TALLINN UNIVERSITY OF TECHNOLOGY
SCHOOL OF ENGINEERING

Department of Electrical Power Engineering and Mechatronics

RESEARCH AND DEVELOPMENT OF THERMAL STORAGE CONTROL MODELS

SOOJUSSALVESTITE JUHTIMISMUDELITE UURIMINE JA ARENDAMINE

MASTER THESIS

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Student code 174765AAAM

Supervisor D.Sc.Eng. Argo Rosin

Co-supervisor Prof. Dr.-Ing. Dr. h.c. Helmuth Biechl

Tallinn, 2018

AUTHOR’S DECLARATION

Hereby I declare that I have written this thesis independently.
No academic degree has been applied for based on this material.
All publications, major viewpoints and data of the other authors used in this thesis have been referenced.

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Research and development of thermal storage control models

Tobias Häring, student code 174765AAAM, January 2018. – 134 pages.

TALLINN UNIVERSITY OF TECHNOLOGY

School of Engineering

Department of Electrical Power Engineering and Mechatronics

Supervisor: D.Sc.Eng. Argo Rosin

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Key words: thermal storage, price based control, voltage based control, control algorithms, demand side management, on-grid system, off-grid system, photovoltaics, battery storage, Matlab

Summary:

The thesis consists of 134 pages, it contains 84 tables, 37 figures and 61 equations.

One objective of this thesis is to study the influence of price based control algorithms for freezers, water heaters and space heating/cooling on cost-savings when being utilized as thermal storages. The second objective is the development of control strategies for those thermal storages in an off-grid system with photovoltaics power supply only, to reduce the capacity of the mandatory battery storage system. To achieve this, all system components were modeled and simulated with Matlab simulation software and various control strategies based on different algorithms were implemented.

The thesis consists of three main parts. The first part is a description of common loads in dwellings that can be utilized as thermal storages. It provides an overview on their typical characteristics and behavior, as well as a review of related standards and requirements. The second part of the thesis shows different modeling methods for each component described in literature. Developed object models for the thermal storages and simplified models for the PV-system and electrical storage are presented. In addition, the complete system with its typical behavior is described. The third part includes the control algorithms for the whole system. Price based and voltage based results for the on- resp. off-grid system are presented and analyzed. This section is followed by a recommendation for dwelling owners and a short view on further investigations and improvements.

Soojussalvestite juhtimismudelite uurimine ja arendamine

Tobias Häring, üliõpilaskood 174765AAAM, jaanuar 2018. – 134 lk.

TALLINNA TEHNIKAÜLIKOOL

Inseneriteaduskond

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Töö juhendaja: D.Sc.Eng. Argo Rosin

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Võtmesõnad: soojussalvesti, hinnapõhine juhtimine, pingepõhine juhtimine, juhtimisaölgoritmid, tarbimise juhtimine, võrguühendusega süsteem, võrguühenduseta süsteem, fotoelektriline süsteem, akupatarei, Matlab

Referaat:

Lõputöö koosneb 134 lehest ning sisaldab 84 tabelit, 37 joonist ning 61 võrrandid.

Käesoleva magistritöö üks eesmärk on uurida sügavkülmikute, veesoojendite ja ruumide kütteseadmete hinnapõhiste juhtimisalgoritmide mõju kulude kokkuhoiule. Töö teine eesmärk on soojussalvestite juhtimisstrateegiate/-mudelite väljatöötamine võrguühenduseta fotoelektriliste päikesepaneelidega (PV-süsteemiga) varustatud mikrovõrgu jaoks, et vähendada elektrisalvesti mahutavust. Selleks modelleeritakse ja uuritakse kõiki süsteemi komponente ja erinevaid juhtimisalgoritme Matlabi simulatsioonitarkvara abil.

Magistritöö koosneb kolmest põhiosast. Esimeses osas kirjeldatakse eluruumides kasutatavaid tüüpilisi soojusenergiat salvestavaid koormusi ja nende iseärasusi. Samuti antakse ülevaade seotud standarditest ja nõuetest. Töö teises osas antakse ülevaade kirjanduses käsitletud mudelitest, mis hõlmavad soojus- ja elektrisalvesteid ning PV-süsteemi. Lisaks vaadeldakse terviksüsteemi mudelit. Töö kolmas osa käsitleb eri objektide ja terviksüsteemi juhtimisalgoritme. Selles osas analüüsitakse võrguühendusega lahendustes kasutatavaid hinnapõhiseid ja võrguühenduseta lahendustes kasutatavaid pingepõhiseid juhtimisalgoritme. Sellele osale järgnevad soovitused kodumajapidamistele ning ettepanekud edasisteks uuringuteks ja parendusteks.

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TALLINN UNIVERSITY OF TECHNOLOGY
Department of Electrical Power Engineering and Mechatronics

COORDINATED

Prof. Ivo Palu..............................

.... 2018

ASSIGNMENT OF THE MASTER THESIS

Tobias Häring, student code 174765AAAM

Thesis topic: Research and development of thermal storage control models

The assignment: Research and development of thermal storage control models for reduction of electricity costs in an on-grid system and electrical storage system capacity in an off-grid system.

Initial data:

3. Scientific papers in Scopus and/or IEEE Explore
4. Nord Pool Elspot electricity prices
5. Hot water/food consumption and power consumption of home appliances in a standard dwelling
6. Datasheets of home appliances, PV-systems, storage systems and batteries
7. Solar irradiation data for Tallinn
8. Physical properties of typical/standard apartment

List of tasks to be solved:

1. Overview of energy consumption in dwellings
2. Description of common storage systems behavior and parameters
3. Review of thermal storage models described in literature
4. Description of thermal storage simplified mathematical models
5. Description of PV-system and electrical storage simplified mathematical models
6. Description of complete system model for simulations
7. Study of existing price based control strategies for reduction of electricity costs in an on-grid system with Matlab
8. Research and development of voltage based control strategy for reduction of electrical storage system capacity in an off-grid system with Matlab
9. Description of recommendations for dwelling owners

Supervisor:	Accepted the assignment:
Argo Rosin	Tobias Häring ....
Senior Research Scientist	Student

APPLICATION IN ENGLISH

03.01.2018

From: Tobias Häring (174765AAAM)

To: Ivo Palu, Argo Rosin

Application

I, Tobias Häring, would like to request the permission to write this master thesis in English due to the following reasons:

This thesis is prepared to obtain the dual master degree from Kempten University of Applied Sciences and Tallinn University of Technology based on the international cooperation agreement between those two universities.

I, as an Erasmus student from Germany, am not sufficiently educated in Estonian to write a Master thesis in Estonian language.

Thank you for your understanding.

Tobias Häring

1. PREFACE

This thesis was written to obtain the dual master degree from University of Applied Sciences (UAS) Kempten and Tallinn University of Technology (TUT).

Originally I planned to study a semester abroad, but my supervisor at UAS Kempten, Prof. Dr.-Ing. Dr. h.c. Helmuth Biechl, introduced me to the possibility of doing the dual master degree based on the international cooperation agreement between TUT and UAS Kempten and I decided to take that offer.

The topic of the thesis was formulated together with my supervisor at TUT, Dr. Argo Rosin. In my bachelor thesis, I could already gain experience in the field of control power and energy and with my general interest in power engineering, I appreciated the chance of working on a demand side management topic for my master thesis.

I would like to thank my supervisors, especially Dr. Argo Rosin, for their excellent guidance and support before and during my time at TUT. I am also grateful to all other employees at TUT and people I met in Estonia who helped me with their advice and made me feel welcome in Tallinn. And my special thanks go to my Mum who has supported all my decisions and is always there for me.

Tobias Häring

Tallinn, January 03, 2018

2. LIST OF ABBREVIATIONS AND SYMBOLS USED

A_x	(Surface) Area of Object x
AC	Air Conditioning
AGM	Absorbent Glass Mat
α	Coefficient: U_x*A_x
β	Coefficient: $1/(V_f*c_{px})$
β_s	Solar Altitude Angle
COP/COP_x	Coefficient of Performance (of Appliance x)
c_{px}	Specific Heat Capacity of x
C_{user}	User Comfort / Scaling for Algorithm
DOD_{max}	Maximum desired Depth of Discharge of the Battery System
DSM	Demand Side (Energy) Management
Δt	Time Step Width
E_b	Direct Beam Irradiation (W/m²)
E_d	Diffuse Irradiation (W/m²)
EEC	Energy Efficiency Class
EER	Energy Efficiency Ratio
eh	Status of Electric Heaters: off/on {0,1}
eh_{Nr}	Number of Electric Heaters
E_{res}	Total Irradiation (Direct, Diffuse, Reflective) including SHGC and IAC
F	Function-obtained
η_x	Efficiency of Appliance x

HVAC	Heating, Ventilation and Air Conditioning
I/O	Input / Output
IAC	Indoor Solar Attenuation Coefficient
k_i	Number of People in the Room during Time Step i
LiIon	Lithium Ion
m_i	Mass of exchanged Food during Time Step i
MPP	Maximum Power Point
$Nr_{Modules}$	Number of PV-Modules in the PV-System
P_a	Average Annual Power calculated
P_{annual}	Average Annual Power from data sheet
P_c	Rated Electrical Power for Cooling of the Heat Pump
P_{el}	Electrical Power (kW/h) during Time Step i
$P_{el,f}$	Steady State Electrical Power of Freezer
P_h	Rated Electrical Power for Heating of the Heat Pump
φ	Azimuth Angle
P_i	Charging/Discharging Power of the Battery Storage
P_{max}	Maximum Rated Power of Freezer/Heater
$P_{max,c}$	Maximum Charging Power of Battery System for next Time Step
$P_{max,d}$	Maximum Discharging Power of Battery System for next Time Step
POU	Point-of-Use
P_{person}	Heat Dissipation of an Adult during 1 Hour
Pr	Electricity Price during Time Step
Pr_{dev}	Electricity Price Deviation within Calculation Window

Pr_{mavg}	Average Electricity Price within Calculation Window
Pr_{max}	Maximum Electricity Price within Calculation Window
Pr_{min}	Minimum Electricity Price within Calculation Window
P_{solar}	Solar Irradiation Power
PV	Photovoltaics
Pwr	Available Electrical Power during Time Step
Pwr_{dev}	Electrical Power Deviation within Calculation Window
Pwr_{mavg}	Average Electrical Power within Calculation Window
Pwr_{max}	Maximum Electrical Power within Calculation Window
Pwr_{min}	Minimum Electrical Power within Calculation Window
$r_{m,x}$	Thermal Resistivity per Meter for Material/Appliance x
ρ_x	Density of x
RMS	Root-mean-square
ROI	Return of Invest
Sc.No.	Scenario Number
SHGC	Solar Heat Gain Coefficient
s_i	Effect of Solar Irradiation on Windows: off/on {0,1}
SOC	State of Charge
SOC_{min}	Minimum desired State of Charge of the Battery System
T_{amb}	Ambient Temperature
$T_{amb,loss}$	Temperature Change due to Ambient Losses
T_{cw}	Temperature Change due to Water Fluctuation
T_f	Temperature of exchanged Food

T_{fc}	Corrected Temperature of exchanged Food
T_{food}	Temperature Change due to Food Exchange
T_{freeze}	Temperature Change due to Freezing Power
t_{fault}	Storage Period at Power Fault
T_{goal}	Goal Temperature for Algorithm (User defined)
T_{hc}	Temperature Change due to Heating/Cooling
$T_{heating}$	Temperature Change due to Heating Element
T_i	Temperature of Appliance/Room at Beginning of Time Step i
T_{next}	Temperature of Appliance at End of Time Step i
T_{people}	Temperature Change due to People in the Room
T_{pred}	Temperature Change during Time Step without Heating/Cooling
T_{set}	Set Point Temperature for next Time Step
$T_{set,max}$	Maximum Set Point Temperature (User defined)
$T_{set,min}$	Minimum Set Point Temperature (User defined)
$T_{sun.rad}$	Temperature Change due to Solar Radiation
T_{window}	Temperature Change due to Opened Windows
t_x	Thickness of x
U_x	U-value of Object x
V_i	Volume of Air/Water Fluctuation during Time Step i
V_{max}	Volume of Air in the Apartment/House
V_{wood}	Volume of Wood (Furniture) in the Apartment/House
V_x	Maximum Volume of Appliance x
$V_{fr,max}$	Freezing Volume in kg per 24 hours

y_i Status of the Appliance: off/on {0,1}

z_i Status of the Heat Pump: Cooling/Heating {0,1}

3. INTRODUCTION: CONSEQUENCES OF RENEWABLE ENERGY SUPPLY: ON- AND OFF-GRID

The world's need for electric energy is constantly increasing. Between 1971 and 2007, for example, it more than doubled. This is a result of growing population and higher living standards all around the world.

To serve this high demand on electric power, it is necessary to focus more and more on renewable energy sources as the fossil ones, like coal, mineral oil and natural gas, will only last for as much as 30 to 65 more years. [1]

In Germany, this trend started in the 1990s. And as a result of engineering progress and renewable energy laws, the German electricity production with renewable power sources increased from 3.6% in 1990 to 31.7% in 2016. [2] [3] The same development can be seen in Estonia: The share of renewable energy in the final energy consumption of 2006 was at 16.1%, and this number increased already to 28.6% in 2015. [4]

All sources of nearly infinite, emission-free energy, such as biomass, tidal power, hydropower, wind power, photovoltaics (PV) or geothermal power, reduce negative effects like global warming, on the environment. However, there are also several drawbacks. Due to low energy densities, the investment and material costs are high compared to fossil energy. Even more problematic is the permanently changing energy supply as the solar radiation intensity or wind speeds alter and cannot be saved without power conversion. [1] [2]

Electric energy as such also cannot be saved. So there always has to be equilibrium of supply and demand in the electric power grid. If there is too much energy, the grid frequency, which is 50Hz in the European grid, will rise; otherwise, it will be reduced. This can cause damage to electronics like computers etc. If the frequency falls below 47.5 Hz, there can be resonance vibrations capable of destroying power stations. [5]

The increasing number of renewable energy sources in the grid, providing volatile electric power, forces the grid utilities to establish a sufficient control of supply and demand to keep frequency and power levels stable and within their limits. There are two ways to approach this.

First, it is possible to influence the supply side. If there is too much energy in the grid, the production is being reduced, and vice versa. This is called control power and energy and can be distinguished between primary, secondary and tertiary reserve, depending on the reaction and duration times of the power stations.

The second idea is to influence the energy demand. This is done by providing lucrative offers to customers to engage in so-called demand side management (DSM). If there is a lot of energy available, but the demand is low, the market prices decrease and vice versa. Customers pay the market prices, thus they will try to run most of their schedulable energy demand during low price periods, increasing the energy demand during this time and making use of energy that might otherwise not be used. Thus, the produced power has an influence on the volume and price of the electrical energy that is traded. [2]

Germany is part of the European Power Exchange (EPEX) spot market, including some other countries like France and Austria. The EPEX market is coupled to the Nord Pool spot market, representing Nordic countries, including Estonia. So spot market prices can be the same, but do not have to be necessarily due to transportation limits. [2]

Nord Pool consists of two different markets, the Elbas intra-day market and the Elspot day-ahead market. Elspot is an auction-based market where participants can trade electrical energy for the next day. The prices are 12-36 hours ahead in time and biding is possible 24 hours through the day. The prices are calculated on a supply and demand basis and can differ from area to area, as there might be bottlenecks in transmission capacities. Elbas is the after-market for Elspot. Electricity can be traded until one hour before delivery. Members in Elbas can offer how much power they want to buy or sell and at what price. This means that prices in Elbas can differ considerably from the Elspot prices. Demand side management systems typically work with day-ahead prices of the Elspot market. [6] [7]

Further, if a customer wants to take part in the energy trading market to profit from lower energy prices, it usually goes hand in hand with inconveniences. Appliances are being scheduled and it might take a while until, for example, the laundry is ready. A so-called “smart” system can also be very expensive. These drawbacks keep many people from investing in such a system. However, there are ways to manage the energy demand with less influence on the users’ comfort.

Thermal storages that are available in most households can be used for DSM. Take a freezer, for example, it can be cooled down some more degrees if the energy is cheap and then if the prices are high, it can be some degrees warmer inside. The user will not notice a big difference, but it is possible to save some money. The same goes with water heaters and space heating/cooling. Depending on the desired users' comfort, the boundaries for the temperatures within which these storages can operate, might be higher or lower, but it will result in an optimized energy demand.

Several researches have studied price based control of thermal storages, especially freezers and water heaters. But what about off-grid systems? It should also be possible to optimize an islanded system that is powered by a renewable energy source with suitable control strategies for those thermal storages.

The energy supply of such renewable sources is not constant, as was mentioned above. For a PV-system, much energy is available during the day, but nothing during the night, for example. It does not matter whether it is an AC- or DC-system, if at a given time, more energy is consumed than produced, stable voltages (and frequencies) cannot be ensured anymore. This means then that it is necessary to have an electricity storage system to store energy during the day to make use of it at night, based on the PV-system example. For a wind or hydro power station, the supply and demand patterns will differ in other ways.

Scheduling the loads can help reduce the battery capacity that is needed to ensure stable operation, resulting in potential cost reductions, as battery storage is expensive. Energy conversion losses of the battery system are reduced as well due to the instant use of the produced electricity, but thermal losses of the household appliances may increase. Making use of thermal storages that are already in the household can therefore be a useful addition to generate a more efficient off-grid system.

Thus, this work will not only focus on price based control of thermal energy storages, but will also take into account an off-grid system and the corresponding voltage based control model. This will not just be convenient for off-grid systems, but can also help in situations of a grid fault ride through situations in specially configured on-grid systems.

4. DESCRIPTION OF TYPICAL THERMAL STORAGE SYSTEMS IN DWELLINGS

In every household, apartment and office building, there are thermal storages. They come in different shapes and sizes, but they are all contestants for demand side energy management (DSM) systems. Freezers, water heaters, space heating/cooling respectively heating, ventilation and air conditioning (HVAC) systems and designated thermal storage systems are the main objects of study to be used in such DSM systems.

By implementing a suitable control strategy, it is possible to improve energy cost or power quality. There is no difference in the type of the freezer, both upright and chest-type freezers, as well as the freezing compartment of a refrigerator can be utilized for this purpose. The coupling of the freezer unit in a fridge with its fresh food compartment, which is not suitable as a thermal storage, might be an issue in this case. [8] [9]

Another typical thermal storage system is the water heater. There can be several small water heaters at the sinks and shower, also called point-of-use (POU) [10] water heaters, or there is a large tank for every apartment resp. a complete household or office. Small water boilers are usually electrical. Larger tanks for domestic hot water, often also including the central heating system, can be powered by gas, oil, electrical, heat pumps, thermal solar systems or a combination of those, e.g. a combination of heat pump and electrical heating called a hybrid hot water tank. Such a hybrid system can have efficiencies of >200%, but modeling of such a system is much more complex. Huge water reservoirs provide more possibilities and freedom of thermal storage control and simultaneously interfere less with the residents' comfort. [8]

Energy efficient buildings can store energy by space heating/cooling. An HVAC system can be used for thermal storage by either cooling or heating. Structures of these systems are different. There can be a large central air conditioning unit or several small ones. The same is true for heating. Central heating, as mentioned above, can be powered by gas, oil, electrical etc. Radiators, ceiling or floor heating or air ducts transport the heat to the rooms. All these systems have slightly different load profiles, but can be controlled for cost or power quality purposes. If space heating/cooling is done with older buildings, the efficiency will be considerably lower. Furthermore, the influence of solar radiation on the room temperature during sunny days has to be considered, which might include the control of window blinds, light sensitive sensor systems and weather forecasts. People opening and closing windows might also interfere with the temperature control. In office buildings, the number of people and switched on equipment creates a considerable amount of heat during the day, so there will be a cooling need even in colder climate. The ventilation system can be used during the night to naturally precool the building, as there is usually nobody in the office at night. [11]

If there is an electric car connected to the system, it might be possible to preheat or precool the car if typical times of use are known.

Many designated thermal storages are available, such as aquifer storage, borehole storage, snow storage, buried tanks or molten salt technology. These systems are not commonly used, so they will not be regarded further. Neither is district heating available in some urban areas an object of study here.

All these systems have differences in costs, efficiency, environmental impact, lifecycle and the feasibility of a suitable control.

4.1. Energy consumption in dwellings

In every country, the inhabitants use the provided electrical energy for slightly different purposes and in different amounts. Because this work is intended for a dual master's degree of University of Applied Sciences Kempten and Tallinn University of Technology, this chapter will focus on Germany and Estonia. A comparison of the situation is shown provided that suitable data are available.

4.1.1. Energy resources for heating

Figure 1 shows that in Germany and Estonia, the percentage of electrical space heating/cooling is low (~5%), making it less interesting to investigate this kind of thermal storage in regard to DSM. Whereas in Spain, Greece, Portugal, Cyprus or Malta the impact of using space heating/cooling as a thermal storage for demand side control strategies is much higher.

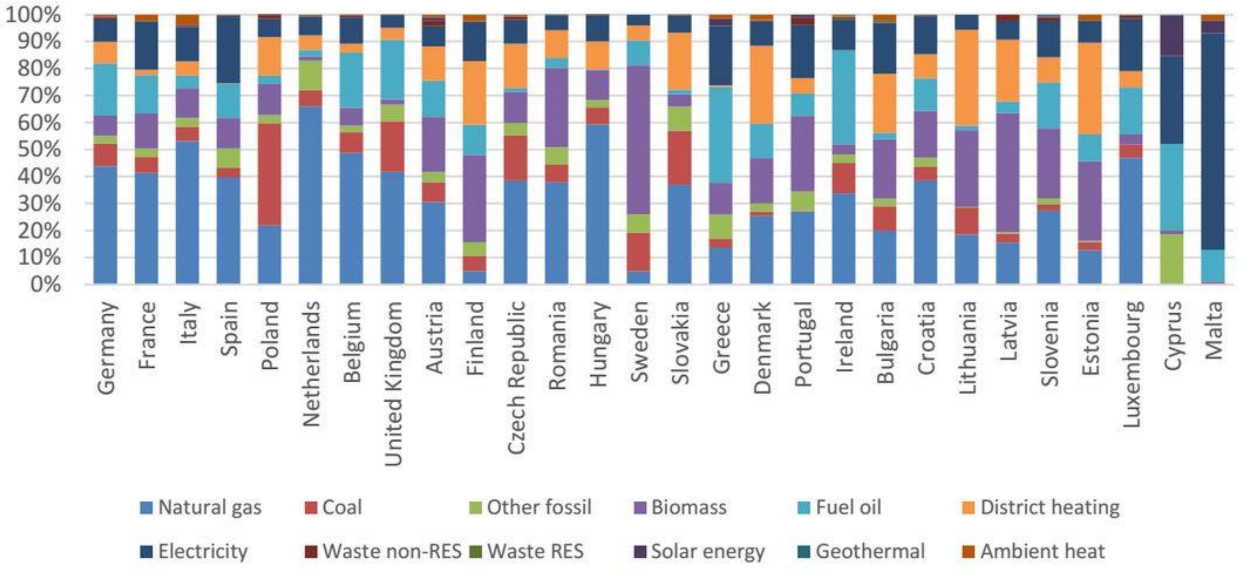

Figure 1: Energy resources for space heating in European countries [12]

Nevertheless, electrical space heating/cooling as a thermal storage can affect many people and influence off-grid systems where there might be no other heating source available. It should also be added that many central heating systems work with old pumps, creating costs of around 200 € per year. These could be replaced with high efficiency pumps, operating at around 10 € p.a., saving energy and reducing loads on- and off-grid. This could also be a useful investment for apartment buildings with weak electrical installations. [13]

4.1.2. Electricity share of thermal uses

About 17% of electrical energy is used by freezers and fridges in a typical German household, 15% for domestic hot water [13]. In general, freezing and heating consumes about 30-50% of the total electrical energy in a household. By optimizing these systems and using them as a thermal storage, a large amount of the electrical energy consumption can be controlled in a DSM manner. In Estonia, a high proportion of electrical energy is consumed for thermal uses, including hot water (cf. Figure 2).

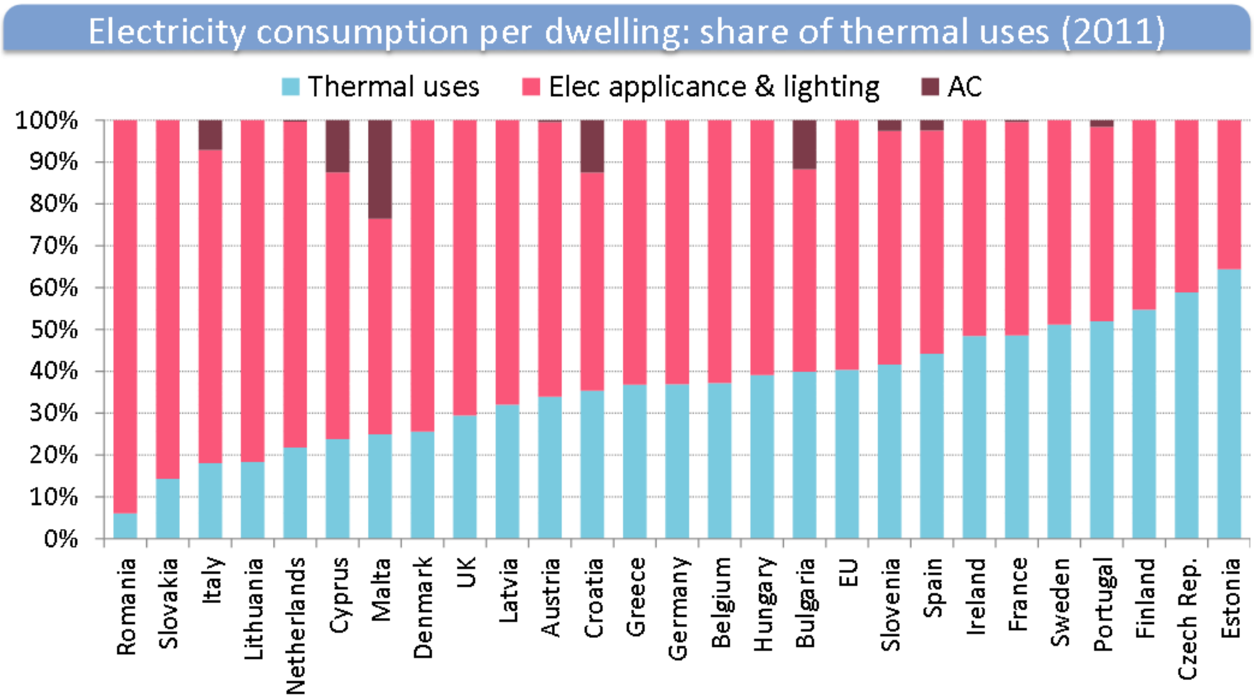

Figure 2: Electricity consumption per dwelling for European countries, normalized [14]

In Germany, the percentage is much lower due to the high consumption of electrical appliances, including freezers, also shown in Figure 3. Therefore, it can be concluded that hot water thermal storage is more relevant for Estonian households. In addition, air conditioning is more or less irrelevant in both countries.

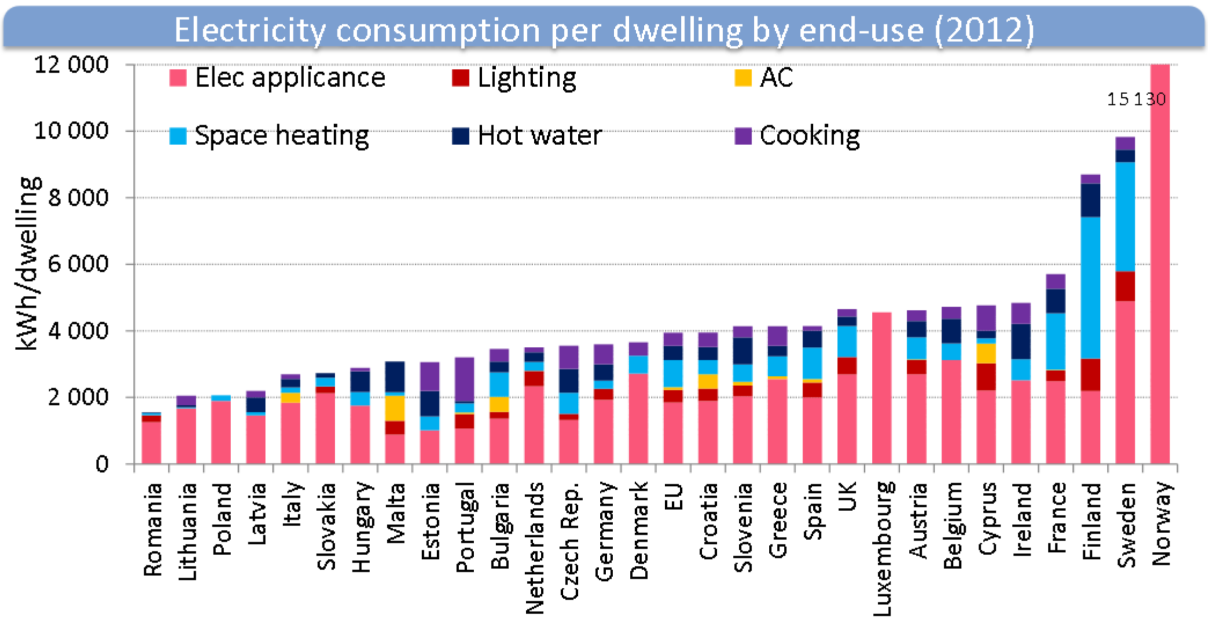

Figure 3: Electricity consumption per dwelling for European countries [14]

Figure 3 shows that the total electricity consumption per dwelling is higher in Germany than in Estonia, but the amount for hot water is larger in Estonia. Electricity for space heating/cooling is relatively small in both countries, as mentioned before.

4.1.3. Typical behavior concerning freezers and water heaters

In Germany, freezers are usually replaced after 15 years [13]. 41% of all devices are older than 10 years, 20% older than 14 years [13]. Lifetime of a freezer is about 16 years (cf. Chapter 4.2.4). Assuming that replacing an old freezer results in savings of 200 kWh per year and that 1 kWh costs approx. 0.29 € [15], the cost reduction will be 58 €/a (1).

$$\frac{200kWh}{a} * \frac{0.29€}{kWh} = 58\frac{€}{a} \qquad (1)$$

Measurements in [16] show the following consumptions (cf. Table 1), confirming the initial assumption:

Table 1: Comparison of annual cost for freezers [16]

Model year	Annual cost [€/a]
2004	92
2014	37

A new A+++ freezer costs about 400 €, resulting in a return of invest (ROI) in 7 years (2):

$$ROI = \frac{400€}{58\frac{€}{a}} = 6.9a \qquad (2)$$

This is much smaller than the expected lifetime of 16 years. In this way, it is possible to save costs and reduce the load. This can be helpful for apartment buildings with weak electrical installations as well.

One kWh in Estonia costs about 0.12 € [15] and a new A+++ freezer approx. 450 €. This results in a ROI in nearly 19 years (3), which is higher than the expected lifetime.

$$ROI = \frac{450€}{200\frac{kWh}{a} * 0.12\frac{€}{kWh}} = 18.8a \qquad (3)$$

Nowadays, tank-less water heating systems are often used for domestic hot water supply because they are more efficient than large tanks.

Statistics show that the daily water demand per person is around 125 l, where 1/3 is warm water [17]. This confirms the dimensioning of the water tank of 50 l per person living in a household. Also, older POU water heaters are often replaced by highly efficient small tank-less systems. This obviously reduces the thermal storage capability.

4.2. Typical parameters of thermal storage systems

As mentioned earlier, there are two types of freezers: upright and chest-type. When opening the door of an upright freezer, much of cold air escapes and is replaced with warmer air. To reduce the formation of ice inside the freezer, no-frost systems with higher energy demand are being used. This problem does not occur with chest-type freezers as the cold air stays down when opening the lid.

The ambient temperature has a huge influence on freezers in general, for fridge-integrated freezers, the temperature of the fresh food compartment is important [9]. Humidity has small effect on the freezer and can be neglected for the modeling. In addition, loading of the appliance has only minor effect, but the fluctuation and temperature of the food directly influences the energy demand. [18]

Freezers are usually controlled by a thermostat at a specific temperature set point, typically -18 °C. For DSM control to improve costs or power quality, the freezer has to be controlled around the temperature set point within a given temperature margin, depending on the comfort limitations. Furthermore, it should be considered to precool the food as an efficient control strategy. Typical parameters and characteristics for modeling a freezer are given in Table 2.

The influences on water heaters are similar to those on freezers. The ambient temperature as well as the fluctuation of water and the inlet water temperature mainly affect the load characteristic. This also applies for a hybrid system with a heat pump.

The temperature of water boilers is usually controlled with a thermostat at a specific temperature set point, which is typically around 60 °C, but differs depending on the system and comfort needs. Like with the freezer, cost or power quality optimization is only possible if a temperature margin around the set point is implemented, again depending on comfort constraints. DSM implementation is reasonable only with an electrical heating system because the other systems need little electricity. If there is an additional thermal solar system installed, the temperature set point might already be set as a margin of several °C to make more use of the solar energy. Such a preheating strategy can also be considered for the control model. Typical parameters and characteristics for modeling a water heater are given in Table 2.

Space heating/cooling resp. the HVAC is a more complex system. There is also a thermostat control at a temperature set point. It is possible to control the temperature around this set point, depending on the user's comfort level. With several small electrical heaters or air conditioning (AC) units, the temperature is influenced by the outside ambient temperature, solar radiation, the number of people and equipment in the room, the insulation of the walls, and the duration of windows' openings. With a central heating/AC unit, it is required to consider the following additional parameters: length of pipes and ducts, number of radiators/outlets, set point of the central unit, set point of the radiators. All of this results in a more complex model than a freezer or water heater. Typical parameters and characteristics for modeling space heating are given in Table 2.

It is obvious that there are more parameters to consider for an accurate space heating/cooling model. This will result in a more complex model. A freezer and a water heater can be modeled in a similar way.

Table 2: Typical modeling parameters for a freezer, a water heater and space heating

Freezer	**Water heater**	**Space heating**
Heat capacity of water (=food)	Heat capacity of water	Heat capacity of air
Rated power of the freezer	Rated power of the heater	Rated power of the units
Efficiency of the freezer	Efficiency of the heater	Efficiency of the unit(s)
Mass of water (=food)	Mass of water	Room volume
Temperature of replacement water (=food)	Temperature of inlet water	Temperature of replacement air
Thermal dispersion of the freezer	Thermal dispersion of the water tank	Thermal dispersion of the wall insulation
		Thermal dispersion of pipes and radiators
		Losses due to opened windows
		Fluctuation of people and switched on equipment
		Solar irradiance through windows

The efficiency of converting electrical energy into thermal energy is essential for building a good model of a storage system. For a more accurate model, losses due to thermal dispersion and similar influences should be added. To acquire a realistic model, values of multiple products of different manufacturers and energy efficiency classes (EEC) available in stores are being used. The typical parameters that will be used for modeling are presented in the following.

4.2.1. The freezer

The freezing volume $V_{fr,max}$ describes the mass of water or food with a temperature of 25 °C that can be frozen to -18 °C within 24 hours. This can be used to calculate the freezer's efficiency and will be explained in Chapter 5.

The U-value of a freezer, which measures how well the product prevents cold air from escaping, can roughly be calculated in the following way (4):

$$U_{fr} = \frac{1}{r_{m,fr} * t_{fr}} = 0.4\frac{W}{m^2 K}\ up\ to\ 1.1\frac{W}{m^2 K} \qquad (4)$$

$$Polystyrene: r_{m,fr} = 35\frac{mK}{W}$$

$$t_{fr} = 2.5cm\ up\ to\ 7.5cm$$

A low U-value means fewer losses due to insulation. [19]

Additional losses due to the door and door seals have to be added to the U-value, so it will be slightly higher.

Estimations of the U-values can be improved using $t_{fault.}$ The calculation will be explained in detail in Chapter 5.

The values in Table 3 and Table 4 also show the higher energy losses of upright freezers due to the no-frost system. According to [20], it costs about 0.01 kWh of electrical energy to open the door of a refrigerator. For an upright freezer, this value will be similar and since it is not opened as often as a fridge, it can be neglected, which is confirmed by [21]. Nevertheless, exact measurements should be conducted to confirm this.

The European Union introduced a mandatory labeling system from G to A resp. A+++ for all air conditioners, heaters, refrigerating appliances and other products. This makes it much easier for customers to see how efficiently a product works. To reduce energy consumption, distributors are nowadays only allowed to sell freezers with a label A+, A++ or A+++. [22]

Typical parameters for freezers are shown in Table 3 and Table 4:

Table 3: Parameters of upright freezers [23] [24] [25]

Manufacturer	**P_{max} [W]**	**t_{fault} [h]**	**V_f [l]**	**P_{Fr} [kg/24h]**	**P_{annual} [kWh/a]**	**EEC**
Bosch	120	25	286	22	174	A+++
Beko	80	30	275	20	255	A++
Gorenje	110	21	230	20	198	A++

Table 4: Parameters of chest-type freezers [26] [27] [28]

Manufacturer	**P_{max} [W]**	**t_{fault} [h]**	**V_f [l]**	**$V_{fr,max}$ [kg/24h]**	**P_{annual} [kWh/a]**	**EEC**
Beko	110	36	288	20	208	A++
Bauknecht	100	60	215	20	120	A+++
AEG	60	53	223	20	122	A+++

4.2.2. The water heater

The U-value for a water heater measures the capability of keeping the heat inside the water tank, depending on the thickness and insulation material (5). The lower the value, the lower are the losses. [19]

$$U_{wh} = \frac{1}{r_{m,wh} * t_{wh}} = 0.2 \frac{W}{m^2 K} \text{ up to } 0.6 \frac{W}{m^2 K} \quad (5)$$

$$Polyurethane: r_{m,wh} = 47 \frac{mK}{W} \text{ up to } 56 \frac{mK}{W}$$

$$t_{wh} = 4cm \text{ up to } 7.5cm$$

Table 5, Table 6 and Table 7 show typical parameters for different types of water heaters necessary to implement sufficient models. These parameters are implemented and used in the simulations.

Table 5: Parameters of POU water heaters [29] [30]

Manufacturer	P_{max} [W]	η	V [l]
Bosch	1,440	0.98	10/15/25
Eemax	1,440	0.95	6/10/15/22

Table 6: Parameters of large water heaters [31] [32]

Manufacturer	P_{max} [W]	η	V [l]
AO Smith	4,500	0.95	150
Whirlpool	5,500	0.95	150

Table 7: Parameters for a hybrid water heater (heat pump + electrical) [33]

Manufacturer	P_{max} [W]	η	V [m^3]
GE	9,000	<3.25	0.19

4.2.3. The space heating/cooling

Small electric space heaters, which can be placed in every room, typically have a power of 2 kW and an efficiency close to 100%.

Small AC units for spaces of 70-100 m³ need 2-3.5 kW (=7,000-12,000 BTU/h) of electrical power. It can be assumed that they consume about 1 kWh per hour. AC units are labeled in categories G to A, depending on their energy efficiency ratio (EER) or coefficient of performance (COP). [34]

Either typical central heating systems are connected to the warm water tank (cf. Table 6) or they are realized as tank-less systems. These have an electrical power input of 13-36 kW and can heat 7.5-23 l/min (25 °C temperature rise). The efficiency is usually 99%. The heat transfer depends on the size and design of the radiators. Alternatively, a heat pump HVAC system can be used, which will have a higher COP of about 3-4. It is also required to consider defrosting of the heat pump in cold climate.

The power of a central HVAC system depends on the size of the building, location, number of people, insulation efficiency etc. A rough rule of thumb recommends 1 ton of cooling, which is 12,000 BTU/h or 3.5 kW, for 50 m² and an additional 180 BTU/h for every additional m². For rooms with full sunlight it is advised to add 10% cooling power, for a kitchen an additional 4,000 BTU/h and for every person 600 BTU/h. Because the climate in Estonia and Germany is not really hot, smaller dimensioning of the air conditioning will be sufficient. It is not possible to give a general statement about the power rating; concrete values have to be calculated for a specific building. [19] [34] [35] [36]

This calculation mainly includes the insulation heat losses typical for outer walls (6) (7):

$$Old\ Buildings: U_{b,old} = \frac{1}{t_{br} * r_{m,br} + t_{rw,old} * r_{m,rw}} = 0.7\frac{W}{m^2K} \quad (6)$$

$$Energy\ Efficient\ Buildings: U_{b,eff} = \frac{1}{t_{br} * r_{m,br} + t_{rw,eff} * r_{m,rw}} = 0.2\frac{W}{m^2K} \quad (7)$$

$$Brick: r_{m,br} = 2\frac{mK}{W}$$

$$Rock\ wool: r_{m,rw} 25\frac{mK}{W}$$

$$t_{br} = 20cm;\ t_{rw,old} = 4cm;\ t_{rw,eff} = 20cm$$

For old buildings, the insulation thickness is considered to be 4 cm and the brick-walls are 20 cm thick. An energy efficient building has 20 cm of insulation and 20 cm brick-walls.

4.2.4. Lifetime of thermal storage systems

The typical lifetime of a freezer according to different sources lies in-between 12-20 years with an average of 16 years. This depends on the maintenance and quality of the product's components. [37] [20] [38] [39]

Water heaters have a lifetime of approximately 10 years, but this depends highly on the water quality. The harder the water, the shorter the lifetime. [37] [39]

The heat pump of a hybrid system (electrical and heat pump) also has a lifetime of about 10-15 years, so the overall expected lifetime is approximately 10 years, like that of a purely electrical water heater. [37] [39]

Lifecycles for HVAC systems and small AC units differ between 10-15 and 15-20 years according to different sources. Nevertheless, that depends highly on the maintenance, the product quality and annual checkups. Ventilators usually have a lifetime of 7 years, but they can be replaced without changing the whole system. [37] [39]

Electric space heaters are very robust, so they can work up to 40 years without any trouble. [39]

A tank-less water heating system can last for 10-25 years, again highly depending on the water hardness. [37] [39]

All thermal storage systems have an expected lifetime of over 10 years. The longer the lifetime of an appliance, the longer it can be used for thermal storage purposes, thus making higher cost savings or cheaper power quality optimization possible. Battery storages for demand side management usually have a lifetime of about six years, which is considerably less compared to thermal storages.

A summary of these typical lifetimes is shown in Table 8.

Table 8: Lifetime of thermal storage systems

Appliance	Typical Lifetime
Freezer (Upright/chest type)	~16a
Water heater (POU/ large tank)	~10a
Hybrid (Electric/heat pump)	~10a
HVAC, small AC units (Ventilators)	~15a (7a)
Electric space heaters	Up to 40a
Tank-less water heater	10-25a

5. MATHEMATICAL MODELS OF THERMAL AND ELECTRICAL STORAGE SYSTEMS

Before developing control strategies, it is necessary to create sufficient models of the thermal storages. The models should not be too complex for reasonable computing time, but complex enough to obtain useful results. To acquire an idea of different modeling methods for freezers, water heaters and space heating, a review of scientific articles about these appliances will be presented and various ideas combined to set up the most suitable model for each storage system. These models will then be implemented using parameters introduced in Chapter 4. The models are based on simplified discretized equations derived from differential equations. The correct function of the models will be verified subsequently to avoid mistakes in the modeling.

Numerous scientific papers and articles address modeling and control of thermal storages. Different models for freezers, water heaters and space heating resp. HVAC are described with varying levels of complexity. Some of these models that are relevant for the development of the storage models used in this work will be presented in the following sections to outline the various possibilities.

The focus in this thesis is on the models as simple as possible, but also as complex as necessary to receive sufficient data and develop useful control algorithms.

All the models have been developed using Matlab, a software environment for engineering and scientific projects. To make the whole simulation as adaptable and flexible as possible, the models are developed and tested modular. Specific parameters for the different models taken from their datasheets were stored in explicit files and an additional general file was added to allow a simulation with custom input parameters. Every model was stored in an extra file to make a later change of a model possible, without having to change the whole simulation. All the models need an index to load the specific parameters and the time interval of the simulation. In this way, the models are not restricted to a fixed time basis.

To verify the correct modeling of the appliances, test files were created to check key parameters and visualize typical curves. This also shows model quality and scope of errors.

As those models have several simplifications, they should be considered as a first basis, which can be improved for future work. At some points, several tests would be necessary to obtain good reference values for more accurate modeling. The models developed here should also be generally applicable and not only represent a specific object that has been measured. Calculations are based on datasheet values, typical parameters and estimations that can be used in general.

Pre-conditions that apply to each model are explained in the respective chapter. Nevertheless, in summary, the following conditions apply to the thermal storage models:

For the freezer:

- The freezer is always completely full. Food is replaced immediately.
- The thermal capacitance of the freezer itself is neglected.
- The food is assumed to behave like water resp. ice.
- The food is uniform.
- Door openings are neglected.

For the water heater:

- The water heater is always completely full. Water is replaced immediately.
- The thermal capacitance of the water heater itself is neglected.
- The water is uniform.

For space heating/cooling:

- Space heating/cooling is performed with a heat pump. Space heating can be switched to an electric heater.
- The thermal capacitance of the walls is neglected.
- People in the room are modeled as heat sources.
- Furniture is considered to be wood and uniform.
- Solar heat gain through windows is based on irradiation data for Tallinn

5.1. Freezer

5.1.1. Review of existing models

The model presented in [8] will be used as a basis for the freezer modeling. It is quite a simple model for calculating the temperature in the cabinet after a certain time step. It is assumed that the food taken out of the freezer is being completely replaced with new food, so that the total amount always stays the same. Replacement food always has the same temperature below -1 °C, so that the specific heat capacity can be used as a constant. The electrical power is switched between the discrete values of zero and rated power. Thermal dispersion of the freezer is also considered. In addition, the ambient temperature is assumed to be constant and not affected by the heat losses. Overall, this is a simple, solid and sufficient model, but there are ways to improve it. A simple overview on the working principle is shown in Figure 4.

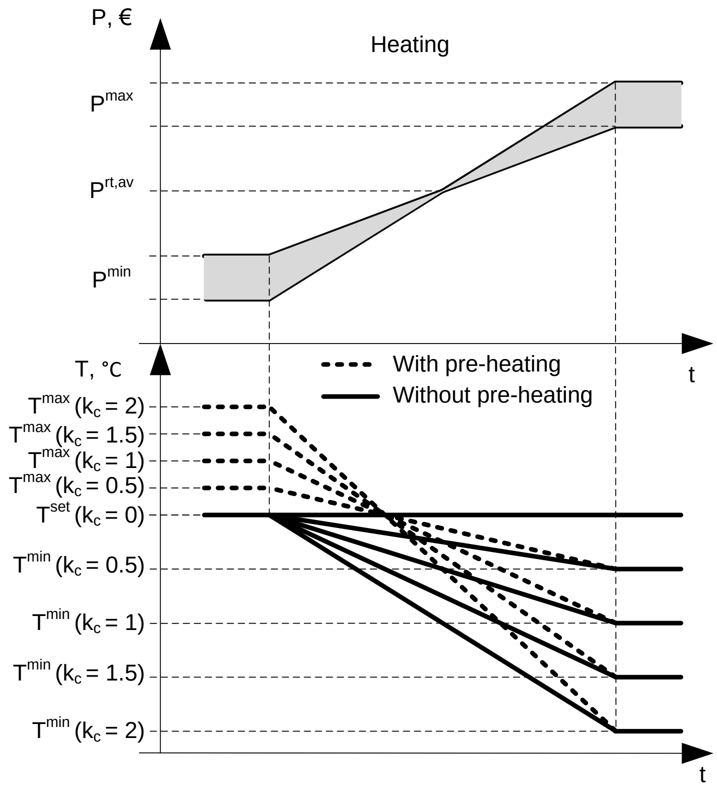

Figure 4: Simplified overview of the comfort coefficient and real time price based set point regulation for models [8]

In [40], the freezer's active power is modeled in the shape of an exponential decay function when the compressor is turned on. This addition makes the model more complex, which results in additional computation time. In addition, the exponential function has to be calculated to correlate with the measurement data of a specific freezer. Another difference in this model is the heat loss calculation. The authors assume that 60% of the cabinet losses are due to convection, calculated as a function of the thermal insulation.

The authors of [41] developed a model for a fridge-freezer. Therefore, there are additional calculations for the heat transfer between the freezer and the fresh food compartment. An interesting suggestion in this work is the changing ambient temperature during the day. It changes +/-2 °C within 24 h, modeled as a sine wave.

5.1.2. Description of the model

As mentioned in Chapter 5.1.1, the freezer model is based on [8].

In general, it is assumed that the freezer is always completely full. All food that is taken out of it will be replaced immediately with new food. Like in [8], for this model, the thermal capacitance of the freezer itself has not been taken into account. The influence of the food in a full freezer is higher than the influence of the appliance itself. But tests on that subject should be conducted to obtain exact values. The food itself is assumed to behave like water resp. ice and is therefore modeled with its parameters.

Constants and specific parameters of the selected freezer are loaded from separate files first (cf. Appendix 1, Table 24, Appendix 2, Figure 16).

The U-value of the freezer (U_f) is calculated using the time (t_{fault}) it takes a full freezer to reach -9 °C, starting from -18 °C, when being switched off (8):

$$U_f = ((((V_f * c_{pi} * 9°C)/(3.6 * (10^6)\ kJ/Wh))/9°C)/t_{fault})/A_f \qquad (8)$$

V_f is the volume of the freezer and A_f is the surface area.

If the replacement food temperature is higher than 0 °C, the specific heat coefficient of water has to be considered. To be able to use the specific heat coefficient of ice for the whole temperature spectrum, it is required to calculate a corrected food temperature for the food warmer than 0 °C (9):

$$T_{fc} = T_i - \frac{(m_i * c_{pi} * T_i) + \left(m_i * c_{pw} * (-T_f)\right)}{m_i * c_{pi}} \qquad (9)$$

Otherwise, T_{fc} is equal to T_f.

The coefficients α (11) and β (12) enable calculation of the coefficient of performance (COP) of the freezer (10):

$$COP_f = \frac{\left(\frac{V_{fr,max}}{V_f}\right) * (-18°C - T_{fc25}) + \beta * 24h * \alpha * (-18°C - 20°C)}{\beta * 24h * P_{el,f} * (-1)} \qquad (10)$$

$$\alpha = U_f * A_f \qquad (11)$$

$$\beta = \frac{1}{V_f * c_{pi}} \qquad (12)$$

$V_{fr,max}$ is the amount of food with a temperature of 25 °C that can be frozen within 24 h to a temperature of -18 °C, without a change in the cabinet temperature. The ambient temperature is considered 20 °C.

T_{fc25} is the corrected food temperature for T_f =25 °C and T_i=-18 °C.

$P_{el,f}$ is the electrical power of the freezer.

Now it is possible to calculate all the temperature changes during the time step (13)-(15):

$$T_{freeze} = \beta * \Delta t * P_{el,f} * COP_f * y_i \qquad (13)$$

$$T_{food} = \left(\frac{m_i}{V_f}\right) * (T_i - T_{fc}) \qquad (14)$$

$$T_{amb,loss} = \beta * \Delta t * \alpha * (T_i - T_{amb}) \quad (15)$$

With these temperature changes, the cabinet temperature at the end of the time step (T_{next}), which is also the output variable, can be obtained as follows (16):

$$T_{next} = T_i - T_{freeze} - T_{food} - T_{amb,loss} \quad (16)$$

The electrical power of the freezer during the time step P_{el} in W/h is also an output variable.

As mentioned earlier, it is required to calculate the electrical power Pel,f for each freezer model. This is done with the "calc_freezer_power.m" file (cf. Appendix 7, Figure 19). This function only needs the number of the freezer model (frz_nr) as an input variable. It calculates a thermostatic control with a fixed set point of the freezer model for 24 h and uses the results to estimate the annual average power consumption (P_a). It uses the following initial parameters (Table 9).

Table 9: Initial values of parameters in power calculation file

Initial parameter	Value
T_i	-18 °C
Δt	1/12 h (=5 min)
T_{amb}	20 °C
T_f	25 °C
m_i	0.014 kg/5min [8]
k	P_{max} (Rated power in data sheet)
P_a	$5*10^{10}$ kWh/a

The thermostatic control is set between -17.9 °C and -18.1 °C. If the calculated P_a is larger than the annual average power specified in the datasheet (P_{annual}), k is reduced by 1 kW.

When the correct value for k is found, it is stored in the specific freezer file as $P_{el,f}$.

This calculation is only needed for the freezer model as there is only the rated power given in the datasheets. For usual operation, P_{annual} represents the consumption under typical conditions, which are represented by the thermostatic control model with food exchange. This is simulated with the calculation file. The rated power of a freezer represents the maximum power consumption, which will occur during some seconds after starting the compressor. The steady state power is much lower. This is also shown in [42]. $P_{el,f}$ represents this steady state power consumption.

This calculation is not necessary for water heater and space heating/cooling.

The Matlab file for the freezer model is called "model_freezer.m" (cf. Appendix 3). The following input and output parameters are needed (Table 10). It is also shown if the parameter is a constant during simulations or if it changes over time.

Table 10: Input and output (I/O) parameters for the freezer model

Parameter	Description	Constant	I/O
model	{0,1,…,6} Selecting the freezer specification	Yes	I
y_i	{0,1} Freezing power during time step i (off/on)	No	I
T_i	Temperature inside the freezer at the beginning of time step i (°C)	No	I
T_{amb}	Ambient temperature during time step i (°C)	Yes	I
T_f	Replacement food temperature in time step i (°C)	Yes	I
Δt	Length of time step (h)	Yes	I
m_i	Mass of replaced food (kg)	No	I
k	Variable for calculation of the electrical power $P_{el,f}$ (kW); {0} otherwise;	Yes	I
T_{next}	Temperature inside the freezer at the end of time step i (°C)	No	O
P_{el}	Electrical power during the time step (W/h)	No	O

5.1.3. Verification of the model

The first test of the freezer model was conducted to check if the temperature in the cabinet is changing when replacing the maximum amount of food during 24 h, as specified in the datasheet. Therefore, the freezer was turned on permanently and $V_{fr,max}$ was distributed equally over 24 h. Ambient temperature was 20 °C, food temperature was 25 °C and the time step was 5 min. The results of this test and all other tests are presented with reference to the Bosch freezer mentioned above; results for the other freezers comply with those from the Bosch freezer. It can be observed that the temperature stays perfectly at -18 °C, suggesting that the model is working properly (cf. Appendix 8, Figure 20).

For the next test, the food load will not be distributed, but all the food will be replaced in the first time step. All other parameters are the same. The temperature first rises sharply, as expected and then slowly falls back towards -18 °C. The reason why -18 °C is not reached exactly is due to the smaller ambient losses when the cabinet temperature is higher (cf. Appendix 8, Figure 21).

To check if the ambient loss calculation is correct, the freezer was turned off for the third test and no food was exchanged. The temperature of the cabinet should reach -9 °C within the specified time (t_{fault}). The cabinet temperature at the beginning was -18 °C. It is evident that the Bosch freezer reaches -9 °C within the specified 25 hours. It can also be seen that the temperature is decreasing in the shape of an exponential function like expected. The result is shown in Figure 5.

The last test for the freezer model is a thermostatic control test between -17.9 °C and -18.1 °C (cf. Appendix 8, Figure 22 and Figure 23). The ambient and exchange food temperatures are constant as well as the typical food consumption of 0.014 kg/5min [8]. For this test, Matlab displays 174.1 kWh/a as the annual power consumption, which aligns with the 174 kWh/a given in the datasheet for the Bosch freezer. It is also possible to change the food mass, ambient temperature and food temperature to a sinusoidal pattern, to see the effects on the thermostatic control, cabinet temperature and annual power consumption.

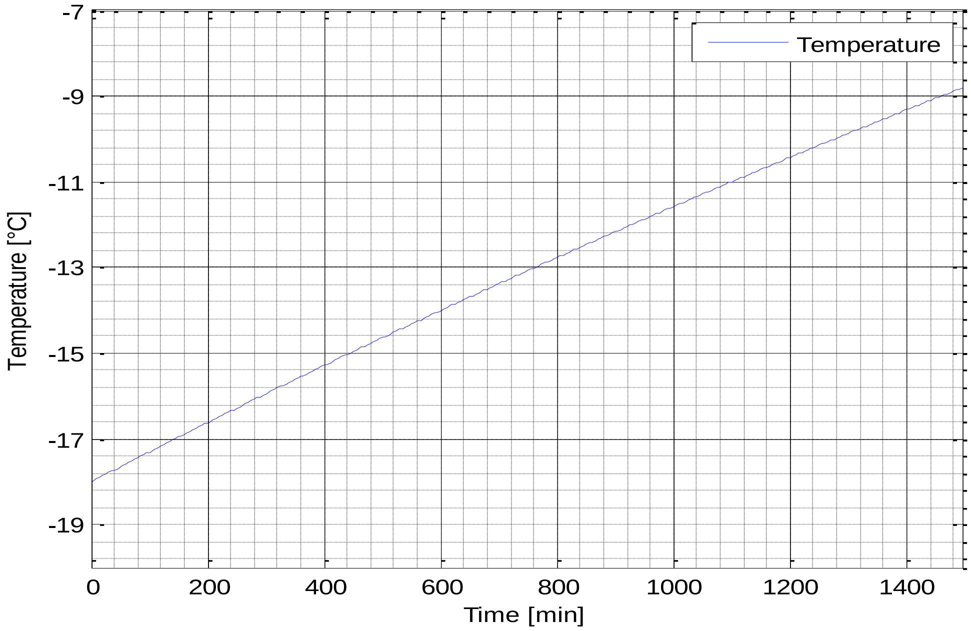

Figure 5: Freezer test ambient losses

5.2. Water heater

5.2.1. Review of existing models

For the water heater model, the basic idea suggested in [8] was used as a starting point. Like in the freezer model, all hot water withdrawn from the tank was replaced immediately. The cold replacement water temperature and ambient temperature are again assumed to be constant. The electric heating power can be switched between zero and rated power and thermal dispersion of the boiler, which is not affecting the ambient temperature, was also taken into account. Like the freezer model in [8], this water heater model is also a simple, solid and sufficient solution and can be refined with some additional variables.

The model in [43] is very similar to the one in [8]. It is actually a simplified model, as the efficiency of the heating element is not taken into account. The thermal conductivity of the tank was estimated using temperature measurements.

In [44] the authors propose a partial differential equation model, which is compared with a one-mass and a two-mass composite model for the water in the tank. The model shows excellent performance, but it is very complex, thus time-consuming to develop, and raising the computational time considerably, as compared to a one-mass model.

The most simplistic model is shown in [45]. Most of the variables are considered constant and the water temperature is uniform. For further simplification, the heat losses during the heating periods are neglected. This results in simple equations but at the same time, in inaccurate results.

An interesting suggestion in [46] is the use of different water consumption profiles for winter and summer season and different ambient temperatures.

A questionable approach is the modeling with an arbitrary power value for the heating element instead of a discrete one, like that presented in [47], as a usual thermostatic control switches between zero and maximum resp. rated power.

As an additional model, a hybrid heat pump water heater, like proposed in [48], could be implemented to see its differences from regular water heaters.

Many other papers present models for water heaters, but they are very similar to those already discussed.

5.2.2. Description of the model

Using the knowledge gained in previous chapters, it is possible to develop a mathematical model of the water heater, which is similar to that proposed in [8].

The withdrawn warm water is assumed to be replaced immediately with cold water. The thermal capacitance of the water tank itself is neglected, as the influence of the water inside a full water heater is much higher. Nevertheless, that subject should be tested to gain exact values and eventually improve the model. The water is assumed to be uniform.

Constants and specific model parameters are loaded first (cf. Appendix 1, Table 25, Appendix 2, Figure 17). The maximum water withdrawn from the tank (V_i) cannot be higher than the maximum tank volume (V_{wh}). α (17) and β (18) were calculated as follows:

$$\alpha = U_{wh} * A_{wh} \tag{17}$$

$$\beta = \frac{1}{V_{wh} * c_{pw}} \tag{18}$$

U_{wh} is the U-value of the water heater. A value of 0.4 $Wm^{-2}K^{-1}$ was used as suggested in Chapter 4.2.2. A_{wh} is the surface area of the tank.

The temperature changes during the time step can be calculated as follows (19)-(21):

$$T_{heating} = \beta * \Delta t * P_{max} * \eta_{wh} * y_i \tag{19}$$

$$T_{cw} = \left(\frac{V_i}{V_{wh}}\right) * (T_i - T_{cw}) \tag{20}$$

$$T_{amb,loss} = \beta * \Delta t * \alpha * (T_i - T_{amb}) \tag{21}$$

P_{max} is the rated heating power and η_{wh} is the heating efficiency given in the datasheet.

The output variable T_{next}, representing the temperature of the water inside the boiler at the end of the time step, is obtained with the temperature changes (22):

$$T_{next} = T_i + T_{heating} - T_{cw} - T_{amb,loss} \tag{22}$$

In addition, the electrical power consumption of the water heater P_{el} during the time step in W/h is returned.

Calculations were done in the “model_water_heater.m” file (cf. Appendix 4).

The following input parameters are required in order to obtain the output variables (Table 11). Constants do not change their value during simulations.

Table 11: Input and output parameters for the water heater model

Parameter	Description	Constant	I/O
model	{0,1,…,4} Selecting the water heater specification	Yes	I
$\mathbf{y_i}$	{0,1} Heating power during time step i (off/on)	No	I
$\mathbf{T_i}$	Water temperature inside the boiler at the beginning of time step i (°C)	No	I
$\mathbf{T_{amb}}$	Ambient temperature during time step i (°C)	Yes	I
$\mathbf{T_{cw}}$	Replacement water temperature in time step i (°C)	Yes	I
Δt	Length of time step (h)	Yes	I
$\mathbf{V_i}$	Volume of replaced water (l)	No	I
$\mathbf{T_{next}}$	Water temperature inside the boiler at the end of time step i (°C)	No	O
$\mathbf{P_{el}}$	Electrical power during the time step (W/h)	No	O

5.2.3. Verification of the model

The first test deals with the ambient losses. Starting at 60 °C, the boiler was turned off and there was no water fluctuation. The test ran until Tamb+1 °C was reached. All tests were conducted for the AOSmith water heater mentioned earlier. Results for the other boilers comply with those of the AOSmith. Temperature is decaying in a nice exponential function shape, suggesting the model works properly for the ambient losses (Figure 6).

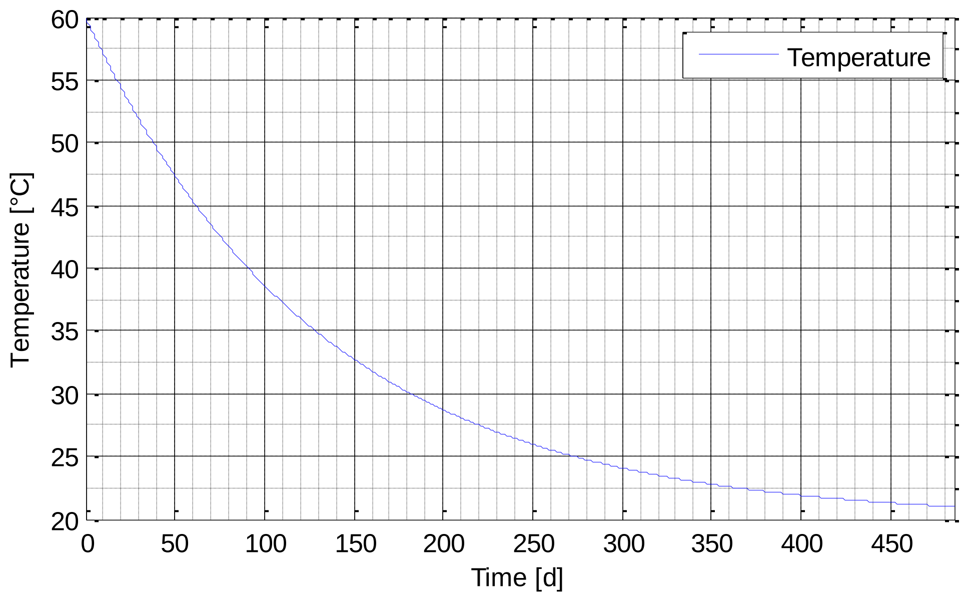

Figure 6: Water heater test: Ambient losses

The second test shows the theoretical heating curve and the maximum theoretical temperature. Water temperature started at 0 °C and the heating element was turned on. The graph shows again an exponential function as expected, confirming correct modeling of the boiler (cf. Appendix 9 Figure 24).

In the third test, the maximum amount of water that can be withdrawn from the boiler within 5 min without changing the temperature was calculated and then applied to the model. The conditions were: heater on, ambient temperature at 20 °C and cold water temperature at 15 °C. For the AOSmith water heater, the maximum fluctuation rate is about 6.7 liters per 5 min. The temperature is changing slightly when applying this fluctuation rate to the model due to rounding errors, but this can be neglected (cf. Appendix 9, Figure 25).

The last test was a thermostatic test (cf. Appendix 9, Figure 26 and Figure 27). The temperature limits were 59.9 °C and 60.1 °C. Without water exchange and at an ambient temperature of 20 °C, the simulation showed an overshoot in temperature due to the 5 min interval. If the time step width is smaller, the overshoot would be smaller. To acquire a more accurate value for the annual power consumption, the test is simulated for 72 hours. The average annual power consumption for these parameters would be 411 kWh/a.

5.3. Space heating/cooling

5.3.1. Review of existing models

The authors of [49] propose a space heating model for a house. It consists of a solar system, a hot water tank, pipes and the model for the insulation losses. Instead of the solar system with the hot water tank, a modified model for an electric water heater could also be used. The model seems to be quite complex, so some simplifications are reasonable.

In [50], a model for a chiller is presented, which could also be used for modeling the HVAC system.

A model of an air conditioner including a house and an insulation model is shown in [51]. It includes thermal resistance and capacity of air and the house (wall, base and roof) and disturbances by solar irradiation, occupants and equipment.

Focus in [52] is on a dynamic model of zone temperatures. In that way it is possible to simulate different temperatures in adjacent rooms and apartments. In addition, a two mass approach, considering slow and fast thermal capacitances is introduced. The load is based on the occupants' behavior.

5.3.2. Description of the model

The model for space heating/cooling was developed similar to the water heater and freezer models. With some additions, it is possible to create a mathematical model that can show the behavior of space heating/cooling in the same fashion as in the other thermal storage models.

Constants and specific apartment/house parameters were loaded first (cf. Appendix 1, Table 26, Appendix 2, Figure 18). The heat dissipation of an adult during 1 h (P_{person}) was set according to [53].

Maximum air and wood volumes (*Vmax*, *Vwood*) were calculated with areas of floor and roof and the height of the room. The maximum air fluctuation during one time step was set to the maximum air volume.

To obtain a more exact U-value of the outside walls, the λ-values or insulating capacities of bricks and insulation with their thicknesses were used (23).

$$U_{wall} = \frac{1}{\left(\frac{1}{\lambda_{ins} * t_{ins}}\right) + \left(\frac{1}{\lambda_{wall} * t_{wall}}\right)} \tag{23}$$

with λ_x being the λ-values and t_x the thicknesses.

The variables α (24) and β (25) can be obtained as follows:

$$\alpha = U_{wall} * \left(A_{wall} - \sum A_{window}\right) + U_{window} * \sum A_{window} \tag{24}$$

$$\beta = \frac{1}{V_{max} * \rho_{air} * c_{p,air} + V_{wood} * \rho_{wood} * c_{p,wood}} \tag{25}$$

using the densities (ρ_x) and c_p values of air and wood.

In the case of space heating, α does not only depend on one material, but on walls and windows, so it is necessary to take both into account. The variable β only takes air and furniture in the room into account. Furniture is assumed to be made of wood. The thermal capacitance of the walls is not taken into account although it has considerable influence on the temperature in long-term durations. But for time steps of 5 min, the influence is much smaller than the temperature change due to opened windows. In addition, it is difficult to estimate how much of the wall volume should be considered as thermal storage as there is a temperature difference between inside and outside, and various wall materials differ in their thermal capacities. A test should be conducted to obtain a basis for a good estimation. To obtain general applicable results, this should be done with different apartments or houses with and without furniture.

The solar irradiation power due to the windows (P_{solar}) (26) was calculated in multiple Matlab files:

$$P_{solar} = \sum A_{window} * E_{res} \tag{26}$$

E_{res} was calculated in the "calc_solar.m" file (cf. Appendix 7, Figure 19): Direct beam and diffuse irradiation values and several angles were used to obtain the effective direct beam, diffuse and reflective irradiation values, which were then multiplied by the solar heat gain coefficient (SHGC) and the indoor solar attenuation coefficient (IAC).

To calculate the direct beam, diffuse irradiation, azimuth angle and solar altitude angle, the "calc_irradiation.m" file (cf. Appendix 7 Figure 19) can be used. It includes longitude and latitude values for Tallinn together with clear sky average irradiation data at noon [54]; so the calculation is only valid for Tallinn. Otherwise, these data have to be changed. In addition, a normal distribution model is applied to match the clear sky irradiation data to measured values in [55]. As an input, only day of the year and hour of the day are required.

The next step was the calculation of the COP of the heat pump. First, it is necessary to assign T_{amb} and T_i to T_h and T_c. Typical values for a heat pump are COP=1.0 at -18 °C and COP=3.5 at 10 °C. With these values, it is possible to make a linear approximation and limit the COP to a maximum of 4.5 and a minimum of 0.5. Because the COP is also affected by the difference of T_c and T_h, it is necessary to include a lift effect as described in [56]. In [57] a second order polynomial as an approximation for measured data was shown to be sufficient.

The temperature changes during time step i can be calculated as (27)-(31):

$$T_{people} = k_i * P_{person} * \Delta t * \beta \tag{27}$$

$$T_{window} = \left(\frac{V_i}{V_{\max}}\right) * (T_i - T_{amb}) \tag{28}$$

$$T_{amb,loss} = \beta * \Delta t * \alpha * (T_i - T_{amb}) \tag{29}$$

$$T_{sun,rad} = P_{solar} * \Delta t * \beta * s_i \tag{30}$$

$$T_{hc} = \beta * \Delta t * \left(z_i * P_h + \left((z_i - 1) * (-1)\right) * P_c\right) * COP_{sp} * y_i \quad (31)$$

The temperature changes due to the number of people (T_{people}), the air fluctuation of opened windows (T_{window}), ambient losses through the walls and windows ($T_{amb,loss}$), the solar irradiation through the windows ($T_{sun,rad}$) and the heating/cooling with the heat pump (T_{hc}).

If the electric heaters are switched on, T_{hc}, P_h and P_c have to be corrected for that time step (32)-(34):

$$P_h = eh_{Nr} * 2000 \quad (32)$$

$$P_c = 0 \quad (33)$$

$$T_{hc} = \beta * \Delta t * P_h * y_i \quad (34)$$

using the number of electric heaters (eh_{Nr}) and the corrected P_h for the recalculation of T_{hc}.

The temperature at the end of the time step (T_{next}), the temperature prediction (T_{pred}) and the electrical power consumption (P_{el}), which are also the output variables, can be calculated as shown in (35)-(37):

$$T_{next} = T_i + T_{hc} - T_{window} - T_{amb,loss} + T_{people} + T_{sun,rad} \quad (35)$$

$$T_{pred} = -T_{window} - T_{amb,loss} + T_{people} + T_{sun,rad} \quad (36)$$

$$P_{el} = \left(z_i * P_h + \left((z_i - 1) * (-1)\right) * P_c\right) * y_i \quad (37)$$

The temperature prediction can later or in future work be used for a predictive algorithm.

The model of space heating/cooling was stored in the "model_space_heating.m" file (cf. Appendix 5). These input and output parameters and functions are needed, the constants do not change their values during simulations (Table 12):

Table 12: Explicit and function-obtained (F) input and output parameters for the space heating/cooling model

Parameter	Description	Constant	I/O
model	{0,1} Selecting the apartment/house specification	Yes	I
$\mathbf{y_i}$	{0,1} Heating/cooling power during time step i (off/on)	No	I
$\mathbf{T_i}$	Room temperature at the beginning of time step i (°C)	No	I
$\mathbf{T_{amb}}$	Ambient temperature (outside) during time step i (°C)	Yes	I
$\mathbf{\Delta t}$	Length of time step (h)	Yes	I
$\mathbf{V_i}$	Volume of replaced air due to open windows (m^3)	No	I
$\mathbf{z_i}$	{0,1} Cooling (=0) or heating (=1) mode	Yes	I
$\mathbf{k_i}$	Number of people in the room during time step i	No	I
day	Day of the year (1st Jan. = 1)	No	I
hour	Hour of the day (12 p.m. = 12)	No	I
$\mathbf{s_i}$	{0,1} Solar irradiation effect during time step i (off/on)	Yes	I
eh	{0,1} Use electrical heaters instead of heat pump (off/on)	No	I
$\mathbf{E_{res}}$	Resulting irradiation (direct, diffuse and reflective) including SHGC and IAC	No	I, F
$\mathbf{T_{next}}$	Room temperature at the end of time step i (°C)	No	O
$\mathbf{T_{pred}}$	Predicted temperature change for next time step (°C)	No	O
$\mathbf{P_{el}}$	Electrical power during the time step (W/h)	No	O

5.3.3. Verification of the model

The test file contains several tests on the space heating/cooling model to verify the correct behavior of the temperature on different influences, shown in Table 13:

Table 13: Space heating/cooling tests

Test	Changing parameter	Conditions	Description
Test 1	Heating	Winter	Heating with thermostatic control; other influences turned off;
Test 2	Air fluctuation	Winter	Heating with thermostatic control; fluctuation of air is changing over time;
Test 3	Solar irradiation	Winter	Space heating/cooling off; solar radiation on;
Test 4	Ambient losses	Winter	Everything switched off;
Test 5	Number of people	Summer	Changing number of people; other influences turned off;
Test 6	Cooling	Summer	Cooling with thermostatic control; other influences turned off;
Test 7	Solar irradiation	Summer	Space heating/cooling off; solar radiation on;
Test 8	Air fluctuation	Summer	Cooling with thermostatic control; fluctuation of air is changing over time;
Test 9	Heating source	Winter	Heating with thermostatic control; changing ambient temperature; switching between electric heater and heat pump with power quality based approach;
Test 10	Heating source	Winter	Heating with thermostatic control; changing ambient temperature; switching between electric heater and heat pump with price based approach;

All these tests showed satisfying results for the different modeled influences, so the space heating/cooling model seems to be working properly.

5.4. Simplified electrical models

Both the battery storage and the PV-system model were reduced to their basic working principles. These simplifications are sufficient, as those electrical components are only necessary to make the whole off-grid system operational and do not represent the central elements of this investigation. Thus, small errors occurring due to the simplified models have a minor influence on the results and can be omitted.

In summary, the following conditions apply to the electrical models:

- The solar irradiation is based on data for Tallinn. [54]
- The PV.model is based on approximations and datasheet values. [58] [59]
- Ambient conditions are fixed for the PV-model like described in [58].
- The battery storage model is based on approximations and datasheet values. [60] [61]
- Ambient conditions are fixed for the battery storage model. (cf. Chapter 5.4.2)
- Inverter and battery controller are modeled within the complete system model. (cf. Chapter 5.5)

5.4.1. The PV-model

The PV-model is the only component that uses only one general specification instead of different specifications. The direct beam, diffuse irradiation, azimuth angle, and solar altitude angle were calculated in the "calc_irradiation.m" file like in the space heating/cooling model (38). Together with the horizontal and azimuth angle of the solar panels (39) (40), it is possible to calculate the resulting irradiation on the solar panels per square meter within a few calculation steps (41)-(45). These steps are based on approximations presented in [53].

$$E_b, E_d, \varphi, \beta_s = calc\_irradiation(day, hour) \quad (38)$$

$$\gamma = \varphi - surface_{azimuth} \quad (39)$$

$$\vartheta = \cos^{-1}(\cos\beta * \cos\gamma * \sin horiz_{angle} + \sin\beta * \cos horiz_{angle}) \tag{40}$$

$$if \ \cos\vartheta > 0: E_{tb} = E_b * \cos\vartheta$$
$$otherwise: E_{tb} = 0 \tag{41}$$

$$Y = \max(0.45;\ (0.55 + 0.437 * \cos\vartheta + 0.313 * \cos^2\vartheta) \tag{42}$$

$$E_{td} = E_d * (Y * \sin horiz_{angle} + \cos horiz_{angle}) \tag{43}$$

$$E_{tr} = (E_b * \sin\beta + E_d) * 0.2 * \frac{1 - \cos horiz_{angle}}{2} \tag{44}$$

$$E_{res} = E_{tb} + E_{td} + E_{tr} \tag{45}$$

For the PV-modules, a model of a Mitsubishi Electric PV-MLU255HC module [62] was created. Because PV-modules work very similar, this simplification of implementing only one specific model is acceptable. From the datasheet, a formula for the short circuit current depending on the irradiation can be derived (46). The current in the maximum power point (MPP) is approximately at 85% of the short circuit current value (47). From the datasheet, a formula for the voltage in the MPP that also depends on the irradiance can be obtained (48). With current and voltage of the MPP, it is possible to calculate the maximum available power for a given value of irradiance (49). [58]

$$I_{SC} = \frac{I_{SC_{1000}}}{1000} * E_{res} \tag{46}$$

$$I_{mpp} = mpp_{appr} * I_{SC} \ (Approximation) \tag{47}$$

$$V_{mpp} = \frac{offset_{mpp}}{m_{mpp} - I_{mpp}} \ (Datasheet) \tag{48}$$

$$P_{mpp} = I_{mpp} * V_{mpp} \tag{49}$$

The complete PV-power (P_{pv}) available during the time step length was then calculated by multiplying the MPP power with the number of modules and Δt (50):

$$P_{pv} = P_{mpp} * Nr_{Modules} * \Delta t \quad (50)$$

The model was then verified by simulating a summer day, a winter day and a complete year. The test over a complete year shows that it is better not to use the model for such a long period, but only a selected number of days within a month. This is due to the fixed irradiation values in the irradiation calculation file. The same is true for the space heating/cooling model, if the irradiation through the windows is considered.

The model of the simplified PV-system needs different input and output parameters to make it work. Some parameters were obtained via functions that are called within the model. The following table shows all input and output parameters and whether their values are constant or not during simulations (cf. Table 14).

Table 14: Explicit and function-obtained input and output parameters for the PV-model

Variable	Description	Constant	I/O
day	Day of the year (1^{st} Jan. = 1)	No	I
hour	Hour of the day (12 p.m. = 12)	No	I
Δt	Length of time step (h)	Yes	I
$\mathbf{Nr_{Modules}}$	Number of the PV-modules	Yes	I
$\mathbf{E_b}$	Direct beam irradiation (W/m^2)	No	I, F
$\mathbf{E_d}$	Diffuse irradiation (W/m^2)	No	I, F
φ	Azimuth angle (°)	No	I, F
$\mathbf{\beta_s}$	Solar altitude angle (°)	No	I, F
$\mathbf{P_{pv}}$	PV-power during time step (W)	No	O

5.4.2. The battery model

First, the typical parameters of the selected battery type were loaded (cf. Appendix 1, Table 27) and the minimum state of charge (SOC) of the battery can be obtained by using the maximum depth of discharge from the battery's datasheet (51) [61]. Then the charging efficiency was calculated according to the battery type, as Absorbent Glass Mat (AGM) batteries have a different charging behavior than Lithium Ion (LiIon) batteries (52).Therefore, approximation functions for these efficiencies were fit according to typical parameters stated in [60]. Slope and offset of these functions were estimated. The charging efficiency depends on the SOC in case of AGM batteries. It was also necessary to calculate the current in order to check if it exceeds the maximum values (53). The discharging efficiency is dependent on the battery type, battery capacity and on the discharging current (54). Slope and offset for approximation functions were fit to typical values presented in [60]. Afterwards, the new SOC of the battery can be calculated according to charging or discharging operation (55).

$$SOC_{min} = 1 - DOD_{max} \qquad (51)$$

$$AGM: if\ SOC < 0.6: \eta_c = -\frac{0.04}{0.6} * SOC + 0.99$$

$$otherwise: \eta_c = -\frac{0.9}{0.4} * SOC + 2.3 \qquad (52)$$

$$LiIon: \eta_c = 0.98$$

$$if\ P_i > 0: I = \frac{P_i}{V_{charge}}$$

$$if\ P_i < 0: I = \frac{P_i}{V_{bat}} \qquad (53)$$

$$otherwise: I = 0$$

$$AGM: \eta_d = -\frac{0.3}{0.2} * \left(-\frac{I}{C_{bat}}\right) + 1$$

$$LiIon: \eta_d = -\frac{0.7}{2} * \left(-\frac{I}{C_{bat}}\right) + 1.055 \quad (54)$$

$$if\ P_i > 0: SOC_{new} = \frac{(SOC * C_{bat} * V_{bat}) + \left(I * V_{charge}\right) * \Delta t * \eta_c}{C_{bat} * V_{bat}}$$

$$if\ P_i < 0: \frac{(SOC * C_{bat} * V_{bat}) + (I * V_{bat}) * \Delta t * \eta_c}{C_{bat} * V_{bat}} \quad (55)$$

To make an estimation about the maximum charging and discharging power for the next time step, a recalculation of the charging and discharging efficiencies is necessary (58) (60) (61). First, the power values were obtained for the general maximum charging resp. discharging current (56) (57). The maximum power values were then corrected according to the new SOC not to overcharge the battery or fall below the minimum SOC level (59) (61). It is basically the reverse calculation to the SOC calculation described in (51)-(61). The same approximation fuctions derived from [60] are used. From the difference between the new SOC calculated previously and the minimum (SOC_{min}), it is possible to obtain a value for the maximum discharging power (61). Because the discharging power is dependent on the discharging efficiency and vice versa, the values have to be recalculated several times to obtain a sufficient approximation. The difference between the new SOC and 1 is used to calculate the maximum allowed charging power (59).

$$P_{max,c} = C_{bat} * I_{max,c} * V_{charge} \quad (56)$$

$$P_{max,d} = -C_{bat} * I_{max,d} * V_{bat} \quad (57)$$

$$AGM: if\ SOC_{new} < 0.6: \eta_{c,new} = -\frac{0.04}{0.6} * SOC_{new} + 0.99$$

$$otherwise: \eta_{c,new} = -\frac{0.9}{0.4} * SOC_{new} + 2.3 \quad (58)$$

$$LiIon: \eta_{c,new} = 0.98$$

$$P_{max,c} = (1 - (SOC_{new} * C_{bat} * V\_bat)) * (\frac{C_{bat} * V_{bat}}{\Delta t * \eta_{c,new}}) \quad (59)$$

$$AGM: \eta_{d,Imax} = -\frac{0.3}{0.2} * \left(\frac{I_{max,d}}{C_{bat}}\right) + 1$$

$$LiIon: \eta_{d,Imax} = -\frac{0.7}{2} * \left(\frac{I_{max,d}}{C_{bat}}\right) + 1.055 \quad (60)$$

$$P_{max,d} = \left(SOC_{min} - (SOC_{new} * C_{bat} * V_{bat})\right) * (\frac{C_{bat} * V_{bat}}{\Delta t * \eta_{d,new}})$$

$$AGM: \eta_{d,new} = -\frac{0.3}{0.2} * \left(-\frac{\frac{P_{max,d}}{V_{bat}}}{C_{bat}}\right) + 1$$

$$LiIon: \eta_{d,new} = -\frac{0.7}{2} * \left(-\frac{\frac{P_{max,d}}{V_{bat}}}{C_{bat}}\right) + 1.055 \quad (61)$$

The SOC value was saved to the battery parameter file and the returned values are the SOC, maximum charge power ($P_{max,c}$) and maximum discharge power ($P_{max,d}$) for the next time step.

The maximum charging and discharging currents depend on the battery's capacity and it is assumed that the battery is placed in a controlled environment with no temperature changes to allow the use of a constant capacity value.

The batteries have a nominal voltage of 12 V for AGM resp. 12.8 V for LiIon and their capacities are defined in Ah. All specifications were taken from the Victron Energy catalogue [61].

In the verification with the test file, complete charging and discharging cycles for both battery types were conducted with the maximum possible charging/discharging power. It showed satisfying results.

The model of the battery storage was also simplified in many ways. This again reduces the number of parameters that are needed. It uses the following input and output parameters, of which some are constant during simulations (cf. Table 15).

Table 15: Input and output parameters for the battery model

Variable	Description	Constant	I/O
model	{0,1} Selecting the battery specification (AGM/LiIon)	Yes	I
P_i	Charging (>0) or discharging (<0) power during time step i	No	I
Δt	Length of time step (h)	Yes	I
SOC	State of charge at the end of time step i	No	O
$P_{max,c}$	Maximum charge power for next time step	No	O
$P_{max,d}$	Maximum discharge power for next time step	No	O

5.5. Description of the complete system model

To achieve a simpler and clearer structure, all previously described models were combined to one system model (cf. Appendix 6). This model also includes a simplified combined PV-inverter and battery controller. All the connections between the components are considered to be ideal. This means that there are neither losses nor parasitic elements taken into account. The working principle of the model is shown in the schematic in Figure 7 for on-grid operation and in Figure 8 for the off-grid situation. Further explanation concerning price calculations, SOC and voltage check, control and consumption data / initial parameters can be found in the following chapters.

Input and output parameters for the system model are the variables of the individual models, which are relevant for the control purposes. All the other constant variables are provided by a parameter file. To reduce the computation time of the complete simulation, it is possible to deactivate components by setting their y_i variable to "2". The freezer, water heater and space heating/cooling were activated according to the selected scenario (cf. Chapter 6). Deactivating skips the calculation of the model completely and uses predefined values instead. After calculating the freezer, water heater, space heating/cooling and PV-system, given that they were activated, the PV-inverter efficiency was added and with the cleaned household profile (cf. Chapter 6.1), a preliminary power value can be calculated.

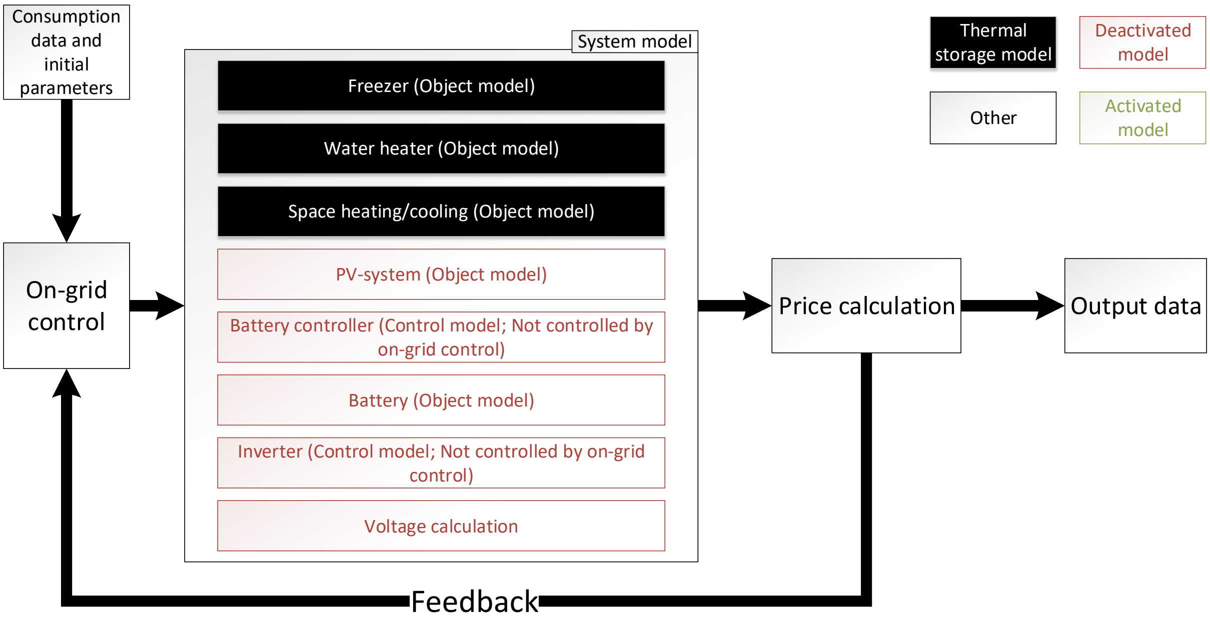

Figure 7: Simulation schematic in on-grid operation

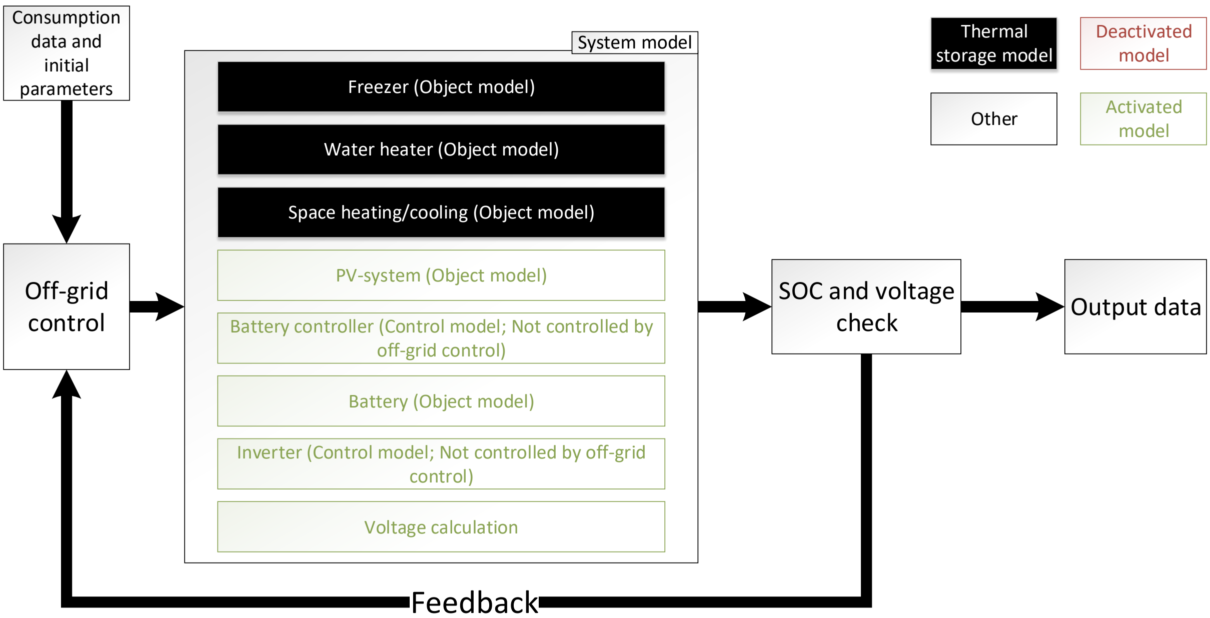

Figure 8: Simulation schematic in off-grid operation

This preliminary power was then used by the battery controller to determine whether to charge the battery in case there is more power produced than consumed, or discharge it vice versa. Afterwards the battery model for this time step will be calculated and can be added to the preliminary power to have the total power value. This way of implementing the battery controller will result in an instant reaction of the battery system. The alternative of calculating the battery response in the next time step will cause large peaks and deviations and an unrealistically long reaction delay of 5 min (cf. Chapter 6.1). For these simulations, an instant reaction of the battery system is a sufficiently accurate model.

With the total power, the behavior of the PV-inverter can be modeled. It basically represents a MPP-tracker with a DC-DC converter.

During grid operation, the PV-inverter injects its power into the grid, or it is turned off. Thus, it would be possible to limit the average output power between zero and maximum available PV-power. However, the PV-system is off during grid-connected operation (cf. Chapter 6.1). It would add more complexity to the simulation and increase the computation time. It is also necessary to model energy supply to the grid and consider the market prices for doing so. This is not relevant for the goal of this work. Nevertheless, such operation should be considered for further investigations on price based algorithms with the on-grid system.

In an off-grid system, the PV-inverter works as follows. The frequency is considered to be kept constant in any case. The voltage is limited to the nominal root-mean-square (RMS) voltage of 230 V (V_N). It cannot be exceeded. If the battery is charged and the PV-system produces more energy than the household consumes, the average PV-power during the time step will be reduced. As this is a very simplified model, it is not specified in the simulation how the PV-power is reduced. It can be turned off for a specific percentage of the time step or a special developed hardware that changes the operation point of the PV-system might be used to reduce the average output power. When using more accurate models in the future work and reducing the time step width of the model, this has to be considered. Further, in a real system, the battery controller and PV-inverter keep the voltage within given limits; otherwise the system will turn off. For simplification, the frequency is assumed to be constant in any case and the voltage is limited, as mentioned above. Thus, if the battery is discharged and the PV-system does not provide enough power, the modeled system shows a voltage drop. If this voltage drop exceeds the defined limits, the simulation will be aborted (cf. Chapter 6.1), because the real system would shut down completely as a protection precaution. This simple implementation of a voltage drop might be solved differently in a real system, as the battery controller / inverter notices power shortages. A special device may be used that can provide a signal if the system is close to a safety shutdown. The result will be the same like with the voltage drop detection. Thus, for simplification reasons, the voltage drop assumption will be sufficient and the exact implementation can be investigated in future work.

Finally, the voltage will be calculated. The RMS values of the current of energy consuming components, including the battery during charge operation, are calculated. Then the power of all energy producing components is added, including the battery during discharging, and divided by the RMS current value to obtain a RMS voltage value. For the on-grid operation, this value can be ignored, because the grid will keep the voltage level stable.

A specific DC-AC converter between the battery/PV-system and the other components was omitted for simplification. The error added to the results will be sufficiently small.

For this complete system model, it is also assumed that the PV-system and battery storage are independent systems, which are not controlled by the algorithms developed in this work. These algorithms only deal with the control of the thermal storages. For a more complex and maybe more efficient control, the PV-system and the battery storage should be considered in the algorithms and control strategies. Nevertheless, developing such algorithms exceeds the time frame of this work, but is a good scope for future work.

6. MATLAB SIMULATIONS OF CONTROL STRATEGIES

There are different ways to control the behavior of the thermal storages. They are implemented in a separate Matlab file, which just needs the scenario and algorithm number and a selection of winter/summer mode as inputs. The 16 scenarios were categorized into three, defined by their control algorithm type. The scenario numbers (Sc. No.) are used to identifiy the correct scenario in the Matlab code. The first digit represents the control type and the second digit the activated appliances and grid status.

For **on-grid situation**, the following scenarios apply:

- Freezer
- Water heater
- Space heating/cooling
- All previous appliances

To do comparisons afterwards, each of these grid-connected scenarios is conducted once at summer and once at winter settings for:

- Fixed set point thermostatic control
- Price based control with price based algorithms 0-6 resp. 0-7 (cf. Chapter 6.3.1)

The scenarios conducted for **off-grid situation** are similar:

- Freezer
- Water heater
- Space heating/cooling
- All previous appliances

All these scenarios are conducted without grid connection. To do comparisons, each one is completed once at summer and once at winter settings for:

- Fixed set point thermostatic control
- Voltage and PV-power based algorithms 0-6 resp. 0-7 (cf. Chapter 6.4.1)
- Voltage (and SOC) based algorithms 8-11 (cf. Chapter 6.4.1)

An overview on the scenarios with the resp. scenario numbers is shown in Table 16:

Table 16: Scenarios for simulation

Sc. No.	Activated appliances	Control type	Grid
10	Freezer	Fixed set point	On
11	Water heater		
12	Space H/C		
13	All three		
14	Freezer		Off
15	Water heater		
16	Space H/C		
17	All three		
20	Freezer	Price based	On
21	Water heater		
22	Space H/C		
23	All three		
30	Freezer	Voltage based	Off
31	Water heater		
32	Space H/C		
33	All three		

All scenarios were conducted for each single thermal storage because many dwellings do not have all of those components. This provides a chance to see the influence of each appliance on the costs resp. power consumption. The combination of all three storages can provide results on the possibilities and also negative influences in-between them if they are controlled together. The results of the different scenarios will later be compared to each other, as shown in Figure 9 and Figure 10.

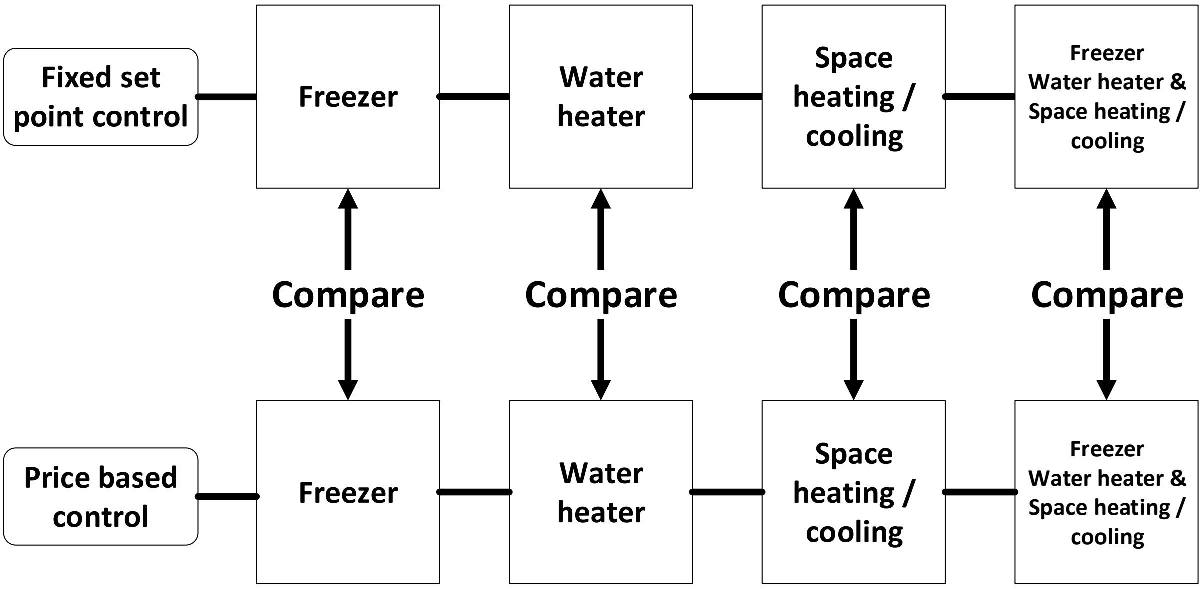

Figure 9: Comparison of on-grid scenarios

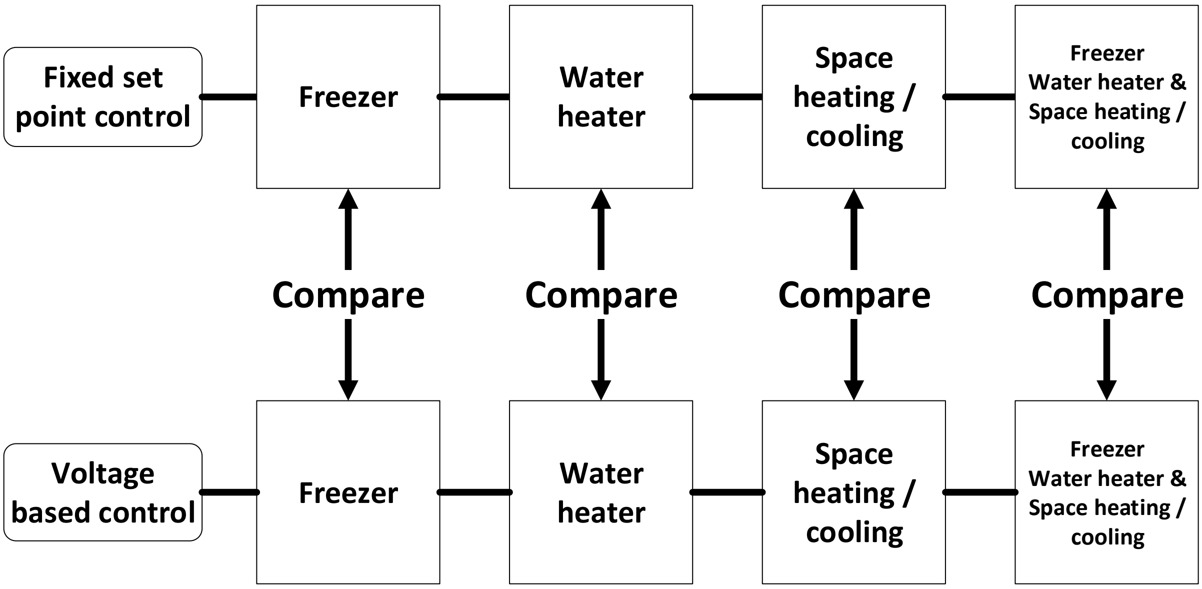

Figure 10: Comparison of off-grid scenarios

6.1. General patterns, variables and boundaries for all simulations

Initial parameters and variables were chosen as follows:

- All necessary variables were initialized and set to zero or a more appropriate initial value, like -18 °C for the initial temperature of the freezer.

- All components were deactivated by default and were activated in and according to the chosen scenario.
- The simulation can be conducted with winter settings or with summer settings. This affects some parameters, like the ambient temperature or the number of PV-modules. A simulation over the whole year is not possible, only one week with winter or summer settings.
- Rough calculations showed that for the worst-case scenario in winter, 600 PV-modules would be needed and for the optimum case in summer, it is 20. So in Estonia, an off-grid system completely relying on PV-modules is not efficient in winter. For the simulations, 30 modules for summer and 120 for winter mode were selected to ensure enough power for the off-grid system.
- As a time step $\Delta t = 1/12[h]$ (= 5 min) was chosen. With 5 min data, the simulations take an acceptable amount of time to calculate and provide more precise results than hourly values. For calculations that are more detailed it would be possible to change the time step to 1 min by doing some changes to the code, like the different patterns for food etc.
- The day needs to be chosen according to the winter/summer mode input variable. Furthermore, it is necessary to change an hour and a day inside the simulations according to their real behavior, meaning a new day starts after 24 h at 0 o'clock.

For all the simulations, different **patterns** are needed. These were chosen in the following way:

- All patterns are given as 5 min data arrays or in the case of 1 min and hourly data, processed to 5 min data.
- The data for the apartment are given as 1 min data. To create a clean household pattern without the consumption data of the appliances to be controlled later, the measured energy consumption of the water heater and floor heating have to be subtracted from the complete energy consumption pattern. The data are given for one week, starting from Monday, 20 February 2010. The apartment is assumed to have a gas stove instead of an electric one.
- Warm water and food consumption patterns are given as 5 min values and represent a whole week.

- The pattern for people being in the apartment is an estimation and assumes three people to be in the apartment from 0:00-9:00 and 17:00-24:00 on workdays and the whole day on weekends.
- The windows are opened for 10 min at 16:45 and 21:00 every day.
- The day-ahead market prices are hourly data from the Nord Pool Elspot database for Estonia. Values from Monday, 20th of February, to Sunday, 26th of February 2017, were used for the winter mode. Summer mode used data from Monday, 21st of August, to Sunday, 27th of August 2017.
- To verify the results later, it would be necessary to repeat all simulations with different patterns and profiles. Unfortunately, there is only one household, food and warm water consumption pattern available.

In the **on-grid simulations**,

- the resulting price was calculated from the resulting amount of power that is drawn from the grid. Therefore, one simulation over the seven days was conducted. The price was calculated afterwards as well as an average price per day, to make it easy to compare the results.
- the simulations were run without a PV-system and battery storage (cf. Figure 7, Chapter 5.5) to reduce errors and coincidences introduced to the complete system by these components. Another justification for this decision is that many dwellings have no PV-system with battery storage. Therefore, the results would not be directly applicable. Furthermore, it will be easier to see the influence of the thermal storage control on the price.

The **off-grid simulations** work in a different way:

- A simulation starts with the smallest battery capacity of 10Ah and a SOC of one.
- If the voltage during the simulation is below the reference voltage minus 15% for more than two time steps, all parameters are reset and the simulation restarts with a 10Ah larger battery capacity. The voltage boundaries are based on the EN 50160:2010 grid norm to ensure stable operation. This voltage check is also shown in Figure 8, Chapter 5.5.

- Before completion, the simulation checks if the SOC at the end is lower than the SOC at the beginning (cf. Figure 8, Chapter 5.5). If it is lower, the simulation restarts with that SOC value again. This ensures that the off-grid system is able to maintain stable operation for more than one week. This is based on the assumption that the household profile used in the simulation represents a typical or in best case, a profile slightly higher than average.
- If the simulation runs 4 times with decreasing SOC, it will also pass as a stable configuration.
- The lowest battery capacity that passes the simulation and can provide a constant SOC represents the minimum possible capacity. Then the control switches to a more accurate step width of 1Ah steps to receive values that are more exact.
- This minimum capacity can be compared with the battery capacities available by companies, e.g. from the Victron Energy catalogue, to check if such a configuration is possible. For a real design, it is common to add a sufficient safety margin to cover unexpected and further events.

Additional remarks to the simulations:

- After the simulations, all important variables and arrays are saved to a file and the most interesting graphs are plotted immediately.
- The current step in the simulation is displayed in the Matlab console to show what is processed at that moment.
- The working principle of the whole simulation and the structure of the complete Matlab code is shown in Figure 7, Chapter 5.5 and Appendix 7, Figure 19.
- Additionally, it may be interesting to use the space heating room temperature as the ambient temperature for the freezer and water heater, as these appliances may be placed in the temperature-controlled room. This could give insight into the influence of the space heating/cooling on other equipment.

In summary, the following **pre-conditions** apply to the complete system for all simulations:

- The ambient conditions of the freezer model are fixed during the simulation.
- The ambient conditions of the water heater model are fixed during the simulation.

- The ambient conditions of space heating/cooling model are fixed during the simulation except the ambient temperature. It depends on the winter/summer settings.
- The thermal storage models do not influence each other thermally.
- The ambient conditions of the PV-system and battery storage are fixed during the simulation.
- Connections between the components are considered ideal.
- The on-grid system does not use the PV-system or battery storage.
- The off-grid system only has the PV-system and battery storage as a power source.
- The number of PV-modules is fixed.
- The frequency of the off-grid system is fixed in any case.
- The voltage of the off-grid system is limited. If there is more energy production than consumption, the average PV-power is reduced. If there is more consumption than energy production, the voltage is considered to show a drop.
- The price based set point calculation algorithms have been pre-selected.
- Fees and taxes are neglected for cost calculations (cf. Chapter 6.2).
- The voltage based set point calculation algorithms have to be developed.
- Safety margins for the battery capacity calculations are neglected.

6.2. Thermostatic control with a fixed set point

The thermostatic control with a fixed set point is the easiest way to operate a freezer, water heater and space heating/cooling. This kind of control is also typical for the components and therefore will be used to create reference values for the comparison with the price based and voltage based control. Simulations are conducted for each of the thermal storages and then for all three combined, first on-grid and then off-grid.

The freezer is turned on if its temperature is below -17.9 °C and is turned off above 18.1 °C for a set point of 18°C. The operating range for the water heater is between 60 °C and 65 °C. The set point is 60°C. Thermostatic control with a fixed set point of 20°C is for keeping the room temperature between 20 °C and 21 °C. This is also called 2-step control or bang-bang control. Figure 11 shows this control for cooling applications like the freezer or space cooling resp. for heating applications like the water heater and space heating. This control was used for all simulations. For the price and voltage based control only the set point was recalculated according to the algorithm.

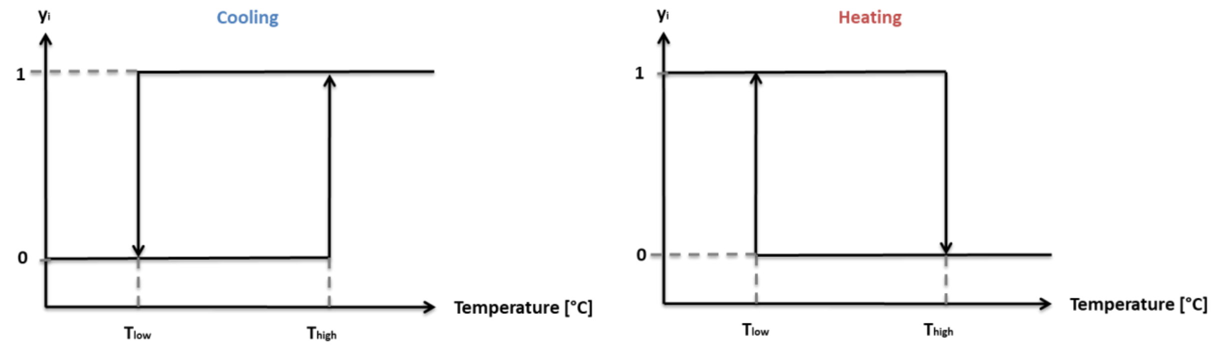

Figure 11: 2-step control for cooling resp. heating applications

All the results of the thermostatic control simulations with a fixed set point at standard conditions (cf. Appendix 10, Table 28) are shown in Table 17.

Table 17: On- and off-grid results for thermostatic control scenarios with a fixed set point

Thermostatic control with fixed set point	**On-grid: Average costs per day [€/d]**		**Off-grid: Minimum battery capacity [Ah] (Battery voltage: 12.8 V)**	
Activated thermal storages	Summer	Winter	Summer	Winter
No thermal storages / household only	0.27	0.21	25	38
Freezer	0.29	0.23	26	40
Water Heater	0.88	0.66	116	149
Space H/C	0.44	0.34	38	54
All three	1.07	0.80	145	153

Obviously, the freezer does not contribute much to the overall energy consumption in comparison with the water heater or space heating/cooling. Compared to the household only simulations, it just slightly increases the needed minimum battery capacity and average price per day. For the water heater and space heating/cooling, greater changes due to the later applied algorithms can be expected because of their higher energy demand. Clearly, the results between summer and winter differ. The different Elspot price patterns cause these variations in the on-grid system. Regarding the off-grid system, the variance in the power provided by the PV-system changes the results between summer and winter simulations, even without any appliances activated.

Thus, additional research on the influence of the over-dimensioning of the PV-system compared to the influence on the battery storage size would be possible.

These results are the basis for the comparisons in Chapters 6.3.2 and 6.4.2.

Therefore, no fees are included in the electricity prices, as there will only be a comparison between the various algorithms and the fixed set point control to see the savings in percent. This means that the fees can be neglected.

For some simulations, it is required to repeat the thermostatic control scenario with a fixed set point to obtain the correct percent-wise changes, e.g. if the ambient temperature for space heating/cooling is altered.

6.3. Price based control for on-grid system

The price based control algorithms calculate a set point for the thermostatic control for each time step, depending on the electricity market prices. Seven different algorithms were implemented and can be compared to each other and the thermostatic control with a fixed set point as described in Chapter 6. The algorithms under investigation were pre-selected by the supervisor based on a previous work.

6.3.1. Algorithms

The algorithms are based on those proposed in [8]. A user comfort level as a scaling factor for the algorithm was implemented. For the results presented here, it was set to one. The difference to the algorithms in [8] is the calculation of the maximum and minimum temperature set points. Instead of calculating those values, the user has to set a minimum, maximum and a goal temperature for each appliance. In this way it can be assured that the temperature will stay within the individually preferred boundaries of the user. An automatic calculation of those values for simpler, but less individual use, which would be more suitable for the consumer market, could be added to the simulation without major effort, but the design of this simulation is made with focus on high flexibility and individualization. Now it is possible to compare the influence of price based control regarding the different appliance, algorithms and environmental conditions. For simplification, the environmental conditions will be considered constant and a comparison will be made for the various appliances and algorithms only. For the last price based scenario with a freezer, a water heater and space heating/cooling combined there is an option available to calculate the optimum combination of algorithms automatically to achieve the lowest price possible. This is algorithm 7.

Figure 12 is a simplified visualization of the linear price based algorithms. The price determines the set point of the thermal storages. A high price results in a low energy consumption set point. The calculations of the algorithms are slightly different (cf. Table 18). A 2-step control like shown in Chapter 6.2 is used with this calculated set point to control the thermal storages.

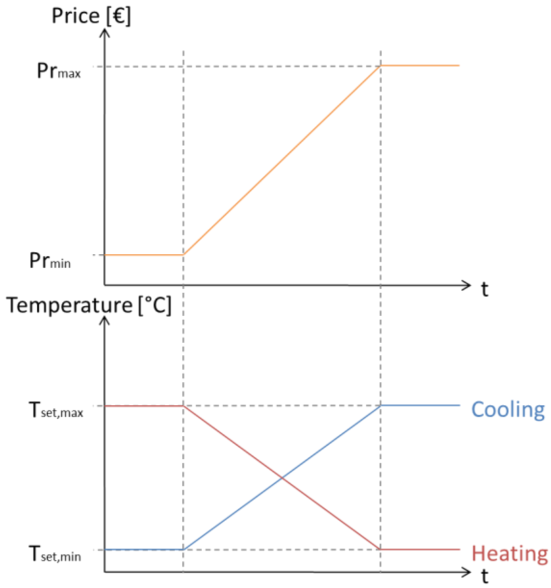

Figure 12: Linear price based set point calculation algorithm visualization for heating and cooling appliances

The initial values of the price based control simulations are the same as in the thermostatic control scenarios with a fixed set point. The user defined goal temperatures and the fixed set point temperatures of the thermostatic control are equal to obtain comparable results. To minimize errors in the beginning of the simulation due to averaging the prices and determining the maximum and minimum price levels, for 1/5 of the calculation time frame of the algorithms, fixed set point control like in the reference scenario was used.

Table 18: Price based control algorithms [8] [63] [64]; Cooling = Freezer and space cooling (summer); Heating = Water heater and space heating (winter)

Number	Description of set point calculation algorithm
0	Cooling: $T_{set} = T_{set,min} + C_{user} * (\mathrm{Pr} - \mathrm{Pr}_{\mathrm{min}}) * \frac{\mathrm{T}_{\mathrm{set,max}} - T_{set,min}}{\mathrm{Pr}_{\mathrm{max}} - \mathrm{Pr}_{\mathrm{min}}}$ Heating: $T_{set} = T_{set,max} - C_{user} * (\mathrm{Pr} - \mathrm{Pr}_{\mathrm{min}}) * \frac{\mathrm{T}_{\mathrm{set,max}} - T_{set,min}}{\mathrm{Pr}_{\mathrm{max}} - \mathrm{Pr}_{\mathrm{min}}}$
1	Cooling: $T_{set} = T_{goal} + C_{user} * \left(\mathrm{Pr} - \mathrm{Pr}_{\mathrm{mavg}}\right) * \frac{\lvert \mathrm{T}_{\mathrm{set,max}} - T_{goal} \rvert}{\mathrm{Pr}_{\mathrm{dev}}}$ Heating: $T_{set} = T_{goal} - C_{user} * \left(\mathrm{Pr} - \mathrm{Pr}_{\mathrm{mavg}}\right) * \frac{\lvert \mathrm{T}_{\mathrm{set,min}} - T_{goal} \rvert}{\mathrm{Pr}_{\mathrm{dev}}}$
2	Cooling: $T_{set} = T_{goal} + C_{user} * \left(\mathrm{Pr} - \mathrm{Pr}_{\mathrm{mavg}}\right) * \frac{\mathrm{T}_{\mathrm{set,max}} - T_{goal}}{\mathrm{Pr}_{\mathrm{max}} - \mathrm{Pr}_{\mathrm{mavg}}}$ Heating: $T_{set} = T_{goal} - C_{user} * \left(\mathrm{Pr} - \mathrm{Pr}_{\mathrm{mavg}}\right) * \frac{\mathrm{T}_{\mathrm{set,min}} - T_{goal}}{\mathrm{Pr}_{\mathrm{min}} - \mathrm{Pr}_{\mathrm{mavg}}}$
3	Cooling: $T_{set} = T_{goal} + C_{user} * (\mathrm{Pr} - \mathrm{Pr}_{\mathrm{min}}) * \frac{\mathrm{T}_{\mathrm{set,max}} - T_{goal}}{\mathrm{Pr}_{\mathrm{max}} - \mathrm{Pr}_{\mathrm{mavg}}}$ Heating: $T_{set} = T_{goal} - C_{user} * (\mathrm{Pr} - \mathrm{Pr}_{\mathrm{min}}) * \frac{\mathrm{T}_{\mathrm{set,min}} - T_{goal}}{\mathrm{Pr}_{\mathrm{min}} - \mathrm{Pr}_{\mathrm{mavg}}}$
4	Cooling: $T_{set} = T_{goal} + C_{user} * \left(\mathrm{Pr} - \mathrm{Pr}_{\mathrm{mavg}}\right) * \frac{\mathrm{T}_{\mathrm{set,max}} - \mathrm{T}_{\mathrm{set,min}}}{\mathrm{Pr}_{\mathrm{max}} - \mathrm{Pr}_{\mathrm{min}}}$ Heating: $T_{set} = T_{goal} - C_{user} * \left(\mathrm{Pr} - \mathrm{Pr}_{\mathrm{mavg}}\right) * \frac{\mathrm{T}_{\mathrm{set,max}} - \mathrm{T}_{\mathrm{set,min}}}{\mathrm{Pr}_{\mathrm{max}} - \mathrm{Pr}_{\mathrm{min}}}$
5	Cooling: $T_{set} = T_{goal} + C_{user} * (\mathrm{Pr} - \mathrm{Pr}_{\mathrm{min}}) * \frac{\mathrm{T}_{\mathrm{set,max}} - \mathrm{T}_{\mathrm{set,min}}}{\mathrm{Pr}_{\mathrm{max}} - \mathrm{Pr}_{\mathrm{min}}}$ Heating: $T_{set} = T_{goal} - C_{user} * (\mathrm{Pr} - \mathrm{Pr}_{\mathrm{min}}) * \frac{\mathrm{T}_{\mathrm{set,max}} - \mathrm{T}_{\mathrm{set,min}}}{\mathrm{Pr}_{\mathrm{max}} - \mathrm{Pr}_{\mathrm{min}}}$
6	Cooling: $\mathrm{Pr} \geq \mathrm{Pr}_{\mathrm{mavg}} \rightarrow T_{set} = \mathrm{T}_{\mathrm{set,max}}\ ;\ Otherwise \rightarrow T_{set} = \mathrm{T}_{\mathrm{set,min}}\ ;$ Heating: $\mathrm{Pr} \geq \mathrm{Pr}_{\mathrm{mavg}} \rightarrow T_{set} = \mathrm{T}_{\mathrm{set,min}}\ ;\ Otherwise \rightarrow T_{set} = \mathrm{T}_{\mathrm{set,max}}\ ;$
7	Determines the optimum combination of algorithms for scenario 23.

Due to the heating and cooling function of the space heating/cooling, in a real system, it is required to establish communication between the controller and the heating/cooling unit to determine the correct algorithm for use depending on the operation mode.

6.3.2. Results

Using the set point calculation algorithms from the previous chapter for all on-grid scenarios described in Chapter 6, the following results can be described after the comparison of the different control strategies:

The complete system model, as shown in Chapter 5.5, was used for all simulations at standard conditions (cf. Appendix 10, Table 28).

The percentagewise cost reduction compared to the fixed set point thermostatic control was calculated based on the appliances energy consumption only. The costs for the household energy consumption were subtracted.

The algorithms react differently to various price patterns, which causes deviations in savings between summer and winter settings. This is higher especially with space heating/cooling, because the system has to switch from cooling to heating mode, which also inverts the algorithms. Excluding the freezer, it is evident that algorithms 3 and 5 present the highest cost reductions. With the combination of the optimum algorithms, it is possible to save about 20% of the costs for the appliances energy consumption, which is about 15% of the whole electrical energy costs of the apartment.

The space heating results in winter settings for algorithm 1 and 6 seem unusual. The costs increase with the price based control. This has the following reasons: during low price periods, occasionally there is no need to heat the apartment due to the low ambient losses of the chosen model and with window openings, it is then necessary to heat to a low amount when there are high prices. This shows that it is difficult to predict the behavior of space heating/cooling, as there are many more influences on the system that can introduce errors. Also, in algorithm 6 there is only a maximum or a minimum set point, and in some situations, a set point in-between would be more efficient.

Example graphs for price based algorithms are presented in Appendix 20, Figure 28-Figure 31. It can be seen that the temperature for the thermal storages changes within their maximum and minimum values according to the chosen algorithm. In this example, algorithm 6 has been applied, so the set points switch between maximum and minimum values.

The different price based scenarios show the following results (cf. Table 19, Appendix 11, Table 29 and Table 30) at standard conditions (cf. Appendix 10, Table 28). For algorithm 7, the chosen algorithm for each thermal storage is written in brackets.

Table 19: Cost reductions with different price based algorithms in comparison with thermostatic control with a fixed set point (standard conditions)

Algorithm	**Summer settings**				**Winter settings**			
	Freezer	Water Heater	Space H/C	All	Freezer	Water Heater	Space H/C	All
0	-5%	-7%	-13%	-8%	-4%	-6%	-3%	-5%
1	-14%	-9%	-13%	-10%	-10%	-4%	5%	-2%
2	-10%	-9%	-15%	-10%	-7%	-5%	-4%	-5%
3	-11%	-19%	-22%	-20%	-10%	-18%	-28%	-20%
4	-14%	-10%	-15%	-11%	-10%	-5%	-6%	-5%
5	-11%	-19%	-22%	-19%	-10%	-18%	-26%	-19%
6	-15%	-6%	-2%	-5%	-11%	-4%	13%	-1%
7	(6)	(3)	(5)	-20%	(6)	(3)	(3)	-20%

To see the influence of different variables on the algorithms, additional simulations were conducted:

- First, the calculation time of the algorithm was changed from 24 h to 12 h (cf. Appendix 12, Table 33-Table 36). This could show different results if the algorithms take just half a day instead of the whole last day (24 h) into account. The results showed similar results to standard conditions, but the savings were smaller. The last algorithm showed just 17% resp. 13% cost reduction whereas at standard conditions, it was 20%. This is mainly caused by space heating/cooling where the algorithms do not perform as well on a 12 h basis.

- Changing the calculation duration to 48 h, in order to take the last 2 days into account for the algorithms, had the same effect (cf. Appendix 13, Table 41-Table 44). It is still possible to reduce the electricity costs, but it will be 18% with summer resp. 19% with winter settings. All appliances showed slightly lower savings than at standard conditions, but still algorithms 3 and 5 seem to perform best for a water heater and space heating/cooling.
- All other parameters set to standard conditions, it is also possible to change the user comfort or algorithm scaling factor. Changing it to 0.5 has a negative effect on most algorithms (cf. Appendix 14, Table 49-Table 52). The results for algorithm 6 are unaffected, because it is not scalable. It always just switches between the minimum and the maximum set points without considering the user comfort scaling factor. Only algorithm 1 shows improvements for more than one kind of thermal storage. With the optimum algorithm combination, it is possible to reduce the electricity costs for the appliances by just 15%. This result was expected because the algorithms are scaled less, thus the set points are closer to the fixed set point of the thermostatic control scenario with a fixed set point.
- Now changing this value to 2.0 results in the opposite effect, at least for algorithms 0, 3 and 5. Algorithms 1, 2 and 4 show worse results (cf. Appendix 15, Table 57-Table 60). The scaling seems to work better for some algorithms than for others. Nevertheless, in most simulations there are still savings compared to the thermostatic control with a fixed set point. Moreover, the algorithms which scale well can create cost reductions for the appliances of up to 23%. This is 3% more than with standard conditions.
- Because the simulation was designed very modular, it is possible to change the specifications of the models with no effort. To see the influence of the models, simulations with an old, less efficient freezer (Specification 6: General), a small POU water heater (Specification 0: Bosch) and a complete floor of a house (Specification 1:

General) were conducted (cf. Appendix 1, Table 24-Table 26, Appendix 16, Table 65 and Table 66). The results are comparable to standard conditions. Algorithms 3 and 5 are working best for a water heater and space heating/cooling. Due to the larger volume that has to be heated resp. cooled, space heating/cooling consumes more energy whereas the water heater uses less because of the smaller water volume. Overall savings are 15% in summer and 21% in winter. That drop in savings with summer settings can be explained with the increased heating of the rooms through the windows due to the sun irradiation, which has to be cooled down with the heat pump.

- Another important influence on the algorithms is the user's choice of minimum and maximum set points. Everything else at standard conditions, the results for an increased temperature range with higher maximum and lower minimum values (cf. Appendix 17, Table 69-Table 73) showed that the freezer is performing better in general. This is due to the higher time constant. The freezer seems to stay near the highest temperature most of the time and cannot cool down fast enough to reach the coolest temperature. The other thermal storages seem to work better with algorithms 3 and 5 again. The other algorithms even show negative results with those appliances. The overall savings increased to 30% resp. 29%, but the temperature changes were higher and the appliances tend to operate closer to the minimum allowed temperature for heating resp. maximum allowed temperature for cooling.
- The last variation to be simulated was extreme ambient temperatures (cf. Appendix 18, Table 78-Table 80). This only applies to space heating and shows that algorithms 3 and 5 are the preferred choice for both summer and winter settings.

6.4. Voltage based control for off-grid system

Twelve voltage based algorithms were implemented to calculate set points for the thermostatic control. These algorithms are based on power, voltage and state of charge values that are available from the other system components. The results were then compared to the fixed set point thermostatic control.

6.4.1. Algorithms

All the voltage based algorithms had the following nonlinear condition implemented: If the grid-voltage in the off-grid system is dropping below the limit of 85% of the nominal voltage (V_N), the minimum energy consumption set point was chosen. Otherwise the set point was calculated according to the available PV-power (Algorithm 0-7) or SOC (Algorithm 9-11). The voltage drop reaction itself can be visualized like shown in Figure 13. In the green area, the set point is calculated according to PV-power or SOC based algorithms. It can be near the maximum or near the minimum set point.

Consider a heating device, the water heater for example. There is a lot of PV-power available, so the set point is calculated to be at the maximum value (cf. Figure 14, Left). The battery's SOC is at the minimum, so it cannot provide any energy. If the consumption of the household is higher than the available PV-power, the voltage will show a drop reaction and the set point for the water heater will be set to the minimum, even though the PV-power generation is high.

Consider the same example for a SOC based algorithm: The water heater's set point will be set to the minimum because the SOC is at the minimum (cf. Figure 14, Right). If the energy consumption is higher than the generated PV-power, the system shows a voltage drop and the set point for the water heater stays at the minimum.

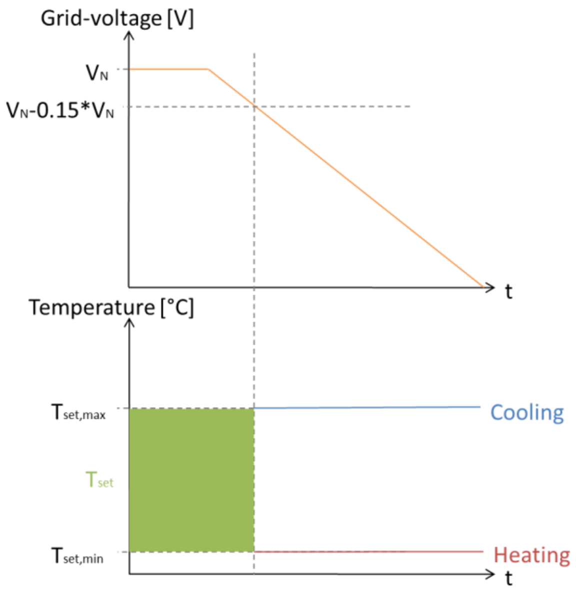

Figure 13: Voltage drop reaction visualization for heating and cooling appliances

The first eight algorithms (Algorithm 0-7) are similar to the ones for price based control. Instead of the price, the basis for calculation was the estimated maximum power the PV-system could provide. To make the algorithms work properly, they have to be adapted like shown in Figure 14 because their behavior has to be exactly the opposite. If the available power is high, the consumed power should be high whilst in the price based control, a low price leads to high consumption. Algorithm 7 again represents a mixed approach with the best algorithms 0-6 for each appliance in a system with all three of them activated.

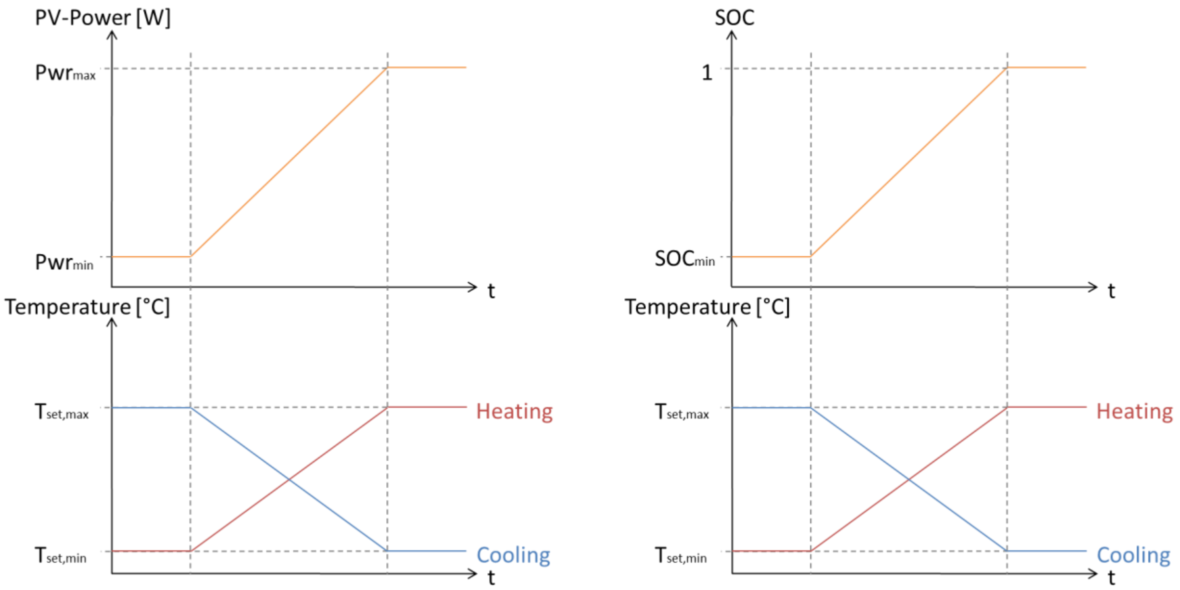

Figure 14: Algorithm visualization for heating and cooling appliances; Left: Linear PV-power based set point calculation; Right: Linear SOC based set point calculation

The initial values of the voltage based control simulations were the same as in the thermostatic control scenarios with a fixed set point. The user defined goal temperatures and the fixed set point temperatures of the thermostatic control were equal to obtain comparable results. To minimize errors in the beginning of the simulation due to averaging the PV-power and determining the maximum and the minimum PV-power levels, for 1/5 of the calculation time frame of the algorithms, fixed set point control like in the reference scenario was used. This only applied for algorithms 0-7.

Algorithm 8 is a simple voltage drop reaction. If the voltage is stable, it operates at the fixed or goal set point, otherwise at the minimum or maximum in the case of cooling (cf. Figure 13).

Algorithm 9 is a SOC limit-based control algorithm. If the battery's state of charge drops below a certain value, it switches from the fixed or goal to the minimum (heating) resp. maximum (cooling) set point. Algorithm 10 changes the set point according to the SOC of the battery in a linear way. A similar approach like in algorithm 0. Algorithm 11 switches between the minimum and the maximum set point according to the battery's state of charge, comparable to algorithm 6.

These algorithms are shown in Table 20 and Table 21.

Table 20: Voltage and PV-power based control algorithms [8] [63] [64]; Cooling = Freezer and space cooling (summer); Heating = Water heater and space heating (winter);

Number	Description of set point calculation algorithm
0	Cooling: $T_{set} = T_{set,max} - C_{user} * (\mathrm{Pwr} - \mathrm{Pwr}_{\min}) * \frac{\mathrm{T}_{\mathrm{set,max}} - T_{set,min}}{\mathrm{Pwr}_{\max} - \mathrm{Pwr}_{\min}}$ Heating: $T_{set} = T_{set,min} + C_{user} * (\mathrm{Pwr} - \mathrm{Pwr}_{\min}) * \frac{\mathrm{T}_{\mathrm{set,max}} - T_{set,min}}{\mathrm{Pwr}_{\max} - \mathrm{Pwr}_{\min}}$
1	Cooling: $T_{set} = T_{goal} - C_{user} * \left(\mathrm{Pwr} - \mathrm{Pwr}_{\mathrm{mavg}}\right) * \frac{\lvert \mathrm{T}_{\mathrm{set,min}} - T_{goal} \rvert}{\mathrm{Pwr}_{\mathrm{dev}}}$ Heating: $T_{set} = T_{goal} + C_{user} * \left(\mathrm{Pwr} - \mathrm{Pwr}_{\mathrm{mavg}}\right) * \frac{\lvert \mathrm{T}_{\mathrm{set,max}} - T_{goal} \rvert}{\mathrm{Pwr}_{\mathrm{dev}}}$
2	Cooling: $T_{set} = T_{goal} - C_{user} * \left(\mathrm{Pwr} - \mathrm{Pwr}_{\mathrm{mavg}}\right) * \frac{\mathrm{T}_{\mathrm{set,min}} - T_{goal}}{\mathrm{Pr}_{\min} - \mathrm{Pr}_{\mathrm{mavg}}}$ Heating: $T_{set} = T_{goal} + C_{user} * \left(\mathrm{Pwr} - \mathrm{Pwr}_{\mathrm{mavg}}\right) * \frac{\mathrm{T}_{\mathrm{set,max}} - T_{goal}}{\mathrm{Pwr}_{\max} - \mathrm{Pwr}_{\mathrm{mavg}}}$
3	Cooling: $T_{set} = T_{goal} - C_{user} * (\mathrm{Pwr} - \mathrm{Pwr}_{\min}) * \frac{\mathrm{T}_{\mathrm{set,min}} - T_{goal}}{\mathrm{Pwr}_{\min} - \mathrm{Pwr}_{\mathrm{mavg}}}$ Heating: $T_{set} = T_{goal} + C_{user} * (\mathrm{Pwr} - \mathrm{Pwr}_{\min}) * \frac{\mathrm{T}_{\mathrm{set,max}} - T_{goal}}{\mathrm{Pwr}_{\max} - \mathrm{Pwr}_{\mathrm{mavg}}}$
4	Cooling: $T_{set} = T_{goal} - C_{user} * \left(\mathrm{Pwr} - \mathrm{Pwr}_{\mathrm{mavg}}\right) * \frac{\mathrm{T}_{\mathrm{set,max}} - \mathrm{T}_{\mathrm{set,min}}}{\mathrm{Pwr}_{\max} - \mathrm{Pwr}_{\min}}$ Heating: $T_{set} = T_{goal} + C_{user} * \left(\mathrm{Pwr} - \mathrm{Pwr}_{\mathrm{mavg}}\right) * \frac{\mathrm{T}_{\mathrm{set,max}} - \mathrm{T}_{\mathrm{set,min}}}{\mathrm{Pwr}_{\max} - \mathrm{Pwr}_{\min}}$
5	Cooling: $T_{set} = T_{goal} - C_{user} * (\mathrm{Pwr} - \mathrm{Pwr}_{\min}) * \frac{\mathrm{T}_{\mathrm{set,max}} - \mathrm{T}_{\mathrm{set,min}}}{\mathrm{Pwr}_{\max} - \mathrm{Pwr}_{\min}}$ Heating: $T_{set} = T_{goal} + C_{user} * (\mathrm{Pwr} - \mathrm{Pwr}_{\min}) * \frac{\mathrm{T}_{\mathrm{set,max}} - \mathrm{T}_{\mathrm{set,min}}}{\mathrm{Pwr}_{\max} - \mathrm{Pwr}_{\min}}$
6	Cooling: $\mathrm{Pwr} \geq \mathrm{Pwr}_{\mathrm{mavg}} \rightarrow T_{set} = \mathrm{T}_{\mathrm{set,min}}$; $Otherwise \rightarrow T_{set} = \mathrm{T}_{\mathrm{set,max}}$; Heating: $\mathrm{Pwr} \geq \mathrm{Pwr}_{\mathrm{mavg}} \rightarrow T_{set} = \mathrm{T}_{\mathrm{set,max}}$; $Otherwise \rightarrow T_{set} = \mathrm{T}_{\mathrm{set,min}}$;
7	Determines a predefined combination of algorithms for scenario 33.

Table 21: Voltage and SOC based control algorithms; Cooling = Freezer and space cooling (summer); Heating = Water heater and space heating (winter);

Number	Description of set point calculation algorithm
8	Cooling: $T_{set} = T_{goal}$ Heating: $T_{set} = T_{goal}$
9	Cooling: $\mathrm{SOC} \geq \mathrm{SOC}_{\mathrm{min}} + 0.2 \rightarrow T_{set} = T_{goal}$; $Otherwise \rightarrow T_{set} = \mathrm{T}_{\mathrm{set,max}}$; Heating: $\mathrm{SOC} \geq \mathrm{SOC}_{\mathrm{min}} + 0.2 \rightarrow T_{set} = T_{goal}$; $Otherwise \rightarrow T_{set} = \mathrm{T}_{\mathrm{set,min}}$;
10	Cooling: $T_{set} = T_{set,max} - C_{user} * (SOC - SOC_{min}) * \frac{\mathrm{T}_{\mathrm{set,max}} - T_{set,min}}{\mathrm{DOD}_{\mathrm{max}}}$ Heating: $T_{set} = T_{set,min} + C_{user} * (SOC - SOC_{min}) * \frac{\mathrm{T}_{\mathrm{set,max}} - T_{set,min}}{\mathrm{DOD}_{\mathrm{max}}}$
11	Cooling: $\mathrm{SOC} \geq (1 + \mathrm{SOC}_{\mathrm{min}})/2 \rightarrow T_{set} = \mathrm{T}_{\mathrm{set,max}}$; $Otherwise \rightarrow T_{set} = \mathrm{T}_{\mathrm{set,min}}$; Heating: $\mathrm{SOC} \geq (1 + \mathrm{SOC}_{\mathrm{min}})/2 \rightarrow T_{set} = \mathrm{T}_{\mathrm{set,min}}$; $Otherwise \rightarrow T_{set} = \mathrm{T}_{\mathrm{set,max}}$;

6.4.2. Results

To obtain results for comparison, the scenarios for off-grid situation from Chapter 6 were simulated with all set point calculation algorithms presented in the previous chapter. The complete system model described in Chapter 5.5 was used at standard conditions (cf. Appendix 10, Table 28).

It can be seen that the first six algorithms seem to work opposite to the price based simulations. Algorithms 3 and 5 show poor results, whereas algorithm 0, 1 and 6 perform best. Algorithm 7, as a combination of the best algorithms for each thermal storage alone, shows the best results here. For an off-grid system and for an on-grid system with weak electrical installations, to prevent simultaneous turn-ons, it might be better to use different algorithms for different thermal storages.

The SOC based algorithms also show good results. With number 9, 10 and 11, it is possible to reduce battery storage by 27%-36%. This is around 1/3. In summer settings, algorithm 10 even shows the best overall results. This is an important finding, as the value for the maximum available PV-power might not be obtainable, whereas the SOC-state always is. Further, these algorithms do not depent on the energy source of the microgrid.

Another important conclusion can be drawn from the results of algorithm 8. Just by switching to the minimum set point if the voltage starts dropping, it is possible to reduce the battery capacity by up to 18%. That is a very good result, as this algorithm only relies on the voltage measurement and needs no additional measurements in a real system. It is totally independent of the system configuration whether there is a PV-system, wind turbines, a battery storage, a flywheel or any other component.

The result for space cooling in summer settings is unusual. Due to a coincidence between the algorithm set point calculation, the power consumption and the SOC of the battery system, the minimum capacity even increased. Such coincidences can happen any time, also with fixed set point control. For that reason, safety margins are typically added to the minimum battery capacity.

Further, it can be observed that large savings in systems with one thermal storage each do not necessarily lead to large savings in a system with all three of them and vice versa.

Example graphs are shown in Appendix 21, Figure 32-Figure 37. It can be observed that the temperature set points follow the SOC of the battery storage. The voltage remains constant, while the PV-system is utilized as much as possible.

Simulations for the voltage based algorithms determine the following results (cf. Table 22, Table 23, Appendix 11, Table 31 and Table 32). The values in the tables show the percentage of the reduction of the battery storage for the complete household compared to the fixed set point thermostatic control.

Table 22: Battery capacity reductions with different voltage based algorithms in comparison with thermostatic control with a fixed set point (standard conditions; PV-power based)

Algorithm	**Summer settings**				**Winter settings**			
	Freezer	Water Heater	Space H/C	All	Freezer	Water Heater	Space H/C	All
0	-4%	-32%	-34%	-46%	-3%	-34%	-6%	-29%
1	0%	-34%	-34%	-48%	-3%	-32%	-6%	-29%
2	0%	-16%	-34%	-39%	-3%	-17%	-6%	-17%
3	-4%	-12%	-29%	-17%	-3%	-15%	-6%	-7%
4	-4%	-23%	-34%	-40%	-3%	-26%	-6%	-14%
5	-4%	-10%	-26%	-17%	-3%	-15%	-6%	-9%
6	0%	-38%	-34%	-50%	-3%	-34%	-6%	-31%
7	(0)	(6)	(1)	-50%	(0)	(6)	(1)	-34%

Table 23: Battery capacity reductions with different voltage based algorithms in comparison with thermostatic control with a fixed set point (standard conditions; SOC / voltage based)

Algorithm	**Summer settings**				**Winter settings**			
	Freezer	Water Heater	Space H/C	All	Freezer	Water Heater	Space H/C	All
8	0%	-1%	0%	-12%	0%	-15%	0%	-18%
9	0%	-21%	0%	-30%	-3%	-30%	0%	-27%
10	0%	-25%	-24%	-35%	-3%	-31%	-30%	-35%
11	0%	-21%	3%	-36%	0%	-36%	-4%	-30%

Changes in different variables for the simulations show the following:

- In general, the performance of simulations with the 12 h resp. 48 h algorithm calculations (cf. Appendix 12, Table 37-Table 40, Appendix 13, Table 45-Table 48) is worse compared to standard conditions. In the main, space heating/cooling seems to be influenced. On a 12 h basis, the obtained results show poor performance, especially in winter conditions. For the 48 h calculations, it is the other way round, also mainly at winter settings.
- Changing the user comfort to 0.5 has a negative impact on most affected algorithms with the exception of space heating (cf. Appendix 14, Table 53-Table 56). Whereas a scaling factor of 2.0 shows mainly a positive impact (cf. Appendix 15, Table 61-Table 64). Only algorithm 10 seems to perform worse in both cases.
- With other thermal storage models, like in the price based simulations, the state of charge based algorithms are superior to the others (cf. Appendix 16, Table 67 and Table 68). Additionally, it can be observed that a combination of the optimum algorithms for each thermal storage alone does not necessarily lead to a better result in a system with all three of them. Even though using the same algorithm for all three appliances in the system might simplify the implementation, it can lead to a worse performance than the fixed set point thermostatic control. This is caused by all thermal storages turned on at the same moment, caused by the algorithm. It can be observed for algorithm 3 at summer settings.
- A larger temperature range leads to a larger reduction of battery storage (cf. Appendix 17, Table 69,Table 74-Table 77). The exception is again space heating. Unfortunately, the temperature cannot fall to the minimum set point in time, so it permanently stays near the maximum. Because this maximum is set higher, the energy consumption is as well leading to larger mandatory battery capacities.
- For the extreme temperature simulations, it is necessary to increase the number of solar modules for the winter settings. Otherwise, there is not enough electrical energy available. Because there is a higher energy demand, the potential for savings is greater. This is shown by the results as well (cf. Appendix 18, Table 78, Table 81 and Table 82)

- Using AGM batteries instead of those of LiIon will increase the necessary battery capacity, but it will also increase the percent-wise reduction compared to the corresponding thermostatic control with fixed set point results (cf. Appendix 19, Table 83 and Table 84). Moreover, it has to be considered that the price for the same capacity is lower for AGM batteries. Additional research can be conducted in this direction as well.

Figure 15 shows voltage drops during a simulation. This case is handled as a successful pass, because the drops only last for one time step. However, the voltage level can go very low within 5 min and a real system would have shut down in that state already. For future work, it is required to select a smaller time step for the voltage calculation. Then it will represent the real system more accurately.

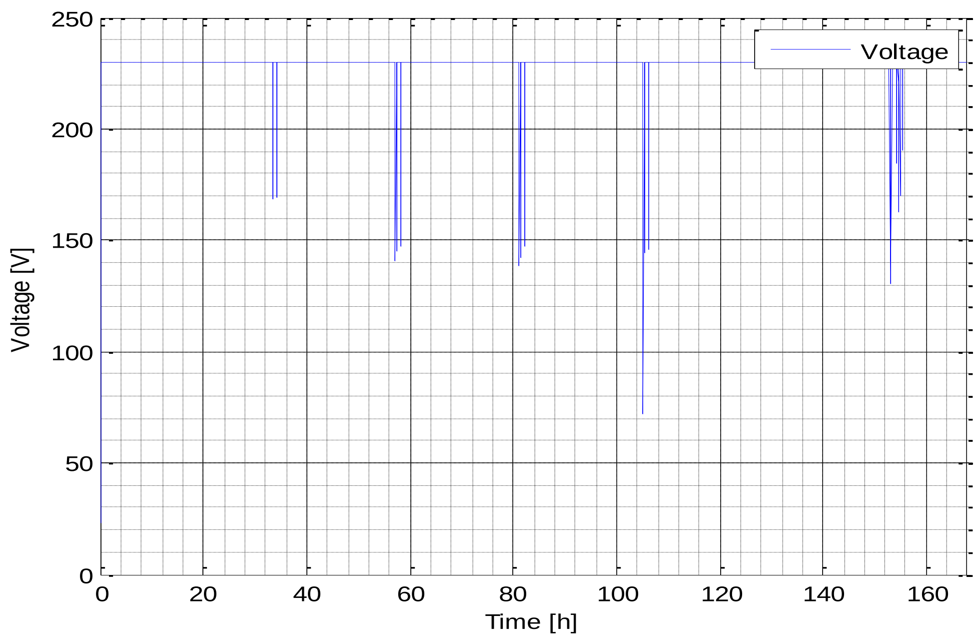

Figure 15: Voltage drop example; all thermal storages activated; algorithm 6; winter settings

7. CONCLUSIONS

For a typical household, different loads can be used as thermal storages. A freezer, a water heater and space heating resp. cooling could be identified as such thermal storages, which can potentially be controlled in a demand side management manner. All these systems have a fair share in the electrical energy consumption of households in Estonia and Germany; thus, it is important to investigate their load scheduling possibilities. Various parameters and characteristics of each system, like lifetime and typical dimensioning, have been identified to provide a basis for object modeling. In addition, some differences between Estonia and Germany have been pointed out.

In the next step, scientific articles on modeling freezers, water heaters and space heating/cooling were reviewed and some interesting modeling possibilities were highlighted and evaluated. All the models developed in this work are described separately, thermal and electrical calculations in the models are shown. Subsequently, the whole system consisting of all the modeled components is illustrated with all its behaviors. The models were simplified, especially the PV-system and the battery storage, but due to a modular structure it is possible to improve those later.

In the last step, the control strategies were implemented. Therefore, a fixed set point thermostatic control simulation for every scenario was conducted to obtain a basis for comparison with other control strategies. The scenarios include on- and off-grid situations for a system with each thermal storage alone in a household, and a system using all three of them. Different price based algorithms proposed in literature were implemented and the results reviewed. On that basis, it is possible to develop voltage based algorithms, depending on different input parameters. Results for price based and voltage based control are as follows.

Applying price based control strategies shows that in most cases algorithm 3 and 5 result in the largest savings. For space heating/cooling and water heater a control system like that should be considered for electricity cost reduction, using one of those algorithms. For a freezer alone, the savings are quite low due to the low power consumption, so investing in such a system only for a freezer configuration will not pay off soon. If there are different thermal storages in the system, it is better to run the different appliances with different algorithms, especially if there are weak electrical installations, to reduce the probability for simultaneous turn-ons. Maximum savings of up to 20% cost reduction could be achieved.

Using similar algorithms based on power, voltage and SOC measurements instead of the price shows useful results for off-grid systems. Since the freezer has low power consumption, the difference to the fixed set point control is negligible. For the other appliances, the SOC based algorithms show good performance similar to those based on PV-power. However, SOC values are usually available whereas the PV-power does not necessarily have to be, so a SOC based control is preferable. Further, a simple voltage drop based algorithm, which is switching to minimum energy consumption set points, can already reduce the size of the battery storage. Therefore, the recommendation for off-grid systems is the use of SOC based algorithms, or just a voltage based one. Battery capacity reductions by 1/3 could be achieved.

During this work, many simplifications had to be made, so there are many opportunities for future work. The battery storage and PV-system models can be optimized. Solar irradiation, cold water temperature and ambient temperatures profiles can be measured. The space heating/cooling temperature can be used as the ambient temperature for the freezer and water heater, to identify the influences. Another possibility is the research on the influence of the number of PV-modules resp. the over dimensioning of the PV-system on the whole system. Further, the system's efficiency based on the different conversion losses can be analyzed. In addition, it is required to consider an optimization of the battery's lifetime and cycle costs, especially when integrating a battery and PV-system into the algorithm control. The algorithms can also be revised and it is required to investigate their influence on each other, with more than one thermal storage in an off-grid system. More household profiles need to be tested to verify the results of this work and it is advisable to consider algorithms including household measurements for better power quality in the off-grid system. In addition, the time step width of the simulation has to be reduced to obtain results that are more accurate. The PV-inverter and battery controller models can be improved as well. For the thermal storage models, several improvements are possible, like the addition of thermal capacities for the freezer and water heater themselves or the thermal capacity for the walls of the apartment or house model. Other renewable energy sources can also be modeled.

In summary, it is possible to reduce the capacity of the electrical storage in an off-grid system by controlling thermal storages that are already available. Therefore, modified price based control algorithms can be used. The results suggest that the battery storage can be reduced in this way up to a value of 2/3 of the capacity needed for a typical fixed set point control. This enables a large reduction of initial investment costs in an electrical storage system. It is required to conduct further investigations as well as measurements of a test system in order to obtain results that are more accurate and to verify them.

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APPENDIX

Table 24: Freezer specification numbers

Specification Number	Manufacturer
0	Bosch (cf. Table 3)
1	Beko (Upright) (cf. Table 3)
2	Gorenje (cf. Table 3)
3	Beko (Chest type) (cf. Table 4)
4	Bauknecht (cf. Table 4)
5	AEG (cf. Table 4)
6	General (Old, low efficiency)

Table 25: Water heater specification numbers

Specification Number	Manufacturer
0	Bosch (cf. Table 5)
1	Eemax (cf. Table 5)
2	AO Smith (cf. Table 6)
3	Whirlpool (cf. Table 6)
4	General

Table 26: Space heating/cooling specification numbers

Specification Number	Manufacturer
0	Example apartment
1	General (Complete floor of a house)

Table 27: Battery specification numbers

Specification Number	Manufacturer
0	Lithium Ion
1	AGM

APPENDIX 2. EXAMPLE SPECIFICATIONS FOR OBJECT MODELS

Name	Value
A_f	5.86
P_annual	174
P_el_f	27
P_max	120
V_f	286
V_fr_max	22
t_fault	25

Figure 16: Freezer specification 0 (Bosch)

Name	Value
A_wh	2.493
P_max	4500
U_wh	0.4
V_wh	150
eta_wh	0.95

Figure 17: Water heater specification 2 (AO Smith)

Name	Value
A_floor	67.4
A_roof	67.4
A_wall	42.375
A_wall_in	48.875
A_window1	7.2
A_window2	4.705
A_window3	0
A_window4	0
P_c	2000
P_h	2000
U_roof	0
U_window	0.6
V_furn	0.05
eh_nr	1
h	2.5
r_ins	0.037
r_wall	0.18
surface_azimuth1	90
surface_azimuth2	180
surface_azimuth3	-90
surface_azimuth4	0
t_ins	0.1
t_wall	0.25

Figure 18: Space heating/cooling specification 0 (Example apartment)

APPENDIX 3. MATLAB CODE FOR THE FREEZER MODEL

```
function [ Tnext, P_el ] = model_freezer(model, yi, Ti, Tamb, Tf, dt, mi,
k)

%MODEL_FREEZER models of different freezers
%   model of freezer; calculation of temperature at end if time step i;
%   Author: Tobias Häring;

%load constants like specitic heat capacities

load ('constants');
cpi=cpi/3.6;
cpw=cpw/3.6;

%P_el_f, eta_f, V_f, t_fault and A_f are selected with the input parameter 'model'
by loading a parameter file accordingly

switch model
    case 0
        load ('freezer_models/freezer_bosch_spec');
    case 1
        load ('freezer_models/freezer_beko_U_spec');
    case 2
        load ('freezer_models/freezer_gorenje_spec');
    case 3
        load ('freezer_models/freezer_beko_C_spec');
    case 4
        load ('freezer_models/freezer_bauknecht_spec');
    case 5
        load ('freezer_models/freezer_aeg_spec');
    case 6
        load ('freezer_models/general_spec');
end

%k is used for calculating P_el_f; for normal operation: k=0;

if k ~= 0
    P_el_f = k;
end


%Claculate U-value of freezer, t_fault is the time it takes a full freezer to heat
up from -18°C to -9°C when switched off

U_f = ((((V_f*cpi*9)/3600*1000)/9)/t_fault)/A_f;

%If food temperature >0°C, a corrected food temperature Tfc is calculated, to use
the heat capacity of ice for temperatures >0°C

if Tf > 0 && mi > 0
    Tfc = Ti-(((mi*cpi*Ti)+(mi*cpw*(-Tf)))/(mi*cpi));
else
    Tfc = Tf;
end

%Calculate alpha, beta and the efficiency eta

alpha = U_f*A_f;
beta = 1/(V_f*cpi);
```

```
eta_f = ((V_fr_max/V_f)*(-18-45.65217)+beta*24*alpha*(-18-20))/(beta*24*P_el_f*(-
1));


%Calculate Temperature changes during time step i

T_freeze = beta*dt*P_el_f*eta_f*yi;
T_food = (mi/V_f)*(Ti-Tfc);
T_amb_loss = beta*dt*alpha*(Ti-Tamb);

%Calculate temperature at the end of time step i

Tnext = Ti-T_freeze-T_food-T_amb_loss;
P_el = P_el_f*yi;
```

APPENDIX 4. MATLAB CODE FOR THE WATER HEATER MODEL

```
function [ Tnext, P_el ] = model_water_heater( model, yi, Ti, Tamb, Tcw, dt, Vi )
%MODEL_WATER_HEATER Model of a Water heater
%   Model of a water heater, calculating the temperature for the next timestep;
%   Autor: Tobias Häring;

%load constants like specitic heat capacities

load ('constants');
cpw=cpw/3.6;


%P_max, eta_wh, V_wh and A_wh are selected with the input parameter 'model' by
loading a parameter file accordingly

switch model
    case 0
        load ('water_heater_models/wh_bosch_spec');
    case 1
        load ('water_heater_models/wh_eemax_spec');
    case 2
        load ('water_heater_models/wh_aosmith_spec');
    case 3
        load ('water_heater_models/wh_whirlpool_spec');
    case 4
        load ('water_heater_models/general_spec');
end

%Tank cannot be more than 100% full:

if Vi > V_wh
    Vi = V_wh;
end

%Calculate alpha and beta

alpha = U_wh*A_wh;
beta = 1/(V_wh*cpw);

%Calculate Temperature changes during time step i

T_heating = beta*dt*P_max*eta_wh*yi;
T_cw = (Vi/V_wh)*(Ti-Tcw);
T_amb_loss = beta*dt*alpha*(Ti-Tamb);

%Calculate temperature at the end of time step i

Tnext = Ti+T_heating-T_cw-T_amb_loss;
P_el = P_max*yi;
```

APPENDIX 5. MATLAB CODE FOR THE SPACE HEATING/COOLING MODEL

```
function [ Tnext, Tpred, P_el, cop ] = model_space_heating( model, yi, Ti, Tamb,
dt, Vi, zi, ki, day, hour, si, eh )
%MODEL_SPACE_HEATING model for space heating
%   calculating the temperature for the next time step of an apartment or house
model
%   Author: Tobias Häring

%load constants like specitic heat capacities

load ('constants');
cpa = cpa/3.6;
cpwood = cpwood/3.6;

P_person = 75*0.58; %heat dissapation of a human during 1 hour [W] according to
ASHRAE;

%P_max, eta, etc. are selected with the input parameter 'model' by loading a
parameter file accordingly

switch model
    case 0
        load ('space_heating_models/apartment_spec');
    case 1
        load ('space_heating_models/general_spec');
end

%Calculate Air Volume in m^3

V_max = (((A_floor+A_roof)*0.5)*h)*(1-V_furn);
V_wood = (((A_floor+A_roof)*0.5)*h)*V_furn;

%Room cannot be more than 100% fresh ambient air:

if Vi > V_max
    Vi = V_max;
end

%Calculate U value of the outside walls

U_wall = 1/((1/(r_ins*t_ins))+(1/(r_wall*t_wall)));

%Calculate alpha and beta

alpha = U_wall*(A_wall-
(A_window1+A_window2+A_window3+A_window4))+U_window*(A_window1+A_window2+A_window3+
A_window4)+U_roof*A_roof; %Walls, Windows, Roof;
beta = 1/(V_max*density_air*cpa+V_wood*density_wood*cpwood);

%Solar heat power calculation

P_solar = A_window1 * calc_solar(day, hour, surface_azimuth1 )+ A_window2 *
calc_solar(day, hour, surface_azimuth2 )+A_window3 * calc_solar(day, hour,
surface_azimuth3 )+A_window4 * calc_solar(day, hour, surface_azimuth4 );

%COP estimation of the heat pump

if Ti < Tamb
    Tc = Ti;
```

```
    Th = Tamb;
else
    Tc = Tamb;
    Th = Ti;
end

cop = (2.5/28)*Tc+((2.5/28)*18+1);

if cop > 4.5
    cop = 4.5;
elseif cop < 0.5
    cop = 0.5;
end

if (Th-Tc) > 20 && (Th-Tc) < 70
    %cop = cop * 1.433922*exp(-0.018021*(Th-Tc)); %modeling as exponential function
    cop = cop * ((16/70875)*((Th-Tc)^2)-(149/4725)*(Th-Tc)+(4367/2835)); %modeling
as polynomial
elseif (Th-Tc) >= 70
    %cop = cop * 1.433922*exp(-0.018021*(Th-Tc)); %modeling as exponential function
    cop = cop * 0.44; %modeling as polynomial
end

%Calculate Temperature changes during time step i

T_people = ki*P_person*dt*beta;
T_window = (Vi/V_max)*(Ti-Tamb);
T_amb_loss = beta*dt*alpha*(Ti-Tamb);
T_sun_rad = P_solar*dt*beta*si;


T_hc = beta*dt*(zi * P_h + ((zi-1)*-1) * -P_c)*cop*yi; %zi=0: Cooling; zi=1:
heating

% Electric heaters with 2kW, heat pump turned off

if eh == 1 && zi == 1
    P_h = eh_nr*2000;
    P_c = 0;
    T_hc = beta*dt*P_h*yi;
end

%Calculate temperature at the end of time step i and prediction if it is
%heating or cooling mode;

Tnext = Ti+T_hc-T_window-T_amb_loss+T_people+T_sun_rad;
Tpred = -T_window-T_amb_loss+T_people+T_sun_rad;
P_el = (zi * P_h + ((zi-1)*-1) * P_c)*yi;
```

```
function [ Ti_f_o, Ti_wh_o, Ti_sp_o, Tpred_sp, cop, SOC, P_el_f, P_el_wh, P_el_sp,
P_pv_max, P_pv_c, Pi_bat, P_c, P_d, P_tot, P_tot_c, V_off ] = system_model( dt,
yi_f, Ti_f, mi_f, yi_wh, Ti_wh, Vi_wh, yi_sp, Ti_sp, Vi_sp, zi, ki, eh, yi_pvbat,
day, hour, P_bat_c, P_bat_d,P_hh )
%SYSTEM_MODEL On grid system model
%   Freezer, Water heater, Space heating, PV, battery and grid connected system
used for price based control
%   Author: Tobias Häring

% Variables

V_eff = 230;

% load parameters from file

load('system_parameters');

% freezer

if yi_f < 2
    [Ti_f_o P_el_f]=model_freezer(model_f,yi_f,Ti_f,T_amb_f,T_food,dt,mi_f, 0);
else
    Ti_f_o = -18;
    P_el_f = 0;
end

I_eff_f = P_el_f/V_eff;

%water heater

if yi_wh < 2
    [Ti_wh_o
P_el_wh]=model_water_heater(model_wh,yi_wh,Ti_wh,T_amb_wh,T_coldwater,dt,Vi_wh);
else
    Ti_wh_o = 60;
    P_el_wh = 0;
end

I_eff_wh = P_el_wh/V_eff;

%space heating

if yi_sp < 2
    [Ti_sp_o Tpred_sp P_el_sp cop] = model_space_heating(model_sp, yi_sp, Ti_sp,
T_amb_sp, dt, Vi_sp, zi, ki, day, hour, solar_sp, eh);
else
    Ti_sp_o = 20;
    Tpred_sp = 0;
    P_el_sp = 0;
    cop = 0;
end

I_eff_sp = P_el_sp/V_eff;

%PV system

if yi_pvbat < 2
    P_pv = model_pv(day, hour, dt, nr_modules)/dt;
```

```
else
    P_pv = 0;
end

P_pv_max = P_pv * eff_inverter;

%Power preliminary

P_prel = P_hh + P_el_sp + P_el_wh + P_el_f - P_pv_max;

%battery controller

if P_prel < 0 && yi_pvbat < 2
    Pi_bat = min([abs(P_prel),(P_bat_c/dt)])*dt;
elseif P_prel > 0 && yi_pvbat < 2
    Pi_bat = (-1)*min([abs(P_prel),abs(P_bat_d/dt)])*dt;
else
    Pi_bat = 0;
end

if Pi_bat > 0
    I_eff_bat = (Pi_bat/dt)/V_eff;
else
    I_eff_bat = 0;
end

%battery

if yi_pvbat < 2
    [ SOC P_c P_d ] = model_battery(model_bat, Pi_bat, dt);
else
    SOC = 0;
    P_c = 0;
    P_d = 0;
end

%Power total

P_tot = P_prel+(Pi_bat/dt);

%Inverter: current control mode: Power can be set between 0 and P_pv; voltage and
frequency provided by Grid;

if P_tot < 0
    P_pv_c = P_pv_max+P_tot;
    if P_pv_c < 0
        P_pv_c = 0;
    end
P_tot_c = P_tot+P_pv_max-P_pv_c;
else
    P_pv_c = P_pv_max;
    P_tot_c = P_tot;
end

% Voltage calculation

if Pi_bat < 0
    P_prod = P_pv_c-(Pi_bat/dt);
else
    P_prod = P_pv_c;
end

I_eff_hh = P_hh/V_eff;
I_eff = I_eff_f + I_eff_wh + I_eff_sp + I_eff_bat + I_eff_hh;
```

```
if yi_pvbat < 2 && I_eff ~=0
    V_off = P_prod/I_eff;
else
    V_off = 230;
end
```

APPENDIX 7. MATLAB CODE STRUCTURE

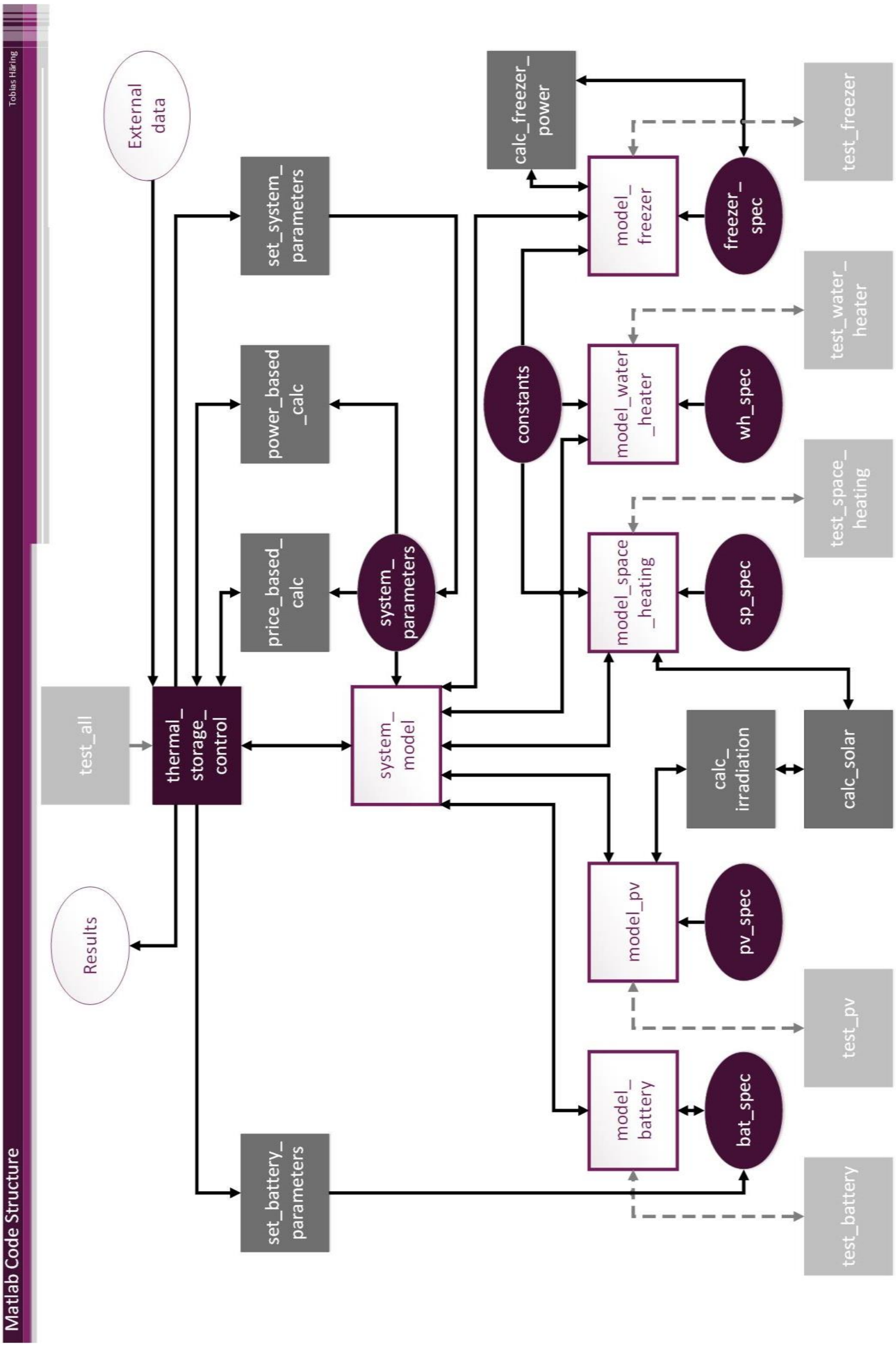

Figure 19: Matlab code structure

APPENDIX 8. VERIFICATION GRAPHS FOR THE FREEZER

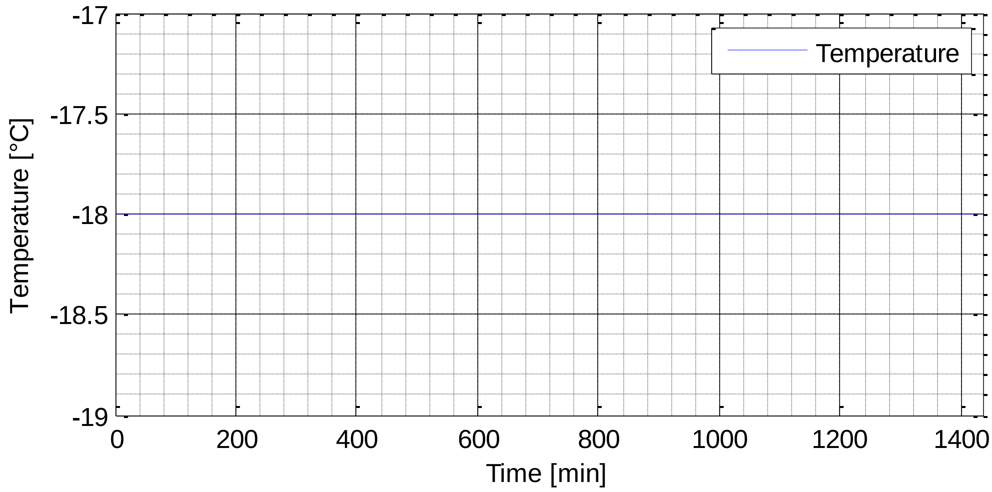

Figure 20: Freezer test: Distributed maximum food exchange

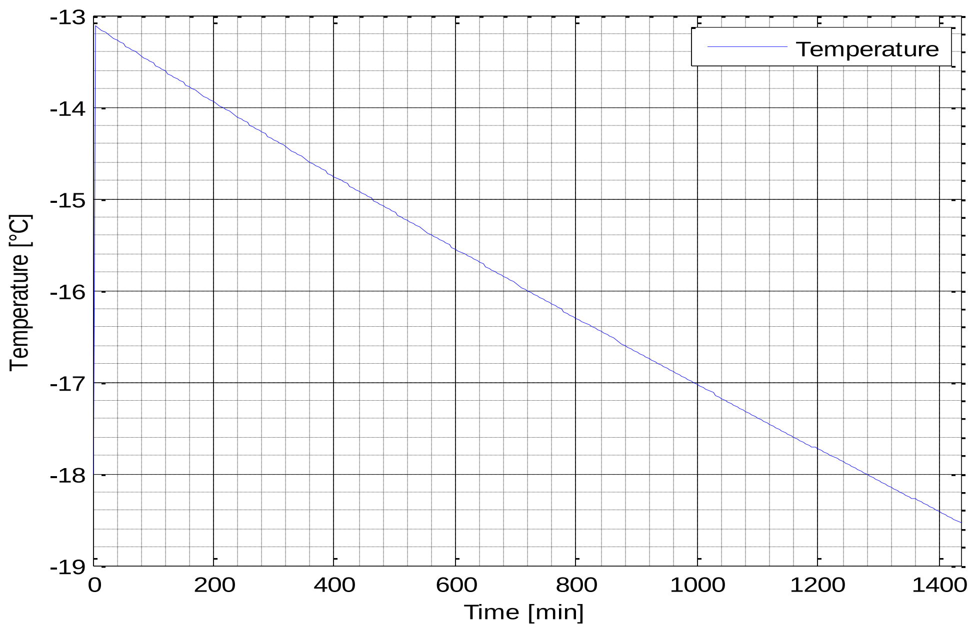

Figure 21: Freezer test: Complete maximum food exchange at once

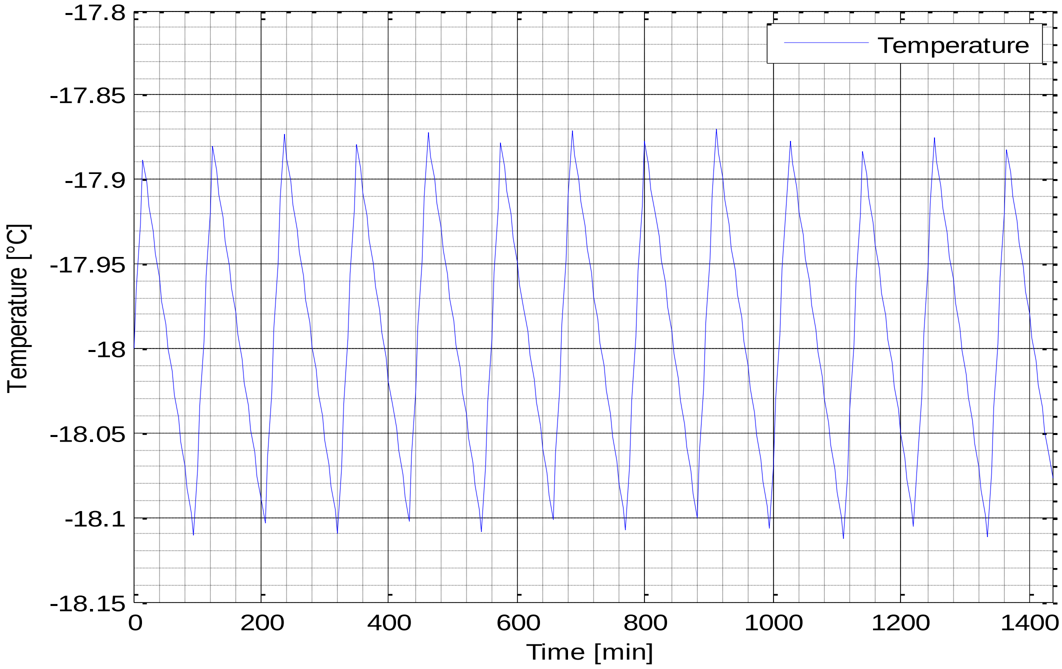

Figure 22: Freezer test: Thermostatic control temperature

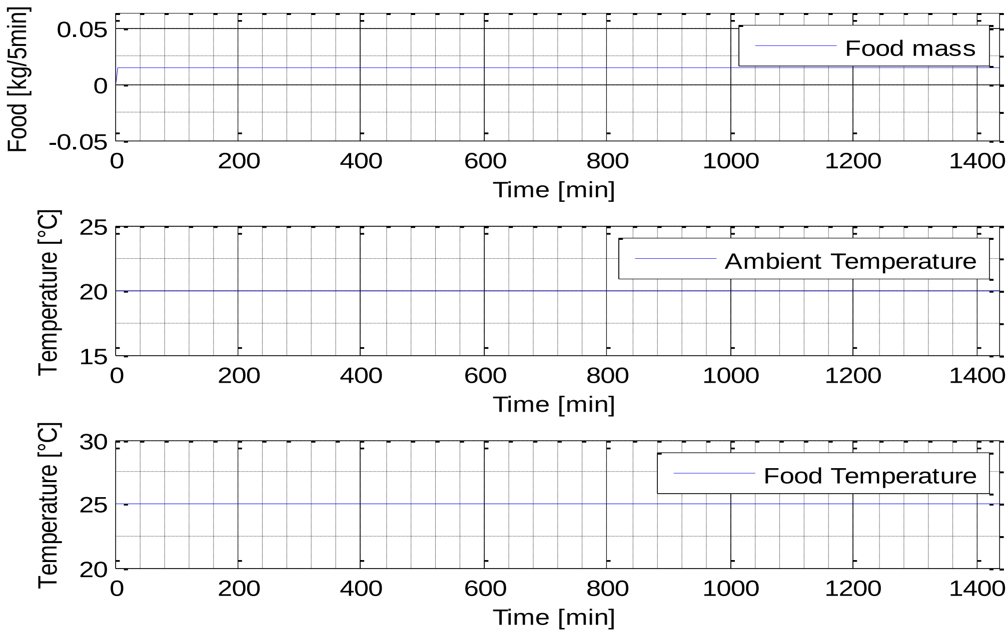

Figure 23: Freezer test: Food mass, ambient temperature and food temperature for thermostatic control

APPENDIX 9. VERIFICATION GRAPHS FOR THE WATER HEATER

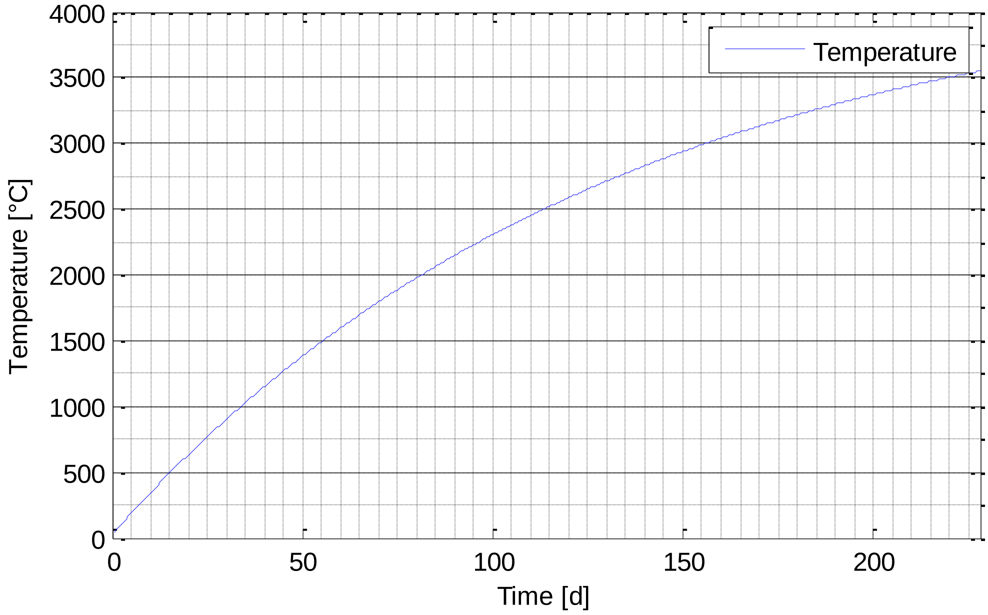

Figure 24: Water heater test: Heating

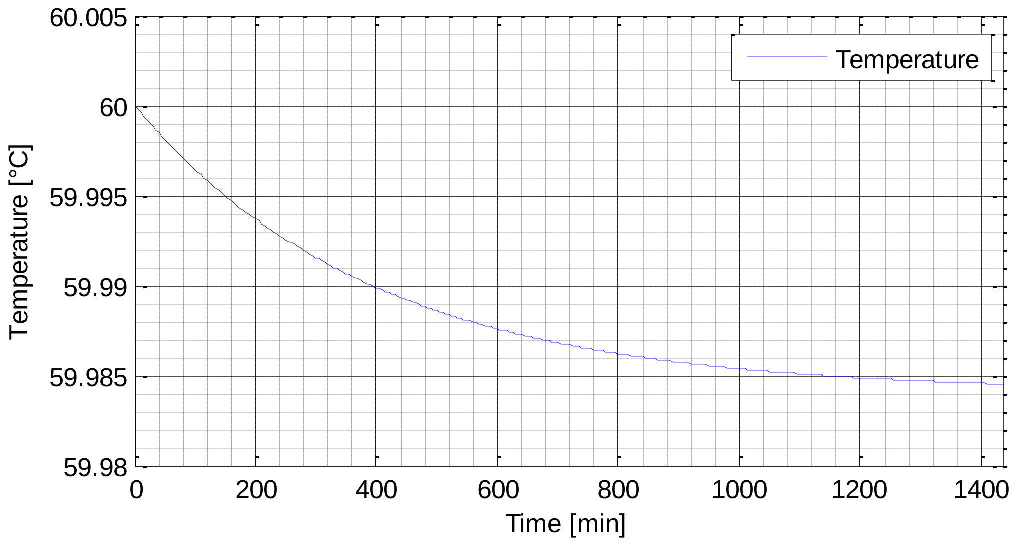

Figure 25: Water heater test: Maximum water fluctuation

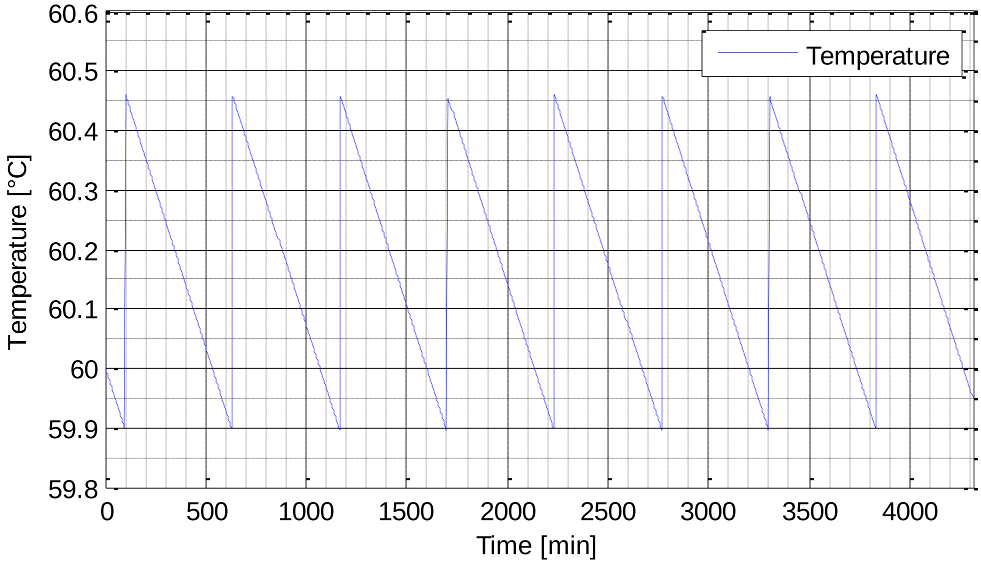

Figure 26: Water heater test: Thermostatic control temperature

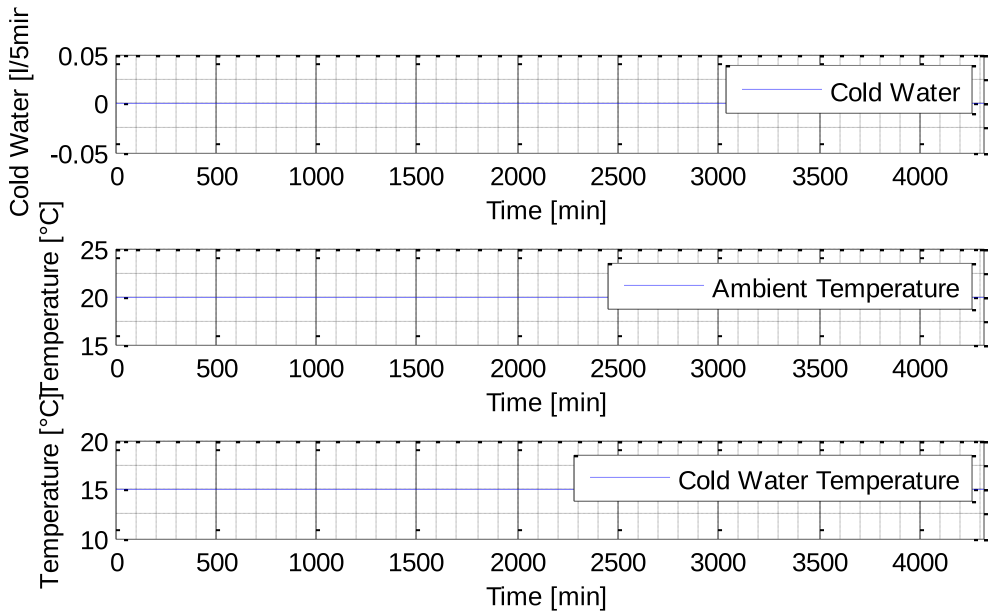

Figure 27: Water heater test: Cold water fluctuation, ambient temperature and cold water temperature for thermostatic control

APPENDIX 10. STANDARD CONDITIONS

Table 28: Standard conditions

Variable	Value
C_{user}	1
T_{amb} Freezer	20 °C
T_{amb} Water heater	20 °C
T_{amb} Space heating/cooling	Winter: 0 °C; Summer: 30 °C;
T_{cw} (Cold water)	10 °C
T_f (Food)	10 °C
T_{goal} Freezer	-18 °C
$T_{set,max}$ Freezer	-16 °C
$T_{set,min}$ Freezer	-23 °C
T_{goal} Water heater	60 °C
$T_{set,max}$ Water heater	70 °C
$T_{set,min}$ Water heater	50 °C
T_{goal} Space heating/cooling	20 °C
$T_{set,max}$ Space heating/cooling	22 °C
$T_{set,min}$ Space heating/cooling	18 °C
Efficiency of PV-inverter	98%
Battery model	0 (Lithium Ion)
Freezer model	0 (Bosch)
Water heater model	2 (AO Smith)
Space heating/cooling model	0 (Example apartment)
Solar irradiation for space heating/cooling	1 (On)
Use of electrical heaters if COP < 1	Yes
Number of PV-modules	Winter: 120; Summer: 30;
Algorithm calculation time frame	24 h

Table 29: Results for summer settings at standard conditions (price based)

Algorithm	0	1	2	3	4	5	6	7
Freezer	-4.69%	-14.06%	-9.90%	-10.94%	-14.06%	-11.46%	-15.10%	(6)
Water H	-6.61%	-8.74%	-9.14%	-19.43%	-10.11%	-18.95%	-5.99%	(3)
Space H/C	-12.51%	-13.40%	-15.23%	-21.87%	-15.06%	-21.99%	-2.19%	(5)
All	-7.83%	-9.86%	-10.46%	-19.74%	-11.25%	-19.40%	-5.39%	-19.87%

Table 30: Results for winter settings at standard conditions (price based)

Algorithm	0	1	2	3	4	5	6	7
Freezer	-4.14%	-9.66%	-6.90%	-9.66%	-9.66%	-10.34%	-11.03%	(6)
Water H	-5.96%	-4.16%	-4.77%	-18.25%	-4.61%	-17.67%	-4.43%	(3)
Space H/C	-3.40%	5.10%	-4.02%	-27.88%	-5.79%	-26.49%	13.20%	(3)
All	-5.35%	-2.26%	-4.67%	-20.16%	-5.00%	-19.43%	-0.71%	-20.19%

Table 31: Results for summer settings at standard conditions (voltage based)

Algorithm	0	1	2	3	4	5	6	7
Freezer	-3.85%	0.00%	0.00%	-3.85%	-3.85%	-3.85%	0.00%	(0)
Water H	-31.90%	-34.48%	-15.52%	-12.07%	-23.28%	-10.34%	-37.93%	(6)
Space H/C	-34.21%	-34.21%	-34.21%	-28.95%	-34.21%	-26.32%	-34.21%	(1)
All	-45.52%	-47.59%	-38.62%	-17.24%	-40.00%	-16.55%	-49.66%	-49.66%

Algorithm	8	9	10	11
Freezer	0.00%	0.00%	0.00%	0.00%
Water H	-0.86%	-20.69%	-25.00%	-20.69%
Space H/C	0.00%	0.00%	-23.68%	2.63%
All	-11.72%	-29.66%	-35.17%	-35.86%

Table 32: Results for winter settings at standard conditions (voltage based)

Algorithm	0	1	2	3	4	5	6	7
Freezer	-2.50%	-2.50%	-2.50%	-2.50%	-2.50%	-2.50%	-2.50%	(0)
Water H	-34.23%	-32.21%	-16.78%	-14.77%	-25.50%	-14.77%	-34.23%	(6)
Space H/C	-5.56%	-5.56%	-5.56%	-5.56%	-5.56%	-5.56%	-5.56%	(1)
All	-28.76%	-29.41%	-16.99%	-6.54%	-14.38%	-9.15%	-31.37%	-33.99%
Algorithm	**8**	**9**	**10**	**11**				
Freezer	0.00%	-2.50%	-2.50%	0.00%				
Water H	-14.77%	-29.53%	-30.87%	-35.57%				
Space H/C	0.00%	0.00%	-29.63%	-3.70%				
All	-17.65%	-27.45%	-35.29%	-30.07%				

Table 33: Results for summer settings for 12 h calculation (price based)

Algorithm	0	1	2	3	4	5	6	7
Freezer	-6.77%	-10.94%	-9.38%	-11.46%	-11.46%	-10.94%	-14.06%	(6)
Water H	-4.43%	-3.48%	-4.35%	-16.37%	-4.33%	-17.28%	-2.77%	(5)
Space H/C	-4.27%	-5.04%	-4.56%	-18.02%	-3.62%	-16.95%	4.27%	(3)
All	-4.45%	-3.98%	-4.50%	-16.61%	-4.34%	-17.06%	-1.56%	-17.36%

Table 34: Results for summer settings for 12 h calculation (price based) compared to standard conditions

Algorithm	0	1	2	3	4	5	6	7
Freezer	-2.19%	3.64%	0.58%	-0.58%	3.03%	0.59%	1.23%	(6)
Water H	2.34%	5.77%	5.27%	3.79%	6.42%	2.06%	3.42%	(5)
Space H/C	9.42%	9.65%	12.59%	4.93%	13.47%	6.46%	6.61%	(3)
All	3.66%	6.53%	6.65%	3.91%	7.79%	2.91%	4.06%	3.13%

Table 35: Results for winter settings for 12 h calculation (price based)

Algorithm	0	1	2	3	4	5	6	7
Freezer	-6.90%	-8.97%	-7.59%	-8.97%	-8.97%	-8.97%	-10.34%	(6)
Water H	-1.82%	-0.97%	-1.35%	-14.07%	-1.58%	-14.09%	0.70%	(5)
Space H/C	16.22%	17.30%	14.75%	-9.11%	13.59%	-9.11%	18.76%	(3)
All	2.02%	2.86%	2.02%	-12.85%	1.56%	-12.85%	4.40%	-12.88%

Table 36: Results for winter settings for 12 h calculation (price based) compared to standard conditions

Algorithm	0	1	2	3	4	5	6	7
Freezer	-2.88%	0.76%	-0.74%	0.76%	0.76%	1.54%	0.78%	(6)
Water H	4.40%	3.33%	3.59%	5.12%	3.19%	4.35%	5.37%	(5)
Space H/C	20.30%	11.61%	19.55%	26.02%	20.57%	23.63%	4.91%	(3)
All	7.79%	5.23%	7.03%	9.15%	6.91%	8.16%	5.15%	9.16%

Table 37: Results for summer settings for 12 h calculation (voltage based); Algorithms 8-10: No change

Algorithm	0	1	2	3	4	5	6	7
Freezer	-3.85%	0.00%	0.00%	0.00%	0.00%	-3.85%	0.00%	(0)
Water H	-34.48%	-34.48%	-23.28%	-12.07%	-25.86%	-12.07%	-37.07%	(6)
Space H/C	-34.21%	-34.21%	-34.21%	-13.16%	-34.21%	-34.21%	-34.21%	(1)
All	-47.59%	-48.97%	-38.62%	-28.97%	-40.69%	-29.66%	-49.66%	-49.66%

Table 38: Results for summer settings for 12 h calculation (voltage based) compared to standard conditions; Algorithms 8-10: No change

Algorithm	0	1	2	3	4	5	6	7
Freezer	0.00%	0.00%	0.00%	4.00%	4.00%	0.00%	0.00%	(0)
Water H	-3.80%	0.00%	-9.18%	0.00%	-3.37%	-1.92%	1.39%	(6)
Space H/C	0.00%	0.00%	0.00%	22.22%	0.00%	-10.71%	0.00%	(1)
All	-3.80%	-2.63%	0.00%	-14.17%	-1.15%	-15.70%	0.00%	0.00%

Table 39: Results for winter settings for 12 h calculation (voltage based); Algorithms 8-10: No change

Algorithm	0	1	2	3	4	5	6	7
Freezer	-2.50%	-2.50%	-2.50%	-2.50%	0.00%	-2.50%	-2.50%	(0)
Water H	-27.52%	-25.50%	-18.79%	-8.05%	-22.82%	-8.05%	-27.52%	(6)
Space H/C	38.89%	38.89%	38.89%	38.89%	38.89%	38.89%	38.89%	(1)
All	-1.96%	0.65%	4.58%	22.22%	1.96%	22.22%	-3.27%	-3.92%

Table 40: Results for winter settings for 12 h calculation (voltage based) compared to standard conditions; Algorithms 8-10: No change

Algorithm	0	1	2	3	4	5	6	7
Freezer	0.00%	0.00%	0.00%	0.00%	2.56%	0.00%	0.00%	(0)
Water H	10.20%	9.90%	-2.42%	7.87%	3.60%	7.87%	10.20%	(6)
Space H/C	47.06%	47.06%	47.06%	47.06%	47.06%	47.06%	47.06%	(1)
All	37.61%	42.59%	25.98%	30.77%	19.08%	34.53%	40.95%	45.54%

APPENDIX 13. RESULTS; 48 H ALGORITHM

Table 41: Results for summer settings for 48 h calculation (price based)

Algorithm	0	1	2	3	4	5	6	7
Freezer	-1.04%	-13.02%	-8.33%	-8.33%	-12.50%	-9.90%	-8.85%	(1)
Water H	-2.36%	-7.55%	-8.01%	-17.85%	-8.14%	-15.44%	-2.17%	(3)
Space H/C	-4.92%	-11.38%	-14.82%	-17.19%	-11.03%	-18.20%	1.84%	(5)
All	-2.87%	-8.48%	-9.44%	-17.48%	-8.84%	-15.88%	-1.47%	-17.81%

Table 42: Results for summer settings for 48 h calculation (price based) compared to standard conditions

Algorithm	0	1	2	3	4	5	6	7
Freezer	3.83%	1.21%	1.73%	2.92%	1.82%	1.76%	7.36%	(1)
Water H	4.55%	1.31%	1.25%	1.95%	2.19%	4.33%	4.07%	(3)
Space H/C	8.67%	2.33%	0.49%	5.99%	4.75%	4.86%	4.12%	(5)
All	5.37%	1.53%	1.13%	2.81%	2.71%	4.37%	4.15%	2.57%

Table 43: Results for winter settings for 48 h calculation (price based)

Algorithm	0	1	2	3	4	5	6	7
Freezer	-2.07%	-6.90%	-4.83%	-8.97%	-6.21%	-9.66%	-8.28%	(5)
Water H	-2.93%	-1.28%	-2.25%	-17.53%	-2.07%	-16.97%	2.99%	(3)
Space H/C	-2.08%	6.41%	2.32%	-22.93%	2.70%	-23.94%	23.71%	(5)
All	-2.72%	0.27%	-1.33%	-18.53%	-1.12%	-18.32%	7.28%	-18.75%

Table 44: Results for winter settings for 48 h calculation (price based) compared to standard conditions

Algorithm	0	1	2	3	4	5	6	7
Freezer	2.16%	3.05%	2.22%	0.76%	3.82%	0.77%	3.10%	(5)
Water H	3.23%	3.01%	2.65%	0.88%	2.67%	0.85%	7.77%	(3)
Space H/C	1.36%	1.25%	6.60%	6.85%	9.02%	3.47%	9.28%	(5)
All	2.78%	2.59%	3.51%	2.04%	4.08%	1.37%	8.05%	1.81%

Table 45: Results for summer settings for 48 h calculation (voltage based); Algorithms 8-10: No change

Algorithm	0	1	2	3	4	5	6	7
Freezer	-3.85%	0.00%	0.00%	-3.85%	-3.85%	-3.85%	0.00%	(0)
Water H	-30.17%	-32.76%	-13.79%	-11.21%	-26.72%	-16.38%	-37.93%	(6)
Space H/C	-34.21%	-34.21%	-34.21%	-31.58%	-34.21%	-34.21%	-34.21%	(1)
All	-35.86%	-35.86%	-20.00%	-7.59%	-26.21%	-6.90%	-37.93%	-37.93%

Table 46: Results for summer settings for 48 h calculation (voltage based) compared to standard conditions; Algorithms 8-10: No change

Algorithm	0	1	2	3	4	5	6	7
Freezer	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	(0)
Water H	2.53%	2.63%	2.04%	0.98%	-4.49%	-6.73%	0.00%	(6)
Space H/C	0.00%	0.00%	0.00%	-3.70%	0.00%	-10.71%	0.00%	(1)
All	17.72%	22.37%	30.34%	11.67%	22.99%	11.57%	23.29%	23.29%

Table 47: Results for winter settings for 48 h calculation (voltage based); Algorithms 8-10: No change

Algorithm	0	1	2	3	4	5	6	7
Freezer	-2.50%	-2.50%	-2.50%	-2.50%	-2.50%	-2.50%	0.00%	(0)
Water H	-28.19%	-19.46%	-12.08%	-8.72%	-17.45%	-8.72%	-28.19%	(6)
Space H/C	-29.63%	-29.63%	-29.63%	-29.63%	-29.63%	-29.63%	-29.63%	(1)
All	-28.10%	-19.61%	-11.11%	-3.27%	-17.65%	-3.27%	-28.10%	-28.10%

Table 48: Results for winter settings for 48 h calculation (voltage based) compared to standard conditions; Algorithms 8-10: No change

Algorithm	0	1	2	3	4	5	6	7
Freezer	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.56%	(0)
Water H	9.18%	18.81%	5.65%	7.09%	10.81%	7.09%	9.18%	(6)
Space H/C	-25.49%	-25.49%	-25.49%	-25.49%	-25.49%	-25.49%	-25.49%	(1)
All	0.92%	13.89%	7.09%	3.50%	-3.82%	6.47%	4.76%	8.91%

Table 49: Results for summer settings for user comfort 0.5 (price based)

Algorithm	0	1	2	3	4	5	6	7
Freezer	4.17%	-9.38%	-5.21%	-5.73%	-9.90%	-11.98%	-15.10%	(6)
Water H	5.23%	-9.01%	-6.76%	-14.39%	-5.76%	-13.26%	-5.99%	(3)
Space H/C	0.53%	-15.53%	-17.13%	-13.10%	-15.95%	-18.26%	-2.19%	(5)
All	4.21%	-10.40%	-8.92%	-13.90%	-8.01%	-14.27%	-5.39%	-15.21%

Table 50: Results for summer settings for user comfort 0.5 (price based) compared to standard conditions

Algorithm	0	1	2	3	4	5	6	7
Freezer	9.29%	5.45%	5.20%	5.85%	4.85%	-0.59%	0.00%	(6)
Water H	12.68%	-0.29%	2.62%	6.25%	4.84%	7.02%	0.00%	(3)
Space H/C	14.91%	-2.46%	-2.24%	11.23%	-1.05%	4.79%	0.00%	(5)
All	13.06%	-0.60%	1.72%	7.28%	3.65%	6.36%	0.00%	5.81%

Table 51: Results for winter settings for user comfort 0.5 (price based)

Algorithm	0	1	2	3	4	5	6	7
Freezer	8.28%	-6.21%	-3.45%	-6.90%	-6.21%	-10.34%	-11.03%	(6)
Water H	7.09%	-4.91%	-3.85%	-12.76%	-3.40%	-13.77%	-4.43%	(5)
Space H/C	16.60%	0.77%	-0.54%	-16.83%	-2.93%	-18.22%	13.20%	(5)
All	9.21%	-3.69%	-3.11%	-13.51%	-3.38%	-14.67%	-0.71%	-14.69%

Table 52: Results for winter settings for user comfort 0.5 (price based) compared to standard conditions

Algorithm	0	1	2	3	4	5	6	7
Freezer	12.95%	3.82%	3.70%	3.05%	3.82%	0.00%	0.00%	(6)
Water H	13.88%	-0.78%	0.97%	6.72%	1.27%	4.73%	0.00%	(5)
Space H/C	20.70%	-4.11%	3.62%	15.31%	3.03%	11.24%	0.00%	(5)
All	15.39%	-1.46%	1.64%	8.32%	1.70%	5.91%	0.00%	6.90%

Table 53: Results for summer settings for user comfort 0.5 (voltage based); Algorithms 6, 8, 9&11: No change

Algorithm	0	1	2	3	4	5	7	10
Freezer	0.00%	-3.85%	-3.85%	-3.85%	0.00%	0.00%	(1)	-3.85%
Water H	-25.86%	-15.52%	-4.31%	-0.86%	-7.76%	-4.31%	(6)	-18.10%
Space H/C	-15.79%	-34.21%	-34.21%	-34.21%	-13.16%	-5.26%	(1)	-15.79%
All	-40.69%	-33.79%	-22.76%	-20.69%	-26.90%	-8.97%	-49.66%	-32.41%

Table 54: Results for summer settings for user comfort 0.5 (voltage based) compared to standard conditions; Algorithms 6, 8, 9&11: No change

Algorithm	0	1	2	3	4	5	7	10
Freezer	4.00%	-3.85%	-3.85%	0.00%	4.00%	4.00%	(1)	-3.85%
Water H	8.86%	28.95%	13.27%	12.75%	20.22%	6.73%	(6)	9.20%
Space H/C	28.00%	0.00%	0.00%	-7.41%	32.00%	28.57%	(1)	10.34%
All	8.86%	26.32%	25.84%	-4.17%	21.84%	9.09%	0.00%	4.26%

Table 55: Results for winter settings for user comfort 0.5 (voltage based); Algorithms 6, 8, 9&11: No change

Algorithm	0	1	2	3	4	5	7	10
Freezer	0.00%	-2.50%	-2.50%	-2.50%	0.00%	0.00%	(1)	-2.50%
Water H	-34.23%	-16.78%	-9.40%	-6.04%	-12.75%	-10.74%	(6)	-27.52%
Space H/C	-29.63%	-5.56%	-20.37%	-20.37%	-20.37%	-5.56%	(0)	-3.70%
All	-32.03%	-15.69%	-7.19%	-4.58%	-10.46%	-14.38%	-39.22%	-28.76%

Table 56: Results for winter settings for user comfort 0.5 (voltage based) compared to standard conditions; Algorithms 6, 8, 9&11: No change

Algorithm	0	1	2	3	4	5	7	10
Freezer	2.56%	0.00%	0.00%	0.00%	2.56%	2.56%	(1)	0.00%
Water H	0.00%	22.77%	8.87%	10.24%	17.12%	4.72%	(6)	4.85%
Space H/C	-25.49%	0.00%	-15.69%	-15.69%	-15.69%	0.00%	(0)	36.84%
All	-4.59%	19.44%	11.81%	2.10%	4.58%	-5.76%	-7.92%	10.10%

Table 57: Results for summer settings for user comfort 2.0 (price based)

Algorithm	0	1	2	3	4	5	6	7
Freezer	-13.54%	-15.63%	-14.06%	-11.98%	-15.10%	-9.90%	-15.10%	(6)
Water H	-15.85%	-7.15%	-7.07%	-22.44%	-8.43%	-21.53%	-5.99%	(3)
Space H/C	-20.63%	-7.82%	-11.50%	-25.01%	-10.67%	-26.26%	-2.19%	(5)
All	-16.79%	-7.50%	-8.17%	-22.73%	-9.07%	-22.25%	-5.39%	-23.08%

Table 58: Results for summer settings for user comfort 2.0 (price based) compared to standard conditions

Algorithm	0	1	2	3	4	5	6	7
Freezer	-9.29%	-1.82%	-4.62%	-1.17%	-1.21%	1.76%	0.00%	(6)
Water H	-9.89%	1.74%	2.28%	-3.75%	1.86%	-3.18%	0.00%	(3)
Space H/C	-9.28%	6.43%	4.41%	-4.02%	5.16%	-5.47%	0.00%	(5)
All	-9.73%	2.62%	2.56%	-3.72%	2.46%	-3.53%	0.00%	-4.01%

Table 59: Results for winter settings for user comfort 2.0 (price based)

Algorithm	0	1	2	3	4	5	6	7
Freezer	-11.03%	-11.03%	-9.66%	-10.34%	-11.03%	-9.66%	-11.03%	(6)
Water H	-13.84%	-4.34%	-3.80%	-20.64%	-4.37%	-20.35%	-4.43%	(3)
Space H/C	-13.51%	7.88%	7.03%	-30.58%	5.56%	-31.20%	13.20%	(5)
All	-13.70%	-1.82%	-1.58%	-22.57%	-2.33%	-22.49%	-0.71%	-22.59%

Table 60: Results for winter settings for user comfort 2.0 (price based) compared to standard conditions

Algorithm	0	1	2	3	4	5	6	7
Freezer	-7.19%	-1.53%	-2.96%	-0.76%	-1.53%	0.77%	0.00%	(6)
Water H	-8.38%	-0.19%	1.02%	-2.92%	0.26%	-3.25%	0.00%	(3)
Space H/C	-10.47%	2.65%	11.50%	-3.75%	12.05%	-6.41%	0.00%	(5)
All	-8.82%	0.45%	3.25%	-3.02%	2.81%	-3.80%	0.00%	-3.00%

Table 61: Results for summer settings for user comfort 2.0 (voltage based); Algorithms 6, 8, 9&11: No change

Algorithm	0	1	2	3	4	5	7	10
Freezer	-3.85%	0.00%	0.00%	-3.85%	0.00%	-3.85%	(0)	0.00%
Water H	-34.48%	-37.07%	-34.48%	-15.52%	-37.07%	-7.76%	(6)	-9.48%
Space H/C	-34.21%	-34.21%	-34.21%	-18.42%	-34.21%	-26.32%	(1)	5.26%
All	-47.59%	-49.66%	-47.59%	-17.93%	-49.66%	-20.69%	-49.66%	-12.41%

Table 62: Results for summer settings for user comfort 2.0 (voltage based) compared to standard conditions; Algorithms 6, 8, 9&11: No change

Algorithm	0	1	2	3	4	5	7	10
Freezer	0.00%	0.00%	0.00%	0.00%	4.00%	0.00%	(0)	0.00%
Water H	-3.80%	-3.95%	-22.45%	-3.92%	-17.98%	2.88%	(6)	20.69%
Space H/C	0.00%	0.00%	0.00%	14.81%	0.00%	0.00%	(1)	37.93%
All	-3.80%	-3.95%	-14.61%	-0.83%	-16.09%	-4.96%	0.00%	35.11%

Table 63: Results for winter settings for user comfort 2.0 (voltage based); Algorithms 6, 8, 9&11: No change

Algorithm	0	1	2	3	4	5	7	10
Freezer	-2.50%	-2.50%	0.00%	-2.50%	-2.50%	-2.50%	(0)	-2.50%
Water H	-34.90%	-35.57%	-32.21%	-14.77%	-34.90%	-14.77%	(1)	-8.05%
Space H/C	-5.56%	-5.56%	-5.56%	-5.56%	-5.56%	-5.56%	(1)	0.00%
All	-32.03%	-32.03%	-29.41%	-7.19%	-31.37%	-5.88%	-33.33%	-1.31%

Table 64: Results for winter settings for user comfort 2.0 (voltage based) compared to standard conditions; Algorithms 6, 8, 9&11: No change

Algorithm	0	1	2	3	4	5	7	10
Freezer	0.00%	0.00%	2.56%	0.00%	0.00%	0.00%	(0)	0.00%
Water H	-1.02%	-4.95%	-18.55%	0.00%	-12.61%	0.00%	(1)	33.01%
Space H/C	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	(1)	42.11%
All	-4.59%	-3.70%	-14.96%	-0.70%	-19.85%	3.60%	0.99%	52.53%

Table 65: Results for summer settings for other appliances (price based)

Algorithm	0	1	2	3	4	5	6	7
Freezer	-4.59%	-12.18%	-8.78%	-9.18%	-12.38%	-9.78%	-13.57%	(6)
Water H	-2.01%	-4.81%	-4.63%	-13.14%	-4.14%	-12.68%	-4.58%	(3)
Space H/C	-7.30%	-12.24%	-10.70%	-13.92%	-10.49%	-16.18%	-10.49%	(5)
All	-5.03%	-9.24%	-8.15%	-13.38%	-8.03%	-14.44%	-8.27%	-14.82%

Table 66: Results for winter settings for other appliances (price based)

Algorithm	0	1	2	3	4	5	6	7
Freezer	-3.43%	-8.18%	-6.07%	-8.71%	-7.92%	-8.97%	-9.23%	(6)
Water H	-2.65%	-3.01%	-2.12%	-12.66%	-2.37%	-12.20%	-4.67%	(3)
Space H/C	-2.70%	5.20%	-1.83%	-27.83%	-2.54%	-32.20%	17.64%	(5)
All	-2.75%	0.16%	-2.28%	-18.89%	-2.85%	-20.55%	4.58%	-20.78%

Table 67: Results for summer settings for other appliances (voltage based)

Algorithm	0	1	2	3	4	5	6	7
Freezer	-3.70%	-3.70%	0.00%	-3.70%	-3.70%	-3.70%	0.00%	(0)
Water H	-9.68%	-8.06%	-3.23%	-1.61%	-6.45%	-1.61%	-9.68%	(6)
Space H/C	-51.79%	-51.79%	-51.79%	-42.86%	-51.79%	-35.71%	-42.86%	(1)
All	-10.62%	-10.62%	-10.62%	33.63%	-1.77%	7.08%	-19.47%	-10.62%

Algorithm	8	9	10	11
Freezer	0.00%	0.00%	0.00%	0.00%
Water H	0.00%	-3.23%	-4.84%	-4.84%
Space H/C	-5.36%	-8.93%	-46.43%	-17.86%
All	-10.62%	-23.01%	-39.82%	-18.58%

Table 68: Results for winter settings for other appliances (voltage based)

Algorithm	0	1	2	3	4	5	6	7
Freezer	-4.55%	-4.55%	-4.55%	-6.82%	-4.55%	-4.55%	-4.55%	(3)
Water H	-2.41%	-2.41%	0.00%	0.00%	-1.20%	0.00%	-12.05%	(6)
Space H/C	-33.70%	-33.70%	-33.70%	-31.52%	-33.70%	-29.35%	-32.61%	(1)
All	-15.38%	-15.38%	-15.38%	-1.40%	-15.38%	-1.40%	-15.38%	-15.38%

Algorithm	8	9	10	11
Freezer	-2.27%	-4.55%	-6.82%	-4.55%
Water H	0.00%	-7.23%	-3.61%	-4.82%
Space H/C	-9.78%	-7.61%	-55.43%	-29.35%
All	-1.40%	-11.89%	-36.36%	-24.48%

APPENDIX 17. RESULTS; MINIMUM/MAXIMUM SET POINTS

Table 69: Minimum and maximum temperature set point values for wider temperature range

Variable	Value
$T_{set,max}$ Freezer	-14 °C
$T_{set,min}$ Freezer	-25 °C
$T_{set,max}$ Water heater	80 °C
$T_{set,min}$ Water heater	45 °C
$T_{set,max}$ Space heating/cooling	23 °C
$T_{set,min}$ Space heating/cooling	17 °C

Table 70: Results for summer settings for wider temperature range (price based)

Algorithm	0	1	2	3	4	5	6	7
Freezer	-6.25%	-18.75%	-14.06%	-19.27%	-17.71%	-21.35%	-23.44%	(6)
Water H	-1.36%	-10.39%	-11.85%	-30.16%	-11.12%	-28.50%	-3.97%	(3)
Space H/C	-10.79%	-12.39%	-16.12%	-26.97%	-15.29%	-29.93%	7.35%	(5)
All	-3.49%	-10.20%	-12.79%	-29.21%	-12.17%	-28.63%	-2.04%	-29.95%

Table 71: Results for summer settings for wider temperature range (price based) compared to standard conditions

Algorithm	0	1	2	3	4	5	6	7
Freezer	-1.64%	-5.45%	-4.62%	-9.36%	-4.24%	-11.18%	-9.82%	(6)
Water H	5.62%	-1.80%	-2.98%	-13.32%	-1.13%	-11.78%	2.15%	(3)
Space H/C	1.96%	1.16%	-1.05%	-6.53%	-0.28%	-10.18%	9.76%	(5)
All	4.71%	-0.38%	-2.61%	-11.80%	-1.03%	-11.45%	3.54%	-12.58%

Table 72: Results for winter settings for wider temperature range (price based)

Algorithm	0	1	2	3	4	5	6	7
Freezer	-6.90%	-13.79%	-11.03%	-18.62%	-12.41%	-18.62%	-19.31%	(6)
Water H	-0.77%	-2.03%	-3.89%	-26.49%	-3.31%	-28.47%	1.40%	(5)
Space H/C	2.63%	15.06%	4.63%	-30.97%	3.47%	-30.89%	25.17%	(3)
All	-0.19%	1.44%	-2.19%	-27.28%	-2.06%	-28.78%	6.12%	-28.79%

Table 73: Results for winter settings for wider temperature range (price based) compared to standard conditions

Algorithm	0	1	2	3	4	5	6	7
Freezer	-2.88%	-4.58%	-4.44%	-9.92%	-3.05%	-9.23%	-9.30%	(6)
Water H	5.53%	2.23%	0.92%	-10.08%	1.37%	-13.12%	6.10%	(5)
Space H/C	6.24%	9.48%	9.01%	-4.28%	9.84%	-5.99%	10.57%	(3)
All	5.46%	3.79%	2.60%	-8.92%	3.10%	-11.60%	6.88%	-10.78%

Table 74: Results for summer settings for wider temperature range (voltage based)

Algorithm	0	1	2	3	4	5	6	7
Freezer	-3.85%	-3.85%	-3.85%	-3.85%	-3.85%	-3.85%	-3.85%	(0)
Water H	-45.69%	-50.86%	-37.07%	-20.69%	-41.38%	-23.28%	-53.45%	(6)
Space H/C	-34.21%	-34.21%	-34.21%	-34.21%	-34.21%	-34.21%	-34.21%	(1)
All	-58.62%	-62.76%	-49.66%	-15.86%	-51.72%	-15.86%	-62.76%	-62.76%

Algorithm	8	9	10	11
Freezer	0.00%	0.00%	0.00%	0.00%
Water H	-0.86%	-29.31%	-31.03%	-41.38%
Space H/C	0.00%	0.00%	-23.68%	5.26%
All	-11.72%	-35.17%	-35.86%	-42.76%

Table 75: Results for summer settings for wider temperature range (voltage based) compared to standard conditions

Algorithm	0	1	2	3	4	5	6	7
Freezer	0.00%	-3.85%	-3.85%	0.00%	0.00%	0.00%	-3.85%	(0)
Water H	-20.25%	-25.00%	-25.51%	-9.80%	-23.60%	-14.42%	-25.00%	(6)
Space H/C	0.00%	0.00%	0.00%	-7.41%	0.00%	-10.71%	0.00%	(1)
All	-24.05%	-28.95%	-17.98%	1.67%	-19.54%	0.83%	-26.03%	-26.03%
Algorithm	8	9	10	11				
Freezer	0.00%	0.00%	0.00%	0.00%				
Water H	0.00%	-10.87%	-8.05%	-26.09%				
Space H/C	0.00%	0.00%	0.00%	2.56%				
All	0.00%	-7.84%	-1.06%	-10.75%				

Table 76: Results for winter settings for wider temperature range (voltage based)

Algorithm	0	1	2	3	4	5	6	7
Freezer	-2.50%	-2.50%	-2.50%	-2.50%	-2.50%	-2.50%	-2.50%	(0)
Water H	-44.30%	-51.01%	-30.87%	-25.50%	-38.26%	-24.16%	-44.97%	(1)
Space H/C	12.96%	12.96%	12.96%	12.96%	12.96%	12.96%	12.96%	(1)
All	-40.52%	-46.41%	-26.80%	-14.38%	-33.99%	-7.84%	-46.41%	-46.41%
Algorithm	8	9	10	11				
Freezer	0.00%	-2.50%	-2.50%	0.00%				
Water H	-14.77%	-37.58%	-37.58%	-45.64%				
Space H/C	0.00%	0.00%	-29.63%	-3.70%				
All	-17.65%	-33.33%	-37.25%	-39.87%				

Table 77: Results for winter settings for wider temperature range (voltage based) compared to standard conditions

Algorithm	0	1	2	3	4	5	6	7
Freezer	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	(0)
Water H	-15.31%	-27.72%	-16.94%	-12.60%	-17.12%	-11.02%	-16.33%	(1)
Space H/C	19.61%	19.61%	19.61%	19.61%	19.61%	19.61%	19.61%	(1)
All	-16.51%	-24.07%	-11.81%	-8.39%	-22.90%	1.44%	-21.90%	-18.81%

Algorithm	8	9	10	11
Freezer	0.00%	0.00%	0.00%	0.00%
Water H	0.00%	-11.43%	-9.71%	-15.63%
Space H/C	0.00%	0.00%	0.00%	0.00%
All	0.00%	-8.11%	-3.03%	-14.02%

APPENDIX 18. RESULTS; EXTREME TEMPERATURES

Table 78: Ambient temperature settings for extreme ambient temperatures and increased number of solar modules

Variable	Value
T_{amb} Space heating/cooling	Winter: -30 °C; Summer: 40 °C;
Number of PV-modules	Winter: 200; Summer: 30;

Table 79: Results for summer settings for extreme ambient temperatures (price based)

Algorithm	0	1	2	3	4	5	6
Space H/C	-9.16%	-14.14%	-14.80%	-14.76%	-12.35%	-16.71%	-5.97%

Table 80: Results for winter settings for extreme ambient temperatures (price based)

Algorithm	0	1	2	3	4	5	6
Space H/C	-3.04%	-3.75%	-2.11%	-9.85%	-2.67%	-9.61%	-7.39%

Table 81: Results for summer settings for extreme ambient temperatures (voltage based)

Algorithm	0	1	2	3	4	5	6
Space H/C	-41.86%	-41.86%	-41.86%	-41.86%	-41.86%	-18.60%	-41.86%
Algorithm	8	9	10	11			
Space H/C	0.00%	0.00%	-20.93%	-4.65%			

Table 82: Results for winter settings for extreme ambient temperatures (voltage based)

Algorithm	0	1	2	3	4	5	6
Space H/C	-22.36%	-24.22%	-14.29%	-11.80%	-19.25%	-15.53%	-11.18%
Algorithm	8	9	10	11			
Space H/C	-0.62%	-13.66%	-13.04%	-11.18%			

Table 83: Results for summer settings for AGM battery storage (voltage based)

Algorithm	0	1	2	3	4	5	6	7
Freezer	0.00%	0.00%	0.00%	-1.43%	0.00%	-1.43%	0.00%	(3)
Water H	0.00%	0.00%	0.00%	-11.90%	0.00%	-11.90%	0.00%	(5)
Space H/C	-6.76%	-6.76%	-6.76%	-6.76%	-6.76%	-6.76%	-6.76%	(0)
All	-43.43%	-43.43%	-43.43%	-39.39%	-43.43%	-38.38%	-43.43%	-50.17%
Algorithm	**8**	**9**	**10**	**11**				
Freezer	-1.43%	-1.43%	-1.43%	-1.43%				
Water H	-11.90%	-11.31%	-11.90%	-11.90%				
Space H/C	-6.76%	-6.76%	-6.76%	-6.76%				
All	-16.16%	-50.17%	-50.17%	-50.17%				

Table 84: Results for winter settings for AGM battery storage (voltage based)

Algorithm	0	1	2	3	4	5	6	7
Freezer	0.00%	0.00%	0.00%	-1.37%	0.00%	-1.37%	-1.37%	(6)
Water H	-23.45%	-23.45%	-30.53%	-12.39%	-23.45%	-16.81%	-23.45%	(2)
Space H/C	-7.69%	-7.69%	-7.69%	-7.69%	-7.69%	-7.69%	-7.69%	(0)
All	-46.93%	-34.66%	-28.53%	-7.36%	-46.63%	-11.96%	-35.58%	-41.41%
Algorithm	**8**	**9**	**10**	**11**				
Freezer	-1.37%	-1.37%	-1.37%	-1.37%				
Water H	-30.97%	-30.97%	-30.97%	-30.97%				
Space H/C	-7.69%	-7.69%	-7.69%	-7.69%				
All	-28.53%	-52.15%	-52.15%	-52.15%				

APPENDIX 20. EXAMPLE GRAPHS FOR PRICE BASED CONTROL

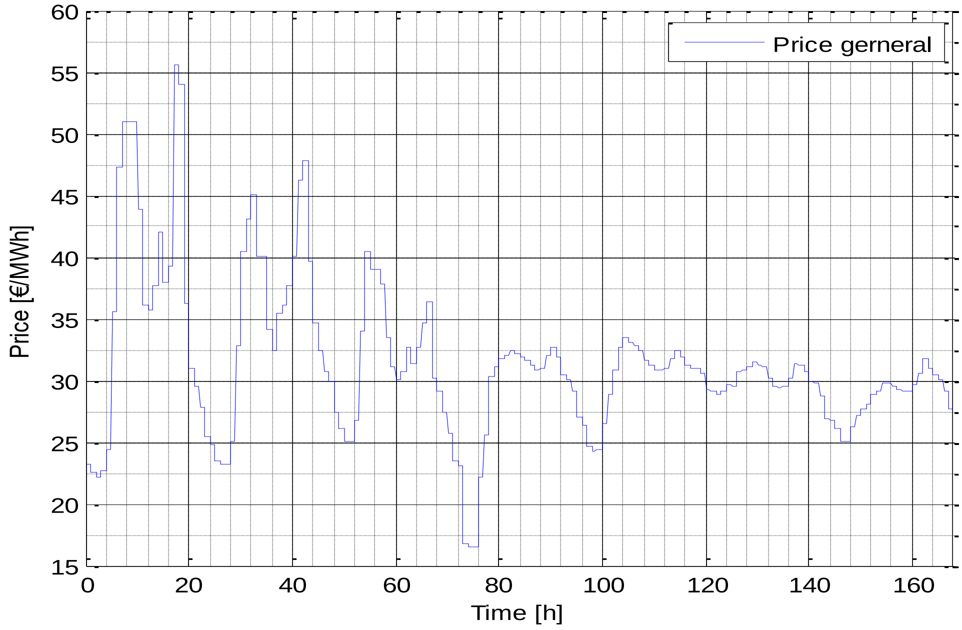

Figure 28: Price pattern for winter settings

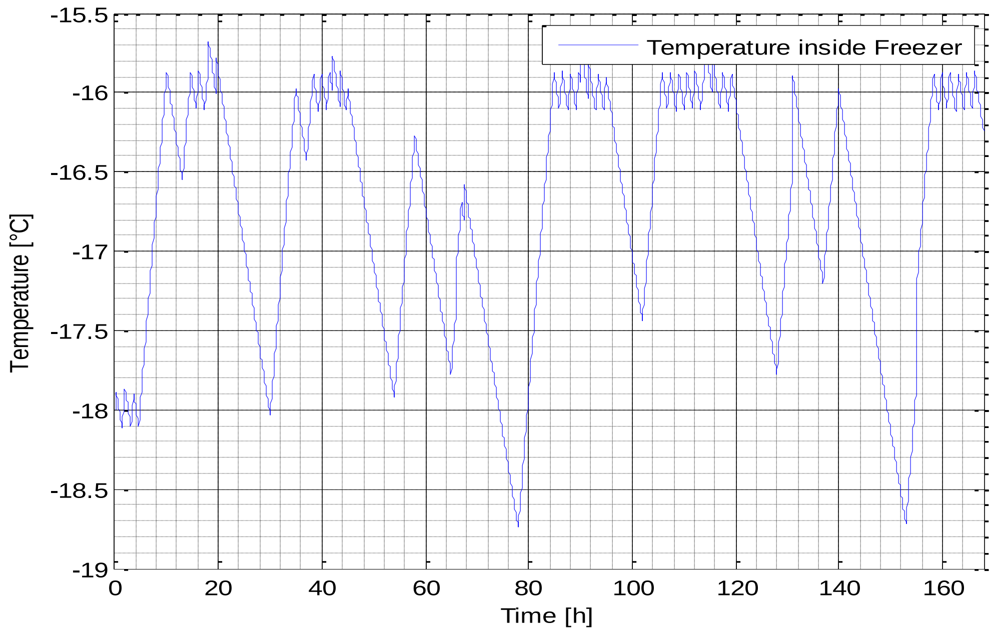

Figure 29: Temperature inside freezer; Algorithm 6; Standard conditions; Winter settings

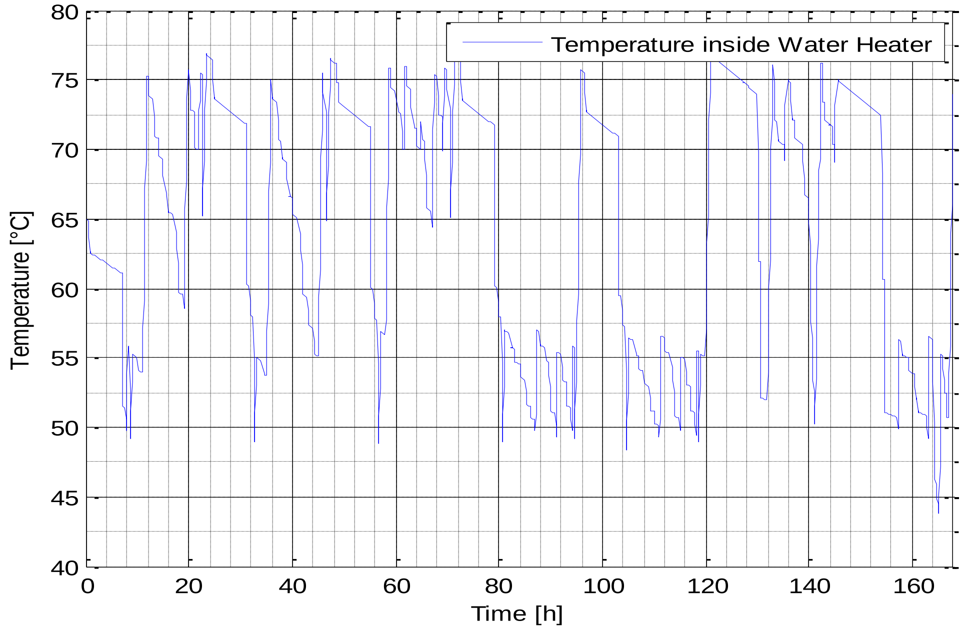

Figure 30: Temperature inside water heater; Algorithm 6; Standard conditions; Winter settings

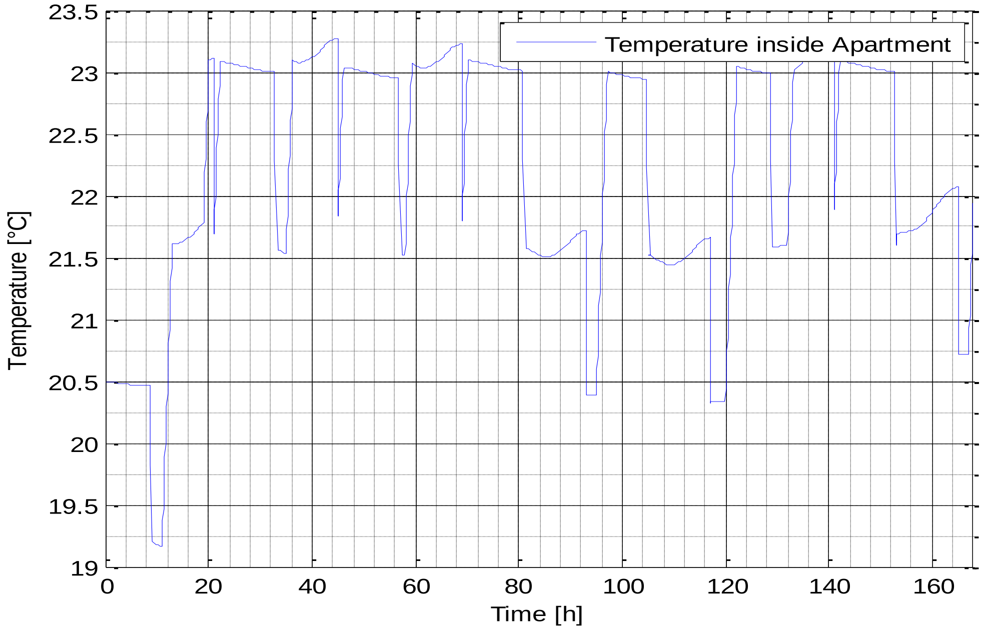

Figure 31: Temperature inside apartment; Algorithm 6; Standard conditions; Winter settings

APPENDIX 21. EXAMPLE GRAPHS FOR VOLTAGE BASED CONTROL

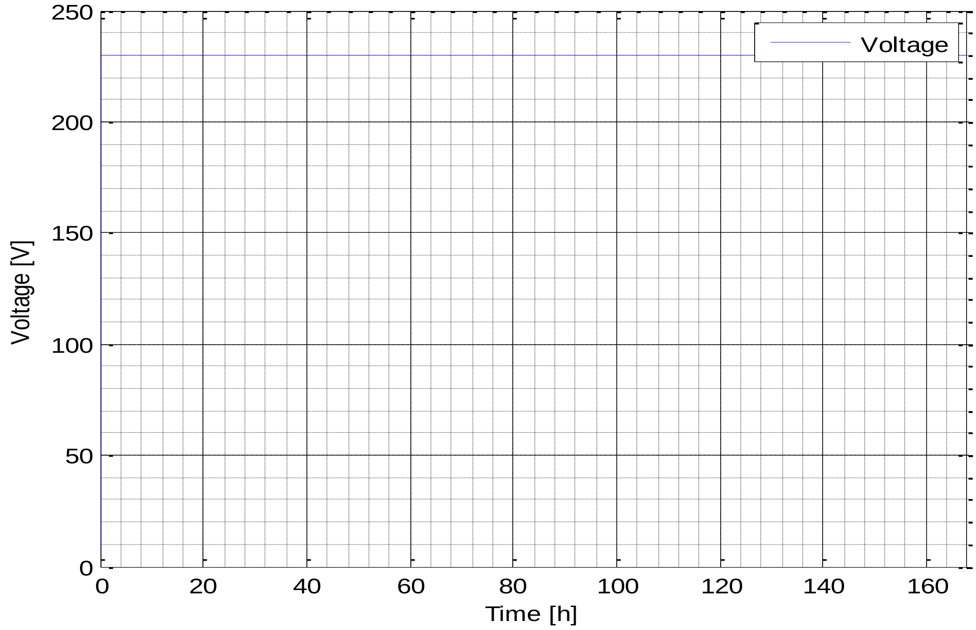

Figure 32: System voltage; Algorithm 10; Summer settings

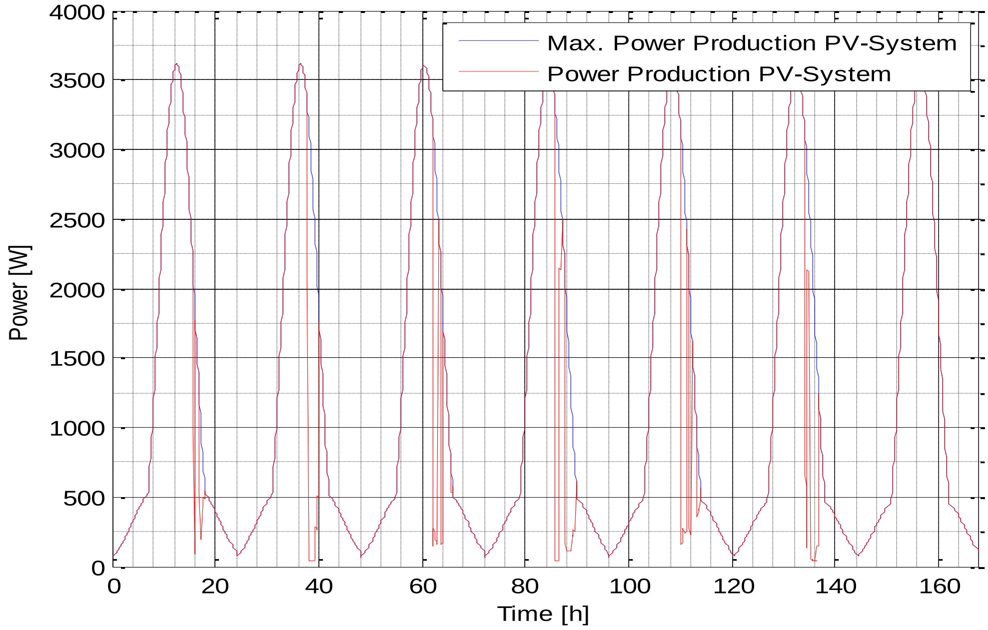

Figure 33: Power production of PV-system; Algorithm 10; Summer settings

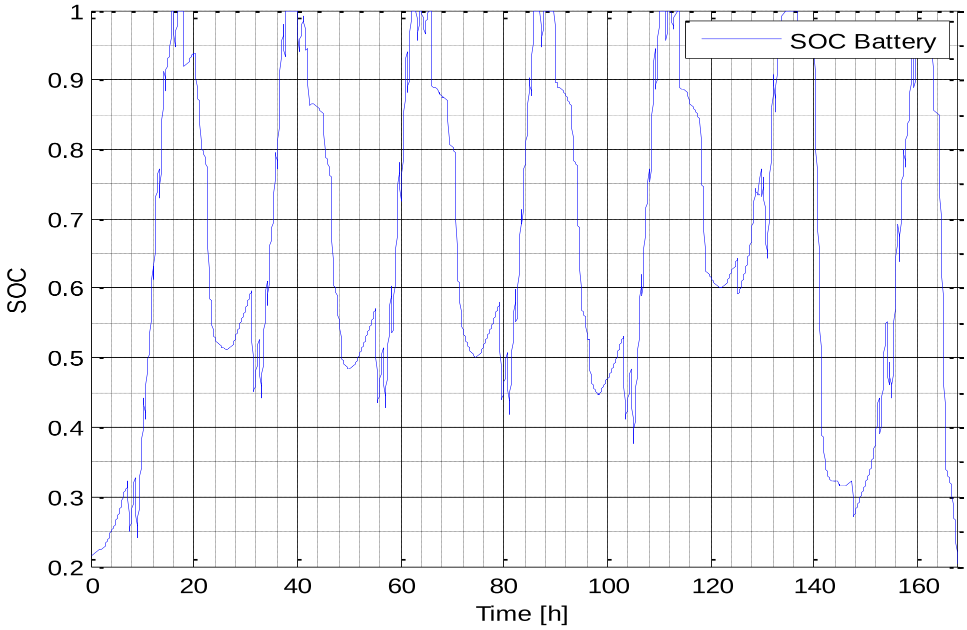

Figure 34: Battery SOC; Algorithm 10; Summer settings

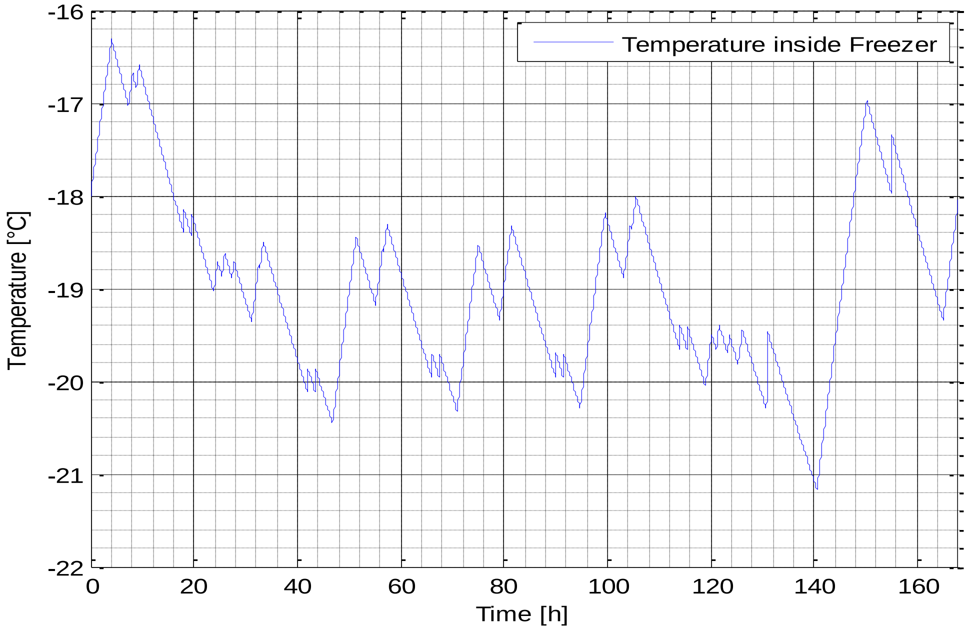

Figure 35: Temperature inside freezer; Algorithm 10; Summer settings

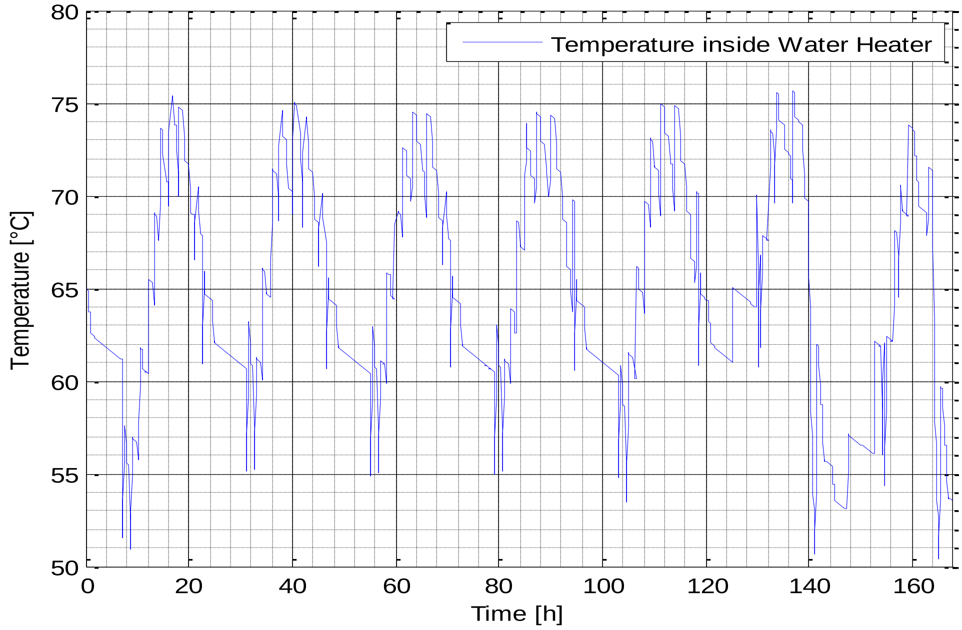

Figure 36: Temperature inside water heater; Algorithm 10; Summer settings

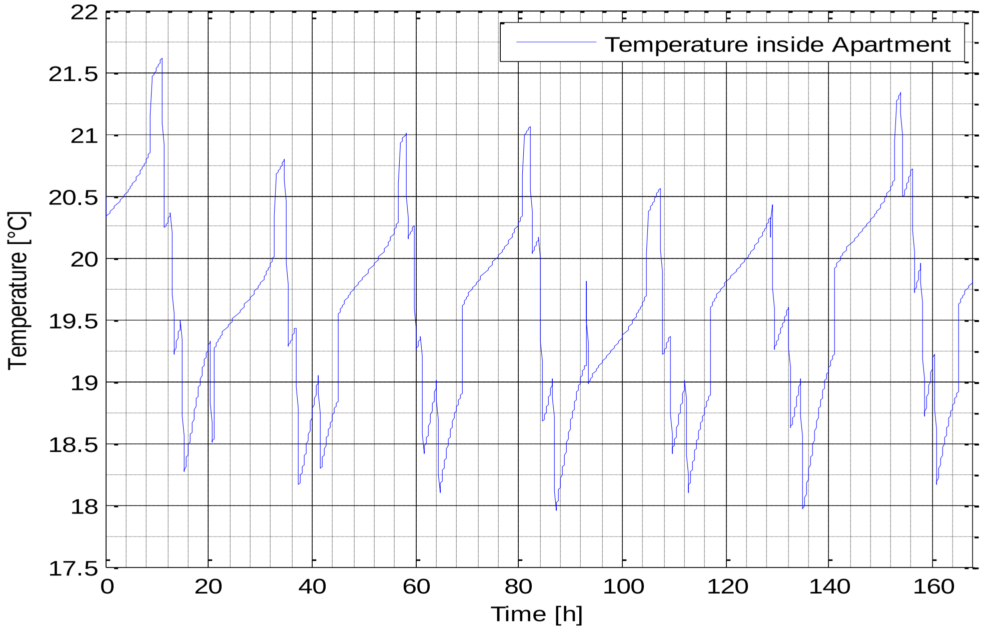

Figure 37: Temperature inside apartment; Algorithm 10; Summer settings