means and k-medoids algorithms. These two algorithms are very similar but differ in the way they construct cluster representatives. In the k-means, the representative is constructed as the means of the cluster elements, while in the k-medoids it is chosen among the input data as the element closest to the mean of all elements inside the cluster.

The k-means algorithm iteratively tries to find the best clusters. The problem can be formulated as finding the sets S defined by:

$$\underset{S}{arg\,min} \sum_{i=1}^{k} \sum_{x \in S_i} ||x - \mu_i||^2 \tag{2.2}$$

where μ_i is the mean of the points in the set S_i.

It starts by an initialization step consisting of setting the initial cluster representatives. This step is important and can lead to clusters that are only local optimums. The basic approach is to choose randomly in the data, but several other methods exist, including the k-means++ [14].

After the initialization two steps are repeated until convergence. The first is assigning all the elements to clusters by computing the distance (usually Euclidean, but other definitions can also be used) to the candidate cluster representatives. The second step is to recalculate the means of each cluster. They become the new candidate cluster representatives and the process continues until a convergence is reached, i.e. the clusters remain the same.

This clustering method can give different results depending on the initialization. Hierarchical clustering is an alternative method giving more consistent results. This type of clustering algorithm creates clusters with a bottom-up (usually) approach, grouping the closest points or clusters together.

2.5 Literature review

This section presents an overview of the existing literature relevant to the general scope of this thesis, i.e. the design of the energy systems of local energy communities, including net zero energy and net zero emission concepts at the building or neighborhood level. A literature overview more specifically relating to the particular topics of each paper can be found in their introductory sections.

The literature on ZEN covers various fields: including architecture, social sciences, Computational Fluid Dynamics (CFD), energy systems, etc.; and various topics: energy demand simulation, building envelope simulation, ventilation, energy flexibility, urban planning, energy system planning, etc. The main topic of the thesis is the design of energy systems for ZENs and the focus of this literature review is on existing approaches to solve the more general problem of the design of energy systems of neighborhoods or buildings.

Reference [15] gives an overview of the different definitions of ZEBs and of the existing uses of optimization in the corresponding literature.

Table 2.3 presents information about various examples of models for designing the energy system of one or more buildings. This literature review does not aim at exhaustivity but should offer a good overview of the literature on the topic. The scope and goal of each paper is different in terms of method, temporal scope, spatial scope, technologies included and level of the detail of the models of the technologies. Those parameters are chosen in each paper in order to be able to answer the research question and to have computationally tractable optimizations depending on the available hardware to solve it. In addition to the table, a literature review of modeling of multi-energy systems in districts was recently published [16].

Two main modeling approaches can be distinguished, metaheuristic and traditional optimization. Out of the 46 papers from Table 2.3, seven use metaheuristics, three use a combination of both approaches and the rest use traditional optimization. There is also a noticeable divide between single- and multi-objective (MO) approaches; MO being used in 17 cases. Most papers take a MILP approach, with only a few non-linear or non-integer cases. Most papers do not consider the DHW and SH load separately but either only consider SH or consider SH and DHW together. Ten papers co-optimize the heating grid along with the energy system design, including one that does not optimize the layout and two that also design the electrical grid.

The meta-heuristic approaches seem to be typically used when dealing with a high level of details in the modeling of technologies, when combining building simulation tools in a co-optimization of building characteristics and energy system or when specific complicating constraints are necessary.

An hourly resolution is the most common approach in order to represent hourly variations in the load or electricity price for instance. However, the number of timesteps in each model varies greatly between one summer, winter and mid-season day and one complete year.

A few of the publications are in the context of net or nearly Zero Energy Buildings, including one at the district level [17]. In this concept, primary energy factors are used instead of emission factors. None of the literature found deals directly with Zero Emission Neighborhood or corollaries (district, communities). Two publications ([18], [19]) deal with Zero Emission Buildings. However, even though those concepts are not directly applied, emissions of CO_2 are still often considered. One important aspect standing out of the analysis is the widespread use of yearly average emission factors. These factors are used inside an objective function minimizing total emissions in the multi-objective models or inside the minimization of the costs as a carbon tax in single-objective approaches. They can also be used in a constraint setting an upper bound on the emissions or in the analysis of the results. Only [20] and [21] use hourly emission factors, and only [21] considers the use of marginal emission factors.

The two publications using a zero emission framework take two different approaches to the definition of the zero emission constraint. [19] defines it in equation 69 of the paper. It is defined as an inequality; the emissions inside the building boundaries (from burning fuel and importing electricity) should be less or equal to the total emissions for covering the electric, heating and cooling demand from grid electricity multiplied by a factor representing the ambition level. This factor allows to set the ambition level for the building, with zero corresponding to a zero carbon building. No compensation mechanism is set, so it is unclear how this constraint can be satisfied with phi set to 0. The advantages of the method for choosing the days used in the optimization (instead of clustering for example) are also unclear. The zero emission constraint in [18] is similar but an important difference is the compensation mechanism from exports of electricity to the grid. The constraint is here an equality constraint and a reference value for the emissions of the building is used.

Reference [18] is also part of the thesis of K. Lindberg [22], which explores investment in the energy system of net zero energy and net zero emission buildings, including modeling the loads of different types of buildings.

Reference [66] presents a two-stage iterative process approach in the context of microgrids where the operation problem is solved by a MILP in a second step after a GA design. Similarly [26], [27] and [60] decompose the model into an iterative loop of investment then operation, thus allowing the use of more details in the modeling of the operation. The approach can also be compared to [36] who investigates the modeling of seasonal storage and first solving the investment and operation problem with a simplified storage description and then using a complete year for the operation only.

In [65], unacceptably long computational times are reported when directly applying the MILP problem formulation. The optimization is therefore run with sets of fixed value for the CHP and wind turbine capacities to explore the solution space faster. [39] completely removes the investment part of the model to focus on an exploration of the solution space by a MILP model focusing on operation using various combinations of elements sizes.

A decomposition method based on timeseries aggregation is proposed in [67]. The process consists of finding a lower bound by solving the problem with one temporal cluster, and then solving the operation problem with the whole dataset for finding an upper bound. The convergence is checked and the number of clusters for the lower bound search is increased if the convergence criterion is not met.

Reference [68] uses a Multi-Objective Genetic Algorithm to invest in a building envelope (types and thickness of insulation and walls, roofs, windows). It takes a life-cycle assessment approach to incorporate exergy as one of the components

Table 2.3: Comparison of existing literature in the domain of the investment/design in the energy system of neighborhoods.

Paper	Type of Model	SH+DHW	Grids design	Time resolution	Duration considered	Nb Buildings
[23]	MILP	No	Heat	Periods	6 periods for three seasons	10-20
[24]	LP	No	No	hourly	12 days	3
[18]	MILP	No	No	hourly	1 year/period in lifetime	1
[25]	MILP	No	Heat	15 minutes/1h	1 year	6 (3 types)
[26]	two-stage stochastic MILP	Yes	No	15 minutes	1 year in 2-week blocks	70 into 4 clusters
[27]	Evolutionary MOO[1] and MILP MPC[2]	Yes	No	hourly	1 year in 18 day clusters	1
[28]	MILP	Yes	No	hourly	1 year	1
[29]	MO[1]MILP and Evolutionary Algorithm	No	No	months	12 months + 1 peak	1
[30], [31]	MILP	No	Heat and Electricity	2h	1 typical days for 3 seasons	5, 4
[32]	MILP	No	No	hourly	3 typical days per month	4
[20]	MILP	Yes	No	hourly	1 day for 3 seasons	1
[33], [34]	MILP	No	Heat	2-hourly	2 days per month	4
[21]	MO[1]MILP	No	Heat and Electricity	hourly	4 weeks clusters	3 clusters
[35]	MILP	Yes	Heat	6 periods per day	1 day for three seasons	35
[36]	two-stage MILP	No	No	hourly	design days + 1 year for operation	1, Altstetten Zurich
[37]	MO[1]GA[3]	No	No	hourly	1 year (?)	1
[38]	MO PSO[4]	Yes	No	hourly	1 year	1
[39]	MPC with various component sizes	Yes	No	hourly	1 year	1
[40]	MO[1]GA[3]	Yes	No	hourly	1 year (?)	1
[41]	NLP[7] GRG[8]	No	No	hourly	1 year	1
[42]	LP	Yes	No	hourly	1 year (?)	1
[43]	robust MILP	No	Heat	4-hourly	1 day for 3 seasons	5
[44]	MILP	No	No	hourly	1 year	10
[45]	MO[1]GA[3]	No	No	hourly	1 year	15 in 3 clusters
[46]	stochastic MILP	No	Heat inside clusters	hourly	1 day for 3 seasons	60 in 12 clusters
[47]	robust/stochastic MOO[1]	No	No	6 periods per day	1 day in 3 seasons	6
[48]	MO[1]stochastic MINLP	No	No	hourly	1 year (?)	1
[19]	MILP	No	No	hourly	1 day for three seasons	1
[49]	MILP	No	No	hourly	1 day for 3 seasons	3
[50]	MILP	No	Heat	hourly	1 day for 3 seasons	11
[51]	MILP	No	No	monthly	12 months + 2 peaks	6
[52]	GA[3]	No	No	hourly	1 year (?)	1
[53]	MO[1]GA[3]	Yes	No	hourly (?)	1 year (?)	1
[54]	MILP	Yes	No	hourly	1 day per month	1
[55]	MO[1]MILP	No	No	half-hourly	typical days (up to 39)	1
[56]	MINLP	No	No	hourly	1 day	6
[57]	MO[1]MILP	No	No	2 hourly	1 day for 3 seasons	4
[58]	MO[1]MILP	Yes	No	hourly	1 day per season	1 cluster of 30
[59]	MO[1]MILP	No	Heat, only pipe size	4-hourly	1 year	9
[60]	Tri-level MO[1]GA[3] and MILP	No	No	hourly	1 year	1
[61]	MO[1]MILP	No	No	hourly	1 week per month	9
[62]	robust (minmax) MO[1]MILP	No	No	?	7 days	1
[63]	Dual Dynamic Programming	No	No	15 minutes	1 year	1
[64]	non-linear GA[3]	No	No	monthly (?)	$\approx 20 years$ (?)	1
[65]	MILP	No	No	hourly	1 year	1
[17]	MO[1]MILP	No	Heat	6 periods per day	1 day per season	7

[1] Multi-Objective (Optimization) [2] Model Predictive Control [3] Genetic Algorithm [4] Particle Swarm Optimization [7] Nonlinear Program
[8] Generalized Reduced Gradient

of the life-cycle's environmental impact which is used as one of the objectives. The other objective is minimum life-cycle cost. This paper shows an application of optimization on something different than the energy system of green buildings. Tackling a similar problem, [69] uses a multi-objective harmony search algorithm to minimize the life-cycle cost and emissions of a building's envelope. These approaches can be of particular interest when dealing with refurbishment of buildings and could inspire a combination of this kind of modeling with the model presented in this thesis towards a co-optimization of buildings' characteristics and energy system in the ZEN framework. [60] could be an example of such a linkage outside of the ZEN framework.

Some papers are relevant to the topic but do not fit in Table 2.3. Among these, [70] presents a practical example of involving communities into the developments

Table 2.3: Comparison of existing literature in the domain of the investment/design in the energy system of neighborhoods (Cont.)

Paper	Emissions considered, emission factor	Part Load	Costs function	Min. Inv. Size	Other
[23]	Carbon tax, yearly average Factor	No	linear homogeneous	Yes	
[24]	Included, no factors given	No	linear homogeneous	No	Focus on microgrid
[18]	Zero emission criteria, yearly average	Yes	linear	Yes	
[25]	calculated post-optimization,	Yes	linear	Yes	compares different time resolutions
[26]	No	Yes	linear	No	Decompose the problem. Only sizes the storages.
[27]	No	Yes	linear	Yes	objectives are cost and self-sufficiency
[28]	upper bound on emissions, yearly average	Yes	linear	No	piece-wise linear penalty cost outside the comfort temperature range
[29]	One of the objectives, yearly average	No	linear homogeneous	No	compares integer cut constraints, ϵ constraints and evolutionary algorithm
[30], [31]	No	Yes	linear homogeneous	Yes	
[32]	carbon tax, hourly marginal	No	linear	No	considers voltage constraint in electric grid
[20]	No	Yes	piece-wise linear	Yes	uses block angular structure to decompose
[33], [34]	No	Yes	linear	No	detailed model of the heating plant
[21]	one of the objectives, both hourly marginal and average	No	linear	No	combines two open source models
[35]	upper bound on emissions, yearly average	Yes	piece-wise linear	Yes	
[36]	upper bound on emissions, yearly average	Yes	piece-wise linear	Yes	compares formulations for seasonal storage operation
[37]	one of the objectives, yearly average	No	?	No	validates model data with an existing ZEB
[38]	one of the objectives, yearly average	No	linear	No	
[39]	calculate GWP[5]-	No	linear homogeneous	No	
[40]	No, but one objective is minimum PE[6]-	No	linear homogeneous	No	detailed building model in EnergyPlus
[41]	one of the selection criteria	Yes	quadratic	No	
[42]	No, but considers a net zero primary energy balance	No	linear	No	
[43]	No	No	linear homogeneous	Yes	
[44]	upper bound on emissions, yearly average	No	linear	Yes	Global sensitivity analysis of inputs (spot price, loads, emission factor,...)
[45]	one of the objectives, yearly average (?)	No	linear	No	Life-cycle approach
[46]	No	Yes	linear homogeneous	No	
[47]	one of the objectives, yearly average	No (?)	linear homogeneous	Yes	comparison of robust and stochastic optimization with single- or multi-objective
[48]	one of the objectives, yearly average	Yes	linear homogeneous	No	
[19]	zero carbon constraint, yearly average	No	integer investments	Yes	
[49]	in analysis, no factor for electricity (?)	No	linear homogeneous	No	game theory approach
[50]	No	No	linear homogeneous	Yes	
[51]	No	Yes	integer	Yes	focus on detailed part loads and efficiencies
[52]	No	No	linear homogeneous	No	Zero energy building
[53]	No	No	linear	No	Zero energy building considering both energy system and building characteristics
[54]	in analysis, yearly average	No	linear homogeneous	No	
[55]	one of the objectives, yearly average	Yes	integer	Yes	
[56]	No	Yes	linear homogeneous	No	
[57]	one of the objectives, yearly average	Yes	integer	Yes	
[58]	No	Yes	integer	Yes	
[59]	one of the objectives, yearly average	Yes	integer	Yes	
[60]	one of the objectives, yearly average	Yes	linear	Yes	co-optimize building envelope and energy system
[61]	one of the objectives, yearly average	No	linear homogeneous	Yes	
[62]	one of the objectives, yearly average	No	piece-wise linear	No	uncertainty on the loads and emission factor
[63]	No	No	linear homogeneous	No	uses Benders' decomposition and includes retrofitting of envelope
[64]	No	Yes	integer (polynomial)	Yes	nearly zero energy building
[65]	No	Yes	linear homogeneous	No	
[17]	one of the objectives, yearly average	No	linear homogeneous	No	net Zero Energy District

[5] Global Warming Potential [6] Primary Energy

of an energy concept. In practice, they set up a process including the community based on workshops and presented choices to the community for the setup of the study, the criteria and their importance, the different case study scenarios and the follow-up on the results. It presents an idea of what is possible to achieve by using models such as the ones presented in the table and by involving the communities whose energy system is optimized. ZENs are an extreme case in terms of emission constraints and the communities should be involved in the decision process regarding the importance of cost and emissions in the optimization and the technologies to include or limit.

Reference [71] uses a version of the TIMES model including only the heat part to investigate the scale effect of low energy building heat supply in three neighborhoods representative of what is found in Sweden. It finds that, it is preferable to use centralized heating plants especially within or near urban areas.

Reference [72] uses dynamic programming for cost-optimal routing, sizing and investment timing into a grid serving loads that are growing during the planning horizon. They show a decomposition of the problem which allows to reduce the solving time. Even though the model does not consider energy system investment, the approach presented could be relevant when dealing with a combination of both problems.

The existing literature shows various ways to design the energy system of buildings and neighborhoods, with their specific goals and characteristics, but none investigates the case of ZENs. This thesis and the accompanying papers aim at covering this gap in the literature.

Chapter 3

Model and methodology for optimal ZEN energy system design

This section presents the Zero Emission Neighborhood Investment Tool (ZENIT) for cost-optimal design of ZEN energy systems and multiple other aspects surrounding the optimization model. It details the methodology used rather than analyzing the results derived from using the model. The analyses of results from using the models are presented in section 4.

3.1 The ZENIT Tool

The ZENIT (Zero Emission Neighborhood Investment Tool) tool was created during the course of this PhD to answer the research questions presented earlier. It uses optimization to find the cost-optimal design of the energy system which enables the possibility to reach net zero emissions.

The tool uses the description of the neighborhood, including all the buildings and their loads, to choose from a pool of available technologies (either inside the building or in a central plant) the types and sizes that will make it least expensive to install and operate. The complete mathematical description of the model is presented in section 3.2.

The main types of technologies that can be chosen are presented below. Boilers are a very common type of system providing heat. There are many types of boilers using different fuels to heat water through combustion or electrical resistance in the case of electric boilers. Different technologies are more or less efficient at capturing this heat. In ZENIT, we consider electric boilers, gas boilers, biomass boilers (biogas, biomethane, wood chips, wood logs and wood pellets).

Radiators are also considered, particularly when the use of a hydronic system is taken into account in the model.

Combined Heat and Power (CHP) plants produce both heat and electricity. They offer a more efficient solution by recuperating the heat that would otherwise be lost while generating electricity. A simple example could be a plant burning a fuel to boil water and produce electricity from the steam while the remaining heat can be used for district heating. There are many types of CHPs, with more or less focus on heat or electricity generation.

Two types of solar technologies are included in the model. Photovoltaic (PV) modules or solar panels can produce electricity from sunlight. They are made from semi-conductors that release electrons when hit by photons and create an electric current thanks to the electric field of the PN junction. Solar Thermal collectors (ST) are a type of technology that can provide heat for SH or DHW purposes by heating water from solar irradiance.

Heat Pumps (HPs) transfer heat between two sources by using electrical energy. In practice the source can be the outside air or the ground and the heat can be transferred to the inside air or to water. In ZENIT we consider air-air heat pumps, air-water heat pumps and water-water heat pumps (or ground source heat pumps).

3.2 ZENIT optimization model

This section presents the optimization formulation inside of ZENIT in the most general form. The formulations used in the papers are variations around this model with specific elements not used or modified. The symbols used can be found in the list of symbols.

Objective function

The objective function minimizes the total cost of investing in the energy system and operating it. It includes investment in the heating grid, the energy technologies in the central plant and in the building, the cost of refurbishment and of a hydronic system (when refurbishment is considered). It also includes operational costs such as the operation and maintenance (O&M) costs, fuel costs, cost of electricity imports and revenues of electricity exports. It uses an hourly resolution.

The objective function of the optimization is: *Minimize*:

$$
\begin{aligned}
b^{HG} \cdot C^{HG} + \sum_b \sum_i \Big((C_{i,b}^{var,disc} + \frac{C_{i,b}^{maint}}{\varepsilon_{r,D}^{tot}}) \cdot x_{i,b} + C_{i,b}^{fix,disc} \cdot b_{i,b} \Big) \\
+ \sum_b \Big(b_b^{refurb} \cdot C_b^{refurb} + b_b^{H2Onics} \cdot C_b^{H2Onics} \Big) + \frac{1}{\varepsilon_{r,D}^{tot}} \Bigg(\sum_{t_\kappa} \sigma_\kappa \\
\Big(\sum_b \sum_f f_{f,t,b} \cdot P_f^{fuel} + (P_t^{spot} + P^{grid} + P^{ret}) \cdot (y_t^{imp} \\
+ \sum_b \sum_{est} y_{t,est,b}^{gb\_imp}) - P_t^{spot} \cdot y_t^{exp} \Big) \Bigg) \quad (3.1)
\end{aligned}
$$

The investment costs in the objective function are discounted using linear depreciation and taking into account reinvestments and salvage value: $\forall i$

$$
C_i^{disc} = \left(\sum_{n=0}^{N_i-1} C_i^{inv} \cdot (1+r)^{(-n \cdot L_i)} \right) - \frac{N_i \cdot L_i - D}{L_i} \cdot C_i^{inv} \cdot (1+r)^{-D} \quad (3.2)
$$

with:

$$
N_i = \left\lceil \frac{D}{L_i} \right\rceil \quad (3.3)
$$

and the discount factor:

$$
\varepsilon_{r,D}^{tot} = \frac{r}{1-(1+r)^{-D}} \quad (3.4)
$$

Zero Emission constraint

In order to qualify as a ZEN, a neighborhood needs to have net zero emission of GHG in its lifetime. We use a representative year to reduce the temporal complexity of the model. Clusters can also be used to reduce the complexity even further when other parameters make the problem hard to solve (e.g. high number of buildings or high number of binary variables).

$$\alpha_{ZEN} \cdot \sum_{t_\kappa} \sigma_\kappa \Bigg(\phi_t^{CO_2,el} \cdot \Big(y_t^{imp} + \sum_b \sum_{est} y_{t,est,b}^{gb\_imp} \Big) + \sum_b \sum_f \phi^{CO_2,f} \cdot f_{f,t,b} \Bigg) \leq$$

$$\sum_{t_\kappa} \phi_t^{CO_2,el} \cdot \sigma_\kappa \Bigg(\sum_b \sum_{est} \eta_{est} \cdot \Big(\alpha_{ZEN} \cdot y_{t,est,b}^{gb\_exp} + y_{t,est,b}^{pb\_exp} + (1 - \alpha_{ZEN}) \cdot y_{t,est,b}^{selfc} \Big)$$

$$+ \sum_b \sum_g \Big(y_{t,g,b}^{exp} + (1 - \alpha_{ZEN}) \cdot g_{t,g,b}^{selfc} \Big) \Bigg) \quad (3.5)$$

The emission constraint contains the emissions from imports of electricity and from burning fuel and the compensations from exports of electricity. The term α_{ZEN}, between zero and one, is used for designing neighborhoods that are not completely ZEN. When it is one, the neighborhood will need to compensate for all of its emissions, while setting a value below one lessens the constraint. For example, at $\alpha_{ZEN} = 0.3$, the neighborhood compensates only 30% of its emissions. This can be useful when designing neighborhoods that want to be more sustainable without the entire cost of being zero emission or for calculating the marginal cost of emission reduction.

Each battery is separated into two independent batteries sharing the invested capacity dynamically in order to keep track of the origin of the electricity inside the battery. Fig. 3.1 shows the schematic representation of the modeling of electrical flows in the neighborhood. The separation is necessary in order to account for the origin of the electricity stored in the battery. This is of particular importance when $\alpha_{ZEN} < 1$ or in case asymmetrical CO_2 factors are used for imports and exports of electricity. Indeed, when $\alpha_{ZEN} < 1$, the emissions are weighted by $alpha$; if the battery was not virtually separated in two entities, the battery could import from the grid at a discounted emissions count and then export with full compensation. With this modeling separation, both the imports from the grid to the battery and the exports from the battery to the grid are weighted by the factor $alpha$.

Equation 3.5 also includes a term with the self-consumption of energy (produced from on-site technologies in the same hour or stored in the battery), that only comes into effect when $\alpha_{ZEN} < 1$. This term corrects a problem arising from the use of the α factor. Indeed, let us assume that there is on-site production of electricity in hour h of g_h (or consumption of previously stored production), the model has the choice to consume it or to export it. However, these choices are not equivalent in terms of compensation; by consuming it, the net load is reduced, meaning less imports of electricity reducing the emissions by $\alpha_{ZEN} \cdot g_h \cdot \phi^{CO_2,el}$; while by exporting it the compensation is increased by $g_h \cdot \phi^{CO_2,el}$ (the imports

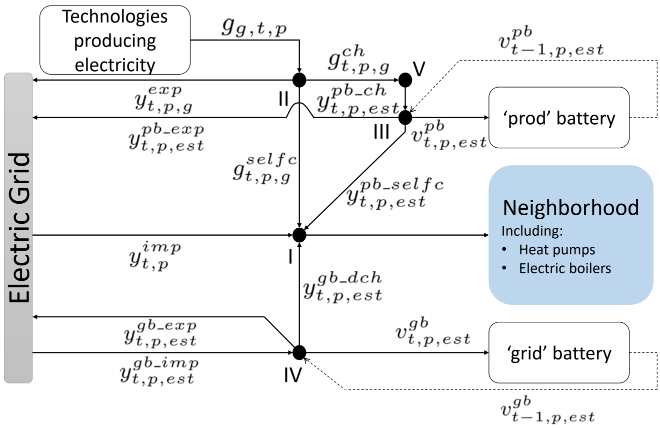


Figure 3.1: Schematic representation of the modeling of the electricity flows and storage in the neighborhood, which also represents the energy balance equations. Inspired by Fig. 3 in [18].

of electricity and associated emissions remains at the base level). This imbalance between self-consumption and export is corrected by the introduction of the term $(1-\alpha_{ZEN}) \cdot g^{selfc}_{t,g,b}$ which combined with the emission reduction from the lower imports results in the same amount of compensation as exporting. In addition to giving the correct amount of compensation, this formulation also avoids the introduction of binary variables to prevent imports and exports in the same timestep that would otherwise happen.

Energy balances

The electricity balance of the electricity in the neighborhood as illustrated by Fig. 3.1 is described by Eq. 3.6, 3.9 and 3.10.

Eq. 3.6 is the main part of the electricity balance and describes the way the electric load of the neighborhood is met:$\forall t$

$$y^{imp}_t + \sum_b \left(\sum_{est} (y^{gb\_dch}_{t,est,b} + y^{pb\_selfc}_{t,est,b}) \cdot \eta_{est} + \sum_g g^{selfc}_{g,t,b} \right) = \sum_b (E_{b,t} + \sum_e d_{e,t,b}) \tag{3.6}$$

The exports of electricity in Eq. 3.1 are defined as:$\forall t$

$$y^{exp}_t = \sum_b \sum_g y^{exp}_{t,g,b} + \sum_b \sum_{est} (y^{gb\_exp}_{t,est,b} + y^{pb\_exp}_{t,est,b}) \cdot \eta_{est} \tag{3.7}$$

The imports and exports of electricity are limited by the size of the connection to the grid:$\forall t$

$$(y_t^{imp} + y_t^{exp} + \sum_b \sum_{est} y_{t,est,b}^{gb\_imp}) \leq GC \tag{3.8}$$

Eq. 3.9 describes the flow of electricity of the on-site production of technologies and Eq. 3.10 describes the interface between the on-site production and the PB batteries. $\forall t, g, b$

$$g_{g,t,b} = y_{t,g,b}^{exp} + g_{g,t,b}^{selfc} + g_{t,g,b}^{ch} + g_{t,g,b}^{dump} \tag{3.9}$$

$\forall t, b$

$$\sum_g g_{t,g,b}^{ch} = \sum_{est} y_{t,est,b}^{prod\_ch} \tag{3.10}$$

The electricity in the neighborhood is handled in an aggregated way, or as a copper plate. The heat is, on the other hand, not aggregated and considers heat loss in the heating grid. The heat in buildings is also separated between space heating (SH) and domestic hot water (DHW), giving two heat balances:$\forall t, b$

$$\begin{aligned}\sum_q q_{q,t,b}^{DHW} + \sum_{hst}(\eta_{hst} \cdot q_{t,hst,b}^{DHWdch} - q_{t,hst,b}^{DHWch}) + q_{t,b}^{HGusedDHW} = \\ B_b^{refurb} \cdot \Big(H_{b,t}^{DHW} \cdot A_b\Big) + \Big(1 - B_b^{refurb}\Big) \cdot \Big((1 - b_b^{refurb}) \cdot H_{b,t}^{DHW} \cdot A_b \\ + b_b^{refurb} \cdot H_{b,t}^{refurbDHW} \cdot A_b\Big) + q_{t,b}^{dump}\end{aligned} \tag{3.11}$$

$$\begin{aligned}\sum_q q_{q,t,b}^{SH} + \sum_{hst}(\eta_{hst} \cdot q_{t,hst,b}^{SHdch} - q_{t,hst,b}^{SHch}) + q_{t,b}^{HGusedSH} = \\ B_b^{refurb} \cdot \Big(H_{b,t}^{SH} \cdot A_b\Big) + \Big(1 - B_b^{refurb}\Big) \cdot \Big((1 - b_b^{refurb}) \cdot H_{b,t}^{SH} \cdot A_b \\ + b_b^{refurb} \cdot H_{b,t}^{refurbSH} \cdot A_b\Big)\end{aligned} \tag{3.12}$$

At the Production Plant (PP) the balance considers the heat flowing out instead of a load: $\forall t$

$$\begin{aligned}\sum_q q_{q,t,'PP'} + \sum_{hst}(\eta_{hst} \cdot q_{t,hst,'PP'}^{dch} - q_{t,hst,'P'}^{ch}) = \sum_{b \backslash 'PP'} q_{t,'PP',b}^{HGtransfer} \\ + q_{t,'PP'}^{dump}\end{aligned} \tag{3.13}$$

Constraints on the technology options

General Constraints

The investment in each technology is limited. The minimum corresponds to either the capacity already installed in the neighborhood or the minimum possible investment size and the maximum is chosen to limit the search space:$\forall i \cup est \cup hst, b$

$$X_{i,b}^{pre\_cap} \leq x_{i,b} \leq X_i^{max} \tag{3.14}$$

$$x_i \leq X_i^{max} \cdot b_{i,b} \tag{3.15}$$

$$x_i \geq X_i^{min} \cdot b_{i,b} \tag{3.16}$$

At the production plant, where larger-scale technologies than those available inside the buildings are available, the size of technologies is also limited and requires an investment in the heating grid: $\forall i$

$$x_{i,'ProductionPlant'} \leq X_i^{max} \cdot b^{HG} \tag{3.17}$$

Most of the technologies considered in the optimization are modeled using their efficiency, linking either their heat or electric production and their fuel consumption: $\forall \gamma \in \mathcal{F} \cap \mathcal{Q}, t, b$

$$f_{\gamma,t,b} = \frac{q_{\gamma,t,b}}{\eta_\gamma} \tag{3.18}$$

$\forall \gamma \in \mathcal{E} \cap \mathcal{Q}, t, b$

$$d_{\gamma,t,b} = \frac{q_{\gamma,t,b}}{\eta_\gamma} \tag{3.19}$$

The heat and electricity production is limited by the installed capacity:

$\forall q \setminus HP, t, b$

$$q_{q,t,b} \leq x_{q,b} \tag{3.20}$$

$\forall g, t, b$

$$g_{g,t,b} \leq x_{g,b} \tag{3.21}$$

Some technologies can only be operated in a certain range of their nominal capacity. This requires adding additional constraints with binary variables:

$$\overline{x_{i,t}} \leq X_i^{max} \cdot o_t \tag{3.22}$$

$$\overline{x_{i,t}} \leq x_i \tag{3.23}$$

$$\overline{x_{i,t}} \geq x_i - X_i^{max} \cdot (1 - o_t) \tag{3.24}$$

$$q_{i,t} \leq \overline{x_{i,t}} \tag{3.25}$$

$$q_{i,t} \geq \alpha \cdot \overline{x_{i,t}} \tag{3.26}$$

The type of heat that technologies can provide is enforced with: $\forall q, t, b$

$$q_{q,t,b} = q_{q,t,b}^{DHW} + q_{q,t,b}^{SH} \tag{3.27}$$

$$q_{q,t,b}^{DHW} <= M \cdot B_q^{DHW} \quad (3.28) \qquad q_{q,t,b}^{SH} <= M \cdot B_q^{SH} \quad (3.29)$$

CHP constraints

For Combined Heat and Power (CHP) plants, the amount of heat produced is obtained using the efficiency, while the amount of electricity produced is derived from the heat-to-power ratio: $\forall t,' CHP', b$

$$g_{CHP,t,b} = \frac{q_{CHP,t,b}}{\alpha_{CHP}} \tag{3.30}$$

Heat Pump constraints

Heat pumps are modeled differently than other technologies. They have a Coefficient of Performance (COP) instead of an efficiency. This COP depends on the temperature to supply and the temperature of the source used by the heat pump as well as the characteristics of the unit used. The temperature to supply being different for SH and DHW leads to having different COPs. The coefficients in Eq. 3.31, 3.32 and 3.33 are obtained from the datasheets of manufacturers and are used to calculate the COPs and the maximum electricity consumption (linked to the maximum heat production). Equation 3.32 is used for air-air heat pumps while Eq. 3.33 is used for air-water and water-water heat pumps. The source temperature is the outside ambient temperature or the ground temperature depending on the type of heat pump. For heat pumps in the production plant and for DHW, the temperature to supply is 65°C. For SH, the supply temperature is a function of the outside temperature and of the type of building (in particular its standard).

$\forall t, b, hp$

$$COP_{t,b,hp} = \sum_j k_{j,hp} \cdot (T_{t,b}^{supply} - T_t^{source})^j \tag{3.31}$$

$$P_{aa,b,t}^{input,max} = \sum_j k'_{j,aa} \cdot (T_{t,b}^{supply} - T_t^{source})^j \tag{3.32}$$

$$P_{aw-ww,b,t}^{input,max} = \sum_j k'_{j,aw-ww} \cdot (T_{t,b}^{supply})^j \tag{3.33}$$

The heat pumps at the production plant are then modeled as: $\forall hp, t$

$$d_{hp,'ProductionPlant',t} = \frac{q_{hp,'ProductionPlant',t}}{COP_{hp,'ProductionPlant',t}} \tag{3.34}$$

$$d_{hp,'ProductionPlant',t} \leq x_{hp,'ProductionPlant'} \cdot P_{hp,'ProductionPlant',t}^{input,max} \tag{3.35}$$

In other buildings they are modeled differently to account for the production of both SH and DHW. In addition, if the building is refurbished, the supply temperature and thus the COPs and maximum power input will change. $\forall hp, t, b \setminus' ProductionPlant'$

if $B_b^{refurb} = 1$:

$$d_{hp,b,t}^{SH} = \frac{q_{hp,b,t}^{SH}}{COP_{hp,b,t}^{SH,P}} \quad (3.36) \qquad d_{hp,b,t}^{DHW} = \frac{q_{hp,b,t}^{DHW}}{COP_{hp,b,t}^{DHW}} \quad (3.37)$$

$$\frac{d_{hp,b,t}^{DHW}}{P_{hp,b,t}^{input,max,DHW}} + \frac{d_{hp,b,t}^{SH}}{P_{hp,b,t}^{input,max,SH,P}} \leq x_{hp,b} \quad (3.38)$$

if $B_b^{refurb} = 0$:

$$d_{\gamma,t,b} = d_{\gamma,t,b}^{SH,P} + d_{\gamma,t,b}^{SH,NP} + d_{\gamma,t,b}^{DHW} \quad (3.39)$$

$$q_{\gamma,t,b}^{SH} = q_{\gamma,t,b}^{SH,P} + q_{\gamma,t,b}^{SH,NP} \quad (3.40)$$

$$d_{\gamma,t,b}^{SH,P} \leq M \cdot b_b^{refurb} \quad (3.41) \qquad d_{\gamma,t,b}^{SH,NP} \leq M \cdot (1 - b_b^{refurb}) \quad (3.42)$$

$$d_{hp,b,t}^{SH,P} = \frac{q_{hp,b,t}^{SH,P}}{COP_{hp,b,t}^{SH,P}} \quad (3.43) \qquad d_{hp,b,t}^{SH,NP} = \frac{q_{hp,b,t}^{SH,NP}}{COP_{hp,b,t}^{SH,NP}} \quad (3.44)$$

$$d_{hp,b,t}^{DHW} = \frac{q_{hp,b,t}^{DHW}}{COP_{hp,b,t}^{DHW}} \quad (3.45)$$

$$\frac{d_{hp,b,t}^{DHW}}{P_{hp,b,t}^{input,max,DHW}} + \frac{d_{hp,b,t}^{SH,P}}{P_{hp,b,t}^{input,max,SH,P}} + \frac{d_{hp,b,t}^{SH,NP}}{P_{hp,b,t}^{input,max,SH,NP}} \leq x_{hp,b} \quad (3.46)$$

Solar Technology constraints

The solar technologies are also modeled differently. Indeed, they require information about the solar irradiance: $\forall t$

$$g_t^{PV} + g_t^{curt} = \eta_t^{PV} \cdot x_{PV} \cdot IRR_t \quad (3.47) \qquad q_t^{ST} = \eta_{ST} \cdot x_{ST} \cdot IRR_t \quad (3.48)$$

The efficiency of the PV panel is defined as in [73]:

$$\eta_t^{PV} = \frac{\eta^{inv}}{G_{stc}} \cdot \left(1 - T_{coef} \cdot \left(\left(T_t + \left(T_{noct} - 20\right) \cdot \frac{IRR_t}{800}\right) - T_{stc}\right)\right) \quad (3.49)$$

The formula for calculating the irradiance on a tilted surface is shown below.

$$IRR_t^{Tilt} = DHI_t \frac{1 + cos(\phi_1)}{2} + \alpha \cdot \Big(DNI_t + DHI_t\Big) \frac{1 - cos(\phi_1)}{2} + DNI_t \Bigg(\frac{cos(\varphi_t) \cdot sin(\phi_1) \cdot cos(\phi_2 - \psi_t)}{sin(\varphi_t)} + \frac{sin(\varphi_t) \cdot cos(\phi_1)}{sin(\varphi_t)}\Bigg) \quad (3.50)$$

We assume that for some sun positions (sun elevations (φ) below 1 degree and sun azimuths (ψ) between -90 and 90 degrees), no direct beam reaches the panels. This means that the last term of equation 3.50 is removed at such times. We use a constant albedo factor (α) of 0.3 for the whole year. Hourly albedo values could also be used to better represent the reflection of light on the ground in different conditions, in particular snow in the winter. However, no good source of such timeseries was found. The tilt angle of the solar panel is ϕ_1; the orientation of the solar panel regarding the azimuth is ϕ_2. We do not consider snow or dust covering the solar panel.

Heating grid constraints

The heating grid is modeled in a radial way, meaning that the buildings cannot feed heat into it and no loop is allowed. The flows are limited by the size of the pipes. If there is no hydronic system in the building, then the heat cannot be used. The heating grid is used to supply the buildings with heat coming from the central production plant, where larger-scale technologies are available. $\forall b, t$

$$\sum_{b'} q_{t,b,b'}^{HGtrans} \leq \sum_{b''} \Big(q_{t,b'',b}^{HGtrans} - Q_{b'',b}^{HGloss}\Big) \quad (3.51)$$

$\forall b, b', t$

$$q_{t,b',b}^{HGtrans} \leq \dot{Q}_{b',b}^{MaxPipe} \quad (3.52)$$

$\forall b, t$

$$q_{t,b}^{HGused} = \sum_{b''} \Big(q_{t,b'',b}^{HGtrans} - Q_{b'',b}^{HGloss}\Big) - \sum_{b'} q_{t,b,b'}^{HGtrans} \quad (3.53)$$

$$q_{t,b}^{HGused} = q_{t,b}^{HGusedSH} + q_{t,b}^{HGusedDHW} \quad (3.54)$$

$$q_{t,b',b}^{HGusedSH} \leq M \cdot b_b^{H2Onics} \quad (3.55)$$

$$q_{t,b',b}^{HGusedDHW} \leq M \cdot (b_b^{H2Onics} + B^{DHWH2Onics}) \quad (3.56)$$

Energy storage constraints

The storages are modeled with their charge and discharge efficiencies and following the representation of Fig. 3.1. The storage levels in the different timesteps inside a cluster are linked with: $\forall t \in \mathcal{T}^*, est, b$

$$v^{pb}_{t,est,b} = v^{pb}_{t-1,est,b} + \eta^{est} \cdot y^{pb\_ch}_{t,est,b} - y^{pb\_exp}_{t,est,b} - y^{pb\_selfc}_{t,est,b} \tag{3.57}$$

$$v^{gb}_{t,est,b} = v^{gb}_{t-1,est,b} + \eta^{est} \cdot y^{gb\_imp}_{t,est,b} - y^{gb\_exp}_{t,est,b} - y^{gb\_dch}_{t,est,b} \tag{3.58}$$

$\forall t \in \mathcal{T}^*, hst, b$

$$v^{heatstor}_{t,hst} = v^{heatstor}_{t-1,hst} + \eta^{heatstor}_{hst} \cdot q^{ch}_{t,hst} - q^{dch}_{t,hst} \tag{3.59}$$

The charge and discharge of the storage are limited by its specifications. $\forall hst, t, b$

$$q^{ch}_{t,hst,b} = q^{DHWch}_{t,hst,b} + q^{SHch}_{t,hst,b} \tag{3.60}$$

$$q^{dch}_{t,hst,b} = q^{DHWdch}_{t,hst,b} + q^{SHdch}_{t,hst,b} \tag{3.61}$$

$$q^{SHch}_{t,hst,b} \leq M \cdot b^{H2Onics}_{b} \tag{3.62}$$

$$q^{SHdch}_{t,hst,b} \leq M \cdot b^{H2Onics}_{b} \tag{3.63}$$

$\forall t, b$

$$\sum_{hst} q^{SHch}_{t,hst,b} \leq \sum_{q} q^{SH}_{q,t,b} \cdot b^{H2Onics}_{q} + q^{HGusedSH}_{t,b} \tag{3.64}$$

$\forall t, est, b$

$$v^{prod\_bat}_{t,est,b} + v^{grid\_bat}_{t,est,b} = v^{bat}_{t,est,b} \tag{3.65}$$

$$v^{bat}_{t,est,b} \leq x_{est,b} \tag{3.66}$$

$$y^{prod\_ch}_{t,est,b} + y^{gb\_imp}_{t,est,b} \leq \dot{Y}^{bat}_{max,est} \tag{3.67}$$

$$y^{grid\_dch}_{t,est,b} + y^{gb\_exp}_{t,est,b} \leq \dot{Y}^{bat}_{max,est} \tag{3.68}$$

$\forall t, hst, b$

$$v^{heatstor}_{t,hst,b} \leq x_{hst,b} \tag{3.69}$$

$$q^{ch}_{t,hst} \leq \dot{Q}^{hst}_{max} \tag{3.70}$$

$$q^{dch}_{t,hst} \leq \dot{Q}^{hst}_{max} \tag{3.71}$$

The storage values at the end and at the beginning of the period are set to be equal:

$\forall p, est, b, \kappa$

$$v^{bat}_{\kappa_{start},est,b} = v^{bat}_{\kappa_{end},est,b} \tag{3.72}$$

$\forall p, hst, b, \kappa$

$$v^{heatstor}_{\kappa_{start},hst,b} = v^{heatstor}_{\kappa_{end},hst,b} \tag{3.73}$$

This way of modeling the storage does not allow for seasonal storage (unless a full year is used). Another modeling solution allowing for seasonal storage is presented in Paper 3.

3.3 Heating grid estimator module

In order to obtain information about the heating grid, a python module is used to optimize the grid layout, including the pipe size that enables to meet the maximum peak heat demand at the lowest cost. This optimization could be performed endogenously inside ZENIT to find the optimal layout, cost and size of pipe. This would however be a significantly harder optimization problem. Doing it exogenously gives a conservative solution where all buildings are always part of the grid and that may be oversized. For the purpose of investing in the energy system of ZENs, a layout of the heating grid in the area such as that provided by this module allows us to investigate investment in higher-scale technologies and thus fits the purpose of ZENIT. This tool could be further improved significantly. See suggestions for further improvement and research in Chapter 5.

The objective function is to minimize the cost of the heating grid:

$$min \sum_{\varnothing} \sum_{arc} C^{pipe}_{\varnothing} \cdot b_{arc,\varnothing} \cdot L_{arc} \tag{3.74}$$

The constraints set a limit of one pipe per arc, prevent loops and limit the flow in the pipes. $\forall arc, \varnothing$

$$\dot{q}_{arc,\varnothing} \leq b_{arc,\varnothing} \cdot \dot{Q}^{max}_{\varnothing} \tag{3.75}$$

$$\dot{q}_{arc,\varnothing} \geq -b_{arc,\varnothing} \cdot \dot{Q}^{max}_{\varnothing} \tag{3.76}$$

$\forall arc$

$$\sum_{\varnothing} b_{arc,\varnothing} = 1 \tag{3.77}$$

$$\sum_{\varnothing \backslash 0} \sum_{arc} b_{arc,\varnothing} = N - 1 \tag{3.78}$$

In the equations above $C^{pipe}_{\varnothing}$ is the cost of pipe of certain diameter $\varnothing$, L_{arc} is the length of the arc, $b_{arc,\varnothing}$ is the binary controlling investment in the pipe, $q_{arc,\varnothing}$ is the flow in the arc and N is the number of nodes. The flow between node follows the following constraints: $at\,'ProductionPlant$

$$\sum_{arc \in \overline{arc}_{node}} \sum_{\varnothing} \dot{q}_{arc,\varnothing} = \sum_{node} D_{node} \tag{3.79}$$

where D_{node} is the heat demand in the node (corresponding to the maximum heat demand in the timeseries used in ZENIT for the building that the node represents).

$\overline{arc}_{node}$ is the subset of arcs that start with the node; similarly, $\underline{arc}_{node}$ is the subset of arcs that end with the node. $\forall node \setminus' ProductionPlant'$

$$\sum_{arc \in \underline{arc}_{node}} \sum_{\varnothing} \dot{q}_{arc,\varnothing} - \sum_{arc \in \overline{arc}_{node}} \sum_{\varnothing} \dot{q}_{arc,\varnothing} - D_{node} = 0 \tag{3.80}$$

The nodes are made up of the buildings using their coordinate on a 2D grid, in addition the central production plant location where the radial network will start can be freely chosen. The arcs resulting from all combinations of those nodes are then generated and their length calculated. A simple heuristic approach is used to reduce the number of arcs considered and simplify the optimization. All arcs have three elements: the two nodes (arc.point1 and arc.point2) and the length.

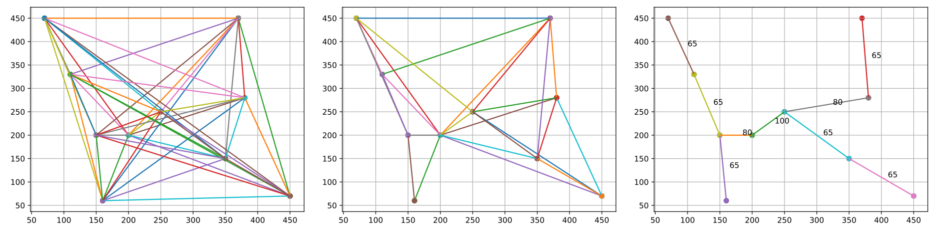
```
input  : all arcs
output: arcs considered
for arc1 ∈ all arcs do
    if arc1.point1 and arc1.point2 ≠ 'Production Plant' then
        for arc2 ∈ all arcs do
            if arc2 links a point of arc1 to the 'Production Plant' then
                if arc1.length ≤ arc2.length then
                    append arc1 to arcs considered;
                end
            end
        end
    else
        append arc1 to arcs considered;
    end
end
```

Algorithm 1: Heuristic used to reduce the number of arcs considered.

The figure presents an example of a hypothetical neighborhood and different sets of arcs: all the arcs, the arcs considered after applying the heuristic and the resulting layout.

The optimization problem has a polynomial complexity and can only be reasonably used when there are fewer than around 13 buildings. If there are more buildings a solution is to spatially cluster the buildings into groups based on their load profiles, categories or only location and use the heating grid module on the different resulting levels.

The heat losses are calculated after the optimization has reached a solution based



(a) All Arcs **(b)** Arcs after Heuristic **(c)** Resulting Heating Grid

Figure 3.2: Example of the arcs at the various stages with a neighborhood of 10 nodes. The production plant is in (200,200) and the diameters of the pipes for the resulting heating grid are indicated next to them.

on the formula from [74] as:

$$\dot{Q}_{loss} = \frac{2\pi\lambda^{ins}(T_{water} - T_{ground})}{log(\frac{2s^{ins}_{\varnothing}+\varnothing}{\varnothing})} \tag{3.81}$$

where λ^{ins} is the thermal conductivity and $s^{ins}_{\varnothing}$ the insulation thickness for a pipe of a given diameter. The ground temperature can sometimes be obtained as timeseries from measuring station for low depth ($< 1m$) and for higher depth it be can assumed to be constant based on location or mean annual air temperature ([75], see chapter 3.3 and 3.5 in particular).

3.4 Clustering

The principles of clustering were presented in section 2.4. Paper 3 investigated the use of clustering in ZENIT.

The need for clustering arises when more binary variables are introduced to the model formulation, for example for part load limitations. Indeed, due to the difficulty in collecting reliable data (even more at an hourly level) for future conditions and the model complexity of using several years of data, we decided to use a representative historical year in ZENIT. This gives us 8760 timesteps due to the hourly resolution necessary to capture the variations of electricity price, loads and weather conditions. However, the time to solve the ZENIT model with all the timesteps is not acceptable. Clustering is one of the ways of reducing this computational time by grouping together timesteps. An alternative to this could be to increase the MIP gap, therefore accepting a less optimal solution. This solution can improve runtime significantly if the optimization has a hard time converging but the resulting computational time may not be consistent. This can also be used in addition to clustering.

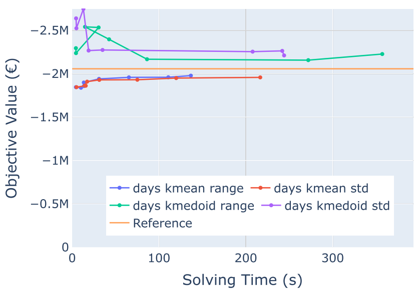
Many clustering algorithms exist and in power system applications the k-mean and k-medoid algorithms are the most commonly used. Figure 2.5, in the presentation of the concept of clustering section 2.4 uses k-mean clustering. The k-medoid algorithm differs in the way the cluster representative is chosen. In k-medoid clustering, the cluster representative is chosen among the original datasets as the point with the lowest distance to the mean. In addition to the choice of algorithm, the preparation of the data is also important and in the literature of power systems, the reasons for those choices are often unclear. Among these choices are the choice of clustering days instead of hours for use in models with hourly timesteps and the normalization method of the data. The best clustering algorithm depends on the application ([76]). Therefore, we investigated these three choices in Paper 3 in order to determine the best approach when it comes to the design of the energy system of ZENs.

In this paper, we compared the results obtained using combinations of these three aspects of clustering on the quality of the clusters obtained as well as the resulting design, objective value and run time. We also investigated two ways of modeling storage, including one allowing seasonal storage, and impacting the choice of clustering method. Indeed, hourly clusters cannot be used for modeling storage in the way presented in section 3.2.

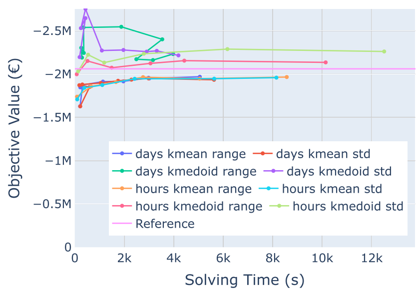
Paper 3 showed that using the k-mean algorithm and hourly factors gives clusters of better quality. The other factors are less important, and the best choice may differ depending on the relative importance of the clustered timeseries. In practice in ZENIT, using the k-medoid algorithm with an increasing number of clusters approached the optimal solution from above and from below using the k-mean algorithm with similar levels of error. Using the normalization based on the range of values gave better results than the standard deviation. The runs performed with days were significantly faster than the ones using an equivalent number of clustered hours.

Fig. 3.3 presents new and previous results in another format and illustrates the conclusion above. The number of clusters chosen should be large enough to ensure the quality of the results.

In that paper, a limitation is that the clusters were used directly, resulting in noise in the results. Indeed, such clustering can give local optimum and not the overall best clusters. This is illustrated in Tables 3, 4 and 5 of Paper 3 where, in some cases, increasing the number of clusters gives higher error or in the figures of section 4 highlighting the impact when clustering days in particular. It is thus recommended to proceed to either hierarchical clustering (which gives consistent results) or to cluster multiple times and select the best set of clusters.



(a) M0



(b) M1

Figure 3.3: Objective value against solving time for different cluster designs and number of clusters. The number of clusters increases along the lines (left to right) taking the following values: M0: 4, 5, 6, 12, 18, 24, 30, 36 days and M1: 3, 4, 5, 6, 12, 18, 24, 30, 36 days and 24, 48, 72, 96, 120, 144 hours.

It is important to remember that clustering is only one way to achieve more tractable computation. The complexity of ZENIT had several components: the high number of timesteps, the number of constraints using binary variables, the zero emission balance (linking many variables across all timesteps) and potentially the number of different buildings to consider. The clustering presented in Paper 3 is only one way of reducing the complexity. Clustering could also be used on the buildings' characteristics (loads and location) in the case of large neighborhoods. It may be also worthwhile to consider whether all binaries are useful for the specific application of ZENIT.

3.5 Hourly average and marginal CO_2 factor calculation

In order to run ZENIT, assumptions on the CO_2 factors of fuels and electricity are necessary. The emission factor of fuel can be directly measured, and different sources provide values for various fuels ([3] or [10]). For electricity, the emission factors depend on the generator type and fuel used to generate it. The electricity consumed from the electrical grid cannot be attributed to any generator in particular and the average emission factor for the area (typically bidding zone or country) is used. For practical reasons, yearly average emission factors are often used instead of hourly average ones. However, hourly average emission factors can be used by smart energy systems to decide when to buy electricity, to store or consume, in order to reduce the CO_2 emissions.

Another type of emission factor that can be used when it comes to electricity is the marginal emission factor. Marginal emission factors represent the emissions that are emitted or avoided by consuming or not consuming a small additional amount of electricity. They are defined as the emission factor of the most expensive generator that is producing electricity in that hour. Marginal emission factors are therefore more suited to investigating the impact of changes in consumption habits or new consumption or savings sources on the amount of CO_2. Variants of the definition also account for the impact on energy system investment on a longer-term perspective [77]. [78] defines the different dimensions to account for in the choice of emission factor for power system applications. Four dimensions are to be taken into account: the timeframe (prospective or retrospective), the system boundaries (which area to use), temporal resolution and type (marginal or average) of emission factor.

The influence of the choice of emission factor on the design of the energy system of a ZEN is discussed in Paper 4 and Paper 6.

3.5.1 Calculation of hourly average emission factor

In a closed system, calculating the average CO_2 factor is not difficult. It can be achieved by calculating the average of the emission factors of the units that are running weighted by their production:

$$\phi_t^{CO_2} = \sum_i \phi_i^{CO_2} \cdot g_{i,t} \tag{3.82}$$

The calculation becomes more complicated when it comes to actual power systems because of the interconnection between the grids of different bidding zones or countries. The imports and exports of electricity between adjacent areas must also be taken into account but the emission factor associated with them is also dependent on their own imports and exports. This creates a problem where one needs to find the global sources of electricity in each country. [79] presents an approach based on input-output algorithms to allocate the generation to each zone. This approach is presented below. When the imports and exports are not critical, it is also possible to either ignore them or to assign a CO_2 factor to the zone.

The calculation process (based on [79]) is presented below. For each timestep, a matrix T_t is built containing the electricity production of each of the technologies and imports in each bidding zone:

$$T_t = \begin{bmatrix} g_{1,1,t} & \cdots & g_{n,1,t} \\ \vdots & \ddots & \vdots \\ g_{1,m,t} & \cdots & g_{n,m,t} \end{bmatrix} \tag{3.83}$$

where $g_{i,j,t}$ is the generation of technology i in the zone j, including the imports from other zones, in timestep t.

The diagonal matrix N_t contains the inverse of the total production and imports in each bidding zone:

$$N_t = \begin{bmatrix} \frac{1}{\sum_i g_{i,1,t}} & & 0 \\ & \ddots & \\ 0 & & \frac{1}{\sum_i g_{i,n,t}} \end{bmatrix} \tag{3.84}$$

The share of each generator in the production of each zone is P_t:

$$P_t = T_t \cdot N_t \tag{3.85}$$

It can be separated between the share of the generators and the share of the imports:

$$P_t = \begin{bmatrix} P_{gen,t} \\ P_{imp,t} \end{bmatrix} \tag{3.86}$$

The electricity balance between production and consumption, or in this case between generation plus imports and consumption plus exports, can be defined following the input-output methodology presented in [79] as:

$$M_t = P_{gen,t} + M \cdot P_{imp,t} \tag{3.87}$$

where M_t represents the generation mix, i.e. the share of each generator in the total production, in each bidding zone including the imports allocated to generation types. Equation 3.87 can be expressed as:

$$M_t = P_{gen,t}(I - P_{imp,t})^{-1} \tag{3.88}$$

Finally, the emission factor of electricity in zone j can be calculated:

$$\phi_{j,t}^{CO_2} = \sum_i \phi_i^{CO_2} \cdot m_{t,i,j} \tag{3.89}$$

where $m_{t,i,j}$ is the element in row i and column j of the matrix M_t.

This method can be used in both coupled and decoupled approaches, with any system boundaries and timeframe. For example, it can be used in a decoupled retrospective approach using data from ENTSO-e for computing the emission factors of European bidding zones or in a coupled prospective approach by using the results from European market and expansion planning models such as EMPIRE[1] ([80]).

[1] https://github.com/ntnuiotenergy/OpenEMPIRE/

3.5.2 Calculation of hourly marginal emission factor

The marginal emission factor is harder to determine. Indeed, one needs to find the most expansive producing unit in each timestep. Several methods can be used to estimate that factor. It is possible to recreate the merit order curve from historical data based for example on data from ENTSO-e or in a prospective manner using models such as EMPIRE by assigning to each generation type a marginal cost and using it to determine the most expensive unit running in each timestep. Figure 3.4 presents an example of a merit order curve in the case of the EMPIRE model. The methodology presented in section 3.5.1 can be used to deal with the imports and determine the generation mix in different zones.

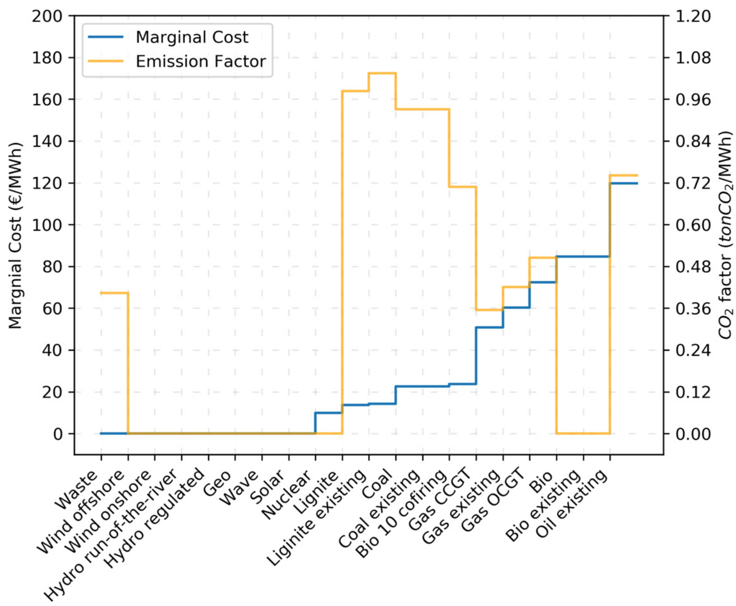


Figure 3.4: Example of a merit order curve in EMPIRE with the corresponding emission factors.

Another method is presented in [81]. It defines the marginal emission factor as the change in emission factor resulting from a certain change in the demand and calculates an emission factor by using a linear regression of the change in emission factor as a function of the change of demand. However, this method does not appear to be suitable for Norway. The scatter plot of the variations of the electricity CO_2 factor against variations of the load in NO1 is presented in Fig. 3.5.

It is not possible to obtain a good interpolation of the data and to use it for creating marginal CO_2 factor timeseries. Moreover, the general distribution tends

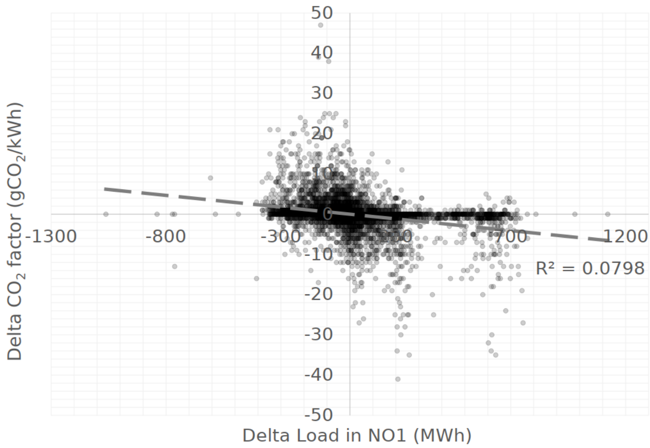
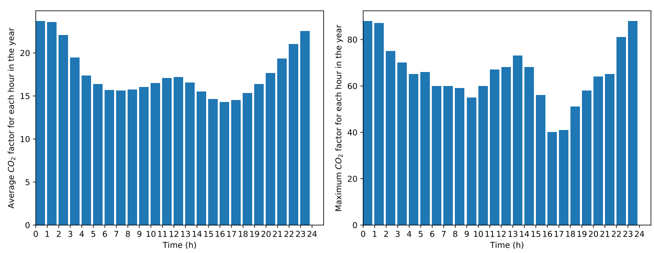


Figure 3.5: Variations in CO_2 Factor for variations in load in NO1 in 2016.

to a negative slope contrary to what is found in [81] for the UK. This can be explained by the situation of Norway. In Norway, the electricity mainly comes from hydropower which has a low emission factor. The hydropower plants are operated with regard to reservoir levels, inflow conditions and load (giving a certain water value) in order to maximize profits. This leads to hydropower production during the peaks and during the day in general when the prices and loads are high. At night, when prices are lower, it is more likely that there are imports from Europe. This can be observed in Fig. 3.6, where the average and the max CO_2 factor for each hour of the day in NO1 are presented. This can be approximated as when the load increases, the price increases and the hydropower plant produces more, leading to lower CO_2 factors.



(a) Average **(b)** Max.

Figure 3.6: Average day and maximum per hour over the year of the CO_2 factors of electricity in NO1.

3.6 EMPIRE

The EMPIRE model is not a part of this thesis work itself, but it has been used in combination with ZENIT in Paper 6 and in a conference paper [82]. This section gives a broad description of the model necessary to understand the methodology used in Paper 6 and the results presented in Section 4.

The EMPIRE (European Model for Planning Investments in high shares of Renewable Energy) is a linear long-term capacity and transmission expansion planning model at a European level including a stochastic representation of the short-term variability of loads and renewable sources.

The model has been developed at the department of industrial economics and technology management and the department of electric power engineering at NTNU and [80] contains a complete model description. An open version of the model is also available[2].

The European energy system is represented in EMPIRE as nodes and arcs. The model focuses on Norway, so it uses the five Norwegian bidding zones for Norway as nodes. Other countries are represented as a single node. Arcs represent the transmission between the nodes. The nodes contain the energy (heat and electric) demand and the technology options to supply them. EMPIRE is a two-stage stochastic optimization model whose objective function is to minimize the cost of the European energy system considering the investment and the operation costs. It looks ahead to 2060 with periods of 5 years represented by several load and renewable scenarios containing a week per season plus two peak days at an hourly resolution.

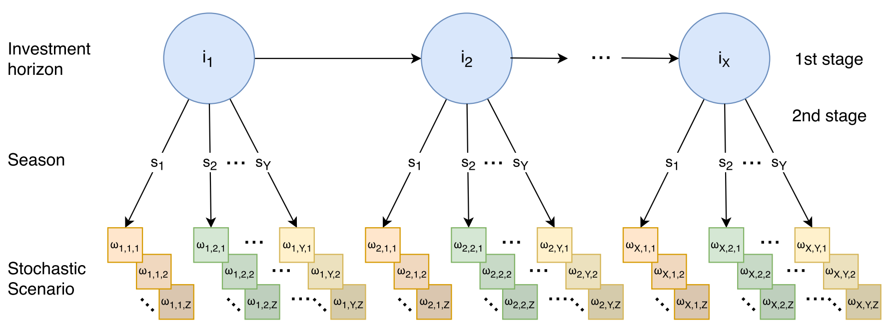


Figure 3.7: Illustration of the two-stage structure of EMPIRE, reproduced from [80].

The model takes initial existing capacity as well as technology prices and charac-

[2] https://github.com/ntnuiotenergy/OpenEMPIRE/

teristics as input and gives in the output the system capacity and operation profiles in the different periods. The main constraints are the electric and heat balances in each node together with the operational constraints specific to each technology, including ramping constraints for thermal generators.

Chapter 4

Main Findings

This section presents the main findings from the papers included in this thesis. The structure of this chapter is detailed in Fig. 4.1. It is divided into four sections answering part of one or several of the research questions answered in this thesis.

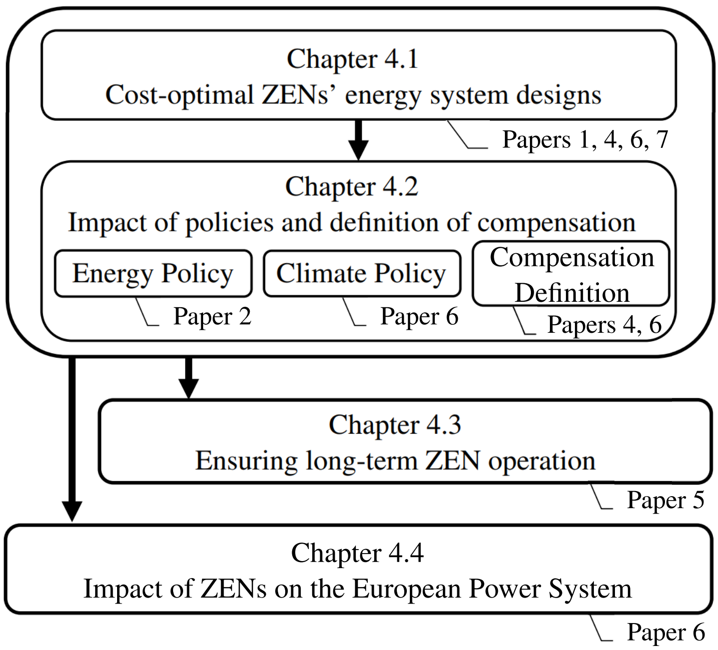


Figure 4.1: Structure and related articles in Chapter 4 of the thesis.

4.1 Cost-optimal ZEN energy system designs

All the articles presented in this thesis provide examples of ZEN energy system designs in different contexts. In this section, a panel of different ZEN designs are presented. In the first part, the designs are focused on a Norwegian case while the last extends the discussion to the rest of Europe.

Paper 1: aggregated ZEN design

In this paper, a preliminary version of the ZENIT model presented in Chapter 3 was used to study the energy system of a university campus in Norway. The choice of the level of details of the model is an important one and will impact the quality of the results and the time it takes to solve. It can be interesting, especially in the early phases of projects, to start with a less detailed tool to orientate the decision-making process. More detailed model descriptions can be used later on in the project. One way to simplify the model presented in Chapter 3 is to consider all the buildings aggregated together. This is what Paper 1 presents.

In this paper, the loads of the buildings at the university campus are considered together. In order to maintain a certain level of details, the investment in a heating grid is still considered and gives access to certain technologies but the operating constraints linked to it are not considered. This neglects the flow constraints and the losses in the heating grid but allows us to consider the cost and overall impact of the heating grid. In that paper, the heat pumps are considered for each building in order to find the COP corresponding to the output temperature needed for the buildings. The technologies considered are: at the building level; PV, solar thermal, air source heat pump, ground source heat pump, biomass boiler, electric boiler, gas boiler and at the neighborhood level; gas CHP, biomass CHP, heat pump, electric boiler and gas boiler. Batteries and heat storage are also available. The different buildings of the campus are gathered in three groups based on their level of performance and age. The buildings at a zero emission standard form a first group, the student housing at a passive standard a second group and the rest of the buildings, at lower standards, the last group. It represents a total floor area of around $10000m^2$.

One of the aims of the paper is to compare the investments with and without considering the energy system already installed at the case site. Indeed, the site used for the case study was part of a research center on ZEB and had already invested in renewable energy sources. The pre-existing capacity appears to reduce the need for PV investment but results in an overall bigger energy system. Large exports of electricity from the neighborhood are caused by the investment in the energy system and in particular by the PV. The heating system consists of heat pumps and

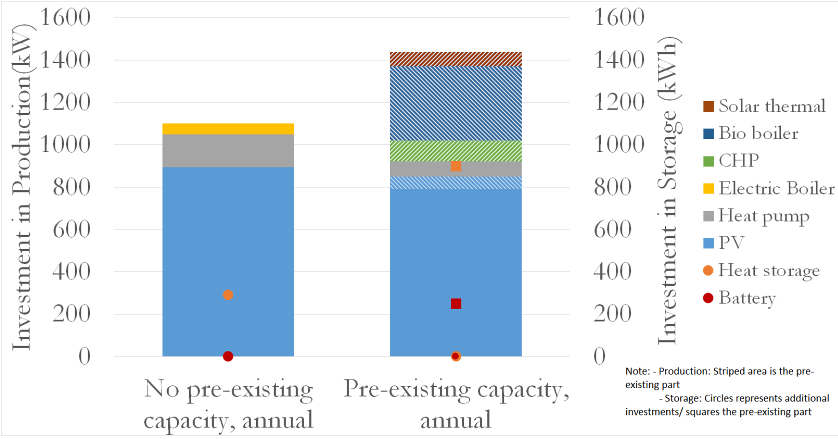


Figure 4.2: Energy system resulting from the aggregated run of ZENIT on the case of Evenstad.

electric boilers.

Figure 4.2, taken from Paper 1, presents the resulting energy system in the two cases.

Paper 4: non-aggregated ZEN design

The optimal energy system design in a non-aggregated neighborhood is a part of several papers but we will focus on the results from Paper 4 here. The results from the other papers show a similar selection of technologies. A disaggregated version of ZENIT takes longer to solve but allows us to better represent the flows and losses in the heating grid. It also enables us to choose energy systems that better suit the load profiles.

In Paper 4, different emission factors and definitions of compensations are compared. Here, we only focus on the results with the highest price of external compensation (which leads to no purchase of external compensations) and hourly average Norwegian emission factor. We use the same Evenstad case as in Paper 1 but the implementation differs due to the disaggregation and the modification to the models and input data (including the technologies considered).

The resulting energy system in that case consists of a large amount of PV (1461 kW), air source heat pumps (367kW) and biomethane boilers (53kW). SH and DHW storage are also invested (respectively 301kWh and 87kWh).

Paper 6: ZEN design considering refurbishment

Existing building stocks and their refurbishment are an important open question. Indeed, with existing neighborhoods, there is a cost trade-off between the gains from insulation in terms of emissions and operation cost and the investment costs. This trade-off can be considered in the optimization as presented in Chapter 3 but it raises an important question: What is the relation between the insulation (and its cost) and the reduction in the space heating load profile? One way to approach this is to model the building in a building performance simulation tool such as in [83] or [84]. In a first approach, in Paper 6, we simply make a sensitivity analysis of the cost assuming a certain load reduction. We assume the load reduction based on regressions from measurements of building loads from several categories of buildings and different building standards presented in [22]. Investment in a hydronic system, using hot water for space heating purposes, is also considered. In this paper, the case is based on a neighborhood generated based on GIS data of Oslo (area and mix of buildings). It represents a ground area of $250000m^2$ and $100000m^2$ of heated floor area. The neighborhood is comprised of nine buildings, representing aggregates of the seven different building types.

The results suggest that the hydronic system is important, giving access to a larger selection of technologies but that the refurbishment cost needs to be less than $13€/m^2$ for an average load reduction of around $65kWh/m^2/year$ for the refurbishment to be selected in all buildings. This corresponds to half of the cost presented in [85]. The technologies selected are PV, solar thermal, heat pumps (primarily air-water), biomass technologies (wood boiler, biomethane boiler), electric boiler. A large amount of heat and electric storage are also installed. With higher refurbishment cost, it is no longer selected, and the energy system relies less on batteries. A biogas engine at the neighborhood scale is also chosen.

Paper 7: ZEN designs in other European countries

The design of ZEN energy systems in the different European countries is a part of Paper 6, and figures are also presented and discussed below. More detailed results are also available in a report from the ZEN research center [86]. The case used for this paper is the same as in Paper 6.

The ZENs are designed using the same neighborhood as in Paper 6, i.e. a generic neighborhood based on data from Oslo. However, the temperatures, solar conditions and loads are specific to each country.

The total discounted cost of the ZEN's energy systems for the lifetime of the neighborhood (Fig. 4.4) is impacted by the latitude of each country. Indeed, while the amount of PV (Fig. 4.5) is mostly limited by the roof area, the impact on the PV production and the compensations obtained is important, thus leading to more or less need for additional investment to reach the zero emission balance. The investment in heat storage is quite different between countries and even between the different Norwegian bidding zones. We can link this size to the heat demand and to the emission factor profiles, heat storage providing a way to take advantage of arbitrage opportunities for cost or compensations.

The most important technology apart from PV in the energy systems of these ZENs are water-water heat pumps (Fig. 4.3). They are chosen in every country to some extent and are a bigger contributor to the heat production than the figure could lead to believe due to their high COP. Other types of heat pumps are also chosen, in particular in countries with low emission factors, but to a lesser extent. Solar thermal collectors and biogas engines are favored by countries with low emissions. In countries with higher emission factors, gasified biomass and, to a lesser extent, gas boilers seem to be preferred.

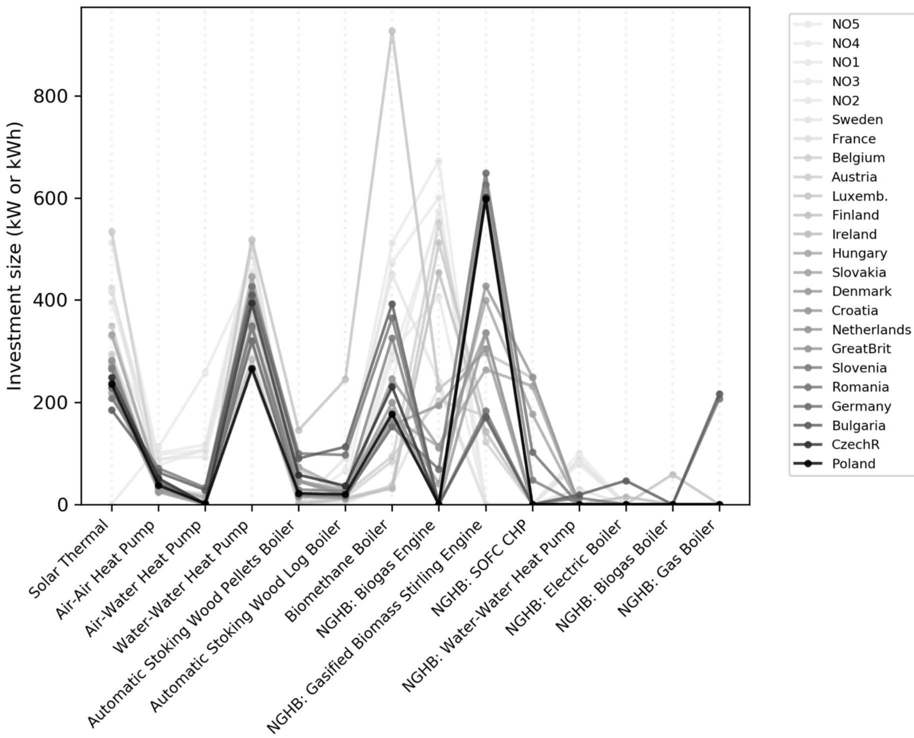


Figure 4.3: Investment in technologies apart from PV in the ZENs in each country considered. The countries are ordered based on their yearly average emission factor from low/clear to high/dark.

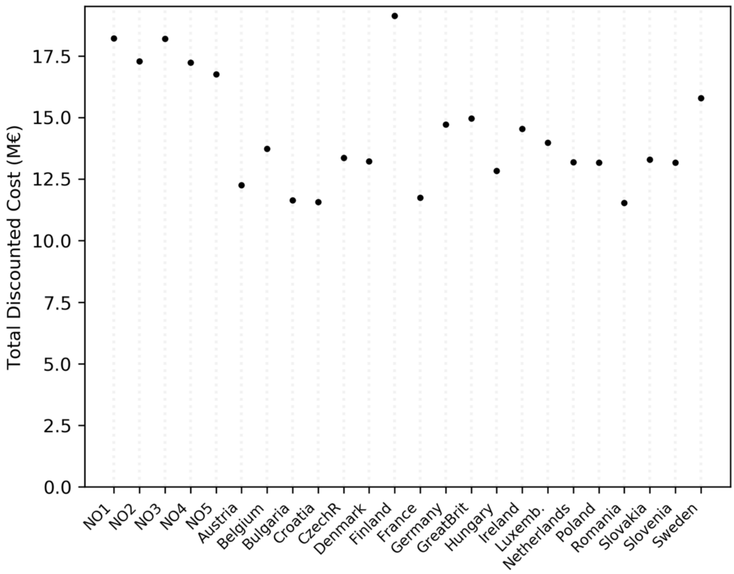


Figure 4.4: Total discounted costs of the ZENs in each country considered.

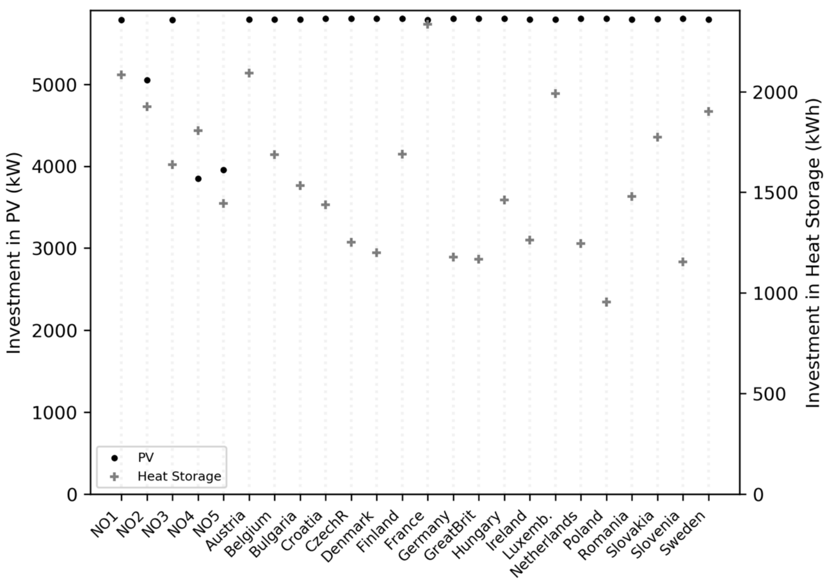


Figure 4.5: Investment in PV and heat storage in the ZENs in each country considered.

4.2 Impact of policies and definition of compensation

The impacts of several major policies were assessed in the papers constituting this thesis. The policies that are investigated are related to climate, energy and the definition of compensation and accounting of emissions in general. They are chosen because they can greatly impact the results of the optimization and are subject to some degree of political uncertainty.

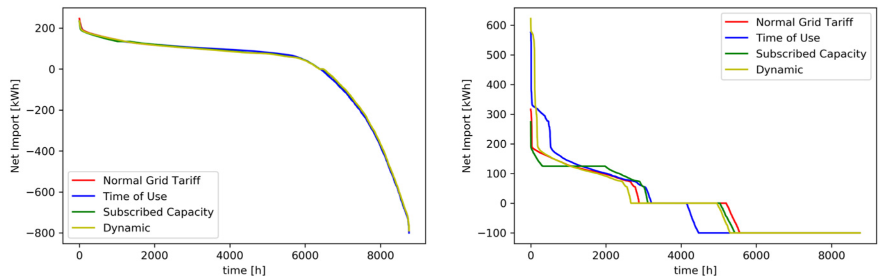
4.2.1 Energy Policy

The main aspect of energy policy that has been studied as part of this thesis is grid tariffs in Paper 2. Other energy policies can have an impact and could also be considered. For instance, different incentives could be compared: tax credit, feed-in tariffs, and VAT exemptions, among others. In this thesis, grid tariffs are the only energy policy setting that is considered.

Paper 2: Impact of grid tariffs

The research question of the article was to assess the impact of different grid tariff structures on the design of ZEN's energy system and to measure their impact on electricity import and export profiles. Indeed, ZENs rely on large amounts of PV to reach the zero emission balance, leading to over-production and considerable exports to the grid in certain periods. This policy is of particular interest in Norway due to the on-going discussion around new grid tariff structures ([87]). The paper presents four grid tariff structures: energy based, time of use (ToU), subscribed capacity and dynamic, and uses them inside the ZENIT model in addition to the spot price of electricity. The dynamic tariff stands out because it is based on the hours with the highest loads in the grid and because it is the only structure we consider that rewards exports. Two limits on exports were considered, the grid connection of 800kWh/h and a lower one of 100kWh/h. The case of Evenstad, as in Paper 4, is used.

The results show that the amount of installed PV is not changed by the grid tariff. The amount of storage is, however, impacted, with more storage necessary with the energy-based tariffs. In the case with a grid connection size, there is no electric storage and more heat storage is necessary with the energy-based tariffs. The share between the buildings is also impacted. In the case with limited exports, the heat storage is not impacted by the different tariffs, but the battery is. The battery becomes necessary to reach the zero emission balance and takes over the role of flexible asset from the heat storage. This investment significantly impacts the total costs of ZENs but allows to respond to the tariffs more effectively. Changing from energy-based tariffs seems to increase the DSO revenues coming from ZENs but these entails additional costs for the ZENs. The time of use tariffs is, however,



(a) Max Exports $800kWh/h$ **(b)** Max Exports $200kWh/h$

Figure 4.6: Duration curve of net imports for the ZEN in the cases with the different grid sizes in Paper 2.

beneficial to both the DSO and the ZENs. The import peaks are only reduced by around 5% with the new tariffs and no export limitations. With the export limitations, the new tariffs almost double the peak value in the time of use and dynamic case while for the subscribed capacity tariff it is reduced by around 13%.

The behavior seen from the grid when using the different tariffs is not significantly different when the export limitation is $800kWh/h$. With the smaller export limitation, the subscribed capacity tariff has the lowest peak imports (Fig. 4.6). Moreover, due to the investment in a battery to enable increased exports, the other tariffs create high import peaks taking advantage of lower electricity prices.

4.2.2 Climate Policy

Climate policies have an important role in bringing down carbon emissions, and in Europe the main climate policy in the energy sector is the EU ETS (see section 2.2.3). The way the cap is defined and the reduction of the cap towards 2050 has an impact on the whole energy sector: investments, electricity costs and emissions. This will also affect ZENs' development.

Paper 6: impact of European climate policy on ZEN energy system designs

In Paper 6, two definitions of the cap are considered to study the development of the European power system towards 2050 and in particular the potential of ZENs. More details on those results will be presented in section 4.4.

Two aspects are considered: the diminution of the cap and the definition of the cap itself, i.e. to which unit the cap applies. The cap is reduced until it reaches zero in order to meet the ambitions set by the EU. Two cap definitions are used. The first one "BAU" corresponds to the current system and applies to all units over 20MW of capacity. The second cap definition "ALL" corresponds to a cap applying to all units, including smaller units inside the ZENs. The spot prices and emission factors come from the EMPIRE model (see section 3.6) where a cap is applied according to the two definitions.

The resulting costs for the ZEN in each European country are presented in Figure 4.7. The cost reduction towards 2050 is evident and mainly results from the cost reduction of technologies, such as SOFC and batteries allowing to reach the emission target at a lower cost. In the majority of the cases, the costs of the ZEN energy systems for the BAU and the ALL cases are the same but there are some exceptions, notably Romania, Bulgaria and Croatia in 2030 and to a smaller extent Slovakia, and Slovenia in 2030. These countries are among the southernmost countries considered in the study. They also have significantly higher average emission factors in the BAU case than in the ALL case and this is the main reason that we can identify for the price differences. In Romania and Bulgaria for example, the different energy systems and emission factors of electricity lead to almost three times as much emissions and compensations in the case BAU compared to the case ALL as well as an excess of compensation only in the case BAU. Plotting the difference in the hour-to-hour emission factors reveals that the higher emission factor of electricity takes place in particular around the summer months in the BAU case. This leads to more compensations available from the same PV amount and allows to invest in a gas boiler (Fig. 4.9), reducing the energy system costs. The cost differences in the other countries can be explained for similar reasons. There is no over-compensation in the BAU case, but the level of emissions and compensations is twice as high in the BAU case than in the ALL case. The differences between the investment in the BAU and ALL cases are presented in Fig. 4.8, and Fig. 4.9 has the same results but only for the countries mentioned earlier.

From Fig. 4.9, we see that the biggest investment differences for the countries where a significant cost difference exists between the case BAU and ALL are in the amount of heat storage and biomass, biogas or gas technologies. We can take the example of Slovenia, which seems to be slightly simpler than some other countries, between the BAU and ALL case, a small amount of solar thermal and biomethane boiler is changed for a solid oxide fuel cell (SOFC) and more heat storage. A biogas engine also seems to be frequently chosen in the ALL case.

Some investment differences between the two cases are larger on Fig. 4.8 than in 4.9 due to local conditions, but still result in a similar total cost.

In Paper 6, the effect of the cap reduction through time is also shown. However, this effect is more difficult to highlight because the ZEN designs are also greatly impacted by the cost reduction of certain technologies (batteries and SOFC for example). The reduction of the cap forces the adoption of more renewable energy in the power system, which in turns affects the emission factors of electricity. The

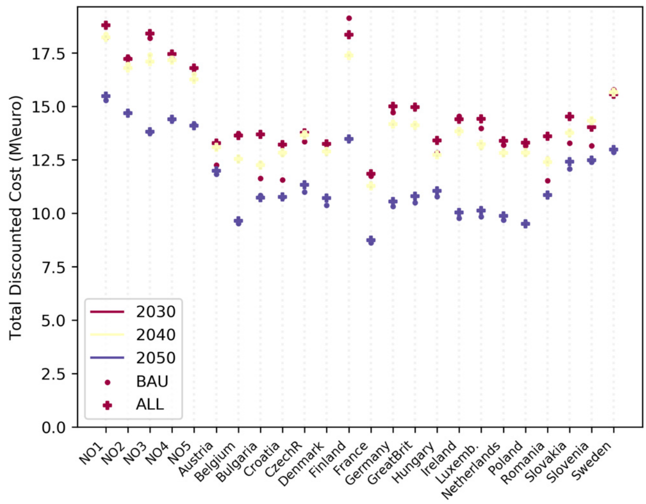


Figure 4.7: Total discounted costs of ZENs in two cases: BAU and ALL, using different definitions of the EU ETS cap in several European countries.

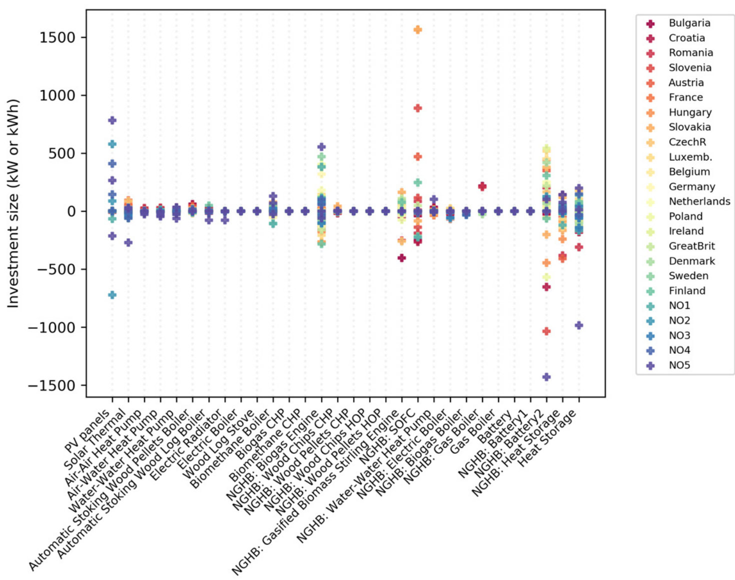


Figure 4.8: Difference in investments in the energy systems of ZENs in two cases: BAU and ALL, using different definitions of the EU ETS cap in several European countries.

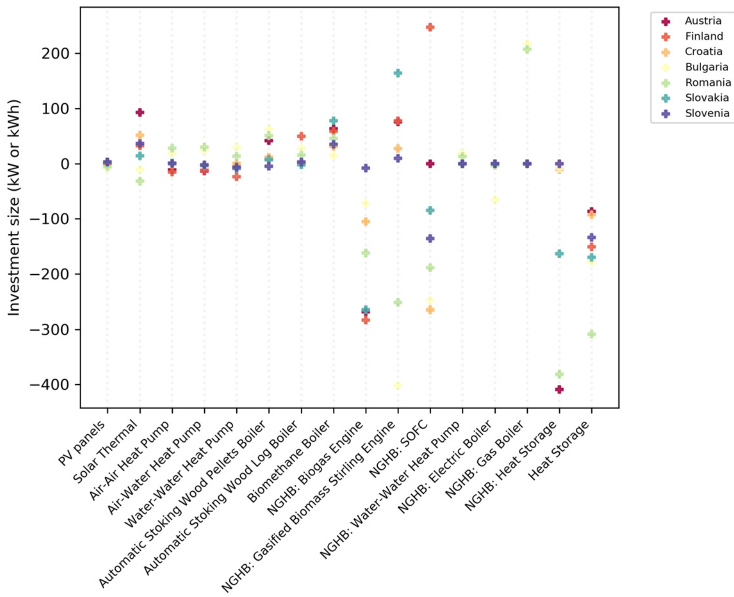


Figure 4.9: Difference in investments in the energy systems of ZENs in two cases: BAU and ALL, using different definitions of the EU ETS cap in several European countries focusing on the countries with a significant difference between the cases: Romania, Bulgaria, Croatia, Finland, Slovakia, and Slovenia in 2030.

reduced emission factors force more electrical heating as well as low emissions biomass heating into ZENs. The cost reduction of batteries and SOFC on the other hand, facilitate reaching the zero emission balance. These two elements together lead to cost reduction of ZENs of 20% on average (between 3.5 and 33%) between 2030 and 2050.

4.2.3 Compensation and emission factor definition

The selection of compensation mechanisms and of emission factors is crucial to the design of ZENs. They are set in definitions or standards and it is important to understand their impact in order to guide those policy settings. These aspects were primarily studied in Paper 4, but were also studied in the same settings as in Paper 6, although these results are not a part of the paper.

Paper 4: the case of Norway

Paper 4 studies the effect of the definitions of both compensation and emission factors in the particular case of Norway. It uses ZENIT to invest in ZENs considering different emission factors for electricity and compensation mechanisms. The typical compensation mechanism is based on export of locally produced renewable generation. In the paper we consider the possibility to purchase external compensations. This is an abstract form of compensation that could take several forms in practice: for instance, financing of CCS, emission compensation companies, purchase of allowances on the EU ETS, etc. Different aspects of the emission factor definition are considered. The first aspect is marginal against average emission factors. Another aspect is the temporal resolution (hourly vs yearly) and spatial resolution (Norway vs Europe). A final aspect is specific to the case of marginal emission factors and concerns which flows are the marginal emission factors applied to.

One of the main results is that the hourly average Norwegian emission factors, instead of yearly average, results in relatively small investment differences. Choosing yearly European average emission factors, which are several times higher than the ones for Norway, leads to lower PV investment and smaller heat pumps. Indeed, the emission factor of electricity is now higher than the one of biomethane. This difference is sufficient, considering the costs, emission and efficiencies, to prefer the solution using the biomethane over the heat pumps in our case study. This also leads to a reduction of the electricity use and thus also the size of the PV.

When external compensations are allowed, the overall cost of the ZEN goes down. This effect is more important when the amount of PV that can be installed is limited. The cost reduction is due to the smaller need for local electricity generation to provide compensation. The size of the PV system increases with increasing external compensation price. The bigger PV system also leads to bigger heat pumps to take advantage of the local electricity when using Norwegian emission factors.

When using marginal emission factors, choices need to be made regarding what they apply to. Indeed, it does not seem rational to apply this emission factor to all the imports and exports. The use of a marginal emission factor implies an additionality or an unexpected variation of the load which cannot reasonably apply to the total electric load of the ZEN. The question is then which imports and exports of electricity, in particular considering batteries and local renewable generation, should be subject to the marginal emission factor. The paper highlights the importance of defining where to apply marginal emission factors by comparing several counting approaches in the case study. It finds significant differences between the amount of PV in particular between the case of marginal emission factors for all flows of electricity and the others.

Additional results in the setting of Paper 6

We use the setup of Paper 6 to study the changes to the energy system coming from the use of marginal emission factors and from the use of external compensation in European countries. These results were not part of the paper and the figures can be found in Appendix A.

Figure 4.10 shows a yearly averaged version of the emission factor used for this analysis. The emission factors come from EMPIRE results for the year 2030 and are computed following the methodology presented in sections 3.5.1 and 3.5.2. The figure shows significant differences in the emission factors of European countries. As the marginal emission factor is based on the most expensive unit in the unit commitment, it is somewhat more consistent than the average emission factors. In most countries, the average emission factor is below the marginal one, except in countries with particularly high average emission factors such as Poland.

The use of marginal emission factors of electricity leads to different changes depending on the countries and specifically on their emission factors. In countries such as Norway, the marginal emission factor is significantly higher and contributes to increased compensation from PV. In countries with a higher average emission factor (which applies to the import of the neighborhood) than marginal emission factor, the cost compensations obtained are reduced and lead to the need for adjusted investments. Those investments favor low-carbon technologies to replace more carbon-intensive ones.

The use of EU ETS allowances in the compensation mechanism leads to energy system design and costs very similar to the case not considering the zero emission balance. This is a result of the relatively low cost of allowance used in the setup

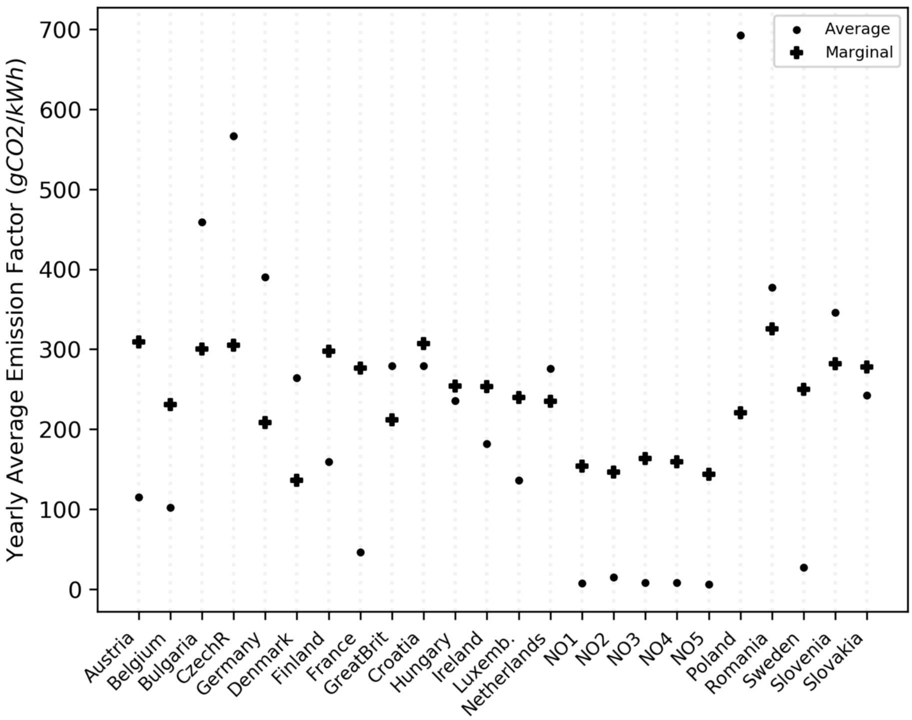


Figure 4.10: Yearly average and marginal emission factors of the European countries where ZENs are considered in Paper 6.

of the study (15€$/tonCO_2$ in 2030, note that this price is a result of the EMPIRE run). This should, however, be nuanced. Indeed, the purchase of allowances by ZENs may impact the allowance price and several iterations of ZENIT and EMPIRE would be necessary to account for this.

4.3 Ensuring long-term ZEN operation

The use of ZENIT can provide ZEN energy systems that are designed to meet the zero emission requirement. However, reaching this net zero emission balance requires following a similar operation strategy as in the optimization. This is not necessarily easy to perform. Moreover, it is difficult to take into account such long-term considerations while trying to find solutions to short-term operation problems due to the mismatch in temporal scale of both problems.

This concern is what Paper 5 focuses on and the main results are presented in this section. Another example of a possible solution, using SDP (Stochastic Dynamic Programming), is presented in [88].

In Paper 5, we design the energy system of a ZEN in a first stage and then compare three approaches that could be used for its operation. One year is used for the design and three others are used for comparing the operation strategies. The reference strategy uses perfect information, perfect foresight and is completely deterministic. It represents the best possible outcome in terms of minimizing costs while meeting the zero emission balance. The three actual strategies that are compared only have a limited horizon with perfect foresight. The first strategy is a rolling horizon approach only considering cost minimization of the operation (we refer to it as MPC for its analogy with model predictive control approaches). This strategy, which has no consideration of emissions, might not be able to reach a net zero emission balance. Thus, another MPC formulation including a penalization for deviating from an emission curve target is also presented. A third approach uses a receding horizon with a full year of data, the data for the reference year and the short-term horizon using the actual data. The case study is performed using the same Evenstad case as in Paper 4. The data and horizon used in each case are presented in Fig. 4.11.

The results show that in energy systems relying solely on PV for compensation and with an electrified heating system, there is no need for specific operation strategies. However, in some cases relying less on PV, for instance due to the roof area limit, other technologies can appear that create a need for more specific control strategies. Despite a high computational load, the receding horizon approach shows promising performances. The MPC with penalized emissions deviation is not well suited in the state presented in the paper. Indeed, it leads to excess com-

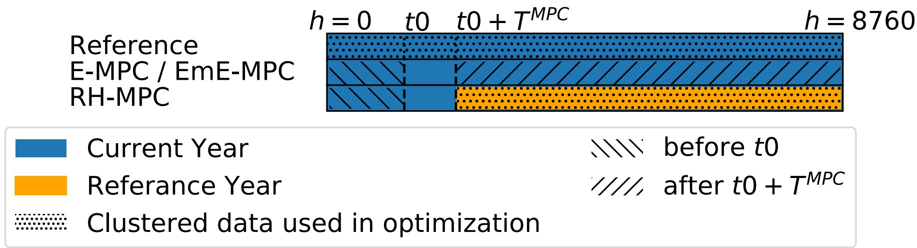


Figure 4.11: Data and horizon for the different cases studied in Paper 5. The model is run for one year (8760 hours) with different data. The reference year corresponds to the year used in the planning using ZENIT. T^{MPC} corresponds to the horizon length. The dashed areas are not considered inside the optimizations.

pensation and operation costs. It could be improved by tuning the piece-wise linear penalization costs. Indeed, for the paper, the factors were chosen after trying a set of different factors, but a more thorough investigation of these factors can lead to improved performance, and in particular avoid to overly penalize deviations from the reference compensation.

4.4 Impact of ZENs on the European Power System

The impact of ZENs on the power system has principally been studied in Paper 6. In addition to this paper, a ZEN report ([86]) presents additional figures and results. The EMPIRE model is shortly described in section 3.6.

In the paper, the ZENIT and EMPIRE models are soft-linked to allow an analysis that is not possible by using either of the models on their own. The EMPIRE model is first used to find the evolution of the European power system under a reducing emission cap. The spot prices and emission factors resulting from this evolution of the power system are used to design ZEN energy systems in several European countries. Following this, a new EMPIRE run including those ZENs as investment options is performed and their impact on the European power system can be analyzed. Two caps are studied, as introduced in section 4.2.2. A flowchart summarizing this is presented below (Fig. 4.12).

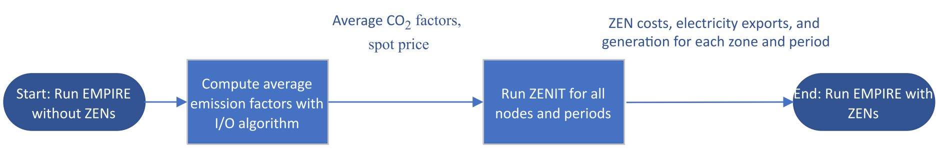
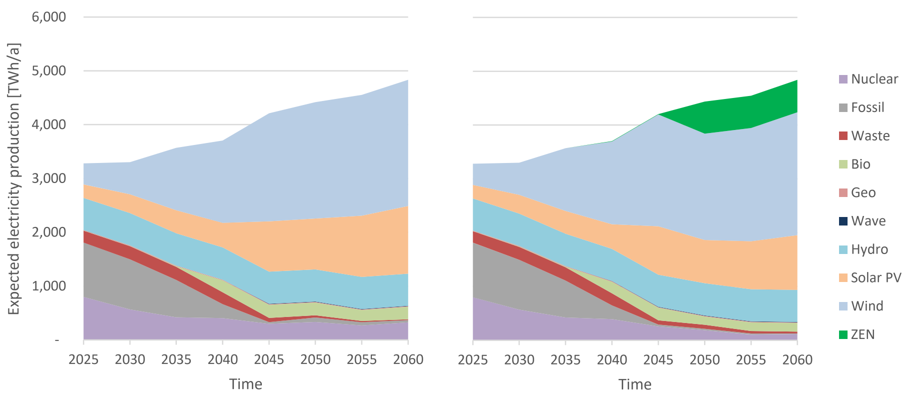


Figure 4.12: Flowchart of the process used in Paper 6 and in [86].

From this paper and this report, the main result is that when ZENs are included, the total cost for the system is reduced by 4%. The ZENs are chosen in every country (with most investments in Germany and France) where it is available with the exception of Norway. Despite this, the introduction of ZENs in other countries still has an impact on Norway. Indeed, the introduction of ZENs in Europe reduces the investment in nuclear, wind power (as can be observed from the electricity generation from Fig. 4.13) and bio-based heating in Norway. More generally at the European level, the ZENs replace some fossil and nuclear generation and decrease the need for storage (or rather it is replaced by storage inside ZENs). The transmission expansion plans remain the same with and without ZENs and there is no decrease in conventional dispatchable supply. The ZENs are mostly invested in the 2050 period as they become cheaper from the reduced investment costs. Some ZENs appear in specific countries in earlier periods, such as in Slovakia in 2030 and in Romania and Bulgaria in 2040. The investment in ZEN is due to several elements. As mentioned, the reduction of the cost of certain technologies reduces the cost of ZEN energy systems. In addition, new technologies are used inside ZENs (SOFC and batteries) and replace some of the PV production with season-independent production and flexibility that is more beneficial to the European power system. Finally, in those later periods, the cap on emissions at the European level limits the number of technologies available.



(a) Baseline **(b)** With ZEN

Figure 4.13: Expected electricity production by source for Europe as a whole in 5-year steps towards 2060 in Paper 6.

An important result of the paper is that emissions are not reduced when introducing the ZENs in the power system (see Fig. 4.14). Indeed, the cap system means that the ZENs are “freeing” emissions that can be used by other generators. On the other hand, one can say that the ZENs allow to reach the targets of the reducing cap at a lower cost. The planned cap reduction leads to a sharp increase in allowance price in 2040. This is even more the case when ZENs are part of the system due to an anticipation of the optimization, choosing to not invest in earlier periods due to the ZEN option available in 2050. However, the sharp increase is present regardless of the presence of ZENs. This raises the question of the emission reduction path and their consequences, for businesses, people, the environment, and the cost reduction of technologies. Indeed, a less abrupt reduction between 2035 and 2040 could lead to a smoother evolution of the allowance price but also has environmental implications.

The two cap definitions introduced in 4.2.2 were studied in [86]. Despite the difference in the definition of each cap, the amount of emissions is set to be the same for both. This makes the ALL case more emission constrained. However, the two cases have very similar results overall. The ALL case is slightly more expensive but has 25% less emissions than the BAU case. In practice the change of the cap definitions would most likely also be adjusting the amount of the cap to account for its broader scope.

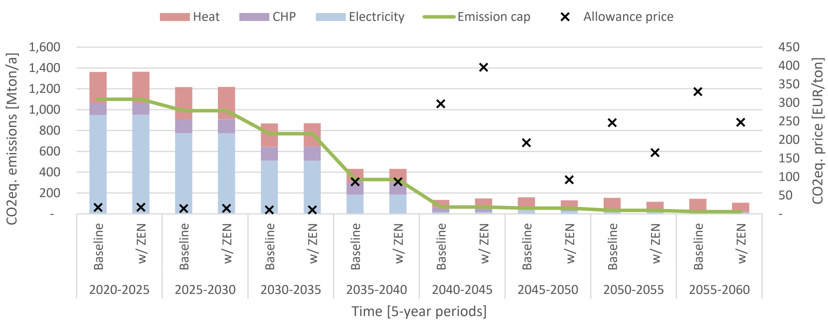


Figure 4.14: Expected CO_2eq. emissions (left) and expected CO_2eq. allowance price (right) for the European heat and electricity system towards 2060 in EMPIRE for the baseline and with ZEN in Paper 6.

Chapter 5

Discussion

This section aims at discussing and putting into perspective the results presented in the previous chapters with the existing literature and examining their practical implications for ZENs. It also highlights some limitations of the work and suggests directions for additional work. The results of this thesis are valid for ZENs but are also relevant more generally for local energy systems and local energy communities. The methods can easily be adapted to work in those frameworks and several of the findings also apply to those cases.

5.1 Results summary

The main research question of this thesis concerns models for designing cost-optimal energy systems of ZENs and the related questions of important influencing factors. The ZENIT optimization model that can be used to help answering these questions is presented, in different versions (aggregated, non-aggregated, with refurbishment) and with a discussion of important modeling choices (clustering, emission factors, zero emission percentage). The model is also used in case studies, allowing us to investigate the impact of various factors on the design of the energy system of ZENs. This gives an insight into the research question presented in the introduction. The main results are the following. Certain technologies are recurrent in the energy systems of ZENs. In particular, PV panels are crucial in order to reach the zero emission balance. Heat pumps (air or ground source depending on the conditions) are also recurrent. Other technologies such as ones based on biomass are also often used but their type can vary. Around 2050, batteries and SOFC are expected to become major contributors to the ZENs due to their cost reduction and the benefits that their flexibility brings to the energy system. Allowing external compensation permits a reduction of the cost of ZENs.

The choice of emission factor is important but annual average factors seem to be sufficient (by comparison with hourly average emission factors) for the design of the energy systems of ZENs in Norway. The design of the cap does not generally affect the energy systems of ZENs but the reduction of the cap together with reducing costs towards 2050 changes the system designs by introducing SOFC and batteries and reducing the amount of PV. Grid tariffs also have no significant impact on the design of the ZEN energy systems but they change the operation and export patterns. Designing the energy system of ZENs to be zero emission is not necessarily enough to achieve the zero emission target during their lifetime when it contains elements that are not completely carbon neutral. Considering the operation strategy of the ZEN is thus crucial. At the European level, ZEN energy systems contribute to a reduction of the cost of the power system and slightly affect the technology mix, but due to the cap system they do not reduce the emissions.

5.2 Further Discussions

In Paper 6, one result is that ZEN energy systems do not reduce emissions, due to the cap system, but can allow a decarbonized European energy system at a lower cost. The cap sets the allowed emission level and ZENs only allow to reduce the power system cost because their low emissions allow other, cheaper, units to pollute more. In practice, we model the EU ETS as a cap, i.e. a constraint on the maximum amount of emissions in the system, while the EU ETS is slightly different. The EU ETS works by handing out emission allowances to companies, which can then exchange them inside a market to meet their needs or profit from their surplus. The amount of allowances given is what is represented by the cap in the EMPIRE model. Despite this, we can expect the results obtained in Paper 6 to remain valid. Indeed, in the BAU case, the units inside the ZENs are too small to be taken into account by the cap (by definition of the cap in the BAU case) and both representations are equivalent. In the ALL case, the situation depends on whether small units now also receive allowances and if their total amount is increased to account for that.

This raises another question on the role of the ZEN energy systems in the decarbonization of society and on the role of compensation in the definition. Indeed, if the energy systems of ZENs do not really contribute to reduced emissions because they only free allowances to be used elsewhere, they do not achieve their goal (note that ZENs still contribute through their choice of material, architecture and construction practices for example; one should also note that the investment in ZEN energy systems contributes to the interest in innovative technologies and to their cost reduction). This question can be generalized to investments in renewable energy generation, but the EU ETS framework is regularly updated with new mechanisms[89] and we will not discuss it further. Nonetheless, we can use some of the results of the other papers to outline possible solutions to this inadequacy of the current ZEN framework when it comes to an actual reduction of emissions from ZEN energy systems. One way to increase the impact of the ZENs would be to allow them to use other kinds of compensation as in Paper 4. These, for example, could be allowances from the EU ETS, ensuring an actual impact on the emissions at the European level. Another possibility could be to leave the zero emission framework and focus on the benefits of ZENs to the power system. This can be achieved by using local renewable electricity generation or flexibility measures. The ZEN can then help the system by responding to price signals or emission signals when using hourly emission factors (Paper 4). A drawback of removing the compensations and thus the zero emission requirement is the loss of a clear and easy-to-communicate indicator of the environmental performances of the neighborhood. Other indicators could be found to replace it but most likely without these attributes. The attractiveness and acceptability of the ZEN concept gives them an advantage over some other forms of renewable generation such as onshore wind generation. It can allow bottom-up actions to increase the share of renewable and empower local communities without the divisions created by onshore wind. These divisions are particularly visible in Norway, with reindeer herders and bird enthusiasts opposing the technology, and it is often a topic in the news. Similar problems are also common throughout Europe.

More generally, the method used in this thesis for obtaining the optimal investments in the energy system of ZENs can be discussed and compared to the methods presented in Section 2. Other approaches or choices could be used for answering the research questions of this thesis, each having certain advantages and disadvantages. The MILP model used in this thesis can for example be compared to multi-objective and meta-heuristic approaches found in the literature for non-ZEN applications. A multi-objective approach would allow us to explore the solution space and find other solutions that are sub-optimal but with more variety. In the context of ZEN, the zero-emission criterion can be easily expressed as a constraint which leads to the choice of a MILP. In addition, from the various results presented in this thesis, the same technologies often have a central role in the energy system of the ZEN, which can indicate a certain robustness of the results. It is also possible to explore different designs by changing the ambition of the ZEN in terms of compensation. However, having multiple diversified solutions is preferable for decision-makers and multi-objective models can systematically generate them. A possible solution using the same optimization model presented in this paper would be to embed it in an algorithm that adds upper constraints on the technologies chosen at each iteration (such as in the ϵ-constraint method). Meta-heuristic methods are also a popular class of methods and despite the loss of information about optimality, they allow to approach or find optimal solutions of complex problems in a time-efficient manner. Thus, they could constitute an option to be considered in particular when dealing with large neighborhoods, when clustering the spatially buildings is not appropriate. Comparing the performance of this approach to spatial clustering and nested clustering for the design of the energy systems of large buildings constitutes a possible extension of the work presented in this thesis.

When it comes to the technologies, PV, heat pumps and heat storage appear to be cornerstones of the ZEN energy system designs in the future decarbonized power system. If the decrease in the investment cost of batteries and SOFC is as expected, they will also become important technologies. A high penetration of ZENs with large amounts of PV under the current framework and definition may add large constraints on the electrical grid and result in a need for grid reinforcement. This is somewhat mitigated by the use of heat and electric storage in the neighborhoods, but Paper 2 suggests that under certain grid tariffs, these storages could also lead to undesirable rebound effects, by taking advantage of low-tariff periods. A high penetration of ZENs could also result in a large amount of simultaneous electricity exports, affecting the compensations and the ability of the neighborhoods to reach their net zero requirement. This could lead to the emergence of other technologies inside ZENs, producing or storing electricity, or over-sized PV size to increase the PV production outside of the summer. However, according to the results of Paper 6, such high penetrations of ZENs are not expected. While Paper 3 explores seasonal storage, most of the other papers in this thesis use a storage model description that does not allow for seasonal storage. The potential of seasonal thermal energy storage needs to be studied further.

5.3 Main Limitations

One of the major limitations of the model presented in this thesis is that it uses retrospective data for a single reference year (except in Paper 6). From a modeling perspective, it is not difficult to make the model multi-period, but the difficulty lies in the increase of the computational complexity and obtaining prospective data to use in the model. This last point can partly be achieved by the use of, for instance, the EMPIRE model, such as in Paper 6. The prospective temperature series and irradiance would still be needed and can have a significant impact on PV production and heat demand and in the end on the results. Considering the role of PV in ZENs and the expected impact of the climate crisis, this could potentially affect the results significantly. While it is possible to find prospective scenarios of the evolution of, for example, average temperatures, finding more spatially and temporally detailed data is a problem. It is possible to simply scale the temperature timeseries based on prospective average temperatures, but the impact of the climate crisis also lies in the increased occurrence of extreme climatic events, making this approach inadequate.

Another limitation of the work is that it mainly focuses on the compensation of the emissions from the operation phase of the buildings' life-cycle and it also does not consider emissions from sources such as transportation. The emissions from other life-cycle phases could be included with an additional term in the zero emission constraint. Moreover, the emissions of the technology options could also be included and impact the results, but finding a reliable source for this information may be difficult, and even for a single technology the values may differ greatly based on manufacturing countries and brands. A thorough life-cycle analysis may be necessary in order to include these emissions. Modeling and including the emissions from transport would also require further research. In particular, the electrification of transport leads to lower direct emissions for combustion engines and higher electricity loads but is also a potential help in reaching net-zero emissions through vehicle to grid services.

5.4 Suggestions for future work

The work presented in this thesis could be extended in several directions. One important aspect missing from the work shown in the thesis is the handling of large-scale neighborhoods and the additional computational complexity that comes with the problem size. One possible solution can be to spatially aggregate the buildings, for example by using clustering. Several approaches could be studied. It is also important to carefully consider the technologies that are available based on the neighborhood size.

Including refurbishment of older building stock is important when designing the energy system. The model presented in this thesis is a first step, but some issues remain. In particular, linking this optimization to a building performance simulation software (such as IDA ICE) could allow to find out the load reduction and cost of several refurbishment options and to include and compare them in the ZENIT model.

The heating grid model could also be improved in multiple ways. First, it is currently unable to deal with large number of buildings. A possible solution could be to use a nested multi-level approach to deal with the design of multiple grids containing fewer nodes. This approach could also be used to accommodate large numbers of buildings in ZENIT. Using a meta-heuristic approach could also allow to reduce the computational burden. Another possible improvement of the heating grid module concerns the sizing of the pipes. In its current version, it only considers the maximum heat demand of each building when designing the grid. Using the load timeseries could allow to obtain a more precisely dimensioned heating grid by taking advantage of peak demands occuring in different timesteps. A more detailed model formulation could also be implemented, to account for pressure losses and elements such as pumps and district heating substations.

Additional work could also be performed in the soft-linking of ZENIT and EMPIRE. Setting up the convergence procedure and studying its impact on the results is of particular interest. This may be computationally challenging, but it could be addressed by only considering ZENs in a subset of countries.

Finally, the work presented in Paper 5 for the short-term operation of a neighborhood considering a long-term emission constraint can also be extended. Indeed, the selection of a reference year can be improved with the use of newer data and accounting for multi-period optimization. The approaches presented in the paper can also be refined and used for the operation of a system with smaller time intervals and considering forecast uncertainties.

Chapter 6

Conclusion

This thesis deals with models for designing the energy system of ZENs in a cost-optimal way. A methodology is suggested and used to investigate the effect of several elements on the design of the energy systems of ZENs. The methodology is further separated into models for aggregated, non-aggregated and refurbishment cases. The research questions of this thesis were presented in Section 1.1.

In chapter 3, a methodology based on a MILP and several variations around it is presented in order to find the optimal design of the energy system of ZENs, in particular a variation with electric and heat load aggregated for the neighborhood, a variation where the loads are disaggregated and a variation for considering the refurbishment of older buildings. The computational complexity is dependent on the modeling choices made, in particular, for constraints using binaries. The number of buildings and technologies considered is also a major contributor to the computational time. A way of mitigating the effect of added complexity on the computational time, namely temporal clustering, was presented and studied in Paper 3. Once designed, it is also important to ensure that the ZENs are operated in such a way that they will have net-zero emissions of CO_2 in their lifetime. This is studied in Paper 5. In ZEN energy systems relying predominantly on the compensations from PV panels, a specific monitoring of the compensation throughout the lifetime is unnecessary. However, in energy systems including bio-based fuels or emission-intensive peak generators, an active control of the energy system is needed. A receding horizon approach thus seems to be a promising way to control the energy system.

A particular definition and framework are used to define ZENs in the ZEN research center. This framework is susceptible to change and can affect the optimal ZEN energy system designs. Moreover, other factors are likely to influence the designs of ZEN energy systems. The impact of the ZEN definition and of several regulatory aspects on the optimal ZEN energy system design were studied in this thesis. Among the factors investigated (grid tariffs, emission factor of electricity, compensation definition and design of the European cap and trade system), the change of the compensation definition would have the biggest impact. Another major result from this study is that, in Norway, the use of a yearly average emission factor instead of an hourly average one does not significantly impact the result of the investment optimization.

At the European scale, the development of ZENs does not reduce emissions due to the principle of the cap-and-trade system but it slightly lowers system costs. Investments in wind power and bio-based heating are also reduced.

While the focus of this thesis is mainly Norway and Europe, the concept of ZEN and the methods presented in this thesis can also find applications outside of Europe. Indeed, PV panels are well suited to local energy communities and, as important elements in ZEN energy systems, they make ZEN a particularly interesting concept where good solar conditions exist. The decreasing price of solar panels also makes it relevant globally. In order to be applicable to more conditions and countries, the model should be extended to include cooling.

The model presented in the thesis can also be adapted to more general contexts of local energy communities. In addition, some of the results of this thesis are also relevant in such cases. For instance, the results from Paper 2 are relevant in local energy communities and not just ZENs. Indeed, ZENs offer an extreme case of local energy community in terms of on-site energy production and are therefore a good benchmark for highlighting possible undesirable consequences of different grid tariff designs that could also take place at a lower scale in other local energy communities. The results from Paper 3 can also be relevant more generally to neighborhoods that will rely heavily on PV. Finally, the technologies chosen by the optimization in the different papers are valid options to consider for local energy communities, even though their amounts have to be adjusted to each case and their own goals.

The work of this thesis can be extended in several directions. The impact of the scale of the neighborhood on the results should be quantified and ways to deal with the complexity of including large number of buildings explored. The model including the refurbishment of neighborhoods can be improved and linked to building performance simulation tools to provide refurbishment alternatives. The short-term operation approaches can be refined and applied to cases including uncertainties. The linking of the ZENIT and EMPIRE models can be improved by setting up convergence criteria and an iterative process. The model can be extended to include transportation and its role as an additional load, source of emissions and source of flexibility to the neighborhood. Finally, more practically, the heating grid module could be improved in several respects and in particular to handle a larger number of buildings.

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Appendix A: Additional results in the context of Paper 6

In paper 6, it was decided to focus on the role of the cap in the development of ZEN in Europe. Thus, results considering extra dimensions that were also explored were not presented. In this appendix, the effect of marginal factors and of allowing purchase of allowances on the EU ETS are shown. The case “Base” represent the case with hourly average emission factor and the strict definition of compensation. The two other cases each vary only one of those parameters. The case ”Marginal” uses the hourly marginal values and the case “ETS” allows to buy allowances on the EU ETS and to count them as a part of the compensation. The price of those allowances, coming from a first run of EMPIRE, is around $15€/tonCO_2$. The corresponding yearly average and marginal emission factors for each considered countries are presented in section 4.2.3.

The discounted costs presented in Fig. 6.1 allows to compare the changes between the case ”Base” and the cases “ETS” and “Marginal”. An additional case is added here, called “Ref”, using average factor and without a zero emission objective. In most cases, the cases “ETS” have almost the same cost as the “Ref” cases. This can be explained by the low cost of allowances coming from EMPIRE, allowing to buy allowance for only a small additional cost instead of having to reach the zero emission balance through investments.

In Norway, as well as in a few other countries the costs for the “ETS” and “Marginal” cases are similar. It means that the zero emission balance is also not affecting the results for those countries. This can be explained by the average and marginal emission profiles in those areas. In the case of Norway for example, the average emission factor is generally low and increases at night when prices are lower and imports increase. When the marginal factor is considered instead, the emission factor is more often higher, in particular in the summer, allowing to use the PV much more efficiently for compensation (PV is chosen, even without the

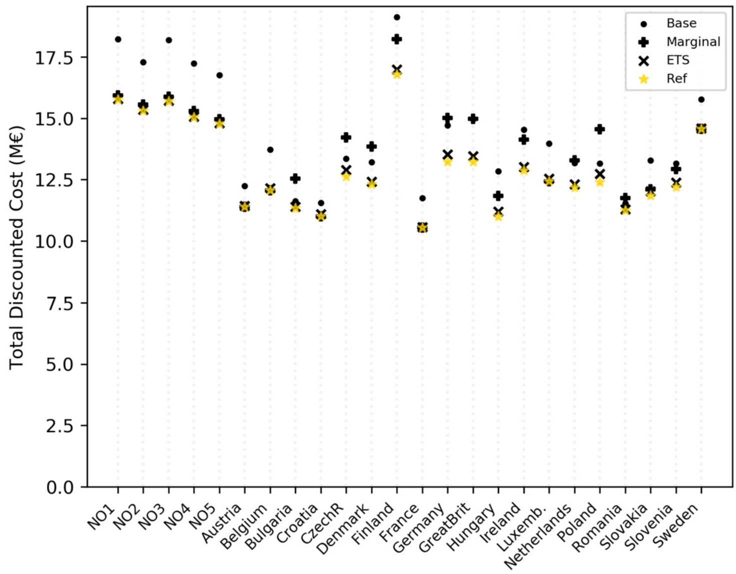

Figure 6.1: Total discounted costs of the ZENs in each country considered and the three cases.

zero emission balance, to some extent).

In most other countries, the cost of the cases "Marginal" are higher than the cases "ETS" and in some countries, it is even higher than the "Base" cases. Comparing Fig. 6.1 to Fig. 4.10, this latter case seems to be for the countries with the highest average emission factors. While a lower emission factor reduces the emissions from imported electricity, it also hinders the compensations obtained from exporting electricity, leading to a globally negative effect on the emission balance as non-electric technologies emissions also need to be compensated or on the costs, to replace those technologies.

PV panel is one of the main investment in ZENs and Fig. 6.2 shows the change in investment between the "Base" and other cases. Investment in PV panels reflects the discussion regarding the costs of the different cases, with investment in PV being reduced significantly in Norway and Finland. The reduction is bigger in the "ETS" cases.

From Fig. 6.3, it appears that the use of marginal factor and the use of allowances as compensations leads to bigger needs for flexibility, fulfilled by heat storage.

The various technology investments are affected in different ways by the "ETS"

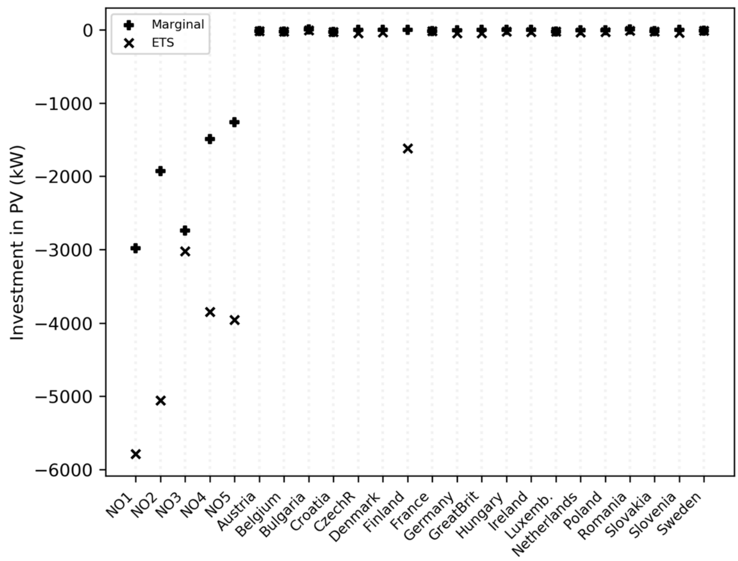

Figure 6.2: Investment in PV panels in the ZENs in each country considered and in the "Base", "ETS" and "Marginal" cases.

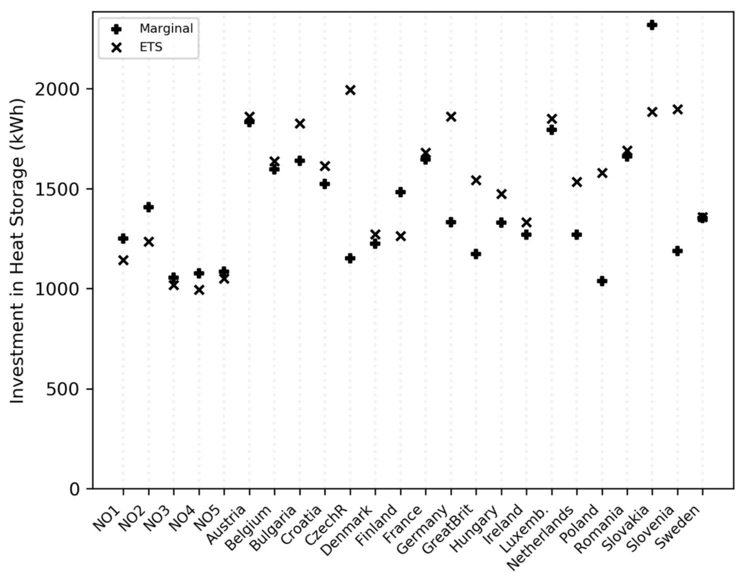

Figure 6.3: Investment in heat storage in the ZENs in each country considered and in the "Base", "ETS" and "Marginal" cases.

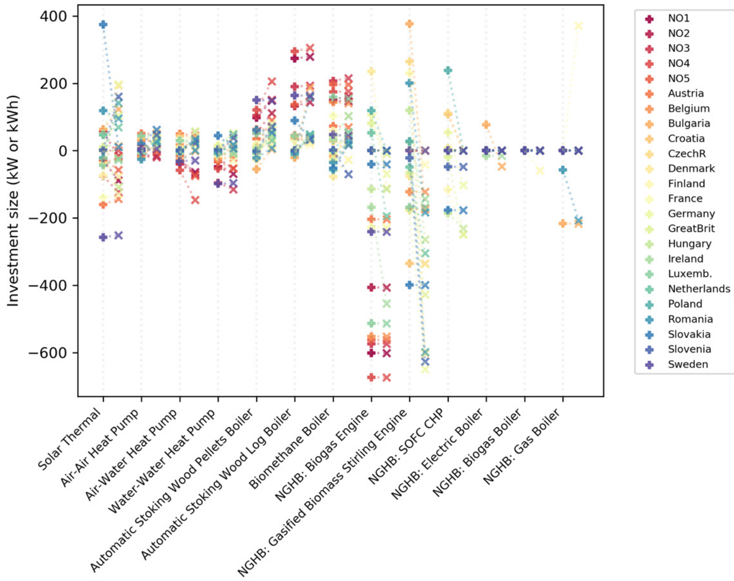

Figure 6.4: Investment in technologies apart from PV in the ZENs in each country considered and in the “Base”, “ETS” and “Marginal” cases.

and “Marginal” cases. In the “ETS” cases, technologies with some emissions can be chosen. We observe in particular investment in wood and biomethane boilers, while more expensive technologies using biogas (with no emissions in our assumptions) are reduced in most countries. Solar thermal collectors are also reduced in most countries.

The amount of allowances bought is very dependent on the emission factor of each zone and is also influenced by the amount of compensations obtained from the base amount of PV.

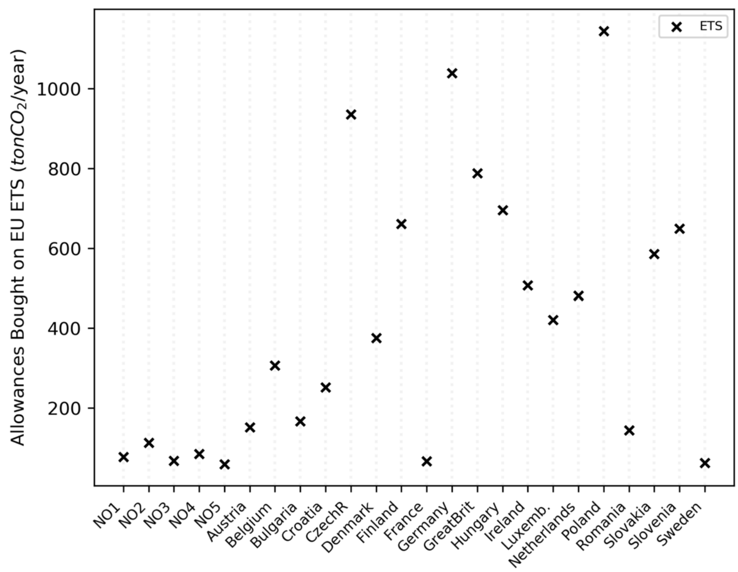

Figure 6.5: Amount of allowances bought by the ZENs in each country considered in the case “ETS”.

Paper 1

Cost Optimal Design of Zero Emission Neighborhoods' (ZENs) Energy System

Model Presentation and Case Study on Evenstad

Dimitri Pinel, Magnus Korpås, and Karen B. Lindberg

Abstract Zero Emission Neighborhoods (ZEN) is a concept studied in particular in the research center on ZEN in smart cities in Norway to reduce the CO_2 emissions of neighborhoods. One question coming along this concept is how to design the energy system of such neighborhoods to fit the ZEN definition[1]. From this definition we extract the CO_2 balance, requiring an annual net zero emission of CO_2 in the lifetime of the neighborhood. This paper proposes a MILP model for obtaining cost optimal design of ZEN's energy system and demonstrates it on a case study. Different technologies are included as investment options and, notably PV as a mean of producing electricity on-site. Wind turbines are not included in this study because they would not be suitable in the context of most cities. The results highlight the importance of PV investment in reaching the ZEN requirements. For example, around 850 kW of solar is needed for our test cases of 10,000 m^2 of floor area, for an annual energy demand of around 700 MWh of electricity and 620 MWh of heat. The investments in other technologies are small in comparison.

Keywords ZEN · Sustainable neighborhoods · Zero emission Neighborhoods · Energy system · CO_2 emissions · Optimization

1 Introduction

A ZEN is a neighborhood that has a net zero emission of CO_2 over its lifetime. Many aspects are embedded in the idea of ZEN. Energy efficiency, materials, users behavior, energy system integration are all aspects that need to be accounted for

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in this concept. In addition, different parts of the life cycle can be included but in this paper we only consider the operation phase and no embedded emissions. Two types of action exist to make neighborhoods more sustainable. One is to act on the demand, via better insulation, user behavior or other efficiency measures. The other is to act on the supply and have a local energy system minimizing the CO_2 emissions. There is consequently a need for a way of designing the energy system of such neighborhoods. The questions to be answered are, which technologies are needed to satisfy the demand of heat and electricity of a neighborhood, and how much of it should be installed so that it is as inexpensive as possible. The problem is then to minimize the cost of investment and operation in the energy system of a neighborhood so that it fulfills the ZEN criteria. This paper presents an optimization model to solve such problems with a focus on operations research methodology.

2 State of the Art and Contribution

The ZEN concept is specific to this particular project, however similar topics have been studied in different settings either at the neighborhood level, the city level or the building level, for example during the research center on Zero Emission Building. In this context, K B Lindberg studied the investment in Zero Carbon Buildings [2] and Zero Energy Buildings [3] which are variations around the concept of Zero Emission Buildings. In both papers an optimization based approach is used to study the impact of different constraints on the resulting design. The second one [3] in particular uses binary variables to have a more realistic representation of the operation part (part load limitation and import/export). In [4], Gabrielli et al. tackle the problem of investment and operation of a neighborhood system and show an approach allowing to model the system complexity while keeping a low number of binary variables. It also constrains the total CO_2 emissions. It uses design days and proposes two methods for allowing to model seasonal storages while keeping the model complexity and reducing the run time. In [5], Hawkes and Leach look at the design and unit commitment of generators and storage in a microgrid context using 12 representative days per season in a linear program. It is particular in that it defines how much the microgrid would be required to operate islanded from the main grid and include this in the optimization. It also discusses the problematic of market models within microgrids. In [6], Weber and Shah present a mixed integer linear programming tool to invest and operate a district with a focus on cost, carbon emission and resilience of supply. A specificity of this tool is that it also designs the layout of the heat distribution network taking into account the needs of the buildings and the layout of each area. It uses the example of a town in the United Kingdom for its case study. In [7], Mehleri et al. study the optimal design of distributed energy generation in the case of small neighborhoods and test the proposed solution on a Greek case. Emphasis is put on the different layouts of the decentralized heating network. In [8], Schwarz et al. present a model to optimize the investment and the energy system of a residential quarter, using a two stage stochastic MILP. It emphasizes on how it tackles the stochasticity of the problem in the different stages, from raw data to the input of the optimization, and on the computational performance and scalability of the proposed method. In [9], he also studies the impact of different grid tariffs on the design of the system and on the self-consumption of the PV production. In [10], Li et al. separate the investment and the operation into a master and a follower problem. The master problem uses a genetic algorithm to find the optimal investment while a MILP is used to find the operation in the follower problem. In [11], Wang et al. also use a genetic algorithm, but at the building level and using a multi objective approach focused on environmental considerations. A life cycle analysis methodology as well as exergy consumption are used to assess the design alternatives. In [12], Mashayekh et al. uses a MILP for sizing and placement of distributed generation using a MILP approach including linearized AC-power flow equations. In [13], Yang et al. also use a MILP approach for the placement and sizing problem but consider discrete investment in technologies at the district scale. These papers give us an overview of different methods for optimal investment in the energy system of neighborhoods or buildings, but none apply the ZEN concept and the influence of tight requirements on the CO_2 emissions on the modelling and on the results has not been demonstrated.

In this paper, the focus is put on getting a fast yet precise solution that can take long term trends, such as cost reduction of technologies or climate. To this end, the proposed model uses a full year representation, ensuring a correct representation of seasonal storage of heat and electricity, and allows to divide the lifetime of the neighborhood into several periods, each represented by one year. It is also different by using the Zero Emission framework on a neighborhood level as a guide for the emission reduction constraint. This adds an integral constraints coupling each timestep and increasing the complexity of the problem. The use of binary variables is limited to the minimum.

3 ZENIT Model Description

ZENIT stands for Zero Emission Neighborhoods Investment Tool. It is a linear optimization program written in Python and using Gurobi as a solver. It minimizes the cost of investing and operating the energy system of a ZEN using periods, with a representative year in each period. Different technologies are available, both for heat and for electricity. It is most suited for greenfield investment planning but can also take into account an existing energy system. The objective function is presented below:

$$\begin{aligned}
&\sum_i C_i^{disc} \cdot x_i + b_{hg} \cdot C_{hg} + \frac{1}{\varepsilon_{r,D}^{tot}} \sum_i C_i^{maint} \cdot x_i \\
&+ \sum_p \varepsilon_{r,p} \Bigg(\sum_t \Big(\sum_f f_{f,t,p} \cdot P_{f,p}^{fuel} + (P_{t,p}^{spot} + P^{grid} \\
&+ P^{ret}) \cdot (y_{t,p}^{imp} + \sum_{est} y_{t,p,est}^{gb_imp}) - P_{t,p}^{spot} \cdot y_{t,p}^{exp} \Big) \Bigg)
\end{aligned} \tag{1}$$

The objective is to minimize the cost of investing in the energy system as well as its operation cost.

The operation phase can be separated in different periods during the lifetime of the neighborhood, and one year with hourly time-steps is used for each period. In addition to technologies producing heat or electricity, there is also the possibility to invest in a heating grid represented by the binary b_{hg} that also gives access to another set of technologies that would be inappropriate at the building level. In the equation above, the $\mathcal{E}$ represent discount factors either global for the whole study (3) or for each period (2). They are calculated in the following way:

$$\varepsilon_{r,D}^{tot} = \frac{r}{1 - (1+r)^{-D}} \tag{2}$$

$$\varepsilon_{r,p} = \frac{(1+r)^{-p \cdot YR}}{\frac{r}{1-(1+r)^{-YR}}} \tag{3}$$

The calculation assumes that reinvestment in this technology is made for the whole lifetime of the neighborhood, and is discounted to year 0. The salvage value is also accounted for. The formula used is:

$$\begin{aligned}
C_i^{disc} = &\left(\sum_{n=0}^{N_i - 1} C_i^{inv} \cdot (1+r)^{(-n \cdot L_i)} \right) \\
&- \frac{N_i \cdot L_i - D}{L_i} \cdot C_i^{inv} \cdot (1+r)^{-D}
\end{aligned} \tag{4}$$

$$with : N_i = \left\lceil \frac{D}{L_i} \right\rceil \tag{5}$$

In the objective function, $y_{t,p}^{exp}$ represent the total export from the neighborhood. It is simply the sum of all exports from the neighborhood: $\forall t, p$

$$y_{t,p}^{exp} = \sum_g y_{t,p,g}^{exp} + \sum_{est} (y_{t,p,est}^{gb\_exp} + y_{t,p,est}^{pb\_exp}) \cdot \eta_{est} \tag{6}$$

The most important constraint, and what makes the specificity of the "Zero Emission" concept, is the CO_2 balance constraint. It is a net zero emission constraint of CO_2 over a year. It takes into account the emissions from the used fuels and electricity with the corresponding CO_2 factors for the emission part and the exports of electricity for the compensation part. In this study the same factor is used for imports and for exports of electricity. This constraint is expressed below, $\forall p$:

$$\begin{aligned}\sum_t((y^{imp}_{t,p} + \sum_{est} y^{gb\_imp}_{t,p,est}) \cdot \varphi^{CO_2}_e) \\ + \sum_t \sum_f (\varphi^{CO_2}_f \cdot f_{f,t,p}) \le \sum_t (\sum_{est} (y^{gb\_exp}_{t,p,est} \\ + y^{pb\_exp}_{t,p,est}) \cdot \eta_{est} + \sum_g y^{exp}_{t,p,g}) \cdot \varphi^{CO_2}_e\end{aligned} \tag{7}$$

In the particular ZEN framework of this study, the idea behind the compensation is that the electricity exported to the national grid from on-site renewable sources allows to reduce the national production, and thus to prevent some emissions from happening. The corresponding savings, the compensation, stand on the right-hand side of the equation. In the ZEN framework, this constraint is set as an annual constraint. It can however also be used for shorter periods of time.

Other necessary constraints are the different electricity and heat balances which guarantee that the different loads are served at all times. The electricity balance is represented graphically in Fig. 1. The corresponding equations are also written below. The electricity balance is particular because, we want to keep track of the origin of the electricity sent to the battery. It is managed by representing each battery

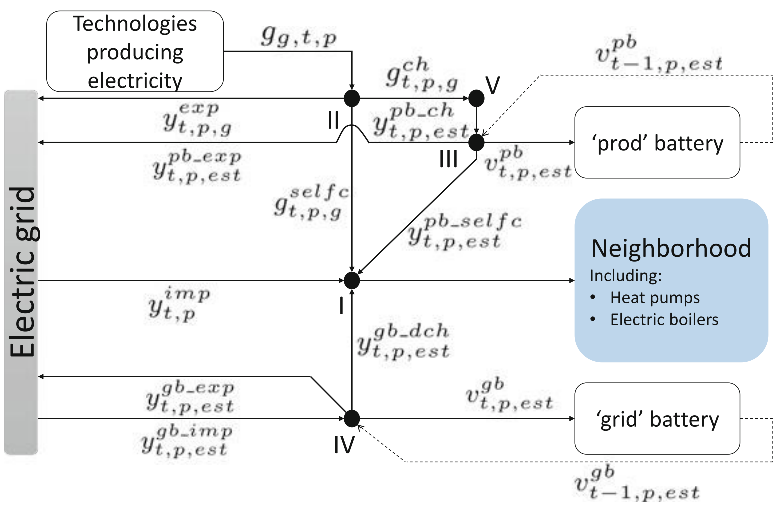

Fig. 1 Graphical representation of the electricity balance in the optimization

as a combination of two other batteries: one is linked to the on-site production technologies, while the other is connected to the grid. It allows to keep track of the self-consumption and to differentiate between the origin of the energy for the CO_2 balance.

Node I (8) represents the main electric balance equation while II (9) and V (10) are only related to the on-site production of electricity. Node II (9) describes that the electricity produced on-site is either sold to the grid, used directly or stored, while node V (10) states that at a given time step what is stored in the batteries is equal to what is in excess from the on-site production.

Electricity balance I: $\forall t, p$

$$\begin{aligned} y_{t,p}^{imp} + \sum_{est}(y_{t,p,est}^{gb\_dch} + y_{t,p,est}^{pb\_selfc}) \cdot \eta_{est} + \sum_{g} g_{g,t,p}^{selfc} \\ = \sum_{e} d_{e,t,p} + \sum_{b}\sum_{hp} d_{hp,t,p,b} + \sum_{b} E_{b,t,p} \cdot A_b \end{aligned} \tag{8}$$

Electricity balance II: $\forall t, p, g$

$$g_{g,t,p} = y_{t,p,g}^{exp} + g_{g,t,p}^{selfc} + g_{t,p,g}^{ch} \tag{9}$$

Electricity balance V: $\forall t, p$

$$\sum_{g} g_{t,p,g}^{ch} = \sum_{est} y_{t,p,est}^{pb\_ch} \tag{10}$$

Heat also has its own balance, that guarantees that the demand of each building is met:

$$\begin{aligned} \sum_{\gamma \in \mathcal{Q} \setminus \mathcal{HP}} q_{\gamma,t,p} + \sum_{b}\sum_{hp} q_{hp,t,p,b} \\ + \sum_{hst} \eta_{hst} \cdot q_{t,p,hst}^{dch} = \sum_{b} H_{b,t,p} \cdot A_b + q_{t,p}^{ch} \end{aligned} \tag{11}$$

Note that the demand is not divided between domestic hot water (DHW) and space heating (SH).

The batteries are represented, as mentioned earlier and as seen on Fig. 1, as two entities: one on the on-site production side and the other on the grid side. This means that we have two "virtual" batteries with their own set of constraints as well as constraints linking the two.

The first constraint is a "reservoir" type of constraint and it represents the energy stored in the battery at each time-step: $\forall t \in \mathcal{T}^*, p, est$

$$v^{pb}_{t,p,est} = v^{pb}_{t-1,p,est} + \eta_{est} \cdot y^{pb\_ch}_{t-1,p,est} - y^{pb\_exp}_{t-1,p,est} - y^{pb\_selfc}_{t-1,p,est} \tag{12}$$

$$v^{gb}_{t,p,est} = v^{gb}_{t-1,p,est} + \eta_{est} \cdot y^{gb\_imp}_{t-1,p,est} - y^{gb\_exp}_{t-1,p,est} - y^{gb\_dch}_{t-1,p,est} \tag{13}$$

Equations (14), (16) and (17) link both batteries. They make sure the sum of the stored energy in the "virtual" batteries is less than the installed capacity, and making sure the rate of charge and discharge of the battery is not violated. $\forall t, p, est$

$$v^{pb}_{t,p,est} + v^{gb}_{t,p,est} \leq v^{bat}_{t,p,est} \tag{14}$$

$$v^{bat}_{t,p,est} \leq x_{bat,est} \tag{15}$$

$$y^{pb\_ch}_{t,p,est} + y^{gb\_imp}_{t,p,est} \leq \dot{Y}^{bat}_{max,est} \tag{16}$$

$$y^{gb\_dch}_{t,p,est} + y^{gb\_exp}_{t,p,est} \leq \dot{Y}^{bat}_{max,est} \tag{17}$$

The storage level at the beginning and the end of the periods should be equal. $\forall p, est$

$$v^{bat}_{start,p,est} = v^{bat}_{end,p,est} \tag{18}$$

The heat storage technologies also have the same kind of equations as the batteries, for example: $\forall t \in \mathcal{T}^*, p, hst$

$$v^{heatstor}_{t,p,hst} = v^{heatstor}_{t-1,p,hst} + \eta^{heatstor}_{hst} \cdot q^{ch}_{t,p,hst} - q^{dch}_{t,p,hst} \tag{19}$$

Equations (14) to (18) also have equivalents for the heat storages. However the heat storages are not separated in two virtual entities since there is no export of heat from the building.

The power exchanges with the grid are limited depending on the size of the connection: $\forall t, p$

$$(y^{imp}_{t,p} + y^{exp}_{t,p} + \sum_{est} y^{grid\_imp,bat}_{t,p,est}) \leq GC \tag{20}$$

In order to not add additional variables, the mutual exclusivity of import and export is not explicitly stated. It is still met however due to the price difference associated with importing and exporting electricity.

In addition to the above equations, different constraints are used to represent the different technologies included. The maximum investment possible is limited for each technology. $\forall i$:

$$x_i \leq X_i^{max} \tag{21}$$

The amount of heat or electricity produced is also limited by the installed capacity:

$$\forall q, t, p : q_{q,t,p} \leq x_q \tag{22}$$

$$\forall g, t, p : g_{g,t,p} \leq x_g \tag{23}$$

The amount of fuel used depends on the amount of energy provided and on the efficiency of the technology: respectively $\forall \gamma \in \mathcal{F} \cap \mathcal{Q}, p, t$ and $\forall \gamma \in \mathcal{E} \cap \mathcal{Q}, p, t$

$$f_{\gamma,t,p} = \frac{q_{\gamma,t,p}}{\eta_\gamma} \tag{24}$$

$$d_{\gamma,t,p} = \frac{q_{\gamma,t,p}}{\eta_\gamma} \tag{25}$$

For CHPs technologies, the Heat to Power ratio is used to set the production of electricity based on the production of heat. $\forall t, p$

$$g_{CHP,t,p} = \frac{q_{CHP,t,p}}{\alpha_{CHP}} \tag{26}$$

For the heat pumps, the electricity consumption is based on the coefficient of performance (COP).
$\forall hp, b, t, p$

$$d_{hp,b,t,p} = \frac{q_{hp,b,t,p}}{COP_{hp,b,t,p}} \tag{27}$$

The heat pumps are treated differently from the other technologies because they are not aggregated for the whole neighborhood but are separated for each building. This is because the COP depends on the temperature to supply, which is different in passive buildings and in older buildings and which is also different for DHW and for SH, and dependent on the temperature of the source. The source is either the ground or the ambient air depending on the type of heat pump. The COP is then calculated using a second order polynomial regression of manufacturers data [3] and the temperature of the source and of the outside timeseries. The possibility to invest in insulation to reduce the demand and improve the COP of heat pumps is not considered. The global COP is calculated as the weighted average of the COP for DHW and SH.

The solar technologies, solar thermal and PV, also have their own set of specific constraints. $\forall t, p$:

$$g_{t,p}^{PV} + g_{t,p}^{curt} = \eta_{t,p}^{PV} \cdot x_{PV} \cdot IRR_{t,p} \tag{28}$$

$$q_{t,p}^{ST} = x_{ST} \cdot \frac{IRR_{t,p}}{G_{stc}} \tag{29}$$

The hourly efficiency of the PV system is calculated based on [14], and accounts for the outside temperature and the irradiance. This irradiance on a tilted surface is derived from the irradiance on a horizontal plane that is most often available from measurements sites by using the geometrical properties of the system: azimuth and elevation of the sun and tilt angle and orientation of the panels.

The irradiance on the horizontal plane data comes from ground measurements from a station close to the studied neighborhood which can for example be obtained from Agrometeorology Norway.[1] The elevation and azimuth of the sun is retrieved from an online tool.[2] This calculation takes into account the tilt of the solar panel and its orientation. Several assumptions were necessary to use this formula. Indeed, the solar irradiance is made up of a direct and a diffuse part and only the direct part of the irradiance is affected by the tilt and orientation. However there is no good source of irradiance data that provides a distinct measurement for direct and diffuse parts in Norway as far as the authors know. Thus we make assumptions that allow us to use the complete irradiance in the formula. We assume that most of the irradiance is direct during the day and that most is diffuse when the sun is below a certain elevation or certain azimuths. This assumption gives a good representation of the morning irradiances while still accounting for the tilt and orientation of the panel during the day. On the other hand, this representation overestimates the irradiance during cloudy days, when it is mostly indirect irradiance. Obtaining direct and diffuse irradiance data would solve this problem.

4 Implementation

The model presented in the previous section has been implemented in the case of campus Evenstad, which is a pilot project in the ZEN research center [15]. This implementation of the model and the parameters used are presented in this section. Campus Evenstad is a university college located in southern Norway and is made up of around 12 buildings for a total of about 10,000 m^2. Most of the buildings were built between 1960 and 1990 but others stand out. In particular two small buildings were built in the nineteenth century and the campus also features two

[1] lmt.nibio.no

[2] Sun Earth Tools: https://www.sunearthtools.com/dp/tools/pos_sun.php

Table 1 Technologies used in the Evenstad case and their main parameters

Technology	Inv. Cost (€/kW)	Life-time (Years)	Efficiency (%)
Building			
PV	1600	25	18
Solar Thermal	700	25	70
Air source HP	556	15	COP_t
Ground source HP	444	15	COP_t
Biomass Boiler	350	20	85
Electric Boiler	750	30	100
Gas Boiler	120	25	95
Neighborhood			
Gas CHP	739	25	45_{th}; 35_{el}
Biomass CHP	3300	25	40_{th}; 25_{el}
Heat Pump	660	25	COP_t
Electric Boiler	150	20	100
Gas Boiler	60	25	95

recent buildings with passive standards. The campus was already a pilot project in the previous ZEB center and one of those buildings was built as a Zero Emission Building. In addition, on the heating side a 100 kW CHP plant (40 kW electric) and a 350 kW Bio Boiler both using wood chips were installed along with 100 m^2 of solar collectors, 10,000 L of storage tank, 11,600 L of buffer tank and a heating grid. On the electric side, the same CHP is contributing to the on-site generation as well as a 60 kW photovoltaic system. A battery system is already planned to be built accounting for between 200 and 300 kWh. Based on this we assume in the study an existing capacity of 250 kWh. We keep those technology in the energy system of the neighborhood for one part of the study. In addition, the heating grid is kept in all cases ($b_{hg} = 1$).

The technologies included in the study are listed in Table 1 along with the appropriate parameters.

Two main sources for the parameters and cost of the technologies are used as references for the study. Most of the technologies' data is based on a report made by the Danish TSO energinet and the Danish Energy Agency [16] on technology data for energy plants. The other source includes the technology data sheets made by IEA ETSAP [17] and is used in particular for the gas and the biomass CHP. The cost of PV is based on a report from IRENA [18]. The two efficiencies reported for the CHP plants correspond to the thermal and electrical efficiency, noted by a subscript ($_{th}$ for thermal and $_{el}$ for electrical). Note that: at the neighborhood level, only ground source heat pump is considered (Table 2) and that PV is only considered at the building level but the roof area limit to the size of the PV is not implemented.

The heat storage values are based on a data sheet by ETSAP [17] while the values used for the batteries are based on a report from IRENA [19].

Table 2 Storage technologies used in the Evenstad case and their main parameters

Technology	Inv. Cost (€/kWh)	Lifetime (Years)	Efficiency (%)
Battery	350	15	94
Heat Storage	75	20	95

Table 3 Fuel cost and CO_2 factors

Fuel	Cost (€/kWh)	CO_2 Factor (gCO_2/kWh)
Gas	0.055	277
Biomass	0.041	7
Electricity	$P^{spot}_{t,p}$	17

The values in Table 3 come from different sources. The cost of biomass comes from EA Energy Analyses [20], the cost of gas is based on the cost of gas for non household consumers in Sweden[3] (we assume similar costs in Norway). For the technologies in Table 1, the O&M costs, expressed as a percentage of the investment costs, are respectively: 1, 1.3, 1, 1.3, 2, 0.8, 2.3, 4, 5.5, 1, 1 and 5. For the storage technologies in Table 2, the operating cost is 0. The CO_2 factors of gas and electricity for Norway are based on a report from Adapt Consulting [21] and the CO_2 factor for biomass is based on [22].

The electricity prices for Norway are based on the hourly spot prices for the Oslo region in 2017 from Nordpool.[4] On top of the spot prices, a small retailer fee and the grid charges are added.[5] The prices are rather constant with a fair amount of peaks in the winter and some dips in the summer. This cost structure is close to the actual structure of the electricity price seen by consumers. We assume hourly billing due to its relevance to prosumers and its emergence in Norway.

The irradiance on the horizontal plane and temperatures are obtained and used in the calculations as described in the previous section. The ground station used to retrieve data is Fåvang, situated 50 km to the west of Evenstad. The electric and heat load profiles for the campus are derived from [23]. The load profiles are based on the result of the statistical approach used in these papers and the ground floor area of each type of building on the campus. In addition, the domestic hot water (DHW) and Space Heating (SH) are derived from the heat load based on profiles from a passive building in Finland where both are known [24].

The problems are solved on a Windows 10 laptop with a dual-core CPU (i7-7600U) at 2.8 GHz and 16 GB of RAM. Each case typically has about 450,000 rows, 600,000 columns and 2,400,000 non-zeros. They are solved using the barrier method in Gurobi in about 150 s each.

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[3] http://ec.europa.eu/eurostat/statistics-explained/index.php?title=File:Gas_prices_for_non-household_consumers,_second_half_2017_(EUR_per_kWh).png

[4] https://www.nordpoolgroup.com/Market-data1/Dayahead/Area-Prices/ALL1/Hourly/?view=chart

[5] https://www.nve.no/energy-market-and-regulation/network-regulation/network-tariffs/statistics-on-distribution-network-tariffs/

5 Results

The optimization was run several times with different conditions. It was run with a yearly CO_2 balance with and without including the energy system that already exists at Evenstad. When the pre-existing energy system is included, the pre-existing amounts of heat storage, PV, solar thermal and biomass heating (CHP and boilers) represent the minimum possible investments in those technologies for the optimization. The energy systems resulting from those optimizations are presented on Fig. 2.

Both cases are interesting. Indeed the case with the pre-existing technologies included in the optimization allows to know in which technology to invest to move towards being a ZEN for the campus Evenstad while the case that does not include the pre-existing technologies allows to see how it would look like if it was built today from the ground up using the optimization model presented here and the given ZEN restrictions.

A first observation from Fig. 2 is that the technologies already installed (heat storage ST, biomass boiler BB, CHP, battery) do not get additional investments, except for PV which gets a lot of additional investments to meet the ZEN criteria. In addition to the large investment in PV the only additional investment for Evenstad appears to be a heat pump. In the case without any pre-installed technologies the system is quite different. There is still a need for investment in PV, though it is slightly lower and the optimization does not chose to invest in a battery. On the heating part the chosen design uses heat pumps and electric boiler in addition to a heat storage smaller than already installed in Evenstad.

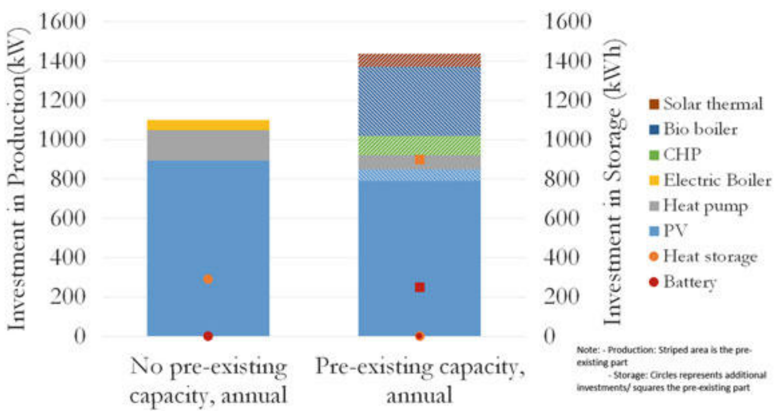

Fig. 2 Resulting energy system

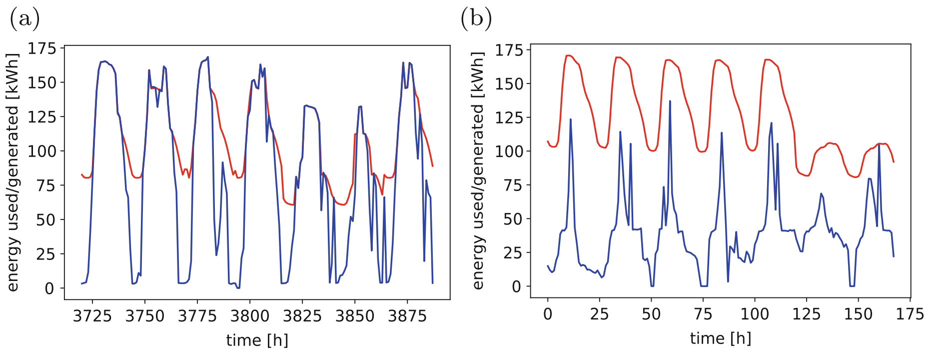

Fig. 3 Self consumed electricity (blue) and total consumption (red) of electricity in the ZEN. (**a**) Summer. (**b**) Winter

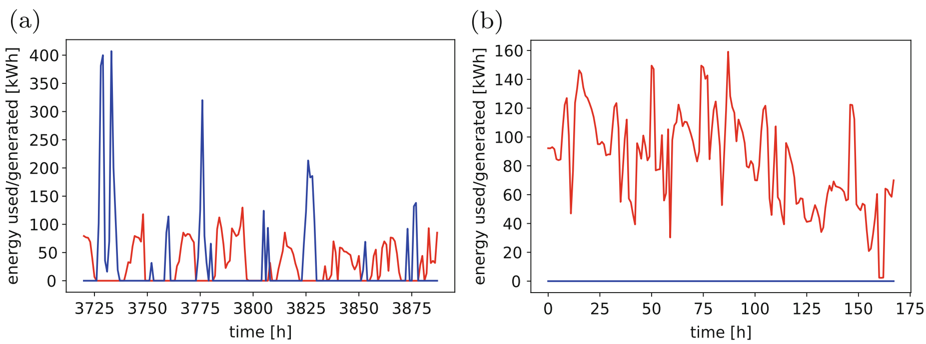

Fig. 4 Import (red) and Export (blue) of Electricity from the ZEN. (**a**) Summer. (**b**) Winter

The results highlight the predominance of PV in the results. This shows that the other possible designs are not cost competitive. Alternative designs, for example relying on biomass CHP, could be incentivized to obtain a better mix of technology. The amount of the incentive could be explored by a sensitivity analysis using this model, but this remains as future work.

On Fig. 3, the self consumption and the total demand of electricity is presented while on Fig. 4 it is the imports (red) and exports (blue) of electricity that are presented. Both figures show a week for the case of the yearly balance and including pre-existing technologies. In the summer the neighborhood produces electricity in excess and needs to send it to the grid. The battery, that is part of the pre-existing technologies, is used but is not large enough to allow for relying on self produced electricity during the night. It is also not large enough to limit the amount of electricity sent to the grid. Figure 4a illustrates this: the exports during the days have highs peaks that represent around four times the night imports in terms of peak power. This has implications on the sizing of the connection to the grid and is especially important in the context of the introduction of new tariffs based on peak power in Norway. Indeed, the introduction of smart-meters enables the use of more complex grid tariff structures. Such tariffs would promote avoiding large peaks in consumption. This may be beneficial to highly flexible neighborhoods such as ZENs and might promote investment in batteries. Investigating the impact of grid tariffs on the design of ZENs remains as future work. Outside of the ZEN context, a positive impact of certain grid tariff designs has been shown on self-consumption and peak electricity import [9]. In the winter, some of the electricity is still self consumed due to the CHP that is part of the pre-existing technologies. This self consumption stays limited and no electricity is exported.

Ultimately, all resulting designs require huge investment in PV to attain the status of ZEN. In those systems, which rely heavily on electricity, heat pumps and electric boilers appear to be the preferred heating solution.

6 Limitations

This study has several limitations, on the methodology and on the case study. For the case study, assumptions were necessary due to the lack of data, in particular for the loads or the insolation (diffuse and direct). For the methodology, the will to limit the use of binary variables meant leaving out constraints such as part load limitations which would be needed to have a better representation of some technologies. In addition, using an hourly resolution leads to an underestimation of the storages and possibly of the heating technologies size. There is a trade off between the solving time and the precision of the results and the resolution needs to be chosen accordingly. Additionally, being deterministic, the model leaves out several uncertainties. Those uncertainties concern the evolution of the price of the technologies, the electricity price or the price of other fuels and the climate conditions. Those can be partially addressed by specifying additional periods in the model. The short-term uncertainties are not included either and induce an overly optimistic operation of the system. Despite those limitations it provides insights in the design methodology that can be used to design the energy system of a ZEN. The choice of CO_2 factors for electricity is also greatly impacting the results and this should be studied in more detail in future work.

7 Conclusion

This paper presented in detail the ZENIT model for investment in Zero Emission Neighborhoods as well as its implementation and the results on a realistic case study of campus Evenstad in Norway, with a focus on methods from the field of operations research. The model is formulated as a MILP, using as few binaries as possible. The Zero Emission constraint complexifies the problematic of designing the energy system of a neighborhood and the long term trends can be accounted for by defining periods. For Evenstad, the results suggest that additional investments, mainly in

PV, are necessary in order to attain the status of ZEN. Investments happen at both levels but mainly at the building level. When the technologies already installed at Evenstad are not included, they are not invested in (except for heat storage). The optimal choice in order to become Zero Emission for Evenstad in the current ZEN framework thus appears to be a massive investment in PV and a heating system fueled by electricity. Further work includes disaggregating the heat part of the model and a more detailed operation part in the optimization.

There are key takeaways for policy makers in this study, in particular for Norway due to the setting of the case study. The results suggest that the Zero Emission constraint used in this study is sufficient to get PV investment without any additional incentive. However, under the CO_2 factor assumptions used in this study, huge investment in PV are made which would be problematic in case of a large-scale application of the concept of ZEN. This suggests the need for incentives in alternative technologies such as biomass CHPs in case the concept of ZEN becomes more common. The methodology presented in this paper can be used to assess such policies and their potential effect on investments in ZEN. Other policies such as the grid tariff structure can also be studied with this model. Finally, the hourly limitation on electricity export from prosumers has recently been replaced in Norway by a tariff on exported electricity. The results of this paper suggest that without this change in policy, ZEN would become even more expensive due to the necessity of large batteries to make the exports more constant. We thus recommend continuing on the path of facilitating the development of the number of prosumers for example with the implementation of capacity grid tariffs. For countries other than Norway, similar methodology can be used to assess the cost and design of ZEN. Further policy recommendations cannot be drawn from this study due to the specificity of the Norwegian electricity mix, that is reflected in its electricity CO_2 factor.

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Nomenclature

Indexes (Sets)

$t(\mathcal{T})$	Timestep in hour within year $\in [0, 8759]$
$b(\mathcal{B})$	Building type
yr	Year within period $\in [1, YR]$
p	Period
$i(\mathcal{I})$	Energy technologies, $\mathcal{I} = \mathcal{F} \cup \mathcal{E} \cup \mathcal{HP} \cup \mathcal{S} \cup \mathcal{QST} \cup \mathcal{EST}$; $\mathcal{I} = \mathcal{Q} \cup \mathcal{G}$:

$f(\mathcal{F})$	Technology consuming fuel (gas, biomass, ...)
$e(\mathcal{E})$	Technology consuming electricity
$hp(\mathcal{HP})$	Heat pumps technologies

$s(\mathcal{S})$	Solar technologies $\in ST, PV$
$qst(\mathcal{QST})$	Heat storage technologies
$est(\mathcal{EST})$	Electricity storage technologies

$q(\mathcal{Q})$	Technologies producing heat
$g(\mathcal{G})$	Technologies producing electricity

Parameters

C_i^{disc}	Discounted investment cost, technology i with re-investments and salvage value [€/kWh]
$\varepsilon_{r,p}$	Discount factor, period p with discount rate r
D	Duration of the study [yr]: $D = P * YR$
P	Number of periods in the study [-]
C_i^{maint}	Annual maintenance cost [% of inv. cost]
$P_{f,p}^{fuel}$	Price of fuel of technology g, period p [€/kWh]
$P_{t,p}^{spot}$	Electricity spot price [€/kWh]
P^{grid}	Electricity grid tariff, period p [€/kWh]
P^{ret}	Retailer tariff on electricity, period p [€/kWh]
η_{est}	Charge/Discharge efficiency of battery est [-]
$\varphi_e^{CO_2}$	CO_2 factor of electricity [g/kWh]
$\varphi_f^{CO_2}$	CO_2 factor of fuel f [g/kWh]
α_{CHP}	Heat to power ratio of the CHP [-]
GC	Size of the neighborhood grid connection [kW]
X_i^{max}	Maximum possible installed capacity of technology i [kW]
$E_{b,t,p}$	Electric specific load of building b in timestep t in period p [kWh/m^2]
A_b	Aggregated area of building b in the neighborhood [m^2]
$H_{b,t,p}$	Heat specific load of building b in timestep t in period p [kWh/m^2]
η_i	Efficiency of technology i [-]
$COP_{hp,b,t,p}$	Coefficient of performance of heat pump hp in building b in timestep t in period p [-]
$\dot{Y}_{max}^{bat}$	Maximum charge/dis- rate of battery [kWh/h]
$\dot{Q}_{max}^{heatstor}$	Maximum charge/discharge rate of heat storage [kWh/h]
$\eta_{t,p}^{PV}$	Efficiency of the solar panel in timestep t in period p [-]
L_i	Lifetime of technology i [yr]
C_{hg}	Cost associated with a heating grid for the neighborhood [€]

Variables

x_i	Capacity of technology i: for $i \in \{f \cup e \cup h \cup s\}$ [kW]; for $i \in \{qst \cup est\}$ [kWh]
$f_{f,t,p}$	Fuel consumed by technology f in hour t [kWh]

$d_{e,t,p}$	Electricity consumed by technology e in timestep t [kWh]
$d_{hp,b,t,p}$	Electricity consumed by the heat pumps hp, in building type b [kWh]
$y_{t,p}^{imp}$, $y_{t,p}^{exp}$	Electricity imported/exported from the grid to the neighborhood at timestep t [kWh]
$y_{t,p,g}^{exp}$	Electricity exported by the production technology g to the grid at timestep t [kWh]
$g_{t,p,g}^{selfc}$	Electricity generated from the technology g self consumed in the neighborhood, timestep t [kWh]
$g_{t,p,g}^{ch}$	Electricity generated from the technology g into the 'prod' batteries at timestep t [kWh]
$y_{\overline{t,p},est}$	Electricity imp/exported by the battery *est* at timestep t [kWh] (gb_exp, gb_imp or pb_exp)
$g_{g,t,p}$	Electricity generated by technology g in timestep t of period p [kWh]
$q_{q,t,p}$	Heat generated by technology q in timestep t of period p [kWh]
$y_{t,p,est}^{gb\_dch}$	Electricity discharged from the 'grid' battery *est* to the neighborhood at timestep t [kWh]
$y_{t,p,est}^{pb\_ch}$	Electricity charged from the neighborhood to the 'prod' battery *est* at timestep t [kWh]
$y_{t,p,est}^{pb\_selfc}$	Electricity to the neighborhood from the 'prod' battery *est*, timestep t [kWh]
$q_{t,p}^{ch}$	Heat "charged" from the neighborhood to the heat storage at timestep t [kWh]
$q_{t,p}^{dch}$	Heat "discharged" from the neighborhood to the heat storage at timestep t [kWh]
$q_{t,p}^{ch}$, $q_{t,p}^{dch}$	Heat "charged"/"discharged" from the neighborhood to the heat storage at timestep t [kWh]
$v_{t,p,est}^{gb}$, $v_{t,p,est}^{pb}$	'grid'/'prod' Battery *est* level of charge at timestep t in period p [kWh]
$v_{t,p}^{heatstor}$	Heat storage level at timestep t in period p [kWh]
$g_{t,p}^{curt}$	Solar energy production curtailed [kWh]
b_{hg}	Binary variable for investment in a heating grid

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Paper 2

Impact of Grid Tariffs Design on the Zero Emission Neighborhoods' Energy System Investments

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***Abstract*—This paper investigates the relationship between grid tariffs and investment in Zero Emission Neighborhoods (ZEN) energy system, and how the grid exchanges are affected. Different grid tariffs (Energy based, Time of Use (ToU), Subscribed capacity and Dynamic) are implemented in an optimization model that minimizes the cost of investing and operating a ZEN during its lifetime. The analysis is conducted in two cases: non-constrained exports and exports limited to 100kWh/h. The results suggest that in the case with no limit on export, the grid tariff has little influence, but ToU is economically advantageous for both the ZEN and the DSO. When exports are limited, the Subscribed capacity allows to maintain DSO revenue, while the others cut them by half. This tariff also offers the lowest maximum peak and a good duration curve in general. The Dynamic tariff creates new potentially problematic peak imports despite its benefits in other peak hours.**

***Index Terms*—Distributed Generation, Investment, Optimization, Photovoltaic Systems**

I. Introduction

The structure of grid tariffs has recently become a more important topic due to the increasing amount of prosumers in the grid and a large implementation of smart meters enabling more complex price structures than is common today. Policy makers, transmission system operators (TSO) and distribution system operators (DSO), need to assess the benefits and drawbacks associated with changing the traditional energy based grid tariffs into more complex formulations such as capacity subscription, time-of-use tariffs, real-time pricing etc. Some of the expected benefits would include reducing grid expansion, peak loads and/or incentivizing end-user flexibility while drawbacks could be a less intuitive pricing structure for consumers or unfairness due to cross-subsidization.

Grid tariffs have specific requirements to meet. They are supposed to reflect the cost of the maintenance, losses and in some cases the cost of grid expansion necessary for new connections [1]. Grid tariffs are made up of one or several of the following components:

- a fixed part paid typically each month or year, independently of the utilization of the grid (€)
- an energy part, based on the amount of energy consumed ($€/kWh$)
- a power part, based on either a subscribed capacity or the size of the connection ($€/kW$)

Variations around these structures can be made by taking into account additional parameters such as time or several power levels for example. Several principles are often mentioned when it comes to how the tariff should be. They aim at having a sustainable economically efficient system while protecting consumers [1]. In more detail, the system should guarantee universal access to electricity with a transparent, simple, stable and equitable pricing system representing each user's contribution to the cost and allowing the grid company to recover the total cost while maintaining it as low as possible [1], [2].

In Norway, the grid tariff varies depending on the region, with more remote areas paying a higher grid tariff. On average for households the tariffs are: a fixed part of $181€/year$ and a variable part of $0,020€/kWh$ [3]. References [3] and [4] also details the law the grid tariffs have to abide by, the situation of the tariffs and the trend in Norway to move towards more power based tariffs in the future.

In parallel, Zero Emission Neighborhoods (ZEN) is a concept being developed in Norway in the ZEN research center and follows the work of the research center for Zero Emission Buildings. ZENs are neighborhoods that reduce their greenhouse gas (GHG) emissions towards zero within their life cycle. This includes not only the fuels consumption in the neighborhood during the operation part but also the construction and deconstruction phase as well as the materials of the Neighborhood. The work of the center is pluri-disciplinary with, among others, work on architecture, energy system, materials and user behavior. In this center, a software for minimizing the investment and operation costs of the energy system of ZENs is developed. It aims at helping stakeholder make decisions about the design of the energy system regarding sizing and choice of technologies in order to be a ZEN.

The main question behind this study is to assess whether and in what way the design of ZEN is affected by grid tariff design. This study is of particular interest for TSOs, DSOs and regulators because ZENs (or local systems based on similar concepts) are expected to be an important class of prosumers with high amounts of installed photovoltaic (PV) leading to potentially large imports of electricity in the winter and exports in the summer. This means they are a good subject for testing different grid tariffs structures and their impact on the neighborhood's import/export profiles of electricity.

II. State of the Art and Contribution

In the introduction, the traditional approach to grid tariffs and the way it is implemented in Norway was presented. This traditional approach is being challenged in the literature by some authors who think it is not suited for the current system or in the near future. The reason that comes up the most often for justifying the need to change the tariffs is the emergence of prosumers and distributed generation in general. An increasing share of consumers are becoming producers of electricity and change the way the grid is used, which calls for a better allocation of costs or savings [1], [5], [6], [7].

In [1], Picciariello et al. discuss the need for new tariff design methodologies because of the growth of distributed generation. He identifies that the current challenges are the exemptions from tariffs for distributed generation and the volumetric tariffs with net metering; where in both cases the pricing does not represent the cost structures of DSO with high fixed cost and low variable costs. He also reviews different proposals of new tariffs structure. In [5], he tackles the problematic of cross-subsidization between consumers and prosumers when net metering is used and suggest a cost-causality tariff structure. He highlights that the cross subsidization problem is particularly pronounced with net metering and energy based tariffs. Fridgen et al. [7], studied the impact of different grid tariffs on residential microgrids. The grid tariffs were a combination of different volumetric tariff share on top of flat, time of use, critical peak or real time structures. He found that volumetric tariffs are more expensive for the consumers and lead to sharp load and generation peaks while the opposite is true when the tariff is not energy based.

Schittekatte [6] analyzes the effects of different grid tariffs against different scenarios for the price of batteries and of PV. He warns against the possibility of distorting investment decision in case of poorly chosen grid tariff.

In a report, Honkapuro et al. [8] study the opportunity for a new grid tariff structure in Finland for small scale customers, in particular incorporating a power part, and find it performs better with regard to cost-reflectivity and incentivizes consumers to be flexible.

Dynamic tariffs is one of the tariff structures that could be a possible improvement over the current grid structure. However other problems could arise such as fairness or cost recovery. Neuteleers et al. [9] studied the fairness of dynamic grid tariffs and pointed that it is important to remember all the principles of tariff design when assessing them.

Several studies looked into the relation between grid tariffs and prosumers with PV and batteries. Bremdal et al. [10] uses measured data and simulation to show that in the Nordic countries, a power component in the tariff would be beneficial but the PV would still not allow to reduce the peak load. Jargstorf et al. [11] takes into consideration the user reaction to the tariff with regard to self-consumption when assessing several grid tariffs based on capacity pricing. Similarly, Schreiber [12] proposes a capacity based tariff, increasing quadratically with respect to power and linearly with energy and updated every 15 minutes, to allow the PV and battery system to benefit the grid in addition to the self-consumption. The optimized operation of the storage in addition to the capacity tariff allows a considerable reduction of peak imports and exports in exchange for only a small reduction of self consumption.

Few articles looked into different grid tariff structures applied to a model for investment in neighborhoods energy system. However, some studies have highlighted the impact in terms of investment in general of choosing a grid tariff structure. Firestone et al. [13] showed that it is the fixed part of the cost that controls the amount of installed distributed generation and that the volumetric part has little influence on it. He suggests that public agencies can design countermeasures based on this result to obtain the desired amount of distributed generation. He also shows some results in terms of the chosen investments. On the contrary Abada et al. [14], warns against the risk of over investment by using a cooperative game theory approach to energy communities formation and investment in PV+battery system under different grid tariffs. They explain the over-investment observed in their results as a snowball effect due to the evolution of the grid tariffs as communities emerge and grid cost has to be recovered.

To the authors knowledge, no article has looked into this investment in neighborhoods energy system in order to look both at the change in investment and at the reaction of the neighborhood to the grid tariff in terms of operation, especially in a context of reduced green houses gases emissions. This paper proposes to look into the impact of grid tariff design from two points of view. From a neighborhood planner perspective, how different grid tariff designs impact the investment choices. From a grid operator, how different tariff designs can shape the import and export of such neighborhoods and the revenue. The neighborhood considered is zero emission in Norway and represent customers with a high amount of on-site production of electricity.

III. ZENIT Model Description and Implementation

ZENIT (Zero Emission Neighborhood Investment Tool) is a tool for minimizing the cost of investing and operating the energy system of a Zero Emission Neighborhood (ZEN). It uses a MILP model to find the optimal type and size of technology needed to provide heat and electricity to a ZEN. The concept contains much more than only the energy system (materials and architecture to name two examples) but this tool's focus is energy systems. The idea behind ZEN is to limit emissions and that it is possible to compensate for the various emissions of CO_2 in the neighborhood by exporting electricity to the grid. Indeed by exporting electricity produced from on-site renewable to the grid, we assume that the production in the system is reduced by the corresponding amount and thus reduces the emission of the total system.

The model used in this paper is based on the model presented in [15]. In this section, the main elements of the model will be repeated and the differences with the model from [15] presented. For the details on the model not repeated, one can refer to that paper. Then the implementation and case chosen will be presented. The optimization is written in Python and uses Gurobi as a solver. In this paper, we interpret the definition of a ZEN as a neighborhood that has 0 emissions over its lifetime, which is set to 60 years. However due to practical reasons and to reduce the computational time, different periods of the lifetime can be defined using one representative year for each. In this study we use a single period. The different decision variables are the amount of investment in each technology for heat, power and energy storage as well as the operation related variables defined for each hour (e.g. amount of electricity produced, amount of fuel consumed). Multiple constraints are used, to enforce the CO_2 limitations necessary in the ZEN context and to represent the operation of the neighborhood and in particular of each technology. It is important to note that part load limitations and start up/shutdown constraints are not implemented. The objective function of the optimization is the following:

Minimize:

$$\begin{aligned}&\sum_i C_i^{disc}\cdot x_i + b_{hg}\cdot C_{hg} + \frac{1}{\varepsilon_{r,D}^{tot}}\sum_i C_i^{maint}\cdot x_i\\&+\frac{1}{\varepsilon_{r,D}^{tot}}\Bigg(\sum_t\Big(\sum_f f_{f,t}\cdot P_f^{fuel} + (P_t^{spot}+P^{grid}\\&+P^{ret})\cdot(y_t^{imp}+\sum_{est} y_{t,est}^{gb\_imp}) - P_t^{spot}\cdot y_t^{exp}\Big)\Bigg)\end{aligned} \tag{1}$$

It minimizes the cost of investing in the different technologies and the operating costs, fuels, electricity and O&M costs and contains the costs of the heating grid and a binary associated with it that also gives access to technologies at a neighborhood level.

The most important constraint in the case of ZENs is the CO_2 balance, whose principle was explained earlier.

$$\begin{aligned}&\sum_t((y_t^{imp}+\sum_{est} y_{t,est}^{gb\_imp})\cdot\varphi_e^{CO_2})\\&\quad+\sum_t\sum_f(\varphi_f^{CO_2}\cdot f_{f,t}) \le \sum_t(\sum_{est}(y_{t,est}^{gb\_exp}\\&\quad+y_{t,est}^{pb\_exp})\cdot\eta_{est}+\sum_g y_{t,g}^{exp})\cdot\varphi_e^{CO_2}\end{aligned} \tag{2}$$

Fig. 1 presents graphically the electricity balance and the different equations associated. Different technologies are included in the study; some of them are only available at the building level and others at the neighborhood level in a centralized production plant. The different technologies are: at the building level : Solar Panels (PV), Solar Thermal (ST), Heat Pumps (HP), Biomass Boiler (BB), Electric Boiler (EB), Gas Boiler (GB); and at the neighborhood levels: CHP (nCHP), Gas Boiler (nGB), Electric Boiler (nEB), Heat Pumps (nHP). In addition Batteries (Bat) and Heat Storage (HS) are available at both levels. Different subcategories can be available to choose from within each category, for instance air-water or water-water heat pumps. In parenthesis is the notation used for the rest of the study for each technology.

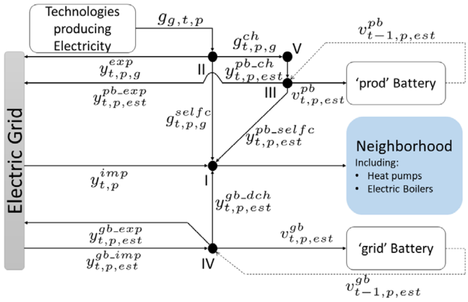


Fig. 1. Graphical representation of the electricity balance in the optimization

Unlike the model in [15], the model used for this paper uses a disaggregrated heat load. The buildings' load are not summed, but types of buildings are identified and the loads are aggregated per building type. It is possible to use a completely disaggregated heat load but the lack of available data motivated not doing it.

The input data necessary to run ZENIT are the electric and heating loads (ideally separated between domestic hot water and space heating), the outside and ground temperatures, the solar insolation and the electricity prices. Hourly timeseries for each representative years are necessary. A description of the neighborhood and its buildings with the floor and the roof area, and the layout of the neighborhoods is also needed. In this study we assume the heating grid is there (and set the corresponding binary to 1) because there is one in the location that inspired this case. Its characteristics (layout, losses and cost) are then necessary but a module can be used to provide an estimate of the losses and cost based on the layout of the neighborhood. The CO_2 factors used were 17 gCO_2/kWh for electricity, 277 gCO_2/kWh for gas [16] and 7 gCO_2/kWh for wood chips [17]. The electricity produced via solar panels or solar thermal on-site do not have CO_2 associated. Embedded emissions were not included. For additional details on the model and the references of the input data used in the model, refer to [15].

IV. Grid Tariffs Description

The Norwegian electricity consumption's recent trend is a consumption where peak demand increases relatively more than annual demand. This trend must be met by new incentives to shave peak load in order to avoid costly distribution grid investments. Grid tariffs are one effective way to solve this issue. In this paper we suggest three new grid tariffs and compare the results with the current grid tariff.

The first analyzed grid tariff is energy based and is the current tariff in Norway. It consists of an annual fixed price and a grid energy cost per kWh consumed. As this rate is flat, it does not incentivize flexible resources nor consumption patterns which results in lower peak demand. The annual cost can be calculated using (3).

$$C^{tot} = 137 + 0,0225 \cdot \sum_t y_t^{imp\_tot} \tag{3}$$

The second grid tariff is a time-of-use based tariff which penalizes import when there is typically scarcity in the grid. The tariff has a basic cost, which is double during peak load hours (7-10am and 6-9pm) and reduced to half during low load hours (11pm-5am). The effect of increasing electric vehicle and demand response penetration on the peak hours is ignored. The total costs are given by (4).

$$\begin{aligned} C^{tot} = \sum_t \big(0,0123 \cdot y_t^{imp\_low} + 0,0246 \cdot y_t^{imp\_med} \\ +0,0492 \cdot y_t^{imp\_peak}\big) \end{aligned} \tag{4}$$

The third tariff was originally described in [18], and is called capacity subscription. It contains a fixed annual cost (€/year), a capacity cost (€/kW), an energy cost (€/kWh) and an excess demand charge (€/kWh). The energy cost is significantly higher when the imports are above the subscription. The main advantage of this tariff is that it incentivizes peak shaving and creates a market for capacity where consumers pay for the resource which in fact is scarce in the distribution grid: capacity. Disadvantages are complexity and the uncertainty in consumer behaviour. In addition, the optimal subscribed capacity is unknown in advance. Finding its value is further discussed in [19]. In this paper, the subscribed capacity is a variable in the optimization. In reality, the consumer would have to choose it and it would most likely not be the optimal value.

$$y_t^{imp\_tot} = y_t^{imp\_below} + y_t^{imp\_above} \tag{5}$$

$$y_t^{imp\_below} \leq c^{sub} \tag{6}$$

Finally the costs are calculated by (7).

$$C^{tot} = 108 \cdot c^{sub} + \sum_t \big(0,005 \cdot y_t^{imp\_below} + 0,1 \cdot y_t^{imp\_above}\big) \tag{7}$$

The fourth tariff is a dynamic tariff where grid scarcity is taken into account. As an extra incentive to reduce impacts on the grid, a penalization C^{sc} is given for consumption in hours with grid scarcity. Scarcity δ_t^{sc} in the system is defined as the 5% of hours in the region (NO1) when the load is the highest. The percentage chosen is arbitrary and could be tuned or changed into a threshold by the regulator. The total costs are given by (8). In addition as an added incentive to help the grid, a bonus for exporting in those hours is added, at the same cost as the scarcity tariff.

$$\begin{aligned} C^{tot} = \sum_t \Big(\big(0,0225 \cdot (1 - \delta_t^{sc}) + \delta_t^{sc} \cdot 0,1\big) \cdot y_t^{imp\_tot} \\ -0,1 \cdot \delta_t^{sc} \cdot y_t^{exp\_tot}\Big) \end{aligned} \tag{8}$$

V. Results

In Norway, the legislation regarding prosumers is changing, moving from a situation where exports are limited to 100kW to a situation of unrestrained export. For this reason, both cases are investigated to explore the consequences on the design of ZENs of the different grid tariffs in these cases. The investment in the energy system can be seen in Table I and in Table II, respectively for the case without and with limitation on exports. The results are presented in the format Prod Plant/ Student Housing/ Normal Offices/ Passive Offices.

TABLE I
CHANGE IN INVESTMENT BETWEEN ENERGY TARIFF CASE AND THE OTHER GRID TARIFFS. FORMAT: (PRODUCTION PLANT/)STUDENT HOUSING/NORMAL OFFICES/PASSIVE OFFICES

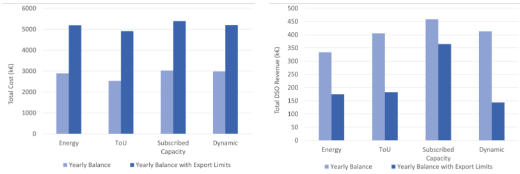
Tech.	Energy	ToU	Subscribed	Dynamic
nPV (kW)	298/298/298	299/298/299	298/298/298	298/298/299
HP (kW)	148/0/0/14.7	144/0/0/14.7	151/0/0/14.3	150/0/0/14.2
nBB (kW)	0/0/1.7	0/0/0.9	0/0/2.2	0/0/2.4
GB (kW)	0/0/0/0.6	3,1/0/0/3.7	0/0/0/2.3	0/0/0/2.5
HS (kWh)	27/119/...	81/104/...	25/114/...	49/134/...
	...47/27	...69/28	...122/33	...71/31

TABLE II
CHANGE IN INVESTMENT BETWEEN ENERGY TARIFF CASE AND THE OTHER GRID TARIFFS, WITH EXPORT LIMITS

Tech.	Energy	ToU	Subscribed	Dynamic
nPV (kW)	411/411/411	412/412/412	410/410/410	411/411/410
HP (kW)	147/0/0/14.6	147/0/0/14.6	147/0/0/14.7	147/0/0/14.6
EB (kW)	89.2/0/0/0	88.7/0/0/0	88.4/0/0/0	89.9/0/0/0
HS (kWh)	320/324/...	320/324/...	335/323/...	323/324/...
	...227/74	...227/72	...227/72	...227/78
Bat (kWh)	1774	1539	1519	1540

The investments stay similar, no new technology is introduced or replaced. However, small variations in the amount of each technology appear, in particular heat storage. The difference between the energy system with and without export limit is greater, namely due to storages. A large battery pack is necessary in order to store the PV production while it waits to be exported, i.e. to accommodate the bottleneck. In addition, large investments in Heat Storage and Electric Boiler are done. The subscribed capacity resulting of the optimization is of 134,5kW for the case with no export limit, and of 124kW in the case with export limits.

Fig. 2 presents the total cost of the neighborhood's energy system (investment and operation) and the total revenue for the DSO, both over the lifetime and discounted to the start of the study. There are small variations in the cost in all cases. Subscribed capacity and Dynamic pricing cause an increase in the total cost for the ZEN between 3 and 5% compared with the energy case. On the other hand, the Time of Use scheme allows for a cost reduction of around 12% in the case without export limit and 5% with export limit.

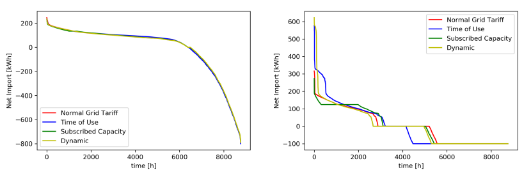


(a) Total Cost of the Neighborhood Energy System (b) Total Revenue of the DSO

Fig. 2. Cost and DSO Revenue, Discounted to the Start

The DSO revenue from the ZEN are higher when using the other pricing schemes than with the energy scheme when there is no export limit. When there is export limits, the DSO revenue stays the same because the battery allows to self-consume more and ”anticipates” the higher price periods and buys electricity when the price is lower. The revenue in the case of export limits are about half of the revenue of the case of no export limit except in the case of subscribed capacity where the subscription tariff allows to maintain the revenue. The cost increase in the ZEN is of the same order of magnitude as the increase in revenue for the DSO except for ToU where the cost of the ZEN decreases while the revenue for the DSO increases. ToU has a beneficial effect from both points of view in this aspect.

The duration curves Fig. 3, in the case of no export limit, are not affected much by the tariff scheme in place. When export limitations are introduced, there are significant differences in the duration curves. The maximum imports from the ZEN are presented in Table III. ToU and Dynamic scheme lead to really high imports, however they are not on peak hours but they still could cause congestion problems locally. In addition ToU has a considerable number of hours with high loads of around 300kWh, which is not the case with the other schemes. On the contrary, subscribed capacity is able to keep imports below the subscribed capacity level most of the time.



(a) No Export Limit (b) Export Limit

Fig. 3. Duration Curve of net Imports for the ZEN

In the case of no export limit, the operation is not affected much. However Subscribed and Dynamic allow to remove the peak import by shifting loads. On Fig. 4, for Subscribed and Dynamic, it seems that there is a peak in mid day but it is simultaneous with a peak in PV production, so the overall import profile is quite flat. However for the other pricing schemes the peak of PV production is decoupled from the peak in imports, which means that the peak remains, with a large dip in between them. This effect probably mitigates depending on the time of the year, since the duration curves on Fig. 3a are almost the same.

TABLE III
MAXIMUM IMPORTS OF ELECTRICITY

Case	Normal	ToU	Subscribed	Dynamic
No Export Limits (kWh/h)	246.6	234.9	231.3	234.6
Export Limits (kWh/h)	316.4	575.8	274.0	622.2

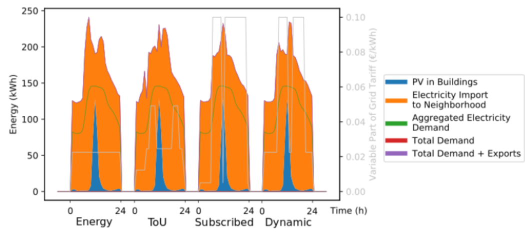


Fig. 4. Operation of ZEN in a day in winter in the case of no export limit

In the case of export limit Fig. 5, the batteries that are part of the system allow for more variations depending on the tariff scheme. In the energy scheme, the battery is used very little. In the ToU scheme, the optimization takes advantage of the low price hours to store energy in the battery and use it in the high price hours. It results in a higher load early in the morning which is most likely not problematic for the grid. In the subscribed capacity scheme, the battery is used to limit to the minimum the import above the subscribed capacity limit. During the peak of PV production, the battery imports from the grid because it is now below the subscription limit again.

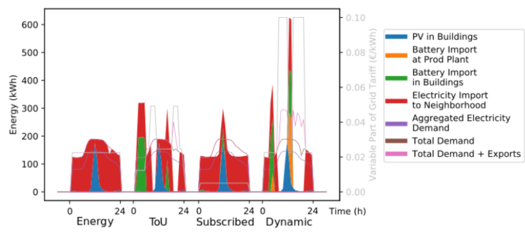


Fig. 5. Operation of ZEN in a day in winter in the case of export limit

In the Dynamic scheme some hours of the day have an activation, meaning that they are part of the 5% highest load in the year. The tariff in that case are extremely high and the battery is used as much as possible in those time periods, there is no import and the grid is relieved which was the intention behind using this scheme. However it also translates in high peaks when there is no activation, in order to fill the battery before the next one. This effect creates huge peak imports and one can wonder if the grid would be able to cope with them. There is no activation so they are not part of the 5% highest load but there might still be an important load and this high peak creates congestion. Thus in the case of ZENs or highly flexible systems, such a dynamic pricing scheme could have unintended side effects.

VI. Conclusion

Both from the DSO perspective and from the ZEN planner perspective, the results are quite dependant on the existence of export limits. Without export limits, it appears that the DSO could increase its revenue from new tariffs but those would translate as new cost to the ZEN. The exception is with the Time of Use tariff which is beneficial for both sides. The peaks are not reduced much by any new scheme and they are even higher in the case of export limitations. In the case where export limits are set, the Subscribed capacity scheme allows to preserve the revenue for the DSO, and offers reductions both in the peak and the number of hours with high imports. This tariff seems to be the most adapted to that case. From the ZEN perspective, this tariff is slightly more expensive but only because you do not profit from the reduction of the DSO revenue of the other tariffs. No matter the tariff implemented, the investments in the system with export limits are higher and costlier than when the export limit is not in place.

The impact of grid tariff on ZEN is really dependent on the conditions for export. It can have very little effect or important impact both for the ZEN planner and for the DSO by simply modifying the conditions for export of electricity. Even though prosumers and consumers with high level of flexibility remain marginal in the grid, those effects should be taken into consideration while designing the tariffs and export conditions in order to maintain or offer suitable environment for prosumers.

Acknowledgment

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Nomenclature

$t(\mathcal{T})$	Timestep in hour within year $\in [0, 8759]$
$i(\mathcal{I})$	Energy technologies: f: technologies consuming fuel; est: electric storage; g: technologies producing electricity
C_i^{disc}	Discounted investment cost in technology i including re-investments and salvage value [€/kWh]
C_{hg}	Cost associated with a heating grid for the neighborhood [€]
ε_r^{tot}	Discount factor for the whole lifetime of the neighborhood with discount rate r
C_i^{maint}	Annual maintenance cost [% of inv. cost]
P_f^{fuel}	Price of fuel of technology g [€/kWh]
P_t^{spot}	Spot price of electricity, hour t [€/kWh]
P^{ret}	Retailer tariff on electricity [€/kWh]
$\varphi_e^{CO_2}, \varphi_f^{CO_2}$	CO_2 factor of electricity and of fuel type f [g/kWh]
δ_t^{sc}	Binary parameter defining hours of scarcity
b_{hg}	Binary variable for investment in a heating grid
$y_t^{\cdot\cdot}$	Electricity transfer, superscript ex: imp: import; exp: export; pb: production battery; gb grid battery; ch: charge
x_i	Capacity of technology i [kW], [kWh] for storages
$f_{f,t}$	Fuel consumption of technology f in hour t [kWh]
$g_{g,t}$	Electricity production of technology g in hour t
c^{sub}	Subscribed capacity

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Paper 3

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Clustering methods assessment for investment in zero emission neighborhoods' energy system

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ABSTRACT

This paper investigates the use of clustering in the context of designing the energy system of Zero Emission Neighborhoods (ZEN). ZENs are neighborhoods who aim to have net zero emissions during their lifetime. While previous work has used and studied clustering for designing the energy system of neighborhoods, no article dealt with neighborhoods such as ZEN, which have high requirements for the solar irradiance time series, include a CO_2 factor time series and have a zero emission balance limiting the possibilities. To this end several methods are used and their results compared. The results are on the one hand the performances of the clustering itself and on the other hand, the performances of each method in the optimization model where the data is used. Various aspects related to the clustering methods are tested. The different aspects studied are: the goal (clustering to obtain days or hours), the algorithm (k-means or k-medoids), the normalization method (based on the standard deviation or range of values) and the use of heuristic. The results highlight that k-means offers better results than k-medoids and that k-means was systematically underestimating the objective value while k-medoids was constantly overestimating it. When the choice between clustering days and hours is possible, it appears that clustering days offers the best precision and solving time. The choice depends on the formulation used for the optimization model and the need to model seasonal storage. The choice of the normalization method has the least impact, but the range of values method show some advantages in terms of solving time. When a good representation of the solar irradiance time series is needed, a higher number of days or using hours is necessary. The choice depends on what solving time is acceptable.

1. Introduction

More than just accuracy, solving time and complexity are key elements that needs to be taken into account when designing optimization models. Indeed, certain applications require certain solving speeds. The unit commitment problem or the control of processes are good examples of applications that need a solution in time. In general, a shorter solving time increases the practicality of using the model. To keep the solving time within acceptable bounds, which needs to be defined on a case-by-case basis, different approaches are available. Some applications can accept sub-optimal solutions within an optimality gap and can simply stop the optimization after a given amount of time. In other cases, the complexity of the model can be reduced, by reducing the number of binary variables or changing the formulation of certain constraints. Finally, it is also possible to reduce the dimensionality of the problem. The time is one of the dimensions that can most commonly be reduced, by reducing the granularity (modelling hourly instead of every 15-min for instance) or by using clustering algorithms to group hours by features. Clustering algorithms can gather similar points from a dataset of any dimensions into groups called clusters. Each clusters is then represented by one point. Several methods can be used to assess how similar the points of the datasets are and how the representative of each clusters should be created.

In this paper, we investigate the use of clustering in a mixed integer linear program (MILP) called ZENIT. The goal is to identify which technique performs best for this application regarding the time necessary to solve the model, the optimality gap, and the representation of some timeseries of particular importance.

ZENIT (Zero Emission Neighborhood (ZEN) Investment Tool) is a program based on optimization that helps design the energy system of neighborhoods in a cost-optimal way and with a goal of having achieved net zero emissions of CO_2 in the neighborhood's lifetime. It is developed as a part of the research center on Zero Emission Neighborhoods in Smart Cities in Norway. The goal of this center is to research solutions to reduce the emission of neighborhoods in various fields such as architecture, urban planning and materials.

In this paper the focus of the clustering is a reduction of the time dimensionality, i.e. using less timesteps. The dimension of the dataset to

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Nomenclature

Nomenclature

$t\,(\mathcal{T})$	timestep in hour within year
$\kappa\,(\mathcal{K})$	cluster representative (centroid)
$t_\kappa\,(\mathcal{T}_\kappa)$	timestep within cluster κ
$b\,(\mathcal{B})$	building or building type
$i\,(\mathcal{I})$	energy technology, $\mathcal{I} = \mathcal{F} \cup \mathcal{E} \cup \mathcal{HST} \cup \mathcal{EST}; \mathcal{I} = \mathcal{Q} \cup \mathcal{G}$
$f\,(\mathcal{F})$	technology consuming fuel (gas, biomass, …)
$e\,(\mathcal{E})$	technology consuming electricity
$hst\,(\mathcal{HST})$	heat storage technology
$est\,(\mathcal{EST})$	electricity storage technology
$q\,(\mathcal{Q})$	technologies producing heat
$g\,(\mathcal{G})$	technologies producing electricity
$b\,(\mathcal{B})$	building or building type
$C_{i,b}^{var,disc}$, $C_{i,b}^{fix,disc}$	variable/fix investment cost of i in b discounted to the beginning of the study including potential re-investments and salvage value [€/kWh]/[€]
$\varepsilon_{r,D}^{tot}$	discount factor for the duration of the study D with discount rate r
$C_{i,b}^{maint}$	annual maintenance cost of i in b [€/kWh]
P_f^{fuel}	price of fuel of g [€/kWh]
P_t^{spot}	spot price of electricity at t [€/kWh]
P^{grid}	electricity grid tariff [€/kWh]
P^{ret}	retailer tariff on electricity [€/kWh]
η_{est}, η_{hst}	efficiency of charge and discharge
η_i	efficiency of i
η_{inv}	efficiency of the inverter
$\phi_t^{CO_2,e}$	CO_2 factor of electricity at t [gCO_2/kWh]
$\phi^{CO_2,f}$	CO_2 factor of fuel type f [gCO_2/kWh]
α_{CHP}	heat to electricity ratio of the CHP
α_i	part load limit as ratio of installed capacity
GC	size of the neighborhood grid connection [kW]
X_i^{max}	maximum investment in i [kW]
X_i^{min}	minimum investment in i [kW]
$E_{b,t}$	electric load of b at t [kWh]
$H_{b,t}^{SH}$, $H_{b,t}^{DHW}$	heat (space heating/domestic hot water) load of b at t [kWh]
$COP_{hp,b,t}$	coefficient of performance of heat pump hp
$\dot{Q}_{st}^{max}$	maximum charge/discharge rate of est/hst [kWh/h]
IRR_t^{tilt}	total irradiance on a tilted plane [W/m^2]
G^{stc}	irradiance in standard test conditions: 1000 W/m^2
T^{coef}	temperature coefficient
T_t	ambient temperature at t [°C]
T^{noct}	normal operating cell temperature [°C]
T^{stc}	ambient temperature in standard test conditions [°C]
σ_κ	number of occurrences of cluster κ in the year
C^{HG}	cost of investing in the heating grid [€]
M	"Big M", taking a large value
B_q^{DHW}	binary parameter stating whether q can produce DHW
Q_{b_1,b_2}^{HGloss}	heat loss in the heating grid in the pipe going from b_2 to b_1
$\dot{Q}_{b_1,b_2}^{MaxPipe}$	maximum heat flow in the heating grid pipe going from b_2 to b_1 [kWh]
$P_{hp,b,t}^{input,max}$	maximum power consumption of hp at t based on manufacturer data and output temperature
b^{HG}	binary for the investment in the Heating Grid
$b_{i,b}$	binary for the investment in i in b
$x_{i,b}$	capacity of i in b
$f_{f,t,b}$	fuel consumed by f in b at t [kWh]
$d_{e,t,b}$	electricity consumed by e in b at t [kWh]
y_t^{imp}, y_t^{exp}	electricity imported from the grid to the neighborhood/exported at t [kWh]
$y_{t,g,b}^{exp}$	electricity exported by g to the grid at t [kWh]
$g_{t,g,b}^{selfc}$	electricity generated by g self consumed in the neighborhood at t [kWh]
$g_{t,g,b}^{ch}$	electricity generated by g used to charge the batteries at t [kWh]
$y_{t,est,b}^{imp}$	electricity imported from the grid to est at t [kWh]
$y_{t,est,b}^{exp}$	electricity exported from the est to the grid at t [kWh]
$g_{g,t,b}$	electricity generated by g at t [kWh]
$q_{q,t,b}$	heat generated by q in b at t [kWh]
$y_{t,est,b}^{dch}$	electricity discharged from est to the neighborhood at t [kWh]
$y_{t,est,b}^{ch}$	electricity charged from on-site production to est at t [kWh]
$q_{t,st,b}^{ch}$, $q_{t,st,b}^{dch}$	energy charged/discharged from the neighborhood to the storage at t [kWh]
$v_{t,st,b}^{stor}$	level of the storage st in building b at t [kWh]
$g_{t,b}^{curt}$	solar energy production curtailed [kWh]
$g_{g,t,b}^{dump}$	electricity generated but dumped by g at t [kWh]
$q_{t,b}^{dump}$	heat dumped at t in b [kWh]
$q_{b_1,b_2,t}^{HGtrans}$	heat transferred via the heating grid from b_1 to b_2 at t [kWh]
$q_{b,t}^{HGused}$	heat taken from the heating grid by b at t [kWh]
$o_{i,t,b}$	binary controlling if i in b is on or off at t
$\overline{x_{i,b,t}}$	maximum production from i [kWh]

cluster depends on the length of the time series used (usually a year: 8760 h) and the number of buildings in the neighborhood. The objective is to contain the solving time as well as keep a good representation of the original timeseries, with a particular focus on the solar irradiance.

Section 2 presents relevant existing literature regarding clustering in power systems applications and in particular for the design of neighborhoods energy systems and present the contribution of this paper. Section 3 presents the clustering methods investigated in this paper and Section 4, the results of those methods with regard to certain metrics. in Section 5 the optimization models are presented and the results of the clustering methods in the optimization are analyzed in Section 6.

2. State of the art and contribution

Clustering algorithms have been studied extensively since the 1930s [1] and improved since then. They are used in various applications across many fields. The principle of those algorithms is to gather similar observations of a dataset into clusters based on a given metric. The outputs of such algorithms are a list of all original data points and the cluster to which they belong as well as a representative vector for each cluster. Many algorithms exist but, in this paper the focus is on the k-means and the k-medoids algorithms because they are the most commonly use for power systems applications. These algorithms differ in the way the representative vector of each cluster are chosen. The k-means algorithm uses a centroid as the representative vector, i.e. the vector with the smallest squared distance to every member of the cluster [2]. The k-medoids algorithm chooses the representatives of the clusters by choosing the vector in the original data with the smallest distance to every other members of the cluster [3]. In the power systems field, it has been for example used in the context of grid expansion planning in [4], national energy system planning [5,6] and unit commitment models [7].

[5] suggests that the best clustering technique depends on the data to process and the model in which they are going to be used. It is thus important to compare different methods in order to find the best choice for our particular needs. It also gives insights in the choice of the

number of clusters to use. Several articles compare, with different approaches, the possible clustering techniques. Among them, [5] compares the performance of downsampling, k-means and hierarchical clustering as well as different heuristics and combinations of previously mentioned methods. It finds that for their energy system planning model and in the context of pluri-annual time series, some heuristics appear promising. The clustering is performed on days, with 4 different time series and multiple locations giving a rather large number of dimensions.

For a grid expansion planning problem, [4] compares systematic sampling, k-means, k-medoids, hierarchical clustering with Ward's linkage and moment matching. It clusters on hours and 5 dimensions. In this case, hierarchical and k-medoids appear to perform equally well.

Closer to the ZENIT model needs, Ref. [8] compared clustering algorithms (k-means, k-centers, k-medoids, k-medians, monthly averaged days, and seasonal days) to find representative days for a model investing and operating the energy system of a building. It finds k-medoids as the best suited method for this application.

Reference [9] also compares different techniques in the context of different local energy systems (averaging, k-means, k-medoids, hierarchical) for obtaining representative days, 3-days or weeks. It finds that medoids perform better than centroids but recommends overall the use of hierarchical clustering due to the reproducibility of the results.

It is also interesting to look at the choices made for other models similar to ZENIT, i.e. model for investment and operation in the energy system of buildings or neighborhoods. Those choices are naturally dependant on factors such as the scale of the neighborhood, the level of detail of the model, the target run time, the machine used to solve the model or its goal: investment and/or operation and in some cases grid layout, but it remains a good indication nonetheless.

Many authors choose to use season based clustering (SBC), where they choose or average the time series to form one representative day for each season [10] or only for the summer, the winter and the mid-season [11–13]. They also have varying choices in terms of number of periods for the chosen days: from hourly (i.e. 24 periods) [12], to twelve [11,12], or six periods [12,13]. Similarly, some choose to use one average day per month [14–16], or several days per month, such as [17] with a week day, a week end day and a peak day per month or [18] with 2 days of 12 periods each per month.

The exact method used to determine the days is not always clear [19]; points this out and suggests a graphical method using the load duration curves. Another method relying on k-means clustering is proposed in [20].

Reference [21] uses weekly downsampling to allow the model to run faster and checks the scheduling with a 24 h rolling horizon model with hourly resolution. Complete years with hourly resolution are also used in some models [22].

Other studies rely on clustering [8]. Reference [23] suggest a way to keep seasonal storage operation while using design days found with k-means clustering. Similarly [24] relies on k-medoids clustering to find design days. However, only outside temperature and global irradiance are used, assuming that the other time series are correlated to either of those two. The other time series are reconstructed from the clusters after the clustering. K-means is also used in [25], where two models are coupled, for providing representative weeks and for providing representative hours. The hours clustering is preceded by the removal of peaks from the time series and followed by their re-introduction.

In this paper different methods of clustering, normalizing and treating peaks are compared in the specific case of ZENIT. In addition, design days and representative hours are compared to find the strengths and weaknesses of each approach. This study stands out from other comparative studies by limiting the number of algorithm used but also considering the choices for normalizing and handling peaks. The Zero Emission context also brings specific problems to overcome. For example, the zero emission balance constraint in the optimization model limits the way one can reduce the number of timesteps. Another example is the strong requirements on the solar irradiance time series due to the importance of PV in the results. To the best of the author's knowledge, no paper tackles clustering in the context of ZEN or in a similar context.

This paper contributes to the existing literature regarding clustering in the context of power systems and in the context of the design of the energy system of neighborhoods by addressing the optimal clustering methods for designing the energy system of ZENs. This is important as the best method is specific to each application ([5]). In particular, it investigates the impact of the zero emission balance and other ZEN's specific requirements on the performance of clustering techniques. It also addresses two aspects that are little discussed in the existing literature: the choice of days or hours for the clusters and the impact of the normalization method.

3. Reduction of the number of timesteps

Many possibilities exist in order to reduce the number of timesteps in the optimization. However some are not adequate for the model. Downsampling for instance is not well suited. With the downsampling method, the time series are reduced by averaging the values on a certain period of time. A six hours downsampling would average the values of the time series on intervals of six hours, dividing by six the total number of timesteps. This method reduces the precision of the data and is not well suited for applications with renewable energies, which vary rapidly. The use of heuristic is often considered, and there are different approaches depending on the application. The heuristic could be reducing the time series to a collection of extreme events found in the time series, such as the hours with the maximum load or the lowest temperature or any combination of such criteria. In the case of ZENIT, this is not an acceptable solution on its own. Despite the reduction of the level of details induced, which could be somewhat overcome by tuning the heuristic chosen, the biggest reason that contraindicates its use is the Zero Emission balance constraint. Indeed, using this constraint requires to take into account every hour in the year, which is difficult with heuristics. On the contrary, clustering allows the use of the Zero Emission balance. In clustering, an algorithm is used to gather similar timesteps into clusters. Each original timestep is then represented by a cluster. We choose this approach over downsampling and heuristic in order to keep the original time granularity and the use of the emission constraint.

Several clustering algorithm exists and we limit this study to k-means and k-medoids clustering. In addition we consider the use of heuristics in combination to the clustering. This approach is recommended in this kind of optimization application because the clustering alone would likely 'dilute' the extreme events' timesteps, such as the hour with the maximum load, into a cluster represented by a lower value, which would lead to an under-dimensioned solution. A simple heuristic in addition to the clustering allows to correct this. In this paper, the heuristic chosen is the time (day or hour) with the highest total load, defined as the sum of the domestic hot water load (DHW), space heating (SH) and electric load, and the time with the lowest irradiance. In addition, normalizing the data before clustering can be beneficial [26]. Several ways to normalize the data before the clustering algorithm exists and we also consider two options: a normalization based on the range of each time series (1) and one based on the standard deviation (2).

$$X' = \frac{X - min(X)}{max(X) - min(X)} \tag{1}$$

$$X' = \frac{X}{std(X)} \tag{2}$$

Lastly, as mentioned in the literature review, mainly two approaches exist for clustering, one clusters directly the hours, the other focuses on design days. The design day approach uses clustering for selecting representative days in the year and then use the hourly values for each representative day. This approach is often favored when storages are modelled. Indeed, because the relation between timesteps inside a day are kept, it allows for daily operation of storages contrary to hours clustering.

The clustering is performed in Python using PyClustering [27] for the k-medoids algorithm and Scipy for the k-means [26,28]. The practical handling of the clustering is described in the flowchart in Fig. 1.

The data entering the clustering process consists of several hourly time series covering one year. The data is composed of the following time series: one domestic hot water load (DHW), one space heating load (SH) and one electric load for each building (or building type) in the neighborhood; outside air temperature, total irradiance and CO_2 factor of electricity.

4. Clustering results

The different clustering approaches presented in the previous section were performed for various number of clusters: for the clustering of design days, up to 100, and for the clustering of hours, up to 2400 (with 6 h steps). This allows to determine which number of clusters to use in the optimization model. The representatives of clusters and their sequence are combined to rebuild a complete year and then compared to the original data to compute errors. In this section, the errors are presented as Root Mean Square Deviations (RMSD) and as Normalized RMSD (NRMSD) when comparing the errors of different time series. All figures below share the same legend presented on Fig. 2.

Fig. 3 presents the NRMSD across all timeseries which can be interpreted as an indicator of the overall performance of the tested methods. It does not however give insight about the errors for individual timeseries.

Considering all figures in this section, it is clear that the k-means algorithm offers a better representation of the original timeseries than its k-medoids counterpart. Indeed in all of the following figures, the green line representing k-means reaches lower levels of RMSD and converges to it faster than the k-medoids ones. This indicates a closer match between the clusters obtained with k-means and the original timeseries than what is obtained with k-medoids for a given number of clusters. This is what we could expect. Indeed, the k-medoids uses vectors from the original datasets instead of creating centroids, which are better representatives. However, this ensures that the chosen representatives of clusters in the case of k-medoids are meaningful and realistic.

Another thing one could expect is that the performance of the clusterings monotonically improves. However, this is not the case of our results, especially in the case of design days. For the performance regarding individual time series, this could be explained because of a better performance of other time series for this particular number of clusters. However, this lack of monotony can still be found in the aggregated result of Fig. 3. One possible explanation for the lack of monotony could be that k-means and k-medoids algorithms do not always find the global optimums but can provide solutions that are only local optimums. Hierarchical clustering or running the clustering algorithms several time with different initial conditions could provide more consistent results.

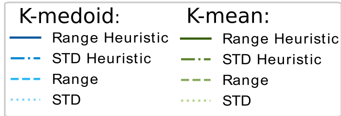
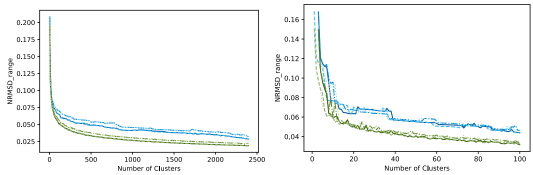


Fig. 2. Legend of the Results.



(a) Hours (b) Days

Fig. 3. Average of the NRMSD of All Clustered Time Series, Normalized with Range.

Looking at Fig. 3, the use of heuristic results in a tiny advantage for the heuristic versions on the overall error of the clustering. This is especially true in the case of clustering on hours. For design days clustering, the difference between clustering with and without heuristic disappears after around 8 design days. The lower the amount of design days, the higher the impact of forcing two days to be extreme events is, while for hours, the forced hours are “diluted” faster.

From all figures, considering an equivalent resulting number of timesteps (translating to the complexity to solve the model) clustering on hours gives much better results than clustering on days. For the overall error, Fig. 3, the error for the hours clustering is about 50% lower than for the design days.

The performance for individual time series is discussed in the following.

For the CO_2 factor of electricity in Fig. 4, the convergence rate is much lower in the case of days than of hours. The decrease is almost linear, compared to exponential. In addition, there are high variations for days that are not present for hours. For 100 days, the RMSD is about 4.5 gCO_2/kWh against 2 for an equivalent number of hours.

In the case of spot price in Fig. 5, the difference between the

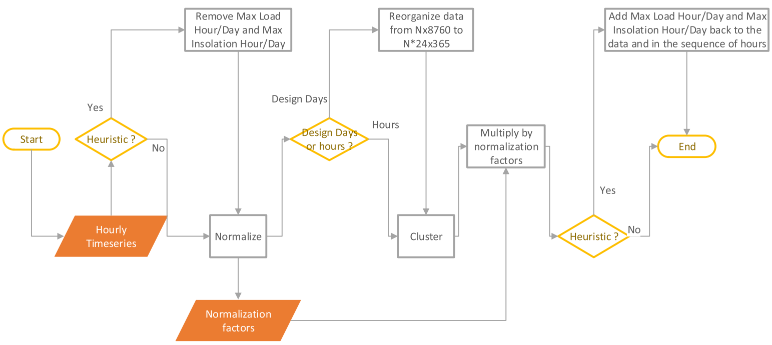
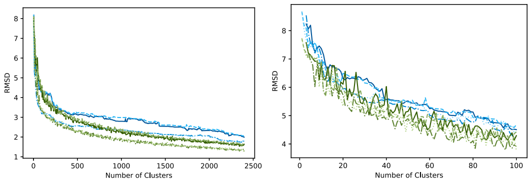
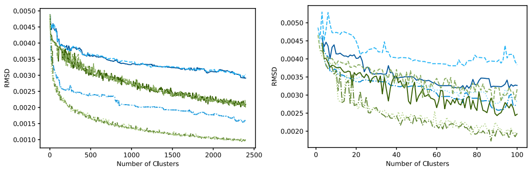


Fig. 1. Flowchart of the Clustering Process.



(a) Hours (b) Days

Fig. 4. RMSD of CO_2 Factor of Electricity.



(a) Hours (b) Days

Fig. 5. RMSD of Spot Price.

clustering performed using the standard deviation method and the range method seems very significant: for hours clustering between 0.001 and 0.0015 €/kWh or a factor of 2, the standard deviation is performing better. The difference between k-medoids and k-means is also considerably to the advantage of k-means: for hours clustering between 0.0005 and 0.001 €/kWh. For design days clustering the overall difference between methods is similar but there is more variability and some differences specific to this case. For instance, there are differences between the cases with and without heuristic, with the heuristic case performing better. Those differences are rather small for the standard deviation normalization and larger in the range case, especially in the k-medoids case.

The errors for the temperature time series are very similar to the overall ones commented before. The RMSD of temperature plateaus rather quickly to around 2 for the hours, and 2.8 for the days.

In the context of Zero Emission Neighborhoods, the irradiance has a very important role. Indeed, solar power is the main source of local (on the site) energy for neighborhoods. This means that solar irradiance and the production from the solar technologies will be crucial in compensating the emissions in the Zero Emission balance. Thus, in order to obtain designs that actually are Zero Emission, the precision of the clustering of the irradiance is essential. The behaviour for the hours clustering, Fig. 6, is similar to the overall behaviour. The RMSD for 100 clusters is around 35 W/m^2 for k-means and 55 W/m^2 for k-medoids. For days clustering, the convergence rate is slow and after 100 cluster, the RMSD is around 80 for k-means and 110 for k-medoids. The slow convergence rate means that for small numbers of clusters the difference between days and hours clustering is even worse. For 10 days, the RMSD is 140 for k-means and 170 for k-medoids. For 240 h, the RMSD is about 60 for k-means and 100 for k-medoids. Those values are high in comparison to the standard test condition (STC) of solar panels of 1000 W/m^2.

Only the performance for one of the three buildings is shown in this section. The other buildings can be found in the appendix.

For the electric load, Fig. 7, in the case of days, the convergence has a steep rate but it happens slightly later around 10 days. After the convergence, the difference between all methods is close to zero. For the clustering on hours, the convergence is fast. The main difference from the behavior in the mean RMSD is that the cases with k-medoids and standard deviation normalization have a higher RMSD. The plateau is around 0.0013 Wh m^{-2} h^{-1} versus 0.0005 Wh m^{-2} h^{-1} for k-means range and 0.0008 Wh m^{-2} h^{-1} for the others.

The RMSD for the SH and DHW time series behave as the mean of the RMSDs. The mean of the RMSD is influenced greatly by the loads because they behave similarly and because of the presence of 3 time series for each building.

Another metric of interest is the Yearly Average Error (YAE), this metric allows us to have information about the distribution of the error. With RMSD, there is no information on the sign of the errors. YAE allows to know if the errors are, on average, compensated or rather accumulate from timestep to timestep.

The results for k-means are not in Table 1 because the YAE stays at 0 for all number of clusters and all cases. Instead the values of the RMSD are presented in Table 2.

Comparing the RMSD and YAE from Table 1 and Table 2 gives us insights in how much the errors in irradiance cancel each other, at least in terms of annual values. In the case of irradiance, the negative signs first informs us that it is under-represented. The difference between the RMSD and the YAE values also suggest that the errors tends to be compensated by one another and they compensate completely in the k-means cases. In general, the hours clustering performs better than the daily one. k-means is better than k-medoids in terms of YAE for the same reasons that it is better for RMSD. The performance of STD or range on their own or in addition to heuristic is not consistent but the gains here are less big than between days and hours clustering.

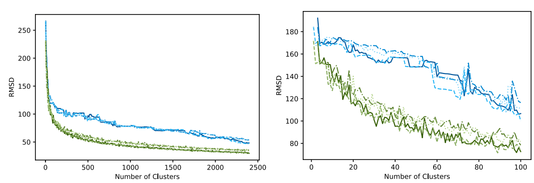
Two other metrics, the covered variance and the correlation error, can also be used in order to assess the clustering methods such as in [6]. They are defined in the same way as in [6]:

$$VC = \frac{var(X^*)}{var(X)} \tag{3}$$

$$CE = |corr(X_1^*, X_2^*) - corr(X_1, X_2)| \tag{4}$$

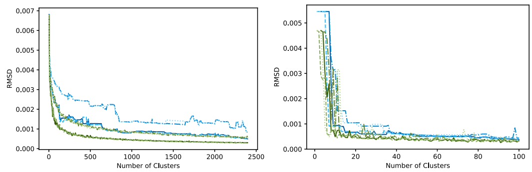
The covered variation (VC) of one timeseries is calculated as quotient of the variance of the timeseries reconstituted from the clusters (X^*) and the variance of the original timeseries (X). The correlation error (CE) between two timeseries is calculated as the absolute difference between the Pearson correlation coefficients calculated using the reconstructed timeseries and using the original timeseries.

These metrics are calculated for different numbers of clusters and the results are presented in Figs. 8 and 9. From both figures, k-medoids performs slightly better for really low number of clusters (less than 10 days/240 h) and the performances even out after that. The normalization based on standard deviation has a little edge over the range-based one but the difference is not large enough to be significant. It takes more day-clusters than hour-clusters to achieve similar performances. For instance, a covered variance of 0.9 is achieved with 250 h versus around 45 days. The combination of k-means clustering with a range normalization is significantly worse (about twice) at representing the correlation between the timeseries for a number of clusters between 20 days (240 h) and 60 days (1440 h). Overall, the results for those metrics are quite good for all methods from about 240 h or 20 days. If we look a bit more into the details, the variability covered is best for the loads and for the temperature. the covered variability of the irradiance is a bit worse and the variability covered for the spot prices and the CO_2 factors are the lowest. The spot price timeserie also has the highest



(a) Hours (b) Days

Fig. 6. RMSD of Irradiance on a Tilted Surface.



(a) Hours (b) Days

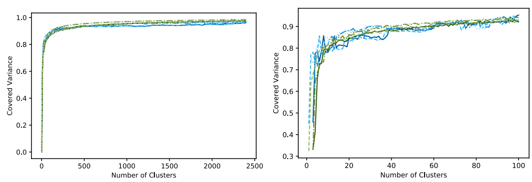
Fig. 7. RMSD of Electric Load in the Normal Offices.

Table 1
Yearly Average Error (YAE) and RMSD for 10 and 100 days and equivalent number of hours for the irradiance with k-medoids (STD.:Standard Devation, H: with heuristic, $\cancel{H}$: without heuristic).

	Days				Hours			
	STD.		Range		STD.		Range	
	H	$\cancel{H}$	H	$\cancel{H}$	H	$\cancel{H}$	H	$\cancel{H}$
YAE 10	−34	−24	−37	−38	−18	−18	−13	−15
YAE 100	−3.5	−0.67	−0.26	−2.3	−3.1	−2.8	−3.0	−2.1
RMSD 10	175	173	169	170	95.3	95.6	107	107
RMSD 100	116	112	107	100	53.9	53.8	48.3	47.8

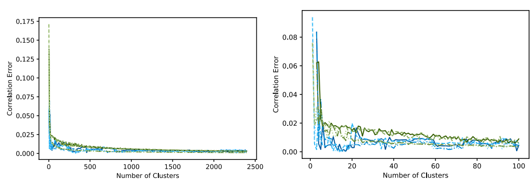
Table 2
RMSD for 10 and 100 days and equivalent number of hours for the irradiance with k-means (STD.:Standard Deviation, H: with heuristic, $\cancel{H}$: without heuristic).

	Days				Hours			
	STD.		Range		STD.		Range	
	H	$\cancel{H}$	H	$\cancel{H}$	H	$\cancel{H}$	H	$\cancel{H}$
RMSD 10	143	133	140	127	71.0	72.2	63.7	66.6
RMSD 100	78.4	81.7	72.6	72.5	35.5	35.1	29.7	30.5



(a) Hours (b) Days

Fig. 8. Mean Covered Variance for all Timeseries Depending on the Number of Clusters.



(a) Hours (b) Days

Fig. 9. Mean of all Correlation Error Between Each Timeseries Depending on the Number of Clusters.

correlation error to the other timeseries. The CO_2 factors, spot price and, to a smaller extent, the irradiance timeseries benefit the most from increases in the number of clusters.

From the results presented in this section, k-means and hours clustering are the best choices. For instance, with a focus on the irradiance, the choice would be range and heuristic. Overall the biggest impact can be made by choosing the correct clustering algorithm and the correct resolution. When it comes to the normalization method and the use of heuristic, the choice has less importance and varies depending on the goal. However there appears to be better results with the range normalization and without the heuristic. These results are however not enough. They only display some metrics for how close the clusters come to the original data. This does not guarantee that the one performing best in this section would also perform best in the optimization.

5. Models and implementation

In this section, the main equations of the ZENIT model are presented along with two variations for using either representative days or hours then the implementation and data used is briefly presented. The variations will be called M0 and M1 and are based on [23].

ZENIT aims is to design the energy system of a neighborhood so that it can be Zero Emission during its lifetime. Thus, it considers the investment as well as the operation of the neighborhood to find the cost optimal solution. The objective function is: *Minimize*:

$$b^{HG}\cdot C^{HG} + \sum_b \sum_i \left(\left(C_{i,b}^{var,disc} + \frac{C_{i,b}^{maint}}{\varepsilon_{r,D}^{tot}}\right)\cdot x_{i,b} + C_{i,b}^{fix,disc}\cdot b_{i,b}\right) + \sum_{t_\varkappa} \frac{\sigma_\varkappa}{\varepsilon_{r,D}^{tot}}\left(\sum_b\sum_f f_{f,t,b}\cdot P_f^{fuel} + \left(P_t^{spot}+P^{grid}+P^{ret}\right)\cdot\left(y_t^{imp}+\sum_b\sum_{est} y_{t,est,b}^{imp}\right) - P_t^{spot}\cdot y_t^{exp}\right) \tag{5}$$

It considers the investment cost in technologies ($C_{i,b}^{var,disc}$, $C_{i,b}^{fix,disc}$) and the heating grid (C^{HG}), as well as operation and maintenance related costs ($C_{i,b}^{maint}$). A binary variable controls the investment in the heating grid (b^{HG}). The subscript used in the equations are b for the buildings, i for the technologies, t for the timesteps, f for fuels and est for batteries. ε are the discount factors with interest rate r for the duration of the study D. $x_{i,b}$ is the capacity of the technologies and $b_{i,b}$ the binary related to whether it is invested in or not. $\sigma_\varkappa$ is the number of occurrences of cluster $\varkappa$ in the full year and $t_\varkappa$ is the timestep in the cluster. P are the prices of fuel, electricity on the spot market, grid tariff or retailer tariff. f is the consumption of fuel and y are the imports or exports of electricity.

In order to fulfill the Zero Emission requirement, the following constraint, called the Zero Emission Balance is necessary:

$$\phi_t^{CO_2,e}\sum_{t_\varkappa}\sigma_\varkappa\left(y_t^{imp}+\sum_b\sum_{est}y_{t,est,b}^{imp}\right)+\sum_{t_\varkappa}\sigma_\varkappa\sum_b\sum_f\phi^{CO_2,f}\cdot f_{f,t,b}\leqslant \phi_t^{CO_2,e}\cdot\sum_{t_\varkappa}\sigma_\varkappa\left(\sum_b\sum_{est}\eta_{est}\cdot y_{t,est,b}^{exp}+\sum_b\sum_g y_{t,g,b}^{exp}\right) \tag{6}$$

It forces the emissions of CO_2 to be at least equal to the compensations. The principle of the compensation is that the energy produced in the neighborhood, by renewable sources, that is exported to the national grid reduces the global production. The corresponding amount of saved CO_2 is counted as compensation for the neighborhood. The CO_2 factors are represented by $\phi_{e,t}^{CO_2}$ for electricity and $\phi_f^{CO_2}$ for other fuels. η_{est} is the charging efficiency of the battery.

Eqs. (7a), (7b) and (7c) represent respectively the equations for the electric load, the DHW load and the SH load. $\forall\ t$:

$$y_t^{imp} + \sum_b \left(\sum_{est} y_{t,est,b}^{dch} \cdot \eta_{est} + \sum_g g_{g,t,b}^{selfc} \right) = \sum_b \left(\sum_e d_{e,t,b} + E_{b,t} \right) \tag{7a}$$

$\forall\ t,\ b$:

$$\sum_q q_{q,t,b}^{DHW} + \sum_{hst} \left(\eta_{hst} \cdot q_{t,hst,b}^{DHWdch} - q_{t,hst,b}^{DHWch} \right) + q_{t,b}^{HGusedDHW} = H_{b,t}^{DHW} + q_{t,b}^{dump} \tag{7b}$$

$$\sum_q q_{q,t,b}^{SH} + \sum_{hst} \left(\eta_{hst} \cdot q_{t,hst,b}^{SHdch} - q_{t,hst,b}^{SHch} \right) + q_{t,b}^{HGusedSH} = H_{b,t}^{SH} \tag{7c}$$

The electricity consumed in the neighborhood (the load and the use of some heating technologies) need to be balanced by the imports, discharges from the batteries or consumption of on-site production. The principles are the same for the heat but separately for each building. At the production plant, the heat produced is either stored, dumped or fed to the heating grid (Eq. (8a)). The heat flow through the pipes is limited (Eq. (8b)). We model the grid in a way that the buildings cannot feed heat into the heating grid (Eq. (8c)). In addition, the larger technologies of the central plant are only available if the optimization invests in the heating grid (Eq. (8f)).

$$\sum_q q_{q,t,'PP'} + \sum_{hst} \left(\eta_{hst} \cdot q_{t,hst,'PP'}^{dch} - q_{t,hst,'PP'}^{ch} \right) = \sum_{b \setminus 'PP'} q_{t,'PP',b}^{HGtrans} + q_{t,'PP'}^{dump} \tag{8a}$$

$\forall\ b,\ b',\ t$

$$q_{t,b',b}^{HGtrans} \leqslant \dot{Q}_{b',b}^{MaxPipe} \tag{8b}$$

$\forall\ b,\ t$

$$\sum_{b'} q_{t,b,b'}^{HGtrans} \leqslant \sum_{b''} \left(q_{t,b'',b}^{HGtrans} - Q_{b'',b}^{HGloss} \right) \tag{8c}$$

$$q_{t,b}^{HGused} = q_{t,b}^{HGusedSH} + q_{t,b}^{HGusedDHW} \tag{8d}$$

$$q_{t,b}^{HGused} = \sum_{b''} \left(q_{t,b'',b}^{HGtrans} - Q_{b'',b}^{HGloss} \right) - \sum_{b'} q_{t,b,b'}^{HGtrans} \tag{8e}$$

$\forall\ i$

$$x_{i,'ProductionPlant'} \leqslant X_i^{max} \cdot b^{HG} \tag{8f}$$

The import and export are limited by the size of the grid connection:

$$y_t^{imp} + \sum_b \sum_{est} y_{t,est,b}^{imp} + \sum_b \sum_g y_{t,g,b}^{exp} \leqslant GC \tag{9}$$

The fuel or electricity consumption depends on the heat produced and the efficiency (Eq. 10) and in the case of CHPs, the Heat to power ratio regulates how much electricity is produced as a by product (10b). In the implementation, α_{CHP} has a fixed value.

$\forall\ \gamma \in \mathcal{F} \cap Q,\ t,\ b$:

$$f_{\gamma,t,b} = \frac{q_{\gamma,t,b}}{\eta_\gamma} \tag{10a}$$

$\forall\ \gamma \in \mathcal{E} \cap Q,\ t,\ b$:

$$d_{\gamma,t,b} = \frac{q_{\gamma,t,b}}{\eta_\gamma} \tag{10b}$$

$\forall\ t',\ CHP',\ b$:

$$g_{CHP,t,b} = \frac{q_{CHP,t,b}}{\alpha_{CHP}} \tag{12}$$

Some heating technologies can only supply the SH. Eq. (14) controls which technology can produce DHW. $\forall\ q,\ t,\ b$:

$$q_{q,t,b} = q_{q,t,b}^{DHW} + q_{q,t,b}^{SH} \tag{13}$$

$$q_{q,t,b}^{DHW} <= M \cdot B_q^{DHW} \tag{14}$$

The solar technologies output depends on the solar irradiance and the module efficiency. In the case of PV, the efficiency is defined as in [29].

$$g_{PV,t} + g_t^{curt} = \eta_{PV,t} \cdot x_{PV} \cdot IRR_t^{tilt} \tag{14a}$$

$$q_{ST,t} = \eta_{ST} \cdot x_{ST} \cdot IRR_t^{tilt} \tag{14b}$$

$$\eta_{PV,t} = \frac{\eta^{inv}}{G^{stc}} \cdot (1 - T^{coef} \cdot (T^c - T^{stc})) \tag{14c}$$

$$T^c = T_t + \left(T^{noct} - 20 \right) \cdot \frac{IRR_t^{tilt}}{800} \tag{14d}$$

Eqs. (15a) and (15b) link the heat produced to the COP and the electrical consumption. The COPs are different for SH and DHW due to different temperature set points. They also depend on the outside temperature and are calculated before the optimization. Eq. (15c) regulates how the heat pump can be used for both SH and DHW and enforces that the capacity invested is not exceeded. $P^{input,max}$ represents the maximum power input to the heat pump at the timestep based on the temperature set point for a 1 kW unit. $d_{hp,b,t}^{SH}$ and $d_{hp,b,t}^{SH}$ represent the electric consumption of the heat pump for SH and DHW while $q_{hp,b,t}^{DHW}$ and $q_{hp,b,t}^{DHW}$ are the heat production.

$$d_{hp,b,t}^{SH} = \frac{q_{hp,b,t}^{SH}}{COP_{hp,b,t}^{SH}} \tag{15a}$$

$$d_{hp,b,t}^{DHW} = \frac{q_{hp,b,t}^{DHW}}{COP_{hp,b,t}^{DHW}} \tag{15b}$$

$$\frac{d_{hp,b,t}^{DHW}}{P_{hp,b,t}^{input,max,DHW}} + \frac{d_{hp,b,t}^{SH}}{P_{hp,b,t}^{input,max,SH}} \leqslant x_{hp,b} \tag{15c}$$

Some technologies have part-load limitations, they cannot be operated from 0 to 100%. This leads to a large number of binary variables in the model:

$$\overline{x_{i,b,t}} \leqslant X_{i,b}^{max} \cdot o_{i,t,b} \tag{16a}$$

$$\overline{x_{i,b,t}} \leqslant x_{i,b} \tag{16b}$$

$$\overline{x_{i,b,t}} \geqslant x_{i,b} - X_{i,b}^{max} \cdot (1 - o_{i,t,b}) \tag{16c}$$

$$q_{i,b,t} \leqslant \overline{x_{i,b,t}} \tag{16d}$$

$$q_{i,b,t} \geqslant \alpha_{i,b} \cdot \overline{x_{i,b,t}} \tag{16e}$$

Some technologies have a minimum investment capacity and are modelled as semi-continuous variables:

$$x_{i,b} \leqslant X_{i,b}^{max} \cdot b_{i,b} \tag{17a}$$

$$x_{i,b} \geqslant X_{i,b}^{min} \cdot b_{i,b} \tag{17b}$$

The electricity production from on-site technologies can be exported, consumed directly, stored or dumped:

$$g_{g,t,b} = y_{t,g,b}^{exp} + g_{g,t,b}^{selfc} + g_{t,g,b}^{ch} + g_{t,g,b}^{dump} \tag{18}$$

To distribute the production to the batteries, we have $\forall\ t,\ b$:

$$\sum_g g_{t,g,b}^{ch} = \sum_{est} y_{t,est,b}^{ch} \tag{19}$$

The handling of the storages is what differentiates model M0 and M1. Model M0 is not able to handle seasonal storage while model M1 can be used for that. In ZENIT, each battery is modelled as 2 separate virtual batteries, with one connecting the neighborhood to the grid: allowing import and export between the grid and the battery, and import from the battery to the neighborhood's loads, and the other connecting the technologies producing electricity in the neighborhood and the neighborhood's loads: allowing exports to the grid and to the neighborhood. This distinction provides traceability of the electricity in the batteries. The origin of the electricity is important because of the different CO_2 factors.

Both models are presented in the following subsections.

5.1. Model M0

Model M0 uses a classical formulation for storages in models using clustering and that do not need seasonal storage. The equation for electric and heat storages are similar, so only a generic equation is presented, fitting both cases.

$\forall\ \kappa,\ t \in [1,\ T^{clu}],\ st,\ b$

$$v^{stor}_{\kappa,t,st} = v^{stor}_{t-1,st} + \eta^{stor}_{st} \cdot q^{ch}_{t,st} - q^{dch}_{t,st} \tag{20}$$

$\forall\ t \in [0,\ T^{clu}],\ st,\ b$

$$v^{stor}_{\kappa,t,st,b} \leqslant x_{st,b} \tag{21}$$

$$q^{ch}_{\kappa,t,st,b} \leqslant \dot{Q}^{max}_{st} \tag{22}$$

$$q^{dch}_{\kappa,t,st,b} \leqslant \dot{Q}^{max}_{st} \tag{23}$$

$\forall\ p,\ st,\ b,\ \kappa$

$$v^{stor}_{\kappa,0,st,b} = v^{stor}_{\kappa,T^{clu},st,b} \tag{24}$$

The state of charge of the storage *st* (either heat or electric storage) is represented by v^{stor} while qch and $qdch$ are the energy charged and discharged. The maximum charge and discharge rate is Q^{max}_{st}. The differences between this model and a model with full year data is that the starting value of the storage is "free" at the beginning of each cluster instead of only at the beginning of the year. This model is valid for different T^{clu} even though in our case it is 24 for days clustering. It allows for a daily operation of the storage. Different values of T^{clu} could be used for allowing different ranges of operation of the storage. A bigger value allows longer operation but probably increases the number of timesteps to get the same clustering precision and reducing it reduces the possible range. The daily range makes sense because of the daily cycle of the loads, that allows us to make the assumption of Eq. (24). This model does not make sense with $T^{clu} = 1$, i.e. the hours clustering, because the resolution of the data used is also one hour; hourly storage operation does not make sense.

5.2. Model M1

In model M1, the main difference with model M0 is that the storage level equation becomes: $\forall\ \kappa,\ t \in [1,\ 8760],\ st,\ b$

$$v^{stor}_{\kappa,t,st} = v^{stor}_{t-1,st} + \eta^{stor}_{st} \cdot q^{ch}_{t_\kappa,st} - q^{dch}_{t_\kappa,st} \tag{25}$$

The end value of the storage constraint is also replaced by: $\forall\ st,\ b$

$$v^{stor}_{0,st,b} = v^{stor}_{8760,st,b} \tag{26}$$

Where t_κ is the time corresponding to t in the cluster. It is found by using the sequence of cluster's representatives (ξ) either directly for the hourly case or with the day number corresponding to t and the hour in the day:

Hours:

$$t_\kappa = \xi(t) \tag{27}$$

$$t_\kappa = \xi\left(\left\lfloor \frac{t}{24} \right\rfloor\right) + t - \left\lfloor \frac{t}{24} \right\rfloor \cdot 24 \tag{28}$$

This means that the storage level is not decoupled between the different clusters. The charging and discharging is defined for each timestep in each cluster but the storage level is defined for every hour in the year. This model comes from the assumption that days or hours with similar conditions in terms of the time series (loads, spot price, temperature, …), i.e. belonging to one cluster will behave in the same way in terms of charging and discharging of the storage. This formulation however comes at the expense of longer computation time. Both hourly and days clustering can be used with M1.

In [23], another variation is presented to improve further model M1 by defining only the variables related to operations binary variables (on/off status) for each cluster while other variables are defined for each hour of the year. That model has not been implemented because it increases the computation time even more.

5.3. Implementation

The model is implemented on a test case based on a small neighborhood, a campus at Evenstad in Norway. The buildings are gathered in three categories to only have three buildings in the optimization. We assume every building has a hydronic system.

The economical and technical data of the technologies are taken from the Danish Energy Agency.[1] In total, 22 technologies are implemented with, at the building level: solar panel, solar thermal, air-air heat pump, air–water heat-pump, ground source heat pump, bio boiler with wood logs or pellets, electric heater and electric boiler, biomethane boiler, biogas and biomethane CHP; and at the neighborhood level: biogas boiler, wood chips and pellets boiler and CHPs, ground source heat pump and electric boiler. When it comes to the storage technologies, lithium-ion is used for electrical storage and hot water tanks for the heat storage. The storage technologies at the neighborhood level are not included to make it easier to compare the objective values obtained from the runs with M0 and M1.

The spot price of electricity is obtained from Nordpool's website.[2] The temperature data comes from Agrometeorology Norway,[3]. The solar irradiance (diffuse horizontal (DHI) and direct normal(DNI)) are obtained from Solcast.[4] The irradiance on a tilted surface IRR^{Tilt} which is an input of the clustering is derived from the DHI and DNI with:

$$IRR^{Tilt}_t = DHI_t \frac{1 + cos(\phi_1)}{2} + \alpha \cdot (DNI_t + DHI_t) \frac{1 - cos(\phi_1)}{2} + DNI_t \left(\frac{cos(\varphi_t) \cdot sin(\phi_1) \cdot cos(\phi_2 - \psi_t)}{sin(\varphi_t)} + \frac{sin(\varphi_t) \cdot cos(\phi_1)}{sin(\varphi_t)} \right) \tag{29}$$

We assume that for some sun positions (sun elevations (φ) below 1 degree and sun azimuths (ψ) between -90 and 90 degrees), no direct beam reaches the panels. This means that the last term of Eq. (29) is removed at such times. We use a constant albedo factor (α) of 0.3 for the whole year. Hourly albedo values could also be used to reflect the impact of snow in the winter better. The tilt angle of the solar panel is ϕ_1; the orientation of the solar panel regarding the azimuth is ϕ_2.

The hourly CO_2 factors of electricity are obtained with the methodology presented in [30] while the other CO_2 factors come from [31].

The prices of wood pellets comes from [32], the price of wood logs from [33], the price of wood chips from [34] and the price of biogas from [35].

The electric and heat load profiles for the campus are derived from [36]. The domestic hot water (DHW) and Space Heating (SH) are then based on the time series from a passive building in Finland [37].

The model is implemented in Python and is solved using Gurobi. It is run on a laptop with an Intel Core i7-7600U dual core processor at 2.8Ghz and 16 GB of RAM.

[1] https://ens.dk/en/our-services/projections-and-models/technology-data.
[2] https://www.nordpoolgroup.com/Market-data1/#/nordic/table.
[3] https://lmt.nibio.no. Fåvang station
[4] https://solcast.com.au.

6. Model results and discussion

In this section we present the results obtained with the different clustering methods and variations from the earlier sections. We always use the heuristic in order to guarantee that the peak load is covered.

6.1. Simplified model

In order to get a reference objective value to base our analysis on, a simplified version of the model is run. This simplified model leaves out several of the constraints using binaries, namely the part load constraints, the minimum investment capacity (turning the semi-continuous variables into continuous variables) and changing the cost function from $a{\cdot}x + b$ to $c{\cdot}x$. Without simplifying the model, solving the model with 365 days or 8760 h would take too long. It is important to note that this simplified model is not directly obtained by removing constraints but by setting the input associated to the binary to zero. For example, the fixed investment costs and the minimum capacity are set to 0 but the constraints are still there. In the case of the minimum load during operation, the minimum loads are set to 0 but the related constraints are not written when the model is generated in Gurobi. The results for the non-simplified model are presented after without a reference value.

Because M1 allows for seasonal storage modelling while M0 does not and in order to obtain results that can be compared more easily between M0 and M1, the storages at the neighborhood level were not included in the technological option input in this study.

We chose the number of days and hours in this section graphically at the elbow of the curves in Fig. 3. The number of clusters is chosen so that adding clusters does not bring considerable improvements. For the case of hours, this corresponds to around 120 h; 96 and 144 h are also studied as a 20% variation. We also consider the corresponding number of days, i.e. 4,5,6. Indeed this gives an equal number of timesteps in the optimization but the performance of the clustering on days for such low numbers of days should give poor result considering Fig. 3. In addition we choose a number of design days with similar graphical elbow considerations. However, we consider Fig. 6 instead of the NRMSD figure because in the case of clustering days the performances for the irradiance were converging slower. This leads us to choose 30 days. We also take the 20% variations, which corresponds to 24 and 36 days.

From Table 3, k-means range seems to be the overall best choice, but it underestimates the objective value. k-medoids constantly overestimates the objective value, with significant errors for low numbers of days. On the other hand, k-means gives good results even for a low number of days.

From Tables 4 and 5 it appears that the hours clustering performs the best on problem M1, especially with the range normalization and k-medoids. For approaching the reference value from below, the best approach is k-means with hours clustering. Here the range method seems slightly better than STD. k-medoids constantly overestimates the objective value while k-means constantly underestimates it. However, in general and for around 30 days and 120 h, the k-means seems to be the appropriate choice. Indeed, even though k-medoids with STD also has good results, it appears less consistent. With this algorithm, the performance does not always improve with an increasing number of clusters; choosing the correct amount of clusters would become harder. k-means, while not completely exempt from this flaw, appears more robust in this regard.

For M1, the average of the run time for days clustering for 24, 30 and 36 days is 3500 s with extreme values of 2 289 and 5628 s. For the hours clustering, the average runtime is 5 973 s with extremes of 2 421 and 12 500 s. Days clustering is on average almost twice as fast as hours clustering on this simplified model despite having more timesteps overall. As a reference, to solve this simplified problem without any clustering (using a complete year) takes around 30 000 s.

For M0 the runtimes are low with all values below 360 s.

It is also interesting to look at the actual systems resulting of each investment run. Fig. 10 shows these investments for the runs with the simplified model.

From Fig. 10, it is noteworthy that there tends to be an investment in the heating grid when using k-medoids while it is not often the case with k-means. In general, the element with the biggest impact on the investment appears to be the clustering algorithm chosen. Indeed, there is are quite distinct groups of investments with k-medoids on the one side and k-means on the other emerging from the figure. Both reference runs have a very similar system, with the exception of the amount of space heating storage. This suggests that only the amount of storage invested will be affected by the choice of M0 or M1, leading to possible over-investment in storage if using M0. The investments resulting from runs with k-medoids seem to be closer to the references in general than the runs with k-means. One important exception is regarding the amount of PV invested where it tends to over-invest more than k-means (which is also over-investing). This over-investment stems from the representation of the solar irradiance in the clustered data; k-means offering a better representation as seen in Fig. 6.

6.2. Complete model

For the complete model, no reference value is presented because running the models with a complete year of data takes too long and it is the reason clustering is explored in the first place.

Fig. 11 presents the objective values resulting from the optimization in the case of M0. Without a reference value, it is impossible to reach a conclusion regarding the performances of each approach. However we can make some remarks. The objective values follow the same patterns as in the case of the simplified model and from the results we can expect that in this case as well k-means underestimates and k-medoids overestimates the objective value. It also appears that even a few days are enough to get satisfying results when using k-means.

Regarding runtime for M0 (Table 6), k-means with STD is clearly the fastest while k-medoids with STD is the slowest being about half as fast. k-medoids range and k-means range have comparable runtimes except for the case of 36 days where the k-medoids version is about 20% slower. k-means range is itself 25% slower than k-means STD.

For M1, the same remarks hold. K-medoids and k-means seem to respectively over- and underestimate the objective value. Fig. 12 confirms that for k-medoids, the range method performs better than STD as in Table 4 and 5. For k-means we also find that the results are similar.

M1 is between 15 and 40 times longer to solve than M0 for the days (Tables 6 and 7). When it comes to the difference between the days and the hours, even though the number of timesteps are the same, the hourly model takes at least 10 times longer to solve than the daily model. This difference is hard to explain. Indeed both models get the same number of timesteps and are identical with the exception of what is presented in Eqs. (27) and (28).

Fig. 13 shows the investment resulting from the runs using the full model. The systems obtained are similar to the ones visible in Fig. 10 but there is a lower diversity of technologies. The systems are comprised of a different amount of biomethane boilers, air–water heat

Table 3
Variations in objective value from the reference for different numbers of representative days for M0 with simplified model (**STD**: Standard Devation, **R**:Range), Reference Value for 365 days: **2,056,849** €.

		Days					
		4	**5**	**6**	**24**	**30**	**36**
k-means	STD	−10.29	−9.50	−9.42	−6.14	−5.21	−4.82
	R	−10.29	−10.64	−9.68	−4.80	−4.74	−3.82
k-medoids	STD	28.27	22.71	33.53	9.61	10.04	7.49
	R	11.57	8.78	23.16	5.36	4.84	8.27

Table 4
Variations in objective value from the reference for different number of representative days for M1 with simplified model (**STD**: Standard Devation, **R**:Range), Reference Value for a complete year: **2,060,612** €.

		4	5	6	24	30	36
k-means	STD	−10.16	−9.18	−8.78	−6.07	−5.38	−6.14
	R	−10.16	−10.38	−9.09	−5.03	−5.38	−4.44
k-medoids	STD	28.42	22.80	33.55	9.64	10.08	7.54
	R	11.78	8.91	23.19	5.40	4.90	8.31

Table 5
Variations in objective value from the reference for different number of representative hours for M1 with simplified model (**STD**: Standard Devation, **R**:Range), Reference Value for a complete year: **2,060,612** €.

		96	120	144
k-means	STD	−5.58	−5.54	−4.95
	R	−4.66	−5.51	−4.60
k-medoids	STD	8.45	11.06	9.73
	R	3.07	4.59	3.62

pumps, PV and heat storages. The heating grid is never chosen. A different system is appearing only in one of the cases of M0 with k-medoids and a low number of days, where solar thermal replaces partly the air–water heat pump. There is still a distinction between k-means and k-medoids as in Fig. 10 but it is less clear, especially in the case of the storage. Furthermore, the investments with model M1 with hours seems to be less sensitive to the number of clusters used, especially when it comes to the storage.

If the use of k-medoids is required for any reason, then using the hourly method can bring significant improvements to the precision over the daily method. These improvements needs to be considered in regard to the increased solving time to choose the method to use. Otherwise, k-means should be preferred. In that case, the improvements of the precision is insufficient to justify using the hourly method. One such possible reason is to have a good representation of the solar irradiance which is the case for ZENIT. By using the day method with low numbers

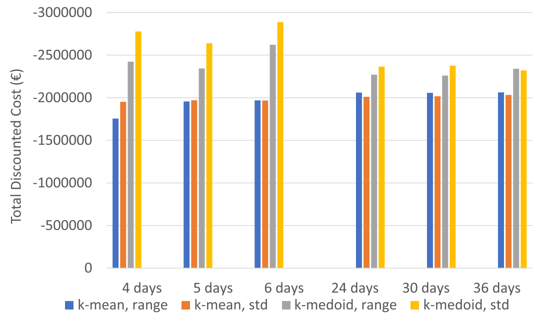


Fig. 11. Objective Values for M0 with Design Days with Complete Model.

Table 6
Runtime for M0 in seconds with days (**STD**: Standard Devation, **R**:Range).

		4	5	6	24	30	36
k-means	STD	70.98	96.47	108.8	1708	2846	3342
	R	116.3	115.2	155.4	1924	3504	4320
k-medoids	STD	63.42	62.98	288.4	3544	4157	6163
	R	57.52	115.0	127.5	2088	3442	5288

of days, even though the solving time and objective values are good, the representation of the solar irradiance is problematic as seen in Fig. 6. In our case and to get a good solar irradiance representation, the use of k-means and hours clustering in M1 is preferable.

Overall, with regards to Zero Emission Neighborhood Energy System, the k-means performs better than the k-medoids algorithm. This is the opposite of what has been found in several studies in other energy system applications, such as in [8] or [6]. However, this is an illustration of the findings of [5] that the best clustering technique is dependant on the data to process and the application. In our particular case, the reason that k-means performs better than k-medoids could be that an averaging of all points inside each clusters leads to a better

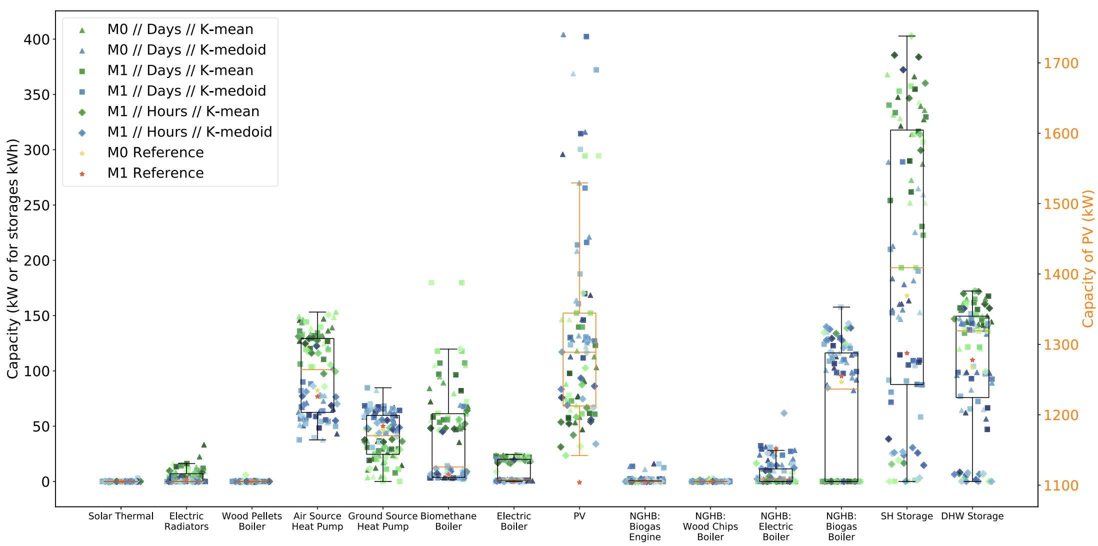


Fig. 10. Investments Resulting from the Runs with the Simplified Model. The color gradient represents the number of clusters, the clearer the least clusters and the darker the more clusters. "NGHB:" Before the technology name means that it is a technology at the neighborhood scale and also implies the presence of the heating grid. The technologies at the building level are aggregated for all the buildings.

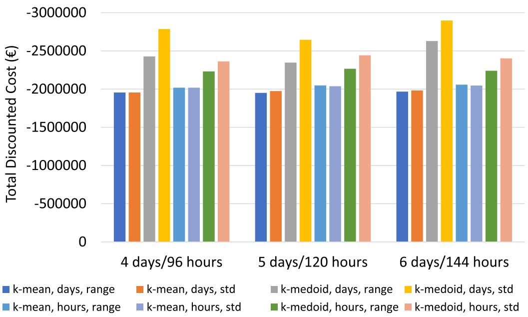


Fig. 12. Objective Values for M1 with Days and Hours with Complete Model.

Table 7
Runtime for M1 in seconds (**STD**: Standard Devation, **R**:Range).

	Days	**4**	**5**	**6**
k-means	STD	1386	2250	4340
	R	2059	3393	3519
k-medoids	STD	1723	1717	5838
	R	1139	2319	2626
	Hours	**96**	**120**	**144**
k-means	STD	14789	29159	62239
	R	13342	45048	60165
k-medoids	STD	20288	55509	105672
	R	18632	19860	59055

representation of the solar irradiance (as can be seen in Tables 2 and 1) while the points closest to the mean of the clusters may be pushed towards a better representation of the loads due to the number of load timeseries and their correlation. The better representation of solar then allows to reduce the investment in PV and to reach an energy system closer to the references cases.

7. Limitations

There are different limitations that should be mentioned regarding this paper. Regarding the studied methods, the fact that only clustering algorithms are studied have been explained; however other clustering algorithms could offer advantages. Many heuristics, either new or variations around the one used, could also be studied and finding the overall best heuristic presents a challenge. The clustering has been used on a specific case and we cannot guarantee that the same result holds true for larger cases or in other countries where the correlation between the different inputs are different. Unfortunately no reference value is shown for the complete model and a simplified model had to be used in order to compare the precision.

8. Conclusion

After introducing the use of reduction techniques and clustering in energy systems and in particular in the design of the energy system of neighborhoods, this paper discussed why clustering is chosen over other solutions such as downsampling. Different clustering methods have then been evaluated, first directly on their ability to come close to the original dataset and then on the results they give when used in ZENIT. K-means and k-medoids have been compared and the study allowed to highlight that counter to what is found for many other energy system applications, k-means performs better than k-medoids. The study also highlights the role of the normalization method on the performances by comparing a method using the standard deviation and one using the range of values. We find occurrences of models using clustered days (or design days) and of instances using clustered hours in the literature but the reason for the choice are not always clear. In this study, both approaches are implemented and the relation between the performance, the solving time and the possible uses of each are reviewed. The impact of the use of a simple heuristic is also studied. Two versions of the optimization models were used with different capabilities when it comes to storage: M0 for daily storage operation and M1 for storage without time limitation. While the use of M0 or M1 should be considered on the basis of the necessity to include seasonal storage, the

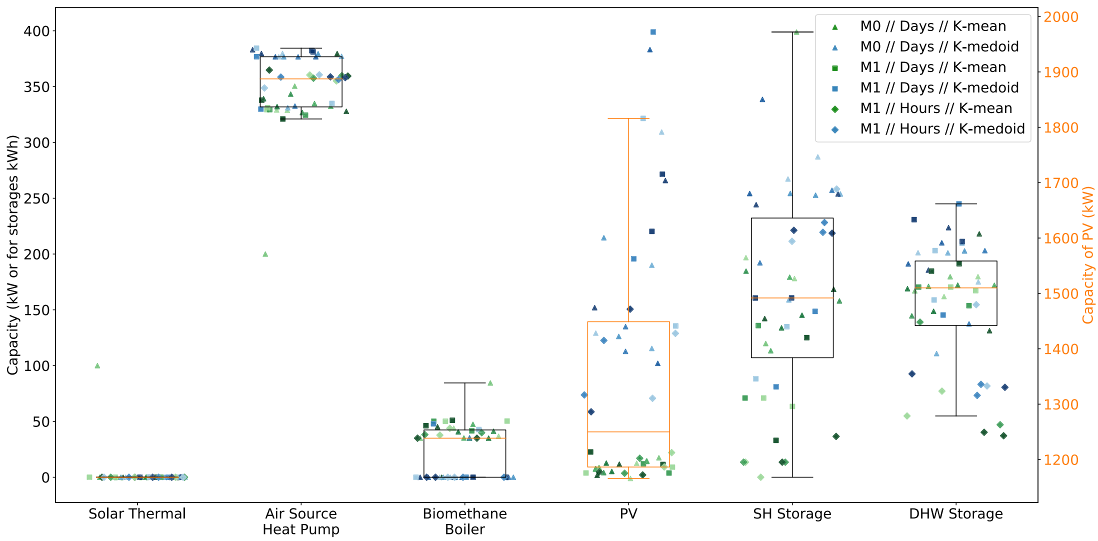
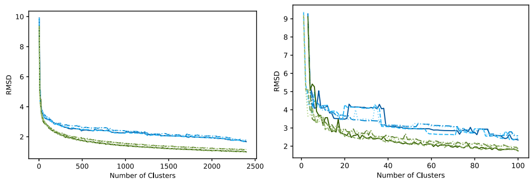
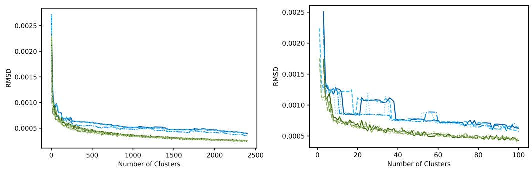


Fig. 13. Investments Resulting from the Runs with the Complete Model. The color gradient represents the number of clusters, the clearer, the least clusters and the darker, the more clusters. "NGHB:" Before the technology name means that it is a technology at the neighborhood scale and also implies the presence of the heating grid. The technologies at the building level are aggregated for all the buildings. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



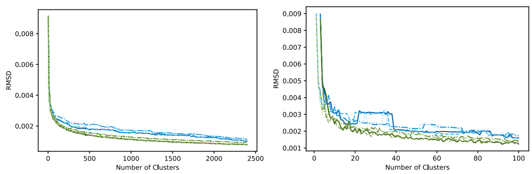
(a) Hours (b) Days

Fig. 14. RMSD of Temperature.



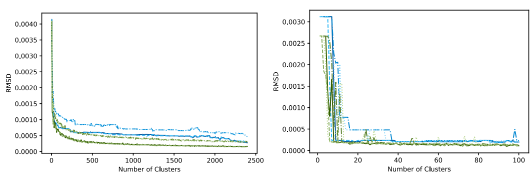
(a) Hours (b) Days

Fig. 15. RMSD of DHW Load in the Normal Offices.



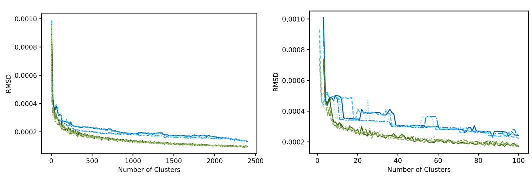
(a) Hours (b) Days

Fig. 16. RMSD of SH Load in the Normal Offices.



(a) Hours (b) Days

Fig. 17. RMSD of Electric Load in the Passive Offices.



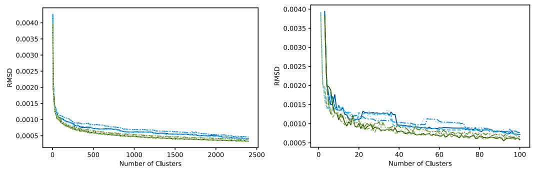
(a) Hours (b) Days

Fig. 18. RMSD of DHW Load in the Passive Offices.

choice of the clustering method (algorithm, cluster type and normalization method) can be made based on the results presented in this paper. For the particular application of designing the energy system of neighborhoods with an objective of zero emissions, the best method appears to be to use the k-means algorithm with the range normalization and days as cluster type. A low number of days is fine but it can be interesting to increase it to improve the representation of the solar irradiance for example. The trade-off between time and precision should then be considered. Further work could extend the result to other cases and study if the results presented in this paper scale to bigger neighborhoods. Other clustering algorithms or heuristics could also be investigated.

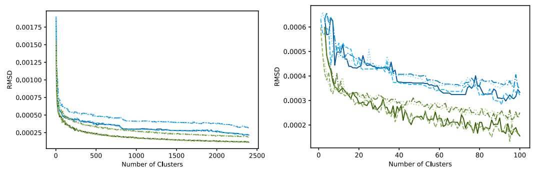
Declaration of Competing Interest

None.



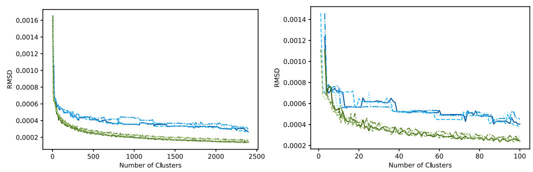
(a) Hours (b) Days

Fig. 19. RMSD of SH Load in the Passive Offices.



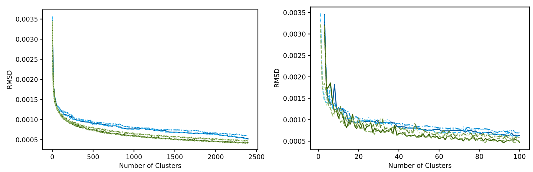
(a) Hours (b) Days

Fig. 20. RMSD of Electric Load in the Student Housing.



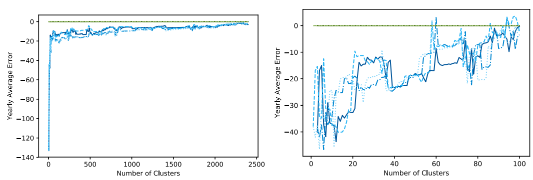
(a) Hours (b) Days

Fig. 21. RMSD of DHW Load in the Student Housing.



(a) Hours (b) Days

Fig. 22. RMSD of SH Load in the Student Housing.



(a) Hours (b) Days

Fig. 23. YAE of Irradiance.

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Appendix A. Additional results of the clustering

Additional results are presented in this appendix. In particular, the RMSD for the time series that were not included in Section 4 are shown in this section.

Table 8
Data of technologies producing heat and/or electricity in the complete model.

Tech.	η_{th} (%)	Fix. Inv. Cost (€)	Var. Inv. Cost (€/kW)	α_i (% Inst. Cap.)	Min. Cap. (kW)	Annual O&M Costs (% of Var Inv. Cost)	Lifetime (year)	Fuel	α_{CHP}	El.	Heat
At building level											
PV[1]		0	730	0	50	1.42	35			1	0
ST[2]	70	28350	376	0	100	0.74	25			0	1
ASHP[3]	f(T_t)	42300	247	0	100	0.95	20	Elec.		0	1
GSHP[4]	f(T_t)	99600	373	0	100	0.63	20	Elec.		0	1
Boiler[5]	85	32200	176	30	100	2.22	20	Wood Pellets		0	1
Heater	100	15450	451	0	100	1.18	30	Elec.		0	1
Boiler	100	3936	52	20	35	2.99	25	Biomethane		0	1
At neighborhood level											
CHP[6]	47	0	1035	50	200	1.03	25	Biogas	1.09	1	1
CHP	98	0	894	20	1000	4.4	25	Wood Chips	7.27	1	1
CHP	83	0	1076	20	1000	4.45	25	Wood Pellets	5.76	1	1
Boiler[7]	115	0	680	20	1000	4.74	25	Wood Chips		0	1
Boiler[7]	100	0	720	40	1000	4.58	25	Wood Pellets		0	1
CHP[8]	66	0	1267	10	10	0.84	15	Wood Chips	3	1	1
Boiler[9]	58	0	3300	70	50	5	20	Biogas		0	1
GSHP[4]	f(T_t)	0	660	010	1000	0.3	25	Elec.		0	1
Boiler	99	0	150	5	60	0.71	20	Elec.		0	1
Boiler	100	0	60	15	500	3.25	25	Biogas		0	1

1 Area Coefficient: 5.3 m^2/kW.
2 Area Coefficient: 1.43 m^2/kW.
3 Air Source Heat Pump.
4 Ground Source Heat Pump.
5 Automatic stoking of pellets.
6 Gas Engine.
7 HOP.
8 Gasified Biomass Stirling Engine Plant.
9 Solid Oxyde Fuel Cell (SOFC).

Table 9
Data of technologies producing heat and/or electricity in the simplified model. There is no fixed investment cost, no minimum size and no part load limitation. The other parameters are the same as in Table 8.

Technology	Var. Inv. Cost (€/kW)	Technology	Var. Inv. Cost
At building level		**At neighborhood level**	
PV	730	Biogas CHP	1035
ST	376	Wood Chips CHP	894
ASHP	670	Wood Pellets CHP	1076
GSHP	1369	Wood Chips Boiler	680
Wood Pellet Boiler	498	Wood Pellets Boiler	720
Elec. Heater	605	Wood Chips CHP	1267
Biomethane Boiler	91	Biogas Boiler	3300
		GSHP	660
		Elec. Boiler	150
		Biogas Boiler	60

Table 10
Data of Fuels.

Fuel	Fuel Cost (€/kWh)	CO_2 factor (gCO_2/kWh)
Electricity	$f(t)$	$f(t)$
Wood Pellets	0.03664	40
Wood Chips	0.02592	20
Biogas	0.07	0
Biomethane	0.07	100

The errors for the temperature time series, Fig. 14, are very similar to the overall ones. The RMSD of temperature plateaus rather quickly to around 2 for the hours, and 2.8 for the days.

The RMSD of the loads of the normal offices are presented in Figs. 15–17. For the offices already at the passivhus standard, the results are presented in Figs. 17–19.

For the student housings, the results are presented in Figs. 20–22.

The figures for the yearly average errors presented in Table 1 are presented in Fig. 23.

Appendix B. Technology Data

The data for technologies in Tables 8 and 9 come mainly from the Danish Energy Agency and Energinet.[5] The data for storages is presented in Table 11.

Table 11
Data of storage.

Index	One way eff. (%)	Inv. Cost (€/kWh)	O&M Cost (% of Inv. Cost)	Lifetime (year)	Min. Cap. (kWh)	Charge/ Discharge rate (% of Cap)
Battery						
1[1]	95	577	0	10	13.5	37
2[2]	938	500	0	15	210	23
3[3]	95	432	0	20	1000	50
Heat Storage						
1[4]	95	75	0	20	0	20
2[3]	98	3	0.29	40	45 000	1.7

[1] Based on Tesla Powerwall.
[2] Based on Tesla Powerpack.
[3] Based on Danish energy agency data.
[4] Same data are used for the heat storage at the building or neighborhood level and for both SH and DHW.

The data for prices of fuels (Table 10) come from different sources. For the wood pellets and wood chips, they come from the Norwegian Bioenergy Association.[6] The data for the biogas and biomethane come from the European Biogas Association.[7].

The data for CO_2 factor of fuels come from a report from Cundall[8].

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Paper 4

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Impact of the CO_2 factor of electricity and the external CO_2 compensation price on zero emission neighborhoods' energy system design

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ABSTRACT

Existing literature on Zero Emission Neighborhoods (ZENs) and Buildings (ZEBs) only allow for reaching the zero emission target locally. This paper evaluates the impact of allowing to buy CO_2 compensation to reach that target in the design of ZENs. This is motivated by questions regarding the relevance of investing in local renewable production (mainly from PV) in a power system dominated by renewable hydropower. Further, it contributes to the existing literature regarding ZENs and ZEBs by highlighting the importance of the choice of the CO_2 factor of electricity for the design of ZENs' energy system.

A case study illustrates the impact of those choices on the resulting energy system design using the existing ZENIT model. Three CO_2 factors for electricity are used in the case study: a yearly average CO_2 factor for Norway (18 gCO_2/kWh), an hourly average CO_2 factor for Norway and a yearly average European factor (at 132 gCO_2/kWh). The energy system design of the ZEN is little affected when using hourly CO_2-factors compared to yearly average factors, while the European factor leads to less investment in PV. Hourly marginal CO_2 emission factors are also investigated using three accounting methods. There large differences in energy system design and emissions depending on where the factor is applied. The price of external compensation is varied between 0–2000 €/$tonCO_2$. A lower price of external CO_2 compensations mainly reduces the amount of PV investment. Allowing the purchase of CO_2 compensations at 250 €/$tonCO_2$ could reduce the total costs by more than 10%.

1. Introduction

Zero Emission Neighborhoods (ZEN) are gaining attention as a solution to the sustainability problem of current buildings and cities. To qualify as a ZEN, a neighborhood should have net zero emissions of CO_2 over the lifetime of its invested assets. Depending on the level of ambition, this can include only the operation part or, in addition, the construction, materials and deconstruction. The net zero emissions are reached when the emissions are completely compensated. To do this, it is necessary to make assumptions on the CO_2 factors, in particular for electricity, and on the compensation mechanism that allows to reach net zero emissions.

In order to guide the design of the energy system of such neighborhoods, a tool called ZENIT, which has been previously developed, is used in a case study. It uses a Mixed Integer Programming (MIP) optimization to minimize the cost of investing in and operating the energy system of a ZEN. In ZENIT, we consider that the electricity from on-site renewable sources exported to the grid prevents an amount of emissions corresponding to the electricity that would have been produced and fed to the grid from more carbon-intensive sources without this export. However, what should the CO_2 factor be for this replaced electricity, and in particular what is the impact of using annual average factors versus using hourly average or hourly marginal CO_2 factors? In addition to this question, we also discuss the value of using different compensation mechanisms in addition to the compensation by exportation of on-site electricity presented earlier. We discuss in particular the purchase of emission allowances on the European Emission Trading System (ETS), the compensation mechanism offered by carbon offsetting companies and finally carbon capture and storage (CCS). The impact on the design of the energy system of a ZEN is investigated analyzing the change in the results from variations of the price of carbon offsetting options.

The existing literature presented in Section 2 does not allow to have a good understanding of the factors to use in investments models for the energy system of ZENs in particular in Norway and does not explore the effects of modifying the definition of compensation to allow for more than only compensation from local sources. Indeed, the literature on designing energy system for Zero Emission Building,

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Nomenclature

$t(\mathcal{T})$	Timestep in hour within year, $\in [0, 8759]$
$\kappa(\mathcal{K})$	Cluster representative (centroid)
$t_\kappa(\mathcal{T}_\kappa)$	Timestep within cluster κ, $\in [0, 23]$
$b(\mathcal{B})$	Building or building type
$i(\mathcal{I})$	Energy technology, $\mathcal{I} = \mathcal{F} \cup \mathcal{E} \cup \mathcal{HST} \cup \mathcal{EST}; \mathcal{I} = \mathcal{Q} \cup \mathcal{G}$
$f(\mathcal{F})$	Technology consuming fuel (gas, biomass, ...)
$e(\mathcal{E})$	Technology consuming electricity
$hst(\mathcal{HST})$	Heat storage technology
$est(\mathcal{EST})$	Electricity storage technology
$q(\mathcal{Q})$	Technologies producing heat
$g(\mathcal{G})$	Technologies producing electricity

Parameters

α_i	Part load limit as ratio of installed capacity
$\dot{Q}_{st}^{max}$	Maximum charge/discharge rate of est/hst [kWh/h]
η_{est}, η_{hst}	Efficiency of charge and discharge
η_{inv}	Efficiency of the inverter
η_i	Efficiency of i
$\phi_f^{CO_2}$	CO_2 factor of fuel type f [gCO_2/kWh]
$\phi_t^{CO_2,e}$	CO_2 factor of electricity at t [gCO_2/kWh]
σ_κ	Number of occurrences of cluster κ in the year
$\epsilon_{r,D}^{tot}$	discount factor for the duration of the study D with discount rate r
C^{HG}	Cost of investing in the heating grid [€]
$C_{i,b}^{maint}$	Annual maintenance cost of i in b [€/kWh]
$C_{i,b}^{var,disc}$, $C_{i,b}^{fix,disc}$	Variable/Fixed investment cost of i in b discounted to the beginning of the study including potential re-investments and salvage value [€/kWh]/[€]
C_{sl}	Cost of external carbon offsetting [€/gCO_2]
$COP_{hp,b,t}$	Coefficient of performance of heat pump hp
G^{stc}	Irradiance in standard test conditions: $1000\ W/m^2$
IRR_t^{tilt}	Total irradiance on a tilted plane [W/m^2]
M	Big M, taking a large value
P^{grid}	Electricity grid tariff [€/kWh]
$P_{hp,b,t}^{input,max}$	Maximum power consumption from manufacturer's data and output temperature [kW]
P^{ret}	Retailer tariff on electricity [€/kWh]
P_f^{fuel}	Price of fuel f [€/kWh]
P_t^{spot}	Spot price of electricity at t [€/kWh]
T^{coef}	Temperature coefficient
T^{noct}	Normal operating cell temperature [°C]
T^{stc}	Ambient temperature in standard test conditions [°C]
T_t	Ambient temperature at t [°C]
X_i^{max}	Maximum investment in i [kW]
X_i^{min}	Minimum investment in i [kW]

Variables

$\overline{x_{i,b,t}}$	Maximum production from i [kWh]
b^{HG}	Binary for the investment in the Heating Grid
$b_{i,b}$	Binary for the investment in i in b
$d_{e,t,b}$	Electricity consumed by e in b at t [kWh]
e^{sl}	Emission compensated via external carbon offsetting [gCO_2]
$f_{f,t,b}$	Fuel consumed by f in b at t [kWh]
$g_{g,t,b}$	Electricity generated by g at t [kWh]
$g_{t,g,b}^{ch}$	Electricity generated by g used to charge the 'prod' batteries at t [kWh]
$g_{t,g,b}^{selfc}$	Electricity generated by g self-consumed in the neighborhood at t [kWh]
$o_{i,t,b}$	Binary controlling if i in b is on or off at t
$q_{t,st,b}^{ch}$, $q_{t,st,b}^{dch}$	Energy charged/discharged from the neighborhood to the storage at t [kWh]
$q_{q,t,b}$	Heat generated by q in b at t [kWh]
$v_{t,st,b}^{stor}$	Level of the storage st in building b at t [kWh]
$x_{i,b}$	Capacity of i in b
$y_{t,est,b}^{ch}$	Electricity charged from on-site production to est at t [kWh]
$y_{t,est,b}^{dch}$	Electricity discharged from est to the neighborhood at t [kWh]
$y_{t,est,b}^{exp}$	Electricity exported from the est to the grid at t [kWh]
$y_{t,est,b}^{imp}$	Electricity imported from the grid to est at t [kWh]
$y_{t,g,b}^{exp}$	Electricity exported by g to the grid at t [kWh]
y_t^{imp}, y_t^{exp}	Electricity imported from the grid to the neighborhood/exported at t [kWh]

Zero Emission Neighborhood or other low emission buildings have only used yearly average [1–7] or monthly average [4] factors. Hourly average factors were used in [8] and [9] but not in the context of zero emission structures. Marginal factors are investigated by [9] but again not in the context of ZEN and with a questionable accounting of the emissions. Therefore, the literature does not provide good insights into the consequences of using hourly average and marginal emission factors for electricity for designing the energy system of ZENs. Moreover, the literature on ZEN only look at the relaxation of the ZEN criteria by reducing the ambition objective (by setting to compensate only a percentage of the emissions) such as in [2] but does not investigate a relaxation of the requirement for the compensation to be "local".

This paper extends the existing literature on low emission neighborhood energy system design, and in particular ZENs' energy system design, with new results on the impact of the CO_2 factor of electricity and relaxation of the "local" constraint on compensation on the design of the energy system of a ZEN.

In this paper, we perform a case study of a neighborhood in Norway, Evenstad, and use an optimization model, ZENIT, that minimizes total cost under the strong requirement of having zero CO2-emission over its entire lifetime. Section 3 presents the concept of ZEN and of compensation and goes into more detail in the calculation and choice of CO_2 factors of electricity. The model is presented in Section 4, the case study in Section 5 and the results in Section 6.

2. Literature review

Choosing the CO_2 factors for a generation type is not problematic thanks to the available data from, for instance, IPCC [10] or the Ecoinvent database [11]. The CO_2 factor of electricity for a country or a bidding zone is more complex. Indeed, not only is the production inside the zone important but also the imports from other zones. The origin of the power thus needs to be traced to obtain a good estimate of the emission factor. Another problem is how the factors change with a change in electricity demand. The marginal factors of CO_2 emissions can be defined as the change in emissions from producing or consuming 1 unit more (or 1 unit less) of electricity. One assumption that can be made is that it is the marginal unit in the merit order curve of the spot market for that hour that sets this marginal factor, but the units of the balancing market could also be considered.

The various possibilities of emission factors raise the question of which one to use. [12] made an algorithm to help select the appropriate emission factor of electricity based on one's application.

It is interesting to look at what emission factors are used in various studies and for different applications. In [13], marginal hourly emission factors are used to analyze the trade-offs between revenue and emission reduction for operating a battery system. The marginal emission factor is used to represent the emission reduction due to the battery intervention.

In [14], the consequences of the electrification of oil platforms on emissions of CO_2 were investigated using, in particular, the EMPS model. Different emission factors (Norway alone, Norway and countries it is connected to, Nordic countries and Europe), both average and marginal, are also presented in a scenario including new policies implemented by European countries.

[15] uses average factors and three different definition of marginal factors on industrial battery systems to study the impact on emissions and on operation. [16] and [17] investigate emission factors of electricity for electric vehicles in California. [16] defines emission factor on three dimension: average/marginal, aggregated/temporally explicit (hourly factors for instance) and retrospective/prospective; and discusses and compares them in the context of electric vehicles in California. [17] used marginal factors for investigating the impact of the additional load from electric vehicles on emissions and compared them with those of conventional vehicles.

The use of marginal factors in the case of electric vehicles or batteries is justified because they add or remove load from the system in a relatively unpredictable way. The use of hourly factors also allows to take advantage of the arbitraging potential of these units.

In the context of designing buildings' envelope (materials, thickness), [18] uses yearly average emission factors for the operation part of the analysis in the multi-objective optimization considering cost and emissions.

We can also look at what kinds of factors have been used in past studies for designing the energy system of neighborhoods or buildings.

The design of the energy system of ZEBs are investigated in [1,2] and [3]. The value of 130 gCO_2/kWh is used for the Nordic countries and 350 gCO_2/kWh when considering the European mix instead. In [1], it is found that using asymmetrical factors (different for imports and exports) in the context of ZEBs leads to a higher investment in PV panels.

It should be noted that ZEB can also stand for Zero Energy Buildings. We can refer to [19] for a review of the various definitions and calculation methodologies. More recently [20] also provides a review of the definitions and of the different existing optimization approaches to designing different aspects of Zero Energy and Emission Buildings.

[4] focuses on Zero Energy Buildings but also investigates the use of yearly and monthly average CO_2 factors for electricity, in a 2010 setting and a scenario for 2050. It finds that using CO_2 factors for the EU 2050, which are relatively low, makes it harder to be zero energy/zero emission because of the higher amount of PV needed, which is most often incompatible with available roof area. This results in systems using the grid as a seasonal storage. Those effects should be taken into account when selecting which factors to use.

In an optimization model investing in the energy system of a neighborhood and considering refurbishment [5] constrains the emissions and uses a yearly average CO_2 factor of Croatia for electricity as well as a carbon cost. A yearly average factor is also used in [6] in a sensitivity analysis on emission reduction for the design of the energy system of a neighborhood in the UK. For a similar model in Switzerland, [7] also uses yearly average value.

In a similar model, [8] uses half-hourly marginal electricity emission factors for the UK calculated based on the method of [21].

The consequences of using hourly factors instead of annual average in LCA (life cycle analysis) evaluation of houses have been demonstrated in [22].

An aggregate average factor is used in [23] in one of the objective functions of its multi-objective optimization model.

Very few instances of the use of marginal factors in the context of the investment in the energy system of neighborhood were found in the literature. For neighborhood energy systems, [9] compares accounting approaches with both hourly average and marginal factors of electricity. The marginal factors of Austria are derived from a merit order approach. When using marginal factors, the study however seems to account for all emissions of the energy system of the neighborhood with that factor. This is a questionable assumption as only the extra production or consumption from a base case scenario should use the marginal factor. [24] uses hourly marginal factors for accounting the carbon tax due to the imports of electricity to a microgrid in the objective function of its model that selects, size- and place-distributed energy resources in a microgrid.

The optimal choice of factors is dependent on the application. [12] is an example of a tool that can help with this choice. The choices and their consequences are not always justified in the literature. The literature on investments in the energy systems of neighborhoods presented above shows the use of many different emission factors. They are most often aggregated factors, in particular yearly, and prospective [4] or retrospective [2,3,5–7,23]. Only [8] and [9] use emission factors at a finer temporal resolution. The variety of choice indicates a lack of consensus on which factors to use for such applications. The higher representation of aggregated factor could be rather due to an ease of access than because they are the best solution. The hourly factors are harder to obtain but could improve the operation to take advantage of variations in hourly CO_2 factors. Marginal factors are even more difficult to obtain and often require many questionable assumptions that limit their use.

Despite the existing literature, there remains gaps in the knowledge regarding the factor to use specifically for the design of the energy system of ZENs. [2] and [4] considers non-symmetrical weighting factors but do not consider hourly factors. In addition, while [4] looks into the impact of different factors, it does so via a simulation and a calculation of the emissions of different existing energy systems, not always at a hourly resolution and finds the amount of PV needed to reach the net zero emissions. The factor to use in the context of ZENs' energy system's investment remains unclear. Another gap in the literature is on the definition of the ZENs and of what can be compensation in particular. The literature only considers strictly local compensations and do not explore the consequences of allowing other compensation means on the design of the energy system of ZENs.

This paper contributes to the existing literature by:

- Discussing the relevance of various compensation mechanisms that can help achieve net zero emission in neighborhoods inside or outside the local setting of the usual framework.
- Investigating the impact of the choice of CO_2 factors for electricity on the resulting energy system of ZENs
- Analyzing the impact of different emission compensation measures price points on the design of the energy system of ZENs

3. CO_2 Factors of electricity and compensations

3.1. ZEN/ZEB concept

Zero Emission Neighborhoods (ZENs) are neighborhoods that should have net zero emissions of CO_2 during their lifetime. This implies a carbon balance with on the one side the emissions and on the other the compensations. There are many sources of carbon emissions in the lifetime of a neighborhood: materials, construction, deconstruction, electricity use and heating of the buildings, transportation of people and goods are the main ones.

The research center on Zero Emission Buildings (ZEBs)[1] defined the CO_2 factors to be used in the design of buildings aiming to be ZEBs with a yearly average value of 132 gCO_2/kWh. This value was set based on the results from [25], and represents an average factor of the electricity mix in Europe for the period of 2010–2050 in a very optimistic European scenario.

Not emitting greenhouse gases is the best way to have a positive impact on the environment and reduce the need for compensations in the neighborhood. However, ZEBs and ZENs eventually do cause CO_2 emissions, and exporting renewable electricity to the grid, most often with PV, is necessary to compensate emissions locally. The concept of zero emission neighborhood (or building) considers that the export of electricity produced on-site from renewable sources and exported to the grid will replace the production of more carbon-intensive sources. In ZENIT, we count the emissions prevented in this way as the compensations. This causes challenges such as high additional investment costs, and, if the concept is generalized, grid stability and dimensioning issues. Thus this paper discusses the possibility of investing in CO_2-reducing measures outside of ZENs as an alternative to reach the balance locally.

3.2. Literature on calculation of CO_2 factors of electricity

The value of the CO_2 factor for electricity used is important for ZENs because it is involved in the accounting of the emissions from the imports of electricity as well as the compensations from exporting on-site renewable electricity.

The existing literature contains several methods for calculating the emission factors of countries. [26] gives an example of a methodology; *annual average* emissions for OECD countries were calculated with a production-based method and a consumption-based method, highlighting the differences in results for certain countries.

A methodology for calculating *hourly average* CO_2 emissions is presented in [27], where they were computed for Europe with a particular focus on Norway. It uses a multi-regional input–output approach to trace the origin of the electricity consumed in each bidding zone to a generation type and calculate the CO_2 factors. [28] and the electricityMap website[2] use a similar approach.

[29] calculates the *marginal* CO_2 factors for the UK by reconstructing the merit order curve using historical half-hourly generation from all plants and assuming that the marginal unit is the last one dispatched in the merit order curve.

Using historical data of actual generation per generator type, [21] calculates the *marginal* emission factor. The sum of the generation gives the demand while using the emission factor of each generation type gives the emissions. A regression is then performed on the emission as a function of the total demand to estimate the CO_2 factor variation when changing the demand. The method is applied to Great Britain. A similar method is applied to Spain in [30]. In [31], the long-run marginal CO_2 factors are calculated with the methodology of [21] but also considering the commissioning and decommissioning of plants, with marginal factors defined as the change in CO_2 emission in the system due to the commissioning or decommissioning of plants and to resulting changes in operation.

In New Zealand, [32] analyzed the average and marginal hourly CO_2 factors for the country, finding that hydropower was the main marginal element. They also make policy proposals based on their findings and argue, for instance, for the use of time-varying factors as a trigger for demand-side responses.

For Finland and the other Nordic countries, [33] calculated hourly average and marginal CO_2 factors for 2009, 2010, and also based on a scenario for 2030 for Europe, the Nordic countries together and each Nordic countries separately.

Both methods for calculating the marginal emissions factor have drawbacks. The method based on recreating the merit order needs to make assumptions and group generators into types and often cannot account for specific cases that arise due to ramping constraints or minimum up- and down-time. The other method is based on a linear regression which simplifies the actual marginal factors and cannot be applied to every countries, the fit of the regression depending on the specific power system. A third approach is to use Expansion planning and market models to obtain prospective marginal factors. Their precision then depends on the quality of the models used to obtain them and their assumptions.

In the case of Norway in particular, [25] also studied the CO_2 factors of electricity, both marginal and average, in a long-term approach based on scenarios from the European Union and the EMPS model. The EMPS models the European power system and market with a particular focus on hydropower production and Norway. However, the emission factors obtained do not allow to account for the hourly and seasonal variations in the electricity mix both now and in the future.

3.3. Considerations for selecting a CO_2 factor of electricity

Several considerations should be taken into account when making the decision on which CO_2 factors of electricity to use when designing a ZEN. One initial choice is whether this factor should be the same for the imported as for the exported electricity. Indeed, what is the carbon intensity of the electricity consumed and exported? When it comes to imported electricity, there should be no difference between the consumption from a ZEN and from any other standard building. In practice, since the electron cannot be traced back to a source at the consumer level, a more global factor needs to be used. The electricity mix of the bidding zone is relevant at the local level and can be computed (such as in [27]), thus making it a good choice for this role.

For the electricity exported, stricto-sensu, the emissions depend on the source and fuel that produced it. No emissions for PV panels, and the emissions corresponding to the burnt fuel for a gas CHP for example. Another approach is to consider the emissions in an LCA approach, i.e. considering the construction and other life cycles of the technology, it changes for example the emissions for PV, which are no longer zero. In the zero emission balance presented earlier, we consider the difference between the emissions from the electricity we export from on-site sources and the electricity it replaces in the grid. This electricity that is replaced also needs to be defined. Do we consider that the electricity replaced is based on the electricity mix, or do we replace the marginal unit, i.e. the last unit on the unit commitment curve, and should therefore use the carbon intensity of that unit?

It is also important to consider the case of a large number of ZENs in the power system. This changes the previous reasoning because it is now reasonable to consider that the ZENs are sufficiently numerous to influence the market. In this scenario, considering their significant power production, the ZENs would take part in the day-ahead market in the load forecast or as actors. In that case, the principle is the same but it becomes difficult to assess what the neighborhoods' electricity replaces. Indeed, the marginal intensity only holds in the vicinity of the clearing point. When moving away from the vicinity of the clearing

[1] https://www.zeb.no/

[2] https://www.electricitymap.org/

point, it is possible that several units have been "replaced" by the ZEN production. Those units are ordered in the market clearing by their costs, but their emissions are not following the same order. A possibility is to use the emission intensity of the replaced units weighted by the replaced amount of electricity. This, nevertheless, cannot easily be used in the investment optimization because the change in power production results in a change in the carbon intensity in a non-linear manner. Furthermore, this would require complete information of the market clearing and each bidding units.

In the same way, a large amount of ZEN would impact the average CO_2 factor of an area. Both of those impacts can be considered by coupling a model such as ZENIT and a European market and expansion planning model. The coupling could be a soft-linking iterating through each model or a hard-linking co-optimizing both the energy system and the ZENs. This approach would allow to obtain ZENs adapted to each zone and to the evolution of the power system, but can only produce generic neighborhoods and not reasonably be used to design the energy system of a specific one. [34] gives an example of such an approach.

4. Model presentation

ZENIT (Zero Emission Neighborhood Investment Tool) is presented in this section. ZENIT searches for the cost-optimal energy system for a given neighborhood to be zero emission through a MILP optimization. One representative year is used instead of the whole lifetime for computation reasons. This model is an extension of [2] and is partially presented in [35].

Minimize:

$$b^{HG} \cdot C^{HG} + \sum_b \sum_i \Big((C^{var,disc}_{i,b} + \frac{C^{maint}_{i,b}}{\epsilon^{tot}_{r,D}}) \cdot x_{i,b} + C^{fix,disc}_{i,b} \cdot b_{i,b} \Big) + \sum_{t_\kappa} \frac{\sigma_\kappa}{\epsilon^{tot}_{r,D}} \Big(\sum_b \sum_f f_{f,t,b} \cdot P^{fuel}_f + (P^{spot}_t + P^{grid} + P^{ret}) \cdot (y^{imp}_t + \sum_b \sum_{est} y^{imp}_{t,est,b}) - P^{spot}_t \cdot y^{exp}_t \Big) + e^{sl} \cdot \frac{C^{sl}}{\epsilon^{tot}_{r,D}} \tag{1}$$

The objective function (Eq. (1)) minimizes the cost of investing in and operating the energy system of the neighborhood as a whole and does not find the optimal investment of each building taken separately. It considers the fix and variable investment cost of the different technologies ($C^{var,disc}_{i,b}$, $C^{fix,disc}_{i,b}$) and the heating grid (C^{HG}), as well as operation- and maintenance-related costs ($C^{maint}_{i,b}$). A binary variable controls the investment in the heating grid (b^{HG}). The subscripts used in the equations are b for the buildings, i for the technologies, t for the timesteps, f for fuels and est for batteries. ϵ are the discount factors with interest rate r for the duration of the study D. $x_{i,b}$ is the capacity of the technologies and $b_{i,b}$ the binary related to whether it is invested in or not. σ_κ is the number of occurrences of cluster κ in the full year and t_κ is the timestep in the cluster. P are the prices of fuel, electricity on the spot market, grid tariff or retailer tariff. f is the consumption of fuel and y are the imports or exports of electricity. The external compensations that can be purchased are e^{sl}.

In ZENIT, the ZEN compensation framework introduced in Section 3.1 is used. In addition, the electric and heat loads of the buildings are inputs to the model so the impact of energy efficiency measures such as better insulation for refurbished houses needs to be accounted for in the load profiles given to the model. The zero emission balance constraint is used to enforce the Zero Emission requirement:

$$\phi^{CO_2}_{e,t} \sum_{t_\kappa} \sigma_\kappa \Big(y^{imp}_t + \sum_b \sum_{est} y^{imp}_{t,est,b} \Big) + \sum_{t_\kappa} \sigma_\kappa \sum_b \sum_f \phi^{CO_2}_f \cdot f_{f,t,b} \le \phi^{CO_2}_{e,t} \cdot \sum_{t_\kappa} \sigma_\kappa \Big(\sum_b \sum_{est} \eta_{est} \cdot y^{exp}_{t,est,b} + \sum_b \sum_g y^{exp}_{t,g,b} \Big) + e^{sl} \tag{2}$$

The CO_2 factors are represented by $\phi^{CO_2}_{e,t}$ for electricity and $\phi^{CO_2}_f$ for other fuels. η_{est} is the charging efficiency of the battery.

Other equations include load balances for electricity, Domestic Hot Water (DHW) and Space Heating (SH). They require the production and import to be equal to the consumption and exports for all timesteps.

The optimization model can choose to invest in a heating grid, giving access to other technologies. We assume that those technologies are located in a central production plant that feed the heating grid. The operation of the heating grid is then constrained by the flow limitation in the pipes and by a constraint preventing buildings from feeding heat into the grid.

The size of the connection to the electric grid limits the exports and imports.

For most technologies, the production of heat or electricity is linked to the fuel consumption using the efficiency of the technology.

$\forall \gamma \in \mathcal{F} \cap \mathcal{Q}, t, b$ $\qquad$ $\forall \gamma \in \mathcal{E} \cap \mathcal{Q}, t, b$

$$f_{\gamma,t,b} = \frac{q_{\gamma,t,b}}{\eta_\gamma} \tag{3a}$$

$$d_{\gamma,t,b} = \frac{q_{\gamma,t,b}}{\eta_\gamma} \tag{3b}$$

For CHPs the electricity produced is the ratio of the heat produced and the heat to power ratio α_{CHP}.

The heat produced can be used for DHW or for SH but some technologies can only provide SH (such as electric radiators or wood stoves).

The production from PV and solar thermal collectors depends on the irradiance on a tilted surface IRR^{tilt}_t and their efficiency. The efficiency for the solar panel η^{PV}_t is defined based on [36] and accounts for the cell temperature T_c and inverter losses.

$$\eta_{PV,t} = \frac{\eta^{inv}}{G^{stc}} \cdot \left(1 - T^{coef} \cdot (T^c - T^{stc})\right) \tag{4a}$$

$$T^c = T_t + (T^{noct} - 20) \cdot \frac{IRR^{tilt}_t}{800} \tag{4b}$$

For the heat pumps in the buildings, the production and electrical consumption are defined as follows:

$$d^{SH}_{hp,b,t} = \frac{q^{SH}_{hp,b,t}}{COP^{SH}_{hp,b,t}} \tag{5a}$$

$$d^{DHW}_{hp,b,t} = \frac{q^{DHW}_{hp,b,t}}{COP^{DHW}_{hp,b,t}} \tag{5b}$$

$$\frac{d^{DHW}_{hp,b,t}}{P^{input,max,DHW}_{hp,b,t}} + \frac{d^{SH}_{hp,b,t}}{P^{input,max,SH}_{hp,b,t}} \le x_{hp,b} \tag{5c}$$

Eqs. (5a) and (5b) link the heat produced to the COP and the electrical consumption of the heat pump. The COPs are different for SH and DHW due to different temperature set points. They also depend on the outside temperature and they are calculated before the optimization. Eq. (5c) regulates how the heat pump can be used for both SH and DHW and enforces that the capacity invested is not exceeded. $P^{input,max}$ represents the maximum power input to the heat pump at the timestep based on the temperature set point and for a 1 kW unit. $d^{SH}_{hp,b,t}$ and $d^{SH}_{hp,b,t}$ represent the electric consumption of the heat pump for SH and DHW while $q^{DHW}_{hp,b,t}$ and $q^{DHW}_{hp,b,t}$ are the heat production. The data used to calculate the heat pumps COP and maximum power is based on manufacturer's data[3]

Other binary variables are used for part load limitations. These binary variables concern the operation and are defined for every timestep for each relevant technology, which can lead to a large number of binary variables. No minimum up- or downtime is used. $\forall i \setminus HP, t, b$:

[3] air–air HP: Bosch BMS500-AAM018-1CSXXA; air–water HP: Stiebel Eltron WPL23; water–water HP: Stiebel Eltron WPF10.

$$\overline{x_{i,b,t}} \le X^{max}_{i,b} \cdot o_{i,t,b} \quad (6a) \qquad \overline{x_{i,b,t}} \le x_{i,b} \quad (6b)$$

$$\overline{x_{i,b,t}} \ge x_{i,b} - X^{max}_{i,b} \cdot (1 - o_{i,t,b}) \quad (6c)$$

$$q_{i,b,t} \le \overline{x_{i,b,t}} \quad (6d) \qquad q_{i,b,t} \ge \alpha_{i,b} \cdot \overline{x_{i,b,t}} \quad (6e)$$

The size of the investment in each technology type is bounded, from below to represent the larger scale of some technologies (Eq. (7)) and from above to limit the size of the research space. $\forall i, b$:

$$X^{min}_{i,b} \cdot b_{i,b} \le x_{i,b} \le X^{max}_{i,b} \cdot b_{i,b} \quad (7)$$

Technologies producing electricity can feed this electricity to the neighborhood directly, store it in batteries, export it or dump it.$\forall t, g, b$:

$$g_{g,t,b} = y^{exp}_{t,g,b} + g^{selfc}_{g,t,b} + g^{ch}_{t,g,b} + g^{dump}_{t,g,b} \quad (8)$$

The storage operation, whether heat or electrical storage, is modeled as follows: $\forall \kappa, t_\kappa \in [1, 23], st, b$

$$v^{stor}_{\kappa,t_\kappa,st,b} = v^{stor}_{\kappa,t_\kappa-1,st,b} + \eta^{stor}_{st,b} \cdot q^{ch}_{\kappa,t_\kappa,st,b} - q^{dch}_{\kappa,t_\kappa,st,b} \quad (9)$$

$\forall t \in [0, 23], st, b$

$$v^{stor}_{\kappa,t_\kappa,st,b} \le x_{st,b} \quad (10)$$

$$q^{ch}_{\kappa,t_\kappa,st,b} \le \dot{Q}^{max}_{st} \quad (11) \qquad q^{dch}_{\kappa,t_\kappa,st,b} \le \dot{Q}^{max}_{st} \quad (12)$$

$\forall p, st, b, \kappa$

$$v^{stor}_{\kappa,0,st,b} = v^{stor}_{\kappa,23,st,b} \quad (13)$$

The state of charge of the storage st (either heat or electric storage) is represented by v^{stor} while qch and $qdch$ are the energy charged and discharged. The maximum charge and discharge rate is Q^{max}_{st}. This model only allows for the use of representative days and daily storage operation. Details of the process of clustering and choosing an appropriate number of clusters can be found in [35]. Some additional equations can be found in Appendix C.

5. Case study presentation

The model is implemented on a test case based on a small neighborhood, a campus at Evenstad in the Innlandet county in Norway where three building types represent the different buildings there. We use the same implementation as in [35]. All the buildings are aggregated into three building types: student housing, normal offices and passive offices. The student housing is a single building of 4200 m^2 of floor area and 1000 m^2 of roof area. The passive offices are buildings built at the ZEB and passive standard and represent 1141 m^2 of floor area and 900 m^2 of roof area. The normal offices comprise the remaining buildings for 3375 m^2 of floor area and 2000 m^2 of roof area. The location of the buildings are also used to create a grid layout that is used inside the optimization. The buildings' envelopes are not necessary as the energy consumption and building dynamics are exogenous to the optimization. In our case, we assume that they are part of the hourly Domestic Hot Water (DHW) and Space Heating (SH) load profiles.

The electric and heat hourly load profiles for the campus are derived from [37]. The share of DHW and SH in the heat load are then based on the time series from a passive building in Finland [38]. The annual loads are presented in Table 1.

Refurbishment of the building envelope is not considered in this study. It can be accounted for exogenously by adapting the timeseries and could also be endogenously integrated to the model but we choose to limit our scope strictly to the energy system of the neighborhood.

Table 1
Yearly total electricity, DHW and SH load for the three buildings groups considered in the optimization of their energy system.

Building group	Electricity load	DHW load	SH load
Student housing	161 414 kWh	45 238 kWh	199 752 kWh
Normal offices	612 336 kWh	45 562 kWh	300 476 kWh
Passive offices	146 092 kWh	6 456 kWh	44 748 kWh

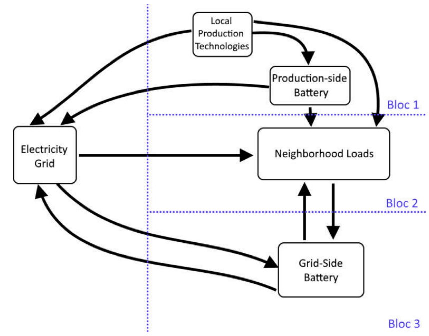


Fig. 1. Representation of the flows of electricity in the neighborhood and in particular between the neighborhood elements and the electricity grid. Three blocs are represented to facilitate the comprehension of the different approaches.

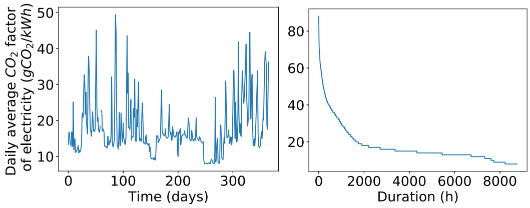
Table 2
Summary of the emission factors used in the three cases when investigating marginal emission factors. M: marginal; A: average.

Case name	Bloc 1	Bloc 2	Bloc 3
Case 1: *All*	M	M	M
Case 2: *Local Prod*	M	A	A
Case 3: *Local Prod + Grid Storage*	M	A	M

We compare the results using a yearly average factor of 18 gCO_2/kWh, a yearly average value of 132 gCO_2/kWh and hourly average values for NO1. In addition, for each of the electricity CO_2 factors, two alternatives are investigated in relation to the solar technologies. The first one considers that the investments in solar technologies are limited by the roof area available. The second one considers that other areas in the proximity of the neighborhoods can be used and thus does not take the roof area as a limiting factor. Further, we investigate the use of hourly marginal factors using different accounting approaches, i.e. different combinations of marginal and average electricity emission factors. Fig. 1 represents the flow of electricity in the neighborhood and the blocs that will be used to describe the accounting approaches. In the first approach, we account all the electricity exchanges between the neighborhood and the grid using the marginal factors (bloc 1, 2 and 3). In a second approach, we consider marginal factors only for bloc 1 and average factors for the rest. In the last approach, we consider marginal factors for bloc 1 and 3 and average for bloc 2. The factors are hourly in all cases. Table 2 summarizes the cases in this study.

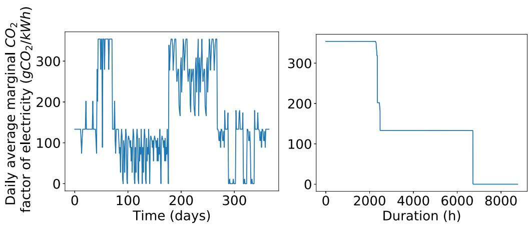
The hourly average CO_2 factor in NO1 is presented in Fig. 2. The yearly average corresponds to the value of 18 gCO_2/kWh introduced earlier but it goes as high as 90 gCO_2/kWh. From the daily average figure, it is clear that there are lower CO_2 factors in the summer months.

The hourly marginal CO_2 factor in NO1 is presented in Fig. 3. This factor is very different from the average one. Indeed, the summer seems to have relatively higher factor than the rest of the year, which should help compensating emissions with PV. Overall the marginal factors are higher than the average factors. Those patterns are not only due to the nature of marginal emission factors but also very specific to Norway where the operation of the high share of hydropower and the



(a) Daily Average (b) Duration Curve

Fig. 2. Daily average and duration curve of the CO_2 factor of electricity in NO1.



(a) Daily Average (b) Duration Curve

Fig. 3. Daily average and duration curve of the marginal CO_2 factor of electricity in NO1.

connection to central Europe leads to electricity imports to Norway when the prices are low.

The three different cases represent different accounting approaches. Case 1 is what is used in [9] but the fact that the whole electricity load of the neighborhood is considered as marginal is dubious. Case 3 addresses that but could lead to the optimization investing in a battery to bypass the average emissions of the neighborhood imports in some cases. This is mostly not relevant in our case due to the particular marginal and average emission factors in NO1 but could be important in other countries. Case 2 does not have this potential bypass but ignore the “unpredictability” of grid side battery operation which would suggest the use of marginal factors. Ultimately the question of what really should be considered marginal remains, and this paper instead shows the outcome of the three approaches.

We also investigate the possibility of external means to reach the necessary amount of compensation. Table 3 presents examples of such means. Carbon offset companies offer the possibility for private individuals and companies to offset their emissions of CO_2 by financing projects such as reforestation, preventing deforestation, or renewable energy in developing countries. There are several companies offering those services[4,5,6,7,8,9] but it is important to note that the efficiency of those companies in reducing CO_2 emissions is debated [39] and depends on specific projects.

The EU Emission Trading System (EU ETS) may also be used as a compensation mechanism. Indeed, if neighborhoods were to buy allowances from the EU ETS and given that the cap on the emission is fixed, this would reduce the amount of available allowances on the market and potentially push more entities towards carbon reduction measures. In the last year, the CO_2 price on the EU ETS has been in the 20 to 30 €/tonCO_2 range.

[4] https://compensate.com/
[5] https://www.atmosfair.de/en/
[6] https://nativeenergy.com/
[7] https://cotap.org/
[8] https://www.myclimate.org/
[9] https://www.cooleffect.org/

Table 3
Examples of external compensation options and their estimated carbon prices.

Compensation type	Compensation price (€/tonCO_2)
Carbon Offset Companies	3–25
EU ETS	20–30
CCS	18–250

Financing carbon capture and storage (CCS) could be another compensation mechanism by financing its use for cases where fossil fuels are still necessary. One of the drawbacks is that it can incentivize to continue using fossil fuels. Various costs from 18 to 250 €/tonCO_2 are reported in the literature [40–42].

The price of the identified external CO_2 compensations (Table 3) may vary between 3 to 250 €/tonCO_2, and to investigate the impact of different price levels, each of the six cases are performed with a price of 0, 15, 30, 50, 75, 100, 250, 500, 1000 and 2000 €/tonCO_2. Those cases are only done with average emission factors.

In the emission balance, we consider only the emissions from the operation phase of the buildings in the neighborhood with a focus on the energy system. This includes the emissions from the use of appliances and for heating. The other emissions could also be included by adding a term to the emission in the zero emission balance, but a good estimate would be necessary. In this study we limit ourselves to the case of a single ZEN, small enough not to influence the clearing of the market. We consider the carbon intensity of on-site sources solely on their production phase (not the LCA approach) and we compare yearly average and hourly average electricity mix carbon intensity both for import and export on the resulting ZEN design. The hourly CO_2 factors for electricity for NO1 are obtained by tracing back the origin of the electricity using the methodology presented in [27]. The production of each generation type and the exchanges between bidding zones are used to determine the resulting mix inside each zone and their corresponding hourly average carbon intensity. This data mainly comes from the ENTSO-E transparency platform and the year 2016 is used. The method presented in [21] for deriving the marginal emission factors does not appear to be suitable for Norway. Applying the same methodology results in a linear regression with a r^2 lower than 0.1. The methodology is not suitable for Norway due to the specificity of the Norwegian electricity market, and in particular the high share of hydropower and the imports of more carbon-intensive electricity. We use results from the EMPIRE model [43], in particular the share of each generation type each hour in NO1 (also considering imports in the same way as for deriving the hourly average emission factors) combined with assumptions on marginal costs of units to find the hourly marginal emissions of electricity in NO1.

The economic and technical data of the technologies are taken from the Danish Energy Agency.[10] In total, 22 technologies are implemented with, at the building level: solar panel, solar thermal, air–air heat pump, air–water heat-pump, ground source heat pump, bio boiler with wood logs or pellets, electric heater and electric boiler, biomethane boiler, biogas and biomethane CHP; and at the neighborhood level: biogas boiler, wood chips and pellets boiler and CHPs, ground-source heat pump and electric boiler. In addition, electric and heat storages are available. Appendix A contains the data used for the different technologies.

The spot price of electricity is obtained from Nordpool's website.[11] The temperature data comes from Agrometeorology Norway.[12] The solar irradiance (diffuse horizontal (DHI) and direct normal (DNI)) are obtained from Solcast.[13] The irradiance on a tilted surface IRR^{Tilt}

[10] https://ens.dk/en/our-services/projections-and-models/technology-data
[11] https://www.nordpoolgroup.com/Market-data1/#/nordic/table
[12] https://lmt.nibio.no, Fåvang station.
[13] https://solcast.com.au

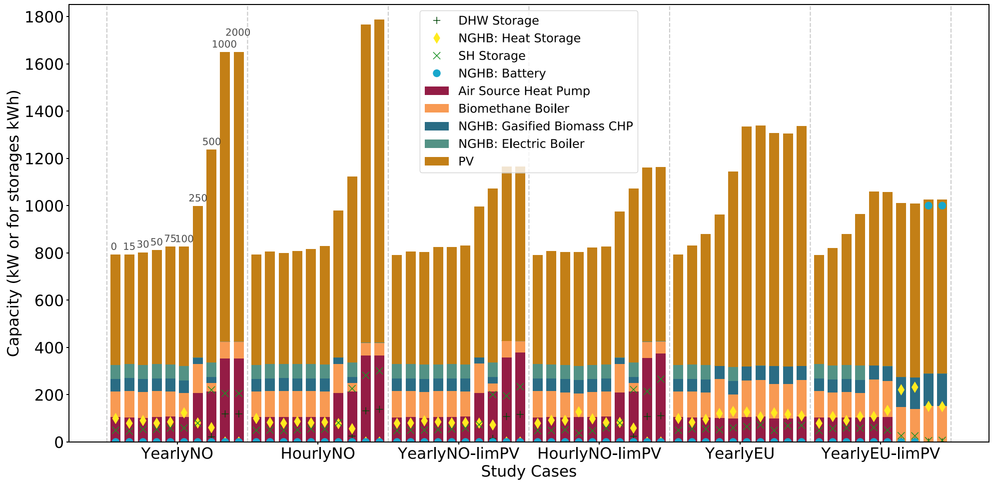


Fig. 4. Investments resulting from the runs grouped by case. The numbers above the bars in the *YearlyNo* case show the CO_2 compensation prices in €/tonCO_2. The same order of prices is used for the other cases. When the technology is at the neighborhood level, its name is preceded by NGHB.

which is an input of the clustering is derived from the DHI and DNI with:

$$\begin{aligned} IRR_t^{Tilt} = {} & DHI_t \frac{1+\cos(\phi_1)}{2} \\ & + \alpha \cdot \left(DNI_t + DHI_t \right) \frac{1-\cos(\phi_1)}{2} \\ & + DNI_t \left(\frac{\cos(\varphi_t)\cdot\sin(\phi_1)\cdot\cos(\phi_2-\psi_t)}{\sin(\varphi_t)} \right. \\ & \left. + \frac{\sin(\varphi_t)\cdot\cos(\phi_1)}{\sin(\varphi_t)} \right) \end{aligned} \tag{14}$$

We assume that for some sun positions (sun elevations (φ) below 1 degree and sun azimuths (ψ) between −90 and 90 degrees), no direct beam reaches the panels. This means that the last term of Eq. (14) is removed at such times. We use a constant albedo factor (α) of 0.3 for the whole year. Hourly albedo values could also be used to better represent the reflection of light on the ground in different conditions, in particular snow in the winter. The tilt angle of the solar panel is ϕ_1; the orientation of the solar panel regarding the azimuth is ϕ_2. We use data from year 2016 for those timeseries as it has been identified as suitable for the investment process [44]. Indeed, out of the years for which the data necessary to compute hourly emission factors are available (i.e. from year 2015), 2016 has electricity prices, temperatures, emission factors and solar irradiance around the average and also has quite low minimum winter temperatures for a good representation of the peak loads.

The price of wood pellets comes from [45], the price of wood logs from [46], the price of wood chips from [47] and the price of biogas from [48].

The model is implemented in Python and is solved using Gurobi. It is run on a laptop with an Intel Core i7-7600U dual core processor at 2.8 Ghz and 16 GB of RAM.

6. Results

6.1. Norwegian CO_2 factors for electricity

Starting with the case using yearly average Norwegian CO_2 factors, *YearlyNO*, and no possibility of external CO_2 compensation (which corresponds in this case to CO_2 compensation prices from 1000 €/ton) we find that the energy system of the neighborhood (Fig. 4) is comprised of around 1 200 kW PV, 350 kW air–water heat pumps and 70 kW biomethane boiler with 200 kWh SH storage and 120 kWh DHW storage. The heat in the neighborhood (Fig. 7) originates almost exclusively from the heat pump. The heat storage is comprised of both SH and DHW with, respectively 205 and 120 kWh.

As the external CO_2 compensation becomes cheaper (below 1000 €/ton for *YearlyNO*), the ZEN's energy system emits more CO_2 locally (Fig. 9) and increases the external CO_2 compensations purchased (Fig. 5). The major change of the energy system design occurs for the PV size, which is drastically reduced. For the heating system, Fig. 4 shows how the size of the heat pump decreases and the biomethane boiler increases. A gasified biomass CHP and electric boiler also appear. This reduces the share of the heat pump in the supplied heat, which only supplies around 35% when the external compensation is free. This heat is principally replaced by the gasified biomass CHP (around 50% of total) and the rest is covered by a mix of the heat from the biomethane and the electric boilers. The heat storage also changes. The DHW disappears and the SH storage is reduced and replaced by storage at the central plant, coinciding with the investment in technologies at the neighborhood level.

Similar results are obtained in the case using hourly Norwegian CO_2 factors *HourlyNO* (Fig. 4). The only difference is the slightly larger PV and heat storage, in particular, above 1000 €/tonCO_2. The reason lies in the hourly CO_2 factors, which are low in summer, when the PV exports occur, but significantly higher than in the *YearlyNO* in the rest of the year (see Fig. 2). In the winter, more CO_2 is emitted due to the difference in CO_2 factor of electricity while the compensation potential of PV is around the same in the *HourlyNO* and *YearlyNO* cases. This leads to a higher amount of installed PV in the *HourlyNO* case. The resulting designs remain comparable because the variations in the CO_2 factors of electricity can be limited by using the heat storage wisely. This also explains the slightly higher heat storage investment, when no external compensation is bought (above 1000 €/tonCO_2).

When the PV size is limited, in the *YearlyNO-limPV* case and *HourlyNO-PVlim* case, the results are also very similar. Compared to the cases when PV is not limited, the amount of PV is reduced by around a third for the cases above 1000 €/tonCO_2. With CO_2 prices below 500 €/tonCO_2, the results are the same as in the cases with unlimited PV (which we will call base cases from here on). This makes sense as the PV restriction is not binding for CO_2 prices below 500 (the limited PV installation is around 750 kW).

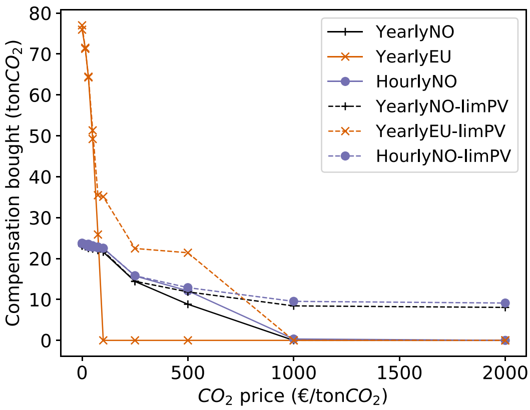


Fig. 5. CO_2 compensations bought for different CO_2 compensation price. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

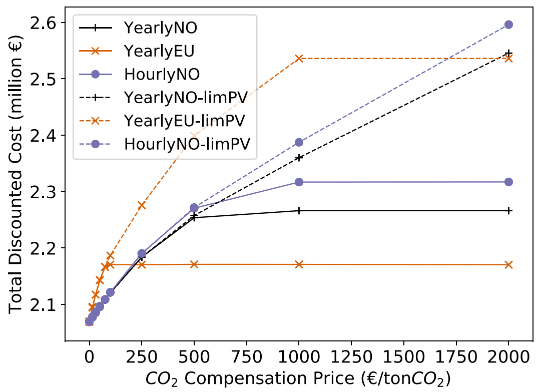


Fig. 6. Total discounted costs of energy system and operation for different CO_2 compensation price.

In all four cases with Norwegian factors, the heating grid and technologies at the neighborhood level are chosen for compensation prices between 0 and 500 €/tonCO_2. The principal reason to invest in technologies at the neighborhood level is the same as for technologies inside buildings, i.e. the cost (investment and operation) and the associated emissions; the main difference is that an additional cost for the heating grid is necessary together with some transmission losses that need to be compensated. Here, for that external CO_2 price range, it invests in an electric boiler and a gasified biomass CHP, thus indicating that they are cost effective to invest in and operate in comparison with the other technologies inside the buildings.

The annual average CO_2 factor of the *HourlyNO* case and the one used in the *YearlyNO* cases are the same, which explains the similarity of the results. PV is found to be the cheapest option to reach the balance with the cost assumptions made in this paper.

In regard to the amount of CO_2 compensations bought, as can be observed from Fig. 5, the four cases with Norwegian CO_2 factors (in blue and green) behave very similarly up to 250 €/tonCO_2. Above that the limPV cases converge towards 10 tons of bought compensation while the base cases go down to zero at 1000 €/tonCO_2. There are still compensations bought at such a price in the limPV cases because no more PV can be installed (the limit is reached) and the external compensation is still the cheapest option to achieve net zero emissions. If we had increased the price of external compensations further, we can expect that the external compensations bought would also have gone to zero and that another technology would have been installed, such as a CHP for instance (and possibly also replacing other technologies).

The amount of CO_2 emitted from the ZEN and the CO_2 compensations (Fig. 9) is also similar across the cases using Norwegian CO_2 factors, with the exception of the limPV cases that we covered above. Overall, when buying external compensation becomes more expensive, lower overall emissions are achieved.

The total discounted costs (Fig. 6) are similar across the four NO cases until 500 €/tonCO_2, after which they diverge. In the limPV cases, they continue to increase linearly with the price of external compensations (the amount of compensation bought remains the same), while in the base cases, they converge at 2.26 and 2.31 million euros for, respectively the *YearlyNO* and the *HourlyNo* case.

6.2. *European* CO_2 *factors for electricity*

To investigate the impact of a higher CO_2 factor for the European condition at 132 g/kWh, we compare the cases with Norwegian factors to the *YearlyEU* case. When no external compensation is available (at 2000 €/tonCO_2), Fig. 4 shows that the investments in PV is around 1300 kW, 400 kW lower than in the *YearlyNO* and *HourlyNO*. There is also a 155 kW biomethane boiler, a 60 kW gasified biomass CHP, and an 107 kW air-source heat pump. Moreover, the heat storage is a combination of SH storage and storage at the neighborhood level.

The lower amount of PV in comparison to the Norwegian factor cases is due to the relatively higher CO_2 factor used, allowing to obtain more compensations from the PV production in the summer. In both the *YearlyEU* and the *HourlyNO* the CO_2 factors are high in the winter. However, in the *YearlyEU* case it is also high in the summer, thus making compensating easier. The comparison between the *YearlyNO* and the *YearlyEU* cases is slightly different. Indeed, in both cases the electricity emission factor is constant throughout the year. If their heating systems were only electricity based, there should be no difference between the energy systems in both cases as the imports of electricity and the exports have the same emission value. This would mean that the amount of PV in both cases should be the same. However, our results show that this is not the case here and this is due to the heating technologies using fuels other than electricity. In the *YearlyEU* case, the heat pump is significantly smaller, leading to relatively less production of heat from it (Fig. 7) and thus less electricity imports and fewer emissions. In addition, the biomethane boiler is significantly larger and there is a gasified biomass CHP. The biomethane boiler is used more than in the *YearlyNO* case and the gasified biomass CHP provides around two-thirds of the heat. In the *YearlyEU* case, the CO_2 factor of electricity is higher than the CO_2 factors of those technologies, thus allowing the exported electricity to compensate for producing heat with these technologies more easily. Moreover, this is amplified by the fact that the CHP also produces electricity that can reduce the imports or be exported, and contribute to the compensations/reduction of emissions.

When the external compensation price is reduced, nothing happens until 75 €/tonCO_2, except for a small reduction of around 30 kW in the amount of PV for 1000 and 500 €/tonCO_2. From 75 €/tonCO_2 and below, external compensations are bought (Fig. 5). It principally affects the amount of PV which gradually reduces to reach the same level as in the other base cases. The size of the biomethane boiler is also reduced to a similar amount as in the other base cases.

In the *YearlyEU* case with PV limitation and when no compensation can be bought (at 2000 €/tonCO_2), PV is still the best technology available to the model to reach net zero emissions and so the amount of PV is similar to the other limPV cases. However, the air-source heat pump is replaced completely by a 150 kW biomethane boiler. The heat storage is covered by a 150 kWh heat storage at the neighborhood

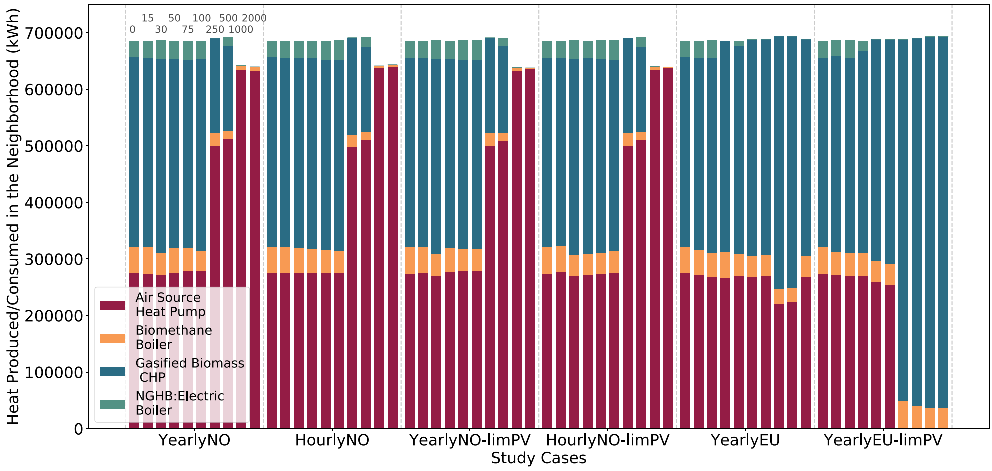


Fig. 7. Heat produced in the neighborhood by each technology in the runs grouped by case.

level. A grid-scale battery of 1000 kWh is also installed. With a higher and constant CO_2 factor, and as it cannot invest in more PV, the optimization chooses to rely on the CHP for the additional electricity exports needed to reach the emission balance. The CHP use (which can be seen in Fig. 7) is primarily driven by the need for electricity and the heat is the by-product. The battery is used to store the electricity from the CHP that cannot be directly exported and/or to maximize the profit from selling the electricity.

At 1000 €/tonCO_2, the system is the same. As the external compensation price is reduced further to 500 and 250 €/tonCO_2, the battery is no longer chosen, and it is replaced by more heat storage and by purchasing external compensations (Fig. 5). Going even further to 75 and 100 €/tonCO_2, the size of the gasified biomass CHP is reduced, some of the neighborhood scale heat storage is converted to SH storage, and an air-source heat pump appears, taking over around 40% of the heat production (Fig. 7). Lowering the price of external compensations further leads to a reduction of the amount of PV invested, replaced by purchasing more external compensations (Fig. 5).

The cost of the system in the *YearlyEU* cases with and without the PV limitation (Fig. 6) is the same up to 75 €/tonCO_2 at which point it is no longer possible to increase the amount of PV in the limPV case, leading to more purchase of external compensations. The cost of the system stays constant from this point in the base case while it continues increasing in the limPV case due to the need of external compensation and from 1000 €/tonCO_2, due to the investment in the battery.

The heating grid is always chosen.

6.3. Marginal emission factors for electricity

The cases using the marginal emission factors for electricity give the following results.

As a reminder, *Case 1* accounts all exchanges of electricity using marginal factors, *Case 2* uses marginal factors only for the exports of locally produced electricity and *Case 3* uses marginal factors for local batteries in addition to the local production of electricity. Fig. 8, shows the resulting energy system investment for the runs using marginal emission factors. The first observation is that *Case 2* and *Case 3* are very similar. Indeed, investment in the battery is not optimal according to the optimization, meaning that both cases are equal. The minor difference in investment illustrates that close to optimality (here within a MIP gap of 0.1%), there can be different solutions.

The investments in the heating system are very similar and the size of PV is the main differentiation, with *Case 1* having a 70% bigger

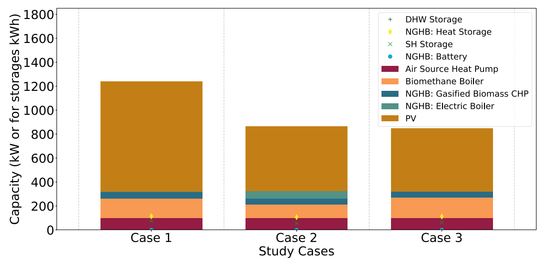


Fig. 8. Investments resulting from the runs with marginal factors. When the technology is at the neighborhood level, its name is preceded by NGHB.

Table 4
Other results from the three marginal cases, including annual emissions, total discounted costs and external compensation bought.

	Case 1	*Case 2*	*Case 3*
Emissions (tonCO_2/year)	83.261	23.964	25.498
Total discounted costs (€)	2 137 299	2 060 269	2 058 756
External compensation bought	0	0	0

PV system. The marginal factors being overall higher than the average factors in NO1, this result was expected.

When comparing the results using marginal factors to the one using average factors, the impact of higher factors, and in particular in the summer, with marginal factors is clear and results in a smaller PV system. The energy system also uses more carbon intensive technologies. Those results are comparable to the investments obtained when decreasing the external compensation price with average emission factors.

Table 4 presents the total discounted costs and the emissions for the three marginal cases. No external compensation is bought in those cases (as intended, the price of external compensation being 10000 €/tonCO_2). This means that the emissions presented in this table also corresponds to the local and total compensations. The overall higher marginal emission factors lead to very high emissions in *Case 1*, due to accounting local imports of electricity with the marginal factors. This number is in a similar range to the amount of emissions in the case *YearlyEU*. This can be explained by the fact that the marginal factor in NO1 is most often driven by imports from Europe. *Case 2* and *Case*

3 have slightly higher emissions than in the case *HourlyNO* due to the extra compensations that they get by using marginal factors on their electricity exports. In terms of total discounted costs, all three cases end up being less expensive than the ones using only average emission factors and a similar price of external compensation, but also for Case 2 and Case 3 lower by about 10000€ than the cases with free external compensation and average emission factors. This minor difference can most likely be attributed to the differences between the clusters of the cases using average and marginal factors.

7. Limitations

This paper's objective is to discuss and highlight the impact of the choice of CO_2 factor of electricity and alternative compensation mechanisms on the design of the energy system of ZENs. The results presented in this paper are only valid under the cost assumptions made and the context of the case study.

Another limitation is that storage operation is only intra-day, and does not consider inter-day or seasonal storage. This limitation arises from the computational complexity of the problem leading to the modeling choice of using clustering and of leaving these storage operations out. Making a model accounting for those storage operations is possible, for example by operating one or several continuous years, at the cost of much higher computational times. It is also possible to model seasonal storage and inter-day storage when using clustering, but again with an addition computational burden [7,35]. There are other ways to reduce the computational complexity of the model, for example by limiting the number of binary variables associated with the technology costs or the part-load limitation. If including those storage applications is important in your particular case, a different trade-off than the one chosen in this paper might be more suitable when designing the model for your application.

The results focus on the compensation obtained from the energy system of the neighborhood and do not consider the load reduction impact that refurbishing the buildings would have on the amount of CO_2 to compensate. There is a competition between the investment in the refurbishment and the energy system. In particular, the refurbishment would reduce the SH load and lead to smaller heating units also leading to less need for compensation and a smaller size of PV. It being chosen by the model would depend highly on the expected load reduction and cost of the refurbishment. Evaluating the potential of refurbishment for older building stock when designing ZENs remains as future work.

The lack of major changes in the choices of technologies when reducing the price of external compensations to zero can appear strange. This is a result of the technology options and their cost and emission assumptions making the same technologies cost-optimal with and without the emission constraint.

8. Discussion

In this paper we discuss and investigate the impact of the CO_2 factors and of altering the ZEN definition to allow for external compensation on the energy system of ZENs.

The carbon offset companies, introduced in Section 5, offer a way to compensate emissions but the real impact of the compensation bought in terms of emission reduction and additiveness is hard to measure. In addition, it might be politically difficult to justify. Indeed, relying on such measures would create a flow of money towards the emission reduction and the development in places other than Norway, which could be seen negatively by a share of the population. A solution to this would be to have compensations paid for emissions reduction inside the country. In the case of Norway, this could mean that the compensation bought could, for instance be used to incentivize EV, incentivize refurbishment of older houses or to finance emission-reduction measures in some carbon-intensive industry. This would allow a refocus of some part of the objective of being a ZEN from an already low emission power system, where gains are hard to achieve, to other more problematic areas where a bigger impact can be made. The main problem of this approach is to quantify the price of CO_2 reduction and the actual emission reduction achieved.

We advocate the use of hourly CO_2 factors which allow the possibility to consider and incentivize, in the optimization, to produce when the carbon intensity is the highest. However, it is not straightforward to compute those emissions for historical years and it is difficult to take into account the changes in the hourly carbon intensity profiles that will arise due to the changing European power system. With the increase of wind and solar capacity, which have significant seasonal and daily variations, as well as the introduction of means to deal with their limited dispatchability, the hourly carbon intensity timeseries is likely to be significantly modified. This can be overcome by using European market and capacity expansion models to extract future CO_2 factor timeseries. Another solution that appears acceptable in Norway is to use yearly average factors, as they give a good approximation of the investments obtained with hourly average factors and make it easier to include future changes in the power system. The use of hourly factors may still be preferable when it comes to the actual operation of the neighborhood.

The limPV cases with Norwegian factors illustrate the difficulty to reach the zero emission balance. In the limPV cases, even with very high external compensation prices, external compensation remains the most cost-effective way to reach net zero emissions along with PV. In this paper, we only included the carbon emissions from the operation of the ZEN's energy system, but the carbon emissions from materials, construction and deconstruction of the neighborhood could also be taken into account depending on the ambition of the project. This would increase the amount of CO_2 to compensate, in turns increasing the investment in PV panels until it reaches the limit. This indicates that for ZENs considering all the emissions in the project life-cycle, the external compensations would be part of the solution (at the price points considered in this study) if they were allowed by the framework.

The results presented in this paper focus only on the Norwegian case and it is important to remember the unique nature of the Norwegian power system when considering the results, and before translating them to other situations. In general, the break-even cost of external CO_2 compensations will depend on their price and on the climatic conditions (in particular the solar irradiance) and the spot price of electricity which affects the investment and compensation obtained from PV panels. From Fig. 5, a lower CO_2 factor of electricity leads to a higher break-even cost of external compensation. We can expect a similar behavior in other countries but the specific costs will depend on the parameters mentioned previously. No conclusions regarding the impact of the choice of an hourly or annual factor can be made for the countries other than Norway based on this paper. The impact of this choice will depend on the level of the yearly factor and on the variations in hourly factors due to the specific power system of the area.

The results obtained using marginal factors and the difference between the marginal and average emission factor profile are very dependent on the area. The results obtained in this study are valid for NO1 and can somewhat be extended to the whole of Norway and to a lesser extent to the Nordic countries.

9. Conclusion

This paper discusses the importance of the choice of the CO_2 factor of electricity for the design of ZENs' energy systems as well as the different compensation mechanisms that can be used to reach the zero emission target. A case study is used to illustrate the impact of the CO_2 factor choice and how different CO_2 compensations' price points would affect the resulting energy system design in Norway. The results suggest that the investments using *YearlyNO* and *HourlyNO* factors are very similar, while using the *YearlyEU* factor results in less investment in PV but assigns more emissions to the neighborhood. The total cost

Table 5
Data of technologies producing heat and/or electricity.

Tech.	η_{th} (%)	Fix. Inv. Cost (€)	Var. Inv. Cost (€/kW)	α_i (% Inst. Cap.)	Min. Cap. (kW)	Annual O&M Costs (% of Var Inv. Cost)	Lifetime (year)	Fuel	α_{CHP}	El.	Heat
At building level											
PV[a]		0	730	0	50	1.42	35			1	0
ST[b]	70	28350	376	0	100	0.74	25			0	1
ASHP[c]	f(T_t)	42300	247	0	100	0.95	20	Elec.		0	1
GSHP[d]	f(T_t)	99600	373	0	100	0.63	20	Elec.		0	1
Boiler[e]	85	32200	176	30	100	2.22	20	Wood Pellets		0	1
Heater	100	15450	451	0	100	1.18	30	Elec.		0	1
Boiler	100	3936	52	20	35	2.99	25	Biomethane		0	1
Boiler	100	3936	52	20	35	2.99	25	Gas		0	1
At neighborhood level											
CHP[f]	47	0	1035	50	200	1.03	25	Biogas	1.09	1	1
CHP	98	0	894	20	1000	4.4	25	Wood Chips	7.27	1	1
CHP	83	0	1076	20	1000	4.45	25	Wood Pellets	5.76	1	1
Boiler[g]	115	0	680	20	1000	4.74	25	Wood Chips		0	1
Boiler[g]	100	0	720	40	1000	4.58	25	Wood Pellets		0	1
CHP[h]	66	0	1267	10	10	0.84	15	Wood Chips	3	1	1
Boiler[i]	58	0	3300	70	50	5	20	Biogas		0	1
GSHP[d]	f(T_t)	0	660	010	1000	0.3	25	Elec.		0	1
Boiler	99	0	150	5	60	0.71	20	Elec.		0	1
Boiler	100	0	60	15	500	3.25	25	Biogas		0	1
Boiler	100	0	60	15	500	3.25	25	Gas		0	1

[a]Area Coefficient: 5.3 m^2/kW.
[b]Area Coefficient: 1.43 m^2/kW.
[c]Air Source Heat Pump.
[d]Ground Source Heat Pump.
[e]Automatic stoking of pellets.
[f]Gas Engine.
[g]HOP.
[h]Gasified Biomass Stirling Engine Plant.
[i]Solid Oxide Fuel Cell (SOFC).

of the system depends on the limitation of PV investment. In addition, when using marginal factors, extra care need to be given to the details of the emission accounting.

The yearly factors ignore the hourly, daily and seasonal variations of the CO_2 factor of electricity but make it easier to implement in regulatory frameworks. The choice of a factor centered on Norway or on Europe depends on the system boundaries that are required. Choosing hourly factors ensures a better representation of the time variability of the factor but obtaining accurate hourly factors with a long-term perspective is more challenging. Yearly Norwegian factors represent a good approximation of the hourly case and can be used to simplify models or regulatory frameworks. This remains true even when considering the possibility to rely on external compensation for reaching the zero emission balance. Furthermore, allowing for external compensation at a price of 250 gCO_2/kWh would reduce the overall cost of ZEN energy systems by more than 10% with the technology options investigated in this paper and in a setting with limited roof area and no additional available space for PV. The price and type of this external compensation as well as whether it makes sense from a global CO_2 reduction perspective has been briefly discussed but it remains beyond the scope of this paper to draw definitive conclusions on this matter. However, the fact that the neighborhood is resorting to buying external compensations even for prices up to 1000 €/tonCO_2, questions the relevance of standards forcing strictly local compensations in reducing the emission in Norway and whether other less costly measures, either external compensations as in this paper or completely unrelated to neighborhood, would allow to have a bigger impact on CO_2 emissions. The use of marginal factors in NO1 leads to reduced energy system costs and different amount of emissions. However, the relevance of its use in the context of ZENs and its impact in other countries remain open questions.

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.

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Appendix A. Technology data

The data for those technologies come from the Danish Energy Agency and Energinet.[14] A summary of the data used is presented in Table 5. The data for storages is presented in Table 7.

The data for prices of fuels come from different sources. For the wood pellets and wood chips, they come from the Norwegian Bioenergy Association.[15] The data for the biogas and biomethane come from the European Biogas Association.[16] The price for gas is estimated based

14 https://ens.dk/en/our-services/projections-and-models/technology-data
15 http://nobio.no/wp-content/uploads/2018/01/Veien-til-biovarme.pdf
16 https://www.europeanbiogas.eu/wp-content/uploads/2019/07/Biomethane-in-transport.pdf

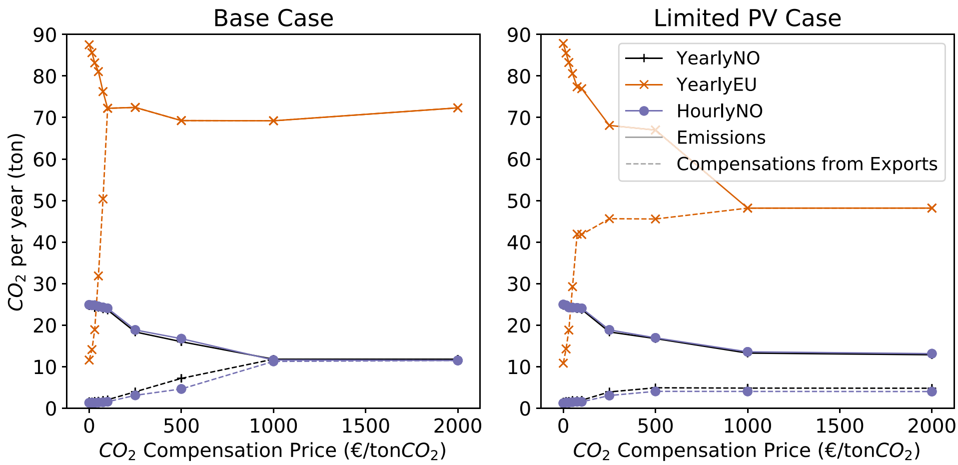

Fig. 9. CO_2 emissions and compensations for different CO_2 compensation price.

Table 6
Data of fuels.

Fuel	Fuel cost (€/kWh)	CO_2 factor (gCO_2/kWh)
Electricity	$f(t)$	$f(t)$
Wood pellets	0.03664	40
Wood chips	0.02592	20
Biogas	0.07	0
Biomethane	0.07	100
Gas (neighborhood level)	0.041	277
Gas (building level)	0.121	277

on the statistics of natural gas price in Europe for non-household consumers[17] (neighborhood level) and households consumers[18] (building level).

The data for CO_2 factor of fuels come from a report from Cundall.[19] A summary of the data for fuel is presented in Table 6.

Appendix B. Additional results

Fig. 9 shows the emissions and compensations for the different cases. The difference between the emissions and compensations are the external compensation bought.

Appendix C. Additional model's equation

Load balances for electricity (Eq. (15a)), Domestic Hot Water (DHW) (Eq. (15b)) and Space Heating (SH) (Eq. (15c)): $\forall t$:

$$y_t^{imp} + \sum_b \left(\sum_{est} y^{dch}_{t,est,b} \cdot \eta_{est} + \sum_g g^{selfc}_{g,t,b} \right) = \sum_b \left(\sum_e d_{e,t,b} + E_{b,t} \right) \tag{15a}$$

$\forall t, b$:

$$\sum_q q^{DHW}_{q,t,b} + \sum_{hst} (\eta_{hst} \cdot q^{DHWdch}_{t,hst,b} - q^{DHWch}_{t,hst,b}) + q^{HGusedDHW}_{t,b} = H^{DHW}_{b,t} + q^{dump}_{t,b} \tag{15b}$$

$$\sum_q q^{SH}_{q,t,b} + \sum_{hst} (\eta_{hst} \cdot q^{SHdch}_{t,hst,b} - q^{SHch}_{t,hst,b}) + q^{HGusedSH}_{t,b} = H^{SH}_{b,t} \tag{15c}$$

The operation of the heating grid is constrained by the following equations: $\forall t$

$$\sum_q q_{q,t,'PP'} + \sum_{hst} (\eta_{hst} \cdot q^{dch}_{t,hst,'PP'} - q^{ch}_{t,hst,'PP'}) = \sum_{b \backslash 'PP'} q^{HGtrans}_{t,'PP',b} + q^{dump}_{t,'PP'} \tag{16a}$$

$\forall b, b', t$

$$q^{HGtrans}_{t,b',b} \le \dot{Q}^{MaxPipe}_{b',b} \tag{16b}$$

$\forall b, t$

$$\sum_{b'} q^{HGtrans}_{t,b,b'} \le \sum_{b''} \left(q^{HGtrans}_{t,b'',b} - Q^{HGloss}_{b'',b} \right) \tag{16c}$$

$$q^{HGused}_{t,b} = q^{HGusedSH}_{t,b} + q^{HGusedDHW}_{t,b} \tag{16d}$$

$$q^{HGused}_{t,b} = \sum_{b''} \left(q^{HGtrans}_{t,b'',b} - Q^{HGloss}_{b'',b} \right) - \sum_{b'} q^{HGtrans}_{t,b,b'} \tag{16e}$$

$\forall i$

$$x_{i,'ProductionPlant'} \le X^{max}_i \cdot b^{HG} \tag{16f}$$

The size of the connection to the electric grid limits the exports and imports.: $\forall t$

$$y^{imp}_t + \sum_b \sum_{est} y^{imp}_{t,est,b} + \sum_b \sum_g y^{exp}_{t,g,b} \le GC \tag{17}$$

The CHP operation use a heat-to-power ratio: $\forall t, 'CHP', b$:

$$g_{CHP,t,b} = \frac{q_{CHP,t,b}}{\alpha_{CHP}} \tag{18}$$

Heat can be DHW or SH and some technologies can only provide SH: $\forall q, t, b$:

$$q_{q,t,b} = q^{DHW}_{q,t,b} + q^{SH}_{q,t,b} \tag{19}$$

$$q^{DHW}_{q,t,b} <= M \cdot B^{DHW}_q \tag{20}$$

[17] https://ec.europa.eu/eurostat/statistics-explained/index.php?title=File:Natural_gas_prices_for_non-household_consumers,_second_half_2019_(EUR_per_kWh).png

[18] https://ec.europa.eu/eurostat/statistics-explained/index.php?title=File:Natural_gas_prices_for_household_consumers,_second_half_2019_(EUR_per_kWh).png

[19] https://cundall.com/Cundall/fckeditor/editor/images/UserFilesUpload/file/WCIYB/IP-4%20-%20CO2e%20emissions%20from%20biomass%20and%20biofuels.pdf

Table 7
Data of storage.

Index	One way eff. (%)	Inv. Cost (€/kWh)	O&M Cost (% of Inv. Cost)	Lifetime (year)	Min. Cap. (kWh)	Charge/Discharge rate (% of Cap)
Battery						
1[a]	95	577	0	10	13.5	37
2[b]	938	500	0	15	210	23
3[c]	95	432	0	20	1000	50
Heat storage						
1[d]	95	75	0	20	0	20
2[c]	98	3	0.29	40	45 000	1.7

[a]Based on Tesla Powerwall.
[b]Based on Tesla Powerpack.
[c]Based on Danish energy agency data.
[d]Same data are used for the heat storage at the building or neighborhood level and for both SH and DHW.

PV and Solar thermal operation uses the units efficiency and irradiance:

$$g_{PV,t} + g_t^{curt} = \eta_{PV,t} \cdot x_{PV} \cdot IRR_t^{tilt} \tag{21}$$

$$q_{ST,t} = \eta_{ST} \cdot x_{ST} \cdot IRR_t^{tilt} \tag{22}$$

Batteries and local production technologies are connected: $\forall t, b$:

$$\sum_g g_{t,g,b}^{ch} = \sum_{est} y_{t,est,b}^{ch} \tag{23}$$

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Paper 5

Enforcing Annual Emission Constraints in Short-Term Operation of Local Energy Systems

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***Abstract*—This paper tackles the problem of the enforcement of life-cycle constraints, here net-zero emissions over the lifetime of a neighborhood, during the short-term operation of an energy system. The paper starts by designing the cost-optimal energy system of a Zero Emission Neighborhood (ZEN) before comparing different optimization approaches to its short-term operation and their performance for meeting the long-term target. In addition, both cases where a limitation on the PV size (PVlim case) is and isn't there (Base Case) are performed. The resulting energy systems are, in the Base case, PV, heat pumps, a gas boiler and heat storage and, in the PVlim case, a smaller amount of PV, a CHP plant, and heat storage. Four operational approaches are used, including one for reference using perfect forecast. The other methods are a purely economic model predictive control (MPC), a MPC with penalty for deviations of emissions and compensations patterns and finally a receding horizon approach. In the PV dominant system of the base case, the compensations from passively exporting the PV production are enough to reach net-zero emissions. In such systems, specific operational strategies are not necessary. In the PVlim case including a CHP and less PV, that approach is not sufficient. The receding horizon manages to reach the long-term target at the lowest cost, with the downside of a higher computational burden, while the MPC with penalties is promising but would require fine-tuning to balance the costs and emissions.**

***Index Terms*—Operation, Design, Optimization, Distributed Energy Resources, Zero Emission**

NOMENCLATURE

Index(Sets)

$t(\mathcal{T})$	Timestep in hour within year, $\in [0, 8759]$
$\kappa(\mathcal{K})$	Cluster representative (centroid)
$t_\kappa(\mathcal{T}_\kappa)$	Timestep within cluster κ, $\in [0, 23]$
$b(\mathcal{B})$	Building or building type
$i(\mathcal{I})$	Energy technology, $\mathcal{I} = \mathcal{F} \cup \mathcal{E} \cup \mathcal{HST} \cup \mathcal{EST}; \mathcal{I} = \mathcal{Q} \cup \mathcal{G}$
$f(\mathcal{F})$	Technology consuming fuel (gas, biomass, ...)
$e(\mathcal{E})$	Technology consuming electricity
$hst(\mathcal{HST})$	Heat storage technology
$est(\mathcal{EST})$	Electricity storage technology
$q(\mathcal{Q})$	Technologies producing heat
$g(\mathcal{G})$	Technologies producing electricity
$b(\mathcal{B})$	Building or building type

Parameters

α_{CHP}	Heat to electricity ratio of the CHP
α_i	Part load limit as ratio of installed capacity
$\dot{Q}^{MaxPipe}_{b_1,b_2}$	Maximum heat flow in the heating grid pipe going from b_2 to b_1 [kWh]
$\dot{Q}^{max}_{st}$	Maximum charge/discharge rate of est/hst [kWh/h]
η_{est},η_{hst}	Efficiency of charge and discharge
η_{inv}	Efficiency of the inverter
η_i	Efficiency of i
$\phi^{CO_2,f}$	CO_2 factor of fuel type f $[gCO_2/kWh]$
$\phi^{CO_2,el}_t$	CO_2 factor of electricity at t $[gCO_2/kWh]$
σ_κ	Number of occurrences of cluster κ in the year
$\varepsilon^{tot}_{r,D}$	discount factor for the duration of the study D with discount rate r
B^{DHW}_q	Binary parameter stating whether q can produce DHW
C^{HG}	Cost of investing in the heating grid [€]
$C^{maint}_{i,b}$	Annual maintenance cost of i in b [€/kWh]
$C^{var,disc}_{i,b}$,$C^{fix,disc}_{i,b}$	Variable/Fix investment cost of i in b discounted to the beginning of the study including potential re-investments and salvage value [€/kWh]/[€]
$COP_{hp,b,t}$	Coefficient of performance of heat pump hp
$E_{b,t}$	Electric load of b at t $[kWh]$
$Em^{0\rightarrow t0}$,$Comp^{0\rightarrow t0}$	Emissions/Compensations between the start and the current timestep $[gCo_2]$
G^{stc}	Irradiance in standard test conditions: $1000W/m^2$
GC	Size of the neighborhood grid connection [kW]
$H^{SH}_{b,t}$,$H^{DHW}_{b,t}$	Heat (Space heating/Domestic Hot Water) load of b at t $[kWh]$
IRR^{tilt}_t	Total irradiance on a tilted plane $[W/m^2]$
M	"Big M, taking a large value
P^{grid}	Electricity grid tariff [€/kWh]
$P^{input,max}_{hp,b,t}$	Maximum power consumption of hp at t based on manufacturer data and output temperature
P^{ret}	Retailer tariff on electricity [€/kWh]
P^{fuel}_f	Price of fuel of g [€/kWh]
P^{spot}_t	Spot price of electricity at t [€/kWh]
$Q^{HGloss}_{b_1,b_2}$	Heat loss in the heating grid in the pipe going from b_2 to b_1
T^{coef}	Temperature coefficient
T^{MPC}	Length of the MPC horizon
T^{noct}	Normal operating cell temperature [°C]
T^{stc}	Ambient temperature in standard test condi-

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	tions [°C]
T_t	Ambient temperature at t [°C]
X_i^{max}	Maximum investment in i [kW]
X_i^{min}	Minimum investment in i [kW]
Variables	
$\overline{x_{i,b,t}}$	Maximum production from i [kWh]
b^{HG}	Binary for the investment in the Heating Grid
$b_{i,b}$	Binary for the investment in i in b
c^{Em},c^{Comp}	Penalization cost for deviating from the emission/compensation targets [€]
$d_{e,t,b}$	Electricity consumed by e in b at t [kWh]
$f_{f,t,b}$	Fuel consumed by f in b at t [kWh]
$g_{t,b}^{curt}$	Solar energy production curtailed [kWh]
$g_{g,t,b}^{dump}$	Electricity generated but dumped by g at t [kWh]
$g_{g,t,b}$	Electricity generated by g at t [kWh]
$g_{t,g,b}^{ch}$	Electricity generated by g used to charge the batteries at t [kWh]
$g_{t,g,b}^{selfc}$	Electricity generated by g self consumed in the neighborhood at t [kWh]
$o_{i,t,b}$	Binary controlling if i in b is on or off at t
$q_{t,st,b}^{ch}$, $q_{t,st,b}^{dch}$	Energy charged/discharged from the neighborhood to the storage at t [kWh]
$q_{t,b}^{dump}$	Heat dumped at t in b [kWh]
$q_{b_1,b_2,t}^{HGtransfer}$	Heat transferred via the heating grid from b_1 to b_2 at t [kWh]
$q_{b,t}^{HGused}$	Heat taken from the heating grid by b at t [kWh]
$q_{q,t,b}$	Heat generated by q in b at t [kWh]
$v_{t,st,b}^{stor}$	Level of the storage st in building b at t [kWh]
$x_{i,b}$	Capacity of i in b
$y_{t,est,b}^{ch}$	Electricity charged from on-site production to est at t [kWh]
$y_{t,est,b}^{dch}$	Electricity discharged from est to the neighborhood at t [kWh]
$y_{t,est,b}^{exp}$	Electricity exported from the est to the grid at t [kWh]
$y_{t,est,b}^{imp}$	Electricity imported from the grid to est at t [kWh]
$y_{t,g,b}^{exp}$	Electricity exported by g to the grid at t [kWh]
y_t^{imp}, y_t^{exp}	Electricity imported from the grid to the neighborhood/exported at t [kWh]

I. Introduction

Zero Emission Neighborhoods (ZENs) are neighborhoods that aim to have net-zero emissions of CO_2 in their lifetime. In order to design the energy system of such neighborhoods, a tool called ZENIT has been developed. It uses a mixed-integer linear program (MILP) to minimize the cost of investing in and operating the energy system of a neighborhood while reaching the net-zero emissions requirement during its lifetime. However, short-term operation of neighborhoods usually does not allow for such long-term considerations, due to the mismatch between a reasonable forecast horizon and the time-frame that needs to be considered for the long-term constraint. In this paper, we investigate the question of whether it is necessary to have specific operation models for reaching net-zero emissions in the neighborhood's lifetime and how we can make sure that the system is operated in a similar way with the short-term operation models as in the investment model, i.e. how can long-term requirements be included in short-term operation of local energy systems.

Several approaches can be used for the short-term operation of local energy systems. The methods vary depending on their focus and the specificities of each energy system. A first approach is to use rule-based methods. [1] presents an example with a focus on maximizing PV self-consumption and compares it to an optimization-based approach. Optimization models are tools that allow to find the maximum or minimum of an objective function, often minimum cost, while satisfying technical constraints. Various optimization approaches can be used. A simple approach is the use of linear programs (LP) or mixed integer LP (MILP) which can be applied to the operation of energy systems, with for example the use of a rolling or receding horizon. Model predictive control (MPC), which originally describes a method for controlling a process through a model-based on-line optimization strategy, can also be used to describe rolling horizon optimization approaches in the context of local energy systems (such as in [2], [3], [4], [5], [6]). A few examples of such models (LP, MILP, MPC) for the operation of local energy systems are presented below. A LP is presented in [7] and used to investigate various time-differentiated electricity tariffs during the operation of a local energy system, while [8] uses a MILP in a system including a fuel cell, PV and batteries. [9] compares different formulations (MILP, receding horizon, and robust approaches) for including the effect of forecast errors into short-term operation. MPC is also a common solution for short-term operation. [2] uses it for a microgrid with battery storage including the possibility to use high power rate momentarily. [3] applies MPC to the operation of thermal and non-thermal appliances, and [4] to a building cooling system. [6] and [5] use it for building heating systems and report results of actual implementations. Dynamic programming (DP) is also a class of model that can be used for operation optimization, such as in [1] where the non-linear energy system control problem is solved in 24h intervals using this method. DPs however can have long solving time and scale poorly, which can make them difficult to implement with rolling horizons. [10] and [11] present energy management systems using a multi agent framework. Here the agents are different components of the energy systems to control, which each have their own controls but also cooperate and coordinate to reach a global objective. [12] also uses this approach and uses a genetic algorithm to control agents in a decentralized manner. In a similar decentralized problem, with information privacy between components, [13] suggests an algorithm based on the alternating direction methods of multipliers (ADMM).

The methods presented in the papers cited above allow to tackle the operation of an energy system but do not address the main question of this paper: how to incorporate long-term considerations to such models. It is possible to draw parallels with problems tackled in other articles in the literature. [14], in a context different from local energy systems, deals with short-term unit commitment and how to include long-term energy constraints. It does it by using a two-step approach solving first a one year model with daily steps to get bounds that can be used in the second, shorter-terms, steps. [9] makes a link between the planning problem and the operation problem and confirms the adequacy of the system obtained in the planning phase by using a receding horizon robust approach considering forecast errors. [15] solves a receding horizon with two stages to reduce complexity. First, a "medium-term" operation of one day with one hour sampling is done, then using the results from the first stage, a "short-term" operation of one hour with five min sampling is performed. [16] uses a similar multi-level structure as in [15] to reduce the complexity of the short-term operation. [17] uses stochastic DP (SDP) for the operation of a local energy system subject to a measured-peak grid tariff. This tariff considers the highest power peak in a month for its pricing. Using SDP allows to find optimal control strategies considering the uncertainties around the highest peak and several stochastic variables. This latter approach can also be compared to the operation of hydropower plants where SDP is an important tool used for linking operation problems with different time horizons (from several years to a few days). In [18] for example, the long-term hydro-reservoir level curves resulting from long-term planning models of the reservoirs are used to constrain the production of the hydropower plant in a rolling horizon framework.

In a context of emission accounting, closer to the problem raised in this paper, [19] uses an integral constraint on the emissions in the daily operation optimization of a chemical process to account for allowances given in an emission cap and trade system. It discusses four approaches to tackle the issue: assigning a cost to emissions from the start or from the moment the allowances are all used, or assigning emission limits or costs based on projections of the emission level in the rest of the year.

While the literature presents examples of similar topics, and methods that can give inspiration for the problem to tackle in this paper, they do not address several key aspects. Indeed, there is still a need to study how a long-term net-zero emission target, at the scale from a year up to a neighborhood lifetime, can be translated into a short-term operation problem. It is also still necessary to figure out if in the context of ZENs it is necessary to include this long-term objective or if it could be reached without specific approaches in the short-term model.

This paper contributes to the existing literature in the following ways:

- Describe the process of selecting a reference year for the design of a ZEN
- Study whether specific operation models are needed for reaching net-zero emissions despite a short-term horizon
- Suggest and compare several potential operation models and their ability to reach net-zero emissions in the long-term

The paper is structured as follows. In section II, the investment models as well as the short-term operation approaches and the case study are presented. Then, the selection process of a reference year is introduced in section III. This year is then used to design the energy system of ZENs, which are presented in section IV-A. These ZENs' energy system designs are finally used as cases to compare the performances of the operational approaches in section IV-B using the years not selected for being the reference year.

II. Methodology

A. Presentation of ZENIT

In this section, the investment model called ZENIT (Zero Emission Neighborhood Investment Tool) and the setup of the study are presented before introducing the resulting systems that will be operated in the following sections.

ZENIT uses optimization to find the cost-optimal energy system for a neighborhood to have net-zero emissions in its lifetime. It uses one representative year instead of the whole lifetime for computational reasons. This description is an extract from [20]. The objective function is:

Minimize:

$$b^{HG} \cdot C^{HG} + \sum_b \sum_i \Big((C^{var,disc}_{i,b} + \frac{C^{maint}_{i,b}}{\varepsilon^{tot}_{r,D}}) \cdot x_{i,b} + C^{fix,disc}_{i,b} \cdot b_{i,b} \Big) + \sum_{t_\kappa} \frac{\sigma_\kappa}{\varepsilon^{tot}_{r,D}} \Big(\sum_b \sum_f f_{f,t,b} \cdot P^{fuel}_f + (P^{spot}_t + P^{grid} + P^{ret}) \cdot (y^{imp}_t + \sum_b \sum_{est} y^{imp}_{t,est,b}) - P^{spot}_t \cdot y^{exp}_t \Big) \quad (1)$$

It considers the fixed and variable investment cost of the different technologies ($C^{var,disc}_{i,b}$, $C^{fix,disc}_{i,b}$) and the heating grid (C^{HG}), as well as operation- and maintenance-related costs ($C^{maint}_{i,b}$). A binary variable controls the investment in the heating grid (b^{HG}). The subscripts used in the equations are b for the buildings, i for the technologies, t for the timesteps, f for fuels and est for batteries. ε are the discount factors with interest rate r for the duration of the study D. $x_{i,b}$ is the capacity of the technologies and $b_{i,b}$ the binary related to whether it is invested in or not. σ_κ is the number of occurrences of cluster κ in the full year and t_κ is the timestep in the cluster. P are the prices of fuel, electricity on the spot market, grid tariff or retailer tariff. f is the consumption of fuel and y are the imports or exports of electricity.

In order to fulfill the zero emission requirement presented in section III, the following constraint, called the Zero Emission Balance is used:

$$\phi^{CO_2,el}_t \sum_{t_\kappa} \sigma_\kappa \Big(y^{imp}_t + \sum_b \sum_{est} y^{imp}_{t,est,b} \Big) + \sum_{t_\kappa} \sigma_\kappa \sum_b \sum_f \phi^{CO_2,f} \cdot f_{f,t,b} \leq \sum_{t_\kappa} \phi^{CO_2,el}_t \cdot \sigma_\kappa \Big(\sum_b \sum_{est} \eta_{est} \cdot y^{exp}_{t,est,b} + \sum_b \sum_g y^{exp}_{t,g,b} \Big) \quad (2)$$

The CO_2 factors are represented by $\phi^{CO_2,el}_t$ for electricity and $\phi^{CO_2,f}$ for other fuels. η_{est} is the charging efficiency of the battery. This constraint ensures that the emissions from fuel use and electricity import are at least compensated for by exports of electricity from local sources.

Other equations include load balances for electricity (3a), domestic hot water (DHW) (3b) and space heating (SH) (3c).

They require the production and import to be equal to the consumption and exports for all timesteps. $\forall t$:

$$y_t^{imp} + \sum_b \Big(\sum_{est} y_{t,est,b}^{dch} \cdot \eta_{est} + \sum_g g_{g,t,b}^{selfc}\Big) = \sum_b \Big(\sum_e d_{e,t,b} + E_{b,t}\Big) \quad (3a)$$

$\forall t, b$:

$$\sum_q q_{q,t,b}^{DHW} + \sum_{hst}(\eta_{hst} \cdot q_{t,hst,b}^{DHWdch} - q_{t,hst,b}^{DHWch}) + q_{t,b}^{HGusedDHW} = H_{b,t}^{DHW} + q_{t,b}^{dump} \quad (3b)$$

$$\sum_q q_{q,t,b}^{SH} + \sum_{hst}(\eta_{hst} \cdot q_{t,hst,b}^{SHdch} - q_{t,hst,b}^{SHch}) + q_{t,b}^{HGusedSH} = H_{b,t}^{SH} \quad (3c)$$

The optimization model can choose to invest in a heating grid (4f), giving access to other technologies. We assume that those technologies are located in a central production plant that feeds the heating grid. The operation of the heating grid is then constrained by the following equations: $\forall t$

$$\sum_q q_{q,t,'PP'} + \sum_{hst}(\eta_{hst} \cdot q_{t,hst,'PP'}^{dch} - q_{t,hst,'PP'}^{ch}) = \sum_{b\setminus'PP'} q_{t,'PP',b}^{HGtrans} + q_{t,'PP'}^{dump} \quad (4a)$$

$\forall b, b', t$

$$q_{t,b',b}^{HGtrans} \leq \dot{Q}_{b',b}^{MaxPipe} \quad (4b)$$

$\forall b, t$

$$\sum_{b'} q_{t,b,b'}^{HGtrans} \leq \sum_{b''} \Big(q_{t,b'',b}^{HGtrans} - Q_{b'',b}^{HGloss}\Big) \quad (4c)$$

$$q_{t,b}^{HGused} = q_{t,b}^{HGusedSH} + q_{t,b}^{HGusedDHW} \quad (4d)$$

$$q_{t,b}^{HGused} = \sum_{b''} \Big(q_{t,b'',b}^{HGtrans} - Q_{b'',b}^{HGloss}\Big) - \sum_{b'} q_{t,b,b'}^{HGtrans} \quad (4e)$$

$\forall i$

$$x_{i,'ProductionPlant'} \leq X_i^{max} \cdot b^{HG} \quad (4f)$$

The energy balance at the central production plant (PP in the equations) is modelled with 4a, the flow limit in the pipes by 4b, the distinction between the heat from the heating grid used for SH or DHW by 4d, and the heat used in the specific building by 4e. Equation 4c sets the maximum for what goes out of the building to what came in, i.e. heat produced in the building cannot be fed to the heating grid.

The size of the connection to the national electric grid limits the exports and imports: $\forall t$

$$y_t^{imp} + \sum_b \sum_{est} y_{t,est,b}^{imp} + \sum_b \sum_g y_{t,g,b}^{exp} \leq GC \quad (5)$$

For most technologies, the production of heat or electricity is linked to the fuel consumption using the efficiency of the technology. $\forall \gamma \in \mathcal{F} \cap \mathcal{Q}, t, b$:

$$f_{\gamma,t,b} = \frac{q_{\gamma,t,b}}{\eta_\gamma} \quad (6a)$$

$\forall \gamma \in \mathcal{E} \cap \mathcal{Q}, t, b$:

$$d_{\gamma,t,b} = \frac{q_{\gamma,t,b}}{\eta_\gamma} \quad (6b)$$

For CHPs, the electricity produced is the ratio of the heat produced and the heat to power ratio α_{CHP}: $\forall t, 'CHP', b$:

$$g_{CHP,t,b} = \frac{q_{CHP,t,b}}{\alpha_{CHP}} \quad (7)$$

In general, the heat produced by any technology can be used for DHW or for SH (8) but some technologies can only provide SH (such as electric radiators or wood stove). Equation 9 translates this constraint. $\forall q, t, b$:

$$q_{q,t,b} = q_{q,t,b}^{DHW} + q_{q,t,b}^{SH} \quad (8)$$

$$q_{q,t,b}^{DHW} <= M \cdot B_q^{DHW} \quad (9)$$

The production from PV and solar thermal collectors depends on the irradiance on a tilted surface IRR_t^{tilt} and their efficiency. The efficiency for the solar panel η_t^{PV} is defined based on [21] and accounts for the cell temperature T_c and inverter losses.

$$g_{PV,t} + g_t^{curt} = \eta_{PV,t} \cdot x_{PV} \cdot IRR_t^{tilt} \quad (10a)$$

$$q_{ST,t} = \eta_{ST} \cdot x_{ST} \cdot IRR_t^{tilt} \quad (10b)$$

$$\eta_{PV,t} = \frac{\eta^{inv}}{G^{stc}} \cdot \big(1 - T^{coef} \cdot (T^c - T^{stc})\big) \quad (10c)$$

$$T^c = T_t + (T^{noct} - 20) \cdot \frac{IRR_t^{tilt}}{800} \quad (10d)$$

For the heat pumps in the buildings, the heat production and electrical consumption are defined as follows:

$$d_{hp,b,t}^{SH} = \frac{q_{hp,b,t}^{SH}}{COP_{hp,b,t}^{SH}} \quad (11a)$$

$$d_{hp,b,t}^{DHW} = \frac{q_{hp,b,t}^{DHW}}{COP_{hp,b,t}^{DHW}} \quad (11b)$$

$$\frac{d_{hp,b,t}^{DHW}}{P_{hp,b,t}^{input,max,DHW}} + \frac{d_{hp,b,t}^{SH}}{P_{hp,b,t}^{input,max,SH}} \leq x_{hp,b} \quad (11c)$$

Equations 11a and 11b link the heat produced to the COP and the electrical consumption of the heat pump. The COPs are different for SH and DHW due to different temperature set points. They also depend on the outside temperature and they are calculated before the optimization based on regression from manufacturers' data and the temperature timeseries. Equation 11c regulates how the heat pump can be used for both SH and DHW and enforces that the capacity invested is not exceeded. $P^{input,max}$ represents the maximum power input to the heat pump at the timestep based on the temperature set point and for a 1kW unit. $d_{hp,b,t}^{SH}$ and $d_{hp,b,t}^{SH}$ represent the electric consumption of the heat pump for SH and DHW while $q_{hp,b,t}^{DHW}$ and $q_{hp,b,t}^{DHW}$ are the heat production.

Another binary variable is used for part-load limitations. This binary concerns the operation and is defined for every timestep for each relevant technology, which can lead to a large number of binary variables. No minimum up- or downtime is used. $\forall i \setminus HP, t, b$:

$$\overline{x_{i,b,t}} \leq X_{i,b}^{max} \cdot o_{i,t,b} \tag{12a}$$

$$\overline{x_{i,b,t}} \leq x_{i,b} \tag{12b}$$

$$\overline{x_{i,b,t}} \geq x_{i,b} - X_{i,b}^{max} \cdot (1 - o_{i,t,b}) \tag{12c}$$

$$q_{i,b,t} \leq \overline{x_{i,b,t}} \tag{12d}$$

$$q_{i,b,t} \geq \alpha_{i,b} \cdot \overline{x_{i,b,t}} \tag{12e}$$

The size of the investment in each technology type is bounded from below to represent the larger scale of some technologies (13a) and from above (13b) to limit the size of the research space. $\forall i, b$:

$$x_{i,b} \leq X_{i,b}^{max} \cdot b_{i,b} \tag{13a}$$

$$x_{i,b} \geq X_{i,b}^{min} \cdot b_{i,b} \tag{13b}$$

Technologies producing electricity can feed this electricity to the neighborhood directly, store it in batteries, export it or dump it.$\forall t, g, b$:

$$g_{g,t,b} = y_{t,g,b}^{exp} + g_{g,t,b}^{selfc} + g_{t,g,b}^{ch} + g_{t,g,b}^{dump} \tag{14}$$

To distribute the production to the batteries, we have $\forall t, b$:

$$\sum_{g} g_{t,g,b}^{ch} = \sum_{est} y_{t,est,b}^{ch} \tag{15}$$

The storage operation, be it heat or electrical storage, is modeled as follows: $\forall \kappa, t_\kappa \in [1, 23], st, b$

$$v_{\kappa,t_\kappa,st,b}^{stor} = v_{\kappa,t_\kappa-1,st,b}^{stor} + \eta_{st,b}^{stor} \cdot q_{\kappa,t_\kappa,st,b}^{ch} - q_{\kappa,t_\kappa,st,b}^{dch} \tag{16}$$

$\forall \kappa, t_\kappa \in [0, 23], st, b$

$$v_{\kappa,t_\kappa,st,b}^{stor} \leq x_{st,b} \tag{17}$$

$$q_{\kappa,t_\kappa,st,b}^{ch} \leq \dot{Q}_{st}^{max} \quad (18) \qquad q_{\kappa,t_\kappa,st,b}^{dch} \leq \dot{Q}_{st}^{max} \quad (19)$$

$\forall st, b, \kappa$

$$v_{\kappa,0,st,b}^{stor} = v_{\kappa,23,st,b}^{stor} \tag{20}$$

The state of charge of the storage st (either heat or electric storage) is represented by v^{stor} while q^{ch} and q^{dch} are the energy charged and discharged. The maximum charge and discharge rate is Q_{st}^{max}. This model only allows for the use of representative days and daily storage operation. Details of the process of clustering and choice of an appropriate number of clusters can be found in [20].

B. Operation Models

In this section we present the different models used to assess the operation of the neighborhood.

1) Reference Model: The reference model operates the neighborhood with perfect foresight. It is able to operate the neighborhood in a perfect way and is thus used as a reference value for the other methods. This is however not a method that can be used in practice due to the increasing errors of forecasts the longer the horizon.

This also represents the way the system would have been operated by the investment optimization. Indeed, we use the same formulation for the optimization with the exception that the investment part is removed. The objective function becomes:

Minimize:

$$\sum_{t=0}^{8759} \Big(\sum_{b} \sum_{f} f_{f,t,b} \cdot P_f^{fuel} + (P_t^{spot} + P^{grid} + P^{ret}) \cdot (y_t^{imp} + \sum_{b} \sum_{est} y_{t,est,b}^{imp}) - P_t^{spot} \cdot y_t^{exp} \Big) \tag{21}$$

2) Economic MPC (E-MPC): The model that we call economic MPC or E-MPC uses the same constraints as the reference model but uses a rolling horizon of 24 hours to operate the system. There is no perfect foresight anymore and the operation thus cannot anticipate future conditions of, for example, prices or temperatures. One optimization is run for each timestep and only the first timestep is implemented. Since there is no actual operation of a system there is no problem regarding the difference between the plan for a timestep and the actual realization for this timestep, which means we assume that the operation plan decided by the optimization is perfectly realized. The objective function becomes:

$\forall t0 \in [0..8759]$: *Minimize*:

$$\sum_{t=t0}^{t0+T^{MPC}} \Big(\sum_{b} \sum_{f} f_{f,t,b} \cdot P_f^{fuel} + (P_t^{spot} + P^{grid} + P^{ret}) \cdot (y_t^{imp} + \sum_{b} \sum_{est} y_{t,est,b}^{imp}) - P_t^{spot} \cdot y_t^{exp} \Big) \tag{22}$$

With T^{MPC} the length of the horizon, which is 24 hours in our case. The constraints stay the same as in the previous models, except that they are defined over the horizon only. The operation of the storages links the different horizons through the storage level at $t0$.

3) Emission Constrained Economic MPC (EmE-MPC): The emission constrained MPC (EmE-MPC) uses the same formulation as for the E-MPC but adds a penalization cost for deviating from emission and compensation targets. The targets are calculated based on the results from the investment runs. One emission target and one compensation target is calculated for each horizon. The penalization is added to the objective function, which becomes: $\forall t0 \in [0..8759]$: *Minimize*:

$$\sum_{t=t0}^{t0+24} \Big(\sum_{b} \sum_{f} f_{f,t,b} \cdot P_f^{fuel} + (P_t^{spot} + P^{grid} + P^{ret}) \cdot (y_t^{imp} + \sum_{b} \sum_{est} y_{t,est,b}^{imp}) - P_t^{spot} \cdot y_t^{exp} \Big) + c^{Em} + c^{Comp} \tag{23}$$

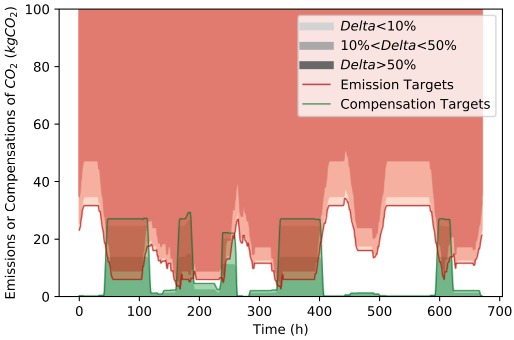

Fig. 1. Representation of the Different Emission and Compensation Targets Ranges (Delta: Difference Between Actual and Target) used in Equations 24 and 25 for Each Horizon for One Winter Month for PVlim Case

The penalization is calculated in the following way:

$$c^{Em} = \delta_1 \cdot (Em^{1.1}) + \delta_2 \cdot (Em^{1.5}) + \delta_3 \cdot (Em^{sup}) \quad (24)$$

$$c^{Comp} = \delta_3 \cdot (Comp^0) \cdot b^0 + \delta_2 \cdot (Comp^{0.5}) \cdot b^{0.5} + \delta_1 \cdot (Comp^{0.9}) \cdot b^{0.9} \quad (25)$$

Where $Em^{1.1}$ are the emissions up to 10% above the emission target, $Em^{1.5}$ the emissions between 10 and 50% above the emission target and Em^{sup} the emissions above the latter. For the compensation, the calculation is different and has discontinuities. $Comp^0$, $Comp^{0.5}$ and $Comp^{0.9}$ are the difference between the compensation target and the actual compensation when this compensation is respectively between 0 and 50%, 50 and 90%, and 90 and 100% of the target value. Figure 1 represents the emissions and compensations targets and ranges for each horizon in one winter month in the PVlim case. The areas above the red line and below the green line are respectively the ranges of penalized emissions and compensations. The white area either below or above represents values of emissions or compensations that represent less emissions or more compensations and as such do not get penalized.

Only one of the three components at most is active in the equation because of the binaries and the following equation (b^{sup} represents the case of compensations higher than the target):

$$b^0 + b^{0.5} + b^{0.9} + b^{sup} = 1 \quad (26)$$

The emissions and compensations are calculated with the same formulas as respectively the left-hand side and the right-hand side of the zero emission balance, equation 2.

The values of δ_1, δ_2 and δ_3 were set after multiple tries to respectively 0.03, 3 and 300€$/gCO_2$.

4) Receding Horizon MPC (RH-MPC): In the receding horizon MPC (RH-MPC) we use a complete year so that we are able to re-introduce the zero emission balance over the year. To maintain similar foresight conditions as in the previous models, we use the timeseries values of the next horizon only from the actual year to operate and we use the reference year values for the rest of the year. From $t0$ to $t0 + T^{MPC}$, the corresponding data in the current year are used and, for $t0 + T^{MPC}$ to 8759, we use the reference year data.

The objective function becomes: $\forall t0 \in [0..8759]$:

$$\sum_{t=t0}^{8759} \Big(\sum_b \sum_f f_{f,t,b} \cdot P_f^{fuel} + (P_t^{spot} + P^{grid} + P^{ret}) \cdot (y_t^{imp} + \sum_b \sum_{est} y_{t,est,b}^{grid\_imp}) - P_t^{spot} \cdot y_t^{exp} \Big) \quad (27)$$

The emission balance constraint is reintroduced in the following form:

$$Em^{0\rightarrow t0} + \phi_t^{CO_2,el} \sum_{t=t0}^{8759} \Big(y_t^{imp} + \sum_b \sum_{est} y_{t,est,b}^{imp} \Big) + \sum_{t=t0}^{8759} \sum_b \sum_f \phi^{CO_2,f} \cdot f_{f,t,b} \leq \phi_t^{CO_2,el} \cdot \sum_{t=t0}^{8759} \Big(\sum_b \sum_{est} \eta_{est} \cdot y_{t,est,b}^{exp} + \sum_b \sum_g y_{t,g,b}^{exp} \Big) + Comp^{0\rightarrow t0} \quad (28)$$

$Em^{0\rightarrow t0}$ and $Comp^{0\rightarrow t0}$ are the emission and compensation from the beginning of the year to the current timestep.

This model is much longer to solve because of the number of timesteps in each iteration. In the other MPC, we chose $T^{MPC} = 24$ timesteps throughout the year, while here, it starts at 8760 timesteps and decreases at each iteration. Those implementation choices can be modulated depending on the computational load, by for example allowing to implement several hours instead of only the first one.

C. Case Study

Before using ZENIT to obtain ZEN designs, we select a representative year to be used in the investment model. The selection process is presented in III.

Then, we perform two investment runs with ZENIT. In the first one the roof area constrains the amount of solar technologies that can be installed. In the second one we assume that there is available area in the proximity that can be used to install solar panels and we do not take the roof area into account. The model is implemented on a test case based on a small neighborhood, a campus at Evenstad in Norway, where three building types represent the different buildings there. We use the same implementation as in [20]. More information on the implementation of the studied case can be found there. The CO_2 factors for electricity are obtained by tracing back the origin of the electricity using the methodology presented in [22]. The data used in this methodology primarily comes from the ENTSO-E transparency platform. The earliest complete data on the platform start in 2015, which explains our choice of years. The investment options details and sources are presented in Annex A.

The ZENs' energy system designs are then used to compare the performances of the different operational approaches. We use a mipgap of 1% and we use clusters for the perfect foresight and the receding horizon model in order to have reasonable solving time. We use 50 clusters for the perfect foresight (the same as in the investment runs) and 30 for the receding horizon. In the receding horizon case, we then have the T^{MPC} hours from the current years and 30 clusters representing the remainder of the reference year instead of the whole reference year. Furthermore, for the receding horizon runs, we decide to implement the first six hours at each iteration instead of the first hour only, in order to contain the computational time. In the MPC runs, we still only implement the first hour at each iteration. Figure 2 presents a summary of which data is used and in which form in the different operational strategies. The data outside of the optimization horizon (before $t0$ and after $t0+T^{MPC}$, hatched on the figure) is not used in the MPC. For all runs, T^{MPC} is set at 24 hours.

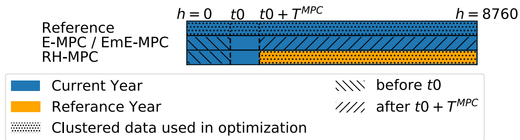

Fig. 2. Representation of which data is used in each formulation.

The steps of the study are summarized in Fig. 3.

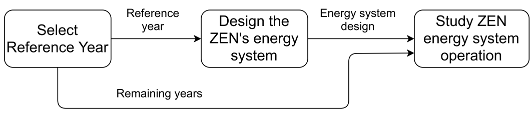

Fig. 3. Flowchart of the process of the study

III. Selection of the Reference Year

A. Zero Emission Objective

For our neighborhood to be a ZEN, the zero emission requirement needs to be met. This means that the neighborhood should have net-zero emissions at the end of its lifetime. What should be included in the emissions of the neighborhood varies depending on the ambition of the stakeholders. It can simply be the emissions from the operation phase but can also include the embedded emissions of the materials and the emissions from the construction and the deconstruction of the neighborhood. In order to reach zero emissions, the emissions also need to be compensated. In this study, we only focus on the emissions coming from the operation phase of the neighborhood's lifetime. The approach in ZENIT is to consider that the export of electricity from on-site renewable generation sources to the grid reduces the amount of electricity produced nationally, that contributes to emissions with a higher CO_2 factor. The emissions that were avoided thanks to the export from the neighborhood are accounted as compensation in the zero-emission balance.

In ZENIT, the optimization model uses one representative year for the lifetime of the neighborhood. In order to give good insights into the necessary investments, the reference year should have average electricity price and temperature levels.

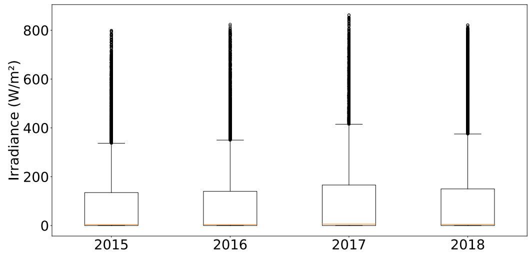

Fig. 4. Boxplot of Solar Irradiance for the Studied Years

The temperatures should also represent minimum temperatures correctly because this will have an effect on the maximum heat demand. In order to ensure a good representation of the compensations from PV it should also have average solar conditions.

When operating a neighborhood that was designed to become a ZEN, the question is if you should try to have a zero emission balance every year. Indeed, what was the case for the reference year is not necessary for specific years, a year with lower than average solar irradiances could, for instance, be compensated by a year with higher than average irradiances and the emission even out over the lifetime. The different methods proposed in section II-B try to impact the operation by considering the reference year's emissions and for that reason they do not take this possibility of year-to-year compensation into account.

B. Statistical analysis of the Inputs over the Years

To get meaningful results, it is important to consider wisely the year to be used in the optimization model. This choice can impact the results significantly ([23], [24]). With a limited availability of data, it is therefore important to consider the available years carefully.

In order to determine the appropriate reference year, but also in order to know the features of the input data for different years and be able to analyze the results in the rest of the paper we present the boxplot, duration curve and density curve of various input timeseries. The inputs selected are the outside temperature, the solar irradiance, the spot price of electricity and the CO_2 factor of electricity. The loads of the buildings are not included because we assume a strong correlation to the outside temperature. The years included are 2015, 2016, 2017 and 2018 because they are the years for which we have the electricity CO_2 factors timeseries.

The solar irradiance is quite similar for the different years with minor variations due to weather conditions. The years 2018 and 2017 have the highest total irradiance. From the density curves Fig. 5, we can see that there is roughly the same probability for the irradiance to be between 0 and 100 than above $100W/m^2$. The boxplot Fig. 4 confirms the distribution, with a median close to 0, a third quartile around 130 and numerous outliers. Figure 6 also confirms this.

From Fig. 7, we can see that the values of spot prices are not noticeably spread, the bands between quartile 1 and 3 are

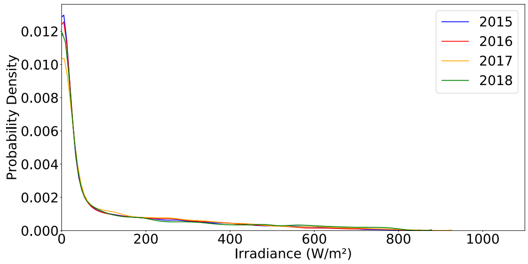

Fig. 5. Density Curves of Solar Irradiance for the Studied Years

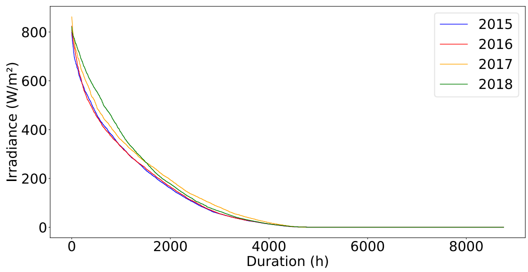

Fig. 6. Duration Curves of Solar Irradiance for the Studied Years

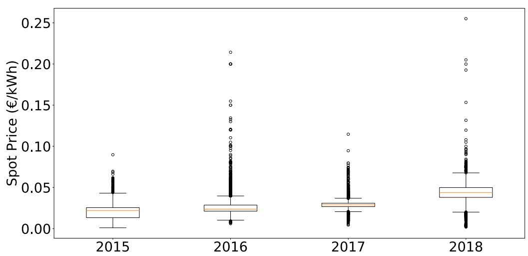

Fig. 7. Boxplot of Spot Prices for the Studied Years

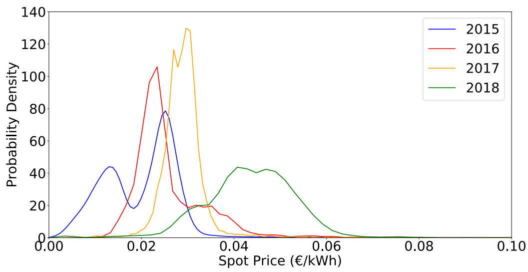

Fig. 8. Density Curves of Spot Prices for the Studied Years

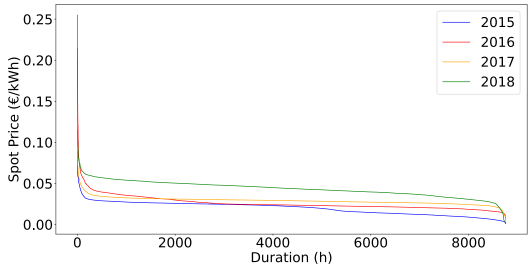

Fig. 9. Duration Curves of Spot Prices for the Studied Years

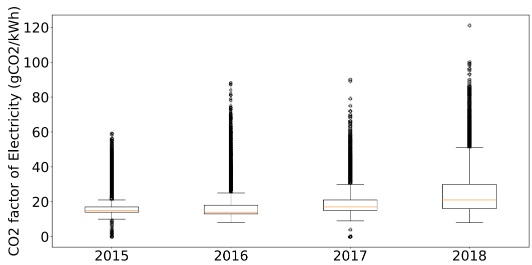

Fig. 10. Boxplot of CO_2 factors of electricity for the Studied Years

narrow. However, there are some outliers, mainly reflecting peaks in prices but also dips for the case of 2017 and 2018. The median values also vary significantly. It is also important to note the difference in highest peak prices in 2016 and 2018 compared to 2017 and 2015. The distribution of the prices shown in Fig. 8 are quite different. They are all relatively wide with the exception of 2017, but the shape and the means are quite different. The year 2018, for instance, is more even while the rest have a peak, denoting the concentration of the prices around that value. In the case of 2015, there are two peaks denoting two price levels where most of the data lie. Those observations are confirmed by the duration curve Fig. 9.

The CO_2 factors for electricity also show 2018 as quite different from other years, with a higher median (Fig. 10) and wider distribution of values (Fig. 11). The other years are

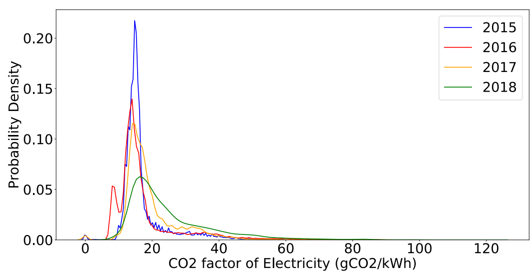

Fig. 11. Density Curves of CO_2 factors of electricity for the Studied Years

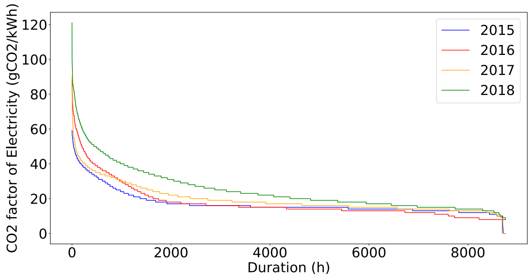

Fig. 12. Duration Curves of CO_2 factors of electricity for the Studied Years

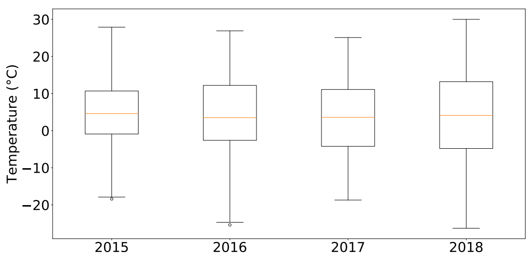

Fig. 13. Boxplot of Temperature for the Studied Years

more similar with a median of around 17 gCO_2/kWh. The year 2016 offers a somewhat middle-ground representation of the peak levels of the CO_2 factors even if the base levels are slightly lower than for other years (Fig. 12).

The median of the temperature lies around $5°C$ for all years, as seen in Fig. 13. There is a bigger spread of values than for the other timeseries and almost no outliers. The distribution of the different years in Fig. 14 is quite similar even if their shape varies.

Overall it seems that 2016 is a good candidate to be used as a reference year for the investment optimization from our sample of years. It has average temperatures while still having high and low extremes (Fig. 15). It also has a somewhat average representation of the solar irradiance and of the spot price. The representation of the CO_2 factors is also average for the "peaks" but slightly lower in the base level. We choose

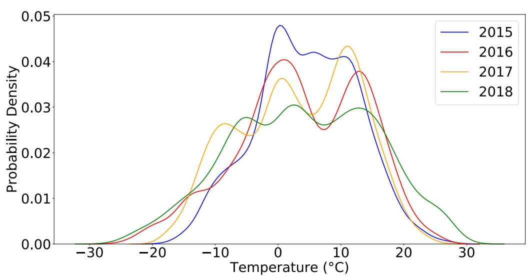

Fig. 14. Density Curves of Temperature for the Studied Years

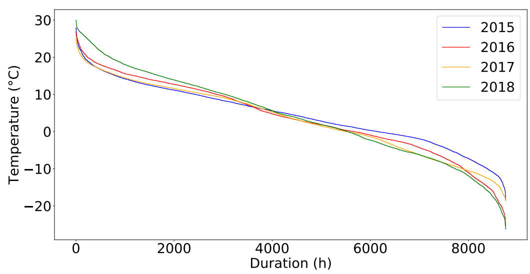

Fig. 15. Duration Curves of Temperature for the Studied Years

this year to make the investment optimization for these reasons and keep the three other years to use them in the comparison of the operation strategies.

IV. Results

A. ZEN Designs from ZENIT

The results from the investment runs are presented in this subsection. In the rest of the paper we will refer to "Base" and "PVlim" for, respectively, the case where PV is not constrained by PV area and the case where it is. The central plant represents the location where the neighborhood scale technologies are and we refer to the existing buildings from the Campus Evenstad as B1, B2 and B3. B1 represents student apartments at the passive standard, B2 conventional offices and B3 offices at the passive standard. The lifetime used for the neighborhood is 60 years and the rate of return is 4%.

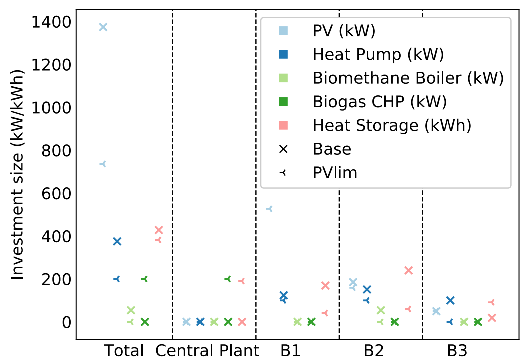

Fig. 16. Results of the Investment Runs in the Base and PVlim case

The investments resulting from the runs for the Base and PVlim cases are shown in Fig. 16. In the Base case, a combination of a large amount of PV, air-source heat pumps are used together with a biomethane boiler in B2. In the PVlim case, the amount of installed PV is around two times lower than in the Base case. The limitation on PV also induces an investment in the heating grid and a biogas engine at the neighborhood level. This partially replaces heat pumps in particular in B3 and completely replaces the biomethane boiler in B2.

The total emissions for one year are respectively 11.69 and 5.25 $tonCO_2$ for the Base and PVlim case. The compensations are strictly equal to the emissions.

TABLE I
DISCOUNTED INVESTMENT AND DISCOUNTED OPERATION COSTS FOR THE BASE AND PVLIM CASES IN K€; THE SUM REPRESENTS THE OPTIMAL OBJECTIVE VALUE

	Disc. Investment Cost	Disc. Operation Cost
Base	1 351.1	993.7
PVlim	1 077.3	1 706.7

The discounted investment and operation costs are shown in Table I.

B. Evaluation of the Operation Strategies

The different operation strategies presented in the previous sections are used to operate the systems resulting from the investment runs (and presented in section IV-A) in the years 2015, 2017 and 2018.

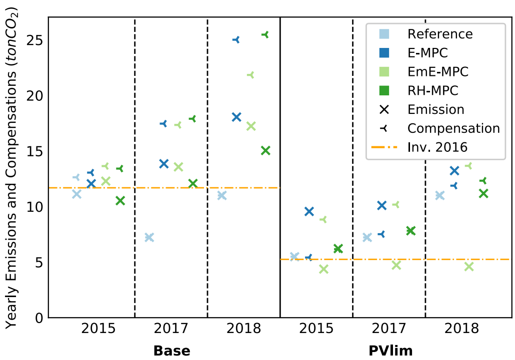

Fig. 17. Emissions and Compensations from the Different Operation Strategies in the Different Years Considered

The yearly emissions and compensations are presented in Fig. 17. The orange line, "Inv. 2016" represents the level of emissions and compensations obtained in the investment run with year 2016. In the Base case, the emissions are always compensated. The energy system with its large amount of PV is quite passive and there is only the need to supply the heating load from the heat pumps and biomethane boiler. Even with the purely economic approach from E-MPC, the emission balance is satisfied. In years 2017 and 2018, the CO_2 factors (and to a lesser extent the spot prices and solar irradiances) are higher, making it harder for EmE-MPC to keep emissions at the level of the investment run. Overall the RH-MPC approach gives the lowest emissions.

In the PVlim case, the system requires a more active management due to the lower amount of PV and the large CHP plant. It is not sufficient to operate the system in a purely cost optimal way because there is then not enough compensations, this is illustrated by the E-MPC approach. The EmE-MPC approach on the other hand keeps the emissions low and the compensations high. It manages to stay around the same level as in the investment run thanks to the penalization of deviating from the emissions and compensations resulting from the investment run. It manages to do so by using the CHP more, even if it means dumping some of the heat produced. The RH-MPC approach gives again the best result. It manages to keep the total emissions and compensations close and they are always around the same level as in the Reference (perfect foresight approach).

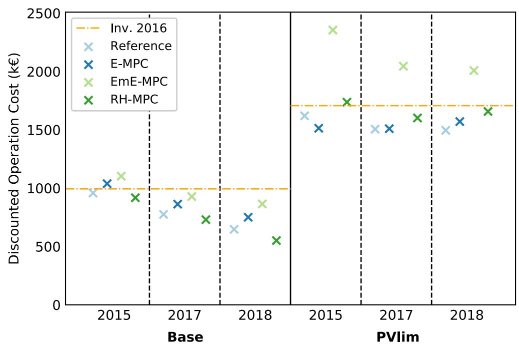

Fig. 18. Discounted Operation Cost from the Different Operation Strategies in the Different Year Considered

The total discounted operation costs are presented in Fig. 18. Note that the "Inv. 2016" represents the operation costs from the investment runs and that the "fictitious" penalization costs in the EmE-MPC are not included. In the Base case, the operation costs are lower for the years 2016 and 2017. This is partially due to the higher irradiance. The EmE-MPC has to follow the same pattern of emissions as in the investment run causing additional costs. RH-MPC has lower operation costs than the Reference, most likely because of the clustering. The Reference has 50 clusters for the year while the RH-MPC has actual data for 24 hours and clusters that are remade at each iteration giving a better representation of the year. In the PVlim case, the extra cost of maintaining the same emissions as in the investment run for EmE-MPC can be observed. They stem from the need to operate the costly CHP to reach the targets and avoid the penalization. The RH-MPC approach allows staying around the operation cost from the investment runs even though they are not as low as they could be (by comparison with the E-MPC for example).

Figures 19, 20 and 21 illustrate the differences in operation for one winter week in the year 2018 of the different operation strategies. This highlights the use of the CHP as a way to increase the compensation by exporting more and to reduce emissions by importing less. Figure 21 in particular amply illustrates the importance of the CO_2 factor of electricity in the choice of when to operate the CHP. The CHP is operated when the factor is high, i.e. when it is the most beneficial. In contrast, for the E-MPC, Fig. 19, the operation is not so correlated to the CO_2 factor level. It is most likely more correlated to the spot price of electricity, which is in line with its purely economical approach.

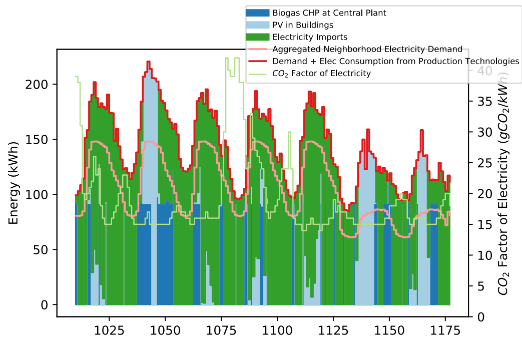

Fig. 19. Origin of the Electricity Consumed in the Neighborhood and CO_2 Factor of Electricity in One Winter Week of 2018 in the PVlim E-MPC Case

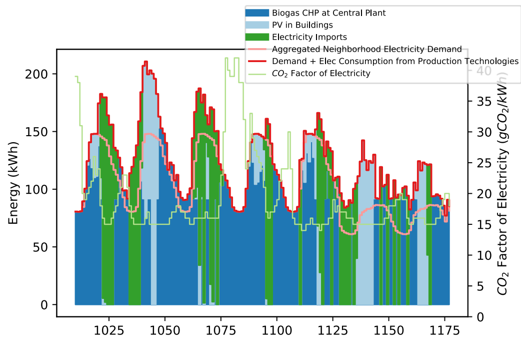

Fig. 21. Origin of the Electricity Consumed in the Neighborhood CO_2 Factor of Electricity in One Winter Week of 2018 in the PVlim RH-MPC Case

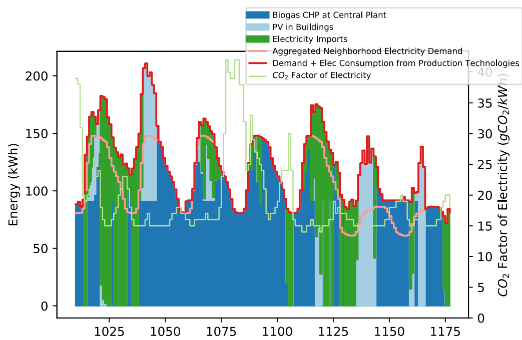

Fig. 20. Origin of the Electricity Consumed in the Neighborhood and CO_2 Factor of Electricity in One Winter Week of 2018 in the PVlim EmE-MPC Case

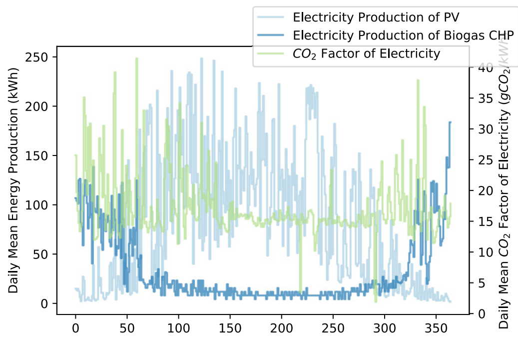

Fig. 22. Daily Mean of CO_2 Factor of Electricity and Daily Mean Production of Electricity from the PV and the Biogas CHP in the PVlim 2015 RH-MPC Case

In the EmE-MPC cases, especially in the PVlim, the CHP is operated to produce electricity that can be exported to the grid even though there is no need for the heat. This leads to a large amount of dumped heat. This is also the case to a lesser extent in the RH-MPC case. This could be solved by adding extra technological options dedicated to electricity production or CHP with heat-to-power ratios more in favor of electricity. In the Base case, there is also a large amount of electricity dumped due to the size of the grid connection. This is also the case in the investment runs. In the Base case in particular it is more cost efficient to over-invest in PV in order to be at maximum export for longer during the year, even if it means curtailing PV production at times.

Both those electricity and heat dumps are linked to the CO_2 factor of electricity profiles. For example, Fig. 22 shows the daily mean production of electricity from the PV and from the Biogas CHP in the PVlim 2015 RH-MPC case. It highlights that the PV production, which cannot be controlled happens for a large part at times when the CO_2 factor is low. The CHP better matches the times of high factors due to its controllability in addition to the matching between the high winter thermal load and the high factors in the winter. This figure shows daily averages for readability ease, but note that the variations of CO_2 factors are larger and more frequent at the hourly level in the winter. In addition, year 2015 is the one with the lowest CO_2 factors of electricity levels and variability as can be seen in Fig. 10, Fig. 11 and Fig. 12. One consequence of the RH-MPC method can be noted from this figure as well. In the last days of the year, the production of the CHP increases a lot. This is likely a result of the receding horizon approach. Due to the replacement of the reference year with the actual value for that year, there is a need to make up for the difference in emissions/compensations between what was expected and is possible with the actual data.

V. Limitations

Several limitations should be kept in mind when it comes to the methodology and the interpretation of results. The first aspect to keep in mind is the effect of using clustering. The need to use clustering arises from the complexity of solving some of the models, in particular the investment model (Base and PVlim), the perfect foresight (PVlim) and the RH-MPC (PVlim) due to the binary variables. In order to keep the same conditions in all cases, clustering was used for all the appropriate cases (i.e. except the E-MPC and EmE-MPC that only consider a fixed "short" horizon). This means the results are affected by the performance of the clustering and more information on this can be found in [20]. Another parameter that was used for all cases for computational reason is a mipgap of 1%. The PVlim investment in particular was converging very slowly below a mipgap of around 1%. Another limitation of the study is the choice of years. We chose years from 2015 to 2018 because these were the only ones where we could compute the hourly CO_2 factor of electricity from data available on the ENTSO-E transparency platform at the time of the study. This means that the interpretation of the results in a longer term setting is more uncertain. The profiles of the different timeseries could be at different levels or with different profiles in some decades and due to climate change. EmE-MPC was only presented with one set of values for the parameters δ, when in fact they would probably require fine-tuning to be used in practice and have an effect that is neither useless or too zealous. The use of clusters for RH-MPC makes it faster to solve but likely reduces its performance. Moreover, this scheme requires more computation, even though the use of clustering partly alleviate this. This could be a problem in practice depending on the frequency of the optimization. A different approach to the RH-MPC would be to keep optimizing over a complete year through the iterations, without having it recede. This would remove the end of the year effect that was observed and give an homogeneous solving time throughout the year.

VI. Conclusion

When dealing with ZENs' energy system, more attention needs to be given to the relation between the design recommendations from investment tools that assume a certain operation and the way the energy system would actually be operated. In particular, the strong requirement on emissions cannot be considered in the same way in the operation and in the investment process. In this paper we suggested and compared different operation approaches and their performance in terms of operation cost and emissions/compensations. The investment tool ZENIT was first used to create designs of ZEN energy systems in cases where the amount is and is not limited. We then compared the performance of four approaches in operating those systems in different years. The first one used as a reference assumes perfect foresight of the year and is used as a reference; the E-MPC approach represents a purely economical operation of the neighborhood; the EmE-MPC approach expends the E-MPC by including a penalization of deviating from emission and compensation targets and the RH-MPC approach uses a receding horizon and a complete year as a way to maintain the annual zero emission constraint in the short-term operation optimization. We also look into the variations between data from different years and how this affects the actual costs. Indeed, in the investment run we use a reference year and expect the operation cost, emissions and compensation for the actual operation of the ZEN to even themselves out throughout the lifetime. The results show that with a system strongly based on PV, the zero emission requirement can be met without any additional specific operation method. However in systems including technologies using carbon-intensive sources or systems where one of the source is expensive to operate (such as the CHP in the PVlim case) the need for a more active operation and for accounting emissions and compensations in some way is greater. To this end, the proposed RH-MPC appears to be the most promising operation strategy. The EmE-MPC method performed less well, but a better tuning of penalization cost parameters could make this another viable solution. This study could be expanded in the future by considering other approaches for the operation of the neighborhood and also by considering a ZEN energy system that includes more carbon-intensive sources, for instance by having a lower requirement for the compensation and only partially compensating emissions partly.

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Appendix A
Technology Data

The data for those technologies come from the Danish Energy Agency and Energinet[1].

TABLE II
DATA OF TECHNOLOGIES PRODUCING HEAT AND/OR ELECTRICITY

Tech.	η_{th} (%)	Fix. Inv. Cost (€)	Var. Inv. Cost (€/kW)	α_i (% Inst. Cap.)	Min. Cap. (kW)	Annual O&M Costs (% of Var Inv. Cost)	Lifetime (year)	Fuel	α_{CHP}	El.	Heat
At building level											
PV[1]		0	730	0	50	1.42	35			1	0
ST[2]	70	28350	376	0	100	0.74	25			0	1
ASHP[3]	f(T_t)	42300	247	0	100	0.95	20	Elec.		0	1
GSHP[4]	f(T_t)	99600	373	0	100	0.63	20	Elec.		0	1
Boiler[5]	85	32200	176	30	100	2.22	20	Wood Pellets		0	1
Heater	100	15450	451	0	100	1.18	30	Elec.		0	1
Boiler	100	3936	52	20	35	2.99	25	Biomethane		0	1
At neighborhood level											
CHP[6]	47	0	1035	50	200	1.03	25	Biogas	1.09	1	1
CHP	98	0	894	20	1000	4.4	25	Wood Chips	7.27	1	1
CHP	83	0	1076	20	1000	4.45	25	Wood Pellets	5.76	1	1
Boiler[7]	115	0	680	20	1000	4.74	25	Wood Chips		0	1
Boiler[7]	100	0	720	40	1000	4.58	25	Wood Pellets		0	1
CHP[8]	66	0	1267	10	10	0.84	15	Wood Chips	3	1	1
Boiler[9]	58	0	3300	70	50	5	20	Biogas		0	1
GSHP[4]	f(T_t)	0	660	010	1000	0.3	25	Elec.		0	1
Boiler	99	0	150	5	60	0.71	20	Elec.		0	1
Boiler	100	0	60	15	500	3.25	25	Biogas		0	1

[1] Area Coefficient: 5.3 m^2/kW
[2] Area Coefficient: 1.43 m^2/kW
[3] Air Source Heat Pump
[4] Ground Source Heat Pump
[5] Automatic stoking of pellets
[6] Gas Engine
[7] HOP
[8] Gasified Biomass Stirling Engine Plant
[9] Solid Oxyde Fuel Cell (SOFC)

The data for prices of fuels come from different sources. For the wood pellets and wood chips, they come from the Norwegian Bioenergy Association[2]. The data for the biogas and biomethane come from the European Biogas Association[3].

The data for CO_2 factor of fuels come from a report from Cundall[4].

TABLE III
DATA OF FUELS

Fuel	Fuel Cost (€/kWh)	CO_2 factor (gCO_2/kWh)
Electricity	$f(t)$	$f(t)$
Wood Pellets	0.03664	40
Wood Chips	0.02592	20
Biogas	0.07	0
Biomethane	0.07	100

TABLE IV
DATA OF STORAGE

Index	One way eff. (%)	Inv. Cost (€/kWh)	O&M Cost (% of Inv. Cost)	Lifetime (year)	Min. Cap. (kWh)	Charge / Discharge rate (% of Cap)
Battery						
1[1]	95	577	0	10	13.5	37
2[2]	938	500	0	15	210	23
3[3]	95	432	0	20	1000	50
Heat Storage						
1[4]	95	75	0	20	0	20
2[3]	98	3	0.29	40	45 000	1.7

[1] Based on Tesla Powerwall
[2] Based on Tesla Powerpack
[3] Based on Danish energy agency data
[4] Same data are used for the heat storage at the building or neighborhood level and for both SH and DHW

[1] https://ens.dk/en/our-services/projections-and-models/technology-data
[2] http://nobio.no/wp-content/uploads/2018/01/Veien-til-biovarme.pdf
[3] https://www.europeanbiogas.eu/wp-content/uploads/2019/07/Biomethane-in-transport.pdf
[4] https://cundall.com/Cundall/fckeditor/editor/images/UserFilesUpload/file/WCIYB/IP-4%20-%20CO2e%20emissions%20from%20biomass%20and%20biofuels.pdf

Paper 6

This paper is awaiting publication and is not included in NTNU Open

Paper 7

100RES 2020 – Applied Energy Symposium (ICAE)
100% RENEWABLE:
Strategies, technologies and challenges for a fossil free future
Pisa, Italy, October 25th – 30th, 2020

Optimal investment in the energy system of Zero Emission Neighborhoods considering the refurbishment of the building stock.

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Abstract. To increase the impact that Zero Emission Neighbourhoods (ZEN) can have in the effort to decrease CO2 emissions, the refurbishment of the existing building stock is a parameter that should be considered. The existing literature contains work on optimization models for the energy system of neighbourhoods taking into account emissions but fails to account for the refurbishment of buildings. This paper addresses this option and presents an optimization model for designing a cost-optimal energy system of a ZEN in the context of existing buildings. The model is presented and used in a case study in Norway and compared to a case with linearized binaries. A sensitivity analysis is performed on the cost of refurbishment. With the original refurbishment cost assumptions, it is not chosen by the optimization, contrary to the hydronic. The system relies mainly on PV, solar thermal collectors (ST), a biogas engine, a battery and heat pumps (HP) and heat storage. From 50% of the original refurbishment cost, it is chosen, and the system does not have a biogas engine and a heating grid anymore, but a much bigger battery and more heating technologies inside the buildings. With linearized binaries, the investments are similar to the case with 50% refurbishment cost, but the value of the linearized binaries cannot be used to indicate the share of building to refurbish.

1 Introduction

Neighborhoods and the energy use of their buildings represent an important share of the global emissions of carbon dioxide. Zero Emission Neighborhoods (ZEN) is a concept that aims at reducing their contribution to the emissions. In the research centre for Zero Emission Neighborhoods in smart cities (FME ZEN) in Norway, several disciplines collaborate towards making more sustainable cities[†]. In this research centre, ZENs are defined as neighborhoods that reach net zero emission of CO2 over their lifetime. One of the problems arising is how to design the energy system of such a neighborhood to reach net zero emission target. ZENIT is an optimization model created for this purpose. This model finds the energy system design which satisfies the emission constraint at the lowest cost [1]. However, this model can only be used for greenfield development.

In order for the ZEN concept to have a bigger impact, it is important to modify the models to be able to account for existing buildings.

This paper aims at investigating one of the gaps in the research literature by addressing the inclusion of refurbishment of buildings in optimization models designing the energy system of ZEN and their impact on the result. This is important in order to facilitate existing buildings and neighborhoods to participate in emission reduction measures and facilitate the transition to a decarbonized future.

In this paper, a model for the investment in the energy system of ZEN is presented and the modifications done to take the refurbishment of buildings into account are introduced. The model is then used on the case of an existing neighbourhood in Norway and the results are discussed and compared to the case when the binaries for refurbishment and hydronics are linearized. A sensitivity analysis is performed on the cost of refurbishment.

2 Literature review

Several models to deal with the investment in the energy system of neighborhoods are presented in the literature [2] [3] [4] [5] [6] [1] [7]. Each model is a Mixed Integer Linear Program (MILP) but emphasizes different elements. For instance, [6] and [7] include the heating

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[†] https://fmezen.no/

grid layout as part of the problem. Seasonal storage is included in [4] and [1]. Voltage constraints and power flow are included in [5] while [3] focuses on combining open source models.

[8] simplifies the MILP optimization problem by separating it in parts and finds near optimal solutions.

[8] also addresses the refurbishment of neighborhoods envelope in the optimization. The impact of changing insulation thickness of windows on the annual heat demand is calculated based on a building standard and an equivalent insulation thickness is added as a variable in the optimization.

[9] takes existing buildings and compares different combination of retrofitting measures and energy system design. One specific feature of the study is the inclusion of façade PV. Cost assumptions for refurbishment as well as impact on annual loads are presented. They find that passive reductions of the loads are not profitable, even when assuming increasing CO2 prices impact on retail electricity prices.

On the other hand, there are models that do not deal with the energy system of neighborhoods but deal with optimising the envelope of buildings. [10] considers the optimization of the envelope of the building in a multi-objective metaheuristic algorithm to look for the optimal life cycle cost and emissions and finds a pareto front of solutions for the materials of the building envelope. Moreover, [11] also uses a multi-objective metaheuristic approach to find building parameters such as the building orientation, aspect ratio, windows, wall and roof type and materials.

Other models fall in between the two types of models presented earlier, with for example optimization of the building's material and windows and investment in PV panels such as [12].

In this paper, we introduce refurbishment into the problem of the design of the energy system of ZENs, but we do not decompose into subproblems and go to the level of detail of the envelope of the buildings.

We show a formulation of a model for the design of the energy system of a ZEN, considering the refurbishment and the hydronic system and their modelling implications. It contributes to the existing literature by introducing refurbishment in the context of ZEN's energy system.

3 Model Presentation

The ZENIT (Zero Emission Neighborhood Investment Tool) is presented in [1] and this section presents an extension accounting for refurbishment. The model minimizes the energy system investment and operation cost for a given neighborhood that allows to be zero emission in the lifetime using a MILP formulation. Clusters are used to reduce the computational complexity.

The objective function is to minimize the following expression (Eq. (1)).

In Eq. (1), b^{HG}, b_b^{refurb} and b_b^{hyd} are the binaries controlling the investment in the heating grid and the refurbishment and hydronic system of the building b.

$$\boldsymbol{b^{HG} \cdot C^{HG} + \sum_b \left(\sum_i \left(\left(C_{i,b}^{var,disc} + \frac{C_{i,b}^{maint}}{\varepsilon_{r,D}^{tot}} \right) \cdot x_{i,b} + C_{i,b}^{fix,disc} \cdot b_{i,b} \right) + b_b^{refurb} \cdot C_b^{refurb} + b_b^{hyd} \cdot C_b^{hyd} \right) + \frac{1}{\varepsilon_{r,D}^{tot}} \sum_\kappa \sum_{t_\kappa} \sigma_\kappa \left(\sum_b \sum_f f_{f,t,b} \cdot P_f^{fuel} + \left(P_t^{spot} + P^{grid} + P^{ret} \right) \cdot \left(y_t^{imp} + \sum_b \sum_{est} y_{t,b,est}^{imp} \right) - P_t^{spot} \cdot y_t^{exp} \right)} \tag{1}$$

The C are the cost associated with it. The capacity of technology i in building b is $x_{i,b}$, the associated discounted investment cost is $C_{i,b}^{disc}$ and the operation and maintenance cost is $C_{i,b}^{maint}$. The discount factor for the lifetime of the neighborhood with the discount rate r is $\varepsilon_{r,D}^{tot}$. The timestep inside cluster κ is t_κ, and σ_κ is the number of elements inside this cluster. The fuel consumption of technology burning fuel f is $f_{f,t,b}$ and the cost of this fuel is P_f^{fuel}. P_t^{spot}, P^{grid} and P^{ret} are respectively the spot price of electricity, the grid tariff, and the retailer tariff. The import and export to the neighborhood are y_t^{imp} and y_t^{exp} while the import to battery est is $y_{t,b,est}^{imp}$. The imports and exports of electricity are limited by the size of the grid connection.

To be a ZEN, the neighborhood needs to have net zero emissions in its lifetime. In the ZEN framework, we consider that the electricity exports from renewable sources in the neighborhood reduce the emissions in Norway by replacing some of the more carbon intensive generation. We call those avoided emissions "compensations" and the emission balance requires at least as much compensations as emissions. The constraint representing this is:

$$\boldsymbol{\phi_t^{CO_2,e} \sum_\kappa \sum_{t_\kappa} \sigma_\kappa \left(y_t^{imp} + \sum_b \sum_{est} y_{t,b,est}^{imp} \right) + \sum_\kappa \sum_{t_\kappa} \sigma_\kappa \sum_b \sum_f \phi^{CO_2,f} \cdot f_{f,t,b} \leq \phi_t^{CO_2,e} \cdot \sum_\kappa \sum_{t_\kappa} \sigma_\kappa \left(\sum_b \sum_{est} \eta_{est} \cdot y_{t,est,b}^{exp} + \sum_b \sum_g y_{t,g,b}^{exp} \right)} \tag{2}$$

In this equation, the CO2 factor for electricity is $\phi_t^{CO_2,e}$ and the factor for other fuels is $\phi^{CO_2,f}$. The efficiency of the battery is η_{est}.

The heat load balances are dependant of the investment in refurbishment, but the electric load is not affected by it:

$$\boldsymbol{y_t^{imp} + \sum_b \left(\sum_{est} y_{t,est,b}^{dch} \cdot \eta_{est} + \sum_g g_{g,t,b}^{selfc} \right) = \sum_b \left(\sum_e d_{e,t,b} + E_{t,b} \right), \quad \forall t} \tag{3}$$

$$\boldsymbol{\sum_q q_{q,t,b}^{DHW} + \sum_{hst} \left(\eta_{hst} \cdot q_{t,hst,b}^{DHW,dch} - q_{t,hst,b}^{DHW,ch} \right) + q_{t,hst,b}^{HG,DHW} = B_b^{refurb} \cdot \left(H_{b,t}^{DHW} \right) + \left(1 - B_b^{refurb} \right) \cdot \left(\left(1 - b_b^{refurb} \right) \cdot H_{b,t}^{DHW} + b_b^{refurb} \cdot H_{b,t}^{refurb,DHW} \right) + q_{t,b}^{dump}, \quad \forall b,t} \tag{4}$$

$$\boldsymbol{\sum_q q_{q,t,b}^{SH} + \sum_{hst} \left(\eta_{hst} \cdot q_{t,hst,b}^{SH,dch} - q_{t,hst,b}^{SH,ch} \right) + q_{t,hst,b}^{HG,SH} = B_b^{refurb} \cdot \left(H_{b,t}^{SH} \right) + \left(1 - B_b^{refurb} \right) \cdot \left(\left(1 - b_b^{refurb} \right) \cdot H_{b,t}^{SH} + b_b^{refurb} \cdot H_{b,t}^{refurb,SH} \right), \quad \forall b,t} \tag{5}$$

The discharge from battery b to the neighborhood is $y^{dch}_{t,est,b}$ (similarly $q^{dch}_{t,hst,b}$ is the heat discharged from the heat storage *hst* to the neighborhood) and the electricity produced by technology g directly consumed is $g^{selfc}_{g,t,b}$. The electricity consumption of heat producing technology e is $d_{e,t,b}$ and the heat-independent electricity consumption is $E_{t,b}$. The heat produced by technology q is $q_{q,t,b}$, distinguished between Space Heating (SH) and Domestic Hot Water (DHW). The heat demand is $H_{b,t}$. B^{refurb}_b is a parameter indicating if building b can be refurbished (1 meaning it cannot); and b^{refurb}_b is a variable controlling the investment in refurbishment (1 meaning it chooses to refurbish).

If the optimization invests in a heating grid, technologies at the neighborhood level, i.e. larger scale technologies, become available.

$$x_{i,PP} \le X^{max}_i \cdot b^{HG} \tag{6}$$

The balance at the production plant (noted PP) where those technologies are located is then:

$$\sum_q q_{q,t,PP} + \sum_{hst}\left(\eta_{hst} \cdot q^{dch}_{t,hst,PP} - q^{ch}_{t,hst,PP}\right) = \sum_{b\backslash PP} q^{HGtrans}_{t,PP,b} + q^{dump}_{t,PP}, \quad \forall t \tag{7}$$

Where $q^{HGtrans}_{t,PP,b}$ is the heat transferred in the heating grid from the production plant to building b in timestep t.

The investment in i is limited by the existing capacity $X^{precap}_{i,b}$, the minimum (X^{min}_i) and the maximum (X^{max}_i) investment size:

$$X^{precap}_{i,b} \le x_{i,b} \le X^{max}_i, \quad \forall i,b \tag{8}$$

$$X^{min}_i \cdot b^{inv}_{i,b} \le x_{i,b} \le X^{max}_i \cdot b^{inv}_{i,b}, \quad \forall i,b \tag{9}$$

A binary b^{inv}_i is necessary for this semi-continuous formulation.

Some technologies also require a hydronic system to be installed (if they do, $B^{hyd}_q = 1$).

$$x_{q,b} \le X^{max}_q \cdot b^{hyd}_b, \quad \forall q,b \tag{10}$$

Some technologies have different costs if the building is new, existing or is refurbished. In the case of buildings that can be refurbished, technologies in this category are represented as two investment options with different costs and the following constraint is needed to use the correct price. If the investment option is for existing buildings:

$$x_{i,b} \le X^{max}_i \cdot (1 - b^{refurb}_b), \quad \forall i,b \tag{11}$$

If the investment option is for refurbished buildings:

$$x_{i,b} \le X^{max}_i \cdot b^{refurb}_b, \quad \forall i,b \tag{12}$$

The fuel or electricity used by technologies producing heat is:

$$f_{f,t,b} = \frac{q_{f,t,b}}{\eta_f}, \quad \forall f,t,b \;;\; d_{e,t,b} = \frac{q_{e,t,b}}{\eta_e}, \quad \forall e,t,b \tag{13}$$

where η is the efficiency of the technology. The heat produced can fulfil SH and/or DHW depending on the technology; B^{DHW}_q and B^{SH}_q control which kind they can provide. An electric radiator for instance can only provide SH. In addition, the hydronic system allows some technologies heating water to deliver SH in addition to the DHW when it is installed.

$$q_{f,t,b} = q^{DHW}_{q,t,b} + q^{SH}_{q,t,b}, \quad \forall q,t,b \tag{14}$$

$$q^{DHW}_{q,t,b} \le M \cdot B^{DHW}_q, \quad \forall q,t,b \tag{15}$$

$$q^{SH}_{q,t,b} \le M \cdot B^{SH}_q, \quad \forall q,t,b \tag{16}$$

For CHPs, the efficiency is the one related to heat and the electricity production is obtained with the heat-to-power ratio (α_{CHP}):

$$g_{f,t,b} = \frac{q_{f,t,b}}{\alpha_f}, \quad \forall CHP,t,b \tag{17}$$

The solar technologies (solar thermal collector and PV panels) are modelled by their efficiency and the solar irradiance.

For heat pumps, the COP is used instead of the efficiency. It is calculated based on a polynomial fit of manufacturer's data and the difference between the supply and the source temperature. The max electric consumption ($P^{in,max}$) is also obtained in the same way. The supply temperature is 65°C for DHW and for SH it differs between recent (or refurbished) and old houses.

If $B^{refurb}_b = 1$, the heat pump is controlled in the following way:

$$d^{SH}_{HP,t,b} = \frac{q^{SH}_{HP,t,b}}{COP^{SH}_{HP,t,b}}, \quad \forall HP,t,b \tag{18}$$

$$d^{DHW}_{HP,t,b} = \frac{q^{DHW}_{HP,t,b}}{COP^{DHW}_{HP,t,b}}, \quad \forall HP,t,b \tag{19}$$

$$\frac{d^{SH}_{HP,t,b}}{P^{in,max,SH}_{HP,t,b}} + \frac{d^{DHW}_{HP,t,b}}{P^{in,max,DHW}_{HP,t,b}} \le x_{HP,b}, \quad \forall HP,t,b \tag{20}$$

If $B^{refurb}_b = 0$, the heat pump is affected by the decision to refurbish the building because of the impact on the supply temperature for the SH. The heat production and electric consumption for SH is separated in two, using the notation P for passive and NP for not passive standard buildings.

$$d_{HP,t,b} = d^{SH,P}_{HP,t,b} + d^{SH,NP}_{HP,t,b} + d^{DHW}_{HP,t,b} \tag{21}$$

$$q^{SH}_{HP,t,b} = q^{SH,P}_{HP,t,b} + q^{SH,NP}_{HP,t,b} \tag{22}$$

$$d^{SH,P}_{HP,t,b} \le M \cdot b^{refurb} \tag{23}$$

$$d^{SH,NP}_{HP,t,b} \le M \cdot (1 - b^{refurb}) \tag{24}$$

$$\frac{d^{SH,P}_{HP,t,b}}{P^{in,max,SH,P}_{HP,t,b}} + \frac{d^{SH,NP}_{HP,t,b}}{P^{in,max,SH,NP}_{HP,t,b}} + \frac{d^{DHW}_{HP,t,b}}{P^{in,max,DHW}_{HP,t,b}} \le x_{HP,b} \tag{25}$$

Constraints such as in Eq. (23) and (24) are called bigM constraints. M takes a very large value, not limiting the left-hand side of the equation if the binary is 1 and forcing it to 0 otherwise.

Some technologies can only be operated in a certain range of their nominal power. The part load limitation constraint ensures that the operation of those technologies is more realistic.

$$\overline{x_{i,t,b}} \le X^{max}_i \cdot o_{i,t,b} \tag{26}$$

$$x_{i,b} - X^{max}_i \cdot (1 - o_{i,t,b}) \le \overline{x_{i,t,b}} \le x_{i,b} \tag{27}$$

$$\overline{x_{i,t,b}} \cdot \alpha \le q_{i,t,b} \le \overline{x_{i,t,b}} \tag{28}$$

Technology i, in b is in operation in timestep t when the binary $o_{i,t,b}$ is 1. The semi-continuous variable of the effective capacity is represented by $\overline{x_{i,t,b}}$.

The heating grid is assumed to be radial and only fed by the central production plant, i.e. the buildings cannot feed heat into the heating grid.

$$q^{HGused}_{t,b} = \sum_{b''}\left(q^{HGtrans}_{t,b'',b} - Q^{HGloss}_{b'',b}\right) - \sum_{b'} q^{HGtrans}_{t,b,b'} \quad ,\forall t,b \tag{29}$$

$$q^{HGused}_{t,b} \ge 0 \quad ,\forall t,b \tag{30}$$

$$q^{HGtrans}_{t,b',b} \le \dot{Q}^{max,pipe}_{b',b} \quad ,\forall t,b,b' \tag{31}$$

$$q^{HGusedSH}_{t,b} \le M \cdot b^{hyd}_b \quad ,\forall t,b \tag{32}$$

$$q_{t,b}^{HGusedDHW} \leq M \cdot (b_b^{hyd} + B_b^{DHWhyd}) \quad ,\forall t,b \tag{33}$$

The size of the pipe limits the heat flow ($\dot{Q}_{b',b}^{max,pipe}$) in the pipe, Eq. (31). The heat from the heating grid can only be used if a hydronic system is installed or for DHW in larger buildings if a hydronic system specifically for DHW already exists ($B_b^{DHWhyd} = 1$) as expressed by Eq. (32) and Eq. (33).

The operation of storage *st* (whether SH, DHW, or electric) is modelled as follows:

$\forall \kappa, t_\kappa \in [1,23], st, b$

$$v_{\kappa,t_\kappa,st,b}^{stor} = v_{\kappa,t_\kappa-1,st,b}^{stor} + \eta_{st} \cdot q_{\kappa,t_\kappa,st,b}^{ch} - q_{\kappa,t_\kappa,st,b}^{dch} \tag{34}$$

$\forall \kappa, t_\kappa \in [0,23], st, b$

$$v_{\kappa,t_\kappa,st,b}^{stor} \leq x_{st,b} \tag{35}$$

$$q_{\kappa,t_\kappa,st,b}^{ch} \leq \dot{Q}_{st}^{max} \;;\; q_{\kappa,t_\kappa,st,b}^{dch} \leq \dot{Q}_{st}^{max} \tag{36}$$

$\forall \kappa, st, b$

$$v_{\kappa,0,st,b}^{stor} = v_{\kappa,23,st,b}^{stor} \tag{37}$$

The storages have a daily operation (Eq. (37)) and a certain charging rate $\dot{Q}_{st}^{max}$.

The heat storage *hst* can only be charged and discharged if a hydronic system is installed in a similar way as in Eq. (32) and Eq. (33). Only technologies that heat up water can be used to charge the SH storage:

$$\sum_{hst} q_{t,hst,b}^{SHch} \leq \sum_q q_{t,q,b}^{SH} \cdot B_q^{hyd} + q_{t,b}^{HGusedSH} \quad ,\forall t,b \tag{38}$$

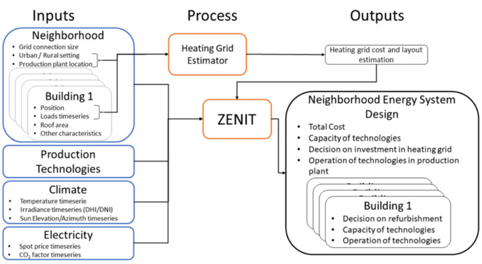

Fig.1. Representation of the inputs and outputs of the model

Fig.1 gives an overview of the different inputs and outputs of the model.

The next section presents the setup of the case study including more details about the inputs used.

4 Case Study

The neighborhood that is used in this model is a 250000m^2 ground floor area, 100000m^2 heated floor area. The floor area and share of each building type is based on the building mix of Oslo. The composition of the building mix and their ground area were obtained using GIS data from Oslo. In this case we consider seven types of buildings: houses (split in two blocks), apartments (split in two blocks), offices, shops, kindergarten, school, and nursing home. The loads timeseries of these buildings are obtained using the results from [13] and [14]. The loads of the buildings when refurbished are also obtained from those articles. The main data about the neighborhood is presented in Table 1 and the refurbishment costs in Table 2. We assume a lifetime of 60 years for the neighorhood and a discount rate of 4%.

Table 1. Characteristics of the building types in the neighborhood

Type	Area (m^2)	Roof Area	B_b^{refu}	B_b^{hyd}	B_b^{DHWhyd}
Houses1	13900	6950	0	0	0
Houses2	13900	6950	0	0	0
Apartments1	2205	4890	0	0	1
Apartment2	22005	4890	0	0	1
Offices	18948	3158	0	0	0
Shops	1230	1230	1	1	0
Kindergarten	460	490	1	1	0
School	5032	1677	0	0	1
Nursing Home	1062	531	1	1	0

Table 2. Refurbishment costs for the different buildings in euros

Type	Refurbishment Cost	Hydronics Cost
Houses1	347500 €	142500 €
Houses2	347500 €	142500 €
Apartments1	550000 €	150000 €
Apartment2	550000 €	150000 €
Offices	474000 €	50000 €
School	12500 €	25000 €

The hydronics costs are assumed based on various online sources and the refurbishment cost are derived from the numbers presented in [15] and set to around 25€/m^2 of floor area. Those costs are assumptions to start with and we also investigate at which cost the optimization decides to refurbish in a sensitivity analysis.

The average load reduction in the SH loads of the buildings is 60%. We assume that the DHW load is not affected by the refurbishment in this study.

Making realistic assumptions when it comes to the cost and the resulting load reduction is difficult and to apply this model to a real case, it would be beneficial to use it in combination with models such as the one presented in [10] and [11].

Several technologies are included in the study. At the building level, there are: solar panel, solar thermal collector, air-air heat pump, air-water heat pump, ground-source heat pump, bio boiler (wood logs or wood pellets), electric heater, electric boiler, biomethane boiler and gas, biogas and biomethane CHP. At the neighborhood level there are: CHP (biogas, wood chips or pellets), boiler (wood chips or pellets or electricity) and ground-source heat pump. The costs, efficiencies and other technical data about these technologies is taken from the Danish Energy Agency‡ and can partly be found in [1].

The prices can be different depending on the status of the building (new, existing, or refurbished) and on the type of building (Apartment complex or single-family house).

‡ https://ens.dk/en/our-services/projections-and-models/technology-data

All timeseries used correspond to year 2016. The timeserie for temperature comes from a measuring station outside of Oslo[§]. The spot prices come from Nordpool[**] and the irradiance data from Solcast[††].

The model is run over one representative year clustered into 20 day-clusters to represent the lifetime. The binaries make this model hard to solve and the clustering counteracts that. More information on the clustering procedure can be found in [1]. If the technologies that are investigated do not require the use of the part load limitation, removing this constraint can yield significant improvements to the solving time and allow for the use of more clusters.

The model is implemented in Python and solved using Gurobi on a desktop with an Intel Core i5-7500 quadcore processor at 3.40Ghz and 24GB of RAM but using only 3 threads.

We perform several cases. The first one is a direct application of the model presented earlier, the second is the same model except the binaries regarding the refurbishment and hydronics are linearized. In addition, we do a sensitivity analysis on the cost of the refurbishment.

5 Results

With a direct application of the model presented in this paper, we get the following investment:

At the production plant, 307kW of biogas engine with heat recovery, 1245kWh batteries and 553kWh of heat storage.

For the building (aggregated results), 5713kW of PV, 341 kW of solar thermal collectors (ST), 1.4kW of air-air heat pump (HP), 664kW of air-water heat pumps, 18 kW of electric water heater and 2116kWh of heat storage.

All the buildings where refurbishment is an option invested in a hydronic system, but none has chosen to refurbish. The total discounted cost for investment and operation of the neighborhood energy system is 16.124M€.

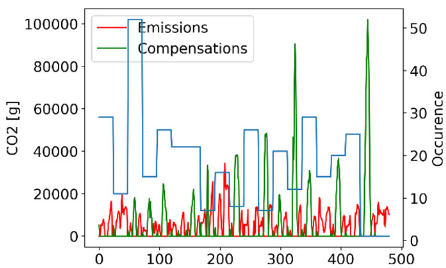

Fig. 2. Emissions and compensations of CO2 in the different clusters as well as the occurrence of the cluster (blue).

The emissions and compensation for each cluster as well as its occurrence in the year is presented on Fig. 2. The CO2 emissions are spread over all clusters while only a few clusters concentrate most of the compensations.

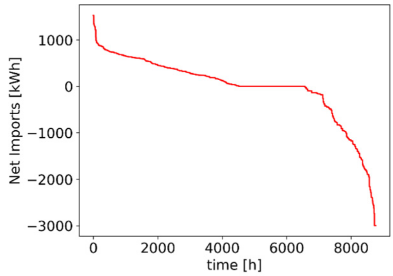

Fig. 3. Duration curve of net imports for the whole year reconstructed from the clusters

The duration curve of net import is shown on Fig. 3. The neighborhood is net importer for most of the year and the exports are concentrated in less than 2000 hours. The battery investment helps somewhat to achieve this by increasing the self-consumption and exporting when the CO2 factors are higher. The full potential of the battery is not fully used however due to the way it is modelled (24-hour operation).

The model is also used with the binaries for hydronics and refurbishment linearized. This gives quite different results:

At the neighborhood level, 5830kWh of battery.

In the buildings, 5661kW of PV, 532kW of ST, 1.47kW air-air HP, 891kW air-water HP, 110kW water-water HP, 40kW wood log manual stoking boiler, 1.5kW electric radiator and 10kW electric boiler, with 643kWh SH storage and 1469kWh DHW storage.

The binaries for refurbishment and hydronics are linearized; the average value of the linearized binaries for refurbishment is 0.0331 and for hydronics it is 0.0657.

The total discounted cost is 14.277M€.

The linearized model gives quite different results than the one with binaries, both in terms of technologies and in terms of the hydronics investment.

The main difference in the energy system are that the heating grid and the biogas engine at the production plant are no longer chosen, and are replaced with other technologies inside buildings for the heat production as well as a bigger battery to allow for more of the PV to be exported. When there is no refurbishment much of the compensation originates from the biogas engine electricity production, that can follow the electricity CO2 factor timeseries, in particular the higher factors in the winter. With only PV, it is then necessary to use a bigger battery to maximize the compensation potential of the PV.

The solving time is longer for the linearized binaries version at around 47 000seconds versus 19 000 seconds for the one with binaries, contrary to what one might expect.

One drawback of using the linearized version compared to the one with binaries has to do with the use of bigM constraints. Indeed, those constraint can be easily bypassed with a low value of the linearized binary due to the high value of M. For example, Eq. (10) and

[§] https://lmt.nibio.no, Skjetten Station

[**] https://www.nordpoolgroup.com/Market-data1/#/nordic/table

[††] https://solcast.com.au

(32) illustrates this. In Eq. (32) a very low value is enough to disregard that equation due to the high value of M; in Eq. (10), the value of the binary only needs to be set high enough to allow for the amount of capacity needed.

The linearized binary version of the model could be used to determine which buildings should be refurbished first or the proportion of a certain building type to be refurbished. However, the investment results might be distorted by the bigM constraints. Moreover, the actual values of the linearized binaries might not actually represent the proportion of buildings that should be refurbished. In our case, the refurbishment binaries have a very low value which indicates that the refurbishment itself is not profitable and the value is chosen only to affect the bigM constraints involving those binaries in order to profit from them without paying the total price.

In practice the investment sizes would depend on the nominal capacity of technologies available on the market. In addition, small investments like the air-air heat pump could be replaced or up-sized.

Since there is high uncertainty regarding a realistic pricing of the refurbishment, we investigate the price at which refurbishment starts to be chosen. The model using binaries is used with refurbishment prices of 75%, 62.5%, 50% and 25% of the original refurbishment price (*Table 2*). At 75%, the model still does not choose to refurbish, at 62.5% the refurbishment is done in just one building, but from 50% and down, it does for all buildings.

We show the energy system for the 50% case to see how the system looks when refurbishment is chosen.

At the neighborhood level, 5754 kWh of batteries.

In the buildings, 5643kW of PV, 599kW of ST, 797kW of air-water HP, 115kW of water-water HP, 40kW of manual stoking wood log boiler, 15kW of electric boiler, 105kW of biomethane boiler and 2420kWh of heat storage.

All buildings choose to invest in refurbishment and hydronic systems.

The total discounted cost is 16.007M€.

Those results are quite similar to the results of the run with the linearized binaries. The amount of PV, ST and batteries are similar, and the main difference lie in the amount of air-water HP (~100kW) and heat storage (~300kWh). This difference is explained by the lower SH demand when choosing refurbishment in the case with binaries.

6 Conclusion

In this paper, a model for investing in the energy system of ZENs, considering the refurbishment of buildings, the hydronics and their impacts on the model, is presented and used on a test case in Norway.

The results show that with the cost assumptions used, the refurbishment is not chosen, but hydronic systems are. The system relies mainly on PV, solar thermal collectors (ST), a biogas engine (connected to the buildings by a heating grid), a battery and heat pumps (HP) and heat storage. From 50% of the original refurbishment cost, refurbishment is chosen, and the system does not have a biogas engine and a heating grid anymore, but a much bigger battery and more heating technologies inside the buildings. With linearized binaries, the investments are similar to the case with 50% refurbishment cost, but the value of the linearized binaries cannot be used to indicate the share of buildings to refurbish.

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