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Stochastic Optimization of Zero Emission Buildings

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Submission date: June 2018
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Abstract

Zero Emission Buildings (ZEBs) are energy efficient buildings that produce on-site renewable energy to compensate for their consumption. The concept of ZEBs is based the EU's Energy Performance of Buildings Directive (EPBD) of 2010, demanding that all new buildings constructed after 2020 are to reach "near zero energy level" [1]. Previous research on energy systems in ZEBs have used *deterministic* linear optimization techniques to determine the cost-optimal design of invested technologies in such sustainable buildings [2].

The main contribution of this thesis is the development of a *stochastic* two-stage model, formulated as a Mixed Integer Linear Program (MILP), that determines the cost-optimal investments and operations of a ZEB. The model accounts for uncertainty in the short-term operational patterns; the fluctuations in the outdoor temperature, the spot price of electricity and solar irradiation. The two the main objectives are: 1) To compare the optimal technology design of the deterministic and stochastic model counterparts and 2) to investigate the possibilities of the investment of an electric battery. Emissions constraints are formulated to fit the ambition level known as the "ZEB-O" level, only considering emissions caused in building operations [3].

The model input data is simulated to fit the hourly demand of electricity and heating in a Norwegian passive house. Time series on simulated demand from 2010 to 2014 are used to construct operational scenarios. Realistic investment costs of building technologies are used based on an extensive survey of Norwegian manufacturers' prices. Clustering analysis is used to reduce the computational effort by selecting seasonally representative hours to imitate a full year of operations.

Results show that a stochastic model can better, than its deterministic counterpart, account for the following: (i) Cover the peak heat demand of periods colder than the deterministic input data, and (ii) avoid over-dimensioning of the installed base-load capacity. The net present value of the total costs can be reduced by 1/6, which represents the quantitative value of using a stochastic model in the place of a deterministic model. Furthermore, the stochastic model is used to analyze the impact of a "power subscription" grid tariff scheme and battery operations in ZEBs. The battery is not a cost-optimal technology in ZEBs due to the forced reinvestments every 10th year imposed by the stochastic two-stage formulation. Sensitivity analysis show that the battery specific investment costs (EUR/kWh of storage capacity) must be reduced by 90 % to become part of the solution.

Sammendrag

Nullutslippsbygg (ZEB) er energieffektive bygninger som produserer fornybar energi lokalt for å kompensere for importert energi. Begrepet er basert på EU's byggdirektiv fra 2010 (EPBD) som krever at alle nybygg etter 2020 skal oppnå "nullenerginivå" [1]. Tidligere forskning på energisystemer i ZEB har brukt en *deterministisk* tilnærming for å finne kostnadsoptimal dimensjonering av investerte teknologier i nullutslippsbygg [2].

Hovedleveransen i denne masteroppgaven er utviklingen av en *stokastisk* to-stegsmodell, formulert som et "Mixed Integer Linear Program" (MILP) som bestemmer de mest kostnadseffektive investeringene og driftsmønster i nullutslippsbygg. Modellen hensyntar usikkerhet i kortsiktige driftsparametere; variasjonene i utetemperaturen, spotprisen på elektrisitet og solinnstråling. De to hovedmålene er: 1) Å sammenligne løsningen til den stoskasticke modellen med den deterministiske motparten og 2) å undersøke mulighetene for å investere i et elektrisk batteri i nullutslippsbygg. Utslippsrestriksjonene er fomulert slik at totale utslipp fra byggets driftfase er tilpasset ambisjonenivået kjent som et "ZEB-O" nivå [3].

Inputparametere er tilpasset timesbehovet av elektrisitet of varme i et norsk passivhus. Tidsserier med det simulerte behovet fra 2010 til 2014, sammen med øvrige usikre parametere, brukes til å konstruere ulike driftsscenarier. Realistiske investeringskostander for ulike energiteknologier er funnet ved en kostnadsanalyse basert på priser fra norske leverandører. "Cluster"-analyse brukes til å redusere modellens kjøretid ved å velge representative timer for hver årstid som totaltsett etterligner et helt driftsår for bygget.

Resultatene viser at en stokastisk modell, sammenlignet med dens deterministiske motpart, er bedre på følgende momenter: (i) Å dekke topplasten av varme i timene der varmebehovet er høyere enn det som er gitt i deterministisk inputdata, og (ii) å unngå overdimensjonering av installert grunnlastkapasitet. Netto nåverdi av totale kostander kan reduseres med 1/6, som representerer den kvantitative verdien av en stokastisk modell sammenlignet med en deterministisk modell. Videre blir den stokastiske modellen brukt til å analysere virkningen av en effektbasert netteleiestruktur og driftsmønsteret til et batteri i nullutslippsbygg. Batteriet er ikke en kostnadseffektiv teknisk løsning i et nullutslippbygg grunnet tvungne reinvesteringer hvert 10. år som følge av den stokastiske to-stegsformuleringen. Sensitivitetsanalyse viser at spesifikke investeringskostnader for et batteri (EUR / kWh lagerkapasitet) må reduseres med 90 % for å bli en del av løsningen.

Preface

This thesis marks the conclusion of the five year Master's degree in Electric Power Engineering and Smart Grids. My field of specialization has been Electrical Power Systems. This thesis addresses energy planning in terms of energy use in buildings and has been carried out during the spring of 2018.

I would like to express my sincere gratitude to my main supervisor Karen Byskov Lindberg for the motivating commitment and honest feedback. Thanks to Pernille Seljom and Magnus Koråps for important inputs and guidance that been of great value to my research. I also owe a special thanks to Harald Svendsen at SINTEF Energy, Harald Endresen at NVE, and the Phd students Martin Hjelmland, Martin Kristiansen and Espen Flo Bødal for sharing knowledge and interest in coding. Your respective expertise have undoubtedly improved the academic quality of this thesis. I am also grateful for the love, support and the monumental proofreading from Silje Andersen and Jonas Bøe.

Trondheim, June 2018.

Ingrid Marie Andersen

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Abbreviations

ASHP Air-source Heat Pump

BA Battery

BB Biomass Boiler

COP Coefficient of Performance

DOD Depth of Discharge

EB Electric Boiler

EPBD Energy Performance of Buildings Directive

GSHP Ground-source Heat Pump

HS Heat Storage

NPV Net Present Value

PEF Primary Energy Factor

PV Photovoltaic panels

SOC State of Charge

SMILP Stochastic Mixed Integer Linear Program

SP Stochastic Programming

VSS Value of the Stochastic Solution

ZEB Zero Emission/Energy Building

ZEN Zero Emission/Energy Neighbourhood

noZEB no Nearly Zero Emission Building

nZEB nearly Zero Emission Building

sZEB strictly Zero Emission Building

Chapter 1

Introduction

1.1 Thesis Motivation

One of the greatest challenges of the 21th century is to restrict global warming. The EU has an ambitious commitment of limiting the temperature rise to +2 ° C. This requires a 90 % reduction of greenhouse gas emissions from the built environment within 2050 (compared to 1990 level) [4]. Buildings are responsible for a large share of the total energy consumption in the EU and in Norway. They account for about 36 % of the GHG emissions in Europe and have great mitigation potentials [5]. The recast of the EU's Energy Performance of Buildings Directive (EPBD), issued in 2010, states that all new buildings constructed within the European Union after 2020 shall reach nearly zero energy level [1]. Nearly Zero Energy buildings (nZEB) have high energy performance because of low energy demands that can be covered by renewable energy sources. From the period from 2009 to 2017, the Norwegian Research Center on Zero Emission Buildings (ZEB Center) was a European lead in investigations of possibilities and challenges of ZEBs. The ZEB Center has proposed a definition that imposes general emission requirements on ZEBs. Furthermore, there has been extensive research on ZEBs within fields as architecture, ventilation and energy systems, life cycle analysis and power system planning. This wide research has resulted in nine nZEB pilot buildings and a research continuation towards Zero Emission Neighbourhoods in Smart Cities (ZEN) for the centre of Environment-friendly Energy Research (FME) [6].

ZEBs affects the energy system by lower energy consumption due to energy efficiency measures, and increased production due to on-site power generation by e.g. Photovoltaic panels (PVs) [2]. Emissions caused by buildings are calculated using weighing factors for the energy carriers, for instance a CO_2 equivalent factor per kWh of imported electricity. The value of the CO_2 factor for electricity is a debated subject and depends on the mix of resources used in electricity production (the energy mix) [3]. In Europe, the energy mix is 73 % non-renewable and based on resources such as nuclear power, coal, crude oil and natural gas [7]. On the contrary, the Norwegian produced electricity is 98 % hydropower based. However, increased energy trade between the Nordic and the European power systems in the future makes it difficult to know which resources the power is coming from [8].

According to the author of [5], upgrading energy systems in buildings can lead to an 80 % reduction of operational costs. Achieving cost-optimal ZEBs is desirable since PV systems today are expensive investments [9]. An optimized design of the energy system is therefore essential to reduce the costs and make ZEBs feasible. This is the motivation for using optimization techniques to customize the design of energy systems in ZEBs. This thesis builds on an optimization model developed in the work of [2]. In that context, a deterministic Mixed Integer Linear Programming (MILP) formulation was used to find the optimal capacities and compositions of the technologies in a ZEB. The model was further developed in pre-work by the author of this thesis [10]. However, the uncertainty of the input parameters was not considered. The main contribution of this thesis is a qualitative and qualitative investigation of the need for a stochastic model, accounting for the operational uncertainty in ZEBs.

1.2 Problem Description

The main objective of this thesis is to develop a stochastic optimization program for optimal investments of ZEBs, in the open-source language Pyomo. The model developed considers the short-term operational uncertainty by accounting for different operational patterns of the building. The uncertain parameters investigated in the stochastic model formulation are the building's heat demand, outdoor temperature, spot price of electricity and solar irradiation. One of the model extensions implemented is a household battery, of which operations will be investigated. The following research questions are to be answered in this thesis:

Question 1: How can a stochastic model formulation better approach the objective of optimal and long-term robust investments in ZEB energy systems, compared to a deterministic model formulation?

(a) *How does a stochastic model solution differ from its deterministic counterpart, given operational uncertainty?*

(b) *How does implementing a stochastic model affect the applicability and computational effort compared to implementing a deterministic model, and what could be possible mitigation measures?*

(c) *Given the above key indicators of a stochastic model's adequacy, could one argue for the suitability and/or necessity of a stochastic model formulation?*

(d) *How can the significance of non-operational parameter uncertainty be assessed in a sensitivity analysis?*

Question 2: What are the incentives for investing in household batteries in Norwegian ZEBs?

(a) *Through a sensitivity analysis, can the investment of a battery be triggered by e.g. a power subscription grid tariff scheme?*

(b) *How does the battery affect optimal operations of ZEBs?*

(c) *Is the battery modelling sufficiently representative for real-life battery operations?*

1.3 Approach and Limitations

The optimization model developed in this thesis is a stochastic two-stage program (SMILP), separating the investment decision (first stage) variables from the operational (second stage) variables. The model's objective is to minimize both the net present value (NPV) of the first stage investment costs and weighted probability of operational costs. Building operations are hourly based and the investments take place in the beginning of year 1 of the 60 years analysis horizon. A realistic case study of a Norwegian passive house is used to validate the model and to compare the deterministic and stochastic solutions. Simulated load profiles for the climatic years 2010 to 2014 based on [2] are used as input.

One consequence of moving from a deterministic to a stochastic model formulation can be the increased model computational effort (runtime). When working with hourly time steps, and expanding from one to multiple scenarios, the runtime can potentially be an obstacle which will reduce the applicability of the stochastic program. To avoid this inefficiency, the methodology of *k-means clustering* analysis is used to reduce the model from a full year of 8760 hours down to a scenario representing a full year by only 672 hours. K-means clustering methodology, of which its applicability and wide range of algorithmic approaches is described in [11], has been widely used in optimization. Examples of energy optimization models using this methodology as a scenario reduction technique are [12] and [13].

The main limitation in this thesis is that only considers the emissions caused in operations. Other phases, such as the production and construction of building materials, should also be accounted for in ZEBs with high ambition levels. In ZEB definition, the ambition level used in this thesis is called a "ZEB – O", which means a ZEB that only balances out the operational phase [3].

1.4 Structure of the Thesis

The following chapters are structured as follows:

Chapter 2 gives an introduction to the theoretical concept of ZEBs, the fundamental principles of stochastic programming and a review of the economic influences on grid-connected ZEBs.

Chapter 3 presents structure of the stochastic model formulation and the model implementation. This is also where the input parameters are analyzed and the procedure for scenario generation is explained.

Chapter 4 is a description of the model's objective function and constraints.

Chapter 5 presents the results of the passive house case study which are readily discussed.

Chapter 6 delivers the final conclusion.

Chapter 7 gives recommendations for further work.

Appendices include additional figures for the clustering analysis, details on the technology investment costs used as model input, together with complete result tables of the model runs presented in Chapter 5, and an extract of the Pyomo model code.

Chapter 2

Background

2.1 Introduction to Background

This chapter contains related literature of three main subjects: Zero Emission Buildings (ZEBs), optimization and Stochastic Programming (SP) and the energy economics of grid-connected buildings. The first part is an introduction to the concept of ZEB and some of its relevant energy system technologies. The second part presents the fundamental theory on optimization under uncertainty through SP, with related terms and relevant formulas. The final part introduces the main drivers for uncertainty in cost-optimal ZEBs, mainly based on the Norwegian power market economy for end-users.

2.2 Zero Emission Buildings

2.2.1 Definition

The concept of Zero Energy/Emission Buildings (ZEBs) was launched by the EU's Energy Performance of Buildings Directive (EPBD) in 2010, stating that all new buildings are to be *nearly zero energy buildings* (nZEB) by 2020 [1]. The EPBD gives the following definition:

A 'nearly zero-energy' building means a building that has a very high energy performance. The nearly zero or very low amount of energy required should be covered to a very significant extent by energy from renewable sources, including energy from renewable sources produced on-site or nearby [1].

The terms *zero energy* and *zero emission* are equivalents [2], and therefore a more specific definition proposed by the Research Centre on Zero Emission Buildings (ZEB Centre) is as follows:

A zero-emission building produces enough renewable energy to compensate for the building's total greenhouse gas emissions throughout the lifetime [3].

Greenhouse gas (GHG) emissions caused by buildings are calculated using weighing factors for each of the energy carriers; the CO_2 factor or the primary energy factor (PEF). The CO_2 factor is related to a zero *carbon* building or a zero *emission* building, while the term zero *energy* building is used together with Primary Energy Factors (PEF) [2]. The use of the term "Zero Emission Buildings" (ZEBs) will from here on embrace both terms.

A net ZEB is by definition a building that can compensate for the accumulated emissions throughout all its phases of study [3]. For a complete lifetime study, all phases must be considered. This include extractions, processing and transportation of construction materials, energy used in construction and operations, demolition and waste management.

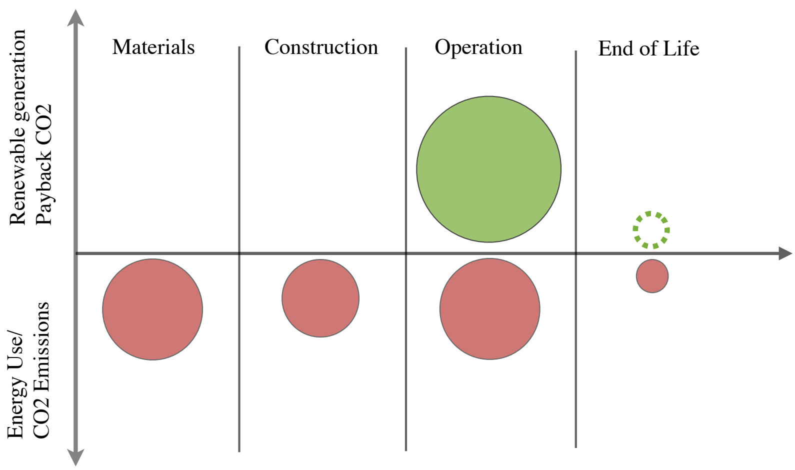


FIGURE 2.1: Emitted and "saved" CO_2 emissions of a building's lifetime. Adopted from [3].

Figure 2.1 illustrates the emission throughout a building's lifetime, showing that there are emissions related to all lifetime phases. However, only the operational phase is compensating with its "payback" emissions. The ZEB definition is characterized through the ambition level, indicating which of the lifetime phases that are recognized [3]. With an "ZEB - O" ambition level, the emission balance between energy use and energy generation can be regarded as the annual balance between import and export of energy. This can be formulated mathematically with equation (2.1) [14]. The emissions related to the amount of energy from energy carrier i is multiplied by a weighing factor f_i, unique for the energy carrier.

$$\sum_i import_i \cdot f_i - \sum_i export_i \cdot f_i = G \qquad \forall i \in \mathcal{I} \tag{2.1}$$

Energy carriers are e.g. electricity import from the power grid, district heating and different types of fuels such as bio fuel and fossil fuels. If G = 0, there is a strict emission balance. Such buildings can be referred to as *strictly* net zero emission building (sZEB) [2]. The balance is a net balance throughout a year or for the entire building's lifetime. Daily and seasonally weather fluctuations, which cause mismatches between the instant export and import of energy, makes it impossible to satisfy the emission balance on a daily or hourly basis.

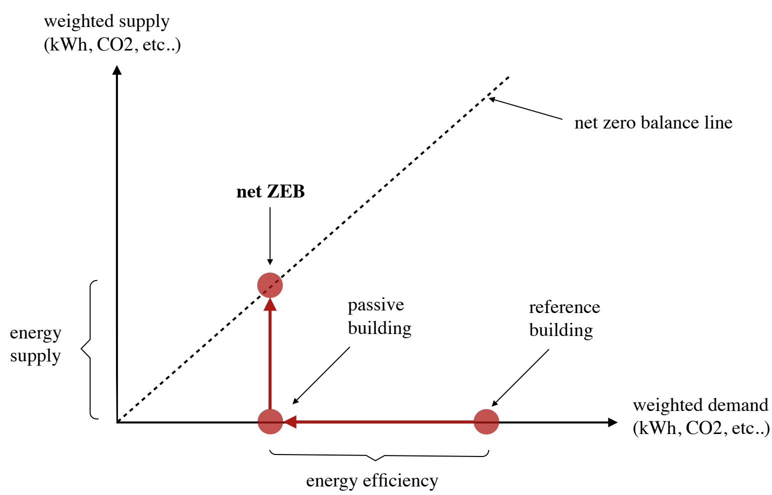


FIGURE 2.2: Net ZEB balance line using PEF or CO_2 factors. Adopted from [14].

Figure 2.2 shows the net zero balance line which illustrates how a sZEB will have the perfect balance between export and import of energy. The x-axis represents the building energy demand. To what extent the building is a net ZEB (sZEB) or a nearly ZEB (nZEB) is relative to the reference emissions and can be calculated according to (2.2) [2].

$$\text{ZEB-level} = \frac{G_{ref} - G}{G_{ref}} \tag{2.2}$$

Where G_{ref} is the emissions from a reference (noZEB) building.

Energy efficient buildings have low energy demands and a lower amount of energy to compensate for. Such buildings are referred to as *passive buildings* and the space heating demand must not exceed 15 kWh/m^2/year for buildings $\leq$ 250 m^2 [15]. To reach ZEB status, energy must be generated on site and exported. Buildings which export electricity are known as *plus buildings* [16]. If the total export is equal or greater than the import, the building obtains the status of a sZEB. Table 2.1 sums up building categorization terminology.

TABLE 2.1: Building categorization terminology, based on definitions from [2].

Building Type	Description
Passive building	Energy efficient building of which the space heating demand is $\leq 15kWh/\text{m}\hat{}2/year$[15]
Plus building	Building exporting surplus electricity exceeding its demand/consumption [16]
Zero emission/carbon building	Plus building satisfying balance equation (2.1) by using a CO_2 factors
Zero energy building	Plus building satisfying balance equation (2.1) by using PEF
Strictly zero emission building (sZEB)	100 % (net) Zero emission building
Nearly zero emission building (nZEB)	1-99 % Zero emission building
No zero emission building (noZEB)	Building without emission requirements

2.2.2 Weighing Factors

The CO_2 Factor
A CO_2 equivalent is a metric measure of GHG emissions from each kWh of energy from a given energy carrier [7]. All types a greenhouse gases are converted to a CO_2 equivalent according to their relative contribution to pollution, as carbon dioxide is the dominant GHG [17].

As stated in chapter 1, the CO_2 factor of electricity depends on the energy mix used in its generation. For proper simulations of the entire lifetime of a building, the CO_2 factor will also have to reflect the trending increase in power trade and the ongoing decarbonization of the European power sector towards 2050. The CO_2 factor suggested by the research ZEB Centre is therefore 132 g per kWh of electricity [3]. However, the estimation of emissions related to Norwegian, hydropower generated electricity was, in 2015, 17 g/kWh in contrast to the current European estimation of ca. 350 g/kWh [8].

Primary Energy Factors
Primary energy measures refers to the extraction of energy from natural resources [7]. The primary energy factor is a ratio of the final energy product in terms of extracted energy. The extracted amount of primary sourced energy is usually transformed multiple times before reaching its end use [18]. The transformations are e.g. processing and transportation, which cause energy losses.

Reducing the primary energy demand in buildings is on of the EPBD's ambitions, as it is an accurate measure of the change in efficiency of buildings [1]. In comparison to the CO_2 factor, the PEFs do not reflect on the benefits of the renewable energy production compared to fossil fuels productions [2]. One way to compensate is to separate renewable PEF and non-renewable PEF, or by indicate renewable primary energy as a factor ≤ 1 [14]. The EPBD suggested PEF is 2.5 kWh primary energy per kWh useful energy. However, the actual PEF of electricity varies with the hourly production mix and there are multiple ways of calculating the factor depending on different assumptions and considerations, such as the time resolution, geographical system boundaries etc. [18].

2.2.3 Relevant Technologies

As ZEBs require on site renewable electricity production, sun power is the most suitable. Other technologies like the combined heat and power (CHP) or a small windmill can also generate electricity locally [2]. This section gives an introduction to each ZEB technology that is considered relevant for this thesis. The following technologies are introduced:

- Photovoltaic solar panels
- Electric battery
- Air-source and ground-source heat pumps
- Hot water storage
- Biomass boiler
- Electric water boiler

Photovoltaic systems (PV)

A PV system, or a PV panel is an electronic device converting sunlight into energy. When sun rays hit the non-reflecting surface, electrons are released and a current is formed [19]. Figure 2.3 shows the structure of a silicon-based PV cell and its working mechanism, which is further explained in [20].

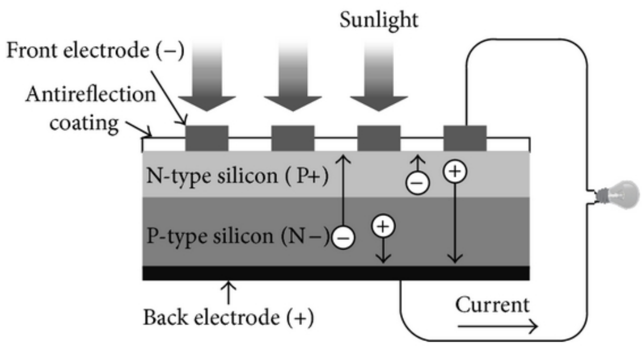


FIGURE 2.3: Basic structure and operation of a silicon-based PV cell. Adopted from [21].

Sun power is a sustainable but volatile energy source because the possible electricity production is intermittently dependent of solar irradiation. About 30 % of the solar irradiation is reflected and do not penetrate the atmosphere. The yearly irradiation in Norway is in between 600 - 1000 kWh/m^2 [22]. Power generation from each m^2 of PV panel is influenced by multiple factors, such as the module temperature, the angle of the sun verses the orientation of the panel, and variation in shading [19]. Estimating the power generation is therefore a complex calculation, usually done by computer software, to simulate the operation of a given system at a given location. The author of [23] suggests a simplified estimation of the generated power in kilowatt hours per kilowatt peak installed (kWh/kWp), by only considering the horizontal irradiation I_t (W/m^2) and the panel's ambient temperature T_{amb}, as in equation (2.3).

$$P_{pv}(kW) = P_{stc} \cdot \frac{I_t}{I_{stc}} \cdot \eta_{rel} \tag{2.3}$$

- Where P_{pv} (kW) is the generated power, P_{stc} is the generation at standard conditions, I_t (W/m^2) is the instant irradiation of a certain time perspective t and I_{stc} is the irradiation at standard conditions; 25°C to 1000 W/m^2.

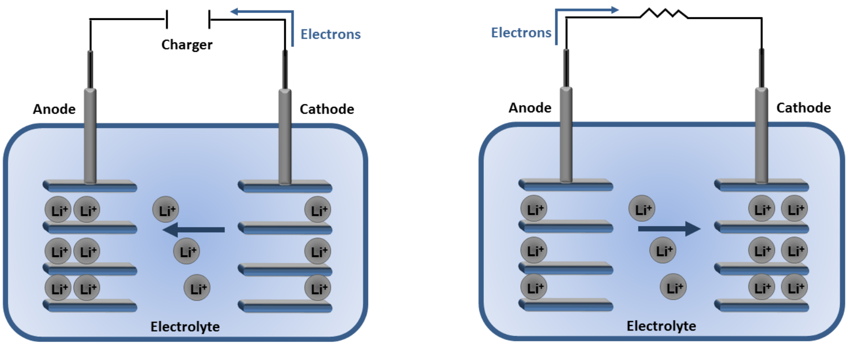
$$\eta_{rel} = 1 + k_1 \ln{(I')} + k_2 \ln^2{(I')} + T_t'(k_3 + k_4 \ln{(I')} + k_5 \ln^2{(I')}) + k_6 T_t^2 \tag{2.4}$$

- Where $I' = I_t/I_{stc}$, $T' = T_{amb} + c \cdot I_t - T_{stc}$ of which the coefficient c $(°CW^{-1}m^2)$ describes how much the PV module is heated by the solar radiation. It depends e.g. on the way the PV module is mounted and the module type.

The optimal orientation of the panel, irradiation and temperature are factors influencing the PV's efficiency and depend on its geographical location. The average efficiency increases with the latitude, as overheated panels generate less electricity. For temperatures higher than 25 ° C, the efficiency degrades linearly [24]. However, the total production throughout the year will be greater in the opposite direction, as locations closer to equator experience more hours of sun in total. A Norwegian roof-mounted PV panel can reach a high efficiency because the temperature seldom exceed 25°C. However, the amount of days and hours throughout the year that can produce sun power is limited. The optimal angle of a Oslo based, roof mounted PV panel is 40° [25].

Electric Battery

Batteries are self-contained power banks that can store and release electricity by moving electrons between two terminals called the electrodes. In between the electrodes, there is a chemical electrolyte which is either a liquid or a powder. The most common technology used together with PV systems is the *lead-acid* or the *lithium-ion* battery, whose names reflect the combination of electrolytes and electrodes [19]. Figure 2.4 shows the operation mechanisms of the charging and the discharging of a battery at an electronic level.



(a) Recharging (b) Discharging

FIGURE 2.4: Operation mechanisms in terms of (a) charging and (b) discharging of a lithium-ion battery. Adopted from [26].

The battery's storing capacity is a measure of the maximum useful energy in kWh or Ah (kilowatts hours or ampere hours), further explained in [19]. The continuous power capacity, known as the charging rate, is measured in kW or A. A general measure for the battery's performance is the round trip efficiency in equation (2.5) which is the product of the charging and the discharging efficiencies, η_{ch} and η_{dch}. The succeeding equations are adopted from [27].

$$\eta_{rt} = \eta_{ch} \cdot \eta_{dch} \tag{2.5}$$

The state-of-charge (SOC), in (2.6) indicates the energy content in a battery using percent point units. A SOC of 100 % indicates a fully charged battery. E_t (kWh) is the energy content in time t, and X_{rated} is the storage capacity (kWh).

$$\text{SOC} \quad (\%) = \frac{E_t}{X_{rated}} \cdot 100 \tag{2.6}$$

The energy content is a balance of the energy e_{ch} entering the storage and the e_{dch} drawn from the storage. Note that the discharging efficiency is a fraction, as the total energy drawn from the storage is greater than the useful energy discharged.

$$E_t = E_{t-1} + e_{ch} \cdot t \cdot \eta_{ch} - e_{dch} \cdot t \cdot \frac{1}{\eta_{dch}} \tag{2.7}$$

The battery is a temporary storage designed for daily cycles; one complete charge and one complete discharge. Charging the battery 25 % and then discharging 25 % equals 1/4 cycle. As the charging and the discharging of a battery are mechanisms of cyclic transfer of charges between electrodes, the lifetime of a battery is a function of the total charging cycles. It is also dependent on the surrounding temperature, the storage time period and the Depth of Discharge (DOD) [19]. DOD is the complement of SOC and co-related to the cyclic lifetime, as seen in figure 2.5.

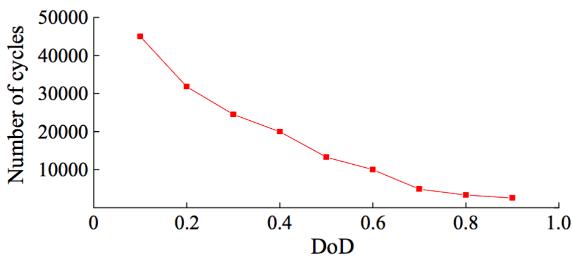


FIGURE 2.5: Life cycles vs DOD for a lithium-ion battery, adopted from [28].

Figure 2.5 shows that the total cycles during the battery's lifetime is a function of the DOD. However, a simplified approach is to estimate the life time in years, based on normal conditions and usage, as commonly given by the manufacturer. More on the different types of batteries and their usage is explained in [29].

Heat pumps

Heat pumps are energy efficient heating (or cooling) technologies that by a small amount of electricity can produce 3-6 times as much energy [30]. The average ratio for an air-source heat pump (ASHP) is about 1 kWh electricity per 3 kWh useful heat. However, this ratio, known as the coefficient of performance (COP) depends on the source temperature and the building required indoor temperature. While the ASHP uses the difference between the outdoor and indoor temperatures, the ground-source heat pump (GSHP) relies on the geothermal sources such as ground water or soil. More on the detailed thermodynamic technology can be explored in [31] and their environmental impact, in [32]. Figures 4.14 and 4.15 illustrates the working principles of the ASHP and GSHP.

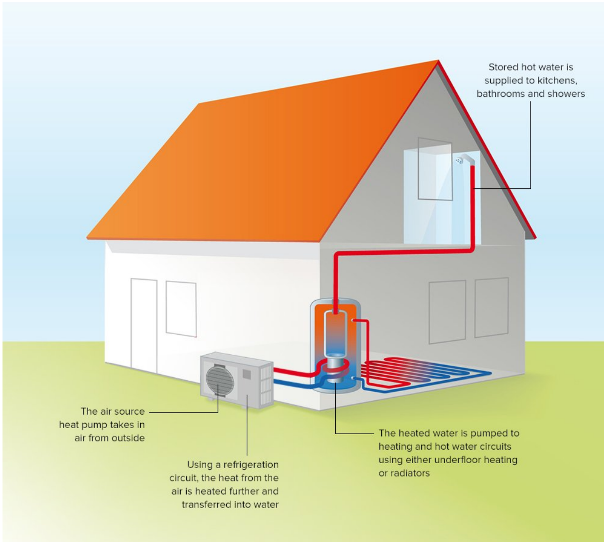


FIGURE 2.6: Air source heat pump principles (air to water). Adopted from [33].

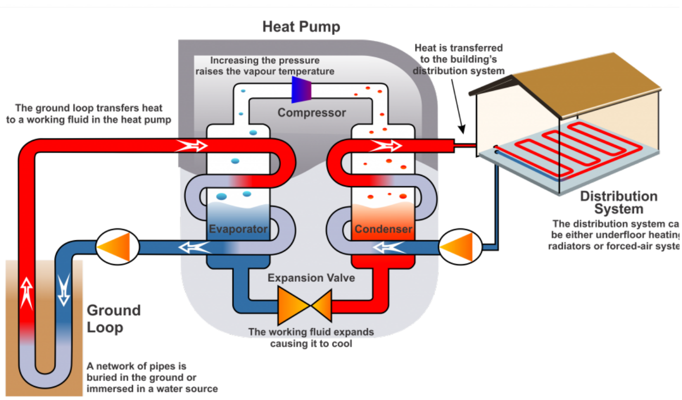


FIGURE 2.7: Ground-to-water heat pump principles. Adopted from [34].

The only difference between the ASHP and the GSHP is the source temperature. The supply temperature can either be hot water demand or indoor air heating, depending on the distribution system. The difference in source, T_{source} and supply, T_{supply} temperatures are the basis for the COP. [35] suggests the following calculation of the COP:

$$\text{COP} = k_0 - k_1 \cdot \Delta T - k_2 (\Delta T)^2 \tag{2.8}$$

Where the k-values differ between manufacturers and ΔT is the difference between the source and supply temperatures, as given in equation (2.9).

$$\Delta T = T_{supply} - T_{source} \tag{2.9}$$

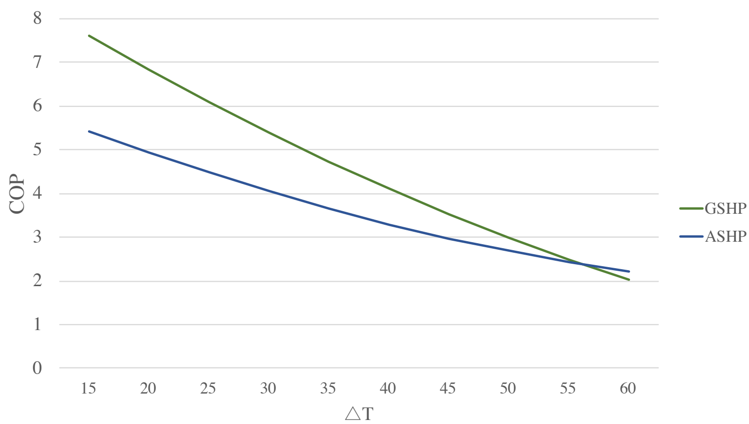


FIGURE 2.8: COP vs. the temperature difference between source and supply. Based on Stiebel Electron manufacturer data in the work of [2].

Figure 2.8 shows the co-relation ΔT and COP from Stiebel Electron heat pumps, based on equation (2.8). The COP curve for the GSHP is higher compared to the ASHP curve because the T_{source} is higher for the GSHP. The ground temperature is stable at around 10 ° throughout the year.

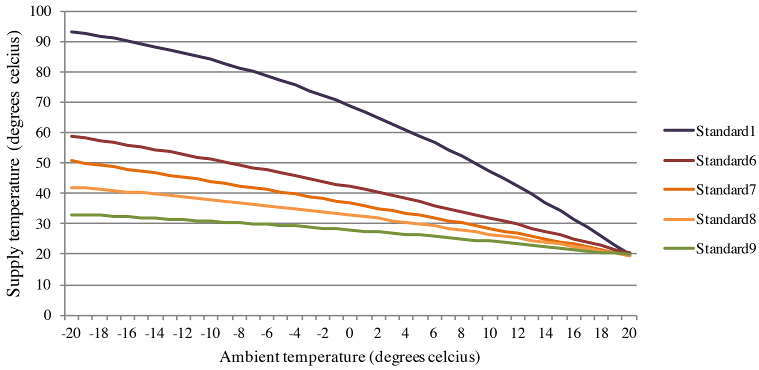


FIGURE 2.9: Supply temperature for different building standards. Adopted from [2].

Figure 2.9 shows the variation of the the required indoor temperature T_{supply} as a function of the outdoor (ambient) temperature. The different standards represent the level heating losses through the insulation levels. Poorly insulated buildings require a larger ΔT than for instance passive buildings. Equation (2.10) can be used to calculate the supply temperature [2].

$$T_{supply} = A \cdot T_{amb}^2 + B \cdot T_{amb} + C \tag{2.10}$$

In waterborne heat distribution systems, the heat pump serve both the space heating (sh) demand and the hot water (hw) demand of the building. Because the supply temperatures of the *sh* demand and the *hw* demand differs, they must be weighted by their respective heating demand to obtain an estimation for the total COP for the heat pump. Equation (2.11) has been used in [2].

$$\mathrm{COP} = \frac{\mathrm{COP}_{sh}\mathrm{D}_{sh} + \mathrm{COP}_{hw}\mathrm{D}_{hw}}{\mathrm{D}_{sh} + \mathrm{D}_{hw}} \tag{2.11}$$

Heat Storage

The heat storage is in brief a hot water accumulator tank keeping the water at a certain temperature and allowing excess thermal energy production to be stored for later use. In a ZEB context, the accumulator tank closes the gap between the energy produced and the energy demand of the building. This leads to a flexible and efficient use of the on-site produced renewable energy. More on heat storage technology and the conversion between liters and kWh accumulated energy can be found in [36].

The Biomass Boiler

Biomass is a general term for combustible remains from organic materials as woods, agriculture and livestock waste. The energy potential in Norwegian biomass regeneration each year can theoretically cover 140 TWh of heating [22]. One type of bio-fuel used in households is wood pellets, which is processed biomass in the shape of small brickets carrying a large heating value. Figure 2.10 shows a general biomass boiler system for waterborne heating systems. For further reading, see for example [37].

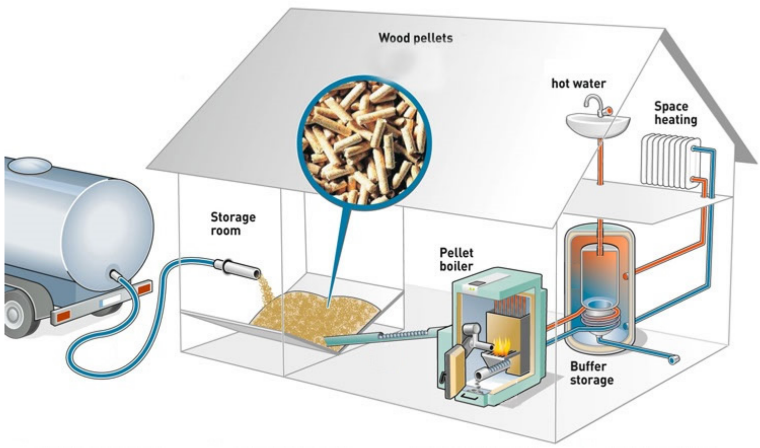


FIGURE 2.10: Principles of the biomass boiler. Adopted from [38]

Electric top-up Boiler

An electric boiler uses electricity to heat the water for the use in waterborne distribution system [39]. The electric boiler is a top-up device for peak heating demand and has low investment costs. Its operational costs are directly linked to the costs of electricity and its efficiency is just below 1 kWh heat for each kWh of electricity.

2.3 Optimization and Stochastic Programming

This chapter introduces the framework for modelling optimization problems involving uncertainty: Stochastic Programming (SP). The intended audience is readers with some basic optimization knowledge. Before preceding to the mathematics behind SP, there is a brief introduction to Mixed Integer Linear Programming (MILP).

2.3.1 MILP

MILP formulation is especially suitable for large operational models involving several hundreds (and thousands) input parameters and processes (e.g. hourly load and weather profiles). Its linearity makes it possible to efficiently solve large problems [40]. Some of the variables in MILPs are required to take integer values. A general formulation of a MILP is given in (2.12), where the objective function, $c(d, x)$ is the cost function which is to be minimized by choosing the right decision variables x by the given parameters d. All constraints ($f(x)_c$ and $g(x)_c$) must be linear functions in a MILP formulation [41].

$$\begin{aligned} \text{Minimize} \quad & c(d, x) \\ s.t \quad & x \in R, \quad \text{integer} \quad x_i \quad \forall i \in I \\ & f(x)_c = 0 \quad\quad c \in Eq. \\ & g(x)_c \leq 0 \quad\quad c \in Ieq. \end{aligned} \tag{2.12}$$

The equation above is a general description of a constrained optimization problem formulated as a MILP. *Eq.* denotes a set of equality constraints and *Ieq.* represents the inequality constraints.

2.3.2 Uncertainty

Uncertainty is the concept of being in doubt about a value. Applied to modelling it means that a given value may or may not occur in the future [42]. Furthermore, there is a difference between random uncertainty and stochastic uncertainty. Randomness can be defined as unpredictable uncertainty that can not be described by previous observations (e.g historical data), while stochastic uncertainty is probabilistic variations in processes over time and space [42]. For long-term investment models it is important to acknowledge how building operations are and will be affected by investments [43], [44]. The right investments (i.e strategic decisions) must be cost-optimal, but also flexible and robust in order for the operational part to respond to varying conditions; long-term and short-term uncertainty. Short-term uncertainty refers to seasonal or hourly fluctuations such as weather conditions, while long-term uncertainty is driven by uncertainty about future pricing levels, energy production mix and the demand due to future expansion planning, among others [44]. Accounting for uncertainty in modelling is known as a *stochastic modelling approach* [45].

2.3.3 Stochastic Programming: The two-stage Model

Stochastic programming (SP) was first introduced by George Dantzig in 1955, when the two-stage model based on linear programming was formulated [46]. In opposition to deterministic programming, SP accounts for uncertainty either in the input parameters or by having probabilistic constraints [47]. A two-stage formulation separates the first stage (investments) variables from the second stage (operational) variables of the problem, and accounts for the uncertainty in the second stage of the recourse problem. In multi-stage and multi-horizon formulations, these two stages can periodically occur multiple times. In such formulations, the total number of scenarios is growing exponentially with the number of periods [48].

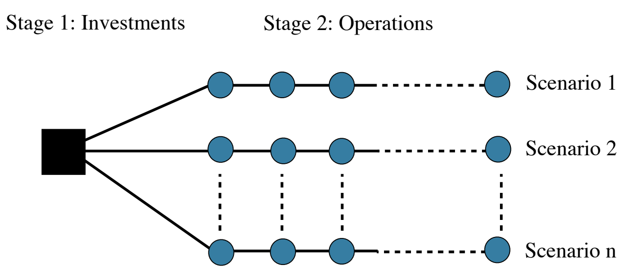


FIGURE 2.11: Scenario fan for a two-stage stochastic model formulation with one strategic stage and multiple operational stages for each of the n scenarios.

Figure 2.11 illustrates the scenario tree (or fan) of a two-stage model with operational scenarios. The square represents the first stage, also known as the strategic stage. Each blue circle is defined by the choice of time resolution, for example one hour, week, year or period of operation, i.e. the second stage. The deterministic equivalent model is shown in figure 2.12, which by definition is a stochastic model of one scenario [49].

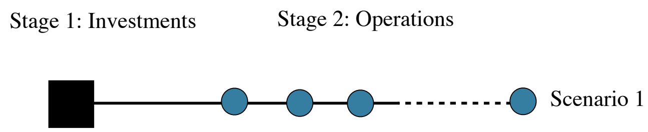


FIGURE 2.12: The deterministic equivalent scenario fan of the two-stage scenario tree in figure 2.11.

The objective function of a two-stage model is separated into two parts, as given in equation (2.13), where each c represents a cost function. The x is the first stage variable vector, the y is the second stage variable vector and ω_s is the conditional probability of scenario s. d and d_s represent the model parameter vectors [47].

$$\begin{aligned} \text{Minimize} \quad & c(d,x) + \sum_{s \in S} c(d_s, y) \cdot \omega_s \\ s.t \quad & f(x) \leq 0 \\ & g(x, y_s) \leq 0 \qquad s \in S \end{aligned} \tag{2.13}$$

Despite the separation of the two stages mathematically, the optimal solution originate from their internal linkage. In a recursive model as the two-stage model, the first stage decisions are based on all possible second stage operational patterns and the first stage (strategic) parameters.

2.3.4 The Value of the Stochastic Model

Taking uncertainty into account can potentially lead to a change in the decision variables and the objective value. In order to estimate the value of upgrading from a deterministic to a stochastic model, their objective values can be compared by applying the following tests:

- Test A: The Value of the Stochastic Solution (VSS)
- Test B: Loss of Using the Skeleton Solution (LUSS)
- Test C: Loss of Upgrading the Deterministic Solution (LUDS)

A. The Value of a Stochastic Solution (VSS)

VSS is a measure of the integrity of the solution when using a stochastic model in place of a deterministic model. It is explained by the author of [49] as the *loss of profits due to the presence of uncertainty.* In effect, a small VSS indicates that a deterministic model is an accurate approximation to the optimization problem, and that there might not be a need for a stochastic model. On the contrary, programs with large VSS require the solution of a stochastic program. VSS can either be a positive or a negative value. To justify the necessity of a stochastic program, the VSS can be calculated by analyzing the solutions of the stochastic model solution and the solution of the deterministic equivalent model. The first stage decisions of the deterministic equivalent solution, known as the Expected Value Solution (EVS), are forced to be the first stage decisions of the stochastic model. This manipulation changes the initial stochastic model to become a two-stage Recourse Program (RP) [50].

The procedure for obtaining VSS is as follows:

(1) Obtaining the EVS by using the average scenario of the stochastic equivalent

(2) Solve the RP* with the first-stage decisions obtained in 1)

(3) Compare the objective values of EVS and RP*

Equation (2.14) denotes the objective function, RP* of a stochastic program with fixed first stage values, $\bar{x}$.

$$\begin{aligned} RP^* \quad &= \quad \min\Big(c^T\bar{x} + \sum_{s\in\mathcal{S}} \omega_s d_s^T y_s\Big) \\ s.t \quad & \quad f(\bar{x}) \leq 0 \\ & \quad g(\bar{x}, y_s) \leq 0 \qquad s \in S \end{aligned} \tag{2.14}$$

VSS as in equation (2.15), is the difference between the objective values, EVS and RP*.

$$\text{VSS} = \text{EVS} - \text{RP}^* \tag{2.15}$$

If the VSS is small and insignificant, a stochastic program formulation can be redundant [49]. On the contrary, if VSS takes a large value or the RP* is insolvable, further investigations are needed to determine the value of upgrading from the deterministic solution. It is of interest to find out what makes the deterministic model weak [51].

B. Loss of Using the Skeleton Solution (LUSS)

LUSS is a quality measure of the deterministic solution. The purpose of LUSS is to see if the EVS gives the right non-zero variables. It is measured by fixing the first stage decision variables of the RP to those that are zero in the EVS. Alternatively, the decision variables can be fixed at their lower bound. When purposely activating the first-stage decision binaries, the obtained model is called the model skeleton [51]. Equation (2.16) gives the calculation.

ESSV* = Expected skeleton solution value.
RP* = Recourse program.

$$\text{LUSS} = \text{ESSV}^* - \text{RP}^* \tag{2.16}$$

A LUSS close to zero means that the variables chosen by the deterministic solution are the same as in a stochastic solution, but it does not indicate whether there might exist a better solution.

C. Loss of Upgrading the Deterministic Solution: (LUDS)

LUDS can be calculated by letting the decision variables of the EVS be the lower bound in the stochastic model, by adding the constraint in equation (2.17). The LUDS is given by equation (2.18).

$$x_i \leq \bar{x}_i(\bar{d}) \quad i\forall I \tag{2.17}$$

Where $\bar{x}_i$ is the deterministic decision variables' value obtained in the optimization using the input vector, $\bar{d}$.

EIV^* = Expected input value.

$$\text{LUSS} = \text{EIV}^* - \text{RP}^* \tag{2.18}$$

If LUSS = 0, the deterministic solution is perfect, but there exists an even better stochastic solution. The deterministic model is hence perfectly upgradable.

2.3.5 Principles of Scenario Generation

The accuracy of a stochastic program depends on the number of scenarios [47]. The true distribution of scenarios would be an infinite number, which is impossible to generate. In order to obtain the most accurate stochastic models, proper generation of scenarios is crucial. The number of scenarios S must be large, or at least highly representative to the true distribution. Successful application of stochastic models with more than one uncertain parameter requires consistency in the internal dependency of the parameters [44]. More specifically, it is desirable that the scenarios capture the following three statistical dependencies, and as stated in [44] (based on [52]):

- The scenarios should capture dependencies between various uncertain parameters
- The scenarios should capture dependencies between geographical regions
- The scenarios should capture dependencies in time

2.3.6 Data Analysis with K-means Clustering

Clustering analysis is a methodology for distance measures, of which the primary goal is to classify and compress data by separate data samples in groups of equal variance [53]. K-means clustering is the most commonly used version as it follows a heuristic algorithm starting by grouping the data samples to K random centers and integrating until a predefined termination criterion is met, as shown in the flow chart in figure 2.13.

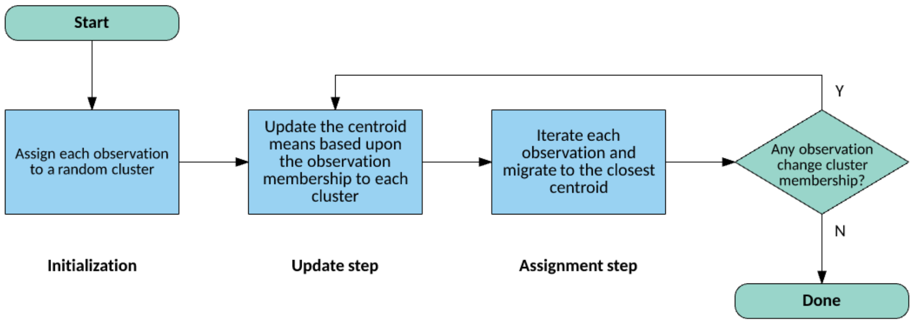


FIGURE 2.13: K-means clustering algorithm flow chart, adopted from [54]

Centroid based K-means clustering allows the predefinition of the wanted K number of centers, known as the centroids. Clustering is used in various scientific disciplines and is especially suitable tool for scenario reduction as the number of centroids can be set to the desired number of scenarios in order to avoid duplication of similar data series. [12] and [13] are examples of energy optimization models using the k-means clustering method for the selection of scenarios. The wide range of algorithmic approaches to clustering is explained in [11].

2.4 Economic Influences on grid-connected Buildings

This chapter seeks to emphasize the importance of the energy market variations and technology costs by introducing some of the principle economic aspects of, and uncertainty drivers for, grid connected buildings.

2.4.1 End-user price of Electricity

The direct cost influences on a plus building are the following:

- The spot price
- Grid tariff policies
- The "prosumer" agreement

The price of electricity for the average Norwegian household consists of three main contributions; the spot price, the grid tariff and value added taxes (VAT) [55], [56]. Equation (2.19) gives the final price per kWh of electricity. The usual revenue of feed-back electricity is the spot price [57].

$$\text{Electricity Price} = \text{Power Price} + \text{Grid tariff} + \text{VAT} \tag{2.19}$$

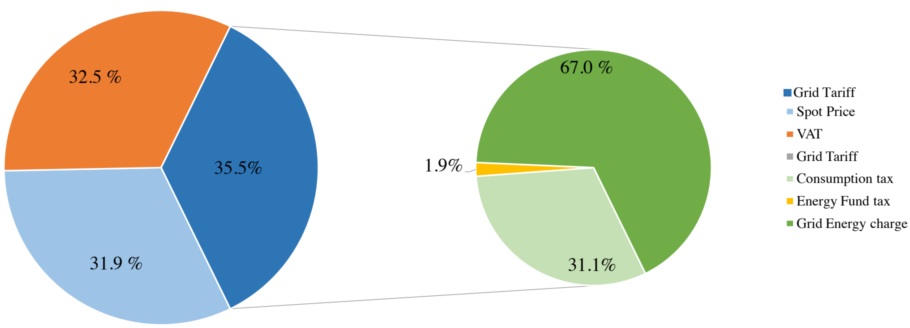


FIGURE 2.14: End-user price of electricity for households. Based on data from [55], [56]

Figure 2.14 shows the price distribution for one kWh of electricity. The spot price includes green certificates charges, explained in section 2.4.2. The grid tariff is further divided into three parts; the grid tariff's energy charge, consumption tax and Enova funding. VAT (25 %) is applied to both the final grid tariff and to the spot price. There are several impacts on the final end-user price of electricity, both in a short-term and a long term perspective.

2.4.2 The Spot Price

Short-term fluctuations

In a short-term perspective, the spot price varies like any other commodity, with the instant demand and the marginal cost of supply (power production) [58]. As the power production is mainly based on hydropower, the marginal cost of supply varies with the yearly rainfall which will impact the reservoir in Norwegian magazines and hence the water values [8]. The electricity demand on the other hand, is negatively co-related with the outdoor temperature. Colder temperatures increase the demand of electricity as the need of space heating escalates, and this causes the spot price to rise [59].

Long-term pricing levels

In a long-term perspective, the spot price level is influenced by the price of CO_2, transferring capacity between markets and the long-term electricity demand. According to [60], the spot price is most sensitive to the European market's carbon price (CO_2 price). The predicted increase towards 2030 is 0.7 ct/kWh compared to 2017 values [60].

The carbon price
The carbon price is designed to set a monetary value to the external costs of carbon emissions. The EU's Emissions Trading Scheme (EU ETS), established in 2005, provides a cap for total CO_2 emissions within the European Economic Area (EU and Norway and Iceland) [61]. A high carbon price increases the marginal cost of generation from carbon-intensive resources. Increased costs of supply in Europe escalate the spot price and leads to an increased demand of Norwegian, low-cost and low-carbon electricity [58]. The carbon price has been relatively low since 2012, but it is predicted to increase in the near future. This is a consequence of European policies of further depressing carbon emissions and a recently suggested "carbon price floor" (CPF) implemented in the UK and is now under considerations in the EU [62]. An increased carbon price will increment the Nordic spot price as the rule of contingency suggests [58]. Increasing interconnected capacity between the Nordic and the continental markets will further expose the Nordic spot price. In addition to the existing links to Denmark and the Netherlands, the "Norlink" will

connect Norway to Germany in 2020 and the "North Sea Link" (NSL) will connect Norway to the UK in 2021 [60].

Future demand of Electricity
Future predictions of the energy market suggest an increase in electricity demand on a national level as a result of the electrification of the transport sector and expansion of aluminum production [60]. Simultaneously, the total power production is predicted to increase as a result of more integration of wind and solar production capacity in the power system. A large integration of power production from volatile resources might jump the spot price during hours of less wind, resulting in greater short-term fluctuations in the spot price. On the demand side, as technologies improve and more buildings become low-energy buildings, the total amount of household PVs and electric vehicles (EVs) increase, the demand of electricity to household can be significantly reduced. The study on a large scale integration of Zero Emission Buildings (ZEBs) has suggested lower electricity prices as a consequence of decreasing demand [2]. The term "Flexible Demand" (FD) is in brief a method of offloading the grid by disconnecting a load (i.e. the consumer) [63]. FD can potentially lead to a reduction in short-term fluctuation in the spot price. When loads can be regulated, there will be smaller differences between supply and demand, thus smaller variations in the spot price.

Green Certificates
The purpose of green certificates is to reward power production from renewable energy sources [64]. Towards 2035, Norwegian consumers pay additional taxes to facilitate the investments in wind power. Reaching the wind power target by 2035 will lead to a large capacity of low-cost marginal production, and potentially a reduced spot price as the grant is being dismissed after 2035.

2.4.3 Grid Utility Tariffs

Pricing models

Energy pricing
The current grid tariff model, energy pricing, is divided into fixed and variable charges. It consists of a fixed monthly charge (rent) and a variable charge per kWh consumed (cost of losses). Equation (2.20) depicts a simplified expression for the yearly grid tariff for private costumers, based on [56]:

$$\begin{aligned}\text{Yearly grid tariff} &= 12 \cdot \text{Monthly fixed charge} \\ &+ \text{Energy charge} \cdot \text{Total energy consumption}\end{aligned} \tag{2.20}$$

where:

- Monthly fixed charge is grid rent (EUR)
- Specific Energy charge covering the cost of losses (EUR/kWh)
- Total energy consumption (kWh/year)

Power subscription pricing

Instant power demand (kWh/h) is increasing faster than the energy supply as a volume (kWh), which leads to requirements of higher capacities in existing transmission lines and thus new investments. Authorities suggest a revised grid tariff model in order to reduce the peak power [57]. The power subscription grid tariff model can be compared to a cellphone subscription plan; including a monthly charge for a fixed amount of service and a penalty charge for service exceeding the subscription plan. The tariff includes a fixed kW-subscription charge (NOK), a penalty charge for the volume exceeding the subscription (NOK/kWh) and an energy charge to account for losses in the transmission line (NOK/kWh). As this tariff model is still under development, the pricing method introduced is based on previous work in [65], [66]. The equation (2.21) depicts as simplified demonstration of the yearly grid tariff.

$$\begin{aligned}\text{Yearly grid tariff} &= 12 \cdot \text{Fixed Charge} \cdot (1 + \text{Subscription}) \\ &+ \text{Penalty charge} \cdot \text{Penalty volume} \\ &+ \text{Energy charge} \cdot \text{Total energy consumption}\end{aligned} \tag{2.21}$$

where:

- Fixed Charge is the fixed monthly charge (EUR)
- Subscription is the subscribed power (kW)
- Penalty charge is the charge for exceeding the subscription (EUR/kWh)
- Penalty volume is the import exceeding the subscription (kWh/year)
- Energy charge is the specific consumption charge, referred to as the cost of losses (EUR/kWh)
- Total energy consumption is the import (kWh)

Short-term fluctuations

Spot price increments will lead to variations in the variable grid tariff charge, due to the cost of losses for energy transmission which applies to the Distribution System Operator (DSO). Other impacts on the grid tariff are e.g. income regulation of DSO's and variations in costs of non-delivered energy wich impact the short-term grid tariffs [58].

Long-term pricing levels

The greatest influence on the grid tariff is the costs of expansion, maintenance and upgrades in the grid [60]. The costs are directly applied to the end-user through the fixed grid tariff charge. A new grid tariff model will not have great impact on the end-user's electricity costs as the intended charges for the power subscription should in total match the current energy pricing tariff. However, according to [57], imposing a subscription limit can potentially lead to a decrease in the required expansion of the power grid.

2.4.4 The Prosumer Agreement

A "prosumer" (producer and costumer) is a grid-connected electricity costumer that in periods can produce more than the house' initial demand and feed back surplus electricity to the grid. The prosumer agreement established in 2010 allows prosumers to have power plants of less than 100 kW, and they are excepted from paying grid rent for the delivered energy [67]. The feed-back revenue is equal to the spot price of electricity [57].

2.4.5 Support for Renewable Power Production

Enova SF is a state-owned energy fund established to stimulate investments in green and sustainable technology in order to reduce emissions and efficiently exploit Norwegian renewable resources. It is governed by the Ministry of Climate and Environment and is funding small and large scale innovative energy projects by making them financially viable. Other types of support mechanisms are explained in [61].

Table 2.2 gives the possible support that costumers can get for domestic energy investments, for the technologies described in section 2.2.3.

TABLE 2.2: Possible Enova Support [68]

Installed component	Enova-support
Bio-fuel Water Boiler	2600 EUR
Air to water heat pump	2000 EUR
Water to water heat pump	3100 EUR
PV panel	1000EUR + 125 EUR/kWp*

*with a total upper limit of 3000 Euro

2.4.6 Investment Costs of PVs and Batteries

In a global perspective, sun power is the fastest growing energy source, mainly driven by the large growth in installed capacity in countries as Germany, China and India. The investment costs of PV systems have dropped 50 % compared to 2009 and is predicted to drop further in the future [69]. This is mainly due to the drop in solar module price (EUR/kWp), which is a consequence of increased efficiency of PV technology and increased experience with installation [39]. The Norwegian market for PV installations is still in an early phase, but according to the author of [9], the price is expected to drop 20-35 % towards 2025 and with 40-70 % towards 2050 (compared to 2015 level). The general impression is that it is not beneficial to invest in residential PV panels. This is because the Levelized Cost of Energy (LCOE) still is high compared to the spot price [61].

Specific investment costs of household batteries have dropped on average 14 % each year between 2007 and 2014 [70]. The motivation for installing a household battery is mainly to store PV generated electricity to consume under high spot prices [71]. Additionally, batteries have great demand side management facilities, such as reduction of peak power imports, which can be of interest should the grid power tariff should become reality. It can therefore facilitate FD, which is of great interest for the power system planners [72]. According to [60], a large scale integration of batteries can lead to a less fluctuating spot price and a reduced need for new investments in the distribution network. Integration of household batteries in Norway is still limited because of high investment costs, but there are predictions that the investment costs will continue to drop and also that the battery will become more efficient [73].

Chapter 3

Methodology

3.1 Introduction to Methodology

This chapter presents the the methodology for the development of the proposed model. A complete mathematical model description can be found in chapter 4. As the model takes in a large share of various input, a crucial part of obtaining precise and reliable results is to choose the input parameters wisely. Therefore, the methodology presented in this chapter contains a detailed data analysis for a specific case study; a Norwegian passive house (single family home). The first part introduces of the system design and general assumptions. The following part gives the methodology for simulations of uncertain parameters. Thereafter comes a description of the model's scenario fan structure and the methodology used to construct scenarios. The strategic parameters are then presented, followed by some remarks on the model implementation.

Table C.3 gives the key information about the building used in the case study.

TABLE 3.1: Key information for the building used as case study

Area	250 m^2
Location	Oslo, Norway
Type	Single family home
Standard	Passive building

3.2 System Design

The model's objective is to design a cost-optimal composition of the technologies introduced in section 2.2.3. Figure 3.1 shows the interaction between these; Photovoltaic solarcells (PV), Battery (BA), Electric top-up boiler (EB), Air-source heat pump (ASHP), Ground-source heat pump (GSHP) and Biomass boiler (BB). Blue lines represent flows of electricity and red lines flows of heat, respectively. Import to the building, such as the power grid or bio pellets are considered to be outside the system boundaries. The heat distribution system in the house is waterborne.

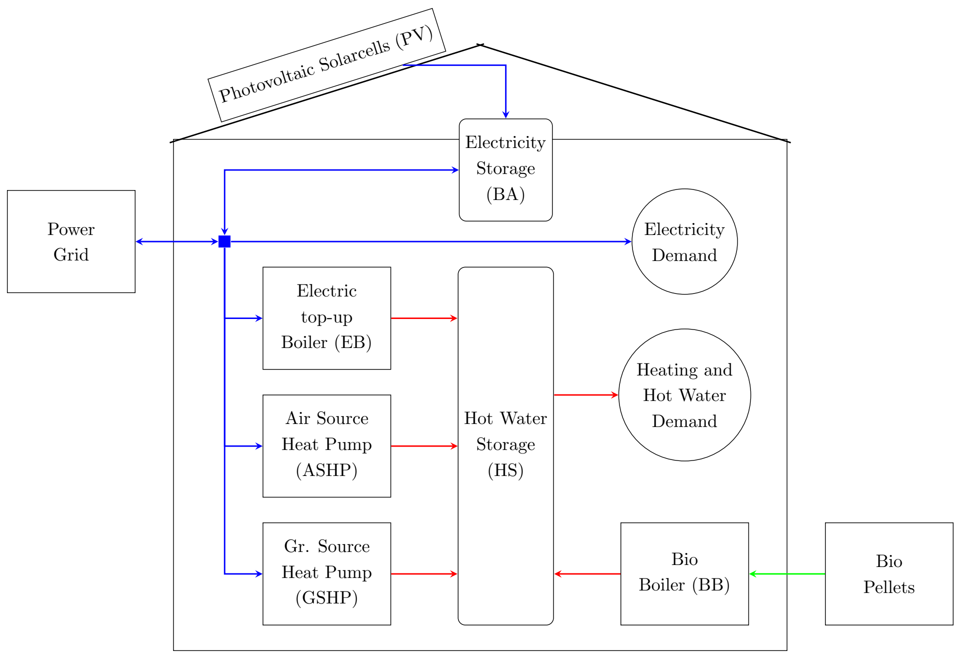


FIGURE 3.1: System design of the waterborne building heating system with available technologies

Energy systems in buildings require a technology for providing base load capacity and peak load capacity [2]. It the system shown in figure 3.1, the base load technology can be the ASHP, GSHP or the BB. The electric boiler is the top-up technology.

3.2.1 Assumptions

Main assumptions for the case study are the following:

- Emissions caused in other phases than in building operations are neglected ("ZEB-O" ambition)
- Technology degradation is based on standard warranties for each of the technologies. However, the true degration of e.g. the battery is dependent on the number of charging cycles, as explained in section 2.2.3
- Emissions from different energy carriers, i.e. the weighing factors are assumed to stay constant throughout the lifetime of the building
- The house is equipped with an existing waterborne heating distribution system
- The house is insulated according to passive house standards
- The roof-top is south-phasing with a 40 ° angle
- Transportation of bio-pellets import is neglected

3.3 Data Input: Scenario Dependent Parameters

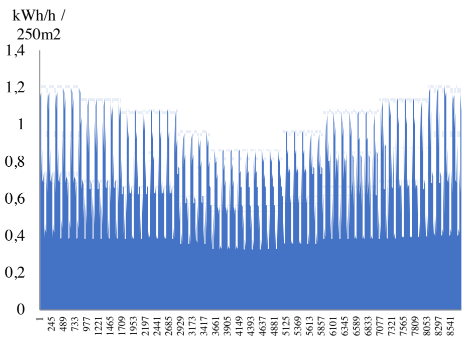
This section presents the simulated data for the hourly values of uncertain parameters. These parameters satisfy all three statistical dependencies explained in section 2.3.5. Table 3.2 lists the parameters and their origin. a-b) are external simulations d-e) are the measured data series, and f-h) are the simulated data series. The input years from 2010 to 2014 are from here on referred to as the climatic years c1 to c5.

TABLE 3.2: Scenario dependent parameters and their origin

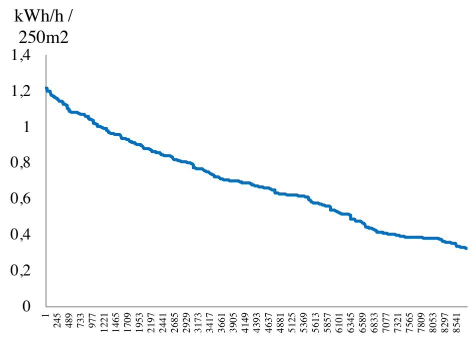
Parameter	Origin
a) Electricity demand (kWh/h)	Simulations given by [2]
b) Heat demand (kWh/h)	Simulations given by [2]
c) Temperature (°C)	Measured data, given by [2]
d) Spot price (EUR/kWh)	Source: NO1 Prices (Oslo) from Nordpoolspot [74]
e) Horizontal Irradiation (kW/m2)	Source: Solar irradiation from [75]
f) PV generation (kWh/kWp)	Simulated by (2.3) by c) and e)
g) COP, ASHP (-)	Simulated by (2.8) and (2.11) by c)
h) COP, GSHP (-)	Simulated by (2.8) and (2.11) by c)

a) Electricity demand

The building's electricity demand shown in figure 3.2, is stable in all of the climatic years (c1-c5). The curves in figure 3.2b are laying above one another. The x-axis refers to the hours of the year.



(a) Hourly electricity demand for c1



(b) Electricity duration curves for c1-c5

FIGURE 3.2: Simulated data: Building electricity demand

b) Heat demand

The building heat demand is high during the winter and stable during the summer, as seen from figure 3.3. The heat duration curves of c1-c5 are drawn in figure 3.4. c1 has a generally higher demand than c2-c4. c5 has the lowest demand.

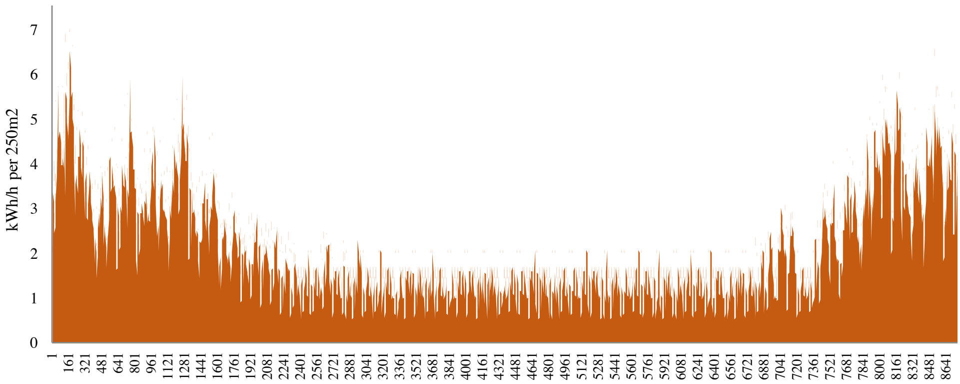


FIGURE 3.3: Simulated data: Hourly values for the building heat demand for c1

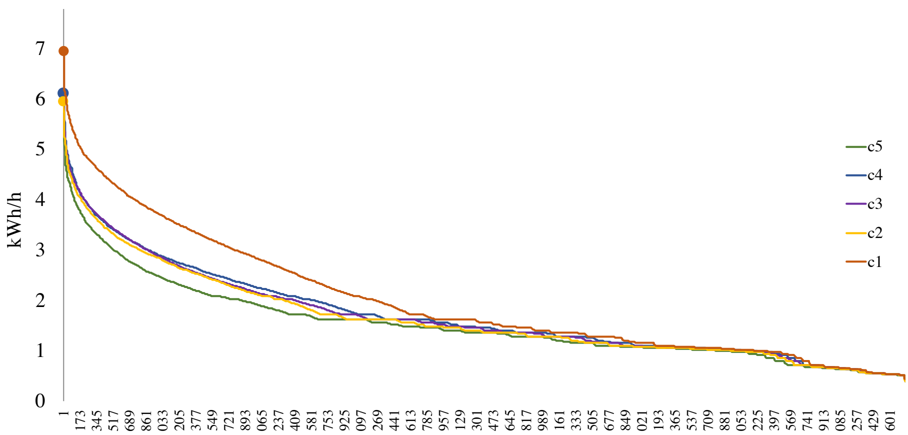


FIGURE 3.4: Simulated data: Heat duration curves for c1-c5

c) Temperature

Figure 3.5 shows the temperature duration for c1-c5. c1 is generally a colder year, while c5 is a warmer year.

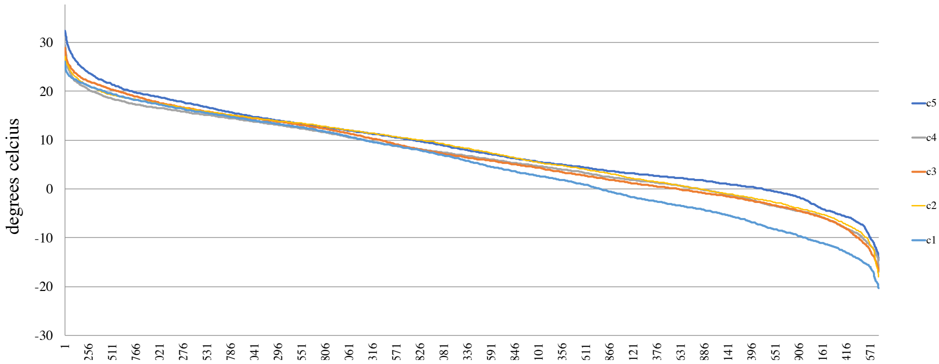


FIGURE 3.5: Measured data: Hourly temperature for c1-c5

d) The Spot price

Figure 3.6 is a plot of the spot price hourly fluctuations throughout the year from c1-c5. Especially c4 and c5 have experienced high peaks of about 200 EUR/MWh for several hours during the winter.

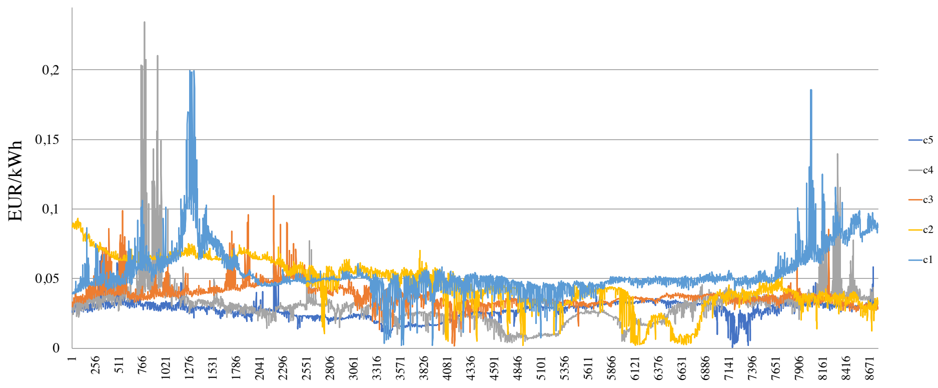


FIGURE 3.6: Measured data: Hourly spot prices for c1-c5

e-f) PV electricity generation

The possible PV generation (kWh/kWp) is a function of the outdoor temperature and the horizontal solar irradiation, as figures 3.7 and 3.8 show. The temperature is measured outside the building, while the irradiation data is from the closest measuring station with hourly values (Aas, Norway).

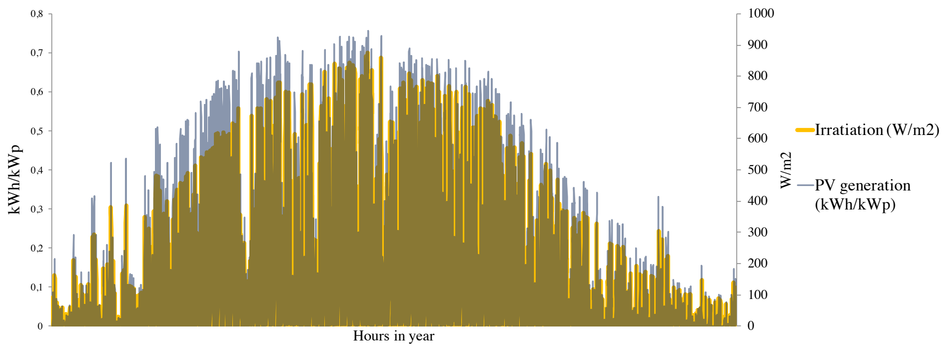


FIGURE 3.7: Simulated data: Measured solar irradiation from Aas, Norway 2013 (right axis) vs. the simulated simulated possible PV generation (left axis)

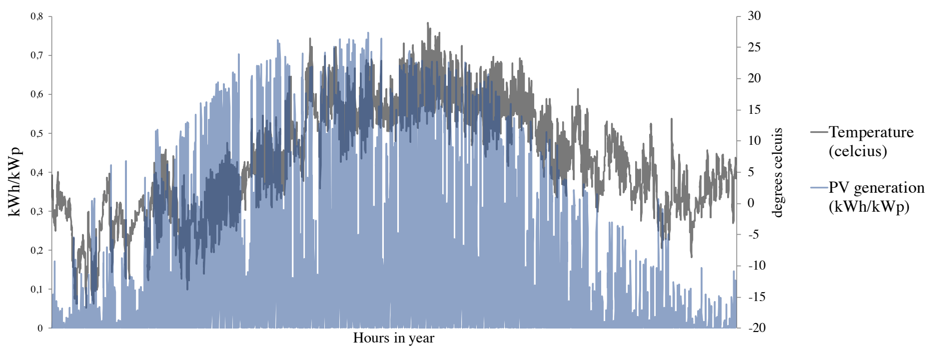


FIGURE 3.8: Simulated data: Measured outdoor temperature from Oslo (right axis), Norway 2013 and the simulated simulated possible PV generation (left axis)

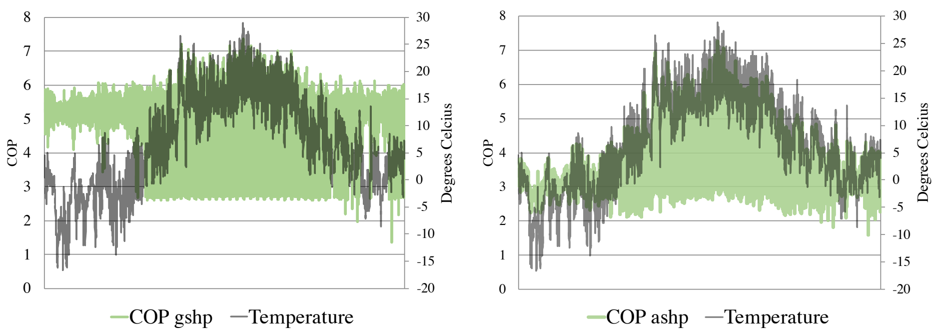
Calculations are carried out by equation (2.3) of which inputs are the k-values given in table 3.3. The c value represents a roof-mounted 40 ° angle PV panel, as stated as the optimal angle in section 2.2.3.

TABLE 3.3: K-values for building integrated PV systems suggested by [23].

k_1	k_2	k_3	k_4	k_5	k_6	c
-0.017162	-0.040289	-0.004681	0.000148	0.000169	0.000005	0.05

g-h) COP for GSHP and ASHP

COP for the GSHP is generally higher as the source temperature is stable (about 10 °C), in contrast to the ASHP's COP which is depending on the outdoor air temperature. Equations and the weighting of hot water and space heating demand is explained in 2.2.3. Simulated COPs are shown in figure 3.9.



(a) COP: Air-source heat pump (ASHP) (b) COP: Ground-source heat pump (GSHP)

FIGURE 3.9: Simulated data: Heat pump COP vs. temperature

The required supply temperature for the heat pump is a function of the outdoor temperature, and can be simulated based on the building standard. Standard 8 is used in accordance with equation (2.10), as in [2].

TABLE 3.4: ABC-values for the supply temperature in COP simulations [2].

	Standard 1	Standard 6	Standard 7	Standard 8	Standard 9
A	-0.0306	-0.0062	-0.0040	-0.0051	-0.0039
B	-1.8333	-0.9633	-0.7767	-0.5633	-0.3333
C	68.775	42.143	36.671	32.844	27.983

3.4 Two-stage SMILP

The proposed model in this thesis is a two-stage stochastic Mixed Integer Linear Program (SMILP). The uncertainty is in the form of hourly co-relations between the scenario dependent parameters presented in section 3.3. The first stage decision variables decide if a technology is invested in or not (binary variable) and of what capacity (kW). The second stage decision variables decide the hourly import from the electricity grid and the generation patterns of on-site technologies. The objective is to minimize the expected net present value, subject to the solution being feasible under all scenarios.

3.4.1 Model Reduction: Clustering Analysis

Each scenario consists of 672 hourly time steps, representing a full year of operations. Five "four-weeks" scenarios represent five different operational patters are separated into groups on the based on their internal co-relations. Scenario 1 represents coldest weeks and scenario 5 the warmest.

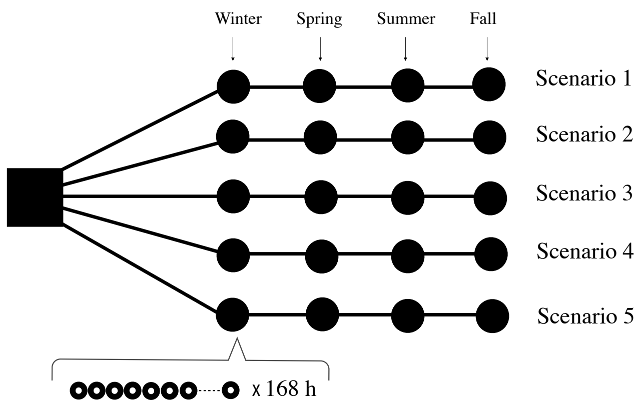


FIGURE 3.10: Scenario fan structure

The scenario fan in figure 3.10 shows the five scenarios sharing the same first stage (square), and hence, the same first stage decision variables. Each of the circles represent 168 hours, on week of operations. The parameters from table 3.2 form one dependency matrix for each week of the four-week scenario. In this matrix, the dominant parameter is the temperature, which influences all the other parameters, except from the building specific electricity demand (lightning and other household appliances). The dependencies between the heat demand and the temperature are explained in section 2.4.2. The dependency between the PV generation and the temperature is explained in section 2.2.3. The PV production is, in addition to the temperature, also dependent on the irradiation. The dependency between the heat pumps and the temperature is explained in 2.2.3.

Centroid-based K-means clustering analysis, as explained in 2.13, is used to select four weeks to each of the scenarios. There are 260 weeks of available data in the years 2010-2014, 65 for each season. In theory, clustering analysis can be done for the seven parameters simultaneously [11]. Considering hourly dependencies for all seven parameters would lead to $260\text{x}168^7$ co-relations (in 7 dimensions). Cluster analysis in more than three dimensions is not intuitive. Therefore, to simplify the analysis, the average temperature of each week is compared to the average of the heat demand.

The procedure for selecting the five representative scenarios for one season is as follows:

(1) The co-relations form a scatter plot of the co-relation of the temperature and heat demand, where each point represents the average value of a week.

(2) By the algorithm in 2.13, each point is assigned to the desired amount of centroids, set to 5 (as there are five scenarios). All points assigned to each centroid form a cluster group. The number of point assigned to each cluster is an indicator of the groups probability.

(3) With a developed selection algorithm, the point closest to the centroid is the representative point, and thus the selected representative week.

The below plots present the selection of five representative weeks of each season assigned to each of the five scenarios. The point closest to the red cross is the selected week. The analysis show the co-relation between the outdoor temperature and the building heat demand. Each point share the color of its associated cluster group.

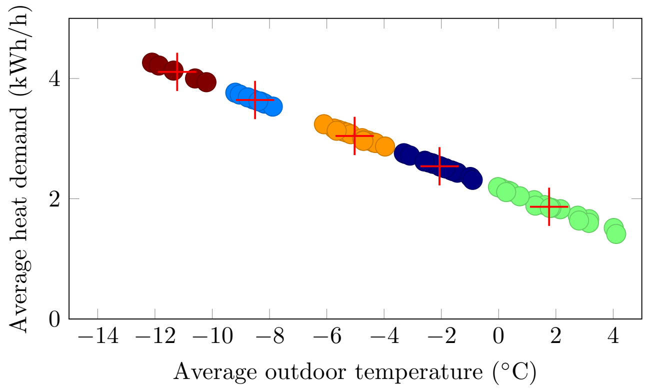


FIGURE 3.11: 65 winter weeks: Clustered co-relation between the average heat demand (kWh/h) and the temperature (°C)

Figure 3.11 shows the clusters groups in different colors for the 65 winter weeks of available data. Winter is assumed to be the 13 weeks of each climatic year between January 1st to March 3rd, and December 12th to December 31st. There span in average temperature is in the interval -13 to +4 °C. Although the coldest hours are found in the week represented by the leftmost dark red point, the hour of the peak demand (kWh/h) occurs in the second leftmost point. The cluster selected week is the third leftmost. A common approach in energy planning is to design systems to have the ability to cover the highest demand [2]. Therefore, the second leftmost point is chosen to represent the winter season for the coldest scenario.

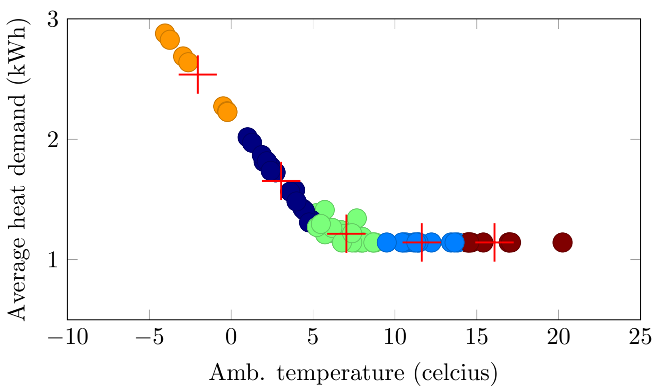


FIGURE 3.12: 65 spring weeks: Clustered co-relation between the average heat demand (kWh/h) and the temperature (°C)

Figure 3.12 shows the clustering analysis for the 65 spring weeks. The 13 spring weeks of each climatic year is assumed from March 5th to June 3rd. The analysis show that when the average temperature is higher than +10 °C, the average heat demand is steadily 1 kWh/h. This constant demand can assumed to be the hot water demand, because there is no need for space heating for higher temperatures.

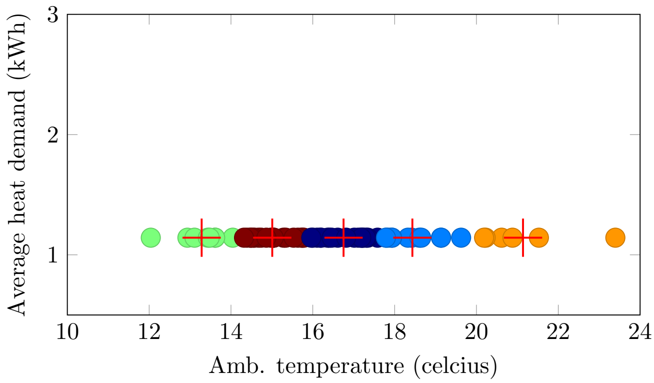


FIGURE 3.13: 65 summer weeks: Co-relation between the average heat demand (kWh/h) and the temperature (°C)

Figure 3.13 shows a that the heat demand in the summer is constant. However, the average temperature varies from +12 to +23 °C. The 13 summer weeks reach from June 4th to September 3rd.

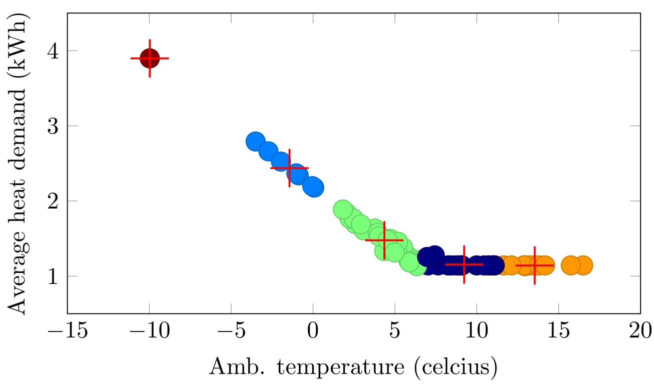


FIGURE 3.14: 65 autumn weeks: Co-relation between the average heat demand (kWh/h) and the temperature (°C)

Figure 3.14 show a wide range of average temperature and the related average heat demand. The 13 autumn weeks reach from September 4th to December 8th. There are great temperature differences between the week beginning with September 4th and the week ending with December 8 that cause this spread. The leftmost, green point represents an especially cold week in December 2010.

Table 3.5 gives the quantitative grouping of scenarios to each cluster and the final probability of each scenario. The equivalent analysis for the other parameters, such as the PV generation and the spot price have proven to give about the same selected weeks. These analysis can be found in Appendix B.

TABLE 3.5: Probabilities of selected scenarios

	Winter	Spring	Summer	Autumn	Probability
Scenario 1	5/65	7/65	7/65	1/65	8 %
Scenario 2	19/65	17/65	16/65	7/65	19 %
Scenario 3	14/65	20/65	16/65	24/65	29 %
Scenario 4	19/65	9/65	19/65	21/65	25 %
Scenario 5	18/65	12/65	7/65	12/65	19 %

As can be observed from table 3.5, the coldest scenario, scenario 1 has the lowest probability. Scenario 3 is the average scenario with the highest probability. The below figures show the representations for the selected weeks.

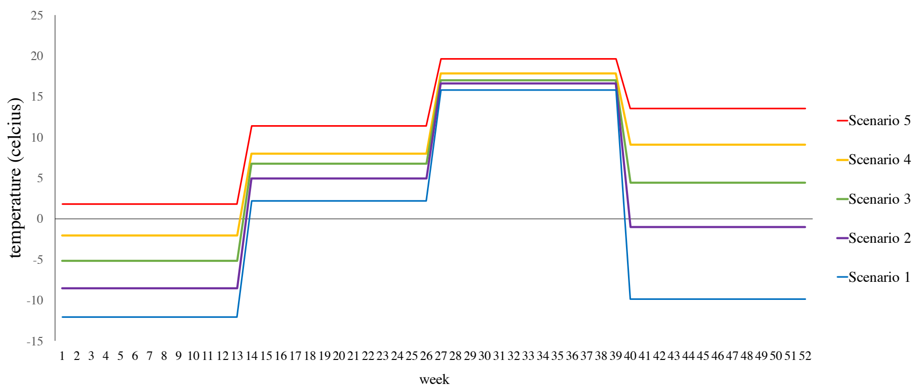


FIGURE 3.15: Average temperatures of the four selected weeks corresponding to each scenario

Figure 3.15 shows the temperature level for the four selected weeks in each scenario; 13 winter weeks followed by 13 spring weeks etc. It must be stressed that the input data in the model are not average values, as it is illustrated in figure 3.15. The input parameters for the model are hourly values.

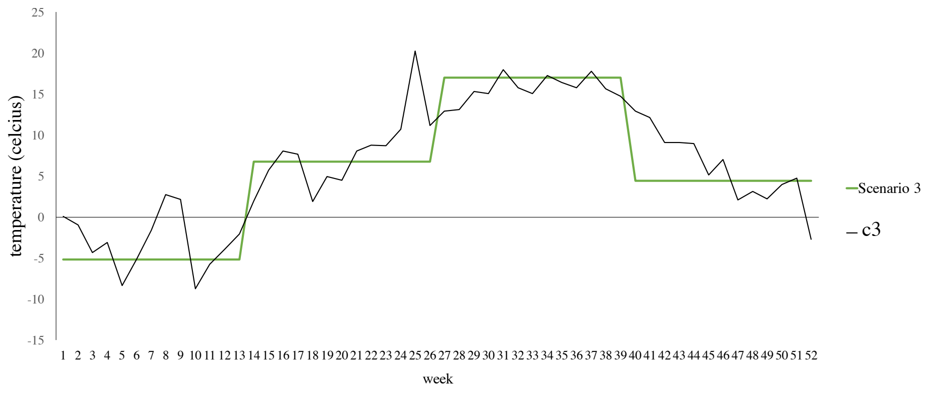


FIGURE 3.16: Average temperature for scenario 3 (reduced model) and c3 (full model)

Figure 3.16 shows the average temperature for scenario 3 as in figure 3.15. The black line is the average temperature for each week in c4 (2013). It can be observed that the average temperature within a season is internally varying.

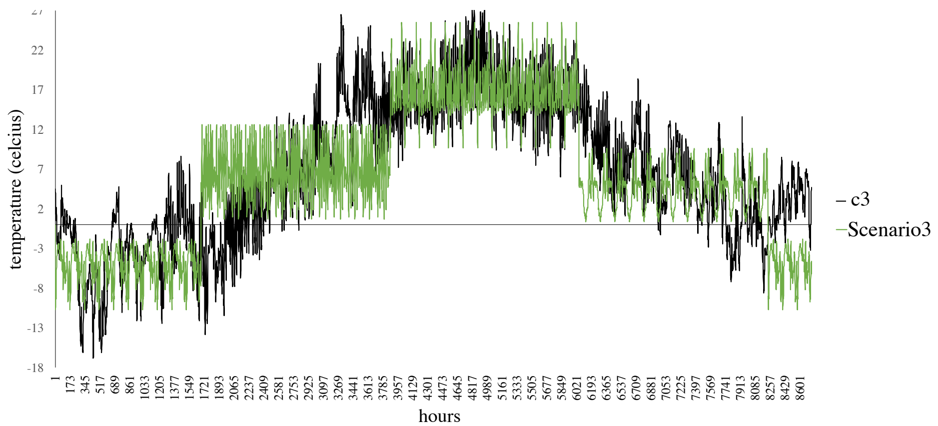


FIGURE 3.17: Hourly temperatures for scenario 3 (reduced model) and c3 (full model).

Figure 3.17 shows the hourly input temperature to the model (in green) for the average scenario. In black is the hourly temperature measured in the climatic year c3.

3.5 Input: Deterministic Parameters

Deterministic parameters are independent of the scenarios. These parameters are carefully selected to fit the case study, to get the most accurate analysis of the investment and the performance of the technologies.

3.5.1 Technology Investment Costs

The investment costs listed in table 3.8 are obtained from Norwegian manufacturers' prices. The fixed costs refer to the installation and/or mounting costs and the specific costs varies with the invested capacity. A detailed cost analysis is attached in Appendix C, including a regression analysis to find this relation between fixed and variable investment costs.

TABLE 3.6: Input: Technology investment costs

	Fixed cost (EUR)	Specific cost (EUR/kW)	O&M cost*	Comment
PV	255	1870	0.01	Fixed costs: Mounting and installation
ASHP	6740	428	0.02	Fixed costs: Mounting and installation
GSHP	11955	961	0.02	Fixed costs: Construction of a well
EB	0	134	0.02	Assumed installed with a HS
BB	2221	229	0.03	Fixed costs: Pellets storage and feeder
BA	0	707	0.0	Prices in EUR/kWh
HS	0	83	0.0	Prices in EUR/kWh

* Operation and maintenance costs given as percentage of specific investment costs

3.5.2 Grid Tariff Prices

While the hourly spot price is simulated as an uncertain parameter, the grid tariff data is gathered from Hafslund, which is the Distribution System Operator (DSO) in the Oslo region and also the largest in Norway [56]. Table 3.7 lists the tariff charges, introduced in 2.4.3. The prices include VAT and the mandatory Enova charge.

TABLE 3.7: Input: Grid tariff prices

Tariff model	Fixed cost	Variable cost	Penalty Charge
Energy pricing	8.61 EUR/month	0.05 EUR/kWh	-
Power sub. pricing	8.61(1+x) EUR/month	0.05 EUR/kWh	0.10 EUR/kWh

* x is subscribed power (kW)

3.5.3 Technology Performance

Technology efficiency originate from the manufacturer's data. Sources are provided together with the cost analysis in appendix C. Lifetimes are estimated as the expected lifetimes/warranty of the technology, given in [39].

TABLE 3.8: Input: Technology performance

i	Expected Lifetime	Efficiency	Upper-lower bound	Comment
PV	25 years	0.106*	1-100 kWp	Prices in EUR/kWp
ASHP	20 years	3.7*	1.5-100 kW	Efficiency simulated as COP
GSHP	20 years	5.39*	1.5-100 kW	Efficiency simulated as COP
EB	20 years	0.98	0.5-100 kW	
BB	15 years	0.91	1.5-100 kW	
BA	10 years	rt = 0.95 $\beta = 0.433$	1-100 kWh	β is charging/discharging rate
HS	20 years	$\eta = 0.99$ $\beta = 0.667$	1-100 kWh	β is charging/discharging rate

*Average value for c1

Comments to table 3.8.

- The heat storage beta (β) is modified from reference as the original value was considered too low, given that the heat storage potentially can discharge close to all of the water within an hour
- The PV efficiency is included in the simulation of the PV generation
- The battery efficiency is the round trip efficiency, rt, from equation (2.5)
- The lower capacity installation bound is set as a result of the heating curves in figure 3.4, as the purpose for some of the technologies to cover the "base load" of the duration curve. The 1.5 values are based on the specific kWh/h where the slope evens out

3.5.4 Weighing Factors

The conversion factors are listed in table 3.9. The CO_2 factor are either "CO_2-NOR" or "CO_2-ZEB". As explained in section 2.2.2, the electricity factor is a debated subject. Hence, two systems are used as input parameters. Table 3.10 gives the emission and primary energy of a reference building, used for calculation of the ZEB-level in accordance to equation (2.2).

TABLE 3.9: Input: Weighing factors

Parameter	Value	Source
CO_2 factors	*NOR/ZEB*	
Electricity import (gCO_2/kWh)	17/132	[8], [17]
Electricity export (gCO_2/kWh)	17/132	[8], [17]
Bio pellets import (gCO_2/kWh)	7/14	[2], [17]
PEF		
Electricity import (kWh_{pe}/kWh)	2.5	[18]
Electricity export (kWh_{pe}/kWh)	2.5	[18]
Bio pellets import (kWh_{pe}/kWh)	0.11	[76]

TABLE 3.10: Input: CO_2 emissions and primary energy for building reference

Reference system	CO_2-ZEB	CO_2-NOR	PEF
Value	1573.96 kg CO_2/year	202.70kg CO_2/year	29809.85 kWh_{pe}/year

3.5.5 Control Parameters

TABLE 3.11: Input: Control parameters

Parameter	Value	Description/Source
Analysis Period	60 years	Expected lifetime of a building
Discount rate	6 %	Based on [77], [78]
Price of pellets	0.05 EUR/kWh	Price of bio fuel [79]
Grid import	3000 kW	Maximum grid import
Grid export	100 kW	According to policies in [80]
Relaxation coefficient	$\sim (0, 1)$	γ=0 for ”sZEB”, γ=1 for ”noZEB”
Exchange rate	9.6590	EUR/NOK, April 2018 [81]

Where ”sZEB” is a strictly Zero Emission Building.

3.6 Model Implementation

The proposed model is implemented in Python, with the optimization-specific extension package, *Pyomo version 5.2.* The solver used to solve the two-stage stochastic optimization problem was *Gurobi Optimizer version 7.5.1.*

Stochastic models in Pyomo can be solved by a *progressive hedging* (PH) algorithm, a heuristic approach that is commonly used in multi-stage models. However, the results in these thesis are obtained from the *extensive form* (EF) which has proven to be as fast as PH for this two-stage model. For further reading, see [82].

With the basis of the Xpress code developed in [2], the following specific extensions are implemented by the author:

Pre-work of [10]:

- Reconstruction of the deterministic program from Xpress to Pyomo
- Implemented an algorithm that makes the discounting and rest value of investment costs directly into the model, simplifying the sensitivity analysis of the here-and-now parameters
- Implemented constraints for an electric battery

Implementation of this thesis:

- Implemented a two-stage stochastic optimization problem in Pyomo
- Implemented scenario selection algorithm based on clustering
- Implemented the possibility for the user to decide the number of scenarios
- Implemented the pricing constraints to facilitate "power subscription pricing"
- Implemented a function that fixes the first stage decisions of the stochastic program to equal the run of the last deterministic solution
- Created a user-friendly data base for scenario extraction in excel

Chapter 4

Model

This chapter gives a mathematical description of the two-stage Stochastic Mixed Integer Program (SMILP) formulation.

Abbreviations used in this chapter:

- ep: energy pricing
- ps: power subscription pricing
- ze: zero emission

4.1 Notation

TABLE 4.1: Declaration of sets and indices

Set	Index	Description	
$\mathcal{I}$	i	Technology i	
$\mathcal{I}^z$	i	Storage technology i	
$\mathcal{E}$	e	Import Energy Carrier e	
$\mathcal{T}$	t	Hourly time step t	
Υ	yr	Yearly time step of analysis period	$\Upsilon_n = 60$
$\mathcal{S}$	s	Scenario s	

TABLE 4.2: Declaration of parameters

Strategic Parameters		
C_i^{fxd}	Fixed investment cost for technology i	€
C_i^{spe}	Specific investment cost for technology i	$€/kW\ (kWh)$
C_i^{run}	Yearly running cost for technology i	% of C_i^{spe}
C_{ep}^{fxd}	Monthly fixed grid tariff for ep (incl. VAT)	€
C_{ps}^{fxd}	Monthly fixed grid charge for ps pricing (incl. VAT)	€/kW
C_{ep}^{spe}	Monthly specific grid tariff for ep (incl. VAT)	€/kWh
C_{ps}^{spe}	Monthly specific grid tariff for ps pricing (incl. VAT)	€/kWh
C^{pty}	Penalty charge for ps pricing (incl. VAT)	€/kWh
Y^{sub}	Power subscription for ps pricing	kW
C^f	Price of bio-fuel (pellets)	$€/kWh$
R	Discount rate	$-$
η_i	Efficiency of technology i	-
β_i	Charging/discharging rate of storage technology i	-
L_i	Expected lifetime of technology i	$Years$
$\overline{X}_i$	Upper capacity bound for technology i	$kW(kWh)$
$\underline{X}_i$	Lower capacity bound for technology i	$kW(kWh)$
Operational Parameters		
C_t^{spot}	Electricity spot price at time t	$€/kWh$
COP_t^{ashp}	Coefficient of performance for ASHP	-
COP_t^{gshp}	Coefficient of performance for GSHP	-
D_t^{el}	Building electricity demand at time t	kWh/h
D_t^{ht}	Total heating demand for building at time t	kWh/h
T_t	Outdoor temperature at time t	$^\circ C$
Y_t^{pv}	Possible supply from PV at time t	kW/kWp
Control Parameters		
$\overline{X}^{imp}$	Maximum grid import capacity	kW
$\overline{X}^{exp}$	Minimum grid export capacity	kW
G_e	CO_2 factor for energy carrier e	gCO_2eq/kWh
G^{ref}	Yearly emissions reference	gCO_2eq/yr
PE_e	PEF for energy carrier e	kWh_{PE}/kWh
PE^{ref}	Total reference emissions	kWh_{PE}/yr
γ	Relaxation coefficient for ze restriction	$\sim (0,1)$
Λ^{ep}	Activation of energy pricing	0/1
Λ^{ps}	Activation of power subscription pricing	0/1
Λ_i	Pre-activation of technology i	0/1
Λ^{imp}	Pre-activation of import	0/1
Λ^{exp}	Pre-activation of export	0/1
ω_s	Conditional probability for scenario s	$\sim (0,1)$

TABLE 4.3: Declaration of variables

Strategic Decision Variables		
x_i	Installed capacity for technology i (storage technology i)	$kW(kWh)$
δ_i	= 1 if technology i is installed	1/0
Operational Decision Variables		
q_t^{ashp}	Heat generated by ASHP at time t	kWh/h
q_t^{gshp}	Heat generated by GSHP at time t	kWh/h
f_t^{imp}	Biofuel (pellets) consumed at time t	kWh/h
q_t^{bb}	Heat generated by bio boiler at time t	kWh/h
q_t^{eb}	Heat generated by electric boiler at time t	kWh/h
q_t^{hs}	Net heat to heat storage (hot water tank) at time t	kWh/h
y_t^{pv}	Generated electricity by the PV at time t	kWh/h
y_t^{ashp}	Consumed electricity by the ASHP at time t	kWh/h
y_t^{gshp}	Consumed electricity by the GSHP at time t	kWh/h
y_t^{eb}	Consumed electricity by the EB at time t	kWh/h
y_t^{ch}	Electricity charging the battery at time t	kWh/h
y_t^{dch}	Electricity drawn from the battery at time t	kWh/h
y_t^{imp}	Electricity imported from grid at time t	kWh/h
y_t^{exp}	Electricity exported to grid at time t	kWh/h
y_t^{pty}	Electricity exceeding subscription within time t	kWh/h
z_t^{hs}	Energy content of heat storage at time t	kWh
z_t^{ba}	Energy content of battery at time t	kWh
δ_t^{imp}	=1 if importing electricity from grid at time t	1/0
δ_t^{exp}	=1 if exporting electricity to grid at time t	1/0
δ_t^{ch}	=1 if charging battery at time t	1/0
δ_t^{dch}	=1 if discharging from battery at time t	1/0
Functions		
c_{inv}	Discounted investment costs	€
$c_{run}(s)$	Discounted operational costs of scenario s	€
Objective function		
c_{tot}^*	Total costs of stochastic model	€

4.2 Objective Function

For the two-stage SMILP, the objective function is as in equation (4.1).

$$c^*_{tot} = \min\left(c_{inv} + \sum_{s\in\mathcal{S}} c_{run}(s)\cdot\omega_s\right) \tag{4.1}$$

Where c_{inv} (4.2) is the investment cost function and $c_{run}(s)$ is the operational cost function of each scenario s, in equation (4.4).

$$c_{inv} = \sum_{i\in\mathcal{I}}(C_i^{spe}x_i + C_i^{fxd}\delta_i)\cdot\alpha_i(R, L_i, \Upsilon_n) \tag{4.2}$$

Where the final discounting factor, α_i (4.3), takes into account forced reinvestments and the rest life of each technology (salvage value).

$$\alpha_i(R, L_i, \Upsilon_n) = \frac{1-(1+R)^{-(Y_n - L_i K)}}{1-(1+R)^{-L_i}}\cdot\frac{1}{(1+R)^{KL_i}} + \sum_{k=0}^{K-1}\frac{1}{(1+R)^{kL_i}} \tag{4.3}$$

The operational costs, c_{run}, is the sum of operation and maintenance costs, bio fuel, spot price costs and the grid charge. The grid charge can be either energy pricing or power subscription, as introduced in section 2.4.3. Activation of the power subscription pricing is given by $\Lambda^{ps} = 1$ and $\Lambda^{ep} = 0$.

$$\begin{aligned} c_{run}(s) = \Bigg(&\sum_{i\in\mathcal{I}}(C_i^{run}C_i^{spe}x_i) \\ &+\sum_{t\in\mathcal{T}} y_t^{imp}C_t^{spot}(s)\cdot 1.25 - y_t^{exp}C_t^{spot}(s) + f_t^{imp}C^f\cdot 1.25 \\ &+(12\cdot C_{ep}^{fxd} + C_{ep}^{spe}\sum_{t\in\mathcal{T}} y_t^{imp})\Lambda^{ep} \\ &+(12\cdot C_{ps}^{fxd}\cdot Y^{sub} + C_{ps}^{pty}\sum_{t\in\mathcal{T}}(y_t^{pty}) + C_{ps}^{spe}\sum_{t\in\mathcal{T}}(y_t^{imp}))\Lambda^{ps}\Bigg)\cdot\lambda(\Upsilon_n, R) \end{aligned} \tag{4.4}$$

Where λ is the total capitalization factor used to obtain a present value of all yearly running costs for all years Υ_n of the modeling period (building lifetime). Run costs are summarized to the end of each year, shown by the second fraction in equation (4.5).

$$\lambda(\Upsilon_{n,R}) = \frac{1-(1+R)^{-\Upsilon_n}}{R}\cdot\frac{1}{(1+R)^1} \tag{4.5}$$

4.3 Constraints

4.3.1 First Stage Constraints

The installed capacity of technology i is equal to zero if technology i is not a part of the solution. M is a large value, known as the "big M" value, and δ_i is the binary activation variable. This is given by equation (4.6).

$$x_i \leq \delta_i M \qquad \forall i \in \mathcal{I} \tag{4.6}$$

Equation (4.7) is a two-sided constraint applied to all technologies to make sure that the installed capacity of technology i is in between given bounds.

$$\underline{X}_i \delta_i \leq x_i \leq \overline{X}_i \Lambda_i \qquad \forall i \in \mathcal{I} \tag{4.7}$$

4.3.2 Second Stage Constraints

Second stage constraints apply to the hourly operation pattern of each scenario. The first group of constraints are the heat and electricity balancing equality constraints.

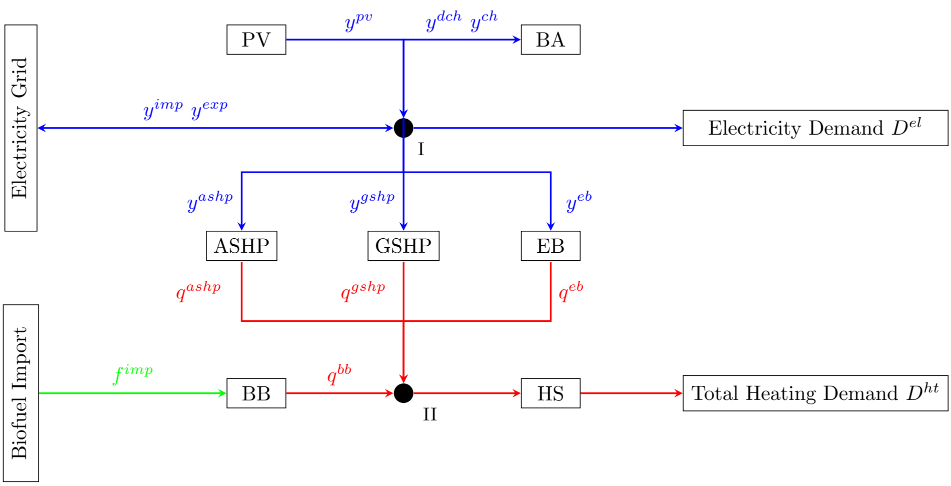


FIGURE 4.1: Heat and electricity flow diagram. y = electricity, q = heat, f = bio-fuel.

Figure 4.1 is a graphical description of the heat and electricity flows when the heating distribution system is waterborne. The figure forms the basis for the equations (4.8) and (4.9).

$$I) \quad D_t^{el} + y_t^{ashp} + y_t^{gshp} + y_t^{eb} = y_t^{imp} + y_t^{pv} + y_t^{dch} - y_t^{exp} - y_t^{ch} \qquad \forall t \in \mathcal{T} \quad (4.8)$$

$$II) \quad D_t^{ht} + z_t^{hs} = q_t^{ashp} + q_t^{gshp} + q_t^{eb} + q_t^{bb} + z_{(t-1)}^{hs} \eta_{hs} \qquad \forall t \in \mathcal{T} \quad (4.9)$$

ZEB Constraints

Either CO_2 factors or PE factors are used. As shown in equation (4.10), the net emission balance is accounted for on a yearly basis, of which the sum of total emissions is constrained. For instance, when optimizing a *strictly* zero emission case, γ equals zero.

$$\sum_{t \in \mathcal{T}} ((y_t^{imp} - y_t^{exp})G^{el} + f_t^{imp} G^f) \leq \gamma G^{ref} \quad (4.10)$$

Using the PE conversion factor as crediting system is done by applying the PEF constraint in equation (4.11).

$$\sum_{t \in \mathcal{T}} ((y_t^{imp} - y_t^{exp})PE^{el} + f_t^{imp} PE^f) \leq \gamma PE^{ref} \quad (4.11)$$

On-site Energy Production

Equation (4.12) represents a constraint used for the heat technologies ASHP, GSHP, EB and BB. The heat produced by technology i must be less than or equal to their installed capacity.

$$q_{i,t} \leq x_i \qquad \forall t \in \mathcal{T}, i \in \mathcal{I} \quad (4.12)$$

Electricity produced by the PV panel, given in (4.13) for hour t, is dependent on the invested capacity, kWp, and the efficiency parameter Y_t^{pv} (kWh/kWp).

$$y_t^{pv} = x^{pv} Y_t^{pv} \Lambda^{pv} \qquad \forall t \in \mathcal{T} \tag{4.13}$$

Equations (4.14) and (4.15) represent the heat produced by the heat pumps, a product of the feed in electricity and the coefficient of performance, COP, which is varying with the ambient temperature, explained in section 2.2.3.

$$q_t^{ashp} = y_t^{ashp} COP_t^{ashp} \Lambda^{ashp} \qquad \forall t \in \mathcal{T} \tag{4.14}$$

$$q_t^{gshp} = y_t^{gshp} COP_t^{gshp} \Lambda^{gshp} \qquad \forall t \in \mathcal{T} \tag{4.15}$$

Likewise, the electric boiler heat production, given in equation (4.16), is dependent on the feed-in electricity y_t^{eb}.

$$q_t^{eb} = y_t^{eb} \eta^{eb} \Lambda^{eb} \qquad \forall t \in \mathcal{T} \tag{4.16}$$

Bio boiler heat production is dependent on imported fuel, f_t^{imp}, given by equation (4.17).

$$q_t^{bb} = f_t^{imp} \eta^{bb} \Lambda^{bb} \qquad \forall t \in \mathcal{T} \tag{4.17}$$

Energy Storage

Energy content, z_t (kWh) in BA and HS must be less than or equal to the invested storage capacities, shown by (4.18).

$$z_{i,t} \leq x_i \Lambda_i \qquad \forall i \in \mathcal{I}^z \quad \forall t \in \mathcal{T} \tag{4.18}$$

Equation (4.19) denotes the change in storage content within one hour of operation. The change in storage content is restricted by the charging rate, β^{hs}, as in (4.20). For $q_{hs} \leq 0$ means that the storage is being charged.

$$q_t^{hs} = z_{t-1}^{hs} - z_t^{hs} \qquad \forall t \in \mathcal{T} \tag{4.19}$$

$$\left|q_t^{hs}\right| \leq x^{hs}\beta^{hs} \qquad \forall t \in \mathcal{T} \tag{4.20}$$

Equation (4.21) is the balancing equation for the battery content z^{ba} within one hour of operation. Because of losses, the charge entering the storage within hour t is larger than the actual charge accumulated in the storage, as explained in 2.2.3. Likewise, the useful discharge of the storage is lower than energy content leaving the storage.

$$z_t^{ba} = z_{t-1}^{ba} + y_t^{ch}\eta^{ch} - y_t^{dch}\frac{1}{\eta^{dch}} \qquad \forall t \in \mathcal{T} \tag{4.21}$$

Equation (4.22) is preventing the accumulated charging from exceeding the remaining volume in the storage at a certain time t, while equation (4.23) prevents the discharge to not exceed the previously stored energy content.

$$y_t^{ch} \leq (x^{ba} - z_{(t-1)}^{ba})\frac{1}{\eta^{ch}}\Lambda^{ba} \qquad \forall t \in \mathcal{T} \tag{4.22}$$

$$y_t^{dch} \leq z_{(t-1)}^{ba}\eta^{dch}\Lambda^{ba} \qquad \forall t \in \mathcal{T} \tag{4.23}$$

Equations (4.24) and (4.25) are logical constraints for the activation of charge/discharge within the hour. Equation (4.26) secures that charging and discharging are mutually exclusive within one hour.

$$y_t^{ch} \leq \delta^{ch} M \qquad \forall t \in \mathcal{T} \tag{4.24}$$

$$y_t^{dch} \leq \delta^{dch} M \qquad \forall t \in \mathcal{T} \tag{4.25}$$

$$\delta_t^{ch} + \delta_t^{dch} \leq 1 \qquad \forall t \in \mathcal{T} \tag{4.26}$$

Equations (4.27) and (4.28) restrict the amount of charge/discharge during one hour of operation.

$$y_t^{ch} \leq x^{ba}\beta^{ba} \qquad \forall t \in \mathcal{T} \tag{4.27}$$

$$y_t^{dch} \leq x^{ba}\beta^{ba} \qquad \forall t \in \mathcal{T} \tag{4.28}$$

Grid Interaction Constraints

Equation (4.29) bounds the possible import of electricity from grid in hour t.

$$y_t^{imp} \leq \overline{X}^{imp}\delta_t^{imp} \qquad \forall t \in \mathcal{T} \tag{4.29}$$

Similarly, (4.30) bounds the maximum export to grid within one hour.

$$y_t^{exp} \leq \overline{X}^{exp}\delta_t^{exp} \qquad \forall t \in \mathcal{T} \tag{4.30}$$

Import and export to grid are mutually exclusive variables, by equation (4.31).

$$\delta_t^{imp} + \delta_t^{exp} \leq 1 \qquad \forall t \in \mathcal{T} \tag{4.31}$$

4.3.3 Power Subscription Pricing

Activation of the power subscription tariff model, activates equations (4.32) and (4.33).

$$y_t^{imp} - Y^{sub} \leq y_t^{pty} \tag{4.32}$$

$$0 \leq y_t^{pty} \tag{4.33}$$

Chapter 5

Results and Discussions

5.1 Introduction to Results

This chapter presents the results of the case study: a single family passive house. The first part is a proof of concept of a no zero emission requirement case (*noZEB*). Chapter 5.3 compares three different ZEB-levels and chapter 5.4 presents a sensitivity analysis including the impact of strategic uncertainties; the spot price of electricity level, different grid tariff schemes and investment costs for PV and the battery. The final part is an investigation of the operation of the PV and the battery. All results have MIP-gaps of 0 %. A summary of the main findings obtained in this thesis are listed at the end of the chapter. Table 5.1 contains a synopsis of terms used in this chapter.

TABLE 5.1: Result abbreviations

Abbreviations	
Full Det.	Deterministic model with t = 52x168 hours
Full Stoch.	Stochastic model with 5 scenarios of t= 52x168 hours
Red. Stoch.	Reduced stochastic model with t = 4x168 hours (5 scenarios)
Red. Det.	Reduced deterministic model with t = 4x168 (average scenario)
CO_2-NOR	Electricity: 17 g/kWh Bio-fuel: 7g/kWh
CO_2-ZEB	Electricity: 132 g/kWh Bio-fuel: 14g/kWh
PEF	Electricity: 2.5/kWh Bio-fuel: 0.11/kWh
noZEB	No ZEB-requirements: 0 % ZEB
nZEB	Nearly ZEB: 50 % ZEB relative to noZEB
sZEB	Strictly ZEB: 100 % ZEB relative to noZEB
EVS	"Expected Value Solution"
RP	"Recourse Program"
VSS	"Value of the Stochastic Solution"
LUSS	"Loss of Using the Skeleton Solution"
LUDS	"Value of Upgrading the Deterministic Solutuion"
ESSV	"Expected Skeleton Solution Value"
EIV	"Expected Input Value"

Scenarios for the full model		*Probability*
c1	2010	0.2
c2	2011	0.2
c3	2013	0.2
c4	2012	0.2
c5	2014	0.2

Scenarios for the reduced model		*Probability*
Scenario 1	Coldest	0.08
Scenario 2	Colder	0.19
Scenario 3	Average	0.29
Scenario 4	Warmer	0.25
Scenario 5	Warmest	0.19

5.2 Proof of Concept

This chapter presents the results of the *noZEB* case to demonstrate the validity, feasibility and weakness of the model. Motivations for this section are the research question 1, 1a, 1b and 1c. Firstly, the deterministic and stochastic solutions are compared to find out if they give the same investments. The second part is a comparison of the full stochastic model and the reduced stochastic model, to prove that the reduced model is a valid substitute. The last part gives the consumption profiles for the *noZEB* case as a model demonstration to prove its credibility. Tables with complete model results for all cases are given in in Appendix A.

5.2.1 Stochastic vs. Deterministic Solutions

Simulated time series of uncertain parameters for a full year of operation, for each of the climatic years c1 to c5, are used as input in this section. c1 is on average the coldest climatic year and have the highest peak of heat demand. To evaluate the stochastic solution, it is compared to the deterministic solutions with the same time resolution. For the stochastic model, c1-c5 are the scenarios of the *Full Stoch.* with equal probabilities.

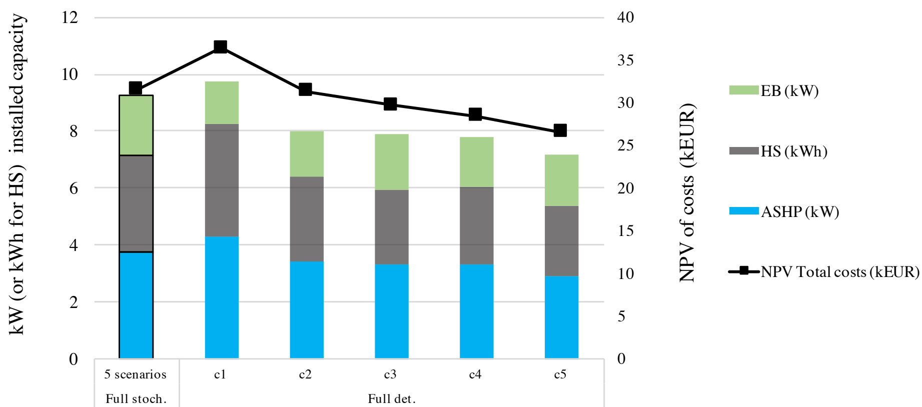


FIGURE 5.1: *noZEB*: Invested technologies (kW or kWh) for the stochastic and deterministic solutions. Right axis: NPV of total costs (kEUR).

Figure 5.1 shows the investment decisions for the full stochastic model to the left and towards the right are the deterministic equivalents. It can be observed that the technology choices are identical for the stochastic model and the deterministic equivalents, with the air-source heat pump (ASHP) for base load, supported by an electric top-up boiler (EB) and a large heat storage (HS). However, the capacities of the technologies differs between the cases. The stochastic model invests in a larger top-up capacity which is on average 71 % larger compared to the deterministic solutions. HS capacity is on average 7 % larger for the stochastic solution and the ASHP capacity is on average 4 % larger. This is a consequence of the different input load profiles of the climatic years, as can be seen from the heat duration curves in figure 3.4. The duration curve is decisive for the proportion between the base load and the peak load.

Figure 5.2 shows the operational costs of the same cases as in figure 5.1. Note that the operational costs of each scenario differs, while the investment costs stay the same. This is because the operational scenarios share the same first-stage decision variables (investments). The first-stage decisions for each deterministic solution varies as the investments are customized for this particular climatic year.

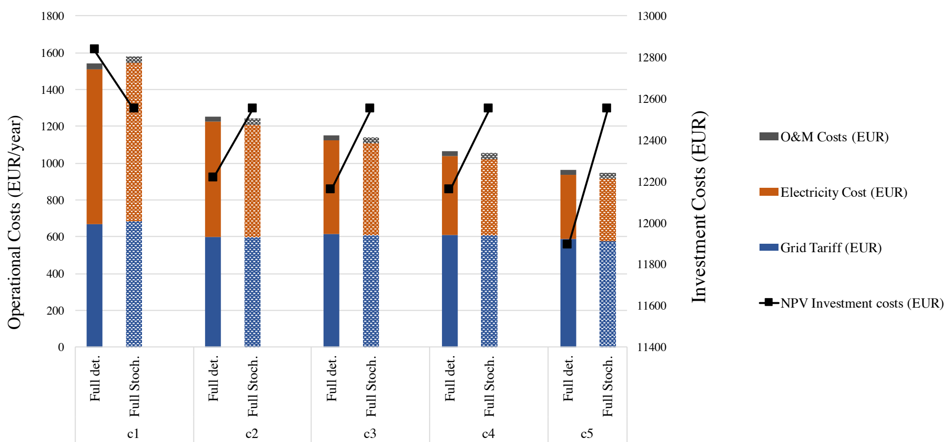


FIGURE 5.2: *noZEB*: Operational costs (EUR/year) and investment costs (EUR) for the stochastic and deterministic solutions

Despite the variation in invested capacities, and hence investment costs, the solutions for the yearly operational expenses of the *Full Stoch.* coincide with the *Full Det.*s. As observed in scenario c1 for the stochastic model, the annual costs are higher than for the deterministic equivalent, while the investment costs are lower. This is a consequence of the stochastic model in opposition to the deterministic equivalent accounts for a more seldom occurrence of c1 (probability of 0.2). The operational costs are higher because the cold days and hours in this scenario lead to higher imports from the electricity grid, as the heating technologies are electricity driven. For warmer climatic years (c2-c5), the impact of a stochastic solution has the opposite effect. Then, investment costs are higher, operational costs lower and the import from the electricity grid is lower than for the deterministic solution.

In order to evaluate the benefits of the stochastic solution, three tests, as introduced in section 2.3.4 are performed. Value of the stochastic solution (VSS) is measured by forcing invested capacities to be the same as in the deterministic solution, called the expected value solution (EVS). The stochastic model is now a recourse program (RP). Loss of using the skeleton solution (LUSS) can be calculated by force the first stage deterministic zero-variables to be zero in the stochastic model. However, there is no need to perform the calculations as it can be seen from figure 5.1 that the deterministic equivalents chooses the same first-stage binaries. Loss of upgrading the deterministic solution (LUDS) is calculated by letting the first-stage decision variables be the lower bound constraint for the investments. Table 5.2 sums up the test results.

TABLE 5.2: Deterministic solutions vs. their stochastic recourse program

Deterministic reference	c1	c2	c3	c4	c5
Deterministic (EVS)	36342.7	31298.4	29720.9	28394.3	26553.5
Stochastic (RP)	30914.78	infeasible	infeasible	infeasible	infeasible
Test A (VSS)	5427.96	∞	∞	∞	∞
Test B (LUSS)	0 (ESSV = RP)	0	0	0	0
Test C (LUDS)	0 (EIV=RP)	infeasible	infeasible	infeasible	infeasible

Test A: *The Value of the Stochastic Solution (VSS)*
For the proposed model, the VSS can only be calculated by using the invested capacities for the deterministic model of the coldest year, c1. This indicates that the value of having a stochastic model is high. Originally, the suggested EVS is the

average scenario, which is c3 for this five-scenario structured model. The invested capacities in the deterministic cases of c2 to c5 can never cover the peak load of c1, and the optimization turns out infeasible. Thus, the VSS for c2-c5 is infinite. Hence, a stochastic solution is crucial to cover the building peak load. Nevertheless, VSS exists for c1. As can be read in table 5.2, ca. 1/6 of the total costs can be saved by using a stochastic solution compared to using the design of the coldest year.

Test B: *The Loss of Using the Skeleton Solution (LUSS)*
LUSS is equal to zero for all the deterministic references and the deterministic equivalents are of "perfect" skeleton solutions. This means that the deterministic and stochastic solutions have corresponding binary variables in stage 1. Thus, the deterministic approximations of the decisions can be used as a good "first guess" to know which technologies that should be invested in.

Test C: *The Loss of Upgrading the Deterministic Solution (LUDS)*
Test C is valid for the coldest year only (c1), where LUDS = 0. This proves that the deterministic equivalent is accurate regardless of the invested technologies and that a stochastic solution can be upgraded to a better solution (in terms of lower costs). A perfectly upgradable solution implies, for this model, that the invested capacities are no higher than this deterministic solution.

To sum up, test results show that the coldest year is a crucial scenario for the design of the energy system capacities, as the coldest year determines the maximum heating capacity. Hence, the conditional probability of this scenario is important for the dimensioning of the installed capacities; the base load, storage and top up technologies.

5.2.2 Reduced Model: Validation

This section seeks to validate the reduced stochastic model (*Red. Stoch.*) by proving that the solution gives the same results as the full stochastic model (*Full Stoch.*). The proposed model is reduced from a full year of operational time steps (8760 hours) down to 672 hours, mainly to reduce the stochastic program's computational effort (runtime). Note that the *Full Stoch.* model uses the climatic years c1-c5 as scenarios with equal probabilities, while for the reduced model, the scenarios are composed by representative weeks, as explained in section 3.4.1. Hence, the scenarios are independent from the climatic year of origin and in opposition to the *Full Stoch.*, the scenarios of the *Red. Stoch.* do not have equal probabilities.

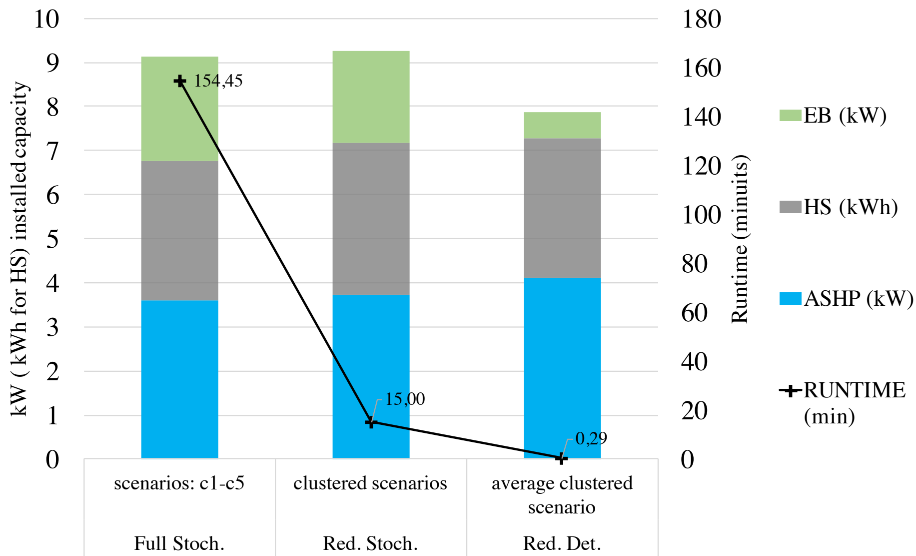


FIGURE 5.3: Model reduction: Invested capacities (kW or kWh) and runtime (minuets). Full stochastic (left), reduced stochastic (middle) and reduced deterministic (right) solutions.

Figure 5.3 shows the invested capacities of the full stochastic model and its reduced equivalent, *Red. stoch.* A reduced deterministic model (*Red. Det.*) solution with input from the average clustered scenario is included (to the furthest right). The program runtime on the right axis is significantly higher for the *Full Stoch.* compared to the *Red. Stoch.* However, it is assumed that the *Red. stoch.* is a good approximation of the true distribution in the *Full stoch.* by the following arguments:

- The total invested capacity is slightly higher in the *Red. stoch.* (9.26 kW vs. 9.12 kW), implying that the heat load is assured to be covered for the coldest hours.
- The total costs have small deviations. The *Red. Stoch.* solution have 2 % (Inv = 0.5 % Op. = 3.5%) higher costs.
- The runtime of the program is reduced by 90.2 %.

To find a reason for the in total higher invested capacity in the reduced model compared to the full version, their respective duration curves of electricity import are examined.

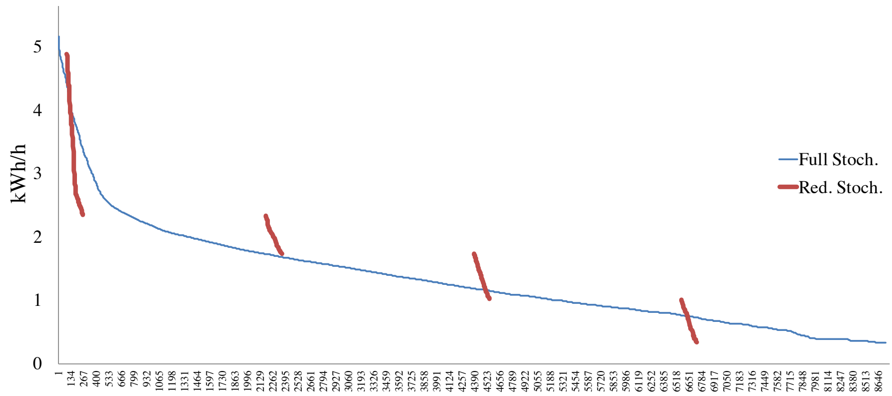


FIGURE 5.4: Model reduction: Electricity duration curves. Full stochastic scenario, c1 (blue line). Reduced stochastic model, scenario 1(red lines)

Figure 5.4 shows the duration curve for scenario c1 of the *Full Stoch.* solution and the four weeks in scenario 1 of the *Red. Stoch.* solution. In effect, it is the final composition of reduced scenarios that together imitate a full year. This figure, which is an exaggeration of how the full composition looks like, shows that the duration curve of the reduced model is slightly higher for the "base load part" of the graph (x-axis: hours 1000-8760). This can be an explanation to the slightly higher invested capacities for the base load technology and for the heat storage, while the top-up capacity is smaller, compared tot the *Full Stoch.* solution.

The reduced deterministic solution, *Red. Det.* is included in figure 5.3 to illustrate that the model reduction methodology is especially suitable for stochastic and not deterministic models. The total installed capacity in the reduced deterministic solution is significantly smaller compared to the *Full Stoch.*. This solution will not be able to cover the peak load of the coldest weeks. Table 5.3 sums the key deviations between the already presented solutions in figure 5.3. Notice that the *Red. Stoch.* solution has smaller deviations than the *Red. Det.* solution. The EB capacity has the highest deviation of both the reduced stochastic and deterministic solutions.

TABLE 5.3: Key differences in the solutions of full and reduced models

	Full Stoch.	Red. Stoch.			Red. Det.		
	Value	Value	Deviation		Value	Deviation	
Objective (EUR)	30763.8	31485.5	721.6	2.0 %	34884.4	4120.6	13.0 %
Inv. costs (EUR)	12484.8	12548.2	63.42	1.0 %	12460.9	-23.9	0.0
Op. costs (EUR)	18279.1	18937.3	658.17	4.0 %	22423.5	4144.41	23.0 %
Run time (min.)	154.4	15.0	-139.4	-90.2 %	0.29	-154.11	-99.8 %
ASHP (kW)	3.60	3.74	0.14	4.0 %	4.11	0.51	14.0 %
HS (kW)	3.16	3.43	0.27	9.0 %	3.16	0.0	0 %
EB (kW)	2.36	2.09	-0.27	-11.0 %	0.60	-1.76	- 75 %

5.2.3 Hourly Model Operation

The hourly operation of the model is here presented for the reduced stochastic model, *Red. Stoch.*, which will be used for the succeeding results in this thesis. It must be stressed that for this demonstration, there is no imposed ZEB-requirements (*noZEB*). The following figures, 5.5 and 5.6 are hourly operations of scenario 1 (the coldest "year") given for the three days of maximum experienced load.

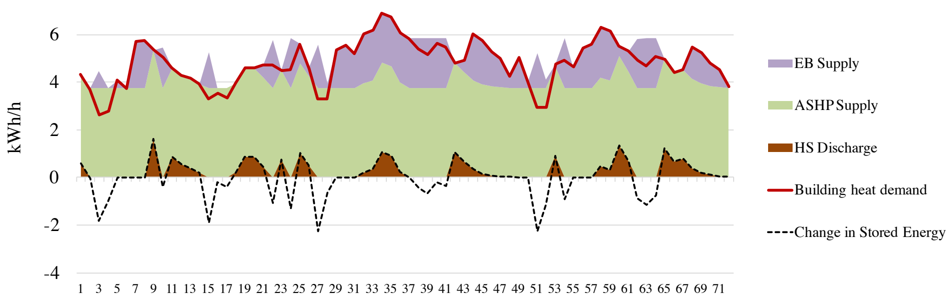


FIGURE 5.5: *noZEB*: 72 hours heat load curve for scenario 1, *Red. Stoch.*

Figure 5.5 shows the heat balance for 72 hours (Friday-Sunday). The building heat demand, represented by the red line, is partially covered by the ASHP supply, EB supply and occasionally by HS discharge.

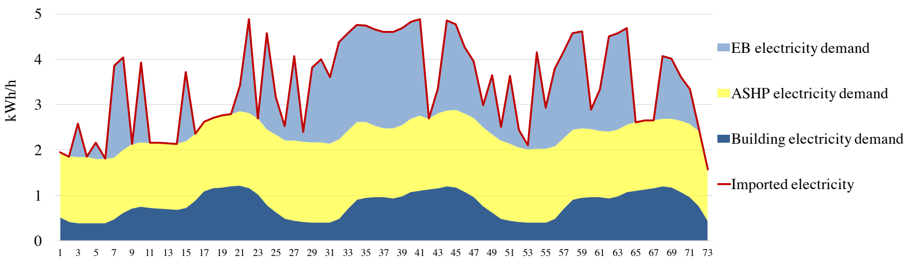


FIGURE 5.6: *noZEB*: 72 hours consumption curve for electricity, *Red. Stoch.*

Figure 5.6 shows the electricity balance for the same 72 hours as in figure 5.6. The imported electricity (red line) covers both the building electricity demand, ASHP demand and EB demand. Building electricity demand is electric specific demand such as lightning and other household appliances.

5.2.4 Discussion

Adapting to uncertainty with flexibility
One of the main purposes of this thesis is to address whether or not a stochastic model is necessary to make accurate investment decisions. Results have shown that a deterministic solution customized for an average warm year, can not cover the load of a year with higher peak demands. This can be seen in figure 5.1, where the total invested capacity differs between the stochastic and deterministic solutions. This is proven by the evaluation of the VSS which gave it an infinite value, as shown in table 5.2. This is a consequence of the strict heat and electricity balancing equality constraints, which imply that the demands are completely inflexible. In reality, the heat demand in a building can be flexible to some extent. Not reaching the peak demand to its full extent can lead to harmless "faults" as reduced comfort for the residents of the house. For example that the one or two hot showers are dismissed or that there is a need to put on more layers of cloths.

Tests evaluating the the deterministic solution have pointed out its accuracy in terms of the choice of invested technologies. This means that the a deterministic model is useful as a "first guess" to find out which technologies that should be invested in. If a cold year is chosen as input data to the deterministic model, results in figure 5.1 shows that the deterministic model tends to overestimate the need for base load capacity. In reality, and as seen from the data analysis in this thesis, the heat duration curve varies with the climatic years. This implies that the average heat duration curve is lower than the cold year, and the need base load capacity is lower. In real life, heat technologies are often designed based on the duration curve of the worst case scenario, that is the coldest climatic year [2], [30]. The stochastic program is simply putting a probability to each duration curve which lower the probability of the worst case scenario and can, according to table 5.2 save 1/6 of the total costs.

Another difference between the stochastic and the deterministic solution is that the stochastic solution suggests significantly larger top-up (EB) and storage (HS) capacities, compared to the deterministic equivalent solutions. It can be assumed that the stochastic model chooses a more flexible composition of technologies, which relies more on grid import during colder hours and less during warmer hours, while the deterministic solution is customized for the operations of one particular climatic year. The results show that the best way of mitigate uncertainty is with flexibility.

A successful reduced model

Results show a successful reduction of the stochastic model. It can be assumed that designing technology capacities only relies on the hour with the peak heat demand. However, one hour of input can not represent the fluctuating heat demand, because this one hour is occurring with a probability equal to 1/8760 in a year. This is why a considerable amount of input data with associated probabilities is important for accurate scenario construction. The clustering analysis in section 3.4.1 gave a probability distribution of the scenarios that seems to impact the allocation between the invested capacities. In the reduced model, the scenarios are one by one not representative for a full year, which the reduced deterministic model has shown by its deviating solution (compared to the full stochastic model). As the results in table 5.3 prove, it is the assembly of clustered scenario-weeks that makes strikingly accurate representations of the full model.

Model shortcomings

One question that arises when selecting the climatic years, is to what extent one can be sure that no larger heat load peaks come in the future than in the coldest scenario. The answer is no, we can not be sure. Therefore, using historical climatic years can only be regarded as a guidance. Hence, the solution will always carry some risk. However, the risk is not equal to weakness. As no one can predict the exact course of the future, there is no stochastic model that comes without risk. The proposed model in this thesis definitely has room for improvements. Other methods of creating scenarios than using historical data can for example be random sampling, as used in [44] and an even more detailed study of the dependencies of the uncertain parameters. In the strive of representing a true course of the uncertainty for the proposed model in this thesis, one could apply more scenarios, use a finer time resolution, or account for both strategic *and* operational uncertainty in a multi-stage model. Remembering that the perfect stochastic model has an infinite amount of scenarios, as stated in 2.3.5. However, more scenarios weakens the program applicability by giving larger runtimes. (An experiment with different numbers of scenarios can be found in Appendix B.) For the subsequent presentations of results, the reader is encouraged to use keep these considerations in mind, and use the proposed model's solution as an indication or a guidance, rather than a true answer.

5.3 Nearly and Strictly ZEB

This chapter presents the optimal solution for three different ZEB-levels; noZEB (0 %), nZEB (50 %) and sZEB (100 %). Both CO_2 weighting factors (CO_2-NOR and CO_2-ZEB) and PEF are used in the presentation for the results. Emissions references are based on the full year c1, as a full year is more representative in terms of a true grid import value, than a clustered scenario.

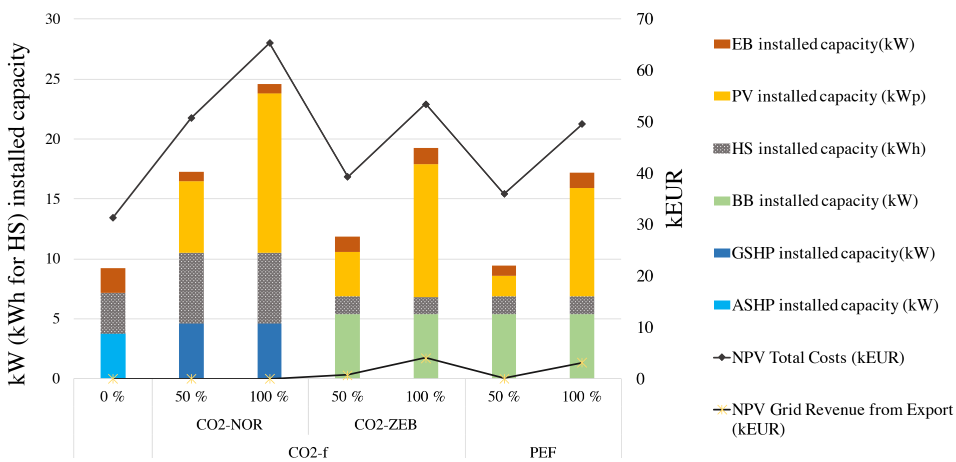


FIGURE 5.7: Invested capacities (kW) and total costs (kEUR) for different ZEB levels.

It can be observed from figure 5.7 that there are several effects of imposing a

ZEB constraint. Firstly, the PV is a solution technology, which is expected. The building must export a great volume of electricity back to the grid in order to meet the net ZEB balance line, as first explained in section 2.2. The amount of export, and hence the PV peak capacity, is dependent on the weighing factors used in the optimization. From *nZEB* to *sZEB*, the only change is the enlargement of the PV peak capacity, leaving the heating technologies unaffected. The use of different CO_2 factors give different base load technologies and affect the size of the heat storage.

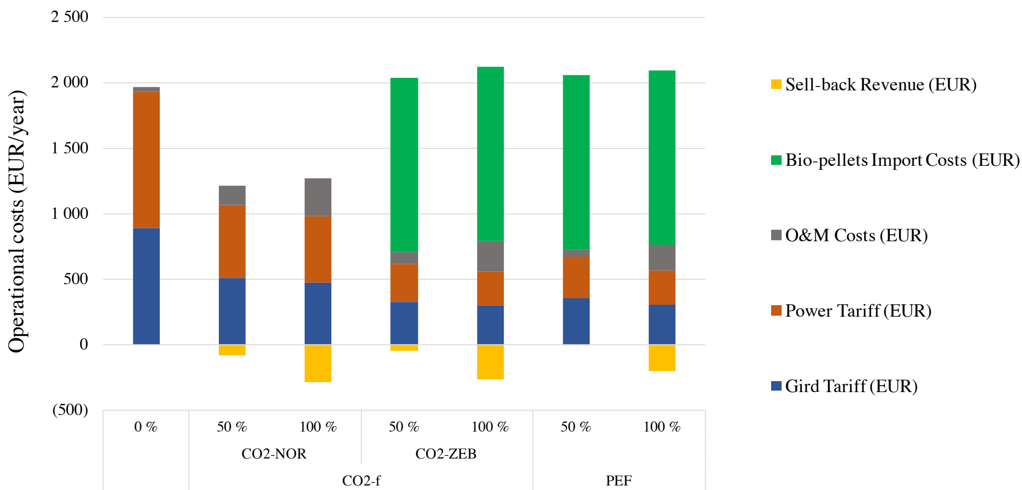


FIGURE 5.8: Operational costs (EUR/year) for different ZEB levels.

Figure 5.8 shows the distribution in operational costs of scenario 1 for the different ZEB-levels. It can be read from the graph that the import of bio-fuel (pellets) is the greatest cost burden for all the *nZEB* and *sZEB* cases with the BB as base load technology. The sell back revenue is propositional to the PV invested capacity. However, the revenue is rather small as is is based on the instant spot price only, representing 1/3 of the average costs of the imported electricity.

5.3.1 Discussion

Results in line with previous research

Observations from figure 5.7 give three indications of that the results are in line with previous research. Firstly, the size of the PV panel is the only change when going from a *nZEB* to a *sZEB*, leaving the other investments unaffected. This was also one of the main findings in [2]. Larger PV panels give larger grid impacts (in terms of peak import and export), according to the same author. Similar results can be read from read table A.4. Secondly, cases with completely electrical based heating technologies (cases with either ASHP or GSHP as base load technology), there is a need for a larger storage capacity. This is due to the variable spot price, causing the electricity-driven heat pump to produce heat to be stored for later use when the spot price is low. Similar observations were made in the case study of [83]. Thirdly, the ratio between the energy carrier weighing factors plays an important role for the choice of base load technology, which was also shown in results of [2], [36].

The importance of the weighing factors

The electricity CO_2 factors proposed in this thesis are the ZEB-research suggested factor (132g/kWh) [3], and the assumed the CO_2 factor for Norwegian produced electricity (17 g/kWh) [8]. The co-existing bio-fuel import factors used in this thesis are 14g and 7g, respectively [2], [17]. The ratio between the el-factor and the bio-factor seems to be of importance for for the choice of technologies. A larger ratio shows solutions with smaller PV panels. In the solutions presented in this thesis, the PV panel peak capacities are within the interval 9 to 13 kW. This span gives significant differences in total investment costs and the building's grid impact, which are both targets of minimization. Possible explanations to this span will now be elaborated. One observation from figure 5.7 is the shift between the base load technology coming from a *noZEB* case to a sZEB (CO_2-NOR) case. When applying the ZEB constraint, the GSHP is chosen in place of the ASHP. The ZEB constraint forces the export of electricity to be equal to the import for such electricity-driven heating systems. This implies that the electricity factor is negligible. It is rather a question of minimizing the grid import, because the grid import in this case is proportional to the size of the PV peak capacity. This causes a trade-off between the ASHP and the GSHP. The GSHP has a higher COP compared to the ASHP, as explained in section 2.2.3. A higher COP reduces the need of electricity import. However, a GSHP has higher installation costs because it requires the construction of a well, in opposition to an ASHP. The trade-off occurs presumably between the marginal cost of installing PV capacity and the break-even cost between the ASHP and the GSHP.

Another significant observation is the shift in base load technology in *nZEB* and *sZEB* cases with different weighing factors. Applying the CO_2-NOR factors gives a GSHP while the CO_2-ZEB and PEF give a BB. This seems to be a consequence of the ratio between the el-factor and the bio-fuel factor. A larger ratio implies that the marginal emissions from bio-fuel is smaller than the marginal emissions of imported electricity. Choosing the BB as base load gives in total less emissions than importing electricity to feed a heat pump. When there are less emissions to compensate for, the PV panel is smaller due to less required export. There must exist a ratio that causes this change in base load technology, and according to table 5.4 it is between 2.42 and 9.42. It must be stressed that the reference values are based on a *noZEB* of which base load is the ASHP. Hence, the reference building has a total import that leads to a large emissions reference. This is also the reason for smaller PV panels in the *nZEB* cases. For the solutions with the BB as base load capacity, the grid import is already reduced to a great extent relative to the *noZEB* case (with ASHP). Because of this, the required amount of export is therefore low and the size of the PV peak capacity accordingly. Table 5.4 shows the optimal base load technology for different weighing factors, both for deterministic and stochastic solutions of the reduced model.

TABLE 5.4: Base load technology and the size of PV panel for different weighting factors (*sZEB*)

	Weighting factor	CO_2-NOR	CO_2-ZEB	PEF
	Ratio: el/bio	2.42	9.42	22.3
Red. Stoch.	Base load tech	GSHP	BB	BB
	PV panel (kWp)	13.3	11.1	9.05
Red. Det.	Base load tech	ASHP	BB	BB
	PV panel (kWp)	13.7	9.55	8.07

The eventual question is which factors to use and which solution to trust. All solutions regardless of the chosen base load technology are valid because they satisfy the ZEB constraint. However, the lack of consistency in the electricity factor for ZEB research can lead to widely different energy systems which again can lead to differences in investment costs and in the building's grid interaction. The span in results does not necessarily make the results weak. As investment decisions seem to rely on the electricity factor and the el/bio ratio, this sensitivity can be used as a tool to explicitly control the investments in ZEBs. Let me explain why: Authorities have the power to decide the CO_2 factor and thus, the choice of base load technology. Imagine if all buildings were to use bio-fuel as heating source. This can potentially lead to increased bio-fuel prices and/or shortage of supply. This can be prevented by increasing the bio-fuel CO_2 factor and thus lower the ratio. However, the draw back of having exclusively electricity-driven technologies is that the required PV panel is larger compared to the cases with BB as base load technology. This can be dissolved by proper subsidizing of PV panels, equal to the the marginal costs for the additional kWp of PV capacity.

Stochastic vs. deterministic and nZEB vs. sZEB
Table 5.4 shows differences between the solutions for the stochastic and the deterministic *sZEB* cases. The deterministic solution seems to invest in a larger PV panel (compared to the stochastic) when the el/bio ratio is low, and the opposite occurs with larger ratios. A possible explanation to this wider span is that the average scenario used as input in the reduced deterministic model. This average scenario is not including the above average warm and sunny days that have the possibility of generating more PV electricity than the average days. Thus, a larger PV panel is required for the *sZEB* (CO_2-NOR) case as there is more electricity import to compensate for. Neither does the average scenario include the colder days, which require a larger import of bio-fuel. Thus, a lower import of bio-fuel implies a smaller PV panel as the emissions are lower and less compensation is needed.

Whether it is crucial to have a stochastic model depends on the required accuracy of the research. If the goal is to obtain a *sZEB*, the size of the PV panel must be large enough to export the right amount of electricity despite the uncertainty of the irradiation and the temperature. In that case, a safer choice is the stochastic solution that accounts for this operational uncertainty. However, the requirement from the EU is that the building has a "near zero emission level", as stated in chapter 1. This is an ambiguous definition and can therefore be interpreted accordingly. As pointed out by the author of [2], *nZEB*s already are highly energy efficient. The CO2-NOR factors give a solution for the *nZEB* case that halves the grid import (down 48 % compared to the *noZEB* case) and that is 55 % self-supplied by the PV. The equivalent *sZEB* case shows a grid import reduction of 52 % and that is only 31 % self supplied. One could argue whether increased investment costs (of 15 000 EUR) coming from a *nZEB* to a *sZEB* justifies the small difference in grid interaction of import and a large amount of export.

Impacts of imposed limitations
The main limitation is neglecting the emissions related to the material extraction and energy used in the construction of the building. Adding these emissions, known

as the "embodied emission" will possibly give a larger PV panel.

5.4 Sensitivity Analysis

The motivations for the sensitivity analysis are research questions 1c and 2a imposed in chapter 1. The cases presented are linked to chapter 2.4; the long-term influences on uncertainty for a ZEB. This part of the results seeks to investigate variations in the spot price level, different grid tariff models and technology investment costs and answer the following questions:

- Are the solution of the *noZEB* and the *sZEB* cases robust to changes in the spot price?
- Will a new tariff model lead to the investment of a battery in *noZEB* and *sZEB* cases?
- At what break-even investment costs will PVs and batteries become a part of the solution in *noZEB* and *sZEB* cases?

5.4.1 The Spot price of electricity

The first study of the variation of the spot price is the impact on the *noZEB* case.

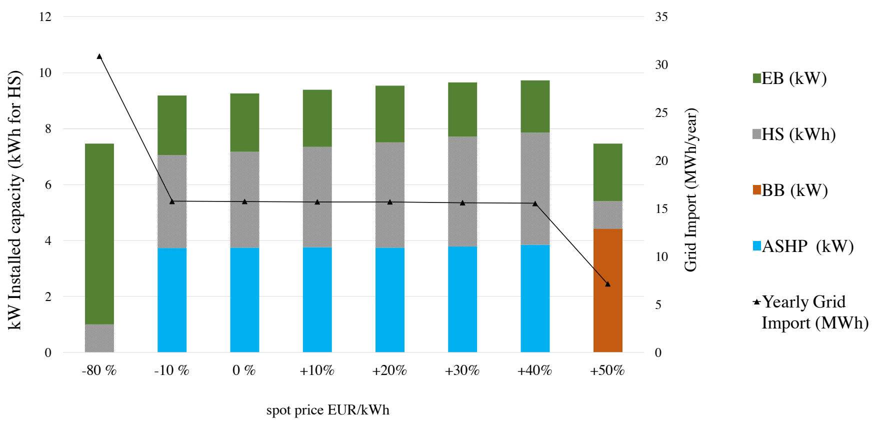


FIGURE 5.9: Sensitivity: Spot price level (EUR/kWh) for a *noZEB*

Figure 5.9 shows the results of the sensitivity analysis of the spot price level. The first observation is the shift in technology investments when the spot price increases to + 50 % of today's level. For the higher spot prices, the BB is the favored base load technology. The second observation in this graph is the distribution of HS and EB capacities. For higher spot prices, the optimal solution results in a smaller EB and a larger HS, while the opposite effect occurs of lower spot prices. It has been observed that a further reduction in spot price leads to the exclusion of the heat pump and a larger invested capacity in the EB, as a result of a low spot price.

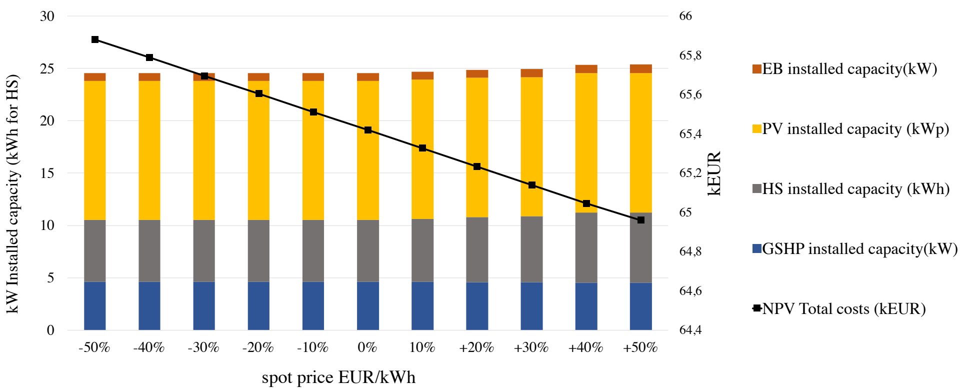


FIGURE 5.10: Sensitivity: Spot price level (EUR/kWp) for the *sZEB* with CO_2-NOR weighting factors

The identical sensitivity analysis is performed with for a *sZEB* case with *CO_2-NOR* weighing factors. As figure 5.10 shows, there is no change in the technologies and *sZEB* solution is not affected by the uncertainty of the spot price level. Results have shown similar trends for the *sZEB* case for both CO_2-ZEB and PEF weighing factors. The decrease in the total costs for an increased spot price is a consequence of the increased revenue of electricity export. The export revenue is exclusively affected by the spot price.

5.4.2 Power Subscription Grid Tariff

The power subscription grid tariff scheme is investigated to find out if it gives incentives to invest in a battery. The first graph shows invested capacities for different power subscriptions. Subscribed power ranges from 100 to 25 % of peak power import of the *Full Stoch.* model solution of c1, ca. 5kW. For the results with for subscription limit "None" means that the current energy pricing model is used. The second graph shows the annual expected costs of scenario 1.

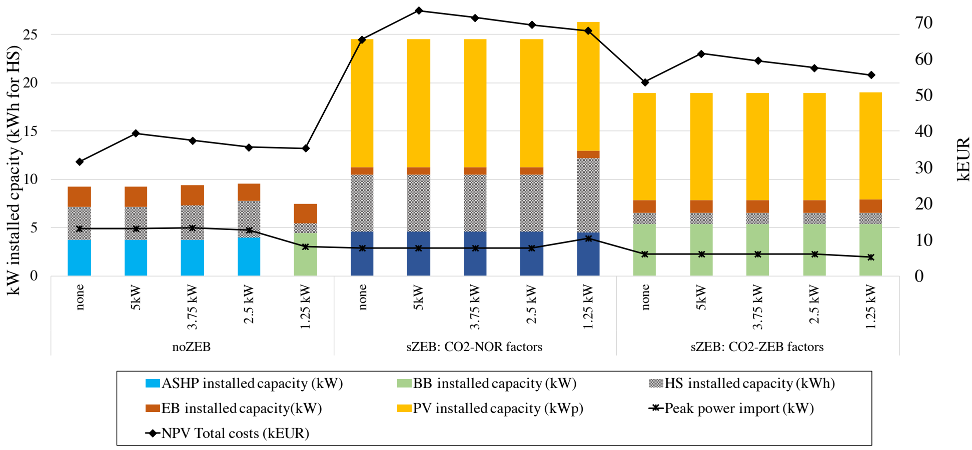


FIGURE 5.11: Sensitivity: Invested capacities (kW) and total costs (kEUR) for different grid tariff models.

The first observation from the *noZEB* case in figure 5.11 is that a subscription limit equal to 25 % of peak power triggers a change in base load technology. The second observation is that a lower subscribed power limit gives slightly lower costs, as the monthly fixed grid charge is a function of the subscribed power. All *sZEB* cases' investments are unaffected by the change in the grid tariff model, except for the CO_2-NOR case with 1.25 kW limit which has a slightly larger HS.

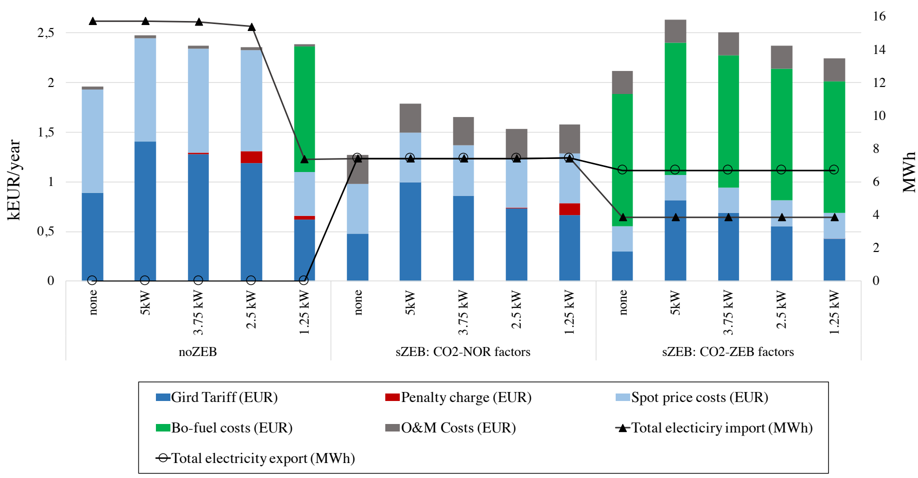


FIGURE 5.12: Sensitivity: Yearly operational costs (EUR/year) and imported/-exported electricity (MWh/year) for different grid tariff models.

Figure 5.12 shows the expected operational costs for the the same cases as in figure 5.11. Note that the figure shows the worst-case costs, for the operations of scenario 1. It can be observed that the CO_2-*NOR* cases give the lowest annual costs.

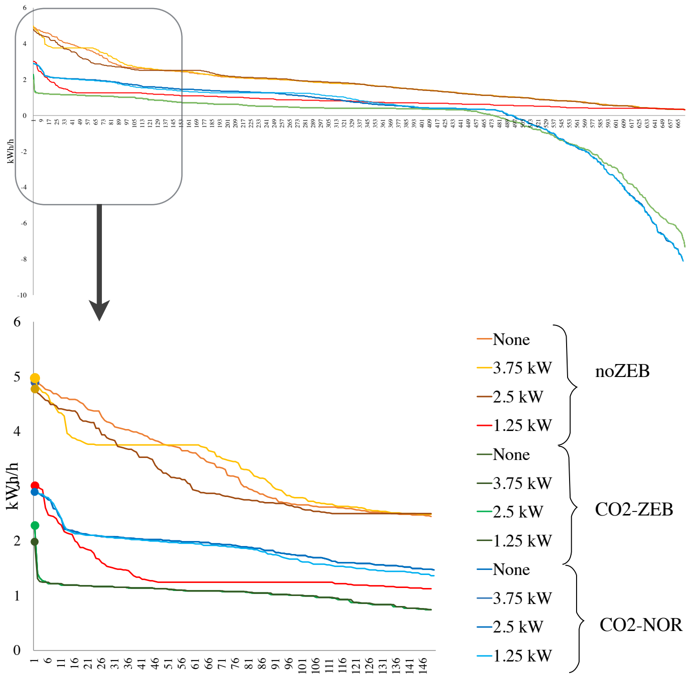


FIGURE 5.13: Sensitivity: Consumption curves for the grid import for the comparison of power tariff subscription limits.

The load duration curves in figure 5.13 represent the imported and exported electricity for the same cases as in figures 5.11 and 5.12. It can be observed from the subscription limits 3.75 and 2.5 kW that the duration curves are flat for a large amount of hours exactly at the imposed limits, implying that the building operations aim to stay under this limit as many hours as possible to avoid the penalty charge. The other appreciable observation is that the load curve is generally at a lower level when the BB is the base heat load technology, which is the case for all *sZEB* cases. This is also the results for the *noZEB* case with subscription limit equal to 1.25kW.

5.4.3 Investment Costs of PV and Battery

This section shows the results of reducing the specific investment costs of the PV (EUR/kWp) and the battery (EUR/kWh).

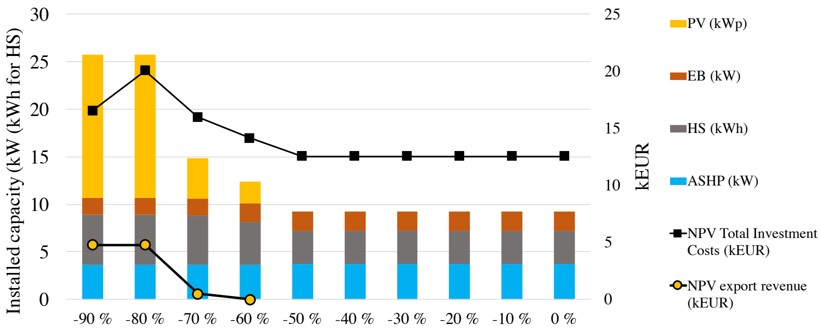


FIGURE 5.14: Sensitivity: Reduced specific investment costs of PV (EUR/kWp)

Figure 5.14 shows the results of a *noZEB* case when reducing the initial specific PV price of 1870 EUR/kWp. The installation (mounting) cost is kept at the original value of 255 EUR. The main observation is that the PV becomes a part of the solution at a specific investment cost equal to 748 EUR/kWp, which is a reduction of 60 % compared to today's costs. Note that this price is exclusive the obtainable Enova support for PV panels, as described in section 2.2.

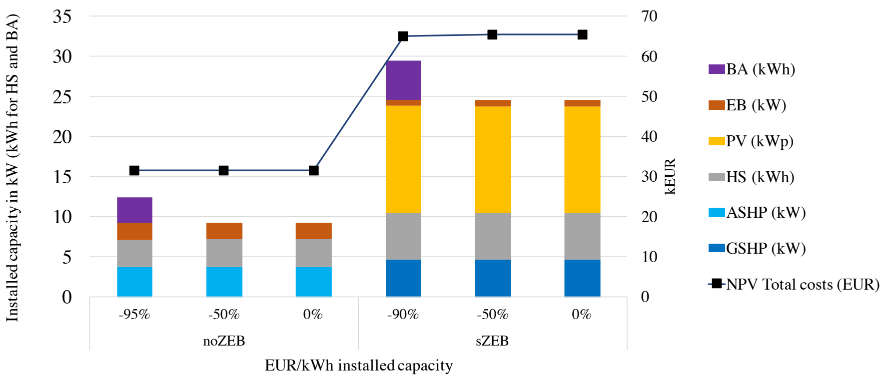


FIGURE 5.15: Sensitivity: Invested capacities (kW and kWh) and total costs (kEUR) for reduced battery specific investment costs (EUR/kWh)

As figure 5.15 proves, the specific investment costs of the battery will have to experience cut from 707 EUR/kWh to 35 EUR/kWh for the battery to become a part of the solution (*noZEB*). For the *sZEB* case, the battery is a solution after a 90 % reduction in the specific costs. The total costs show insignificant differences.

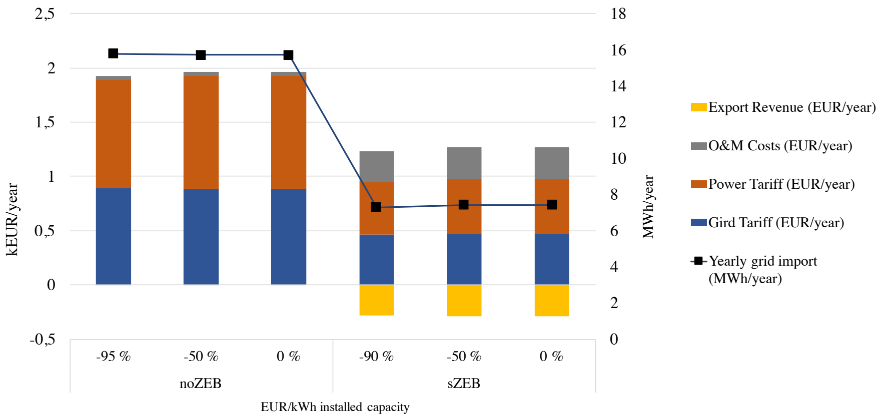


FIGURE 5.16: Sensitivity: Operational costs (EUR/year) and grid import (MWh/year) for reduced battery specific investment costs (EUR/kWh)

Figure 5.16 shows insignificant differences in the annual operational costs and revenue caused by the presence of a battery.

5.4.4 Discussion

Combating increased spot prices with flexibility
Sensitivity analysis has proven that both the *noZEB* and *sZEB* are robust to changes in the spot price level. While all *sZEB* cases are unaffected by changes in the spot price, the *noZEB* case experiences a change in base load technology for a 50 % increase in the spot price. A 50 % increase is unlikely, according to the research of section 2.4.2. One observation from figure 5.9 is that higher spot prices give solutions with larger HS capacities, while the base load heating capacities are unaffected. The larger heat storage provides more flexibility to building operations, by facilitating the ability of storing more of the produced heat at low spot prices. This large amount of stored energy makes the building less dependent grid import. One can argue that the heat storage therefore is an excellent tool for the demand side management, and works just as one would expect for a battery.

Evaluating the power subscription grid tariff
Because the power subscription pricing grid tariff is not imposed and still under consideration, these results should be appreciated with caution. The power sub-

scription grid tariff model has shown, for the *noZEB* case, that an especially strict subscribed power (25% of peak) leads to a change in the base load technology. For the *sZEB* case (CO_2-NOR), the 1.25 kW limit gives a larger HS capacity which increases the flexibility of heat generation. The power subscription grid tariff shows that the penalty charge works as an economic incentive to keep the duration of the peak load low, as seen from figure 5.13. However, the strict power limit does not trigger the investment of a battery. To test if the penalty charge of 0.1 EUR/KWh was too low, the penalty charge was increased to 0.2 EUR/kWh, which lead to no change in the solutions. It seems that it is more cost-efficient to accept the penalty charge than to invest in a battery. One could argue that the obstacle is the battery's high investment costs.

All *sZEB* cases seem to give lower peak imports compared to the *noZEB* cases, because the PV can cover some of the electricity demand. This is favorable seen from the grid. However, the peak power of export is not included in figure 5.11. The ratio between peak import and peak export can be analyzed as a generation multiple (GM) to investigate the grid burden of the *sZEB* cases, as was done in [2]. GM can contribute in evaluating the *sZEB* grid burden. However, this measure is not included in this thesis and will be recommended for further work.

The penalty of forced reinvestments

Based on the expected decrease in the PV investment costs stated in section 2.4.6, a cost-reduction of 60 % for PV-systems does not seem distant. The authors of [9] point out one important aspect of the investment costs that is not considered in the proposed model. That is, if the PV panels can replace original construction materials in a building. For example as roof in new buildings or as a replacement in renovated buildings. Additionally, the Enova support mentioned in section 2.2, is not accounted for in the PV investment costs and will contribute in decreasing the break even cost.

The only sensitivity analysis triggering the investment of a battery is the reduction of its specific investment costs (EUR/kWh). Although the model facilitates both the battery stored- and the PV generated electricity to be exported, results show generally poor export revenues (only 1/3 of the buy price). The investment costs of the battery will have to experience a cut in costs of 90 to 95 % in order for the battery to appear in the *sZEB* and *noZEB* cases, respectively. According to research in section 2.4.6, such reductions seem unlikely in the close future. However, the proposed model does not include other motivations for investing in a battery.

What if the battery already exists in form of an electric vehicle (EV)? Battery operations will be discussed in chapter 5.5.

The two-stage model is designed to force reinvestments when technologies reach their expected lifetime. For the analysis period of 60 years, reinvestments occur twice for the PV and five times for the battery. Although discounting the investment costs and accounting for their rest values, the two-stage model can not capture the expected reduction of investment costs in the future. One can argue that the the penalty of the high investment costs are occurring multiple times with unreasonable high charges. One way of capturing the predicted price reduction is to account for the strategic uncertainty in a multi-stage model. The advantage of a such formulation is that it can also give indication of in what year the PV and/or the battery investment should take place. The multi-stage formulation is advanced to further work, but a suggestion for this implementation is provided in chapter 7.

5.5 Battery and PV Operations

The following results are presented in order to investigate the impact of a battery and PV in *noZEB* and *sZEB*. This section includes the following cases:

- *noZEB with battery*
- *noZEB with PV*
- *noZEB with battery and PV*
- *sZEB with battery*

The motivation for this analysis are the research questions 2b and 2c. For the following results, the 6 kWh ”Nissan xStorage” home battery (from the cost analysis in Appendix C) is purposely fixed as a solution technology. The lower bound is now equal to 6kWh. The original *sZEB* analysis from section 5.3 gave a solution with a 13.3 kWp PV panel. The same PV capacity is used for the *noZEB with PV* cases in this chapter. CO_2-NOR weighing factors are used in the *sZEB* analysis.

noZEB with battery

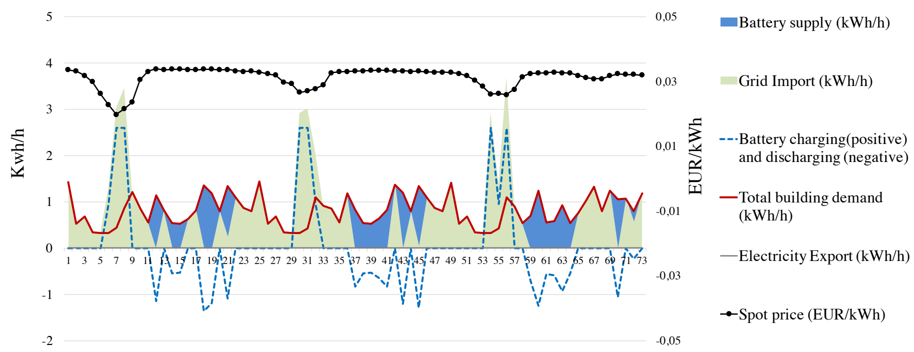


FIGURE 5.17: Electricity balance (kWh/h) of the *noZEB* case with battery (6kWh) for 72 hours in the summer week of scenario 1.

Figure 5.17 shows 72 hours of operations for the *noZEB* case with a 6 kWh battery. The main observation is that the battery discharges to cover the building electricity demand when the spot price is high. The battery is recharged when the spot price is low during the night.

noZEB with PV

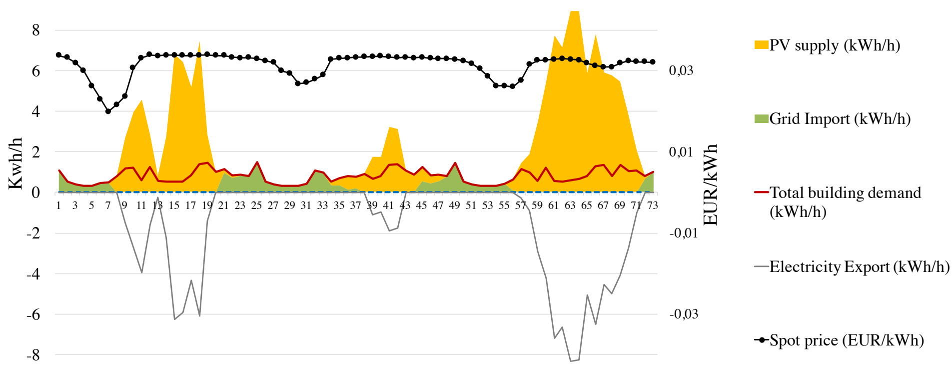


FIGURE 5.18: Electricity balance (kWh/h) of the *noZEB* case with a 13.3 kWp PV, for 72 hours in the summer week of scenario 1.

Figure 5.18 shows the case for a *noZEB* with a 13.3 kWp PV panel. For the hours when the electricity load can not be covered by the PV, the building imports electricity.

noZEB with battery and PV

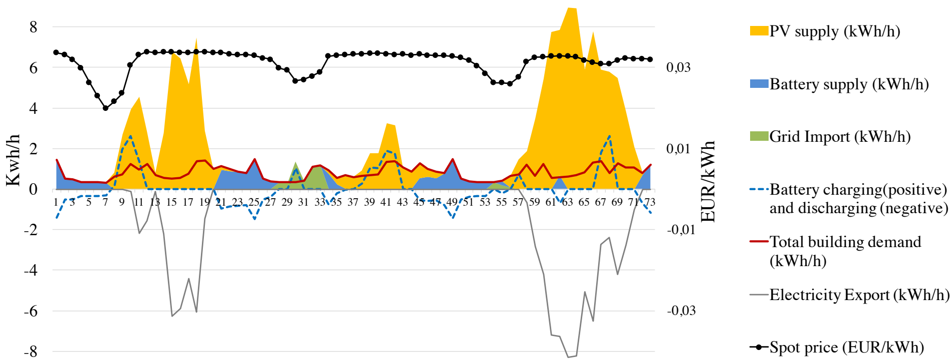


FIGURE 5.19: Electricity balance of the *noZEB* case with battery (6 kWh) and PV (13.31 kWp) for 72 hours in the summer week of scenario 1.

Figure 5.19 shows a case where a 6 kWh battery and a 13.3 kWp PV panel are fixed technologies. This case shows a connection between the PV and the battery as the battery charges when the PV is generating electricity, and discharging during the hours without sun and when the spot price is high. It can be observed that the export of electricity is exclusively dependent on the instant PV electricity generation and independent of the battery operations.

sZEB with battery

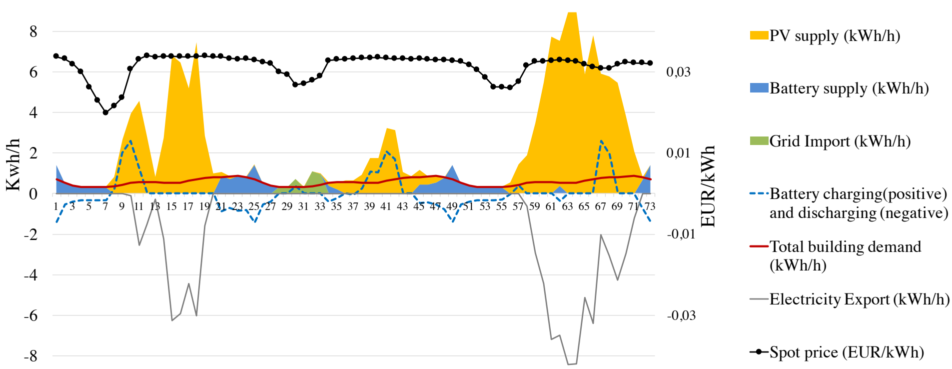


FIGURE 5.20: Electricity balance of the *sZEB*-case with battery (6 kWh) in the summer week of scenario 1 with CO_2-NOR weighing factors.

Figure 5.20 shows the equivalent result for a *sZEB* with a 6kWh battery. The solution gives a PV panel of 13.3 kWp. Figure 5.20 is close to identical to figure 5.19 for the investigated hours. However, throughout the year there are some significant differences that can not be seen from a single plot. Firstly, the base load technology is different between the *noZEB with battery and PV* and the *sZEB with battery*. The *sZEB* case have a lower annual import of electricity and higher export. This is expected as the *sZEB*'s import must equal its export. The most significant difference is the peak power of import which is much lower for the *sZEB* case than all *noZEB* cases. Table 5.5 sums up the key differences.

TABLE 5.5: Key differences of cases with and without battery (6 kWh) and PV (13.3 kWp)

	noZEB				*sZEB*
Additional technologies	none	battery	PV	battery & PV	battery
NPV total costs (EUR)	31485.5	40363.7	56015.0	65419.6	73427.8
Base load technology	ASHP	ASHP	ASHP	ASHP	GSHP
PV production (kWh/year)	0	0	10813.3	10813.3	10813.3
BA discharge (kWh/year)	0	2332.0	0	1765.2	140.8
El. import (kWh/year)	15731.9	15821.98	12005.3	11069.3	7285.9
Peak import (kW)	4.88	7.32	4.7	6.97	2.92
El.export (kWh/year)	0	0	6973.9	5923.5	7285.9
Peak export (kW)	0	0	8.89	11.1	8.71
Net emissions (kgCO_2/year)	202.7	268.9	85.5	87.8	0
ZEB-level (%)	0 %	-25 *	58 %	57 %	100 %

* Increased emissions compared to *noZEB* without battery

5.5.1 Discussion

A spot price dependent battery

Research question 2b addresses how a battery affects operations in *noZEB* and *sZEB*. Based on the knowledge of the battery's advantages, from section 2.4.6, one could suppose that the battery would save the PV generated electricity for later use or export, to even out the grid interaction. However, the results show a cost-minimizing battery that leads to larger peak power import and exports. According to table 5.5, installing a battery in the *noZEB* even causes 25 % higher emissions compared to the *noZEB* without battery. The operational results in this thesis prove that the battery charges solely on low spot prices and discharges under high spot prices.

The results of the *sZEB with battery* case show that the usage the battery in significantly lower compared to the other cases. Only 140.8 kWh/year is discharged from the battery, which presumably is due to the imposed ZEB constraint forcing all of the surplus electricity to be exported and not stored in the battery. It can be assumed that cost-optimal operation of the battery in a sZEB is to not use it. For the *sZEB* case, the battery seems to be redundant.

Most households are not restricted by emission commitments. Therefore, the *noZEB with PV* case can give indications of the dependency of the PV and the battery. Compared to the *noZEB with PV* case, the *noZEB with battery and PV* case gives larger peak power imports and export, which is undesirable. Although the battery charges on PV generated electricity, the peak import increases with the presence of the battery.

A lack of modelling battery control
The final question is whether the results are representative. The motivation for the battery study was to trigger the claimed advantages of the battery, which is not detected by cost-minimizing objective function. Therefore, these results can actually turn out misleading. The cost-optimal operations of a battery leads to higher peak powers. Without any control and restriction of the battery operation, its benefits are not appearing. A controllable battery can potentially regulate both import and export of electricity to avoid peaks. Investigations of the battery's role in the presence of the power subscription grid tariff and other tariffs are forwarded to further work.

5.6 Summary: Main Findings

- A stochastic model can better than its deterministic counterpart account for the following: (i) Cover the peak heat load of periods colder than the deterministic input data, and (ii) avoid over estimating the base load capacity and thereby lower total costs. The costs can be reduced by 1/6, which is the qualitative value of the stochastic solution. A stochastic solution seems to give a more flexible design in terms of a higher storage capacity and top-up capacity and a lower base load technology compared to a deterministic solution.

- Model reduction methodology based on clustering analysis which is reducing the model from a full model of 8760 hours to a reduced version of 672 hours, is especially suitable for a stochastic model and gives about the same solution as a full model. The selection of representative input weeks and the belonging probabilities are crucial to make an accurate imitation of the true distribution.

- All *sZEB* cases are robust to changes in the strategic uncertain parameters, in terms of a robust base load technology. For the *noZEB* case, only a 50 % increase in the spot price of electricity can affect the choice of base load technology.

- Power subscription tariff have little effect of the composition of invested technologies, but gives operations that aim to stay under the subscribed limit. This tariff scheme does not give insentives to install a battery. For the *noZEB* case, a strict subscribed power limit can lead to a shift in the base load technology.

- For a *noZEB* case, the specific investment costs (EUR/kWp) for a PV system will have to experience a 60 % reduction in order for the PV to become an optimal technology. The PV is then used both mostly for self-supply, but also as an extra source of income for the household.

- The battery is a cost-inefficient technology which is not sensitive to any strategic parameter. The specific investment costs (EUR/kWh) will have to experience a cost reduction of 90 to 95 % in order to be an optimal technology for *sZEB* and *noZEB*, respectively.

- Cost-optimal operations of the battery in a sZEB case leads to a battery that charges and discharges seldom, and is independent of electricity exports. The battery in *sZEB* seems to be redundant.

Chapter 6

Conclusion

The main contribution of this thesis is a qualitative and quantitative investigation of the need for a stochastic model, accounting for the operational uncertainty in Zero Emission Building (ZEBs). A two-stage stochastic model, formulated as a Mixed Integerd Linear Program (MILP) is developed in Pyomo/Pyhton. The model separates the first stage investment variables from the second stage operational variables, accounting for the operational uncertainty through five scenarios. Input data is adjusted to fit a single family house located in Oslo.

The first research question was to find out what makes a stochastic model a better approach than the deterministic equivalent in the optimization of ZEBs. Data analysis in this thesis show strong dependencies between the hourly outdoor temperature, building heat demand and the spot price of electricity. The temperature also impact on the efficiency of several building technologies. The main conclusions are the following: (i) A stochastic model can better ensure the coverage of the peak heat loads, when energy system are designed based on historical data for more than one year, compared to its deterministic counterpart. (ii) A stochastic model can avoid overdimensioning the heating capacity by accounting for the probability of occurrence of different operational patterns.

(i) Results have shown that a deterministic solution customized for an average warm year, can not cover the heating demand of a year that has higher peaks. This is because the total peak invested heat capacity is too low. However, the the model has strict heat and electricity balancing equality constraints, which implies that the demands are completely inflexible. In reality, the heat demand in a building can be flexible to some extent. Not reaching the peak demand to its full extent can lead to harmless "faults" as reduced comfort for the residents. Analysis of flexible loads should be carried on in further studies. The stochastic solution chooses larger top-up and storage heating capacities compared to its deterministic counterpart. This is because the stochastic model's investments must account for a wide range of operational patterns occurring with specific probabilities. By this, it can be assumed that the model chooses to mitigate the uncertainty by increasing the flexibility of operations. The final remark is that a stochastic model is necessary to get investments that makes the energy system flexible and robust to cold and warm temperatures. Usually, the capacity of base load technology in heating systems is designed based on the heat duration curve of a deterministic year.

(ii) If a cold year is chosen as input data, results show that the deterministic model tends to overestimate the need for base load capacity. In reality, and as seen from the data analysis in this thesis, the heat duration curve varies with the climatic years. This implies that the average heat duration curve is lower than the coldest year, and the needed base load capacity is lower. Thus, accounting for the operational uncertainty can potentially save investment costs. Results show that the value of having a stochastic solution is saving equal to 1/6 of the total costs. A final remark is that a stochastic model potentially can give a more suitable dimensioning of technologies and lower costs, compared to its deterministic counterpart.

The second research question was to find the incentives of investing in household batteries in Norwegian ZEBs. Results have shown that a strictly ZEB with an installed battery leads to larger power peaks both for import and export compared to a strictly ZEB without a battery. The imposed ZEB constraints lead to building operations where the battery is seldom utilized compared to solutions without the ZEB constraint. All excess PV electricity is directly exported back to the grid to meet the balance requirements. Neither is the investment of a battery triggered by a power subscription tariff. It seems that it is more cost-efficient to pay the penalty charge than investing in a battery. The specific investment costs of the battery (EUR/kWh) must be reduced by 90 % for it to become a part of the solution.

Studying the battery operations lead to a doubt in whether the obtained results can be reliable. The modelling of the battery makes it exclusively motivated by the cost minimization. The battery increase the building's grid import during low spot prices, and decrease the import during high spot prices. The actual benefits of having a controllable battery are not facilitated. A controllable battery increases building flexibility and can potentially regulate both import and export of electricity to avoid peak powers. Additionally, the two-stage model imposes limitations to both the battery and the PV as reinvestments are forced multiple times during the analysis period. The prediction of reduced investment costs in the future is not captured. One solution to this issue is to formulate a multi-stage model which can find the right timing of the investments. It can not be concluded whether a battery should be installed in Norwegian ZEBs. As of today, batteries do not seem to be cost-optimal technologies, either in zero emission- or regular buildings.

Chapter 7

Further Work

This chapter gives recommendations for future extensions to the model developed in this thesis. Some of the suggested extensions have detailed mathematical descriptions.

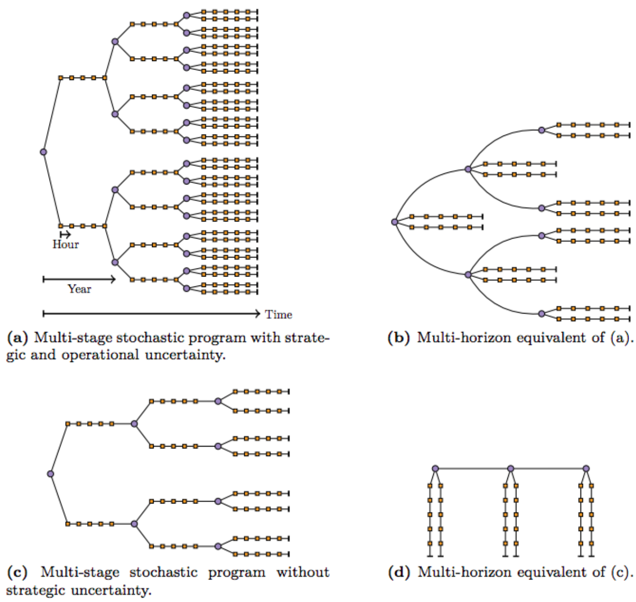
Modelling of Flexible Building Loads

Demand side management (DSM) mechanisms are important to consider in the design of ZEBs as they lead to mismatches between import and export. The heat storage, electric battery and for instance an electric vehicle (EV) are tools to facilitate DSM. In that context, building load flexibility should be further investigated. More specifically, the deterministic and stochastic solutions should be compared under flexible heat and electricity loads. Flexible heat loads can be investigated by relaxing the heat balance equality constraint and find out in which periods of the operational pattern the peak loads will not be entirely covered. Experiments with a controllable heat storage is suggested. Extensions to facilitate control mechanisms of the battery can be implemented. For example by forcing the battery to charge exclusively on PV-generated electricity and investigate the operational patterns under strict limitations of peak power imports and/or exports. I recommend further investigation of the power subscription tariff model's impact together with the battery.

A significant number of Norwegian households will by 2030 have EVs with a battery capacity large enough to cover half of the building's electricity demand [72]. Further work should consider the EV as an additional technology and apply the "Vehicles to Home" concept, using the car battery as a power source for a household to alleviate consumption of power in peak periods when demand is highest.

Multi-stage Model Formulation

One possible approach to account for both strategic *and* operational uncertainty is to expand the model into a multi-stage model. A multi-stage formulation can potentially find the right timing for the investment in for example PV systems. I recommend a simplified version of the multi-stage model called ”multi-horizon” formulation [48]. This approach is used in multiple energy modelling projects, as [84], [85]. The multi-horizon model can have deterministic strategic parameters with the ability to adjust these parameters at the beginning of each period. The scenario tree can look like figure 7.1, of which option (d) is recommended.



(a) Multi-stage stochastic program with strategic and operational uncertainty.

(b) Multi-horizon equivalent of (a).

(c) Multi-stage stochastic program without strategic uncertainty.

(d) Multi-horizon equivalent of (c).

FIGURE 7.1: Multi-stage stochastic scenario trees and their multi-horizon equivalents. Adopted from [85].

The multi-horizon model will be multiple two-stage periods. The objective function is the summation of the Net Present Value (NPV) of each period and can be formulated as in equation (7.1).

$$
\begin{aligned}
\text{Minimize} \quad & \sum_{p \in P} \frac{1}{(1+R)^{(p-1)N}} \Big(c(d_p, x) + \sum_{s \in S} c(d_s, y) \cdot \omega_s \Big) \\
s.t \quad & f(x) \leq 0 \\
& g(x, y_s) \leq 0 \qquad s \in S \qquad p \in P
\end{aligned}
\tag{7.1}
$$

Where:

- P is the number of periods
- R is the discounting factor
- N is the number of years in each period
- $c(d_p, x)$ is the first stage cost function
- $c(d_s, y)$ is the second stage cost function
- S is the number of scenarios
- ω_s is the scenario-specific probability

Stochastic Investigation of Commercial ZEBs

In opposition to residential buildings, commercial buildings have different grid tariff called "peak power pricing". This tariff model is based on the peak power import of each month. This implies higher fixed costs (EUR/kW/month) for months where the peak power is high [86]. The costs of losses remains the same (EUR/kWh), but varies seasonally. I believe that a peak power pricing scheme will be more effective for the reducing peak power imports in ZEBs compared to the power subscription tariff scheme investigated in this thesis. The formulation of the constraint e.g. $y_t^{imp} \leq y_{max}^m$ can be used to obtain the maximum value.

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Appendix A

Result Tables

The following tables are included:

- Results for (full) deterministic model *noZEB*
- Results for (full) stochastic model *noZEB*
- Results for (reduced) stochastic model *noZEB*
- Results for (reduced) stochastic model *noZEB*, *nZEB* and *sZEB*
- Results for (reduced) stochastic model with power subscription tariffs
- Results for (reduced) stochastic model with battery operations

TABLE A.1: Results for (full) deterministic models *noZEB*

	c1 (2010)	c2 (2011)	c3 (2013)	c4 (2012)	c5 (2014)
FIRST STAGE VARAIBLES					
Total costs					
NPV Total costs (EUR)	36342.7	31298.4	29720.9	28394.3	26553.4
NPV Investment costs (EUR)	12835.3	12215.6	12160.6	12158.0	11891.2
NPV Operational costs (EUR)	23507.4	19082.9	17560.3	16236.3	14661.26
Invested capacities					
ASHP installed capacity (kW)	4.31	3.44	3.31	3.34	2.93
GSHP installed capacity (kW)	0	0	0	0	0
BB installed capacity (kW)	0	0	0	0	0
HS installed capacity (kWh)	3.96	2.98	2.65	2.72	2.42
PV installed capacity (kWp)	0	0	0	0	0
EB installed capacity (kW)	1.46	1.56	1.91	1.73	1.81
BA installed capacity (kWh)	0	0	0	0	0
Technology costs					
ASHP investment costs (EUR)	12096.5	11573.0	11490.1	11513.6	11266.0
HS Investment costs (EUR)	462.9	348.2	309.8	317.7	283.1
EB Investment costs (EUR)	275.9	294.3	360.8	326.7	342.1
SECOND STAGE VARIABLES					
ZEB					
Emissions - CO_2-NOR (kg CO_2/year)	192.2	169.2	174.6	173.1	164.4
PE consumed (kWh PE/year)	28263.6	24882.1	25680.0	25443.9	24183.5
ZEB-level (%)	0 %	0 %	0 %	0 %	0 %
Grid Operations					
Total grid import (kWh)	11302.6	9952.9	10272.0	10277.5	9673.4
Peak power import (kWh/h)	4.50	4.19	4.38	4.36	4.02
Total grid export (kWh)	0	0	0	0	0
Peak power export (kWh/h)	0	0	0	0	0
Energy Production					
ASHP generation (kWh/year)	17039.6	13995.4	14561.6	14280.4	12978.6
EB generation (kWh/year)	147.3	153.2	248.8	222.9	262.6
Yearly Operational Costs					
Gird tariff (EUR/year)	668.6	600.9	616.9	612.2	586.9
Spot price costs (EUR/year)	840.6	623.6	508.2	426.0	350.77
O&M costs (EUR/year)	33.0	27.0	26.6	26.6	23.8

TABLE A.2: Results for (full) stochastic model *noZEB*

FIRST STAGE VARIABLES						
Total costs						
NPV Total costs (EUR)			30763.9			
NPV Investment costs (EUR)			12484.8			
NPV Operational costs (EUR)			18279.1			
Invested capacities						
ASHP installed capacity (kW)			3.60			
GSHP installed capacity(kW)			0			
BB installed capacity (kW)			0			
HS installed capacity (kWh)			3.16			
PV installed capacity (kWp)			0			
EB installed capacity (kW)			2.36			
BA installed capacity (kWh)			0			
Technology investment costs						
ASHP investment costs (EUR)			11669.4			
HS Investment costs (EUR)			369.9			
EB Investment costs (EUR)			445.5			
SECOND STAGE VARIABLES						
Scenario	c1	c2	c3	c4	c5	Expected value
Scenario probability	0.2	0.2	0.2	0.2	0.2	-
Grid Operations						
Total grid import (kWh)	11634.5	9912.9	10181.0	10099.0	9508.1	10267.3
Peak power import (kWh/h)	5.20	5.11	4.83	5.10	4.70	4.98
Total grid export (kWh)	0	0	0	0	0	0
Peak power export (kWh/h)	0	0	0	0	0	0
ZEB						
Emissions - CO_2-NOR (kg CO_2/year)	197.8	168.5	173.0	171.7	161.6	174.5
PE consumed (kWh PE/year)	29086.3	24782.4	25453.4	25247.7	23771.7	25668.0
ZEB-level (%)	0 %	0 %	0 %	0 %	0 %	0 %
Energy Production						
ASHP generation (kWh/year)	16540.8	14047.6	14676.5	14380.3	13188.5	14566.7
EB generation (kWh/year)	147.3	153.2	248.8	222.9	263.6	211.3
Yearly Operational Costs						
Gird tariff (EUR/year)	685.0	598.9	612.4	608.3	578.8	616.7
Spot price costs (EUR/year)	863.3	613.7	496.1	414.5	337.5	545.0
O&M Costs (EUR/year)	29.5	29.5	29.5	29.5	29.5	29.5

TABLE A.3: Results for (reduced) stochastic model *noZEB*

FIRST STAGE VARIABLES	
Total costs	
NPV Total costs (EUR)	31485.5
NPV Investment costs (EUR)	12548.2
NPV Operational costs (EUR)	18937.3
Invested capacities	
ASHP installed capacity (kW)	3.74
GSHP installed capacity(kW)	0
BB installed capacity (kW)	0
HS installed capacity (kWh)	3.43
PV installed capacity (kWp)	0
EB installed capacity (kW)	2.09
BA installed capacity (kWh)	0
Technology investment costs	
ASHP investment costs (EUR)	11752.1
HS Investment costs (EUR)	401.22
EB Investment costs (EUR)	394.8

SECOND STAGE VARIABLES (SCENARIO 1)

Scenario	1 coldest	2 cold	3 average	4 warm	5 warmest	Expected value
Scenario probability	0.08	0.19	0.29	0.25	0.29	-
Grid Operations						
Total grid import (kWh)	15731.9	11923.9	10037.5	9410.8	8623.3	11145.5
Peak power import (kWh/h)	4.88	4.85	2.43	2.5	2.2	3.37
Total grid export (kWh)	0	0	0	0	0	0
Peak power export (kWh/h)	0	0	0	0	0	0
ZEB						
Emissions - CO_2-NOR (kg CO_2/year)	267.4	202.7	170.6	159.9	146.5	189.5
Total PE consumed (kWh PE/year)	39329.9	29809.9	25093.8	23527.0	22420.7	2836.3
ZEB-level (%)	0 %	0 %	0 %	0 %	0 %	0 %
Energy Production						
ASHP generation (kWh/year)	22486.1	18265.9	14613.1	13042.7	11337.0	15948.9
EB generation (kWh/year)	1801.9	283.1	4.5	0.0	0.0	417.9
Yearly Operational Costs						
Gird tariff (EUR/year)	889.9	699.5	605.2	573.9	534.5	660.6
Spot price costs (EUR/year)	1042.8	751.6	566.5	449.9	404.4	643.0
O&M costs (EUR/year)	30.0	30.0	30.0	30.0	30.0	30.0

TABLE A.4: Results for (reduced) stochastic model (*noZEB*, *nZEB*,*sZEB*)

	CO2-NOR		CO2-ZEB		PEF	
	nZEB 50%	sZEB 100%	nZEB 50%	sZEB 100%	nZEB 50%	sZEB 100%
FIRST STAGE VARIABLES						
Total costs						
NPV Total costs (EUR)	50782.0	65419.1	39345.0	53560.0	35997.9	49661.8
NPV Investment costs (EUR)	38351.1	55685.7	15300.4	32662.1	10436.4	27850.3
NPV Operational costs (EUR)	12430.1	9733.8	24044.7	20897.9	25561.6	21811.6
Invested capacities						
ASHP installed capacity (kW)	0	0	0	0	0	0
GSHP installed capacity(kW)	4.60	4.61	0	0	0	0
BB installed capacity (kW)	0	0	5.40	5.39	5.42	5.40
HS installed capacity (kWh)	5.9	5.9	1.0	1.12	1.45	1.0
PV installed capacity (kWp)	5.97	13.3	3.75	11.1	1.69	9.0
EB installed capacity (kW)	0.78	0.77	1.25	1.37	0.89	1.32
BA installed capacity (kW)	0	0	0	0	0	0
Technology investment costs						
PV investment costs (EUR)	14439.0	31761.8	9196.2	26522.4	4338.4	21731.2
GSHP investment costs(EUR)	22675.1	22866.0	0	0	0	0
BB Investment costs (EUR)	0	0	5751.8	5750.7	5760.1	5752.7
EB Investment costs(EUR)	146.9	145.1	235.3	258.4	168.3	249.2
HS Investment costs(EUR)	689.8	689.8	116.9	130.5	169.5	116.9

SECOND STAGE VARIABLES (SCENARIO 1)

	CO2-NOR		CO2-ZEB		PEF	
	nZEB 50%	sZEB 100%	nZEB 50%	sZEB 100%	nZEB 50%	sZEB 100%
ZEB (CO_2 factors)						
Emissions (kg CO_2/year)	138.2	126.3	954.6	883.784	1025.857	895.57
Emissions from bio-pellets(%)	0 %	0 %	39 %	42 %	36 %	42 %
Saved emissions (kg CO_2/year)	36.9	126.26	167.6	883.8	20.8	677.6
ZEB-level (CO_2) (%)	50 %	100 %	50 %	100 %	36 %	86 %
ZEB (PEF)						
PE consumed (kWh$_{pe}$/year)	203324	18566.7	13951.7	16738.3	15298.1	12833.8
PE from bio-pellets (%)	0 %	0 %	21 %	23 %	19 %	23 %
Saved PE (kWh$_{PE}$/year)	5427.0	18566.7	3174.3	16738.3	393.2	12833.8
ZEB-level (PE) (%)	50 %	100 %	64 %	100 %	50 %	100 %
Grid interactions						
Total grid import (kWh)	8132.9	7426.7	4410.1	3873.2	4947.7	3962.9
Peak power import (kWh/h)	2.9	2.89	2.1	2.29	1.81	2.2
Total grid export (kWh)	2170.9	7426.7	1269.7	6695.3	157.3	5133.5
Peak power export (kWh/h)	3.4	8.71	2.0	2.29	0.60	5.9
Energy generation						
PV generation (kWh/year)	4852.2	10810.8	3051.4	9009.2	1380.9	7361.7
GSHP generation (kWh/year)	24029.0	24034.9	0	0	0	0
BB generation (kWh/year)	0	0	24209.2	24213.8	24229.2	24288.0
EB generation (kWh/year)	259.0	253.1	78.8	74.2	58.9	79.2
Self-supplied (by PV) (%)	55%	31%	58 %	26 %	89 %	30 %
Yearly operational costs						
Gird Tariff (EUR/year)	509.9	474.7	323.8	296.9	350.8	301.5
Spot price costs (EUR/year)	550.7	505.5	289.8	257.9	318.3	263.3
O&M Costs (EUR/year)	152.3	289.4	93.9	231.2	55.0	193.2
Bio-pellets (EUR/year)	0	0	1330.2	1330.4	1331.2	1330.2
Export Revenue (EUR/year)	82.9	289.3	49.9	267.4	6.1	204.3

TABLE A.5: Results for (reduced) stochastic model with power subscription tariffs

	noZEB				sZEB: CO2-NOR factors				sZEB: CO2-ZEB factors			
Subscribed Power	5kW	3.75 kW	2.5 kW	1.25 kW	5kW	3.75 kW	2.5 kW	1.25 kW	5kW	3.75 kW	2.5 kW	1.25 kW
FIRST STAGE VARIABLES												
Total costs												
NPV Total costs (EUR)	39361.9	37414.4	35613.1	35280.4	73296.0	71326.9	69361.6	67780.0	61436.4	59467.3	57498.2	55532.3
NPV Investment costs (EUR)	12548.2	12566.5	12661.5	5887.4	55685.7	55685.7	55685.8	55836.3	32662.1	32662.1	32662.1	32663.4
NPV Operational costs (EUR)	26813.7	24848.0	22951.7	29393.0	17610.3	15641.2	13675.8	11944.0	28774.3	26805.2	24836.1	22868.9
Invested capacities												
ASHP installed capacity (kW)	3.7	3.8	3.9	0	0	0	0	0	0	0	0	0
GSHP installed capacity(kW)	0	0	0	0	4.6	4.6	4.6	4.5	0	0	0	0
BB installed capacity (kW)	0	0	0	4.5	0	0	0	0	5.4	5.4	5.4	5.4
HS installed capacity (kWh)	3.4	3.6	3.8	1.0	5.9	5.9	5.9	7.7	1.1	1.1	1.1	1.1
PV installed capacity (kWp)	0	0	0	0	13.3	13.3	13.3	13.3	11.1	11.1	11.1	11.1
EB installed capacity(kW)	2.1	2.1	1.8	2.0	0.8	0.8	0.8	0.8	1.4	1.4	1.4	1.4
BA installed capacity (kWh)	0	0	0	0	0	0	0	0	0	0	0	0
SECOND STAGE VARIABLES (SCENARIO 1)												
Grid interactions												
Total electricity import (kWh/year)	15732.0	15692.3	15391.1	7377.6	7426.7	7426.0	7426.0	7438.0	3873.2	3873.2	3873.2	3874.2
Peak power import (kWh/h/year)	4.9	5.0	4.8	3.0	2.9	2.9	2.9	3.9	2.3	2.3	2.3	2.0
Total electricity export (kWh/year)	0.0	0.0	0.0	0.0	7426.7	7426.0	7426.0	7438.0	6695.3	6695.3	6695.3	6696.4
Peak power export (kWh/h/year)	0.0	0.0	0.0	0.0	8.7	8.7	8.7	8.7	7.3	7.3	7.3	7.3
Penalty volume (kWh/year)	0.0	143.5	1193.4	364.7	0.0	0.0	31.2	1198.7	0.0	0.0	0.0	10.4
Yearly operational costs												
Penalty charge (EUR/year)	0.0	14.3	119.4	36.5	0.0	0.0	3.1	119.8	0.0	0.0	0.0	1.0
Gird Tariff (EUR/year)	1406.5	1282.5	1190.9	619.6	991.3	862.1	734.5	664.2	813.6	684.4	555.3	426.7
Spot price costs (EUR/year)	1042.8	1042.6	1018.5	442.7	505.5	505.5	505.5	505.5	257.9	257.8	258.0	257.9
O&M Costs (EUR/year)	30.0	30.1	31.0	21.2	289.4	289.4	289.4	289.2	231.2	231.2	231.2	231.2
Bio-pellets Import Costs (EUR/year)	0.0	0.0	0.0	1266.3	0.0	0.0	0.0	1330.4	1330.4	1330.4	1330.4	1330.4

TABLE A.6: Results for (reduced) stochastic model with battery operations

	noZEB			sZEB
	battery	PV	PV and battery	battery
FIRST STAGE VARIABLES				
Total costs				
NPV Total costs (EUR)	40363.7	56015.0	63950.3	73427.8
NPV Investment costs (EUR)	21852.8	44419.4	53691.0	65004.7
NPV Operational costs (expected) (EUR)	18510.8	11595.6	20259.3	8468.11
Invested capacities				
ASHP installed capacity (kW)	3.76	3.64	3.64	0
GSHP installed capacity (kW)	0	0	0	4.63
BB installed capacity (kW)	0	0	0	0
HS installed capacity (kWh)	3.16	5.29	4.70	5.57
PV installed capacity (kWp)	0	13.3	13.3	13.3
EB installed capacity (kW)	2.12	1.83	1.93	0.79
BA installed capacity (kWh)	6.0	0	6.0	6.0
SECOND STAGE VARIABLES (SCENARIO 1)				
Energy generation				
BA discharge (kWh/year)	2332	0	1765.2	140.8
PV generation (kWh/year)	0	10812.14	10813.3	10813.3
ASHP/GSHP generation (kWh/year)	22529.5	22284.5	22289.7	24042.6
EB generation (kWh/year)	1758.5	2003.6	1998.3	245.4
Grid Interactions				
Total grid import (kWh/year)	15821.98	7737.9	11069.3	7285.9
Peak import (kWh/h/year)	7.32	4.70	6.97	2.92
Total grid export (kWh/year)	0	6973.9	5923.5	7285.9
Peak export (kW/h/year)	0	8.89	11.1	8.71
ZEB				
Net emissions - CO_2-NOR (kg CO_2/year)	268.9	85.5	87.48	0
Net PE (kWh PE/year)	39552.9	30012.9	12864.5	0
ZEB-level(%)	-25 %	58 %	57 %	100 %
Yearly Operational Costs				
Gird tariff (EUR/year)	894.4	703.6	656.8	467.6
Spot price costs (EUR/year)	978.1	829.15	737.4	478.5
O&M Costs (EUR/year)	30.2	277.6	277.8	288.4

Appendix B

Extended Clustering Analysis

Additional figures for the clustering analysis consist have proven that the use of different co-relation (figure B.2) give the same selection of weeks and close to the same probability (figure B.2).

The figures a-h in B.4 and a-b in B.5 show clustering analysis for different numbers of scenarios of which runtime increases with the number of scenarios (figure B.3).

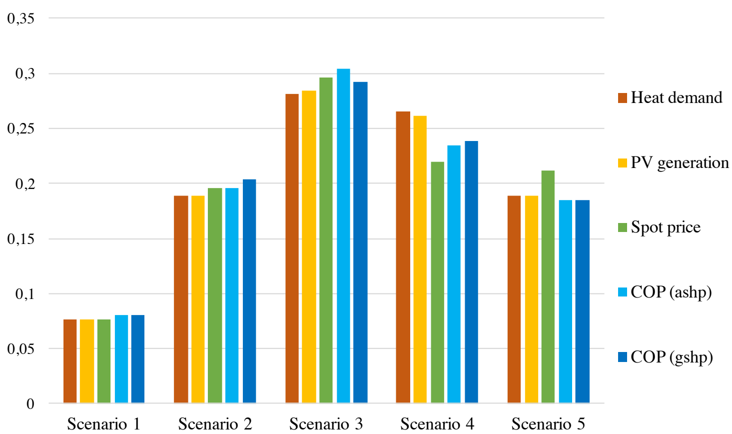
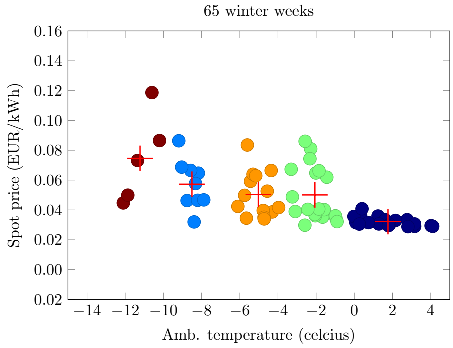
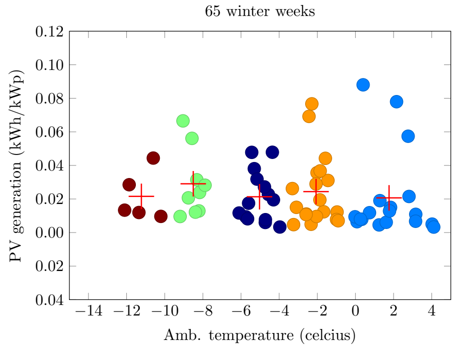


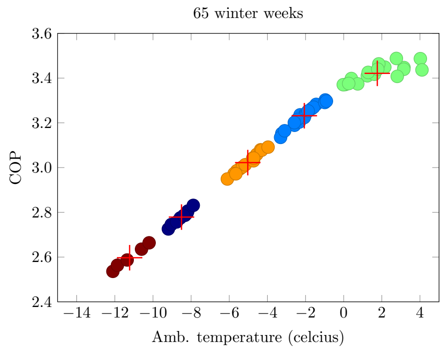
FIGURE B.1: Probability of scenarios for temperature vs. different co-relations



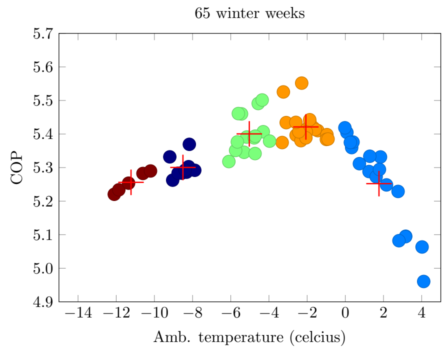
(a) Spot price vs. temperature



(b) PV generation vs temperature



(c) COP (ashp) vs. temperature



(d) COP (gshp) vs. temperature

FIGURE B.2: Clustering of temperature vs. different co-relations

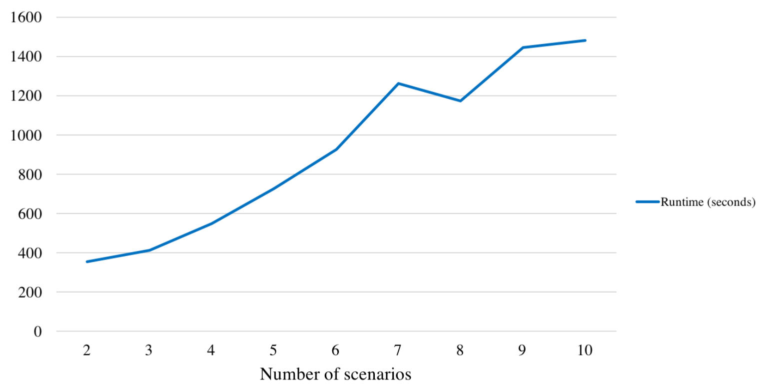
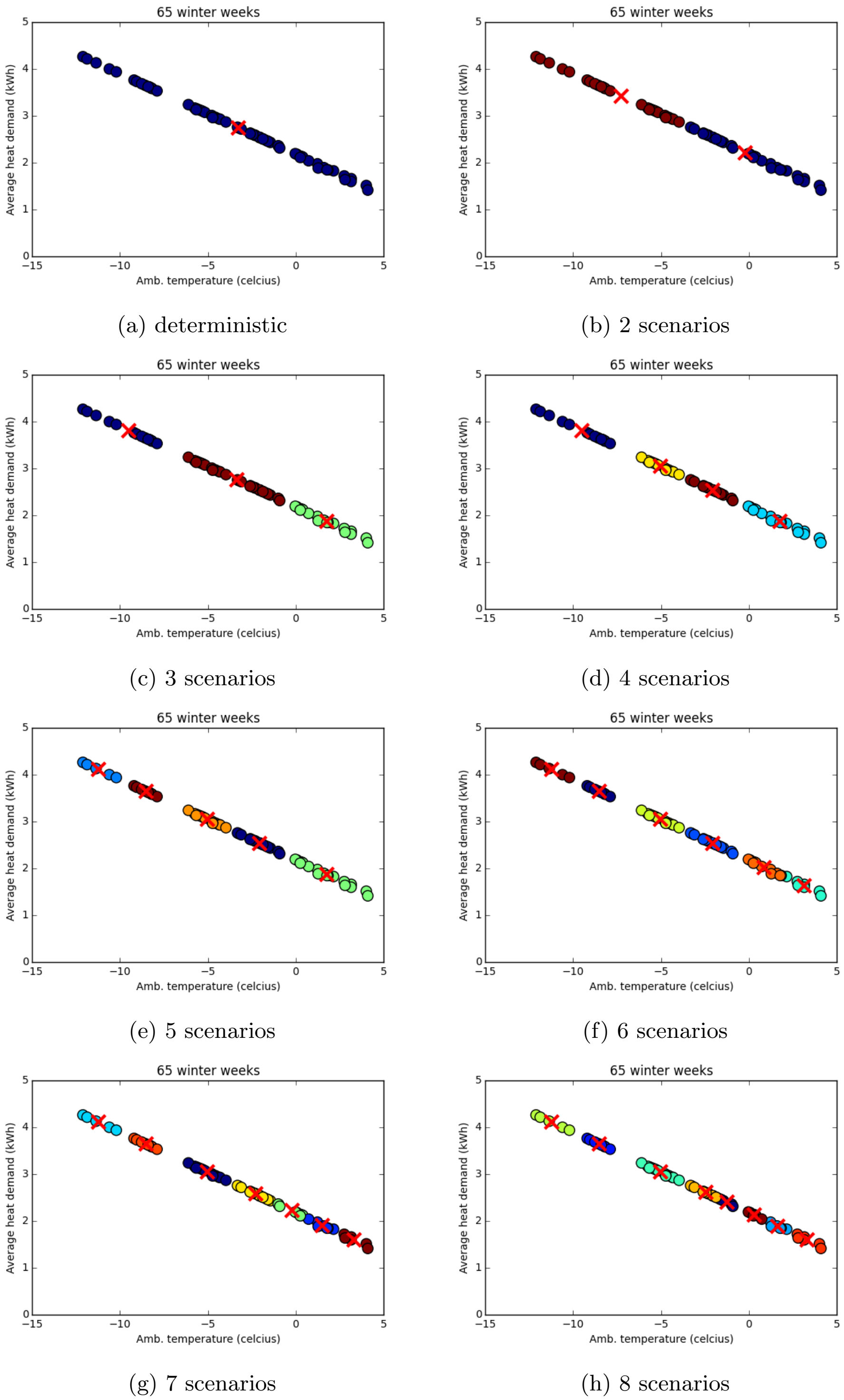
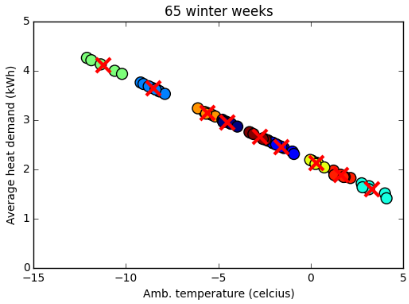


FIGURE B.3: Runtime vs. number of scenarios

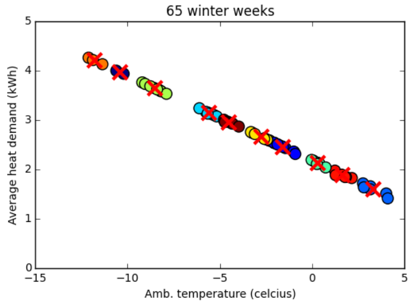


(a) deterministic (b) 2 scenarios (c) 3 scenarios (d) 4 scenarios (e) 5 scenarios (f) 6 scenarios (g) 7 scenarios (h) 8 scenarios

FIGURE B.4: Clustering for different number of scenarios



(a) 9 scenarios



(b) 10 scenarios

FIGURE B.5: Clustering for different number of scenarios

Appendix C

Investment Costs Analysis

<u>*PV Panels*</u>

Table C.1 lists Norwegian prices including hardware, mounting and installation of PV panels for different kWp. Prices include value added taxes (VAT).

TABLE C.1: Costs of complete PV systems. Prices from [87].

PV panel	Inverter	kWp	Price (NOK)	Price (EUR)
IBC Polysol 260 x8	Steca Stecagrid 2300	2.1	42900	4442.8
IBC Polysol 260 x12	Steca Stecagrid 3010	3.1	56900	5892.7
IBC Polysol 260 x16	Steca Stecagrid 4200	4.2	74500	7715.5
IBC Polysol 260 x20	SMA Sunny Boy 5000	5.2	96900	10035.3
IBC Polysol 260 x28	SMA Sunny Boy 5000	7.3	135220	14003.8

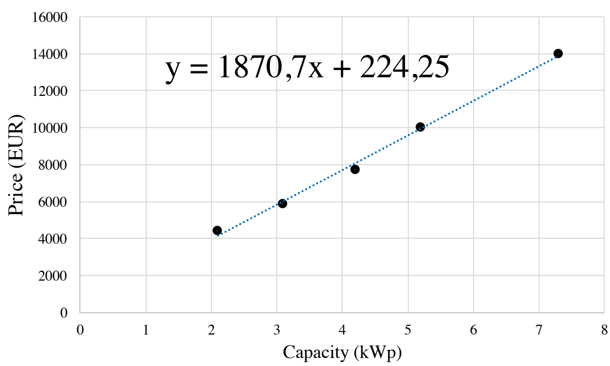


FIGURE C.1: Regression curve for PV costs showing fixed (EUR) and variable (EUR/kWp) costs

Battery

Table C.2 lists battery prices for different types of household batteries available or soon available in Norway or to be available in near future. Because prices of software and installation are varying, the price is set as completely relying on the invested storage capacity and have no fixed costs.

TABLE C.2: Costs of complete battery systems. Prices from: [88], [89]

Battery	η_{rt}	β	Warranty	Capacity	Price
Tesla Powerwall	0.90	0.33	10 years	6.4-13.5 kWh	5178.2 - 8254.0 EUR
LG RESU	0.95	0.5	10 years	6.6-9.8 kWh	5151.3 -6249.9 EUR
Nissan Xstorage	0.97	0.5	10 years	6.6-9.6kWh	5298.1 - 6978.1 EUR
SolaX	0.95	0.33	10 years	11.6 kWh	4762.1 EUR
SimpliPhi PHI3.4	0.98	0.5	10 years	3.4 kWh	4331.1 EUR

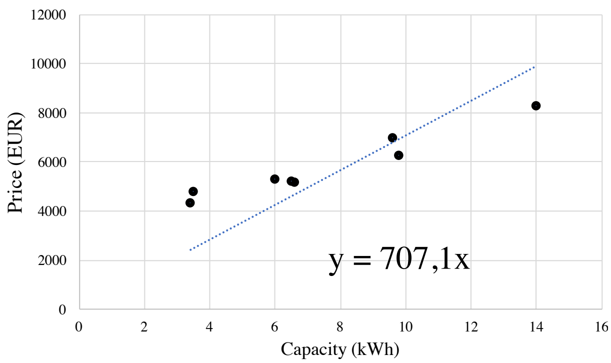


FIGURE C.2: Regression curve for battery variable costs (EUR/kWh)

Heat pumps

Prices for both heat pumps are gathered from Norwegian manufacturers located in Oslo-area. An analysis of average fixed and variable costs resulted in the following:
GSHP: 12785 EUR + 961 EUR/kW
ASHP: 7370 EUR + 428 EUR/kW

TABLE C.3: Investments: Costs of air-source and ground-source heat pumps

Type	Capacity (kW)	Hardware cost (EUR)	Installation cost (EUR)	Enova support	Net fixed cost (EUR)	Specific cost (EUR/kW)	Manufacturer
Ground-source (water-water)							
Nibe 1245	6	13571.2	14023.6	5169.9	8853.6	1475.6	Fossum og Kristiansen AS
Stiebel Electron	10	13872.1	13209.3	3101.9	10107.3	1010.7	Fossum & Kristiansen AS
Lampoassa	10	11632.4	18263.0	3515.5	14747.4	1474.7	Energi-spar AS
Nibe 1245	10	14863.7	14411.3	5169.9	9241.3	924.1	Kald og varm installasjoner
Nibe 1255	12	16802.4	7612.8	3101.9	4510.8	375.9	Herztberg Varmeteknikk
CTC	10	14411.3	13995.1	4135.9	5049.5	504.9	Varme consult AS
Air-source (air-water)							
Mitschubichi	11	6979.4	6979.4	3101.9	3877.4	352.4	Varme Consult AS
Stiebel Electron	10	8220.2	8220.2	3101.9	5118.2	511.8	Fossum & Kristiansen
Nibe	10	7625.7	7625.7	3101.9	4523.7	452.3	Kald og varm Installasjon
Nibe	9	6656.3	6656.3	3101.9	3554.3	394.9	Kald og varm installasjon

Bio-pellets Boiler

Table C.4 lists bio pellets boilers from Norwegian manufacturers, including VAT. Figure C.3 shows the regression curve of fixed and variable costs.

TABLE C.4: Price of bio-pellets boilers systems including pellets storage and feeder. Prices from [39], [90], [91].

Type	Capacity (kW)	Efficiency	Price (NOK)	Price (EUR)
Heta Scan-Line Green 100	5.6	0.9	26750	2770.3
Heta Scan-Line Green 200	9.0	0.97	31550	3267.4
Heta Greenfire 100	5.7	0.9	24900	2578.7
Extraflame Isabella	2.5	0.9	14875	1540.5
Audro H1	5.5	0.86	29990	3105.8

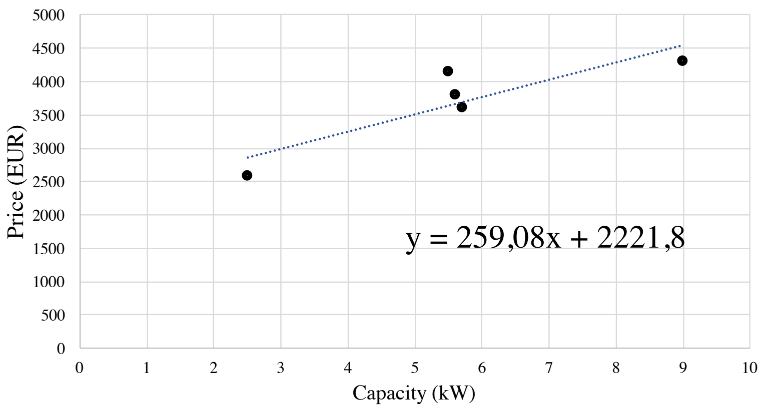


FIGURE C.3: Regression curve for fixed (EUR) and variable costs (EUR/kW) for biopellets boilers

Heat Storage

Table C.5 gives the specific prices (EUR/kWh) of accumulator tanks of different sizes. The conversion from litres to kWh are 19.33 litres/kWh (as calculated in [36]). All prices include VAT.

TABLE C.5: Costs of accumulator tanks. From [92].

Type	Total Costs	Litres	kWh	EUR/kWh	kW	kW/kWh
Oso Super S	669.9	200	10.34	64.8	2	0.193
Høiax Titanium 120	495.0	120	6.206	79.79	2	0.322
Høiax DMK 400	1840.0	400	20.68	88.9	5	0.241
Oso Super SX 300	1240.6	300	15.51	39.9	6	0.386
OSO Saga S 250	1132.7	250	12.92	87.6	3	0.232

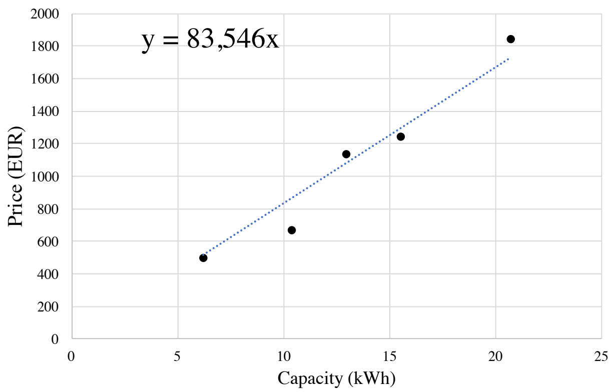


FIGURE C.4: Regression curve for the variable costs (EUR/kWh) of hot water accumulator tanks

Electric Boiler

According to [39], an electric boiler has the average price 134 EUR/kW for the hardware, including VAT. It is assumed that the costs of installation comes with the heat storage.

Appendix D

Pyomo Code

The following is an extract of the Pyomo code of the model. Reading and writing procedures, as well as coding for the clustering algorithm can be requested from the author.

```
#!/usr/bin/env python3
# -*- coding: utf-8 -*-
"""
Created on Tue Feb 20 08:45:42 2018

@author: ingridandersen

STOCHASTIC TWO-STAGE MODEL: 'st_model'
"""

import pyomo.environ as pyo
import networkx as nx
import pyomo.pysp.scenariotree.tree_structure_model as tsm
import xlrd
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import time

class ZEBModel():
```

```
def __init__(self, M_const = 1000):
    """Create Abstract Pyomo model for ZEB
    """
    # Stochastic two-stage model
    self.abstractmodel = self.createTWOSTAGEMODEL()
    self.M_const = M_const

def disco(self, n, r):
    '''Discounting factor'''
    return 1/((1+r)**n)

def annui(self, n, r):
    '''Annuity factor'''
    return r/(1-(1+r)**(-n))

def capit(self, n, r):
    '''Capitalization factor'''
    return (1-(1+r)**(-n))/r

def cost(self, Yn, cost, l, r):
    '''For the two-stage model: calculating forced reinvestment costs'''
    Kn = pyo.floor(Yn/(l*1))
    n = Yn-l*Kn
    Tn = Yn-n
    return cost*(self.annui(l,r)*self.capit(n,r)*self.disco(Tn, r) \
            + sum(self.disco(k*l,r) for k in range(0,Kn)))


def npv_cost_Investments(self, m, st):
    '''Investment function for two-stage/deterministic, including o&m
        costs'''
    investments = 0
    if st==1:
        for i in m.I:
            investments += (m.C_spe[i]*m.x[i]+ m.C_fxd[i]*m.a_i[i])
    else:
        investments = 0
    return investments

def npv_cost_Operations(self, m, st):
    '''Operational costs for two-stage/deterministic
```

```
    Summation of yearly costs for all years in YRN'''
    techrun = 0
    runcosts = 0
    gridtariff = 0
    operations = 0
    if m.lastT == 671:
        '''multiplicationfactor will be 13 if reduced model'''
        f = 13
    elif m.lastT == 8735:
        f = 1

    if st == 2:
        for i in m.I:
            techrun += m.C_run[i]*m.C_spe_0[i]*m.x[i]
        if m.A_ep:
            '''Grid tariff model (includes VAT): Energy pricing'''
            gridtariff = 12*m.C_fxd_ep + m.C_spe_ep*sum(f*m.y_imp[t] for
                t in m.T)
        elif m.A_ps == 1:
            '''Grid tariff model(includes VAT): Power subscription'''
            gridtariff = 12*(m.C_fxd_ps*(1+m.Y_max)) +
                m.C_pty_ps*sum(f*m.y_pty[t] for t in m.T) +
                m.C_spe_ps*sum(f*m.y_imp[t] for t in m.T)
        VAT = 1.25
        runcosts = sum(VAT*m.bf[t]*m.P_bf + VAT*m.y_imp[t]*m.P_spot[t] -
            m.y_exp[t]*m.P_spot[t]*m.A_exp for t in m.T)
        operations = (f*runcosts + gridtariff +
            techrun)*self.capit(m.YRN, m.R)*self.disco(1, m.R)
    else:
        operations = 0
    return operations


def createTWOSTAGEMODEL(self):
    m = pyo.AbstractModel()
    m.name = 'ZEB stochastic two-stage model'

# SETS ##########################################################
    m.T  = pyo.Set(doc = 'Set of all hours, full model: 8736, reduced
        model: 672')
    m.I = pyo.Set(doc = 'Set of all technologies')
```

```
    m.ST = pyo.Set(initialize = [1, 2], doc='STAGE')

# PARAMETERS ##########################################################

    m.lastT = pyo.Param(within=m.T, doc="Last time step")

#---Technology costs
    m.C_fxd_0 = pyo.Param(m.I,within=pyo.NonNegativeReals, default = 0,
        doc='Fixed investment cost for all techs, EUR in year t = 0')

    m.C_spe_0 = pyo.Param(m.I,within=pyo.NonNegativeReals, default =
        0,doc='Investment costs dependent on installed capacity, EUR/kW
        (EUR/kWh) in t= 0')
    m.C_run = pyo.Param(m.I,within=pyo.NonNegativeReals,default =
        0,doc='Yearly running cost of each tech')

#---Grid Tariff pricing
    #Energy pricing
    m.A_ep = pyo.Param(within=pyo.Binary,default = 0,doc = 'Activation
        of energy pricing')
    m.C_fxd_ep = pyo.Param(within=pyo.NonNegativeReals,default =
        0,doc='Fixed charge part of grid tariff for ep')
    m.C_spe_ep = pyo.Param(within=pyo.NonNegativeReals,default =
        0,doc='Specific energy charge part of grid tariff for ep')

    #Power Subscription pricing
    m.A_ps = pyo.Param(within = pyo.Binary, default = 0,doc =
        'Activation of power subscription pricing')
    m.C_fxd_ps = pyo.Param(within=pyo.NonNegativeReals,default = 0,
        doc='Subscriptopn charge for pp')
    m.C_pty_ps = pyo.Param(within=pyo.NonNegativeReals,default =
        0,doc='Penalty charge for pp')
    m.C_spe_ps = pyo.Param(within=pyo.NonNegativeReals,default =
        0,doc='Energy charge charge for pp')
    m.Y_max = pyo.Param(within=pyo.NonNegativeReals,default = 0,doc =
        'Subscription limit')

 #---Bio fuel price
    m.P_bf = pyo.Param(within=pyo.NonNegativeReals, doc='Constant price
        of biofuel')
```

```
#---#Reference System

    #CO2-Factors
    m.A_co2 = pyo.Param(within=pyo.Binary,doc = 'Activation of co2
        crediting system')
    m.G_ref = pyo.Param(within=pyo.NonNegativeReals,doc='CO2 reference
        emissions')
    m.G_el = pyo.Param(within=pyo.NonNegativeReals,doc='gCO2 eq. per
        kWh imported/exported')
    m.G_bf = pyo.Param(within=pyo.NonNegativeReals,doc='gCO2 eq. per
        kWh for technology i, i.e BB')

    #Primary Energy Factors
    m.A_pe = pyo.Param(within=pyo.Binary,doc = 'Activation of primary
        energy crediting system')
    m.PE_ref = pyo.Param(within=pyo.NonNegativeReals,doc='CO2 reference
        emissions')
    m.PE_imp = pyo.Param(within=pyo.NonNegativeReals,doc='PE per kWh
        imported electricity')
    m.PE_exp = pyo.Param(within=pyo.NonNegativeReals,doc='PE per kWh
        exported electricity')
    m.PE_bf = pyo.Param(within=pyo.NonNegativeReals,doc='PE per kWh for
        technology i, i.e BB')

#---Technologies
    m.A_i = pyo.Param(m.I, within=pyo.Binary,doc='Pre-activation of
        each tech')

    m.Eff = pyo.Param(m.I,within=pyo.NonNegativeReals, doc='Technology
        efficiency')
    m.Eff_ba_ch = pyo.Param(within=pyo.NonNegativeReals,doc='Battery
        charging efficiency')
    m.Eff_ba_dch = pyo.Param(initialize = 1, doc='Battery discharge
        efficiency')
    m.Beta_ba =
        pyo.Param(within=pyo.NonNegativeReals,doc='Charging/discharging
        rate')
    m.Beta_hs = pyo.Param(within=pyo.NonNegativeReals, doc='identical
        charging rate for heat storage')

    m.L = pyo.Param(m.I, within=pyo.NonNegativeIntegers, doc='Lifetime
```

```
        of technology i')
    m.X_min = pyo.Param(m.I, within=pyo.NonNegativeReals, doc='Max
        possible installed capacity of technology ')
    m.X_max = pyo.Param(m.I, within=pyo.NonNegativeReals, doc='Min
        possible installed capacity of technology ')

    m.Temp = pyo.Param(m.T, within=pyo.Reals, doc='Ambient temperature
        of certain hour')
    m.Y_pv = pyo.Param(m.T, within=pyo.NonNegativeReals,doc='Possible
        PV output at time t')
    m.COP_ashp = pyo.Param(m.T, within=pyo.NonNegativeReals, doc='Heat
        pump performance at time t')
    m.COP_gshp = pyo.Param(m.T, within=pyo.NonNegativeReals, doc='Heat
        pump performance at time t')

#---Energy Demand
    m.D_el = pyo.Param(m.T, within=pyo.NonNegativeReals, doc='Hourly
        building electricity demand')
    m.D_ht = pyo.Param(m.T, within=pyo.NonNegativeReals,doc='Hourly
        building heating demand')

#---Grid
    m.P_spot = pyo.Param(m.T, within=pyo.NonNegativeReals, doc='Hourly
        price of imported electricity EUR/kWh including certificates')
    m.X_max_imp = pyo.Param(within=pyo.NonNegativeReals, doc='Maximum
        grid import')
    m.X_max_exp = pyo.Param( within=pyo.NonNegativeReals,doc='Maximum
        grid export')
    m.A_imp = pyo.Param( within=pyo.Binary, doc='Binary: Import is
        activated, 1/0')
    m.A_exp = pyo.Param( within=pyo.Binary,doc='Binary: Export is
        activated, 1/0')

#---Control
    m.gamma = pyo.Param( within=pyo.NonNegativeReals, doc='=0 for
        strictly ZEB')
    m.R = pyo.Param(within=pyo.NonNegativeReals, doc='Chosen discount
        Rate')
    m.YRN = pyo.Param( within=pyo.NonNegativeIntegers, doc='Total years
        in modelling period')
    m.VSS = pyo.Param(m.I, doc ='Result of last deterministic run')
```

```
    m.VSS_a = pyo.Param(initialize = 1, doc='=1 for VSS calculations')

    def npv_inv_spe(m, i):
        return self.cost(m.YRN, m.C_spe_0[i], m.L[i], m.R)
    m.C_spe = pyo.Param(m.I, rule = npv_inv_spe)

    def npv_inv_fxd(m, i):
        return self.cost(m.YRN, m.C_fxd_0[i], m.L[i], m.R)
    m.C_fxd = pyo.Param(m.I, rule = npv_inv_fxd)


#VARIABLES #########################################################

    # 1 STAGE : STRATEGIC VARIABLES
    m.x = pyo.Var(m.I,within = pyo.NonNegativeReals,
        doc='Optimal installed capacity (storage size), semi-continous,
        kW (kWh)')
    m.a_i = pyo.Var(m.I, within = pyo.Binary,
        doc='Activation binary decition for technology i, 1/0')


    #2 STAGE : OPERATIONAL VARIABLES
    m.q_hs = pyo.Var(m.T, domain = pyo.Reals,
        doc='Keeping track of HS discharge')
    m.q_eb = pyo.Var(m.T,domain = pyo.NonNegativeReals,
        doc='Net heat supplied from electric boiler at time t, kWh/h')
    m.q_ashp = pyo.Var(m.T,domain=pyo.NonNegativeReals,
        doc='Net heat supplied from heat pump at time t, kWh/h')
    m.q_gshp = pyo.Var(m.T,domain=pyo.NonNegativeReals,
        doc='Net heat supplied from GSHP at time t, kWh/h')
    m.q_bb = pyo.Var(m.T, domain=pyo.NonNegativeReals,
        doc='Net heat supplied from bio boiler at time t, kWh/h')
    m.bf = pyo.Var(m.T, domain= pyo.NonNegativeReals,
        doc='Biofuel input to bio boiler at time t kWh/h')

    m.z_hs = pyo.Var(m.T, domain = pyo.NonNegativeReals,
        doc='Conent in heat storage at the end of time t, kWh')
    m.z_ba = pyo.Var(m.T, domain = pyo.NonNegativeReals,
        doc='Conent of battery at the end of time t, kWh')

    m.y_imp = pyo.Var(m.T, domain = pyo.NonNegativeReals,
```

```
        doc='Electricity imported from grid at time t, kWh')
    m.y_exp = pyo.Var(m.T, domain = pyo.NonNegativeReals,
        doc='Electricity exported to grid at time t, kWh')
    m.y_pv = pyo.Var(m.T, domain = pyo.NonNegativeReals,
        doc='PV production at time t, kWh/h')
    m.y_eb = pyo.Var(m.T, domain = pyo.NonNegativeReals,
        doc='Electricity drawn from electric boiler at time t, kWh/h')
    m.y_ashp = pyo.Var(m.T, domain = pyo.NonNegativeReals,
                        doc='Total electricity consumed by the heat pump
        at time t, kWh/h')
    m.y_gshp = pyo.Var(m.T, domain = pyo.NonNegativeReals)
    m.y_ch = pyo.Var(m.T, domain = pyo.NonNegativeReals,
        doc='Amount of electricity to battery (charging) at time t,
        kWh/h')
    m.y_dch = pyo.Var(m.T, domain = pyo.NonNegativeReals,
        doc='Amount of electricity discharge from battery at time t,
        kWh/h')
    m.y_pty = pyo.Var(m.T, domain = pyo.Reals,
        doc = 'Penalty volume')

    m.a_imp = pyo.Var(m.T, domain = pyo.Binary,
        doc ='Import activation inward time t, 1= activated')
    m.a_exp = pyo.Var(m.T, domain= pyo.Binary,
        doc ='Export actication inward time t, 1= activated')

    m.a_ch = pyo.Var(m.T, domain = pyo.Binary,
        doc ='Charging activation inward time t, 1 = activated')
    m.a_dch = pyo.Var(m.T, domain= pyo.Binary,
        doc ='Discharging activation inward time t, 1=activated')


# CONSTRAINTS #########################################################

# 1 STAGE : INVESTMENTS

    #---Activation and boundary constraints
    def Tech_active(m, i, st):
       return m.x[i] <= m.a_i[i]*self.M_const
    m.Tech_active = pyo.Constraint(m.I, m.ST, rule = Tech_active)

    def Tech_Min(m, i, st):
```

```
        if m.VSS_a:
            return m.x[i] <= m.VSS[i]
        else:
            return m.X_min[i]*m.a_i[i] <= m.x[i]
    m.Tech_Min = pyo.Constraint(m.I, m.ST, rule= Tech_Min)

    def Tech_Max(m, i, st):
        if m.VSS_a:
            return pyo.Constraint.Skip
        else:
            return m.x[i] <= m.X_max[i]*m.A_i[i]
    m.Tech_Max = pyo.Constraint(m.I, m.ST, rule= Tech_Max)


#2 STAGE : OPERATIONS

    #---Balacing constraints

    def El_Balance(m, t, st):
        return m.D_el[t] == m.y_imp[t] + m.y_pv[t] - m.y_exp[t] +
             m.y_dch[t] - m.y_ch[t] - m.y_ashp[t] - m.y_gshp[t] -
             m.y_eb[t]
    m.El_Balance = pyo.Constraint(m.T, m.ST, rule = El_Balance)

    def Ht_Balance(m, t, st):
        if t == 0:
            return m.D_ht[t] + m.z_hs[t] == m.z_hs[m.lastT]*m.Eff['HS']
                 + m.q_ashp[t] + m.q_gshp[t] + m.q_bb[t] + m.q_eb[t]
        else:
            return m.D_ht[t] + m.z_hs[t] == m.z_hs[t-1]*m.Eff['HS'] +
                 m.q_ashp[t] + m.q_gshp[t] + m.q_bb[t] + m.q_eb[t]
    m.Ht_Balance = pyo.Constraint(m.T, m.ST, rule=Ht_Balance)

    #---Capacity
    def ASHP_Restriction(m,t, st):
        return m.q_ashp[t] <= m.x['ASHP']
    m.ASHP_Restriction = pyo.Constraint(m.T, m.ST, rule =
         ASHP_Restriction)

    def GSHP_Restriction(m,t, st):
        return m.q_gshp[t] <= m.x['GSHP']
```

```
m.GSHP_Restriction = pyo.Constraint(m.T, m.ST, rule =
    GSHP_Restriction)

def EB_Restriction(m,t, st):
    return m.q_eb[t] <= m.x['EB']
m.EB_Restriction = pyo.Constraint(m.T, m.ST, rule = EB_Restriction)

def BB_Restriction(m,t, st):
    return m.q_bb[t] <= m.x['BB']
m.BB_Restriction = pyo.Constraint(m.T, m.ST, rule=BB_Restriction)


#---Grid equations
def Grid_Import(m,t, st):
    return m.y_imp[t] <= m.a_imp[t]*m.X_max_imp
m.Grid_Import = pyo.Constraint(m.T, m.ST, rule=Grid_Import)


def Grid_Export(m,t, st):
    return m.y_exp[t] <= m.a_exp[t]*m.X_max_exp
m.Grid_Export = pyo.Constraint(m.T, m.ST, rule=Grid_Export)


def Prosumer_Balance(m,t, st):
    return m.a_imp[t] + m.a_exp[t] <= 1
m.Prosumer_Balance = pyo.Constraint(m.T, m.ST,
    rule=Prosumer_Balance)


#---Storage equations

def HS_Restriction(m, t, st):
    return m.z_hs[t] <= m.x['HS']
m.HS_Restriction = pyo.Constraint(m.T, m.ST, rule=HS_Restriction)

def HS_charge_active(m,t, st):
    return m.q_hs[t] <= m.z_hs[t]
m.HS_charge_active = pyo.Constraint(m.T, m.ST,
    rule=HS_charge_active)

def HS_discharge_active(m,t, st):
```

```
    return - m.z_hs[t] <= m.q_hs[t]
m.HS_discharge_active = pyo.Constraint(m.T, m.ST,
     rule=HS_discharge_active)


def HS_Balance_ch(m,t,st):
    if t == 0:
        return m.q_hs[t] == m.z_hs[m.lastT] - m.z_hs[t]
    else:
        return m.q_hs[t] == m.z_hs[t-1] - m.z_hs[t]
m.HS_Balance_ch = pyo.Constraint(m.T, m.ST, rule = HS_Balance_ch)


def HS_discharge_rate_min(m,t, st):
      return -m.x['HS']*m.Beta_hs <= m.q_hs[t]
m.HS_discharge_rate_min = pyo.Constraint(m.T, m.ST,
     rule=HS_discharge_rate_min)


def HS_discharge_rate_max(m,t, s):
    return m.q_hs[t] <= m.x['HS']*m.Beta_hs
m.HS_discharge_rate_max = pyo.Constraint(m.T, m.ST,
     rule=HS_discharge_rate_max)


def BA_Restriction(m,t, st):
    return m.z_ba[t] <= m.x['BA']
m.BA_restriction = pyo.Constraint(m.T, m.ST, rule=BA_Restriction)


def BA_Balance(m,t, st):
    if t == 0:
        return m.z_ba[t] == m.z_ba[m.lastT] -
             m.y_dch[t]*(1/m.Eff_ba_dch) + m.y_ch[t]*m.Eff_ba_ch
    else:
        return m.z_ba[t] == m.z_ba[t-1] -
             m.y_dch[t]*(1/m.Eff_ba_dch) + m.y_ch[t]*m.Eff_ba_ch
m.BA_Balance = pyo.Constraint(m.T, m.ST, rule=BA_Balance)


def BA_Charge_Balance(m, t, st):
```

```
    if t == 0:
        return m.y_ch[t] <= (m.x['BA'] -
            m.z_ba[m.lastT])*m.A_i['BA']*(1/m.Eff_ba_ch)
    else:
        return m.y_ch[t] <= (m.x['BA'] -
            m.z_ba[t-1])*m.A_i['BA']*(1/m.Eff_ba_ch)
m.BA_Charge_Balance = pyo.Constraint(m.T, m.ST,
    rule=BA_Charge_Balance)


def BA_Discharge_Balance(m,t, st):
    if t == 0:
        return m.y_dch[t] <= m.z_ba[m.lastT]*m.A_i['BA']*m.Eff_ba_dch
    else:
        return m.y_dch[t] <= m.z_ba[t-1]*m.A_i['BA']*m.Eff_ba_dch
m.BA_Discharge_Balance = pyo.Constraint(m.T, m.ST,
    rule=BA_Discharge_Balance)


def BA_charge_active(m,t, st):
    return m.y_ch[t] <= m.X_max_imp*m.a_ch[t]
m.BA_charge_active = pyo.Constraint(m.T, m.ST,
    rule=BA_charge_active)

def BA_discharge_active(m,t, st):
    return m.y_dch[t] <= m.X_max_imp*m.a_dch[t]
m.BA_discharge_active = pyo.Constraint(m.T, m.ST,
    rule=BA_discharge_active)

def Battery_Balance(m,t, st):
    return m.a_ch[t] + m.a_dch[t] <= 1
m.Battery_Balance = pyo.Constraint(m.T, m.ST, rule=Battery_Balance)

def BA_charge_rate(m,t, st):
    return m.y_ch[t] <= m.x['BA']*m.Beta_ba
m.BA_charge_rate = pyo.Constraint(m.T, m.ST, rule=BA_charge_rate)

def BA_discharge_rate(m,t, st):
    return m.y_dch[t] <= m.x['BA']*m.Beta_ba
m.BA_discharge_rate = pyo.Constraint(m.T, m.ST,
    rule=BA_discharge_rate)
```

```
#---Production constraints for generating technologies

def PV_Balance(m,t, st):
    return m.y_pv[t] == m.x['PV']*m.Y_pv[t]
m.PV_Balance = pyo.Constraint(m.T, m.ST, rule=PV_Balance)

def ASHP_Balance(m,t, st):
    return m.q_ashp[t] == m.y_ashp[t]*m.COP_ashp[t]
m.ASHP_Balance = pyo.Constraint(m.T, m.ST, rule = ASHP_Balance)

def GSHP_Balance(m,t, st):
    return m.q_gshp[t] == m.y_gshp[t]*m.COP_gshp[t]
m.GSHP_Balance = pyo.Constraint(m.T, m.ST, rule = GSHP_Balance)

def BB_Balance(m,t, st):
    return m.q_bb[t] == m.bf[t]*m.A_i['BB']*m.Eff['BB']
m.BB_Balance = pyo.Constraint(m.T, m.ST, rule=BB_Balance)

def EB_Balance(m,t, st):
    return m.q_eb[t] == m.y_eb[t]*m.Eff['EB']
m.EB_Balance = pyo.Constraint(m.T, m.ST, rule = EB_Balance)


#---Zero emission/energy constraints
def ZE_Balance(m):
    if m.A_co2==1:
        print('ACTIVE ZEB-carbon RESTRICTION')
        if m.lastT == 8735:
            return sum(m.y_imp[t]*m.G_el - m.y_exp[t]*m.G_el +
                m.bf[t]*m.G_bf for t in m.T) <= m.G_ref*m.gamma
        elif m.lastT == 671:
            return 13*sum(m.y_imp[t]*m.G_el - m.y_exp[t]*m.G_el +
                m.bf[t]*m.G_bf for t in m.T) <= m.G_ref*m.gamma
    elif m.A_pe == 1:
        print('ACTIVE ZEB-pef RESTRICTION')
        if m.lastT == 8735:
            return sum(m.y_imp[t]*m.PE_imp - m.y_exp[t]*m.PE_exp +
                m.bf[t]*m.PE_bf for t in m.T) <= m.PE_ref*m.gamma
        elif m.lastT == 671:
```

```
                return 13*sum(m.y_imp[t]*m.PE_imp - m.y_exp[t]*m.PE_exp
                    + m.bf[t]*m.PE_bf for t in m.T) <= m.PE_ref*m.gamma
        else:
            print('NO ZEB RESTRICTION')
            return pyo.Constraint.Skip
    m.ZE_Balance = pyo.Constraint(rule=ZE_Balance)


#---Subscription power pricing Constraint
    def pty_volume(m, t):
        if m.A_ps == 1:
            return m.y_imp[t] - m.Y_max <= m.y_pty[t]
        else:
            return m.y_pty[t] ==0
    m.pty_volume = pyo.Constraint(m.T, rule = pty_volume)

    def pty_volume2(m, t):
            return 0 <= m.y_pty[t]
    m.pty_volume2 = pyo.Constraint(m.T, rule = pty_volume2)



#   OBJECTIVE FUNCTION ################################################

    def cost_Investments_rule(m, st):
        expr = self.npv_cost_Investments(m, st)
        return expr
    m.cost_Investments = pyo.Expression(m.ST, rule =
         cost_Investments_rule)

    def cost_Operation_rule(m, st):
        expr = self.npv_cost_Operations(m, st)
        return expr
    m.cost_Operations= pyo.Expression(m.ST, rule = cost_Operation_rule)


    def objective_TotalCost(m):
        expr = pyo.summation(m.cost_Investments) +
            pyo.summation(m.cost_Operations)
        return expr
    m.objective_TotalCost = pyo.Objective(rule = objective_TotalCost,
```

```
            sense = pyo.minimize)

    return m

def createConcreteModeltwoStage(self, data):
        '''Function creating instance from input data'''
        concretemodel = self.abstractmodel.create_instance(data =
            {'mymodel':data}, namespace = 'mymodel')
        return concretemodel

def createScenarioTreeModel(self, num_scenarios, probabilities):
    '''Tree model for two-stage formulation'''

    G = nx.DiGraph()
    G.add_node("RootNode")
    for i in range(num_scenarios):
        G.add_edge("RootNode","Scenario{}".format(i+1),
              probability=probabilities[i])
    stage_names=['Stage1','Stage2']

    print("Num_scenarios=",num_scenarios)
    print("Probabilities=",probabilities)
    st_model = tsm.ScenarioTreeModelFromNetworkX(G,
         edge_probability_attribute='probability',
         stage_names=stage_names)

    first_stage = st_model.Stages.first()
    second_stage = st_model.Stages.last()

    #---First Stage
    st_model.StageCost[first_stage] = 'cost_Investments[1]'
    st_model.StageVariables[first_stage].add('x[ASHP]')
    st_model.StageVariables[first_stage].add('x[GSHP]')
    st_model.StageVariables[first_stage].add('x[PV]')
    st_model.StageVariables[first_stage].add('x[BA]')
    st_model.StageVariables[first_stage].add('x[BB]')
    st_model.StageVariables[first_stage].add('x[EB]')
```

```
st_model.StageVariables[first_stage].add('x[HS]')
st_model.StageVariables[first_stage].add('a_i[ASHP]')
st_model.StageVariables[first_stage].add('a_i[GSHP]')
st_model.StageVariables[first_stage].add('a_i[PV]')
st_model.StageVariables[first_stage].add('a_i[BA]')
st_model.StageVariables[first_stage].add('a_i[BB]')
st_model.StageVariables[first_stage].add('a_i[EB]')
st_model.StageVariables[first_stage].add('a_i[HS]')

#---Second Stage
st_model.StageCost[second_stage] = 'cost_Operations[2]'
st_model.StageVariables[second_stage].add('q_hs')
st_model.StageVariables[second_stage].add('q_eb')
st_model.StageVariables[second_stage].add('q_bb')
st_model.StageVariables[second_stage].add('q_ashp')
st_model.StageVariables[second_stage].add('q_gshp')
st_model.StageVariables[second_stage].add('bf')
st_model.StageVariables[second_stage].add('z_hs')
st_model.StageVariables[second_stage].add('z_ba')
st_model.StageVariables[second_stage].add('y_imp')
st_model.StageVariables[second_stage].add('y_exp')
st_model.StageVariables[second_stage].add('y_pv')
st_model.StageVariables[second_stage].add('y_eb')
st_model.StageVariables[second_stage].add('y_ashp')
st_model.StageVariables[second_stage].add('y_gshp')
st_model.StageVariables[second_stage].add('y_ch')
st_model.StageVariables[second_stage].add('y_dch')
st_model.StageVariables[second_stage].add('y_pty')
st_model.StageVariables[second_stage].add('y_max')
st_model.StageVariables[second_stage].add('a_imp')
st_model.StageVariables[second_stage].add('a_exp')
st_model.StageVariables[second_stage].add('a_ch')
st_model.StageVariables[second_stage].add('a_dch')
st_model.ScenarioBasedData=False

nx.draw_networkx(G)
plt.savefig('scenarioTree.pdf', bbox_inches='tight',dpi=300);
return st_model
```