Tampere University

JUHA KOSKELA

# Utilization of Electrical Energy Storage in Residential Buildings with Small-Scale Photovoltaic Production

Techno-economic research perspective

Tampere University Dissertations 1008

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| *Responsible supervisor and Custos* | Professor Pertti Järventausta<br>Tampere University<br>Finland | |
| *Supervisor* | Docent Antti Rautiainen<br>Tampere University<br>Finland | |
| *Pre-examiners* | Professor Peter Lund<br>Aalto University<br>Finland | Professor Ole-Morten Midtgård<br>Norwegian University of Science and Technology<br>Norway |
| *Opponent* | Professor Jero Ahola<br>Lappeenranta-Lahti University of Technology<br>Finland | |

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# ABSTRACT

The need for flexibility in the power system will continue to increase when electrification progresses, and electricity production becomes more weather dependent. Small-scale energy production in residential buildings has become increasingly popular for alleviating rising energy costs. Simultaneously, requirements for the electricity grid increase when the grid should be capable of transferring increasing amounts of energy with a higher variation in demand and production. The grid also needs to be capable of receiving surplus energy from customers. Energy storage in residential buildings can decrease the pressure to reinforce the grid, reducing the costs for all customers. The poor profitability of battery energy storage systems has slowed down to become these systems more common. This thesis studies methods that illustrate how profitability can be increased and how specific factors can impact profitability.

Customers will invest in energy storage more likely if it is profitable. Currently, investment prices have decreased, battery lifetime has been optimized with better manufacturing, and new control systems can ensure the state of health of the battery. Profitability depends on the economic benefits of battery usage. Many incentives can affect the control targets of energy storage. Storage can be used to increase photovoltaic self-consumption or decreasing the maximum peak power or market-price-based control. This thesis examines the profitability of energy storage by utilizing simulations with measured data and modelled energy resources. Further, energy storage utilization is optimized using developed control algorithms with various control targets. Simulations conducted in this study led to many conclusions, including the identification of factors that affect the profitability of energy storage and methods that can determine how profitability can be increased.

Profitability can be increased by sizing photovoltaic systems with a battery and combining different control targets correctly. Distribution system operators can steer storage by correctly designing tariffs. Switching from hourly measurements of electricity billing to 15-min periods can increase the profitability of energy storage. Further, controlling the load in demand response operations can replace some storage capacity requirements; however, this decrease is negligible in terms of the profitability of the parallel-used battery energy storage systems. The use of energy storage can help increase the size of photovoltaic systems. Establishing energy communities expands the potential for utilizing energy storage with even larger photovoltaic systems.

# PREFACE

This dissertation was conducted from 2016 to 2023 at the Department of Electrical Engineering at Tampere University (also referred to as Tampere University of Technology, before the two Tampere Universities merged in 2019). This study was primarily funded by Tampere University. I greatly appreciate the additional funding in the form of personal grants from the Walter Ahlström Foundation. I express my deepest gratitude to Professor Pertti Järventausta, who supervised this thesis. I thank him for presenting me with the opportunity to perform this work in a very supportive environment.

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Kurikka, October 2023

Juha Koskela

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# ABBREVIATIONS

| | |
|---|---|
| BESS | Battery energy storage system |
| DOD | Depth of discharge |
| DR | Demand response |
| DSO | Distribution system operator |
| EES | Electrical energy storage |
| EESS | Electrical energy storage system |
| EOL | End of lifetime |
| EU | European Union |
| EV | Electric vehicle |
| FIT | Feed-in-tariff |
| IRR | Internal rate of return |
| LFP | Lithium-iron phosphate |
| LCOE | Levelized cost of electricity |
| Li-ion | Lithium-ion |
| MAE | Mean absolute error |
| NCA | Nickel cobalt aluminum oxide |
| NMC | Nickel manganese cobalt |
| NPV | Net present value |
| PV | Photovoltaic |
| SOC | State of charge |
| SOH | State of health |
| VRE | Variable renewable energy |

# LIST OF PUBLICATIONS

This thesis is based on the following original publications, referred to in the text as [P1]–[P6]:

[P1] J. Koskela, A. Rautiainen, P. Järventausta, "Utilization Possibilities of Electrical Energy Storages in Households' Energy Management in Finland," *International Review of Electrical Engineering (IREE)*, vol. 11, no. 6, pp. 607–617, 2017.

[P2] J. Koskela, K. Lummi, A. Mutanen, A. Rautiainen, P. Järventausta, "Utilization of Electrical Energy Storage with Power-Based Distribution Tariffs in Households," *IEEE Transactions on Power Systems*, vol. 34, no. 3, pp. 1693–1702, 2019.

[P3] J. Koskela, A. Rautiainen, P. Järventausta, "Using Electrical Energy Storage in Residential Buildings – Sizing of Battery and Photovoltaic Panels Based on Electricity Cost Optimization", *Applied Energy*, vol. 239, pp. 1175–1189, 2019.

[P4] J. Koskela, A. Rautiainen, K. Kallioharju, P. Harsia, P. Järventausta, "Effect of the Electricity Metering Interval on the Profitability of Domestic Grid-Connected PV Systems and BESSs," *International Review of Electrical Engineering (IREE)*, vol. 15, no. 2, pp. 164–173, 2020.

[P5] J. Koskela, A. Mutanen, P. Järventausta, "Using Load Forecasting to Control Domestic Battery Energy Storage Systems," *Energies*, vol. 13, no. 15(3946), 2020.

[P6] J. Koskela, P. Järventausta, "Demand Response Possibilities of Electrical Heating in Detached Houses in Finland and Comparison with Battery Energy Storage Systems," *Energies*, vol. 16, no. 1(497), 2023.

# AUTHOR'S CONTRIBUTION

This thesis was based on six original publications in which the author of this thesis was the corresponding author and responsible for writing and editing most of the content. This thesis developed simulator and control algorithms by utilizing MATLAB®-based programming and performed all simulations. The simulations utilized real data from customer consumption, and these data were received from the smart meters of distribution system operators or measured directly from houses. Prof. **Pertti Järventausta** supervised this thesis and contributed to all publications by providing guidance and valuable comments before publication. Docent **Antti Rautiainen** contributed to publications [P1]–[P4] by providing ideas and comments before publication. Dr. **Antti Mutanen** contributed to publications [P2] and [P5] with comments before publishing and created an original load-forecasting algorithm used in this thesis. His primary helped acquire the electricity consumption data. M.Sc. **Kimmo Lummi** contributed to publication [P2] by providing ideas and comments before publishing; further, he calculated the tariffs utilized in the publication. M.Sc. **Kari Kallioharju** and Lic.Sc. **Pirkko Harsia** conducted measurements utilized in a previous publication [P4].

# 1 INTRODUCTION

This chapter introduces the background and motivation of this thesis, which is driven by the energy transition and role of residential buildings in this transition. Energy storage is expected to become a critical factor in future energy systems. This chapter presents the scope, research questions, and structure of this thesis.

## 1.1 Background

Finland's electrical energy system requires more flexibility because of the increase in weather-dependent variable renewable energy (VRE) production and the rapidly progressing electrification [1]. This progress has been ongoing given the implementation of climate change mitigation measures; however, the energy crisis has been driving this progress as Finland is aiming to be energy self-sufficient. Energy storage and demand response (DR) are key technologies for increasing flexibility [2]. Energy can be stored in various forms, and therefore, many solutions have been proposed for energy storage [3]. Electrical energy storage (EES) systems can be charged directly from electricity, and typical solutions include different types of batteries, although multiple solutions with various features also exist. Further, battery energy storage systems (BESS) are suitable solutions for residential buildings because they can be installed easily, their capacity and power can be sized to meet the requirements of the buildings, and safe options are available [4]. Lithium-ion (Li-ion) batteries are a good choice because of their high efficiency and longevity; however, their high investment cost is a drawback [5].

Poor profitability caused by high investment costs has been the main barrier to the higher prevalence of energy storage in the residential sector [6]. Although the cost of batteries has decreased rapidly over the past decade [7], this cost is expected to decrease further gradually. The decreasing battery costs are expected to affect the retail price of the BESS over time; however, retail prices can drop with an increase in the number of systems used. The generalization of electric vehicles (EV) is the most crucial factor for decreasing battery prices; conversely, EV manufacturers include stationary BESSs to the market for increasing the volume of battery markets and push battery cell prices down [8].

In Finland, residential buildings consume ~20% of the total energy and ~37% of the total electricity [9]. Households are significant factors in electrical energy systems, and ~64% of the total energy consumption goes to space heating; however, in 2020, only 25% of this was electrical [9]. Therefore, households have more electricity–energy consumption factors compared to that for heating. Progressing electrification can increase the share of electrical energy in space heating when heating systems are becoming increasingly electricity-based [10]. High electricity consumption makes residential buildings as a good target for demand response (DR) operations and increasing VRE production, e.g., using photovoltaic (PV) systems. Residential buildings are distributed unequally, and sometimes, the distances are considerably significant, which implies that the required flexibility can be spread all around the grid. Customers are expected to play a larger role in the energy system: If they have their own production, they will become prosumers; if they participate in the flexibility of the grid, e.g., through DR operations, they will become active customers. Further, customers can form energy communities in which shared energy resources can be invested. Multiapartment buildings are natural targets for creating an energy community; however, several detached houses can also form an energy community.

## 1.2 Benefits and drawbacks of electrical energy storage

The EES can be used for many purposes. The EES is used when electric power is required; however, the electricity grid is unavailable or in mobile applications, e.g., in EVs. Mobility and high-energy density are the most important features of energy storage, and they offer advantages of battery-based EESs compared to other energy storage solutions such as pumped hydro storage or flywheels. The increasing need for flexibility implies that the use of EES in on-grid applications has become more common. EESs are easily scalable and can be installed without significantly causing any concerns, such as noise or space constraints.

The use of EES in stationary on-grid residential applications has several advantages. For example, the goal of a residential customer is to achieve benefits using EES; however, this often causes some drawbacks. An increased VRE production creates the need to store surplus energy for later use. If incentivized, an EES owner can obtain economic benefits by storing the surplus energy. When EES and small-scale electric energy production systems are installed in a residential building, self-consumption can be increased via EES. A customer can save costs when increased self-consumption decreases the electricity purchased from the grid and when electricity purchase costs are higher than the compensation from the surplus energy sold to the grid. However, the drawback to this approach is that energy storage causes losses, and therefore, some of the energy produced is lost during storage.

Distributed VRE result in higher requirements for the electricity grid when the electricity distribution is applied in a complex environment. Historically, the basic tasks of grids were designed for transferring and distributing electricity from power plants to customers. Increasing the number of small-scale production units surrounding the grid implies that the grid must be ready to transfer electricity bidirectionally, thereby creating new challenges for grid design. Simultaneously, new production closer to consumption implies that less energy must be transmitted. Locally, bidirectional power is expected to increase, while the total amount of transmitted energy decreases, thereby creating challenges for distribution system operators (DSO) when the grid design is based on peak power. However, income is based on the amount of energy. Using a local EES can decrease the negative effects of the high prevalence of small-scale distributed VRE production.

Further, customers can also benefit from modifying their load profile using an EES. If the DSO charge is based on the maximum power, customers can save costs by decreasing the maximum power with the ESS, thereby relieving the pressure on the grid. Moreover, if electricity prices vary over time, customers can save costs by shifting their consumption from high to low levels. Over time, the changing prices incentivize shifting loads to better correspond to production. From the perspective of the power system, shifting loads during high-price times can decrease the need to produce energy with expensive production methods, which can help reduce peak prices eventually. Residential customers can shift their loads using an EES.

Methods besides EES can also modify the load profile. Different types of DR operations are alternatives for an EES. In residential buildings, DR operations result in some loss of comfort or limitations, e.g., less hot water is available if a water boiler is used for DR operation. All electrical devices may be unavailable for continuous use, or there may be changes in the indoor temperature. When the EES modifies the load profile, customers do not notice any loss of comfort. Further, modifying the load profile is a simple process that can be achieved by setting boundaries using the EES for the storage capacity and maximum powers of charging and discharging. In DR operations, the possibilities (i.e., capacity and power) depend on many factors such as the electricity use of the customer or outdoor temperature.

Further, an EES can be used as a backup power supply. The EES is bidirectional, and its stored energy can be utilized during interruptions in the supply grid, which benefits the owner of the EES, even when its value estimation is difficult. Further, interruptions also occur occasionally in modern power grids, and this can harm customer experiences because of the variation in the interruption.

## 1.3 Scope and research questions

This thesis deals with the control targets of residential EES in the Finnish market environment, providing a direct financial benefits to customers because of control. Fig. 1 illustrates the control targets of this thesis and how they are studied in the original publications.

This thesis aims to discover factors that affect the profitability of EES and study how it can be increased. The research questions in this thesis can be summarized as follows:

- What variables define the profitability of residential energy storage?
- How do different incentives affect the control of energy storage?
- What are the economic risks of the energy storage investment?
- How does energy storage affect the profitability of photovoltaic energy production in the residential sector?
- How can the profitability of residential energy storage be improved?

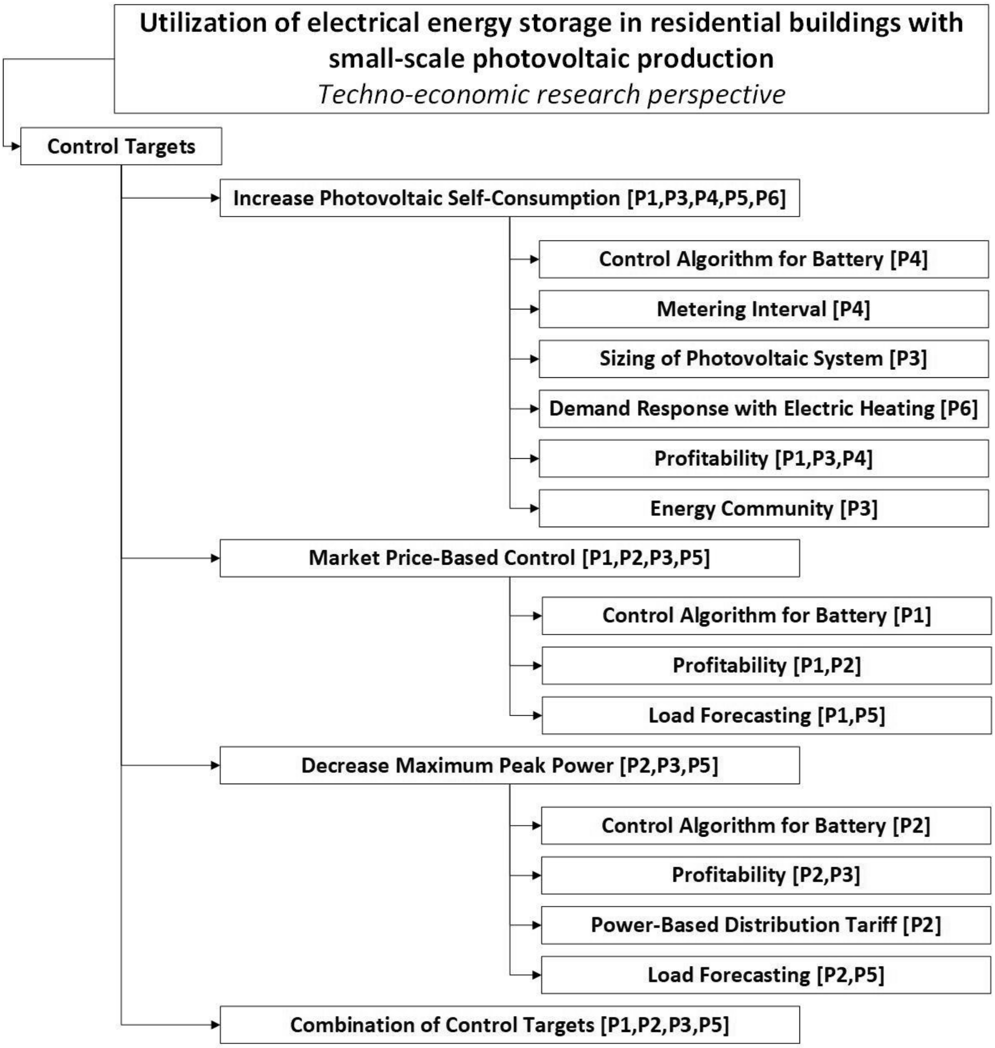


**Figure 1.** Content of this thesis divided into control targets and references to the original publications in which they are discussed.

The thesis focused on simulations using measured data for answering the research questions. Developing an effective control algorithm for a battery with each control target is vital for developing a simulation model. A control algorithm is suitable for research with a large number of customers in a study group; however, the results can also be utilized for developing the control algorithm for commercial applications. The objective is identifying a realistic level of benefit; however, studying the possible pitfalls when attempting to maximize economic benefits is important. Further, the simulations were made from the data of Finnish electricity customers and Finland's market environment as part of the Nordic electricity markets. However, similarities in the markets around Europe make it possible to generalize the results for other market environments while considering the differences. The data used in this thesis were collected from 2013 to 2018. Subsequently, the electricity prices significantly changed because of the "energy crisis" at the end of 2021. This thesis presents a brief comparison with the new data presented in Chapter 4 for studying the effect of these changes.

## 1.4 Structure of the thesis

The rest of the thesis is organized as follows:
Chapter 2 includes the literature review of the topic to be studied. Chapter 3 introduces the research methods, including a simulation model using a battery model and a photovoltaic production model. Further, this chapter presents the used demand response model, control methods used, and how load forecasting can be utilized in control. Moreover, describes the energy community model. Chapter 4 presents the results of the thesis. Results are divided into different control targets and combinations. Chapter 5 summarizes and concludes the thesis, including a discussion and presentation of the main contributions.

# 2 LITERATURE REVIEW

This chapter presents a wide literature review based on the scope of this thesis. The literature review is divided into four topics so that the presented references are closer to the topic of this thesis toward the end. These previous publications verify the methods used in this thesis. The research gaps identified in the review are also addressed.

## 2.1 Economic perspective of a photovoltaic system

Household owners invest in PV systems for several reasons. One survey [11] revealed that the Finns are ready to invest in a PV system for ideological and sociological reasons, even if profitability is low; however, most define economic savings as their most important goal. This trend is currently changing, and economic profitability is now being considered a critical factor by household owners when making investment decisions.

Many studies have recently focused on the economic profitability of PV systems. There are considerable differences in market environments between countries, affecting the profitability and the perspective on how these differences are studied. However, the basic principles remain the same. Meriläinen et al. [12] examined the following factors affecting residential PV profitability in the Finnish market environment: the electricity price, load profile of the building, and orientation of PV panels [12]. Vimpari and Junnila [13] studied differences in the profitability of rooftop PV between the capital cities of EU countries, considering electricity pricing and differences in solar power potential; however, they focused on non-residential buildings. In the south part of Europe, the PV energy yield is higher than that in the north; however, the electricity pricing strongly affects the profitability of PV, and the increase in property value attributed to PV installation varies between countries [13].

Incomes from small-scale PV production initially emerge from self-consumption and subsequently from selling the surplus energy to the grid. Self-consumption implies that PV production reduces the electricity purchased from the grid. Escobar et al. [14] studied the profitability of the self-consumption of PV in Spanish households and compared Spanish regulations with those of other European countries. Their results demonstrated the importance of regulation. Although the total annual solar irradiance in Spain is the highest in Europe, the profitability of the self-consumption of PV remains meager compared to that in other countries such as Finland, where the low total annual solar irradiance decreases profitability but is still higher than Spain because of electricity pricing [14]. In addition, the load profiles differ for customers in different countries. For example, in the northern European countries, there are high heating loads in the cold season, whereas the southern European countries have high cooling loads during summer.

Several tools have been used to evaluate the profitability of PV investments. the levelized cost of electricity (LCOE) and payback period are commonly used to evaluate profitability, similar to that in a case study in Sweden [15]. LCOE is a good assessment tool when the PV system is compared with other energy sources, and it can be calculated by dividing the energy produced by all costs during the lifetime of the system. The LCOE indicates the net present value (NPV) of income from future years. Given the dynamic scenario of world economics, it could be is difficult to estimate the discount rate. To set the NPV to 0 €, we calculate the internal rate of return (IRR), which is an excellent tool to evaluate PV investment profitability, and we compare it with different investment options [16]. LCOE, NPV, and IRR are better tools for assessing PV profitability compared to the payback period when the time value of money is meaningful [17].

The publications presented in this chapter studied the economic perspectives of PV systems from many perspectives. The results of these publications verify the selection made in the studies considered in this thesis and confirm that the employed methods are correct and proven in the scientific community. However, none of the previous publications focused on system sizing or the effect of different energy resources on the economics of PV systems.

## 2.2 Electrical energy storage system with photovoltaics

All energy storage systems, which are charged by electricity and output energy, are also electrical energy storage and have been referred to as EES; e.g., [3] batteries, which are referred to as electrochemical energy storage. In this study, batteries are defined as a group of EES. There are many optional storage solutions that can be used with PV in residential buildings, including PV-flywheel energy storage or PV-compressed air energy storage; however, the PV-battery combination is most commonly used [18]. Liu et al. [19] compared many EES applications and reported that Li-ion batteries are most suitable for storing PV energy in residential buildings in addition to supercapacitors and flywheels. Li-ion batteries are an excellent option because many of their market applications are easily scalable.

Thus far, several possible Li-ion battery chemistries have been reported. The most common cathode materials include nickel-cobalt-aluminum-oxide (NCA), nickel-manganese-cobalt (NMC), and lithium-iron-phosphate (LFP) [20]. Hesse et al. [20] compared the features of different Li-ion battery chemistries and observed that NMC had the lowest cost per kWh and the highest power density, NCA had the highest energy density, and LFP has the best safety features and longest lifetime. These features indicate that LFP and NMC are the most promising Li-ion battery chemistries for residential applications [5]. Diouf and Pode [21] reported that LFP is the most promising battery chemistry for large-capacity energy storage because of its long lifespan and high safety features.

The lifetime of a Li-ion battery is a critical factor for evaluating the potential of a BESS for residential use. The lifetime of the battery strongly affects profitability calculations because it determines the replacement frequency for the battery. Sarasketa-Zabala et al. [22] predicted the lifetimes of LFP battery cells. Battery ageing can be categorized in to calendar and cycling ageing. When a battery is not used, it ages over time because of battery accelerating ageing. The state-of-charge (SOC) range, depth-of-discharge (DOD), temperature, and C-rate are factors that influence the lifetime of a battery [22]. SOC indicates the charge level of the battery (0–100%), and DOD indicates the decrease in the SOC before subsequent charging. Further, the C-rate indicates the charging and discharging powers (kW) of a battery in terms of battery capacity (kWh), i.e., the C-rate indicates the time it takes charge a battery from empty to full, or vice versa.

Battery lifetime is defined by utilizing the state-of-health (SOH) value, which is the measured capacity as a percentage of the nominal capacity [23]. The SOH varies based on the end of lifetime (EOL). In one study [22], the EOL corresponded to 85–90% SOH, whereas in another study [24], it was 80%. The EOL does not imply that the battery can no longer be used; instead, it describes a scenario wherein the battery capacity is diminished, and the losses are too high for the battery to be useful for the original application. Batteries of EVs can be reused in residential buildings after their EOL [25]. Alimardani and Narimani [26] studied the lifetime extension of Li-ion batteries (so-called second-life batteries). Further, the use of EES with PV has already been investigated in previous studies [27, 28]. Häring et al. [29] focused on using common household thermal storage systems to support PV production. Agnew and Dargusch [30] studied customer preferences for BESS at the household level.

These publications, which focused on EES, verified the types and features of EESs selected in this thesis. Many previous publications have investigated battery behaviors and explored approaches for optimizing its lifetime. The results of these publications were used to design the simulation model in this thesis. These features identified in these publications were utilized to maximize the economic benefits in simulated cases in the Finnish environment.

## 2.3 Optimization of battery size and control system

Research on BESS control and sizing has primarily focused on increasing the profitability. The existing publications focused on three main targets: maximizing economic benefits, maximizing battery lifetime, and sizing systems. Vieira et al. [31] presented a control system to maximize the self-consumption of PV. Moshövel et al. [32] studied the effect of PV production on the peak power of the grid, which can decrease battery usage. Nge et al. [33] studied the real-time energy management of BESS based on the electricity market price for maximizing economic benefits. Zheng et al. [34] studied residential peak-shaving strategies from a financial perspective. These publications are representative of research that focus on maximizing economic benefits.

The lifetime of a battery indicates the duration for which benefits can be collected and how long the costs can be distributed, and therefore, it strongly influences economic profitability [35]. Pena-Bello et al. [36] studied battery-lifetime optimization with different electricity tariffs and indicated that combining control targets increases profitability. Förstl et al. [37] showed that a battery aging model is essential for studying battery profitability while considering different control strategies because DOD strongly affects battery ageing. Farinet et al. [38] studied battery lifetime when the self-consumption of PV was optimized for a Danish environment. The control system attempts to balance between maximizing benefits and determining the causes of battery ageing. Avoiding very high or low charges with a low DOD can extend a battery's lifetime. Estimating whether the control act is more valuable than reducing the battery's value can be difficult because of the ageing caused by the control act.

Optimal sizing significantly affects the profitability of BESS. The size of the PV can affect the size of the BESS [39]. Mohamed et al. [40] showed that the load profiles of residential customers strongly affect battery size. Wu et al. [41] used convex programming to optimize battery size, which worked well when the daily load profiles remained similar year-round. A techno-economical PV battery-sizing system was presented in other studies [42, 43], where a PV without a battery was found to be more profitable than a PV with a battery; however, this situation can change in future. These publications were conducted in different market environments from that considered in this thesis, and the batteries were used to increase only the self-consumption of PV. Bianchi et al. [44] focused on maximizing PV production with battery sizing; however, they did not consider the economic perspective. Residential BESS sizing from an Australian perspective was presented in another study [45]. Further, methods to control BESS have been studied previously [46], [47], [48], and [49]. Forecast-based control for enhancing the BESS lifetime was studied in [50]. Further, BESS control with EV for reducing peak powers was studied in [51] and optional DR operations were studied in [52]. Forecasts used in control have also been studied [53].

These previous studies present significant variations in the control methods; however, none of these studies focused on controlling economic targets in the Nordic market environment for increasing the profitability of BESS while considering the requirements of control, i.e., load forecasting. The studies considered in this thesis focus on optimizing the possible benefits of different control targets while considering the potential risks of combining controls.

## 2.4 Profitability of battery energy storage system

Investment costs, benefits, and lifetime are key factors for evaluating the profitability of a BESS. The profitability of a BESS is calculated using PV because batteries are often used to increase self-consumption [16, 54]. BESS can be used for other control targets if electricity pricing generates incentives for it, e.g., through dynamic tariffs [55]. The profitability of the BESS is evaluated to be weak in Finland, and with low investment costs, the payback period is considered very close to the lifetime of the system [56]. With PV, the profitability of the BESS is evaluated to be good, e.g., in Germany [16]. Alavi et al. [57] suggested that BESS with PV had no benefit for prosumers in Belgium. Further, Germany and Belgium used feed-in tariff (FIT) for surplus PV energy, and the electricity price level for household customers was found to be higher than that of the EU's average when the calculations were completed [16, 57]. Contradictory study results have shown that evaluating the profitability of BESS is difficult and that the evaluation method is strongly affected [16, 57]. In addition, different initial data related to the market environment and the studied load profiles affect the results and conclusions.

Studies that investigate the profitability of EES often focus on its improvement. Profitability calculations are used as a tool to evaluate the effectiveness of the improvement methods. Pena-Bello et al. [36] improved profitability using a genetic algorithm for scheduling optimization. Klingler and Teichtmann [58] studied a forecast-based operation strategy; however, the result indicates that a self-consumption maximizing strategy is more profitable. Arcos-Vargas et al. [59] considered increasing storage profitability by decreasing power peaks when an electricity tariff included a demand charge. Munzke et al. [60] studied the profitability of a BESS with different control strategies and demonstrated battery lifetime can be increased with appropriate control.

Policies in different jurisdictions can affect the profitability of BESS. Kazhamiaka et al. [61] compared the profitability of a residential PV and BESS combination in three jurisdictions—Germany. Southern Ontario, and Austin, Texas—and found that policymakers could use the electricity price and upfront subsidies to impact profitability and further generalization. Zakeri et al. [62] studied policy options for increasing the profitability of PV with BESS and found that a battery can be profitable with PV, even in high-latitude countries with the right policy. Further, Fett et al. [63] compared different regulatory settings and noted that residential BESS will become profitable regardless of the regulations, which play a crucial role in the system integration of renewables.

Many factors affect the economics of the BESS. The tariffs used affect possible cost savings that can be achieved using BESS [64]. Forming distribution tariffs has been studied in [65] and [66]. Market electricity prices also affect the attractiveness of DR operations [67]. In addition, the economic perspective of BESS has been studied [68, 69, 70].

In previous studies, the profitability of the BESS focused only on limited control targets. The results of these studies showed that the profitability is weak; however, there are variables that can affect profitability and make BESS more profitable. The scenario changes constantly when electricity prices change, storage functions improve, and investment prices vary, thereby indicating that profitability calculations are updated continuously. This thesis focuses on identifying variables that affect profitability, which can help evaluate profitability in new scenarios.

# 3 RESEARCH METHODS AND DATA

This chapter presents the methods and models used in the simulations. The control methods are also presented. Finally, this chapter summarizes the data used in this thesis.

## 3.1 Modelling the residential battery energy storage system

A Li-ion battery where LFP is used as the cathode material is modelled in this thesis given its good features for residential use. LFPs exhibit good safety features and long cycling and calendar lifetimes [71]. The results of this thesis are valid for other Li-ion battery types; however, there can be small differences in the battery lifetime and initial values of modelling, thereby affecting the results related to charging and discharging efficiencies. When a battery model is used mathematically, some simplifications can cause errors in the results, which are similar to changes that can be attributed to a using a different battery type. Finding a realistic level of storage loss is paramount in battery modelling. Modelling ensures that the models are as simple as possible so that the results present the scenario at yearly levels, and small details in the models cannot significantly affect the results.

The self-discharging capability of the LFP is negligible, and therefore, battery loss can occur during charging and discharging. Charging losses are higher than discharge losses; however, during modelling charging cycles, the charging efficiency can be assumed to be the same as the discharge efficiency [72]. Cycle efficiency is an essential factor in BESS modelling. The charging efficiency $\eta_c$ can be modelled using the internal serial resistance $R_b$ of a battery [73]. The charging efficiency of a battery can be calculated as

$$\eta_c = 100\frac{V_b - I_c R_b}{V_b}, \tag{1}$$

where $V_b$ and $I_c$ represent the battery nominal voltage and charging current (discharge current when calculating the discharge efficiency), respectively.

The battery SOC range is limited to 25–95% in the simulation model for the following reasons: (1) The internal serial resistance is not constant and grows robustly when the SOC surpasses 95% or drops below 10% [74]. A high internal serial resistance indicates high losses during charging and discharging. In this range, the internal serial resistance remains nearly constant, indicating that the voltage remains almost constant, which is an important advantage of Li-ion batteries. (2) Battery ageing depends on the DOD, and a high DOD accelerates aging and increases losses; therefore, an SOC below 25% is avoided. When avoiding the very low and high SOC, the constant value of internal serial resistance 0.026 Ω can be used in the model, as reported in [74] for a Li-ion battery. A battery pack includes cells connected in series or parallel. Serial connections in the cell increase voltage, whereas parallel connections increase capacity. A nominal voltage of the one LFP cell is 3.3 V, and the capacity is 2.5 Ah [74].

The SOC of the battery at time $t$ ($SOC_t$) can be modelled using

$$SOC_t = 100\,\% \times \frac{B_{eff} B_t}{E_{max}} + SOC_{t-1}, \tag{2}$$

where $E_{max}$, $B_{eff}$, and $B_t$ represent the maximum capacity of the BESS, efficiency of the energy transfer to storage, and amount of energy transferred between the BESS and the electricity network of another household, respectively.
The SOC limits set the range of the SOC. Further, temperature dependency is not modelled because it is assumed that the battery is located in the room of a residential building at a constant temperature. The presented battery model is used in all studies considered in this thesis.

## 3.2 Simulation model for residential buildings

The simulations conducted in this thesis aim to simulate the electricity demand of a residential building from the perspective of the grid (*G*). The demand of a household (*D*) represents the initial data in the simulations and is unchangeable in publications [P1–P5]; it is modified only in publication [P6]. Fig. 2 shows how PV production (*P*) and BESS energy (*B*) are added to the electrical network of a household. PV production is not involved in publication [P2]; however, the other parts of the network are similar. Converters can cause losses, and the efficiency of the DC-converters is assumed to be 99%, whereas that of an AC/DC-converter, i.e., the efficiency of an inverter ($\eta_{inv}$), is assumed to be 98% [75].

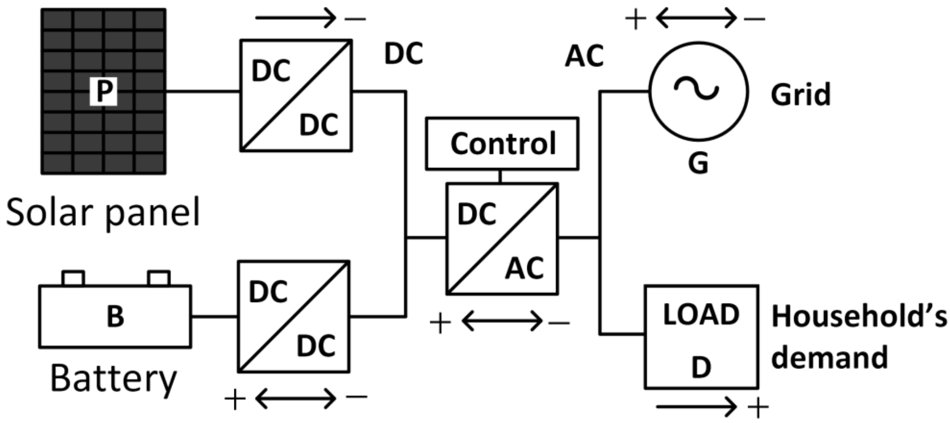


**Figure 2.** Connecting BESS to the electricity system of a residential building [P1].

In practice, the simulated DC converter after the solar panel corresponds to all power electronics required before the inverter, i.e., these losses are modelled, and in simulations, the PV system looks like an entire system, thereby including the converter. Therefore, the produced PV energy ($P_{dc}$) refers to the energy produced after the converter in the equation. The simulated electricity demand is expressed as

$$G = \begin{cases} \dfrac{B_t - P_{dc}}{\eta_{inv}} + D & \| if\ B_t > P_{dc}\ \&\ B_t \geq 0 \\ -\eta_{inv}(P_{dc} - B_t) + D & \| if\ B_t \leq P_{dc}\ \&\ B_t \geq 0 \\ \eta_{inv}(-B_t - P_{dc}) + D & \| if\ B_t < 0 \end{cases} \tag{3}$$

The three abovementioned equations are derived from BESS operations. In the first equation, the PV energy does not require BESS charging and the energy from the grid is used for charging. In the second equation, all charged energy comes from the PV. In the third equation, the BESS is discharged. Electricity demand *(G)* can be negative if the PV production exceeds *D*, and not all surplus energy can be stored in the BESS. The surplus energy is then fed to the grid.

## 3.3 Modelling small-scale photovoltaic electricity production

Small-scale PV production is a key part of this thesis and included in publications [P1, P3–P6]. PV production must be modelled in simulations for two reasons: (1) Production data in the studied buildings do not exist in real life, and using measured data from a different place is an invalid approach because the production profile depends on the location, including the temperature at the site. (2) The production profile varies frequently, and repeating the historical production profile is highly unlikely. Therefore, variations in possible future PV production profiles can be studied through modelling. In addition, BESS control can require a PV production forecast, and modelling makes this forecast possible.

Theoretically, the amount of PV energy produced depends linearly on the size of the PV system. The nominal power of a PV system ($P_{STC}$) is defined under standard test conditions (STC). At the STC temperature, $T_{STC}$ is 25 °C. The PV production ($P_{PV}$) can be calculated using

$$P_{PV} = P_{STC} G_i \big(1 - \beta_P (T_c - T_{STC})\big), \quad (4)$$

where $\beta_p$, $T_c$, and $G_i$ represent the solar cell power temperature coefficient (0.006), solar cell temperature, and total solar irradiance of the solar cell [76], respectively.

PV panels are usually installed as stationary elements, and therefore, the azimuth and inclination angles $\beta$ are constant. The direction of the sun in the sky changes constantly, and therefore, the solar irradiance on the solar cells varies correspondingly. In PV production modelling, the total solar irradiance of the solar cell must be estimated. The model comprises three parts: the direct beam component ($G_{b,i}$), diffuse component ($G_{d,i}$), and reflected component ($G_{r,i}$) [77]. The total solar irradiance $G_i$ of the tilted panel represents the sum of these three components. These components can be calculated using the Reindl model [78]—one of the best diffuse solar irradiance models—particularly for tilted surfaces [79]. The components can be expressed as

$$\begin{cases} G_{b,i} = G_b(\cos\theta_i / \sin\alpha_s) \\ G_{d,i} = G_d\,(1 + \cos\beta)/2 \\ G_{r,i} = \rho_g G_g\,(1 - \cos\beta)/2 \end{cases}, \quad (5)$$

where $\theta_i$, $a_s$, and $\rho_g$ represent the angle of incidence on the surface based on the azimuth angle of the sun, solar elevation, and average reflectance of the reflecting surface [76], respectively.

Equation (5) contains the basic components of the horizontal irradiance, i.e., $G_b$, $G_d$, and $G_g$ represent the horizontal beam irradiance, horizontal diffuse irradiance, and horizontal global irradiance, respectively. In the publications considered in this thesis, the horizontal irradiance is estimated in three ways. Publication [P1] used real PV production data, and the PV model was used to form only a PV production forecast such that the cloudiness corresponded with the real data. In publications [P4] and [P5], these irradiances were considered as measurements from the open data of the Finnish Meteorological Institute [80]. The third version was presented in publications [P3] and [P6], where irradiances were calculated based on the direction of the sun in the sky and the cloudiness probability model in Finland [81]. The selected method depends on the objective of the publication.

## 3.4 Demand response with electrical heating in small-scale residential households

Publication [P6] presents a method to evaluate the demand response potential with electrical heating in detached houses. In the publication demand, the response potential can be compared to the potential of the BESS system for increasing the self-consumption of the PV. Every building has its own thermal features, which must first be determined to study the demand response operations. The studied buildings were heated using direct electric heaters, which implies that the thermal heat produced was equal to the electrical heating load.

These two coefficients describe the thermal features of a building. The total heat loss coefficient ($c_f$, W/K) describes the amount of heating power ($E_h$) required to maintain the indoor temperature ($T_{in}$) stable when the outdoor temperature ($T_{out}$) is lower than the set value of the indoor temperature, i.e., the amount of power required to replace the thermal losses in a building. The second coefficient is the total heat capacity ($c_p$, Wh/K), which describes the capacity of the building to store heat. This coefficient affects the temperature-decreasing speed when the heating power is considerably low to maintain the indoor temperature stable or when the high heating power starts increasing the indoor temperature. A high total heat capacity resists changes in the indoor temperature. The total heat loss coefficient defines the amount of heating power required, which can vary. Further, the total heat capacity defines how long the heating power can be interrupted so that the indoor temperature changes remain tolerable.

From Newton's law of cooling [82], we have

$$c_p \frac{dT_{in}}{dt} = E_h - c_f(T_{in} - T_{out}). \tag{6}$$

Equation (6) shows the effect of changes in different variables and coefficients on the indoor temperature. Further, it is possible to calculate the values of the coefficients when other variables are known. The total heat loss coefficient of a building can be solved by maintaining the indoor temperature at a stable value and measuring the heating power and outdoor temperature. This is a common scenario wherein the thermostat is used to control the heating of a building. Scenarios where changes in temperature can be used to determine the total heat capacity of a building are investigated. Test setups can be performed by interrupting the heating power of a building for a known period and measuring the changes in the indoor temperature. However, in buildings with direct electrical heating, both coefficients can be estimated by utilizing the electricity-load profiles of the building and outdoor temperature measurements, assuming that the setting value of thermostatically controlled indoor temperature is stable. Thermodynamically, the effect is the same regardless of the changing variable (indoor or outdoor temperature) because the temperature difference affects the need for heating power. Utilizing the knowledge from the impact, we can estimate the coefficients of many buildings when their load profiles and the possibilities of the heating demand response of residential buildings are known. This simple model does not consider the internal heat sources or effects of solar heating or wind cooling on the building; however, these effects are minimized for the results using the data from a large number of customers.

## 3.5 Control methods

Control systems play a key role in maximizing the benefits of energy storage or flexible loads. Different parts of the control system are presented in all publications [P1–P6] considered in this thesis. Incentives, i.e., control targets, define how the resources should be controlled. The control algorithm can be divided into two levels: (1) The control algorithm decides what should be done in the next period, and (2) the control (called continuous control in publication [P1]) attempts to execute this decision. The time step of the decision-making process depends on the measurement interval of electricity billing. In Finland, the measurement interval is an hour for smart meters. Electricity billing depends on cumulative consumption over a metering period, and therefore, decision making attempts to impact this value. Controlling at the second level operates during the metering period because there are variations in the load and possible production during these periods. In future, the measurement interval of smart meters will be set to 15 min. The effect of this change has been studied in publication [P4]. The control methods in this thesis focus on controls at the first level because the metering interval in the consumption data is the same as the time step at the first level of control. Publications [P1] and [P4] evaluated the effect of second-level control.

Energy storage and controllable loads are used to achieve various control targets. Electricity tariffs create incentives for control targets. There are three main control targets:

a) Increasing self-consumption (if there is a surplus of self-production).
b) Decreasing the maximum power (if there is a power-based component in the tariff).
c) Decreasing the average electricity price using market-price-based control (if there is a market-price-based tariff).

The incentives for the different control targets are obtained from the electricity tariffs. In Finland, the electricity bill of a customer comprises the energy retailer's fees, DSO's fees, and taxes. If a customer produces their own energy (e.g., a rooftop PV system), the energy produced is more profitable for personal use compared to feeding it to the grid. When self-produced energy replaces the purchased energy, customers can save costs by avoiding distribution fees and taxes. A customer can sell the surplus energy to an energy retailer and receive compensation at a level that corresponds to the purchase price. Energy retailers add margins to purchase prices to cover costs and generate profits. A high volumetric component in distribution tariffs, high volumetric-based taxes, and high margins of the energy retailers increase the incentive for self-consumption.

Power-based distribution tariffs have been discussed actively for small customers in Finland [83]. Such tariffs include a demand charge, where part of the distribution cost depends on maximum power. Although many models exist, the most common are based on the highest power of the sliding year or month [84]. Customers can save costs by decreasing the demand, which includes power-based, thereby incentivizing peak-saving operations with the energy storage of flexible loads. As reported in publication [P2], the control algorithm for peak saving requires memory to store the highest peak of a period; further, the loads can be controlled to avoid exceeding this limit, or the energy storage can be discharged when exceeding these limits is considered a threat [P2].

Energy retailers in Finland offer contracts in which electricity prices change hourly based on the day-ahead electricity market prices. Further, price components can vary depending on time; for example, prices in the daytime can differ from those at nighttime. An on-time price change incentivizes load-shifting control, wherein loads are moved for low-price periods. A scenario wherein the price changes every hour can be a challenging optimization problem for a control system. This optimization problem can be solved easily with linear programming, as indicated in [85]. The following limitations make this issue more challenging:

- In the near future, we will be unable to determine the exact required loads and possible production.
- Electricity prices for the near future's hours are available only for a short period (10–34 h) depending on the hour of the day in Finland.
- Non-constant efficiency of energy storage affects optimization.
- Other possible control targets affect optimization.
- Unknown variables can be forecasted; however, the forecast always include errors.

These factors can follow a scenario where a solution with a traditional optimization algorithm such as linear programming does not provide any cost savings in the actual case, i.e., the optimization fails because of errors in the initial values. Therefore, this thesis develops methods that can yield near-maximal benefits, even with errors in the initial values. Utilizing load and production forecasting can minimize the effect of unknown future profiles. The availability of futures prices limits the length of the optimization period; however, futures prices can also be forecasted. The forecasting errors still negatively affect optimization. Regardless of the energy-storage method, some energy is lost during storage. This can be utilized to form an optimization problem because in many situations, it dramatically limits the number of possible solutions.

The possible length of the optimization period varies between 10 and 34 h because with a 10-h period, we can identify all future hourly prices. After the 35$^{th}$ future hour, we must always forecast the prices. Longer periods make it possible to pursue a better solution and higher savings; however, longer periods increase the effect of forecasting errors. Publication [P1] stated that using longer than 18-h optimization periods provide only minimum extra benefits, and therefore, this thesis used the 18-h optimization period. During this period, electricity prices varied on an hourly basis. However, the variation is not random, and it follows a certain regularity. The price is higher during the daytime than that at nighttime, and there are morning and afternoon peaks. Occasionally, the price changes can be very flat, e.g., if high wind-power production keeps the price low throughout the day. The loss of energy storage indicates that the price difference between charging and discharging must be sufficiently high. In addition, every charging cycle decreases the battery lifetime if a battery is used for energy storage, which further increases the required price difference. This leads to a scenario where, the controls are unprofitable if the price profile is flat; on a typical day, there are individual periods when charging discharging, e.g., for a battery with a C-rate of 1, imply 1 h of charging and 1 h of discharging during the optimization period. In the last decade, prices have varied by only a small number of days, thereby leading to more than one potential charging cycle per day.

Considering all the factors limiting the problem, the nature of the optimization problem changes from solving a linear programming problem to finding extreme values with limitations. To solve this problem, a method was utilized for finding the charging and discharging pairs during the optimization period. If the storage is full or nearly full, it must first find a time slot for discharging, i.e., the hour when the electricity price is the highest. Subsequently, we must find a timeslot for charging (after the discharging timeslot when the electricity price is the lowest. A control command can be provided for secondary control when the price difference between these timeslots is so high that the cycle is profitable even when considering the losses. Then, we can find a second pair using a similar method, which continues until the price difference between the timeslots drops that are so low that the cycle is unprofitable or all timeslots in the optimization period have gone through. In addition, the SOC of the storage must remain inside the set boundaries, which means that, in practice, the next pair must be inside, before, or after the previous pairs. If the storage is closer to empty than full, the algorithm must determine the lowest price for the charging timeslot.

During an 18-h optimization period, there was one pair of charging and discharging timeslots, and depending on the C-rate of the battery, the timeslots ranged from 1 h to a maximum of 3 h. A second pair exists if the price variation is very high. Fig. 3 illustrates this scenario, which shows the average day-ahead market prices in an area of Finland every hour of the day between 2013 and 2022 [86]. The optimization period in which the variation is the highest is marked by red lines. The first pair can be found at hours 5 and 20, whereas the second pair can be found at h 10 and 16. If the price difference between the two is sufficiently high, the second pair of cycles will also be profitable. Fig. 3 shows the average scenario; naturally, there is a considerable variation between the daily price profiles. The second cycle is unprofitable; however, the energy crisis in 2022 involve several profitable cycles per day.

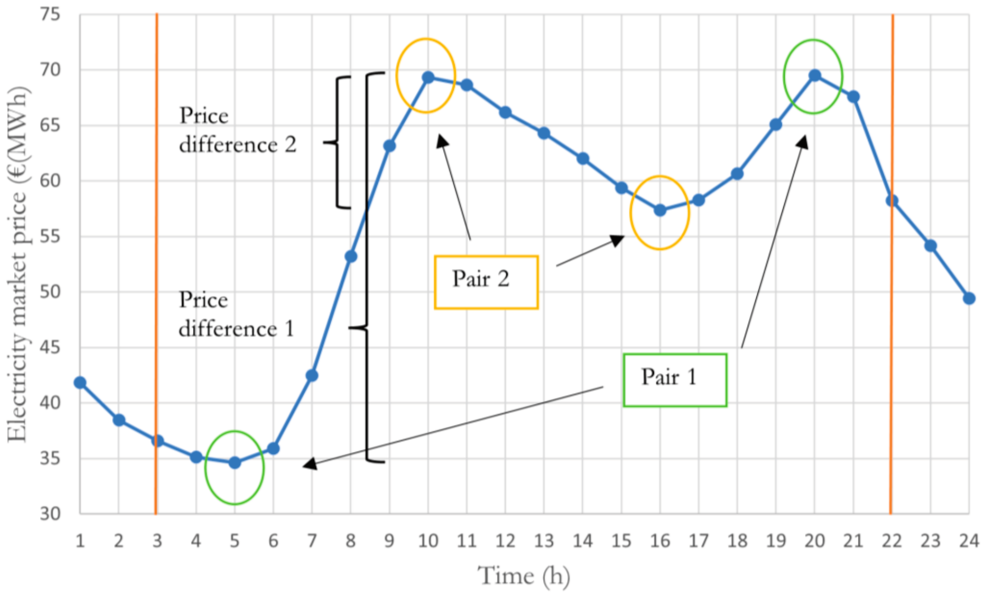


**Figure 3.** Background of market-price-based control.

If the effect of battery lifetime is not considered, the relationship between the price during discharging $C_{t2}$ and charging $C_{t1}$ should follow

$$C_{t2} \geq \frac{1}{B_{eff}{}^{2}} C_{t1}. \tag{7}$$

Equation (7) can be derived from the rule that benefits must be greater than the losses. For example, if the efficiency $B_{eff}$ is 95% and the electricity price is 0.058 €/kWh during charging, as in pair 2 in Fig. 3, we can assume that the distribution costs and taxes total 0.1 €/kWh, and the total price during discharge can be greater than 0.175 €/kWh. Fig. 3 shows that the highest price in pair 2 is only 0.168 €/kWh when considering distribution costs and taxes. Equation (7) provides only the theoretical minimum; moreover, the effect of the battery lifetime needs to be considered. We can estimate that the cyclic lifetime of an LFP battery is ~10, 000 cycles if the DOD is ~50% [87], which means that two cycles per day correspond to a 13.7-year lifetime, i.e., the same level as the calendar lifetime of an LFP battery.

Therefore, two cycles per day represent the maximum usage of the battery, which does not decrease its lifetime.

The control becomes more challenging when storage is used for several control targets. Controlling needs can be opposite for different targets. Publication [P5] closely studied the challenges of combined control. The combination becomes simpler when we can organize control targets in the order of importance. Decreasing the maximum power peaks provides high benefits with low storage usage; however, the entire benefit can be lost if the control fails even once. Therefore, the importance of decreasing the maximum peak power is the highest. Moreover, increasing self-consumption provides relatively high benefits; however, failing a few charging or discharging periods does not dramatically affect the total benefits. Thus, the importance of increasing self-consumption has the second highest importance. Market-price-based control requires many cycles; however, its benefits are still relatively low. In addition, every cycle is individual and does not affect the others. Thus, the importance of market-price-based controls is the lowest. If all control targets are used, the primary control targets decrease the maximum power peaks in winter, and the secondary control targets increase self-consumption during other times. Further, the same battery can be used for market-price-based control when charging is timed for low-price times and discharging is timed for high-price times. Other control acts of these market–price-based controlled pairs can lead to other control targets, such as decreasing maximum peaks. The combination of control targets increases with the importance of accurate forecasting.

## 3.6 Utilization of forecasting in control

We cannot precisely determine the load or production profiles for the future. However, control must be based on future values so that storage can be controlled to prepare for future control acts. Optimization algorithms attempt to obtain the best possible storage usage profile for the optimization period by forming a new load profile for minimizing electricity costs. None of the control targets required forecast-based control. If storage is used only to increase self-consumption, it can be controlled to always charge when the production is higher than consumption and discharge immediately when the consumption surpasses production. However, this does not lead to an optimal solution and utilizes forecasts for timing discharge better. Further, it is possible to obtain higher cost savings. In addition, if a battery is used only to decrease the maximum power peaks, the storage can be controlled to discharge when the power attempts to rise higher than that at an earlier peak. Forecast-based control with maximum power peak decreasing control increases benefits when power peaks can be forecasted, and storage is not used unnecessarily. Further, a forecast-based control algorithm is necessary when market-price-based or combination control is used.

PV production can be forecasted accurately using solar radiation models for tilted panels, as reported in publication [P1]. Cloudiness and shading affect the errors in the PV production forecast; however, the total errors continue to be relatively small. Load forecasting is a considerably more challenging task. The load forecasting model is based on a customer's historical consumption data and the outdoor temperature [88]. All customers can generate individual load forecasts. The temperature-corrected historical consumption data is stored in memory so that every hour of the day has its own average value from the corresponding previous days. Weekdays, Saturdays, Sundays, and weekdays that fall on public holidays are stored separately in the memory. Temperature corrections were performed using the temperature dependence of the load. A temperature correction is made in the opposite direction by forming the load forecast, and the forecasted value corresponds to the average value on a similar day at the prevailing temperature.

Load forecasts always include error. In the method used in this thesis, the average mean absolute error (MAE) is ~0.8 kW for an hourly load in publication [P5]. Even if the error is relatively low, it can be very high at some hours, and therefore, forecasting the peaks is very difficult. Publication [P5] studies the effect of the error level on the potential cost savings with BESS. The load profile of a customer strongly affects the forecasting error level, i.e., a repetitive and flat load profile is considerably easier to predict than a strongly fluctuating profile. Conversely, a high variation increases the need for storage and potential cost savings. The results presented in publication [P5] show that the control algorithms perform well with load forecasts, including errors. If the predictions are errorless, a longer optimization period and linear programming in the optimization can yield better results; however, not in a realistic scenario.

## 3.7 Energy community model

Investing in energy resources such as PV panels or BESS is often unprofitable or even impossible for individual customers. Owners or tenants of apartments in multiapartment buildings are good examples of such customers. The consumption in individual apartments is so low that even small-size resources are unprofitable. In addition, implementing resources in multiapartment buildings, particularly if several owners want to install a system in the same building, can be difficult. The energy resources installed in multiapartment buildings are utilized for common consumption by housing companies, such as lighting, warming of common spaces, and use of lifts. Possible surplus energy can be sold to the grid; however, the compensation price is considerably lower than the cost savings if the same energy is compensated for as the purchased energy. From the perspective of energy flow, the surplus energy goes straight to consumption of the apartment inside the multiapartment buildings. However, the apartments must pay taxes and distribution costs from surplus energy because this energy was purchased from the grid, even if the energy did not come from the grid. The energy community model enables using the energy resources of an apartment building for consumption. The EU Directive 2019/944 [89] defines an energy community of citizens: Citizens can form an energy community for producing affordable energy for its members and increasing energy efficiency at the household level. Membership in the energy community is open to all citizens, and its primary purpose is not to turn a profit but to produce local renewable energy.

Forming an energy community inside an apartment building changes the electricity-metering infrastructure and ownership of the meters. Fig. 4 describes the difference between a typical apartment building, where all apartments have their own meters, and the energy resources are connected with common consumption ("building" in Fig. 4) based on their own meter, and the energy community model, where the entire building uses one meter, and the participants of the energy community have their own sub-meters for distributing costs to the participants inside the community. Finland's Electricity Market Act states that every customer must be able to choose an energy retailer [90]. This must be considered when forming an energy community. All participants must voice their approval to join the energy community, and withdrawing from the community must be possible at any time. Other models show how an energy community can be formed, e.g., virtually, when the metering infrastructure does not change. The problem with these types of communities is identifying how the possible benefits are shared with the participants.

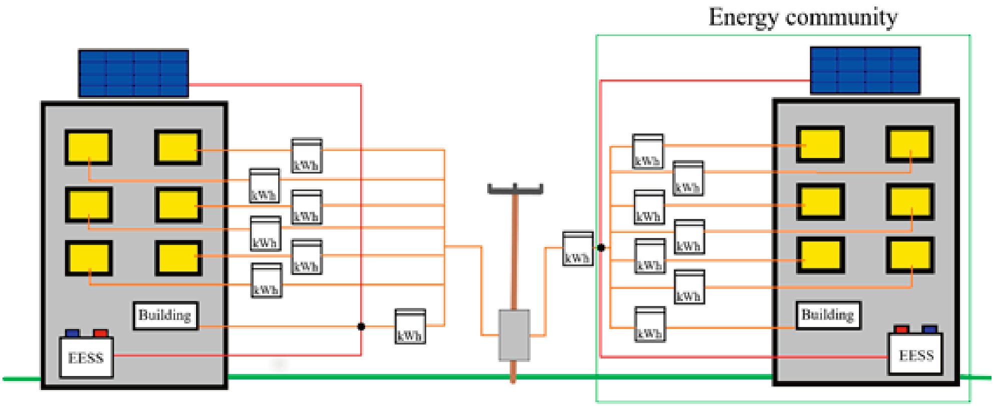


**Figure 4.** Electricity metering in a typical apartment building (left) and utilizing an energy community model (right) [P3].

Forming an energy community increases consumption volume, which increases the size of energy resources. These energy resources can be PV panels and energy storage ("EESS," i.e., electrical energy storage system in Fig. 4). In addition, the load profile is smoothened when several customers coalesce to form an energy community, thereby facilitating the sizing of PV panels. Conversely, this can decrease the need for energy storage when the variation is low. Publication [P3] closely studies these effects. Publications [91] and [92] studied the economic implications of forming energy communities, thereby extending the scope of this thesis.

## 3.8 Initial data

This thesis utilizes real-life data obtained from simulations. The load profiles of customers played a key role in the simulations. The Studies require numerous customers to determine their differences. Data from the smart meters of large Finnish DSOs were used. The customers were located in rural areas or small towns, and the data included over 8000 customers, from which, suitable customers were selected for each study. Publication [P1] used metered data from 2010–2013, and publications [P2–P3], [P5], and [P6] used newer data (2014–2016) from these same customers. These data were measured at hourly intervals. In addition, measurements from individual buildings were used. Publication [P1] used measured data from 2013 with an average 6-s time step from one single-family household for testing continuous control. Publication [P3] utilized four years (2013–2016) of hourly data from a multiapartment building in Tampere, Finland. Another publication [4] used data from three detached houses outside the city of Tampere. These data were measured in 2018 at a one-minute interval.

For modelling, the PV production utilized solar irradiation measures from an open data source at the Finnish Meteorological Institute [61]. Electricity prices were crucial for calculating the economic benefits. This thesis utilized the distribution grid tariffs from the same DSO where the consumption data were measured. Further, the simulations utilized market-price-based energy retailer contracts. The used market prices included the day-ahead prices in Finland during the study periods [67]. All used data were timed so that in the study cases, the data were from a similar period and timed together so that each data point was from the same studied hour.

# 4 RESEARCH RESULTS

This chapter presents the main results from the publications of this thesis and analyses some results for better corresponding to the scenario during the “energy crisis” (2021–2022), which significantly affects electricity prices. The results were used to answer the research questions posed in this study.

## 4.1 Increasing the self-consumption of photovoltaics

The profitability of self-consumption depends on the price difference between the purchase and compensation prices, which a customer can obtain when selling surplus energy to the grid. The amount of surplus energy depends on the differences between the load and production profiles, particularly on the size of the PV system. A larger PV system size increases the amount of surplus energy, whereas the amount of self-consumed energy increases. The share of surplus energy increased with an increase in the PV system size. In a PV system, the sizing is determined when the benefits from self-consumption are the highest compared to the monetary losses caused by surplus energy. Examples in Fig. 5 show that increasing the size of the PV system is beneficial because the green area expands faster than the red area. With “PV 1,” the entire production goes to self-consumption. When the size of the PV system increases, the green area grows faster than the red area until the size of “PV 2,” where “PV 2” corresponds to the ideal size of the PV. Subsequently, with “PV 3,” the red area grows faster than the green area when the surplus energy increases more than the self-consumption. For all customers, the load profile is an individual, and the production profiles change daily based on the cloudiness and day of the year. Therefore, the exact sizing requires data from the entire year and simulations with this data.

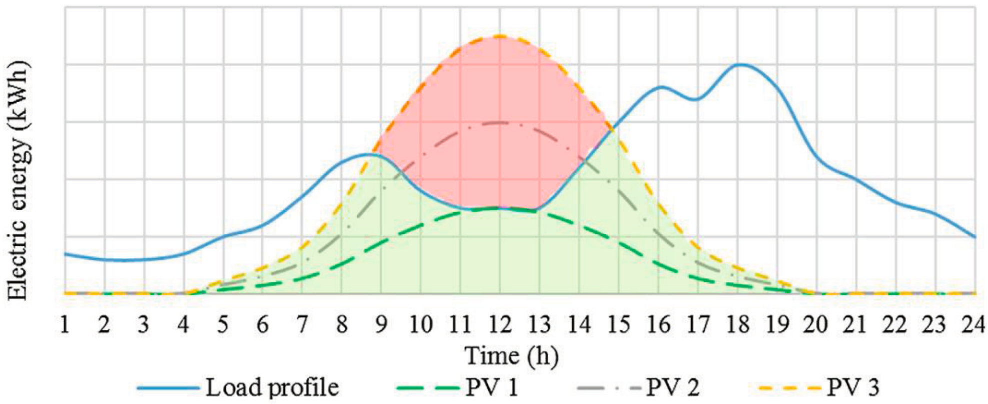


**Figure 5.** Typical load profile of a customer and three PV production profiles for different PV sizes [P3].

The exact size of the PV system depends on the cost of the system. The cost savings increased almost linearly when the green area in Fig. 5 increased faster than the red area. Similarly, when the red area expands faster than the green area, the increase in savings is almost linear but slower than that when the green area increases faster. Fig. 6 illustrates this scenario. Further, we can assume that the annual cost of a PV system (per lifetime of the system) increases linearly as a function of the nominal power of a PV system. Three possible solutions exist for determining the optimal PV cell size. If the yearly PV costs increase faster than the annual cost savings when most of the production is self-consumed, the PV system is unprofitable. If the annual cost increase in a PV system is lower than the annual cost savings when most of the output is surplus energy, the PV system can be so large that installation is possible. In a typical scenario, the increased speed of the annual costs of a PV system is between these two lines when the optimal PV size can be determined from the cutting point of these two annual cost savings lines (*d* in Fig. 6 when the difference *k* is the highest).

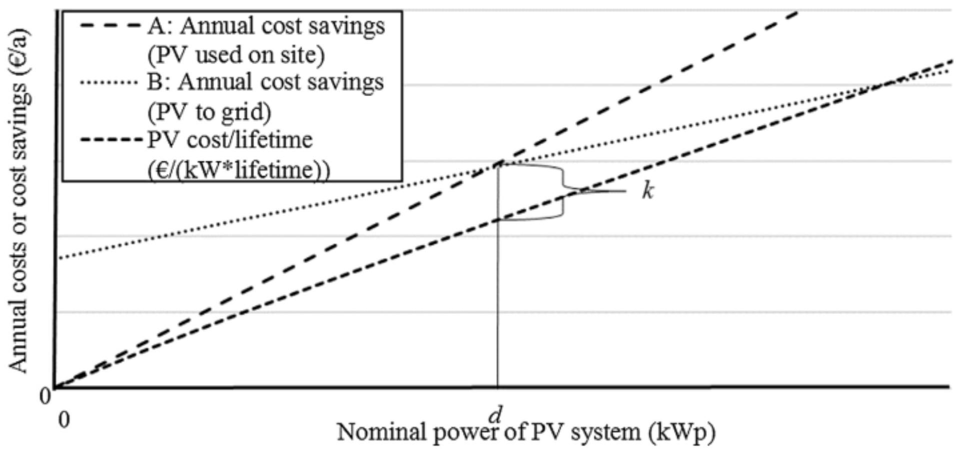


**Figure 6.** Basic principle of PV sizing [P3].

### 4.1.1 Battery energy storage system

It is possible to increase the amount of self-consumption using the BESS. The Surplus energy can be stored and used later when required. Fig. 7 shows an example from one day when the BESS is used to modify the load profile of a customer. All surplus energy (negative power) was stored and used in the evening. In this example, the customer had only one kWp PV panel to study the impact of storage. The measurement interval in this test was six measurements per min. Considerably longer simulations are required to study the economic implications.

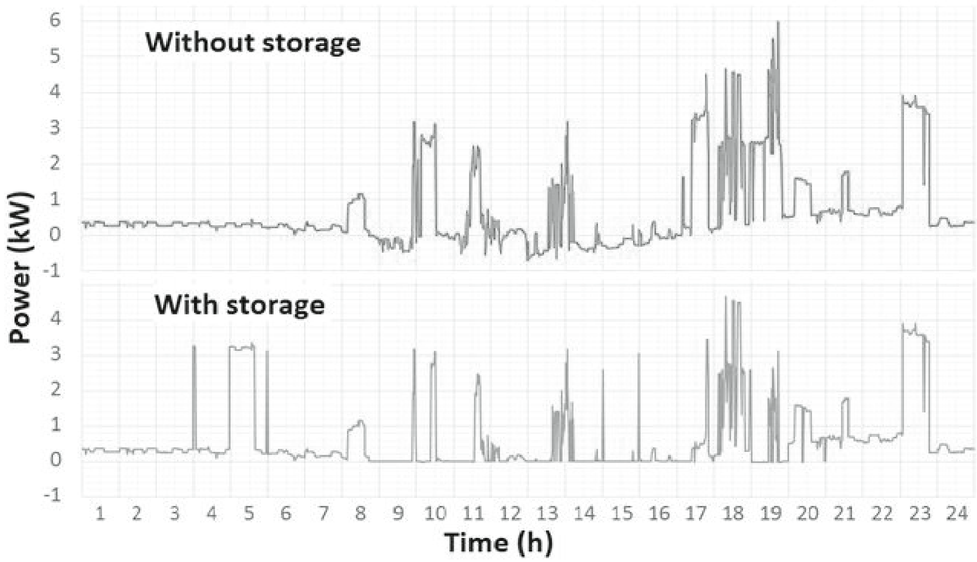


**Figure 7.** Example load profiles of customers (simulated electricity power with 25 measurements per hour) that have small-scale PV production with and without storage [P1].

Economic benefits of increasing self-consumption have been studied in the publications of this thesis from many perspectives. Publication [P1] studied the rise in self-consumption using market-price-based control. The results indicated that, for every customer who can be found, the size of the PV system when cost savings are the highest is related to the system costs. The results indicate that the increase in the benefits from a growing battery size decreases quickly, i.e., the highest benefits can be achieved with small battery sizes because the investment costs of the battery increases faster than the costs of the benefits. This result motivated the detailed studies in publication [P3]. The results in publication [P1] show that the profitability of BESS with possible cost savings is so low that the investment in BESS in 2016 is profitable only in very rare instances. Thus, many factors have changed, e.g., investment prices of BESS have decreased, lifetime of batteries have increased, and electricity pricing has changed. In addition, the studies in publication [P1] focused only on detached houses.

The results of publication [P3] showed that using a BESS increased the size of the PV system. Using BESS creates more possibilities and flexibility in utilizing self-produced energy; however, it does not increase the self-consumption rate when the PV system is optimally sized. This implies that we can increase the PV production when we can avoid surplus energy feeding into the grid, which goes straight to self-consumption by increasing the system size. This indicates that the optimal PV system size depends on the size of the BESS. In other words, the BESS should be sized first, and the PV system should be sized with a usable BESS capacity. An example in publication [P3] shows that the optimal PV system size can be increased by 50% using BESS. However, this increase is often lower. Currently, the investment costs of BESS are so high that using a PV system without BESS is more profitable than using one with it, even if BESS has many positive effects, such as a decrease in the PV grid feeding and total energy purchase from the grid. High taxes and volumetric distribution fees increase the incentive to use BESS for increasing self-consumption. Conversely, low electricity prices disincentivize investments in energy resources. Electricity pricing (including pricing models and price levels) plays a key role in the profitability of increasing the self-consumption of PV with BESS; the investment costs and battery features also impact profitability.

### 4.1.2 Demand response with electric heating

DR operations can be used for energy storage. In publication [P6], using the electric heating of the building to store energy in its mass was studied as energy storage for increasing the self-consumption of PV production, which was compared with BESS in publication [P6]. The results indicated that electrically heated houses in Finland have a thermal capacity where the surplus PV energy can be stored. The amount of energy that can be stored depends on the indoor and outdoor temperature differences and the extent of indoor temperature changes. The highest availability of surplus energy occurs in the summer, when increasing the indoor temperature is impossible because the outdoor temperature is also high. Further, the indoor temperature rapidly makes the enclosure more intolerable. Wintertime has the highest heating demand when storing surplus energy; however, the surplus energy is unavailable during winter. Therefore, spring and autumn are the most critical times for storing surplus energy in the building.

There is high variation among customers in terms of their thermal capacity and heat loss coefficient. These variations, along with the load profile of the customer, strongly affect the amount of surplus energy that can be stored by the building of the customer. Only a few customers from the study group stored a similar amount of energy that can store over 4 kWh BESS when we let the indoor temperature to change to a maximum of 1 °C; for most customers (over 90%), the corresponding

BESS size is under 1.5 kWh. However, approximately half of the customers can store heat, and more than 1 kWh of BESS can store surplus energy. Small BESS sizes provide relatively high profitability, and therefore, the following question arises: "Can DR with electric heating demand replace the need for BESS?" The results in publication [P6] show that the benefit is almost equal to the sum of these individual benefits when the BESS and DR with electric heating are used together, which implies that the BESS and DR with electric heating store surplus energy at different times. Indeed, some overlaps exist; however, the capacities of the others can be used later. The comparison shows that when BESS and DR with electric heating are controlled as primary and secondary controls, the benefit is higher when the surplus energy remains after BESS operations. Further, the results indicate that the first degree of decrease in indoor temperature provides many more benefits than the second degree, and therefore, the benefits from the former start increasing considerably faster than the benefits from the latter.

### 4.1.3 Effect of metering interval

Changing the metering interval from 1 h to 15 min periods affects how the load and production profiles suit each other, as indicated in publication [P4]. Variation between periods will be considerably higher when the day is divided into 96 periods instead of 24, thereby increasing the risk that quarter-hourly netted production is not timed with quarter-hourly netted loads as well as with hourly netted production and loads. This change decreases the profitability of PV production because it increase the amount of surplus energy. Simultaneously, the profitability of the BESS is used for increasing self-consumption because more surplus energy exists for storage.

Publication [P4] studied the effects of different metering periods: hours, quarter-hours, and minutes. A 1-min period was studied as an example of a scenario in which the metering period was very short. The results of the comparison for PV system profitability as an average value of three different typical detached houses in Finland are shown in Fig. 8, where the NPVs are studied with two PV sizes (2 and 3 kWp), two PV system lifetimes (15 and 30 years), and two possible discount rates (1% and 3%). Fig. 8 shows the investment costs of the PV system at three different price levels. Further, Fig. 9 shows similar results for the BESS with two system sizes (2 and 6 kWh) and two system lifetimes (8 and 15 years). The BESS investment costs at the two price levels are also presented. These results support the theory that the profitability of the PV decreases, and the profitability of the BESS increases over shorter metering periods. The effect on the profitability of the PV is not dramatic; however, that on the profitability of BESS is relatively higher. However, the lifetime of the BESS must be high, and the investment price must be very low for it to be profitable. In the near future, reaching low retail prices for BESS systems will be impossible, and these systems can profit customers only when used to increase self-consumption.

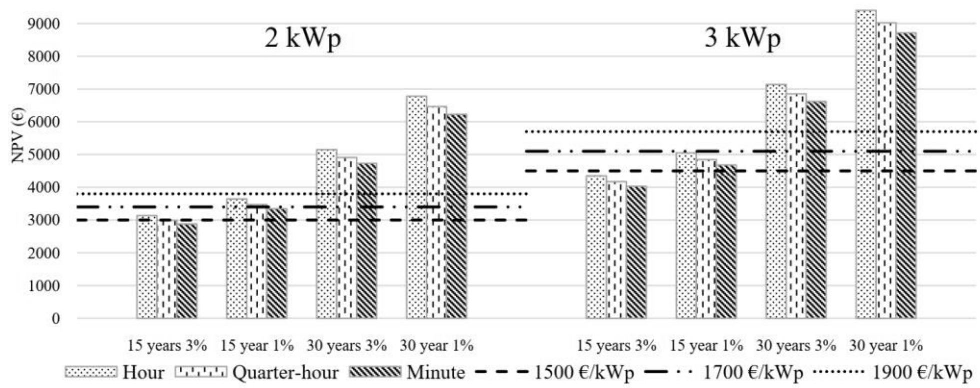


**Figure 8.** Net present value of PV lifetime benefits with different metering intervals and three possible investment prices for 2 and 3 kWp PV systems. Two possible lifetimes (15 and 30 years) and discount rates (1% and 3%) are used [P4].

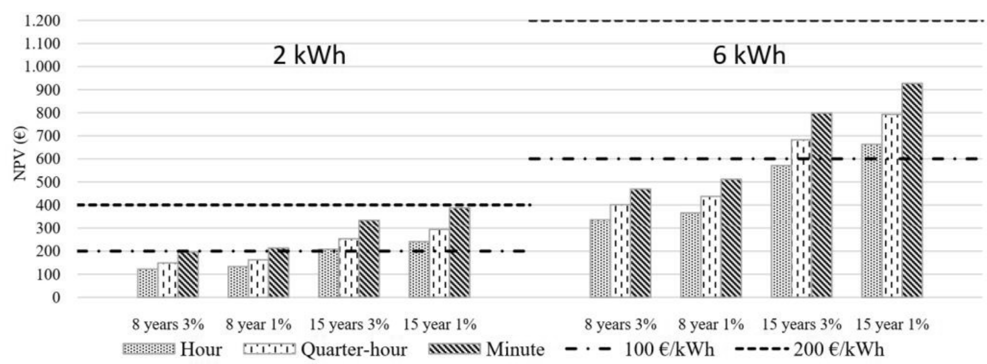


**Figure 9.** Net present value of BESS lifetime benefits with different metering intervals and three possible investment prices for 2 and 6 kWh BESS. Two possible lifetimes (15 and 30 years) and discount rates (1% and 3%) are used [P4].

## 4.2 Market-price-based control

Using BESS only for market-price-based control is unprofitable when considering battery losses, high investment prices, and electricity market prices in the last decade. The annual benefits are only a few tens of euros per customer with decent battery sizes. Therefore, the investment cannot pay for itself before the lifetime of the battery ends, as suggested in publications [P1 and P5]. In addition, this control target requires an accurate control system and load forecasting, as reported in publication [P5]. Market-price-based control can be used with other control targets, where it can yield extra benefits. In addition, the variation in market prices has increased significantly over the last few years because of the increasing amount of wind power production and energy crisis. Fig. 10 shows the largest difference between the highest and lowest daily prices over the last decade. The variation is very low before 2021; however, it strongly increases in the last two years.

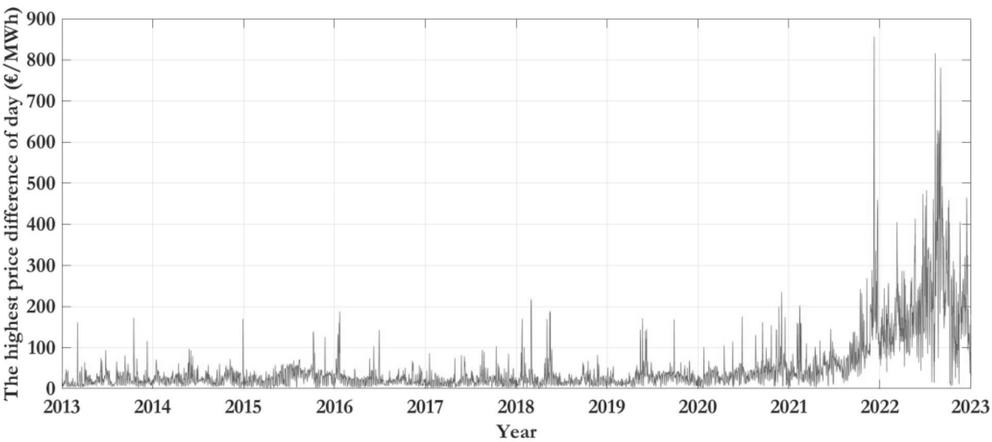


**Figure 10.** Highest difference between the highest and lowest prices of the day in Nord Pool electricity day-ahead markets (area price of Finland) between the beginning of 2013 and the end of 2022.

We can evaluate the potential of the annual cost savings of the market-price-based control when simulating the load that has shifted from the highest price time to the lowest price time of the day. Fig. 11 shows theoretical annual cost savings with a 5-kWh shift in different years over the last decade. This does not indicate the exact cost savings of a specific customer because the load profiles of the customers affect the results; however, it indicates the level of potential savings. Before 2021, the savings varied around 50 €, which means that BESS is unprofitable for market-price-based control, even for the lowest possible investment costs, as discussed in publication [P1]. The potential savings from 2021 can make the BESS profitable if the investment costs are low, and the potential savings from 2022 can make the BESS very profitable for market-price-based control. The BESS requires at least similar years as 2021 during the entire battery lifetime (8–15 years) to be used profitably for market-price-based control. The load profile of the customer should be suitable, and the investment cost of the BESS should be low as discussed in publication [P1].

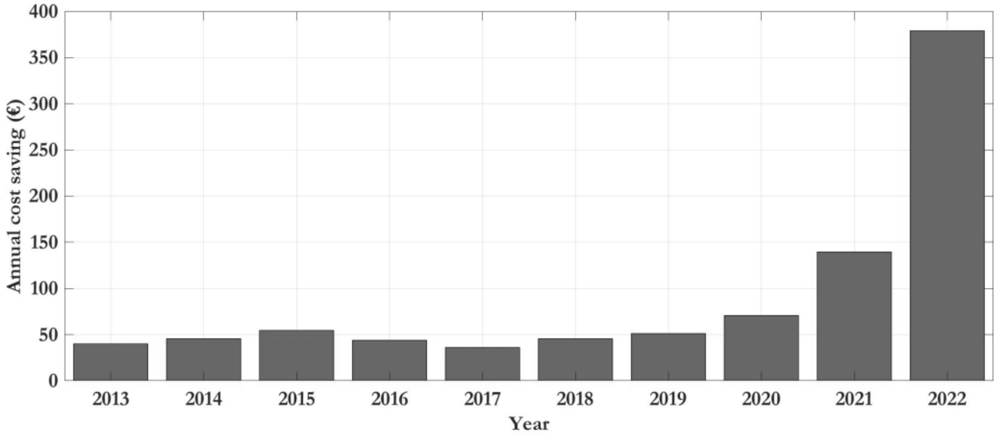


**Figure 11.** Theoretical annual cost savings when 5 kWh is shifted from the day's highest to lowest price time.

## 4.3 Decreasing the maximum peak powers

The profitability of decreasing the maximum peak power using BESS depends on the amount of the demand charge component (€/kW) in the distribution tariff. Although discussions on power-based tariffs are beneficial, only a few DSOs have been implemented for small-scale customers in Finland [65]. For large-scale customers, a low-voltage power tariff that includes a demand charge has been widely used. The level of these demand charges is relatively low for many reasons, e.g., the basis of the demand charge can be difficult for customers to understand, DSOs attempt to increase the weight of basic charges (€/month), and the demand charge is sensitive to changes in load profiles of the customers, which can cause significant changes in costs of the customers and the incomes of DSOs. Several models showed how the demand charge is defined. Publication [P2] studied four power-based tariff models. DSOs' most commonly used model is the power tariff, which has a demand charge (€/kW) parallel to a basic (€/month) and volumetric charge (c/kWh). Other possible models include power limits or power steps, which define when a higher price should be paid or when a demand charge does not have to be paid.

Some DSOs define the maximum demand for every month separately, while others use the highest demand of the sliding year. Fig. 12. shows that the simulated demand decreases with a decent-sized BESS (6 kWh battery) for a group of customers (1525) when the demand is defined monthly or yearly. The maximum power decrease in 1 h was ~4 kW when the storage losses and C-rate were considered. Further, ~80 customers decreased their maximum amount annually. None of the customers decreased their maximum amount every month; however, a few were very close. In the yearly case, there were few customers who could not reduce the maximum demand at all (<100 customers). In these cases, the highest peak follows the earliest highest peak so that the battery is empty at the highest peak and when the load forecasting cannot predict the peak. This scenario occurs in the monthly case; however, this occurring every month for the same customer is highly unlikely, and therefore, the variation in the maximum power decrease between the customers is lower in the monthly case than that in the yearly case. Conversely, the monthly case requires many more cycles (~500 annual cycles on average) than the yearly case (less than 100 annual cycles on average), indicating that the battery ages faster, as indicated in publication [P2].

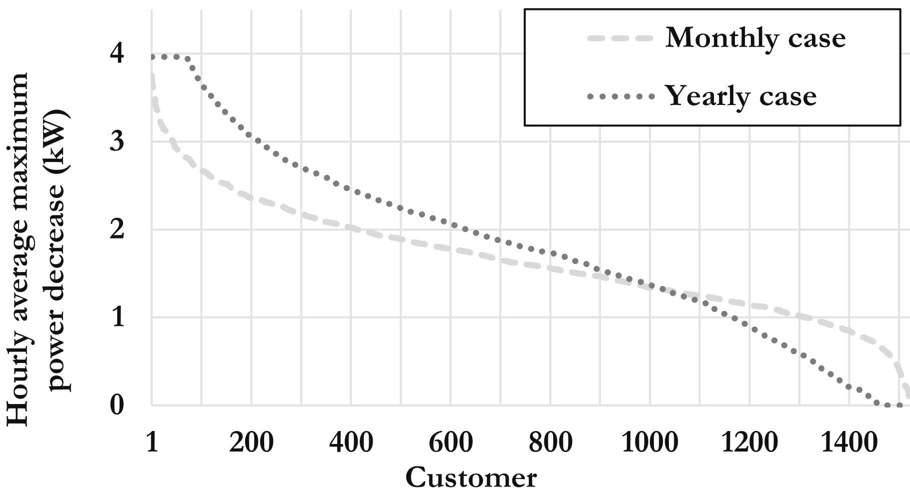


**Figure 12.** Demand decreases with BESS (6 kWh, 0.7 C) for 1525 customers' load profiles when the demand is defined as monthly or yearly [P2].

For evaluating the profitability of the BESS to decrease the maximum peak power, the yearly benefits and investment costs of the BESS need to be considered. Most customers can obtain an ~ 200 €/a cost savings in the study done in P2 by decreasing the maximum peaks with BESS when the components of the power tariff are calculated to correspond to the cost structure of the DSO[P2]. Indeed, considerable variation exists between customers, and the cost savings vary between 0 and 340 €/a, which means that the average investment costs of BESS for the average customer are slightly lower than the lifetime benefits. Thus, in most cases, BESS will be profitable when used to decrease maximum peak powers. The demand charge components in tariffs of the DSOs are considerably lower than they could be, thereby making the BESS unprofitable.

## 4.4 Combining control targets

The profitability of the BESS is poor, or in the best case, weak, when used for individual control targets. As reported in publication [P5], combining different control targets increases the profitability of the BESS. Combining controls makes controlling the BESS more challenging because it can vary the needs of different targets. The BESS needs to be empty to store surplus energy and decrease the maximum peaks when attempting to increase the PV production of self-consumption. Further, the BESS should be full for discharging during peaks. The highest peaks and availability of surplus PV energy are timed differently so that both targets can be combined. Market-price-based control can be combined with other targets if it has the capacity after other targets. Combining controls also requires accurate load forecasting, as discussed in publication [P5].

Combining market-price-based control with the target of increasing the self-consumption of surplus PV energy can make the BESS investment profitable when the load profile of the customer and electricity pricing are suitable, as discussed in publication [P1]. The market price variation should be sufficiently high, and the load profile of the customer should not be similar to the production profile. Combining market-price-based controls with decreasing maximum peak powers increases the profitability of BESS when the charging time of a battery during a high-price time can be measured, as discussed in publication [P2]. Combining other targets with decreasing maximum peak powers significantly increases the risk of control failure, and the potential benefits from power decrease are lost when the load forecast is not ideal. The highest benefits can be achieved when all control targets are combined; however, this increases the risk of losing benefits because the control fails with nonideal load forecasting, as discussed in publication [P5].

Combining different control methods such as BESS and DR using the electrical heating systems of the building, is possible as reported in publication [P6]. The competition between the different methods is minor, even when the methods are used on the same control targets. Combining different methods (BESS and DR) can slightly decrease the profitability of BESS. Further, combining different methods can reduce the risk of failure to control because of the errors in the load forecast when a backup solution for another method exists.

## 4.5 Energy community

The formation of an energy community has several benefits. An energy community allows apartment owners and tenants to participate in energy self-production and increase the flexibility of the power system. Without an energy community, the DSO can charge for energy transfers inside an apartment building, e.g., from PV panels to the consumption of the apartment. Forming an energy community can increase the profitability of investing in energy resources for apartment buildings. Conversely, in an energy community, there is a crossing between the load profiles of customers, which can smooth the variations in the load profile. This smoothing occurs when there is still a typical variation in the load profile; however, the loads are higher in the profile, which indicates that there is a need for storage capacity using different control targets.

Forming an energy community increases the total consumption of one customer, compared to that of several individual customers. This can lead to a scenario where the customer is no longer a small customer from the perspective of the DSO, and the tariff used corresponds to the tariff for small industries (low-voltage power tariff). The tariff change introduces new incentives for the BESS; e.g., the new tariff includes a demand charge. In addition, the total cost of the basic charge usually decreases significantly when several contracts change to one contract. Further, metering and billing within the energy community incur additional costs. Higher total consumption affects the sizing of energy resources and removes the possible limitations of market-price-based control, i.e., discharging during a high-price time is higher without the risk of grid feeding. The results of P3 show that, in an example case using the energy community model, the PV system can be sized to double its size, and if BESS is used, the PV system can be sized to three times larger than the original case, where the PV production can be utilized only in common consumption without BESS, as indicated in publication [P3].

# 5 SUMMARY AND CONCLUSIONS

This chapter presents a discussion, which includes a deep analysis of the methods used and possible error sources that can affect the utilization and generalization of the results. Finally, the contributions of this study are discussed. This conclusion answers the research questions based on the results of the study. Finally, possibilities for utilizing the results of this study are discussed.

## 5.1 Discussion

This thesis examined the results obtained using simulations with actual data. A simulation model was developed for this thesis and included several components. All components may have inaccuracies. Further, a model never exactly corresponded to reality. All models used in this thesis were designed to model actual and possible scenarios. The PV and battery models were constructed using proven methods. These models included errors; however, in the presented references, they were verified carefully. Further, the PV model was verified with real data in publication [P1] by the author of this thesis, who stated that the model was suitable for the conditions in Finland.

This thesis often suggests that the load profile of a customer affects the results. Using a limited number of customers in the study group implies that the results do not represent all possible customer load profiles. Many customers were used, and the differences among them were studied to minimize the effect of this lack of representation. The customers studied represent typical Finland customers. Further, the load profiles correspond well with typical customers in Nordic countries, whereas a lower heating demand needs to be considered if a customer is from the southern area. Similarly, the PV production profile differs when moving southward. A significant change in profiles between summer and winter is typical in Nordic countries. In addition, the results vary across countries. The profiles in southern Finland differed slightly from those in northern Finland. The data used in this thesis were obtained from central Finland.

The electricity prices and systems used (i.e., PV and BESS), are critical and sensitive to the results. The studies in this thesis utilized distribution tariffs in the same area where the data were measured. Tariffs change continuously, thereby affecting the results. This thesis uses market-price-based energy retailer contracts. The market prices vary greatly, and this variation increased strongly, especially after 2021. Studies on the publications in this thesis were conducted using data before 2021. Therefore, the effects of market prices over the last decade has been studied. Changes in market prices are difficult to forecast, and the highest price levels are probably over; however, the high price variations will remain permanent in the near future.

## 5.2 Research contributions

The contributions of this thesis are presented below:

- Developed a simulation model, including accurate PV and BESS models, to study residential buildings with different energy resources.
- Designed a BESS control algorithm to minimize electricity costs with market-price-based energy retailer contracts and power-based tariffs for the DSO.
- Developed a method for sizing PV systems in residential buildings while considering possible energy storage.
- Found the relationship between the level of PV self-consumption and economic benefits by utilizing a PV system and BESS sizing while controlling BESS to maximize self-consumption.
- Developed a method to evaluate the flexibility of electrical heating in residential buildings that utilize only the load profile measured by a smart meter of the DSO and the outdoor temperature measurements.
- Produced knowledge for end users and service providers regarding factors that affect the profitability of BESS investments.
- Produced knowledge for DSOs on how tariff structures should be modified to steer customers to alter their load profile for the benefit of the DSO by utilizing BESS.

## 5.3 Responses to the research questions

This summary answers the research questions of this thesis based on the obtained results. The research questions are as follows:

- What variables define the profitability of residential energy storage?
- How do different incentives affect the control of energy storage?
- What are the economic risks of the energy storage investment?
- How does energy storage affect the profitability of photovoltaic energy production in the residential sector?
- How can the profitability of residential energy storage be improved?

However, the profitability of energy storage in residential buildings remains low. Profitability depends on three main factors: storage cost, storage system lifetime, and benefits during storage. The storage costs include investment and maintenance costs, which can be divided along the lifetime of the storage for evaluating the approximate yearly costs. Li-ion-based BESS are suitable energy-storage technologies for residential buildings. The lifetime of Li-ion batteries has increased in the last decade because of the development of manufacturing and better control methods that can maintain the health of the batteries. The effects of the control targets on battery lifetime should also be noted. The investment costs of BESS rapidly decreased during the last decade; however, they have been seen in retail prices, although with a delay. The retail prices are expected to decline in the near future. Battery lifetime and costs can be considered as almost constant factors, and therefore, when increasing profitability, the focus is on maximizing benefits.

Different incentives affect energy storage control. These incentives follow the electricity tariffs. The energy storage can increase the self-consumption of small-scale local energy self-production, e.g., PV production. The benefits depend on the difference between the purchase price and compensation from feeding the grid surplus energy and the sizing of energy resources. Using energy storage can increase the size of a PV system while increasing its profitability. The energy storage can decrease the maximum power peaks if a tariff includes a power-based component, thereby saving costs and increasing the benefits of storage. The time-of-use tariffs, e.g., market-price-based energy retailer contracts, incentivizes shifting loads during low-price times. The profitability of using the BESS for individual control targets is weak; however, combining different targets will make investments profitable. Using the same storage on different control targets involves a risk in that some benefits are lost if control cannot ideally forecast the following loads and production. Even if the BESS investment is profitable in theory, the benefits could be difficult to achieve in practice. Some of the required storage capacity can be replaced with DR operations, e.g., controlling the indoor temperatures with an electrical heating system.

Residential-level energy storage can considerably benefit different actors in a power system, making it possible to increase the size of PV systems and increase the local fossil-free production. Without local storage, increasing the amount of PV production can increase the surplus energy in the grid, thereby posing challenges to the DSO in protecting the grid components and sizing the grid. In Finland, DSOs cannot bill for transmitting surplus PV energy, and therefore, all customers must pay these costs. Using residential BESS can decrease the surplus energy significantly and maximum peaks in the grid if the tariff includes a power-based component. The grid components are sized based on the maximum power in these parts of the grid. The flexibility of the BESS can smoothen the demand in the grid when it is possible to make the grid components smaller, thereby making grid construction more inexpensive. Further, consumption can be timed with uncontrollable production, e.g., wind power, with increasing flexibility, which can smooth the variation in the electricity market prices.

Given the positive effects of using a BESS, actors in the power system perform supportive acts for residential-level energy storage would be beneficial. DSO tariffs can be designed such that decreasing the maximum peaks and avoiding surplus energy grid feeding is profitable for customers, thereby implying the right ratio between tariff components. This state supports flexible investment. The electricity tax increases the incentive for increasing self-consumption; however, supporting BESS systems parallel to PV makes it possible to make PV systems considerably larger, increasing fossil-free energy production. The profitability of BESS investments will increase when investment costs decrease; however, it is possible to improve the annual benefits by developing a control system with accurate load forecasts.

## 5.4 Further work

The research contributions of this thesis can be utilized widely in scientific and practical applications. Future studies can utilize the developed simulation models. This model is designed such that new components can be added, thereby making it possible to study the effects of different flexible energy resources, e.g., the charging of electric vehicles. Further, the simulation model makes it possible to utilize different tariffs when the effects of tariff components are widely studied. Further, the results of this thesis can be used for the tariff design of the DSO. The DSOs can steer customers to utilize energy resources for minimizing the grid impact by designing tariffs. A method for evaluating the flexibility of heating demand in residential buildings can be widely utilized. For example, this method makes it possible to study the potential of interrupting heating during power shortage scenarios or the energy efficiency of the buildings.

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# PUBLICATIONS

# PUBLICATION 1

**Utilization Possibilities of Electrical Energy Storages in Households' Energy Management in Finland**

J. Koskela, A. Rautiainen, P. Järventausta

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# Utilization Possibilities of Electrical Energy Storages in Households' Energy Management in Finland

J. Koskela, A. Rautiainen, P. Järventausta

**Abstract** – *Electrical energy storage is one option for making the environmental impact of households' energy usage smaller. A storage could improve the profitability of household level electricity production and could also decrease the load in the electricity networks. So far, poor profitability has been the greatest barrier to the use of storages. The battery systems prices have been high and the benefits difficult to predict. The benefit of the use of storage and the factors affecting to the benefits are studied in this paper. For this purpose, a simulator has been designed for modelling the energy storage as part of the household's electricity grid. The control of the storage significantly affects to the amount of benefits. The developed control method of the simulator aims to maximize the benefits. The simulations took into account the variables that are not accurately known when the storage is controlled. For these variables, such as e.g. future consumption, various forecasts were formed.* **Copyright © 2016 Praise Worthy Prize S.r.l. - All rights reserved.**

***Keywords***: *Energy Storage, Battery Storage, Simulator, Photovoltaic, Household Customer, Dynamic Energy Pricing*

## Nomenclature

| | |
|---|---|
| $\eta_{cha}$ | Battery charging efficiency |
| $\eta_{dc}$ | DC-converters efficiency |
| $\eta_{dech}$ | Battery discharge efficiency |
| $\eta_{inv}$ | Inverter efficiency |
| $B_1$ | First element of the optimized estimate vector |
| $B_t$ | Storage energy transmission during an hour $t$ |
| $B_{eff}$ | Efficiency of the storage energy transfer |
| $B_h$ | Storage cumulative energy transfer |
| $B_{max}$ | Maximum charging power |
| $B_{min}$ | Maximum discharging power |
| $C$ | Variable electricity costs |
| $C_t$ | Energy price during an hour $t$ |
| $D_h$ | Household's momentary demand |
| $D_t$ | Demand during hour an $t$ |
| $E_{max}$ | Maximum capacity of storage |
| $E_t$ | Amount of stored energy at time $t$ |
| $G$ | Demand to power grid |
| $G_{max}$ | Maximum power from the grid |
| $G_t$ | Energy transmission from the grid at time $t$ |
| $I_{cha}$ | Battery charging current |
| $p$ | Length of optimization period |
| $P_h$ | Household's momentary production |
| $P_{dc}$ | Production after DC-converter |
| $Q_{lithiumC}$ | Capacity of lithium-ion battery cell |
| $R_b$ | Battery internal serial resistance |
| $R_{b\ lithium}$ | Internal resistance of lithium-ion battery cell |
| $S_{control}$ | Control signal to storage |
| $SOC$ | State of charge |
| $SOC_{max}$ | Upper limit of $SOC$ |
| $SOC_{min}$ | Lower limit of $SOC$ |
| $SOC_t$ | State of charge at time $t$ |
| $V_b$ | Battery nominal voltage |
| $V_{b\ cha}$ | Charging voltage |
| $V_{b\ lithiumC}$ | Nominal voltage of lithium-ion battery cell |

## I. Introduction

Electric energy storage allows the time shifting of households' electricity consumption and more efficient use of own production.

In Finland, the customer can choose the wholesale market price based electric energy pricing, where every hour has its own price.

By shifting consumption from expensive hours to cheaper hours, it is possible to reduce the price paid for electricity energy. In addition, if the customer has their own electricity production, a storage allows a greater part of this energy to be used for own demand. This is more profitable than selling the overproduced energy to the grid and so the customer can also reduce the electricity price to be paid. These two factors compose the cost benefit of the storage and are more closely investigated and quantified in this paper. Cost benefit means the difference between a customer's yearly electricity bill when the storage system is used versus not used.

Energy storage enables the use of electricity during power outages. In the future, storage control can be given to be controlled by the network company, when the storage could be used in demand response for the needs of the network company [1].


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Also, with new potential power-based transmission tariffs a greater cost benefit of the energy storage could be obtained [2]. Energy storage capacity can also be used for frequency control when the storage control is sold to reserve market [3]. Energy storages can also be utilized for a microgrid systems in the future [4].

These opportunities are kept outside of this paper as future studies. Ways to store energy are numerous, but in this study only lithium-ion batteries are considered, because they have been shown to be the best alternative by its characteristics for households' energy storage in the near future [5].

The connection of the electrical energy storage to the household network used in this study is shown in Fig. 1. Production connected with DC-to-DC converter and storage connected with bidirectional converter to controlled inverter, which are connected to household's electricity network. AC-bar in Fig. 1 present household's connection with the power grid. Production and storage system connect to this bar after main fuses and metering. In figure, the positive direction shows how different components affect the demand from the grid.

Energy storage systems for households' use have been investigated a lot. Different storage system types have been compared and their feasibility for household use have been studied, but often efficiency, size or price is the biggest problem [5]. Batteries and specially lithium-ion batteries have proven potential choices for household usage and also for PV production [5]-[7]. Optimal battery control strategy is an important part of the storage system and this has been discussed in many papers [8], [9].

The control systems with battery in distribution substation usage is discussed in reference [10].

Battery control can be part of intelligent control strategy of smart buildings, as in reference [11]. Utilizing energy storage systems in electricity markets is based on maximizing the daily total profit from economic point of view [12]. Price changes in The Nord Pool spot market makes control system design even more challenging but it also makes load shifting possible [13].

The cost benefits for load shifting depend on the electricity energy price changes between hours of the day, and in Finland these changes are Nord Pool's second largest after Denmark [14].

In study [14] results show that benefits are lower than storage system costs in Finland. In study [14] only centralized storages in distribution network are discussed and lithium-ion batteries weren't taken into account.

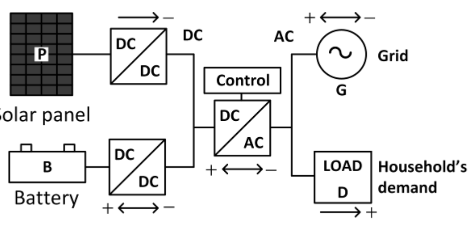


Fig. 1. Connecting electrical energy storage to the household's electrical network

In paper [15] the cost benefits in single-family houses in Finland with energy storage and PV have been studied.

The results of the study show that it is possible to get savings for using storage and no differences were found between different sizes of storages. The storage sizes are 10-30 kWh and savings are optimized monthly.

None of the previous studies took into account all storage system losses, differences between customers' consumption and real control system required forecasts for the same time.

This study examines these matters and investigates the accuracy of customers' cost benefits and the variables affecting it.

## II. Simulation Model

The profitability of the electrical energy storage was investigated by simulating households' storage systems usage with Simulink® modelling. The control of the energy storage is the main issue to maximize the utilization of a storage system [16].

Control is responsible for the use of storage capacity in maximizing the cost benefits. In this case the cost benefits mean how much the customer can save money by using energy storage. By control we can affect the price of electricity variable costs which mean time and demand depending price components. In this paper optimization is done every simulated hour.

They correspond to real-life situations. A new optimization starts every hour and during an hour that must be fixed.

### *II.1. Optimization Problem*

The objective of optimization is to minimize the price of electricity over a given period of time.

Variable costs $C$ can be calculated as following:

$$C = \sum_{t=1}^{p}\left(\left(D_t - P_t\right)C_t\right) + \sum_{t=1}^{p}\left(-B_t C_t\right) \quad (1)$$

where $p$ is length of optimization period. $D_t$ is electricity demand, $P_t$ is self-consumed electric energy $B_t$ is energy transmission between storage and household's network and $C_t$ is energy price during an hour $t$ [17].

Equation's variables' positive and negative directions follows Fig. 1, so when storage is discharged, $B_t$ is positive.

All directions have to be seen from the grid. Energy price for future hours is known and therefore the optimization problem in this case is dividing the demand between the coming optimization period hours in such a way that $C$ will minimize. Assuming that the customer's consumption and production can't be influenced, the only controlled term in equation (1) whose cost we can affect is $B_t$. When the equation's first summation is constant with respect to $B_t$, the second summation forms the optimization problem.

 

### II.2. Constrains of Optimization

To solve the optimization problem, we need to set the solution constraints [17]. For the storage we set capacity upper $SOC_{max}$ and lower $SOC_{min}$ limits that show how full or empty it can be charged or discharged.

The constraint is in the inequality form:

$$SOC_{min} \leq 100\frac{E_t}{E_{max}} = SOC_t \leq SOC_{max} \tag{2}$$

where $E_t$ is the amount of stored energy at time $t$ and $E_{max}$ is maximum capacity of storage. State of charge at time $t$ is $SOC_t$. The lower limit is set according to how much energy is desired to be a minimum stored for the event of failure [6].

The upper limit protects the storage from overcharging. Constraint presented in equation (2) affect the variable $B_t$ which is optimized by the following:

$$SOC_t = 100 \times \frac{B_{eff} B_t}{E_{max}} + SOC_{t-1} \tag{3}$$

where $B_{eff}$ is the efficiency of the energy transfer to storage. In addition to these constraints are set the charging $B_{max}$ and discharging $B_{min}$ speed, and thus limited to maximum currents [18].

This can be represented as follows:

$$B_{min} \leq B_t \leq B_{max} \tag{4}$$

Continuous constrains which are described above, result from the physical limits. Usually self-produced energy isn't profitable supplied to the grid and it is more profitable used in the customer's own consumption [19].

In this case, a constraint can also be set blocking to the grid transmission $G_t$. We can also set a limit for energy taken from grid $G_{max}$. As an equation, this can be expressed as follows:

$$0 \leq G_t \leq G_{max} \tag{5}$$

This constraint isn't strict in this paper's simulations but it is used as a target and energy taken from grid is tried to maintain between these limits. In all cases it is impossible, so sometimes energy must also be supplied to the grid.

The aim of optimization is to find the estimate that minimized equation (1) from the constraints bounded area. Constraints (4) and (5) affect each element of estimate vector, and don't form dependencies between the elements. Constrain (2) affect elements in accordance with Eq. (3), thus establishing a dependency between the elements of estimate. This makes the optimization problem nonlinear, and such problem solving globally is extremely difficult. In problem solving it is necessary to use numerical iterative methods, and none of them guarantee a solution [20].

In addition, when the optimized elements are numerous, it means that also a lot of iteration loops are needed, and the calculation will be heavy [30][31].

Since the optimization in this study has to be done indeed number of times, the used method should be as effective with processing as possible. For these reasons, in this study we used the optimization method which quickly and effectively reaches one nearby locale estimate for a minimum. For this we design our own effective algorithm.

### II.3. Optimization Algorithm

The optimization algorithm, shown in Fig. 2, is based on that always known one certainly allowed estimate vector and direction which improves it. The first allowed estimate vector is the zero vector which corresponds to the situation where the storage is not used at all.

Estimate vector length is the same as the length of optimization period. In this paper the optimization period is sliding and this means that the period moves forward together with time. An optimization period is always the same length with the same amount of hours. The suitable length of an optimization period is calculated in the results of this paper.

The estimate vector improved when the element whose coefficient $C_t$ is the lowest increased, and vice versa. In practice this means that when the price of electricity is low, the storage charged and vice versa.

As illustrated step by step in the flow chart of Fig. 2, the algorithm is as follows:

1. Find the minimum and maximum prices during an optimization period.

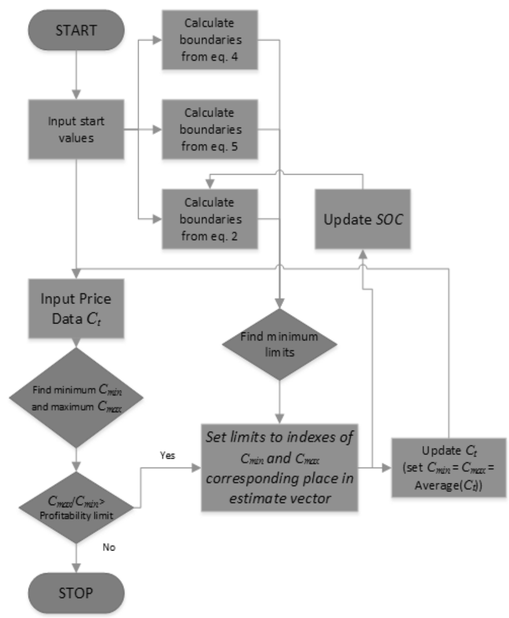


Fig. 2. Overall flow chart of the optimization algorithm

2. Calculate the largest amount of energy that can be charged to the battery during the hours when price is at minimum and the amount that can be discharged from battery during the hours when price is at maximum. Calculate first the minimum or maximum, it depends *SOC*. If *SOC* are closer to upper limit, calculate first the maximum price corresponding boundary, because then the storage has potential to discharge more than charge. Boundaries follow from constraints in equations (2), (4), (5) and estimated *SOC* before these hours, which is calculated by equation (3).
3. Update calculated values in corresponding elements of estimate vector.
4. Find the next minimum and next maximum prices, when the hours calculated earlier aren't taken into account.
5. Go back to step 2 and continue algorithm when all elements of estimate vector are calculated or stop algorithm if profitability falls below the limit. Profitability means the difference between maximum and minimum prices of step round.

With this algorithm we didn't always get the exact optimum storage use model and by using iterative numerical algorithms, even better results can be obtained.

Because, the storage control optimization problem includes many variables and *SOC* optimization variables depends on each other, iterative numerical algorithms have convergence problems. Thus, an effective and fast converging algorithm is needed to solve this kind of a problem. This algorithm is very effective, because it doesn't need many hard calculations and we can get new storage use model very fast. This is a very good feature when we need to calculate many customers' simulations for the whole year in short time.

The errors caused by using this algorithm happens only in a few hours of the whole year simulation and it's very small, so error in simulation results is only marginal. During the model construction process, we tested also many other control or optimization algorithms, but with no other algorithm the cost benefit was smaller than with the above proposed algorithm, or calculations were so heavy that the needed time to get the necessary results was not decent.

### *II.4. Forecasts*

Control needs to know, how the customer's consumption and self-production will behave in the next few hours. Because we can't know in advance exactly the consumption and production, forecasts must be formed. Customers' consumption can be predicted by the model which is based on previous consumption and outdoor air temperature [21]. Forecast for a simulation model is formed with Matlab® function. For forecasting production, we used solar radiation modelling which is shown in literature [22]. Forecasts form input data for the simulator. The accuracy of the forecasts models real-life situation. Simulator takes into account forecast errors which are equivalent with real life errors.

### *II.5. Continuous Control*

The objective of continuous controller is to implement a result of the optimization during the hours and monitor the compliance of the constraints. Since the actual consumption and production are not necessarily in line with forecasts, continuous control must continually react to actual power measurements. Adjustable variable in continuous control is the cumulative energy transfer between storage and household's network $B_h$, which is the cumulative sum of charged and discharged energy of storage from the beginning of an hour.

The first element of the optimized estimate vector $B_1$ is used for the target value for the continuous controller.

The aim is to adjust the whole hour cumulative energy transfer to the target value. Depending on whether the $B_h$ is less than or greater than $B_1$, storage, either charged or discharged. The constraint in equation (4) is to limit the rate of change of the variable $B_h$; how high a current the storage can charge. Continuous controller gives a signal $S_{control}$ to the storage unit, how it has to charge or discharge. Maximum charging signal is 1 and maximum discharging is -1, otherwise the signal is between these figures. Continuous controller must control in addition to the basic adjustment also other constraints and take into account the exceptional cases. If production exceeds consumption, the energy that is produced over own consumption is a profitable to charge to the storage rather than supply to grid. In this case, the control signal is formed:

$$S_{control} = \frac{P_h - D_h}{B_{max}} \tag{6}$$

where $P_h$ and $D_h$ are household's momentary production and demand. However, the control signal maximum is still one. The important part of activities of the continuous controller is also monitoring storage capacity limits. There is derogation compared with Eq. (2), the physical limits of storage constraints can be used in control. It must be taken into account that, during the hours, the available resources can be reduced when compared to the limits set in Eq. (2).

### *II.6. Battery Modelling*

The energy storage system losses mainly consist of the converters and the storage itself. [23] In this paper inverter efficiency $\eta_{inv}$ is 98 % and DC-converters efficiency $\eta_{dc}$ is 99 %. Thus, the energy transfer efficiency between the network and storage have been 97 % and self-produced energy storage efficiency is 99 %.

Energy storage losses occur, during both charging and discharging but most of the loss occurs during charging. [24] In losses modeling, it can be approximated that the battery discharge efficiency $\eta_{dech}$ and the charging efficiency $\eta_{cha}$ is the same. Thus, modeling can be performed by a single equation in both directions. The charging efficiency depends on the nonlinearly charging current [25]. When the battery doesn't charge completely full or discharge to completely empty, efficiency can be expected behave linearly. In this case, the charging losses can be modeled by internal serial resistance $R_b$ and that can be shown:

$$\eta_{cha} = \eta_{dech} = 100 \times \frac{V_b - I_{cha} R_b}{V_b} \tag{7}$$

where $V_b$ is battery nominal voltage and $I_{cha}$ is charging current. The advantages of modeling to the internal serial resistance based model is that the various batteries are easy to compare with each other and also aging of the battery can be modeled using the same resistance [26].

For lithium-ion battery modeling we use the internal serial resistance $R_{b\_lithium}$ values 0.026 Ω, which is resistance of one cell with a voltage $V_{b\_lithiumC}$ 3.3 V and capacity $Q_{lithiumC}$ is 2.5 Ah [27]. This cell type is $LiFePO_4$, which is suitable for household use because it has long cyclic (+4000 cycles) and calendar lifetime (+5 years) and it also has good safety features [28].

Charging and discharging of the electrical energy storage systems are modeled based on the battery, inverter and converters efficiencies. [24] Battery charge can be calculated on the basis of Eq. (3). The efficiency of energy transmission $B_e$ being obtained by multiplying the efficiencies of the $\eta_{dc}$ and $\eta_{cha}$. The energy transfer of storage $B_t$ is calculated by multiplying the charge current $I_{cha}$ and charge voltage $V_{b\_cha}$, which can be calculated as follows:

$$V_{b\_cha} = V_b - I_{cha} \cdot R_b \tag{8}$$

Multiplying the maximum charging current $I_{cha\_max}$ to control signal $S_{control}$, obtained a momentary charging current $I_{cha}$ of the battery. The energy taken into the power grid $G$ is determined by a model which based on the transmission of energy between storage, consumption and production. This is determined by the three options.

When storage is charged, the energy transmission between household and power grid can be presented by equation:

$$G = \begin{cases} \dfrac{B_t - P_{dc}}{\eta_{inv}} + D, & \| P_{dc} < B_t \\ -\eta_{inv} \cdot \left( P_{dc} - B_t \right) + D, & \| P_{dc} \geq B_t \end{cases} \tag{9}$$

where $P_{dc}$ is own energy produced by DC.

The third option is the discharging of the storage, for which the equation is as follows:

$$G = \eta_{inv} \cdot \left( -B_t - P_{dc} \right) + D \tag{10}$$

## III. Initial Data

Measurements of electricity consumption used for the study are hourly measurements of electricity use from real customers, which are measured by automatic meter reading (AMR) in the area of one Finnish distribution system operator's (DSO) power distribution network.

Customers have to pay for the electricity energy and transmission on the basis of these measurements.

Measurements have been made during the period between June 2010 and December 2013. The 2013 measurements are used in the simulation as real consumption of electricity and earlier measurements are used to generate consumption forecasts. A total of 495 customers are divided into three groups based on their consumption type. The first group is a group of electric heating customers whose houses are heated by direct electric heating; there are 270 customers in this group. The second group is electric storage heating customers whose houses are heated by electric storage heaters; there are 53 of them. The third group is the oil-heating customers, who don't use electricity for heating the house and there are 172 of them. For testing the operations of the continuous controller and to view the changes occurring during an hour, the electricity consumption data measured from a single family house is used. In this the measuring frequency is one measuring about 6 seconds. Different customers' behavior during the hours varies a lot, so the examination of a single customer is only indicative. The measurements are made in Kontiolahti during the period between June 2013 and September 2013, the measurements are used in the Current Cost - measuring equipment. In these measurements we can see variations and how fast power changes in household electricity consumption happens during the hour. Solar power production measurements are based mainly on the measurements of radiation which have been made on the roof of the Tampere University of Technology building with the radiation sensors. [29] Horizontal solar radiation is measured by CMP22 Pyrometer and the incident radiation to 45 degrees tilted level has been measured by SPlite 2 Photodiode sensor. The solar panels' azimuthal angle is 22 degrees from the south to the east. Radiation measurements have been made during the years 2012 and 2013. The measurements are mostly minute averages, but one day measurements have been made at intervals of seconds into tilted position level. Because production has to be calculated from the measurements of radiation, calculations caused errors. For this reason, the actual produced apparent power of the panels of a few days is also measured. These measurements are the products of 17 series connected panels, with a total summarized power 3.23 kW in the maximum power point. The panels are the model NP190GK and one panel covers an area of approximately 1.45 m$^2$. Measurements have been made on three different days for weather type and these types are cloudy, partly cloudy and clear.

## IV. Verification of the Simulation Model

When simulating situations corresponding to reality it must be taken into account that even if we have electricity consumption and production data available for the entire simulation period, in the actual situation the future data can't be know in advance. For this reason, the simulations also need to simulate the errors which result from the fact that future consumption can't be forecast perfectly. Forming the production and consumption forecasts, we can simulate the situation which is reality when we need to solve when energy storage charging is profitable and when it isn't.

### *IV.1. Accuracy of Production Forecast*

A solar power production forecast is formed by calculating the future theoretical solar radiation for parallel horizontal panels tilted 45 degrees, and correcting it by using the brightness factor that depends on cloudiness. The energy production forecast can be calculated from solar radiation forecast. The simulation examined different sizes of panels. An example case deals with nominal power 3.23 kW of solar panels.

Production after a single-phase inverter is measured from three different weather types of day from the summer of 2015. Three days of nearby the same level of cloudiness were chosen from over a year of forecasted production. Fig. 3 shows the hourly calculated averages for the production graphs for three different types of day.

Forecasts have been multiplied by efficiency 0.85 so that the maximum points correlate to the measurements.

Because the days which are being compared in Fig. 3 don't correspond to each other exactly for cloudiness, temperature and radiation intensity, also the forecasts and measurements don't correspond exactly. However, the figure shows that the production forecasts' magnitude corresponds well to the actual production with a similar cloudiness. When the sky is cloudy, radiation intensity is more difficult to forecast than when the sky is clear.

The forecast estimates for production are too small when the sun is near the horizon, because the forecast doesn't take into account the possible reflections caused by trees and buildings. In this examination we look at the production of solar power after the power control and the converter, but before the inverter.

### *IV.2. Error Caused by Hour Time Step*

Hourly average values in the simulation input data cause an error for the continuous controller. In reality, consumption and production varies very much during the hours. Hourly averages are used for two reasons. First, initial consumption data from DSO is hourly averages and second. Pricing is also hourly, so this also makes calculations easier. The magnitude of the error can be estimated by simulating short periods of time with shorter discretized time intervals. When we used hourly average values and hour time step in simulation the shortest time period the simulator can calculate is 0.04 times to time step. This is caused by the used discrete calculation method in Simulink. So, with an hour time step, this time period is 2.4 minute. We simulated one customer cost benefit for about a two-month period for 2.4-minute time step and calculated the estimated benefits for one year. These results were compared with the same customer's simulated cost benefits for hour time step. Fig. 4 shows a comparison between the different time steps in such a way that the simulations have been used in various sizes of solar panels. Cost benefit means the difference in the whole year's electricity price for the customer with and without storage. As seen in Fig. 4, use of an hour time step causes only a very small error in the results of the simulation. In the shorter time step, growth of the cost benefits is more stable than hour time step when size of solar panel increasing. But the error caused by used time step is only few euros. So, we can note that this comparison reveal to used hour time step to sufficient accuracy.

Changes in electricity consumption and production can be really fast, so even large changes may happen during just minutes. For this reason, we simulated a one-day simulation for one more customer. We are interested to know what happens during one minute.

So, we simulated storage use during one day with 2.4 second time step. Fig. 5 shows the results of the second-level simulation, with and without energy storage system.

In the simulation, the production of 1 kW solar panel is used. This figure is interesting also for the reason that here we can see accuracy changes in power from the grid side. The graph shows that without storage, power would be supplied to the grid especially at midday, whereas for example in the evening, a lot of power has to be taken from the grid.

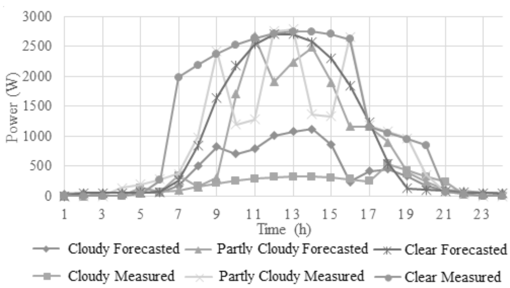


Fig. 3. Measured and forecasted production for three different weather type days

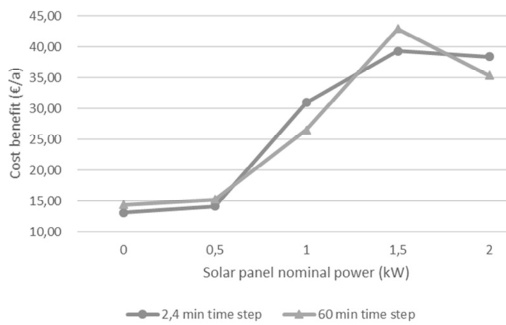


Fig. 4. The simulation time step impact on the cost benefits

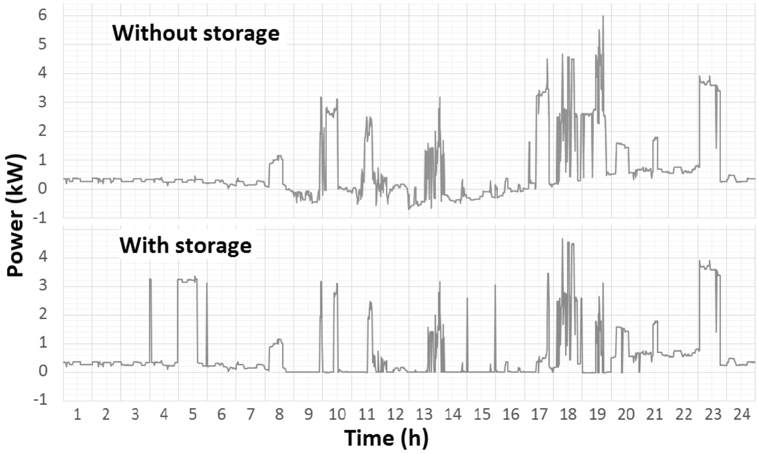


Fig. 5. Household's electricity consumption for one customer for one day with storage and without storage

As seen, consumption is much smoother with the storage than without and the power doesn't need to be supplied to the grid. When we compare the second-level simulation and an hour time step simulation for one day and the same customer, the difference of the cost benefit is only 0.01 €. This comparison shows the same as the simulation with the 2.4-minute time step: by using an hour time step we get a good estimate of the whole year cost benefits.

## V. The Results of the Simulation

Amount of customer cost benefits were calculated for a simulator. First, we had to find the suitable length of optimization time and then we could calculate the other results. The most interesting case is how battery size and nominal power of solar panels affected the amount of cost benefits. Especially, the effect of the battery size is very interesting, because size affected storage costs and further to the profitability of energy storage.

In results, the used electric energy pricing system is hourly real-time pricing. The price consists of the Nordic market price multiplied by value-added tax 24 % and added to electricity sales company's marginal 25 c/kWh.

If customer sales overproduced energy to grid, they would get compensated with the market price minus the company's marginal. In addition, customers have to pay transmission payment 6 c/kWh for electricity that they buy. Transmission payment includes 2,79 c/kWh electricity tax. These are overall prices that are used in Finland and these are used in all calculations in this paper.

### *V.1. Optimization Period*

To determine a suitable length of the optimization time, we simulated 12 different customer's electricity consumption over the year by various lengths of optimization time.

Customers are selected from all three groups so that the consumption differences between customers are maximally large. To avoid errors, the simulations aren't used for forecasts. The used electricity price data is hourly market prices for the year 2013. Production data was from 2 kW nominal power solar panels and energy storage of about 10 kWh lithium-ion batteries.

The results of the simulation are shown in Fig. 6 and in addition the average of the various customers is shown with the red line. According to the simulations, the 18-hour long optimization time had the best cost benefits.

This result is utilized in this paper.

### *V.2. Influence of Battery Size and Nominal Power of Solar Panels*

The amount of households' own production and their impact on cost benefits was studied by simulating the use of electricity with different size lithium ion batteries and various size solar panels of nominal power.

The group of electric heaters elected to customers by total consumption of the year was 18.3 MWh.

Fig. 6 shows the results of simulations made with the 2015 market prices. With small solar panels the cost benefit will be even lower than without own production.

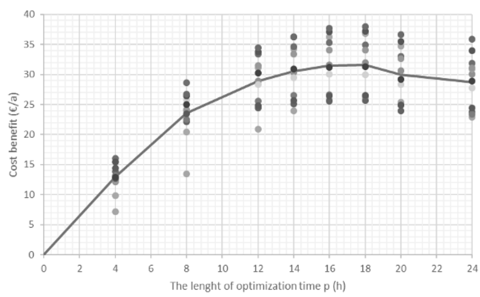


Fig. 6. The length of optimization time impact on the cost benefits

This is due to the fact that from the viewpoint of the grid, consumption is decreased and the amount of consumption begins to limit the cost benefits.

When the panels' power increases above 3 kW, the storage allows to increase the share of production used in own consumption and thereby the overall cost benefit begins to grow. As panel size increases, the cost benefits of growth will slow down, and this is due to the fact that the expensive price hours of time consumption are already largely filled by own production. Fig. 7 also shows that approximately 5 kWh in a battery gives the greatest benefit in relation to the size of the battery.

Simulated results of oil heaters and electric storage heaters groups of customers are very similar to those of the electric heaters customers. In oil heaters the overall consumption is often lower than other groups.

In this case, the magnitude of the consumption already begins to limit the growth of cost benefits faster. With the electric storage heaters, a large part of consumption is already timed to the cheapest hours and the cost benefit will be less than electric heaters for this reason.

### *V.3. Comparison of Storage Control Methods*

This paper presented a control method that was compared with three alternative control methods.

The first optional control method (OC1) is based only on own consumption produced energy charge in storage and its use when consumption surpasses production.

Option 2 (OC2) is based on the power limit, where the storage discharges when consumption exceeds the limit, and when consumption drops below the limit, storage is charged. If *SOC* limits to charge or discharge, storage *SOC* is maintained. The third option (OC3) is based on the intensity of solar radiation, the amount of consumption and the relationship with the production of consumption, as in [6]. The algorithm decides whether or not charging or discharging is profitable at a particular time. The basic idea is that if solar radiation is strong and consumption is small, the storage charges and if radiation and consumption are to the contrary, the storage discharges. Other control depends on *SOC* and other variables.

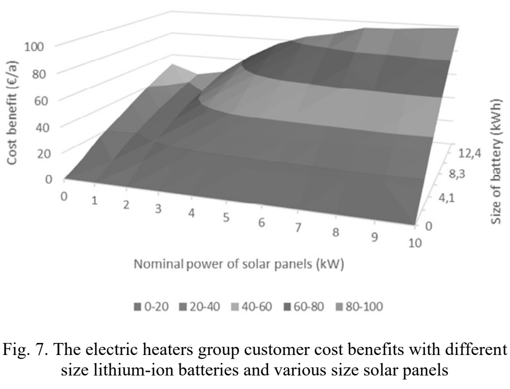


Fig. 7. The electric heaters group customer cost benefits with different size lithium-ion batteries and various size solar panels

Comparative simulation was made with different-sized solar panels and a 6.2 kWh lithium-ion battery.

Fig. 8 shows the results of the simulation of a customer in the electric heaters group. The results of the comparative simulation show that the control method presented in this paper gives the biggest cost benefits, as Fig. 8 shows. Options 1 and 2 are for cost benefits slightly smaller than the best option, but option 3 is clearly the worst. Option 3 is more suitable for use with normal pricing, where energy only has one price and in addition, the production should be very high.

The results of the other customer groups' simulations were also similar.

### *V.4. Energy Storage Payback Period*

According to the simulations households can reduce their annual electricity bill with electrical energy storage.

When looking at the profitability of storage, one must also take into account the cost of the storage. So that storage would be profitable, the benefit during the lifetime must be greater than costs. The simulations showed that the about 5 kWh lithium-ion battery for its size, the most effective solution. Fig. 9 shows the 5 kWh battery storage payback period's dependence on the annual cost benefits in different storage purchasing prices. The life time of a lithium-ion battery is maximum 8-15 years, so the payback period should be shorter than this.

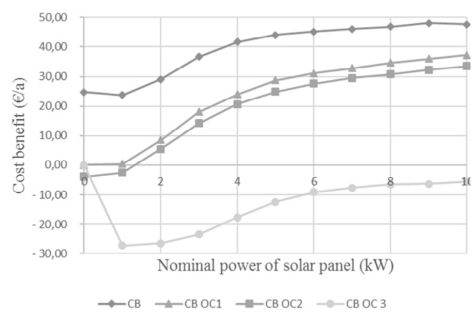


Fig. 8. The result of a comparison of the electric heaters group customer number 13 with 6.2 kWh lithium-ion battery storage

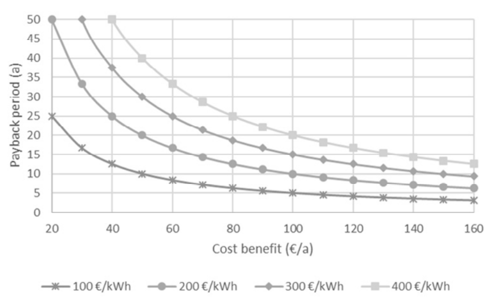


Fig. 9. 5 kWh lithium-ion battery storage payback period dependence of the annual cost benefit in different storage purchasing prices

If the battery acquisition cost is 200 €/kWh, a 15-year payback period could reach about 65 € annual cost benefit and 8-year payback period 125 € cost benefit.

Simulated cost benefit with the 2015 electricity market prices was without own production from 25 to 30 € and with own production 40-50 €. This means at least 20-40 years' payback period at current prices, when the introduction of the system is not profitable. If the battery system succeeds in reducing the price of 100 €/kWh, the payback period would be shortened without own production to 20 years, and with own production to 10 years, when the storage would already be profitable.

This analysis doesn't take into account possible new transmission tariffs or the effects of demand response, which may reduce the payback period in the future.

### *V.5. Effect of Electric Energy Price Trend in Future*

When looking at the development of the electricity market prices between 2013 and 2015, the average difference between the daily minimum and maximum prices has increased from 21.82 € to 29.84 € and price average standard deviation has also increased from 4,59 € to 9,84 €. These factors directly affect the cost benefit which comes from using storage to demand time shifting.

As a result of the change between the years 2014 and 2015, the cost benefit increased by an average of 7%.

Between 2013 and 2014 the change was so big that the entire two-year period, the cost benefit even doubled. If the price trend is to continue in the coming years, the cost benefit will increase substantially.

Fig. 10 shows the simulated situation, how the cumulative total cost benefit would accumulate from the beginning of 2017 with 5 kWh lithium-ion battery storage, without own production (D) and with own production (P). In the simulation three possible price development models have been used for relative price trend of average maximum and minimum price difference and average standard deviation.

First (1), if the price trend will continue similar to the years 2014-2015, the second (2), if the price trend is similar than the whole two-year period 2013-2015, and the third (3), if the price trend stops at the 2015 level.

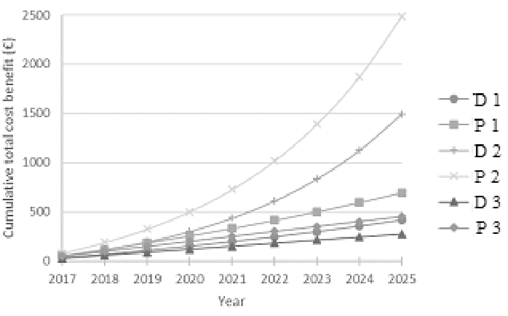


Fig. 10. Electrical energy storage cumulative total cost benefit of 5 kWh lithium-ion battery storage, when the use of the storage will start in the beginning of 2017 with own production and without, three possible electricity price developments

As seen in Fig. 10, the electricity price trends strongly influence the cost benefit and profitability of storage in the coming years. If, for example, storage purchase cost should be over 1,000 €, the price development should be beneficial for the purchase to be profitable.

But it is also possible to achieve large gains. Improving the profitability of the electrical energy storage is significant in lowering storage system acquisition costs. This is one of the most important targets for development in the future. Also improving the battery and power electronics efficiencies could increase cost benefits, but already the devices are so good that growth would only be marginal.

On the other hand, if the variation in the price of electricity will increase, improving the efficiency will also be more profitable. As has been stated, the most impressive factor of the profitability of the electrical energy storage is the price development of the electricity in the future. The electric energy storage also makes it possible to reduce the demand from the grid. For this reason, it is worthwhile to consider if the grid companies would support the purchase of energy storage.

Transmission tariffs also need to develop, because without the power based tariff the use of energy storage may even increase the network load. This means that if electric energy price is low and customer has large storage, it is profitable for him to charge the storage with large power which might make the demand on the grid greater than without storage. So, it is appropriate that the maximum demand is limited in the same way. With the right transmission tariff structure, it is also possible to get a much greater cost benefit with energy storage, but this needs to be examined further.

## VI. Conclusion

Annual energy costs of households can be reduced using energy storage with or without own energy production. The efficiencies of lithium-ion batteries are so high that even small differences in electricity prices between hours make load shifting by battery profitable.

However, in order to obtain the maximum cost benefit of this, the right kind of control method is needed.

Control must be able to take into account the price of electricity over the next few hours and know how to predict future consumption and production. Production of solar power can be predicted quite accurately, but the forecasting of future consumption is challenging. The storage also allows a greater part of self-produced energy to be used in own consumption, which is more profitable for the customer than selling the overproduced energy to the grid. Lithium-ion battery prices are still so high that during the battery lifetime the total economic benefit will be lower than the costs. However, if the electricity price trend continues in the future similar to the past few years and battery prices go down, storage can become profitable in the very near future. Profitability could improve with power-based distribution tariffs, but this has to be explored more in the future.

It is still possible to improve the control algorithm of the storage in order to increase the total benefits.

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## Authors' information


Tampere University of Technology.

**Juha Koskela** received his M.Sc. degree in electrical engineering from Tampere University of Technology in 2016. At present he works as a project researcher in laboratory of Electrical Energy Engineering in Tampere University of Technology. His research focuses in electrical energy storages and these impacts to technical and economical point of view.

**Antti Rautiainen** received his M.Sc. and Dr.Tech. degrees in electrical engineering from Tampere University of Technology in 2008 and 2015, respectively. At present he works as a post-doctoral researcher in laboratory of Electrical Energy Engineering in Tampere University of Technology. His research focuses in various topics related to electricity grids and electricity market.

Prof. **Pertti Järventausta** received his M.Sc. and Licentiate of Technology degrees in electrical engineering from Tampere University of Technology in 1990 and 1992 respectively. He received the degree of Dr.Tech. in electrical engineering from Lappeenranta University of Technology in 1995. At present he is a professor at Tampere University of Technology and the leader of the laboratory of Electrical Energy Engineering. The main interest focuses on the issues of Smart Grids from the grid and electricity market point of view.

# PUBLICATION
# 2

**Utilization of Electrical Energy Storage with Power-Based Distribution Tariffs in Households**

J. Koskela, K. Lummi, A. Mutanen, A. Rautiainen, P. Järventausta

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# Utilization of Electrical Energy Storage with Power-Based Distribution Tariffs in Households

Juha Koskela, Kimmo Lummi, Antti Mutanen, Antti Rautiainen, and Pertti Järventausta

***Abstract*—Energy storage enables modification of the customer load profile from the grid perspective without leading to a decrease in comfort level. To meet the future challenges of the energy sector, distribution system operators (DSOs) in Finland have recently discussed power-based distribution tariffs (PBDTs) for small customers. The current distribution tariffs of small customers do not respond well to current challenges, and they require reform. The peak powers of the customers can be decreased with energy storage, and via incentives included in the PBDTs, energy storage can prove to be profitable for household customers. In this paper, we study the profitability of electrical energy storage under different pricing structures. The study simulates changes in customer consumption with a modeled storage system. Simulations consider the requirement of load forecasting in the storage control system. The results of the study show that energy storage can be profitable if the consumption includes only a small number of high peak loads during the pricing period when applying new distribution tariff structures. However, the price level of the tariffs and the tariff mechanisms affect the results.**

***Index Terms*—Batteries, Cost optimal control, Energy management, Energy storage**

## I. Introduction

DEMAND response (DR) for small customers is not common, mainly because of its poor profitability and various other factors. For example, there is a lack of DR service providers that can offer profitable and easy ways to implement the necessary actions without any loss of comfort for the customers. Electrical energy storage makes it possible to change the load profile of the customer from the grid point of view such that the customer does not notice the changes. Energy storage can be used in DR if, e.g., it is controlled based on the hourly spot price of electricity in the day-ahead market [1]–[2]. In this manner, individual customers can participate in smoothing the demand of the entire power system. However, in recent years, variation of the energy price in Northern Europe has been so low that the profitability of energy storage has been poor [3], and its profitability in Finland has been studied, e.g., in [1]. Profitability can be improved if customers have their own energy production (e.g., solar panels), but currently, profits are still low. The benefits that a customer can derive from self-production depend primarily on the energy-dependent volumetric component of the distribution tariffs. The magnitude of the volumetric portion of the electricity bill can be significantly lowered if the produced electricity is self-consumed on-site. Additionally, the type of electricity contract that the customer has with the energy retailer and the energy-related taxes affect the benefits of self-production. Another possible benefit for the customer who owns energy storage is that it enables the use of electricity during power outages.

Smart metering is a key component in the development of electricity distribution pricing. Due to the decree set by the Finnish Government in 2009, almost all customers (approximately 98%) are currently supplied with a new smart meter that features hourly energy measurements as well as registrations of supply quality and DR functionality [4]. Much discussion of the use of power-based distribution tariffs (PBDTs) for small customers in Finland has ensued [5]. PBDTs have long been available for large customers, but with the help of advanced metering infrastructure, they could also be applied for smaller customers. PBDTs can create an incentive for customers to decrease their hourly average maximum power (HMP) values, which are determined by hourly energy measurements gathered from smart meters. If the HMPs could be decreased for several customers, the entire power system could benefit, e.g., if loading of the distribution transformers can be decreased [6].

PBDTs have been studied, e.g., in [7] and [8]. The operational environment of a distribution system operator (DSO) strongly affects the cost structure of the DSO. The variation in the operational environments between different DSOs means that the price levels of the distribution tariffs vary significantly.

Energy storage has multiple advantages, and it is important to search for new ways to improve the profitability of energy storage because it is currently quite poor. At present, the prices of energy storage with sufficiently high efficiency (e.g., lithium-ion batteries) are high, but in recent years, their acquisition prices have become more affordable, and this trend is expected to continue in the future [9]. Lower acquisition price improves the profitability of energy storage, but in this paper, the focus is on assessing the cost benefits of energy storage in the near future and investigating how profitability could be improved, especially if PBDTs are applied across a wide scale. The cost benefit of the energy storage in this work means a difference in the annual total electricity bills of the customers (i.e., charges of the DSO and the retailer) when the storage is used versus not used.

PBDTs have not been comprehensively studied with energy storage. Storage operations with demand charges have been studied, e.g., in [10]–[11], where the use of energy storage was

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The authors are with the Laboratory of Electrical Energy Engineering, Tampere University of Technology, Tampere, Finland (e-mail: juha.j.koskela@tut.fi)

investigated in a similar setting to the one discussed in this paper. In the U.S., certain utilities apply tariffs, which include demand charges for residential customers. One possibility in designing demand charges for industrial and commercial customers, as presented in [10], is to make the customer pay for the highest 15-minute average power (kW) of the billing period. The results presented in [10] show that customers could achieve cost savings with the use of energy storage. Designs for the demand charge have been more widely introduced, and the impacts on residential customers with storage operations with one presented PBDT structure was studied in [11]. The results presented in [11] also showed that residential customers could achieve cost savings with use of energy storage together with the PBDT and control systems that are considerably different from those in our study. In this paper, different PBDTs and actual consumption data are used, and we highlight the fact that customer consumption must be forecasted for the future. Thermal energy storage with demand charges has been studied, e.g., in [12], but that study did not include electrical energy storage.

The benefits of energy storage have been extensively investigated. Sizing of the energy storage and its optimal management with dynamic pricing and integration of renewable energy production have also been studied, e.g., in [13]. The study presented in [13] investigated the factors on which optimal storage sizing depends and strategies for how to control the storage in a profitable way. The results presented in [12] are similar to our studies in [1], but the problem formulation and the solution are different.

The PBDT structures examined in this paper were presented in [14] and [15]. The studied tariffs and their components are listed as follows:

1. Power tariff (PT), including *basic charge* (€/month), *volumetric charge* (€/kWh) and *power charge* (€/kW) based on the highest HMP of each month;
2. Threshold power tariff (TPT), including *basic charge* (€/month), *volumetric charge* (€/kWh), and *power charge* (€/kW), which is used only if the HMP of the month exceeds a set threshold limit;
3. Power limit tariff (PLT), including *power charge* (€/kW) based on a preordered capacity that the customer can select and commit to not exceed; and
4. Step tariff (ST), including *basic charge* (€/month) and *volumetric charge* (€/kWh), which depends on the average power of each hour. If the average power exceeds a step limit, the unit charge is greater than that below the limit.

The tariff structures have many advantages and disadvantages, and it is important that the properties of different options are studied thoroughly before they are introduced in practical implementation. The properties of various distribution tariff structures were compared from multiple viewpoints in [14]. In this paper, the focus is on household customers with energy storage. The study investigates the benefits of energy storage with PBDTs, and for this purpose, an evaluation method is introduced to assess their profitability.

Energy storage and its benefits have been investigated in previous studies. However, earlier work did not include a simulation case in which control of energy storage is based on PBDTs combined with the market price of electricity. A comparison of the impacts of different PBDTs on the profitability of energy storage by small customers has never been conducted. Additionally, the fact that the consumption of the customer must be forecasted for the control system to compute the amount of energy that must be stored at each moment was not considered in earlier studies.

This paper proposes a novel energy storage control algorithm. Additionally, the profitability of household energy storage is evaluated in an operational environment that includes novel incentives. The evaluations applied in earlier studies did not consider different possible PBDT structures of the DSO combined with control based on the day-ahead market price of electricity. Additionally, this novel perspective simultaneously considers modeling of the energy storage losses, load forecasting and different incentives in use of the energy storage. Therefore, this paper offers a more comprehensive view of the profitability of energy storage compared with the evaluations presented in earlier studies.

In summary, the novelty of this paper results from the following key items that supply a clear contribution to the scientific community. First, the study presented in this paper involves various PBDT structures and their impacts on the profitability of energy storage. These aspects have not been investigated as extensively in recent academic literature. Second, a novel smart control method for cost-based optimization is developed using load forecasting and including various cost incentives. Additionally, we study the impacts of errors in load forecasting. Finally, our study is based on actual load data from a large group of small customers, which increases the value and practicality of our investigations.

The paper is organized as follows. A simulation model that includes battery modeling and control systems is described in Section II. Section III presents the input data used in the simulations. The simulations and their results are discussed in Section IV. Section V presents conclusions of the study.

## II. Simulation Model

The simulation model consists of a two-step control system and a battery model. Two-step control means that the control initially makes a decision as to what strategy is profitable during the next hour based on load forecasting and the state of charge (SOC) of the storage. The first step in the control is known as hourly control. The second control step is known as continuous control, and the purpose is to control the storage during the hour to execute the objective given by the first step. This scenario is rarely possible because the load forecast is not equal to the real consumption in every case, and various control actions must be performed during the hours. Simulation is applied for a large group of customers, and the optimization must be performed for every simulated hour, which requires the algorithm to be efficient. To perform the aforementioned tasks, we apply the following algorithm.

### *A. Battery model*

In battery modeling, the state of charge is the most important variable because all other variables model how the SOC changes between the two different time steps (i.e., hour) [1]. These changes can be modeled by the following (1)

$$SOC_t = 100\frac{E_t}{E_{\max}} = 100\frac{B_{eff}B_t}{E_{\max}} + SOC_{t-1}, \quad (1)$$

where $E_t$ is the amount of stored energy at time $t$, $E_{max}$ is the maximum capacity of the energy storage, the SOC at time $t$ is $SOC_t$, $SOC_{t-1}$ is the SOC of the previous time step from time $t$, variable $B_t$ is the energy transfer to or from the energy storage, and $B_{eff}$ is the efficiency of the transfer.

The energy storage SOC model can be produced with (1) for all different battery types. Differences between battery types derive from losses, which are depicted by the variable $B_{eff}$. The cell type of the studied battery is lithium iron phosphate (LFP, $LiFePO_4$) with graphite as the negative electrode. This alternative is suitable for household use because of its long cyclic and calendar lifetime and its good safety features [16].

The energy storage systems losses mainly occur in the converters and in the storage itself [16]. In this study, the efficiency of the inverter $\eta_{inv}$ is assumed to be 98%, and the DC converter efficiency $\eta_{dc}$ is assumed to be 99%. Thus, the energy transfer efficiency between the network and storage is 97%. Energy storage losses occur during both charging and discharging, but the major portion of the losses occurs during charging [17]. In modeling the losses, it can be approximated that the battery discharge efficiency $\eta_d$ and the charging efficiency $\eta_c$ are equal. Therefore, modeling can be performed with a single equation for both flow directions. The charging efficiency depends nonlinearly on the charging current $I_c$ [18]. When the battery is not charged or discharged completely, charging losses depend linearly on the charging current if the internal serial resistance $R_b$ is assumed constant. In this case, charging efficiency can be calculated by (2).

$$\eta_c = 100\frac{V_b - I_c R_b}{V_b}, \quad (2)$$

where $V_b$ is the nominal voltage of the battery. The advantages of including the internal serial resistance-based model is that the various batteries are easily compared with each other, and the aging of the battery can be modeled using the same resistance [19].

Charging and discharging of the electrical energy storage systems are modeled based on the battery, inverter, and converter efficiencies [16]. The SOC of the battery can be calculated by (1). The efficiency $B_{eff}$ can be obtained by multiplying the efficiencies $\eta_{dc}$, $\eta_{inv}$, and $\eta_c$. The energy transfer of storage $B_t$ is calculated by multiplying the charging current $I_c$ with the charging voltage $V_c$, which can be calculated by (3).

$$V_c = V_b - I_c R_b \quad (3)$$

Based on the transmission of energy among the storage, consumption and power grid, the energy drawn from the power grid $G$ can be determined by (4).

$$G = \begin{cases} \dfrac{B_t}{\eta_{inv}} + D & \| \quad B_t \geq 0 \\ \eta_{inv} B_t + D & \| \quad B_t < 0 \end{cases}, \quad (4)$$

where $D$ is the consumption of customer. The upper portion of the equation is valid when charging, and when discharging, the lower portion of the equation is in effect.

### B. Battery control boundaries

Compliance with certain basic principles is necessary in battery control [1]. Use of a battery in a low SOC is not profitable because when the battery SOC drops, the internal losses increase rapidly as the terminal voltage decreases and the internal resistance of the battery increases, leading to increasing discharging losses [18]. For these reasons, the battery SOC has a lower boundary of 25% of the initial capacity. The limit is lower for an LFP battery, but for hourly control, this boundary is set higher such that the continuous controller can react better in unexpected situations. The battery SOC also has an upper limit of 95% of the initial capacity because with a notably high SOC, the internal resistance of the battery increases rapidly.

### C. Load forecasting

Load forecasting plays a key role in the control system because the future consumption of customers cannot be known exactly. The control system requires information on what will happen in the next few hours such that decisions can be made with respect to the amount of energy that must be stored for the coming hours. The load forecast for the simulation model is constructed using a MATLAB® function, and the forecast is based on the historical consumption of the customers and the outdoor temperature [20].

Consumption variation during the days can be forecasted with sufficient accuracy, as shown, e.g., in [1]. However, the individual daily HMPs are rather difficult to forecast because they depend strongly on customer choices, e.g., how various everyday electrical appliances are used. Forecasting errors are examined later in the simulations. Forecasting of hourly consumption is a highly important task if the control system attempts to minimize the HMP. If the forecasted HMP is too low, it leads to storage over usage when the control attempts to keep the HMP below the set limit. However, if the forecasted HMP is too high, the storage might not be used at all in the worst case.

Because the results of the simulations depend on the accuracy of the load forecast, the effects of the forecasting errors are studied as follows. First, the number of customers in the study group is sufficiently high to enable stochasticity in the simulations. Individual load forecasts for each customer create variability of the forecasting errors in the study group, and this can be observed from the results in the benefit distribution. Second, the simulations are run using two types of load forecast: non-ideal and ideal. An ideal forecast means that the consumption of a customer is known exactly before any control actions are applied. This situation is highly unlikely in reality, but in the simulation, this scenario is used to compare the effects of forecasting errors and to evaluate the ideal cost benefits of the energy storage. When the load is forecasted, it is known as a nonideal load forecast thereafter.

### D. HMP decrease with energy storage

With the PBDTs, customers can decrease their electricity costs by decreasing their HMPs. Discharging the battery energy storage during the peak load hours is one way to accomplish this goal. The problem in this scenario is that the control system must know how much energy can be discharged from the energy storage during different hours such that the HMP is minimized for the entire pricing period. The risk exists that the energy storage is empty when discharging is needed if the past HMPs have decreased the SOC to an excessive extent. For this reason, load forecasting is an essential component of the control system. However, forecasting errors cause unexpected situations in which it is often difficult for the control system to react.

The solution for the optimization problem of decreasing the HMP is based on the optimal power limit, which is the optimized upper limit of the HMP. The control system aims to maintain the HMP below the set value. The power limit can be set based on the structure of the tariff. With the PLT, customers can select the HMP limit, and with energy storage, the control system aims to maintain the power below the set value. If the tariff structure is ST, the step-limit can also be set as the power limit. With TPT, the threshold can be set as the power limit, or if the energy storage capacity is not sufficient, minimization of the power limit must be attempted. The PT is the only tariff structure in this paper in which the power limit is based only on the minimization algorithm and the capacity of the energy storage can be utilized completely.

Minimization of the HMP in this paper is accomplished with an algorithm, which is shown in the flow chart in Fig. 1. In the algorithm, load forecasting for the following 18 hours is performed hourly. The selected forecasting and optimization period is suitable, as presented in [1]. Based on the load forecast and the output power of the energy storage, the algorithm calculates a power that is the theoretical minimum. This power is set as the new power limit. The algorithm subsequently calculates whether it is possible to remain under the power limit when the changes in the SOC during the optimization period are considered. If the limit is not possible to achieve, the power limit is increased until it can be achieved in the set SOC range. The calculated power limit is used in energy storage control. At times, forecasting errors make it impossible to remain under the power limit if the real HMP is higher than the forecasted value. In this situation, the HMP is decreased as much as possible, and the highest HMP is set as the new power limit. The algorithm subsequently moves to the next hour. During the pricing period, the power limit only increases and never scales down because the power charge of the PBDT is billed based on the highest HMP of the pricing period.

*E. Market price-based control of energy storage*

In the Finnish deregulated market, competitive energy retailers are in charge of energy trading, and the DSOs control the power delivery in the distribution networks and operate their businesses as monopolies. In one of the energy tariff options in Finland, the price of energy is based on the hourly spot price of the day-ahead electricity market, which means that a separate price exists for each hour. The customer can benefit from shifting consumption to cheaper hours and avoiding use of energy when the price is high. The benefits of market price-based control have been studied, e.g., in [1]. In this paper, the same market price-based control algorithm is used. The algorithm is based on the near-future day-ahead market spot prices and on the load forecasting.

The goal of the algorithm is to find pairs from the hours of the optimization period, i.e., when the prices are at their highest and lowest. If the price difference between the values is sufficiently high, the energy storage charges during the cheapest hour and discharges during the most expensive hour. The algorithm subsequently searches for the second highest and lowest prices, etc. Charging and discharging are limited such that the SOC must remain within the set boundaries, and feeding of electricity to the grid is not permitted. For this reason, load forecasting is important because it is essential to know how much energy can be discharged from the battery during the target hours.

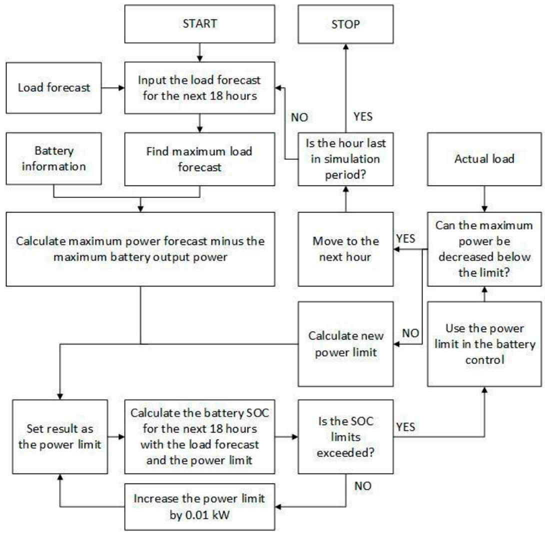

Fig. 1. Flow chart of the algorithm for HMP minimization.

The use of energy storage for load shifting is not profitable if the price difference between different hours is not sufficiently high [1]. The lower price must be cheaper than the higher price multiplied by the efficiency coefficient of the energy storage, but even this is not necessarily sufficient because use of the battery causes aging. A sufficiently high price difference depends on many factors, such as the future load profile of the customer, which is difficult to determine exactly.

*F. Combination of different control methods*

Different control aims can be combined at the same time. For example, energy storage can be simultaneously applied for both HMP decrease and for market price-based control. Fulfilling both objectives simultaneously might prove to be difficult because the benefits from both aims derive from different principles.

The power-based charges of PBDTs are so high in this study that even a small decrease in the HMP gives at least the same benefit as market price-based control. For this reason, we use a control principle in which the energy storage is used first in HMP decrease and second in market price-based control to combine the two control methods. If the variation of the energy price increases as expected in the future market, which includes more weather-dependent renewables, it might change the outcome, i.e., the achievable benefits. In this case, we must calculate the costs of energy storage with different control methods and compare the results against the benefits. Based on this information, the control system attempts to reach the most profitable solution at each moment.

TABLE I
APPLIED PBDT STRUCTURES [15]

| | Basic charge | Energy charge | Power charge |
|---|---|---|---|
| *PT* | 4.74 (€/Month) | 0.72 (c/kWh) | 7.23 (€/kW/Month) |
| *TPT* | 23.61 (€/Month) | 0.72 (c/kWh) | 7.23 (€/kW/Month, if $p$>5 kW) |
| *PLT* | | | 258.84 (€/year/5 kW) |
| *ST* | 4.74 (€/Month) | 4.10 (c/kWh) or 8.43 (c/kWh, if $p$>5 kW) | |

## III. Initial Data

### *A. PBDT prices*

To compare the effect of different PBDTs, we apply the charge components presented in [15] for the example network of the study. The studied network is located in a rural area in Finland. The tariffs aim to fulfill the planned revenue for the DSO when no major changes in the consumption behavior of the customers are expected (i.e., changes based on the tariffs). The tariff design principles are described in additional detail in [21]. The PBDT structures applied in the study are presented in Table I.

### *B. Spot prices*

In spot price-based control, we apply the day-ahead spot prices of the Nord Pool (Finland area price) from the year 2015 [22]. The benefit of load shifting depends on the variation of electricity energy prices from hour to hour. The variation between different years and their effects on the benefits from the DR point of view has been studied, e.g., in [3]. The variation of spot prices was highest during the 2013-2016 period in Finland. In 2015, the average difference between the highest and lowest daily prices, which is also known as the average daily price range, was approximately 30 €/MWh, and during the other years of the same period, the range was approximately 22-25 €/MWh. The average daily price varied in the range 30-41 €/MWh during the 2013-2016 period, and the price was the lowest in 2015.

### *C. Consumption data*

Consumption measurements used in the study are hourly energy measurements collected from actual customers between January 2014 and August 2016. Customer consumption is measured using a smart meter, and the DSO automatically reads the consumption data remotely. The customers under investigation are household customers living in detached houses. Based on the information system of the DSO, the majority of these customers have electrical heating systems, which means that their electricity consumption is more or less dependent on the outdoor temperature. The group also includes a few larger customers, e.g., farms. The total number of customers in the study is 1525.

From the PBDT point of view, it is important to know how high the HMPs of the customers will be. Fig. 2 depicts the distribution of the HMPs in the study group. The average HMP is near 9 kW, but for the majority of the customers, this value is lower. The HMPs, together with average consumption, show how much the demand peaks of the customers could potentially be decreased using energy storage. For example, if the average consumption of the customer is 2 kW and the HMP is 7 kW, then even with an ideal energy storage system, the HMP can be cut by only 5 kW during the peak load hour of the customer.

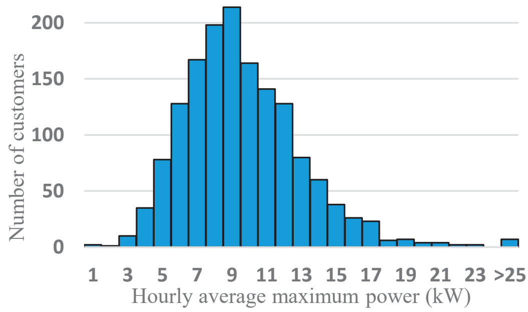


Fig. 2. Distribution of HMPs of the customers in the study group in 2015.

## IV. Simulations and Results

### *A. Forecasting errors*

Because the control algorithm uses the load forecast in decision-making, the forecasting errors affect the results of optimizations in hourly control. Forecasting is difficult if customers have high individual HMPs. Fig. 3 presents the mean absolute error (MAE) of the next hour load forecast as a function of the total annual energy consumption of the customer. We observe that the forecasting errors increase when the total energy consumption increases. The average total annual energy consumption of the customers in the study group is 13.6 MWh, and the average MAE of the next hour load forecast of the customer is 0.8 kW/h.

Although the MAE is not as high, the magnitudes of the HMPs are especially difficult to forecast. The forecasting algorithm is based on the average consumption as a function of temperature and time. The forecasting does not consider individual high HMPs. For example, if the consumption of the customer has been smooth, and if at a certain point in time, the customer uses a high-powered electrical device, the HMP is highly difficult to forecast. For many customers, the HMP forecast is systematically too low because the forecast is based on average values. An HMP forecast that is too low does not cause much loss because the information from HMP timing is much more important than the exact information from the magnitude of the HMP. The size and maximum output power of the energy storage limit the maximum decrease of HMP, and the decrease does not depend on the magnitude of HMP. To evaluate the effects of forecasting errors, the simulations were also conducted using ideal load forecasts.

### *B. Decrease of yearly HMP*

If the power charge of the PBDT is determined by the HMP of the year and the energy pricing is not based on the market spot price, the capacity of the energy storage is only used to decrease the HMP. The potential for how much the HMP can be decreased depends on the load profile of the customer, the forecasting errors and capacity, the efficiency, and the C-rate of the battery energy storage. Our objective is to attempt to find a suitable battery size with a capacity and C-rate that is the most profitable solution for the customer.

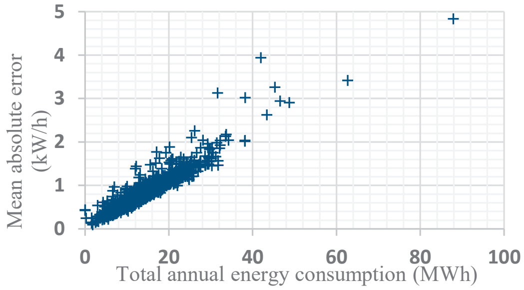


Fig. 3. Mean absolute error of load forecasting relative to the total annual energy consumption.

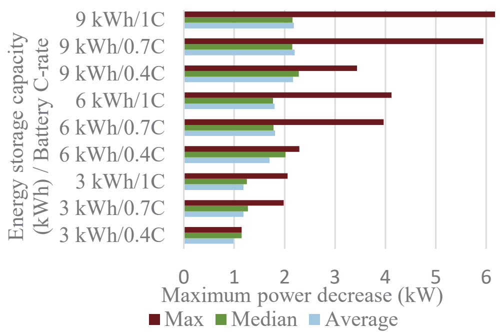


Fig. 4. HMP decrease of 1525 customers with three different energy storage system capacities and three different C-rates.

In the simulations, we assumed that every customer of the study group has an energy storage system. Fig. 4 shows how much the HMP can be decreased with energy storage of different sizes. We use three different capacities (3, 6, and 9 kWh), each of which has three different C-rates (0.4C, 0.7C, and 1C). The average HMP decreases when the storage capacity increases, but the change is higher between 3 and 6 kWh than between 6 and 9 kWh. The same trend is also shown in the median and maximum values. When we look at the effect of the C-rate, we note that the average is highest with 0.7C and the median is highest with 0.4C, except for the 3 kWh storage, for which 0.7C leads to the highest value. The maximum is highest with 1C, but the change between 0.7C and 1C is minimal. We also observe that the increase of the C-rate enables a higher HMP decrease, but it also increases the risk that the control fails and the actual HMP does not decrease at all.

### *C. Impact of pricing period*

The power charge of the PBDT can also be determined by the HMP for the month, which means that the power decrease optimization must be calculated monthly. We can assume that the energy storage must be used approximately 12 times more often than the current yearly rate to gain the same benefit. The theoretical maximum of the HMP decrease is the same as the annual one, but the risk exists that the maximum decrease is not achieved.

The difference between the monthly and yearly pricing periods can be evaluated by comparing the average of the monthly and yearly power decreases. Fig. 5 presents the HMP decrease of the customers when the pricing period is the whole year and the average monthly HMP decreases when the pricing period is one month. Energy storage with the capacity of 6 kWh and a C-rate of 0.7C is used in the simulation.

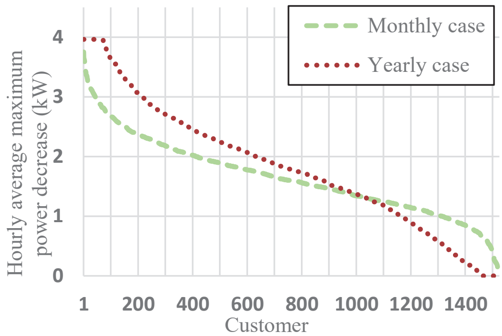


Fig. 5. HMP decrease with yearly pricing period and average decrease with monthly pricing period when customers have 6 kWh energy storage with a C-rate of 0.7C. The customers are not presented in the same order in both cases because the HMP decrease can differ between pricing period changes.

The results show that approximately two-thirds of customers have a higher power decrease with a yearly period and one third has a higher average power decrease when the pricing period is one month. In the monthly case, zero customers achieved the maximum benefit, and only a few customers had high (a decrease of over 75% of the HMP) benefits. Most of the customers had rather similar benefits, and for only a few customers, the benefits turned out to be quite low because of discrepancies between the months and the customer behavior. The same customer can achieve the maximum benefit one month and a low benefit the next. This scenario also means that if certain customers do not receive any benefit from the yearly pricing period, the monthly pricing period can still lead to a near-average benefit for the whole group.

Another difference between pricing periods is how much and how often the energy storage must be used to obtain the benefit. The hours that the energy storage must be discharged compared with the HMP decrease for monthly and yearly pricing periods are shown in Fig. 6. We observe that the number of discharge hours and the magnitude of the HMP decrease do not show much dependency. With the same number of discharge hours, one customer might achieve a 4 kW HMP decrease, whereas another customer might not achieve any decrease in power.

Energy storage must be used much more often with the monthly pricing period than with the yearly period to achieve the same benefit. With the monthly pricing period, the energy storage should be discharged for over 548 hours per year on average such that the average monthly HMP decrease is 1.65 kW, which means that the energy storage must be discharged for over 332 hours on average to achieve a decrease of 1 kW. With the yearly pricing period, a 1.81 kW power decrease can be achieved with 78 discharge hours on average, meaning an average of 43 discharge hours for a 1 kW power decrease, which is approximately 13% of the hours needed in the monthly pricing period case.

### *D. Combination of HMP decrease and market price-based control*

The combination of different control methods produces an ideal situation to sum the benefits from both control methods. There is also a risk that when the spot price-based control is

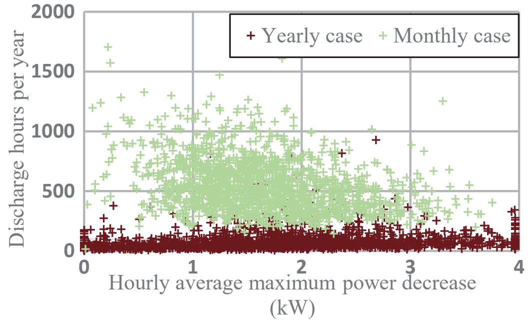


Fig. 6. Discharge hours per year compared with HMP decrease with a monthly or yearly pricing period when customers have an energy storage capacity of 6 kWh with a C-rate of 0.7C.

combined with the power decrease, different control targets can lead to loss of the achievable benefit from both methods. Changes in the HMP decrease of customers when the spot price-based control is used with an energy storage capacity of 6 kWh and a C-rate of 0.7C are shown in Fig. 7. The changes are presented as histograms in which the customers are divided into groups based on their HMP decrease. We note that for the majority, the HMP decrease is lower when the spot price-based control is involved. If the pricing period is one year, the HMP decrease for approximately 26% of the customers remains the same or is better than it was without the spot price-based control. If the pricing period is one month, the same ratio is 16%. Involvement of the spot price-based control caused a loss of benefits for all other customers. The HMP decrease might be higher even if the spot price-based control is involved.

### E. *Profitability of energy storage*

The investment costs and magnitude of tariff components affect the profitability of the energy storage. The investment costs of the energy storage include the costs of the battery and power electronics. These costs are estimated to decrease in the near future. The investment costs of the energy storage were studied, e.g., in [23], where it is stated that in 2015, the LFP battery cell prices were in the 200-350 €/kWh range and the estimated price in 2020 is expected to range from 100 to 200 €/kWh. Taxes, installation costs, management system costs and other costs should be added to these prices. The realistic level of the consumer prices is closer to double what is listed. The cost of the necessary power electronics was in the 100-150 €/kW range in 2015, and it is assumed to be approximately 80-110 €/kW in 2020 [23]. In this paper, we assume that the power electronic costs are 120 €/kW and that the cell price is 200 €/kWh. For a 6 kWh battery and 0.7C rate, the costs are approximately 2900 €. The lowest possible price in 2020 is approximately 1500 €, and the maximum price in 2015 is approximately 4800 €. These prices are used as benchmark values when we estimate the profitability of the energy storage.

Investment in the energy storage system is profitable if the benefit from the annual electricity costs is sufficiently high that the total benefits exceed the investment costs before the lifetime of the energy storage ends. The calendar lifetime of the LFP battery system is approximately 15 years, as presented in [24]. If we calculate a discounted cash flow for the next 15 years of energy storage use, the value of cost benefits in the future will

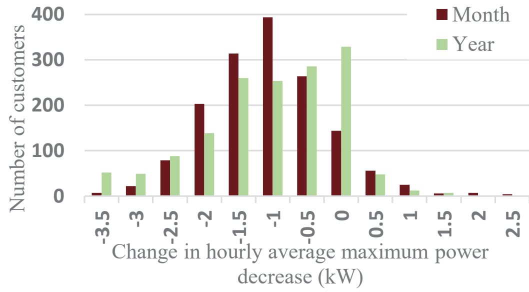


Fig. 7. Changes in HMP decrease of customers when spot price-based control is involved.

be higher than now. Additionally, the changes in energy prices are difficult to forecast. However, if we make a supposition that the prices remain stable and the losses caused by battery degeneracy are compensated with the changes in currency value, we can calculate that the benefit will be constant over a 15-year period. This scenario means that the average yearly benefit must be at least 100 € with 1500 € investment costs, 194 € with 2900 € investment costs, and 320 € with 4800 € investment costs.

Fig. 8 shows the savings in distribution costs with different PBDT structures and control methods when the non-ideal load forecast is used in the control. Similar results are presented in Fig. 9, but the calculation is based on the ideal load forecast. Customers are divided into groups based on their achievable savings in 10 € blocks. We observe that the losses in annual savings caused by the error in the load forecast are minimal. The use of load forecast impacts only a few customers, and the changes are so low that they are not noticeable from the distribution with the 10 € blocks. The results are quite similar in both Figs. 8 and 9. With PT, the annual cost savings are distributed between 0 and 340 €/a such that the majority of the customers achieve savings of approximately 150 €/a. The average savings per customer is 143 €/a with a non-ideal load forecast and 205 €/a with an ideal load forecast. If a threshold limit of 5 kW is included in the power tariff (TPT), the customers with HMP values below this limit do not receive benefits. Other customers can achieve notably high benefits if the HMPs are slightly over the threshold limit, and the best benefit can reach as high as 680 € in a year. The average cost savings per customer are 135 €/a with a non-ideal load forecast and 270 €/a with an ideal load forecast. The tariff and the control method ST lead to significant cost benefits (i.e., over 100 €/a and even 460 €/a) for a small group of customers, but the majority is left either completely without cost benefits or with only a rather low benefit. The average cost savings per customer are 41 €/a with both load forecasts. Benefit distribution among customers with PLT appears highly interesting because almost half of the customers gain a 259 €/a benefit while the other half receives no benefit. The average cost savings per customer is 133 €/a with a non-ideal load forecast and 138 €/a with an ideal load forecast.

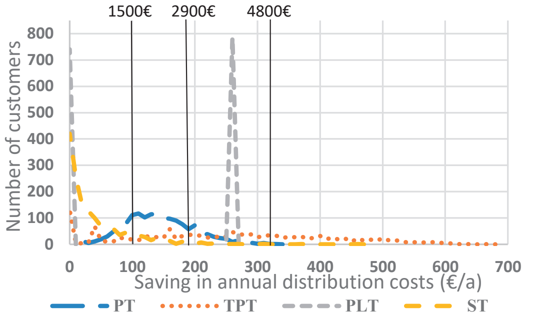


Fig. 8. Savings in annual distribution costs for customers with different energy storage control methods and distribution pricing structures when using a non-ideal load forecast. Profitability limits with three different energy storage system prices are depicted by the vertical lines.

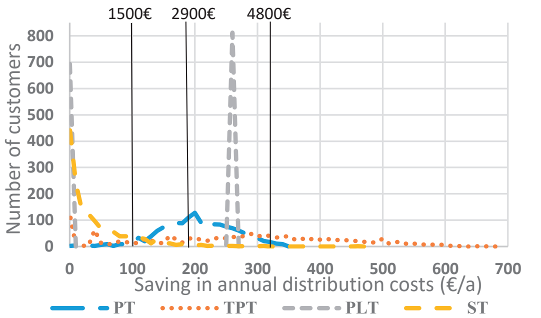


Fig. 9. Savings in annual distribution costs for customers with different energy storage control methods and distribution pricing structures when using an ideal load forecast. Profitability limits with three different energy storage system prices are depicted by the vertical lines.

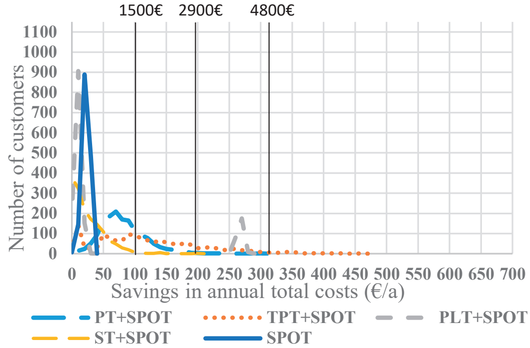


Fig. 10. Total benefits for customers with different control methods and pricing structures when using a non-ideal load forecast. Profitability limits with three different energy storage system prices are depicted by the vertical lines.

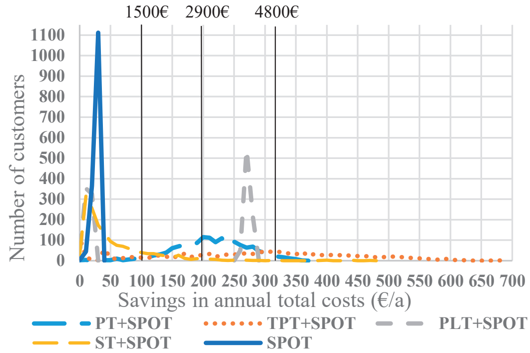


Fig. 11. Total benefits for customers with different control methods and pricing structures when using an ideal load forecast. Profitability limits with three different energy storage system prices are depicted by the vertical lines.

Figs. 10 and 11 show the total benefit achieved from energy and distribution costs with different control methods in which the spot price-based control is combined with the PBDT. In Fig. 10, non-ideal load forecasts were used, and in Fig. 11, ideal load forecasts were used. Additionally, the benefit achieved from spot price-based control without the PBDT is shown in Figs. 10 and 11. The forecasting errors affect the results significantly when spot price-based control is involved. The average savings per customer with different tariffs in PT, TPT, ST, and PLT are 81, 142, 24, and 54 €/a, respectively, with a non-ideal load forecast and 214, 276, 55, and 151 €/a with an ideal load forecast. The average savings per customer with only the spot price-based control are 22 €/a with a non-ideal load forecast and 27 €/a with an ideal load forecast. We observe from Figs. 8 and 10 that with a spot price-based control, the cost benefits are lower on average than without it if the non-ideal load forecast is used in the control. Individual customers can achieve even higher benefits with a spot price-based control, but with all control methods, they are more likely to achieve higher benefits without it. A combination of the PBDT and a spot price-based control makes it possible to achieve higher benefits than with spot price-based control alone.

The benefits from the combination of spot price-based control and control based on the PBDT could be higher if the load forecasts are accurate, and enhancing the accuracy of load forecasting to account for both control aspects requires further research. Based on the results of this paper, it can be stated that the importance of the load forecast accuracy is more critical in the case in which energy storage must be activated more often to gain the benefit. As shown in the study (e.g., in Fig. 6), usage of the energy storage varies between different PBDT structures, although the achievable benefits are similar. Actual cost benefits achieved from the energy storage depend on, e.g., the magnitudes and structure of the tariff components and the actual realized consumption behavior of the customer. When the PBDTs are widely introduced, their structures and prices vary between different DSOs.

The results of this paper do not directly indicate whether energy storage is profitable or not. However, the results show how different tariff structures affect the benefits of customers. The prices of the energy storage system used in the study are rather rough estimates and are used only as benchmark values to compare the annual benefits of the energy storage and related investment costs. In this paper, the only flexible element is the energy storage, but it is also possible to combine the use of energy storage and traditional load control. For example, a portion of the high HMPs can be decreased by controlling the water boiler first, and after doing so, the energy storage can be used in further HMP decrease. The profitability and benefit studies of these types of DR actions require further research.

## V. Conclusions

This paper introduces an evaluation method designed to assess the profitability of the DR, especially in the case of energy storage applied by household customers. The investment costs of energy storage and the load forecast of customers strongly affect the profitability, and the impacts of these factors are evaluated in this paper. Additionally, the electricity market environment, which defines the level of electricity prices and the volatility of the market spot prices, affect the profitability of the energy storage. This paper focuses on the impacts of power-based distribution tariffs (PBDT) on the benefits achieved through the use of energy storage. Novel PBDTs of small customers can significantly change the profitability and control targets of electrical energy storage in households. Without the use of the power-based component of the distribution tariff and with the present volatility of the market spot prices for electricity, energy storage is not profitable. The results of this paper show that energy storage can be profitable with a PBDT, or at least that the profitability can be improved.

The results also show how different tariff structures affect the customer benefits. The tariff structure TPT enables the highest customer benefits for those with an HMP that is high relative to their average consumption. From the DSO viewpoint, this scenario is favorable because the TPT especially encourages these customers to lower their HMPs. With PT, the effect is similar to that of TPT but is not as powerful because the benefits are lower for customers whose HMPs are the highest. The PLT and ST structures are problematic because they include discontinuous steps or boundaries in the structures, which make the storage profitable for a subset of the customers. The benefits are not in line with the relationship of the HMP and average consumption. More accurate load forecasting can increase the profitability of the energy storage with PBDT structures, which requires frequent use of energy storage, e.g., with market price-based control. A topic for further research is the development of a stochastic control method that minimizes the effect of errors in the load forecasts or at least improves their accuracy.

Although the results of this study are achieved in the Finnish electricity market environment, the proposed method and algorithm are globally applicable with modification and consideration of the differences in the given electricity market environment. Additionally, the algorithm can be applied in a home energy management system (HEMS) in the future.

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# PUBLICATION 3

**Using Electrical Energy Storage in Residential Buildings – Sizing of Battery and Photovoltaic Panels Based on Electricity Cost Optimization**

J. Koskela, A. Rautiainen, P. Järventausta

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# Using electrical energy storage in residential buildings – Sizing of battery and photovoltaic panels based on electricity cost optimization

Juha Koskela*, Antti Rautiainen, Pertti Järventausta

*Tampere University, Korkeakoulunkatu 3, FI-33101 Tampere, Finland*

## HIGHLIGHTS

- The basic novel concepts used for the sizing of the solar panel were introduced.
- Use of storage could increase the profitability of photovoltaic power generation.
- Different incentives could be combined in the control of electrical energy storage.
- The size of the solar panel could increase when the community model was applied.

## ARTICLE INFO

*Keywords:*
Cost optimization
Energy community model
Energy storage
Photovoltaic
Residential building
Self-consumption

## ABSTRACT

The popularity of small-scale residential energy production using photovoltaic power generation is predicted to increase. Self-production of electricity for self-consumption has become profitable mainly because of high-distribution costs and taxes imposed by the service providers on commercially produced electricity or because of the subsidies which reduce installation costs. Electrical energy storage can be used to increase the self-consumption potential of photovoltaic power. Additionally, electrical energy storage can lead to other benefits such as demand response or avoiding high load peaks. In this study, the profitability and sizing of a photovoltaic system with an associated electrical energy storage are analyzed from an economic perspective. The novel theory of sizing for profitability is presented and demonstrated using case studies of an apartment building and detached houses in Finland. To maximize the benefits, several alternative models for electricity metering and pricing are used and compared. The results demonstrated that the optimal size of the photovoltaic system could be increased by using electrical energy storage and suitable electricity pricing. This could lead to an increasing amount of photovoltaic production in the residential sector. Additionally, it is possible that when all the incentives are taken into account, electrical energy storage in combination with photovoltaic power generation would be more profitable than photovoltaic power generation alone. Photovoltaic power generation also increased the profitability of electrical energy storage, which could mean that the implementation of electrical energy storage in the residential sector could likewise increase.

## 1. Introduction

Electrical energy storage systems (EESS) could solve many problems in future electricity generation and distribution [1]. The use of renewable energy resources must increase rapidly in the near future in order to mitigate climate change. Renewable energy generation is often weather dependent (e.g., solar and wind power), which leads to rising needs for flexibility in the whole energy system. Flexibility in electrical energy systems can be increased in many ways. The intelligent use of electric devices as well as the implementation of EESS can introduce some of the required flexibility. EESS are very adaptable because there are various available solutions which possess different features. It is possible to choose the most suitable EESS solution a particular purpose.

Residential buildings are an important factor in the development of new flexible power systems. A significant part of annual electricity consumption is residential. For example, in Finland, annual electricity consumption was 85.2 TWh in 2016, and approximately 26.4% (22.5 TWh) of this was in housing [2]. Household appliances were responsible for about 36.4% (8.2 TWh) of the annual domestic electricity consumption, and the rest was consumed in heating spaces, domestic water, and saunas [3]. High flexibility in the load profiles of residential buildings makes them interesting targets for the application of demand

* Corresponding author.
*E-mail address:* juha.j.koskela@tuni.fi (J. Koskela).

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response. The timing of load-use can easily be changed without significant loss of comfort. There are, however, still a lot of loads for which time of use cannot change. Customers' load profiles change a lot, and in the worst cases, load peaks accumulate at the same times for multiple customers. By applying intelligent control, this accumulation can be avoided. Using EESS, it is possible to implement demand response operations so that customers do not sense any significant loss of comfort, without instituting changes in the customer's consumption.

Electricity generation will become more distributed in the future, and to reduce the distribution losses and costs of distribution, it is a reasonable approach to produce energy on-site, where the consumption occurs. Small-scale electricity generation, for example, photovoltaic (PV) power generation, plays an important role in nearly zero energy buildings, where the consumed energy is compensated for by self-production [4]. Renovations of old residential buildings are important in reducing housing-related emissions. In Finland, there are many apartment buildings that were built in the 60 s, 70 s, or 80 s, and their energy efficiencies are poor [5]. It is possible to increase the building's energy efficiency by applying such measures as adding insulation and changing space heating to heat pump–based systems. Old buildings consume a lot of energy despite being renovated, so on-site energy production is also needed. When the electrical energy is produced on-site, it incurs none of the losses associated with electricity distribution. Additionally, the decrease in the total amount of distributed energy could reduce the need to reinforce the grid in future if the load profile can be controlled intelligently, by EESS, for example.

Although EESS could be used to solve many of the problems associated with power systems, they are not yet widely used because of the high attendant cost and poor profitability. The battery energy storage system (BESS) is an EESS in which the storage technology is based on batteries. In the last decade, the price of lithium-ion batteries has fallen rapidly, and this trend is expected to continue [6]. The falling cost of batteries makes them a more interesting solution and increases the attendant profitability. When lithium-ion (Li-ion) battery prices fall and demand rises, mostly due to the increasing demand of the electric vehicle industry, there is a concern that rising lithium prices could in turn increase the costs of Li-ion batteries. The market price of lithium has only a minimal impact on the consumer price of Li-ion batteries, so the fall in the price of batteries could be expected to continue [7]. Another way to increase profitability is to maximize the benefits of EESS, and this is a very interesting research target. In this study, the term BESS is used when referring to batteries. When the case is generalized to include other storage technologies, for example, supercapacitors or flow batteries, the term EESS is used.

The current profitability of EESS both with and without PV in Finnish households is slow, but with a good control system and suitable development of electricity prices, it could become profitable in the future [8]. Power-based distribution tariff structures will increase the profitability of EESS if the pricing structures and the customer's load profiles are suitable [9]. Global study results all appear to be similar, but each country possesses its own special features; the electricity pricing structures and the production profiles of PV depend on geographic location.

In Finland and other Nordic countries, PV production occurs mostly in summer, when the production can be even higher than in Central Europe, because of long days and colder weather [10]. Germany and Italy are the main producers of PV energy in the European Union. Germany is very similar to Finland; the benefits of EESS are associated with Time-of-Use (ToU) tariffs, the increase in self-consumption, and possible dynamic tariffs with load limits [11].

Previous research projects have presented various results for the profitability of PV and EESS, which include some of the following published findings. Surplus PV production can be used to power domestic water heaters or air conditioning, which are more profitable than BESS alone [12]. It could be profitable to use community energy storage (CES) to store surplus energy from rooftop PV production within the residential building group [13]. The results of paper [14] showed that no significant differences could be detected in profitability and benefits between household energy storage (HES) and CES system architecture.

High PV penetration can cause an over-voltage problem [15]. This can be solved using BESS, which is typically connected in parallel with PV, and a control schedule which is locally administered by the HES. Voltage control schemes do not address the primary needs of the BESS owner. An economically-optimal control strategy may have been implemented with a time-dependent grid supply limit, which can lead to an over-voltage problem [16].

Increasing the site self-consumption of PV-generated power is the most common control aim of a BESS installation. Study [17] shows that although this control does decrease the total amount of power exported to the grid from the PV system, the PV power production peaks stay equally as high as without an installed BESS. This outcome is probable if the BESS is not controlled using smart systems. Using a forecast of PV production and household consumption in the control system, it becomes possible to decrease the impact on the grid caused by the PV production supply peaks. Residential buildings are good candidates for increasing self-consumption using BESS because the consumption usually occurs in different time of the day than the high PV production. For example, in commercial buildings, high consumption usually occurs during the daytime, when the PV production also peaks. Thus, the profitability of increasing self-consumption in commercial buildings using BESS is not as attractive [18].

To maximize the techno-economic benefits of BESS, it is important to correctly size the PV and BESS according to the customers' load profile [19]. Sizing a BESS with grid-connected PV is usually done by choosing the PV size first and then optimizing the capacity of the BESS. An example is presented in [20], where the sizing is done for a solar power plant. The same kind of sizing is done in [21], utilizing the Improved Harmony Search Algorithm, and in [22] for a rooftop solar power plant. This often leads to poor profitability of the BESS, but the results depend strongly on how the PV is sized. The sizing of PV systems has been demonstrated in [23] for Northern European conditions, in [24] by utilizing the mixed integer optimization model, and in [25] for a commercial building. In some cases, it was found that using BESS could increase the profitability of PV if the size of PV was increased [26]. This paper evaluates the profitability of PV with associated EESS and the process of sizing them accordingly. A different approach is used in this case which was not used in previous studies, however, since the EESS is sized first.

Residential buildings were chosen as the research target because the PV production profiles and building consumption profiles typically differ significantly. Apartment buildings form an energy community, where the local PV and EESS system benefit all the customers in the community. Local energy communities have been raised as an option in the EU clean energy package as a means to improve efficient energy management [27]. Previous papers have not commonly studied residential buildings while taking into account the differences between apartment buildings and detached houses.

A comprehensive analysis of the electricity pricing scheme and its effects on PV and EESS sizing has not previously been done. The aim of this study is to research how electricity pricing affects the profitability of PV and EESS. The research has been done from the perspective of the Nordic electricity market environment, especially within the Finnish context, but the results can be generalized for other global context by taking environmental differences into account.

The remainder of this paper is divided into six sections. Section 2 presents a theoretical analysis of optimal PV and BESS sizing from a techno-economic perspective considering different BESS control incentives. Section 3 introduces the simulation model, which is used in various case studies. Section 4 includes the input data from the consumption of residential customers, electricity price data, weather data, and data for PV production. Section 5 presents the results of simulation cases, which demonstrate the theory in practice. The discussion is presented in Section 6, and the conclusions of the paper in Section 7.

## 2. Sizing of PV and EESS in residential buildings

### 2.1. Introduction to the effects of electricity pricing and metering on the sizing of PV and EESS

The electricity pricing structure affects the sizing of PV system and EESS. Different countries, energy retailers and distribution system operators (DSO) possess multiple structures for electricity pricing and for accelerating the implementation of renewable energy generation. In this paper, electricity pricing structures, as used in Finland, or as presented in various research papers, are used. Different kinds of possible pricing structures, which affect the sizing of PV and EESS, are introduced in this chapter. Direct prices and structures are presented along with case studies later in the paper. However, the main pricing guidelines which affect sizing, are presented here.

Commonly-used incentives for PV are feed-in tariffs, ToU pricing, and net metering [28]. In many high PV–penetration countries, the implementation of PV is sped up with feed-in tariffs, which means that the customer receives a constant remuneration price for the total amount of generated PV energy (c/kWh) fed back into the grid. The problem with this approach is that feed-in tariffs encourage customers to acquire large PV system which can lead to high levels of power fed back into the grid supply. This can lead to problems in the distribution system. The feed-in tariff also requires extra metering so that all produced energy can be measured before self-consumption. In many countries, feed-in tariffs are slowly being abandoned; for example, Finland has no feed-in tariff for PV. For these reasons, the feed-in tariffs have been left outside of the scope of this study.

Net metering can be implemented on two different levels. A net metering scheme usually requires the customer's entire energy supply to the grid and their consumption to be calculated together. The customer benefits from all produced energy regardless of their consumption level. This type of total net metering obviates the need for a local EESS to increase self-consumption and thus removes the incentive and makes the use of EESS unprofitable [29]. Total net metering can lead to the same problems as those associated with the feed-in tariff because it provides incentive to supply all surplus energy to the grid when customer's total amount of energy supply keep lower than total consumption. Total net metering is not used in Finland and is therefore excluded from this study. Net metering is also sometimes applied as a summation of hourly consumption and energy supply to the grid. Traditionally, grid supply and consumption are measured separately using separate meters. Using a bi-directional meter for hourly net metering, the consumption per hour is measured and the customer is charged per measurement. Hourly net metering removes the incentives for EESS operations which take less than an hour but makes for easier evaluation of PV profitability and sizing. Metering practices vary between countries and DSOs; in Finland, most DSOs use hourly net metering. In this paper, all calculations are made using hourly net metering.

One easy way to influence a customers' consumption is to use ToU pricing, where the price of electricity varies with time. The price can change once a day or even every hour. The price is typically higher when the consumption of the whole power grid is higher. PV production typically peaks at approximately midday, and the highest consumption peaks usually occur in the evening. ToU pricing thus provides an incentive for demand response operations. In Finland, customers with access to self-production can make a contract with the energy retailer in which the retailer will buy surplus energy. Market-price-based real-time pricing is often used in this scenario. The hourly price is determined using an hourly day-ahead spot-price for the region of Finland within the Nordic electricity market [30]. Energy retailers, who can be competitive, apply their own margin that they take off the grid supply price and add to the purchase price. Additionally, value-added tax (VAT) is added to the purchase price. This kind of pricing is used in this study as a market-price-based tariff.

In countries like Finland, where energy retailers and DSOs are separate entities, a distribution tariff provides the biggest incentive for EESS with PV. Another incentive is the electricity tax, which does not have to be paid by small-scale producers (under 100 kVA) in Finland. The electricity tax and distribution price are included in the electricity purchase price, but not in the grid supply price. Therefore, it represents a significant difference between these prices. The electricity tax with a strategic stockpile fee for typical residential customers is 2253 c/kWh plus 24% VAT in Finland [31].

There are multiple structures available for pricing the distribution fee. The basic model consists of the basic charge (€/month) and the volumetric charge (c/kWh), which are commonly used in Finland. Another model is the ToU, in which the volumetric charge varies between day and night. Larger customers command pricing structures. In these, a part of the basic and volumetric charges are replaced by the demand charge (€/kW). The demand charge could be implemented in various ways, for example, power usage to be charged could be taken as the highest average hourly power usage of a sliding year or the three highest power usages of a sliding year. Recently, there has been discussion about how power tariffs could also be implemented for small-scale residential customers. Because part of the profitability of residential PV comes from the volumetric charge, there is a concern that the profitability of PV will decrease if power tariffs are introduced. However, the demand charge provides a new incentive for EESS use [9].

Customers in apartment buildings have separate electricity contracts for each apartment. Their consumption is typically so low that the opportunity to participate in demand response or any energy-saving operation is very limited. These kinds of operations in apartment buildings are typically implemented via their common electricity use, for example, elevators, lighting, and heating. It is possible to change the common metering when the customers of an apartment building form an energy community. Along with this change, PV and EESS can be utilized for the benefit of the entire building and its customers. This change can cause some legislative problems. In countries like Finland, however, it is still a possibility if every customer accepts the conditions. Of course, customers have the option of leaving the community if it is their desire [32]. This approach could lead to problems in the sharing of benefits and costs among customers. Different types of solutions have been developed for this scenario, such as presented in [33]. The energy community model is presented later in this paper.

### 2.2. Sizing of PV panel array

The size of the PV panel array is limited by physical and economic factors. Physical boundaries such as roof area can limit the PV array size, but for the purposes of this study, the sizing is done only from an economic perspective. The aim is to find the size of the PV which maximizes the profit. To maximize the profit, first the annual cost savings have to be determined. Fig. 1 shows the basic principle of dependence between the annual cost savings and the PV nominal power. The wide red[1] curve $C$ shows this dependence. It consists of two straight lines and the curvature between them. Line $A$ ($y = ax + f$) was fitted using linear regression: when all energy produced was self-consumed, it compensated for the energy purchase. The annual cost savings came from the purchase price of electricity, including distribution fees and taxes. Line $B$ ($y = bx + g$) was fitted using linear regression when all produced energy was fed back into the grid, and the annual cost savings came from the sale of energy and thus from its selling price. The variables in Fig. 1 are presented in Table 1.

[1] For interpretation of color in Figs. 1 and 2, the reader is referred to the web version of this article.

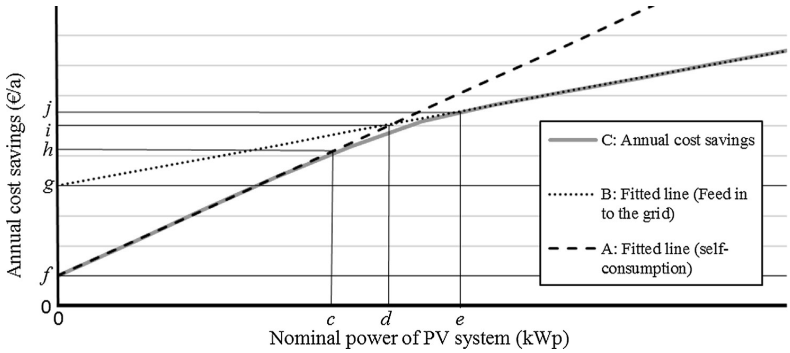


**Fig. 1.** Annual cost savings dependence on nominal PV power.

**Table 1**
Variables in Figs. 1, 3 and 4.

| Variable | |
|---|---|
| $a$ | Slope of line $A$ ($y = ax + f$) |
| $b$ | Slope of line $B$ ($y = bx + g$) |
| $c$ | Nominal power of PV after which energy starts feeding back into the grid |
| $d$ | Crossing point of lines $A$ and $B$ (Nominal power of PV) and optimal size of PV |
| $e$ | Nominal power of PV after which all extra energy is fed back into the grid |
| $f$ | Constant term of line $A$ ($y = ax + f$) |
| $g$ | Constant term of line $B$ ($y = bx + g$) |
| $h$ | Maximum annual cost saving when all produced energy is self-consumed |
| $i$ | Crossing point of lines $A$ and $B$ (Annual cost saving) |
| $j$ | Maximum annual cost saving at maximum self-consumption |
| $k$ | Maximum profit of PV |
| $m$ | Optimal size of PV with EESS |
| $n$ | Maximum profit of EESS |

At some point, as the PV size increases, the produced energy can no longer all be self-consumed, and the production of surplus energy begins (point $c$, $h$ in Fig. 1). If the PV continues to increase in size from this point, the production increase associated with the increased size of the PV array becomes surplus energy (after point $e$, $j$ in Fig. 1). Slope $b$ depends on the electricity grid supply price and slope $a$ depends on the electricity purchase price. Changes between points $c$, $h$ and $e$, $j$ are not linear, and the customer's load profile determines how the line curves.

Using real data from customers, a very large PV array size is typically needed to reach the real point $e$. However, this may actually be impossible because only a small part of the increased production is timed to coincide with periods of high consumption, e.g., in the evening. Yet it is reasonable to accept that thereafter, point $e$ is the point at which an increase in self-consumption becomes negligible. The width of the gap between $c$ and $e$ also depends on the customer's load profile. If the shape of the curve of the customer's load profile is similar to the PV production profile curve, the gap between $c$ and $e$ becomes small and the change between the lines becomes dramatic because an increase in PV array size also has a similar effect during the day. If the customer's load profile curve differs from the shape of the PV production profile curve, the gap between $c$ and $e$ becomes wider because the increasing PV production can supply the load during the mornings and evenings, even if the midday load is already supplied. Fig. 2 shows a sample profile curve for a typical customer's load and three PV production profiles (PV 1, PV 2, and PV 3) for different sizes of PV array. All PV production using profile PV 1 is used on-site to supply the customer's load (green area in Fig. 2). When the size of PV array increases (profiles PV 2 and PV 3), the midday surplus production (red area in Fig. 2) must be fed back onto the grid, but increases in morning and evening production can still be used on-site.

Even the change from only on-site consumption (line $A$ in Fig. 1) to surplus power supply to the grid (line $B$ in Fig. 1) is not dramatic; the most dramatic change occurs when the nominal power of PV is $d$. The annual cost saving $i$ along with its associated PV size depends on the magnitude of the change between lines $A$ and $B$. The constant term $f$ of line $A$ indicates the annual cost benefit without PV, which can come from incentives other than increasing self-consumption. Examples of these other incentives include decreasing peak power usage or the application of market-price-based control.

The investment costs associated with PV depend mostly on its nominal power (€/kWp), but there is also, for example, some of the initial installation costs do not depend on the nominal power. For this reason, the total investment price per kWp can decrease as the number of installed panels increases. However, in reality, the PV investment cost is not directly proportional to its size. In sizing PV, it is assumed that the price per kWp is constant. This supposition is valid when the size of any change is small, and the cost of the panels is large compared with the installation costs. To evaluate the profitability of PV, the benefits and the costs have to be compared. The benefits are calculated using the annual cost savings (€/a) in Fig. 1, so the PV costs also have to be estimated using yearly costs (€/a). The investment costs for PV can be roughly estimated so that they are evenly distributed over the lifetime of the PV system.

Fig. 3 shows the basic principle of comparing the annual costs of PV and the annual cost savings, which are lines A and B in Fig. 1. If the slope of the PV cost line is lower than slope $a$ (as in Fig. 1) but higher than slope $b$ (as in Fig. 1), the highest annual profit $k$ comes with the nominal power $d$ of PV. This is the basic principle used for sizing PV systems. If the slope of the PV cost line is lower than slope $b$, PV is always profitable and only physical or legislative boundaries should limit its size; if the slope of the PV cost line is higher than slope $a$, the use of a PV system of any size is not profitable. In a real situation, the annual profit is lower than $k$, caused by a non-ideal change between lines $A$ and $B$. For this reason, the ideal size of the PV system is slightly lower than $d$. Available sizes of a commercial PV system is discrete, so the customer can invest in a system which size is smaller than $d$. When referring to PV in this paper, the size d is referred to as the optimal size.

### 2.3. EESS use for demand response operations

The use of EESS for demand response (DR) operations has been unprofitable due to its high investment costs and low economic incentives [8]. Li-ion batteries are the main solution for residential EESS because of their high efficiency, long lifetime, and small physical size in relation to its capacity [8,19]. In previous years, the price of Li-ion batteries has fallen rapidly [6]. At the same time, the volatility of the

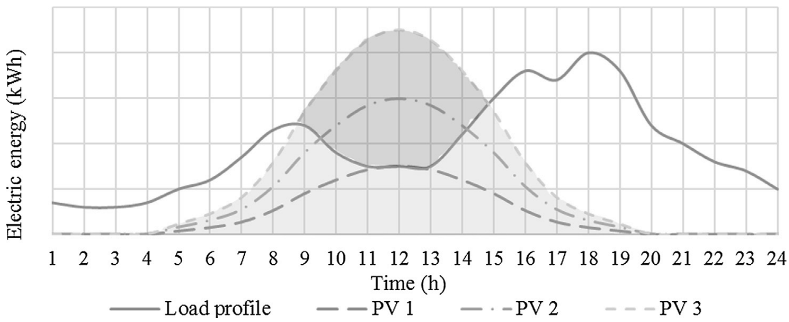


**Fig. 2.** Typical load profile of customer and three PV production profiles from different sizes of PV.

electricity price has increased, therefore increasing the attractiveness of DR [34]. Additionally, the novel structures of distribution tariffs can include new incentives for using EESS for DR [9], so it would be meaningful to research the use of EESS for DR.

The timing of electricity use is modified in DR operations, for example, using the washing machine at night or switching off the electric heating during peak hours. These operations can cause a loss of comfort for the customers, such as a decrease in room temperature or a delay in household operations like washing clothes. Using EESS, it is possible to implement DR without any loss of comfort. In DR operations, EESS discharges when the aim is to decrease consumption, and charges when it is possible to allow the level of consumption to increase. The use of EESS for DR is an operation which is the reverse of the delayed use of electric devices. Delayed use decreases consumption and can be implemented immediately without prior planning, but the use of EESS to decrease peak powers must be planned in advance because the necessary energy should be available in the EESS.

The sizing of EESS for DR operations is based on the load profile of the customer [8]. If the income from DR depends on the amount of shifted load (c/kWh), the maximum income depends on the amount of the load during response hours. These kinds of incentives include, for example, market-price-based dynamic tariffs or ToU tariffs. A suitable EESS size would approximately match the customer's average load during high-cost periods because the load can roughly be fully supported using this size EESS. Theoretically, if the EESS size increases any further, the increase in annual cost saving, which is dependent on the capacity of EESS, starts to drop off and the profit starts to decrease.

With power-based tariffs, the optimal size of the EESS depends on the difference between peak power (hourly average maximum power) and the level of normal daily peaks [9]. It is possible to lop off individual high peaks, which are not daily, repetitive occurrences, using the EESS. Additionally, the structure of the power-based tariff affects the sizing of the EESS. If the power charge is directly proportional to the peak power (€/kW), the EESS can be sized for the full range of the peak difference, but if the structure includes some step boundaries, they could limit the size of EESS.

### 2.4. EESS with PV in residential buildings

The annual profit generated by PV also depends on the nominal power of the PV system. This dependence can be shown when the PV cost line from Fig. 3 is projected onto the horizontal axis, as shown in Fig. 4. In the other words, the profit can be calculated by removing the costs from the savings. The shape of the curve depends on many variables, but Fig. 4 shows the basic principle of the phenomenon. The highest annual profit *k* comes with the nominal power *d* of the PV system. Using EESS, it is possible to increase the on-site use of produced energy. When the load is lower than the PV production (the red area in Fig. 2), the storage is charged, and when the load is higher, the storage is discharged. This increases the constant term *g* of line *B* and can also increase the slope of *B*. These changes lead to an increase in the optimal PV size (PV + EESS). The new optimal size of PV with EESS is *m* and the increase in annual profit from PV with EESS is *n*.

The evaluation of PV and EESS profitability and sizing of these is slightly complicated by the fact that it can be done based primarily on PV or EESS. Either the PV or EESS sizing must be performed first. When the size of PV increases as a result of using EESS, the investment cost associated with PV also increases. However, the part of the increasing annual profit that results from the increased size of the PV or from the use of EESS is still unknown. If only the profitability of EESS was under investigation, its annual profit can be seen to be nearly constant for any PV size which is higher than m. In this case, the annual profit from the

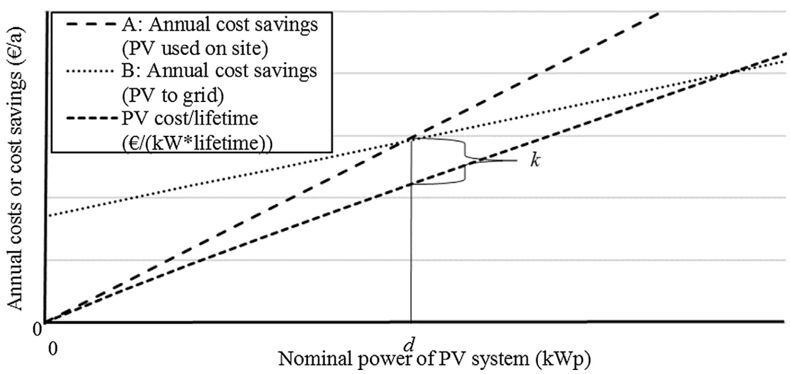


**Fig. 3.** The basic principle of PV sizing with EESS.

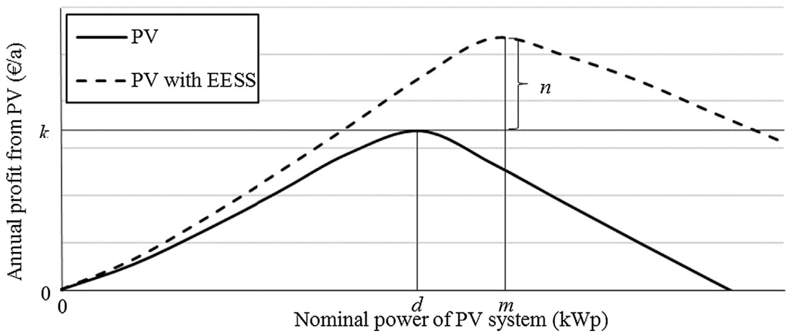


**Fig. 4.** The basic principle of PV sizing.

EESS is higher than n (i.e., the difference between the curves in Fig. 4). When the optimal PV size is applied in this paper, the annual profit from the PV is k with a nominal power for the PV system which is d or higher. The annual profit from EESS is n for the optimal size of EESS. When the EESS is involved in the building's energy system along with PV, the aim in sizing the PV system is to find the nominal power m, as in Fig. 4. The problem with multi-objective optimization is that the optimized variables affect each other. Often, the PV has been sized before the EESS, and the sizing of the EESS is thus based on a constant PV size. In this study, the aim is to size the PV and EESS together.

### 2.5. Evaluation of profitability

The annual profit and internal rate of return (IRR) is used to evaluate the profitability of PV and EESS in this study. The payback period is usually used to evaluate the profitability of PV or EESS as in [35]. The payback period confirms whether the investment was profitable and how long it will take to begin generating profit. This period is not an informative variable for identifying the total profit or for situations in which different applications are being compared.

PV profitability is often evaluated using the levelized cost of electricity (LCOE), as in [36]. This is the price of generated electricity and can be calculated by dividing the entire lifetime cost of the generation system by the amount of electricity generated over its lifetime. Levelized cost of electricity is a good measure to use when the aim is to compare energy sources or to research whether PV production is more profitable than purchasing energy from the grid. When EESS is combined with PV, the use of LCOE is questionable, because there is a risk that the uncertainty of the results will increase due to different lifetimes associated with PV panels, power electronics, and the battery system.

An effective variable in the evaluation of profitability is the IRR (see, e.g., [37]). It is a good variable to use when different solutions are being compared, but it is also sensitive to changes in investment costs. Investment costs are difficult to estimate in this kind of study, so critical evaluation is required. However, all profitability evaluation methods must first be evaluated for annual cost benefits: Figs. 1 and 3 show how annual electricity savings are estimated. From this, it is also possible to calculate annual profit when the annual investment costs are reduced from the annual savings.

## 3. Simulation model

### 3.1. Basic structure of the simulation model

The simulation model consists of a control system and battery model as described in previous studies, such as in [8]. The control works on two levels: hourly and continuously. The hourly control determines the most profitable move for the following hour. In reality, the control decisions are based on load forecasting, PV production forecasting, and the state of the EESS. In these simulations, the principle is the same, but the load and production forecasts are based on the actual load and production, which correspond to the ideal forecasts. The actual load and production are used to avoid errors caused by forecasting errors. The aim of the continuous control is to execute the objective provided by the hourly control. When using ideal forecasts and the consumption data of average hourly consumption, the importance of continuous control is minimal. However, it becomes important in situations where the EESS reaches full charge or is completely discharged at some point within the hour. The type of EESS could be variable, but in the simulations used in this study, the focus was on BESS because it is a commonly used solution in this scale of application.

### 3.2. BESS model

The type of BESS used in the model is a Li-ion battery with a lithium iron phosphate (LFP, $LiFePO_4$) cell-type and a graphite negative electrode. This type of battery is suitable for residential use because of its long cycle and calendar lifetime and good safety features [38]. The BESS system and its connection to the building's electricity network are shown in Fig. 5. The BESS is controlled via an inverter, which requires information from all other components of the system. The battery converter includes a charge controller and the solar panel converter includes the PV controller.

Modeling of the BESS state is based on the state of charge (SOC), as shown in Eq. (1):

$$SOC_t = 100\frac{E_t}{E_{\max}} = 100\frac{B_{eff}B_t}{E_{\max}} + SOC_{t-1}, \tag{1}$$

where $E_t$ is the amount of stored energy at time $t$ and $E_{max}$ is the maximum capacity of the BESS. The SOC at time $t$ is $SOC_t$ and $SOC_{t-1}$ is the SOC of the previous time step. Variable $B_t$ is the energy transfer to or from the energy storage and $B_{eff}$ is the efficiency of the transfer. The positive and negative directions of current flow, if they are possible, are shown in Fig. 5.

The modeling of losses in BESS is based on the efficiencies of its

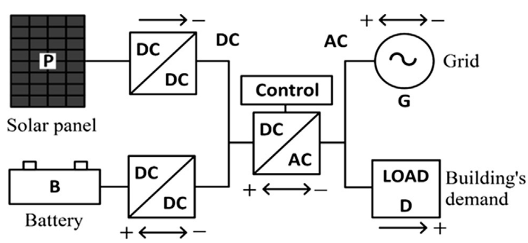


**Fig. 5.** BESS components and connection to building's electricity network [8].

components. To simplify, the losses are assumed to be the same in both directions, even though in reality, the charging and discharging losses are not identical. When the average losses are estimated in both directions, it gives a good approximation of overall losses because the use of BESS is cyclic. In this study, the efficiency of the inverter $\eta_{inv}$ was 98% and the DC-converter efficiency $\eta_{dc}$ was 99%. Thus, the energy transfer efficiency between the network and the storage was 97% and the energy transfer efficiency between the PV and the battery is 98%. BESS losses occur mainly in the converters and in the battery itself [38]. Battery losses increase when the SOC is low or very high [39]. For this reason, the SOC limits of the battery were set at 25–95%. When the battery was not completely charged or discharged, charging losses depended almost linearly on the charging current $I_c$, assuming that the internal serial resistance $R_b$ was constant. [40]. In this case, the charging efficiency $\eta_c$ can be calculated using Eq. (2):

$$\eta_c = 100\frac{V_b - I_c R_b}{V_b}, \tag{2}$$

where $V_b$ is the nominal voltage of the battery. The efficiency $B_{eff}$ in (1) can be obtained by multiplying the efficiencies $\eta_{dc}$, $\eta_{inv}$, and $\eta_c$. The energy transfer of storage $B_t$ is calculated by multiplying the charging current $I_c$ with the charging voltage $V_c$, which can be calculated using Eq. (3):

$$V_c = V_b - I_c \cdot R_b. \tag{3}$$

The battery consists of cells, which are series or parallel connected (as required), so that a suitable capacity and voltage are produced. In simulations, the internal serial resistance value of one modelled cell was 0.026 Ω, the cell voltage was 3.3 V, and the capacity of one cell was 2.5 Ah [26]. The maximum output power of the battery could be expressed using C-rate, which is the battery's ratio of maximum power and capacity. In this study, the C-rate 0.7 C was used because it was the most profitable C-rate employed for this type of use [9]. The effect of BESS and PV on the customer's electricity cost was modelled using equations from the grid perspective. The energy taken from the grid or the supply fed back into the grid ($G$) was determined using a model based on the energy transfer between the BESS, the building's demand $D$ and production. This was determined by the three options. When the battery was charged, the energy transfer between the building's network and the grid could be represented using Eq. (4):

$$G = \begin{cases} \frac{B_t - P_{dc}}{\eta_{inv}}, & ||P_{dc} < B_t \\ -\eta_{inv}\cdot(P_{dc} - B_t) + D, & ||P_{dc} < B_t \end{cases} \tag{4}$$

where $P_{dc}$ is self-produced PV energy after the converter stage but before the inverter. The equation depends on whether the charged energy comes from the PV, or if it also needs to be supplied by the grid. The third option is to discharge the BESS. This can be calculated using Eq. (5):

$$G = \eta_{inv}\cdot(-B_t - P_{dc}) + D \tag{5}$$

### 3.3. Control of BESS

To minimize the costs of electricity, control of the BESS based on economic incentives is introduced in [8]. The main incentive comes from the difference between the purchase price and the grid supply price. For this reason, the main task of the control system is to avoid supplying electricity to the grid if possible. The level of the BESS SOC must be low before the instances when production is higher than consumption. At the beginning of every hour, the control system calculates the optimal BESS-use profile for the next 18 h based on the forecasted loads and production. If there are times when production is higher than the consumption, the control discharges the BESS before these times so that there is space left to accommodate the surplus energy. The control strategy for increasing energy self-consumption is very simple and the frequency of use of the BESS depends on the size of the PV system.

Another incentive for the use of BESS is the power-based price component of the distribution tariff, if one is involved. A control strategy used to decrease the maximum hourly average power has been presented in [9]. This type of BESS use is the reverse of the approach which increases self-consumption because the SOC must be high before the hour in which the BESS is required to decrease the load. Additionally, the highest load and production peaks do not usually happen in the same day, nor even in the same season. Therefore, these two control tasks are not mutually exclusive.

Because the load profiles of customers vary, there are many situations where the BESS is not needed to increase self-consumption or decrease maximum peak power. During these downtimes, BESS can be utilized for other purposes. The third incentive is the ToU pricing, which is less effective in term of profitability than the previous two incentives [9]. In this study, the ToU tariff of the energy retailer was similar to real-time pricing, where the price changes hourly based on day-ahead market prices. Customers may also have another ToU structure in the DSO's tariff, with two constant prices per day: daytime price (7–22) and nighttime price (22–7). These tariffs present an incentive for customers to shift loads out of the high-price hours to low-price hours. For this reason, the control system uses market-price-based controls, which have been introduced in [8]. An effective control algorithm can be based on hour-pairs, such as the lowest price hour and the highest price hour of the optimization period (18 h). The control aims to charge and discharge BESS during these hours if the price difference is so high that the benefit outweighs the losses caused by using BESS or if the other incentives do not prevent it. Few rules are added for improving the control algorithm presented in [8] and the peak power decrease algorithm presented in [9]. If a possible power peak was imminent, the control system fully charged the BESS during the three previous hours, and if it was forecast that surplus energy would be produced, the control system discharged at least the forecasted amount of surplus energy from the BESS before surplus energy was produced.

### 3.4. Simulation of PV production

The PV production model used to model the performance of a tilted solar panel is based on the global solar irradiance components. These are namely the direct beam $G_{b,i}$, the diffuse component $G_{d,i}$ and the reflected component $G_{r,i}$. The model of global solar irradiance based on geographic location is introduced in [41]. In this study, the PV power plant is assumed to be in Tampere; its azimuth angle is 0° and it is tilted at a 45° angle. Global irradiance is the sum of irradiance components $G_i = G_{b,i} + G_{d,i} + G_{r,i}$. Beam irradiance can be modelled accurately if the conditions of the sun are assumed to be constant. Beam irradiance can be calculated using $G_{b,i} = G_b \cos\theta_i/\sin\alpha_s$, where $G_b$ is the horizontal beam irradiance, $\theta_i$ is the angle of incidence onto the surface based on the azimuth angle of the sun, and $\alpha_s$ is the solar elevation [42]. For an isotropic sky, the diffuse irradiance on a tilted surface can be calculated using $G_{d,i} = G_d\,(1 + \cos\beta)/2$, where $G_d$ is the horizontal diffuse irradiance and $\beta$ is the angle of inclination of the panel. The reflected irradiance can be calculated using $G_{r,i} = \rho_g\, G\,(1 - \cos\beta)/2$, where $\rho_g$ is the average reflectance of the ground and $G$ is the horizontal global irradiance, which is used because both the beam and the diffuse irradiance are assumed to reflect isotropically.

Several models have been developed to model diffuse solar irradiance. The Perez All-Weather Sky Model is the best model to use with the conditions associated with Finland, but if the solar panels are tilted toward the south, the Reindl model is superior [42]. The panels used in this study are tilted to south, hence the Reindl model is used. The Perez model is introduced in [43] and the Reindl model in [44]. Additionally, the Reindl model is considered one of the best diffuse solar irradiance models as noted in [45]. The ratio of the horizontal diffuse irradiance and the horizontal global irradiance in the Reindl model is based on the brightening factor $k_T$. In practice, the brightening factor depends on the cloudiness of the sky. Given that the actual cloudiness varies, cloudiness probabilities are used instead. The model for cloudiness probability in Finland is presented in [46] and is utilized in this study. The simulation model is stochastic because of the use of probabilities to model the variability of cloud cover in every simulation.

The average reflectance has two constant values in simulations for the year. During the winter season (December–April), the average reflectance is taken to be $\rho_g = 0.58$, which corresponds to the reflectance of snow. At other times of the year, it is taken to be $\rho_g = 0.24$, which corresponds to the reflectance of dark roof materials and deciduous trees, which are the assumed materials directly adjacent to the solar panels.

The PV production ($P_{PV}$) can be calculated using Eq. (6), where $P_{STC}$ is the nominal power in standard test conditions (STC), $\beta_P$ is solar cell power temperature coefficient (0.006), $T_c$ is the solar cell temperature and $T_{STC}$ is the standard solar cell test temperature (25 °C) [42]. The verification coefficient $C_v$ is added to the equation so that the simulation model for PV production can be verified with real measurements from PV systems.

$$P_{PV} = C_v P_{STC} G_i (1 - \beta_P (T_c - T_{STC})) \tag{6}$$

The same PV production simulation model was used in [8], where it was verified by comparing model values to real values as measured from polycrystalline silicon PV cells. The result was that the model systematically generated values that were too high, leading to the necessity of setting $C_v$ to 0.85. The reason for this could be that the temperature of the solar cell was too low in the model or that the physical solar panels' efficiency was decreased, caused by the aging of the cells, soiling of the panels, or not accounting for shade in the model. Additionally, this is affected by the type of solar cell used for verification. The verified simulation model generated realistic data for PV production.

## 4. Initial data and energy community model

### 4.1. Consumption data

Two case studies were used in this study. Case study 1 was an apartment building for which the consumption data covered four years (2013–2016), including hourly energy consumption measured using an AMR meter. The load data for individual apartments and for the building were separate; the load data for the building consisted of such items as common space lighting, the elevator, and the electrical heating load. Case study 2 consists of a total of 12 detached houses located near the Tampere area. The data was also measured using modern AMR meters. The measurements spanned two years (2014–2015). In simulations, the first year of data represented the comparison year, and the EESS and PV were assumed to be installed at the beginning of the second year. In the apartment building for instance, the simulation was performed over three years and for one year in the detached houses.

In case study 1, the study object, "Tammela" (see e.g., [5]), is the apartment building in central Tampere. The building was constructed in 1980 and has been widely renovated to increase energy efficiency. There are 56 electrical network connection points: the building's electricity, 54 apartments, and a business premises. This kind of large apartment building consumes a lot of energy for warming. Before the renovation, all warming energy had been purchased from the city's district heating network. An exhaust air heat pump (60 kW) was installed in 2014 to increase energy efficiency. The total amount of purchased energy decreased by 41% per year after this installation. The amount of purchased district heating energy has decreased by 66% overall, significantly decreasing energy costs. However, electricity usage has simultaneously increased by 26% (from 170 MWh to 215 MWh per year), even though there was an extensive electricity-saving renovation which included changing old lighting over to LED lighting. The highest annual electricity load peak for the building has also increased significantly. The hourly average maximum power was approximately 50 kW in 2013 and 70 kW in 2016 (40% increase). These kinds of energy-saving renovations will become more common as efforts to decrease energy consumption and to prevent climate change become more popular, but this actually caused an increase in electricity demand and highlighted the need to strengthen the electricity grid.

**Table 2**
Study group of detached house customers.

| Customer | Annual consumption (MWh) | Hourly average maximum power (kW) | Winter consumption (Dec – Feb) (%) | Average of highest consumption hour |
|---|---|---|---|---|
| 1 | 26.9 | 11.4 | 40.2 | 23 |
| 2 | 20.9 | 8.9 | 35.0 | 23 |
| 3 | 9.7 | 8.3 | 39.4 | 22 |
| 4 | 6.7 | 4.6 | 40.0 | 23 |
| 5 | 23.6 | 16.5 | 36.6 | 20 |
| 6 | 7.8 | 11.0 | 28.5 | 17 |
| 7 | 14.1 | 9.4 | 35.1 | 23 |
| 8 | 14.7 | 8.9 | 31.3 | 20 |
| 9 | 21.2 | 11.5 | 33.7 | 22 |
| 10 | 15.6 | 8.4 | 35.9 | 6 |
| 11 | 10.4 | 6.0 | 37.0 | 23 |
| 12 | 14.5 | 7.2 | 38.6 | 9 |
| Average | 15.5 | 9.3 | 35.9 | 19 |

In case study 2, the study subjects were selected from a group of 1525 customers so that the electricity usage behavior varied widely, but they were all still typical detached house customers. More accurate data from selected customers is presented in Table 2, which shows the annual consumption and average hourly maximum power. Additionally, the percentage of winter consumption from December to February and the hour of day when consumption was most likely to be highest are shown.

### 4.2. Energy community model

For legislative reasons, in apartment buildings in Finland, the production of PV can be utilized practically only for the building's own load, not for individual apartment loads. Each apartment has its own electricity contracts with the energy retailer and the DSO. Energy produced by a PV system owned by the housing company is not profitable in apartments because small-scale energy producers can sell surplus energy only to the grid. If this surplus energy is sold to the grid and some apartments purchase it from the grid at the same time, the apartment owner has to pay a distribution fee to the DSO, as with all other electricity vendors. Using EESS makes it even more complicated because apartments cannot use stored energy from a PV system owned by the housing company, for example, unless the housing company has purchased it from the grid. So, in practice, the EESS and PV can be utilized only to supply the loads of individual apartment buildings if the metering is implemented in a typical way. It is also possible that the individual apartment owner could install PV and EESS for their own use, but they can utilize them only to supply their particular apartment's load. The basic principle of the energy community model and the present model are shown in Fig. 6.

EESS and PV could be utilized for the whole building's load only if the energy community model is used. In this case the building forms an energy community and makes only common contracts with the energy retailer and the DSO. All combined electricity (from the building and the apartments) purchased from the grid or supplied to the grid is measured using one meter. Legally, every customer must retain the option to select their own energy retailer, however, this can lead to problems. The energy community model is possible only if all apartment owners accept this model and retain the option of resigning from the community. The apartment building's energy community forms such a large unit that it is possible to choose a low-voltage power

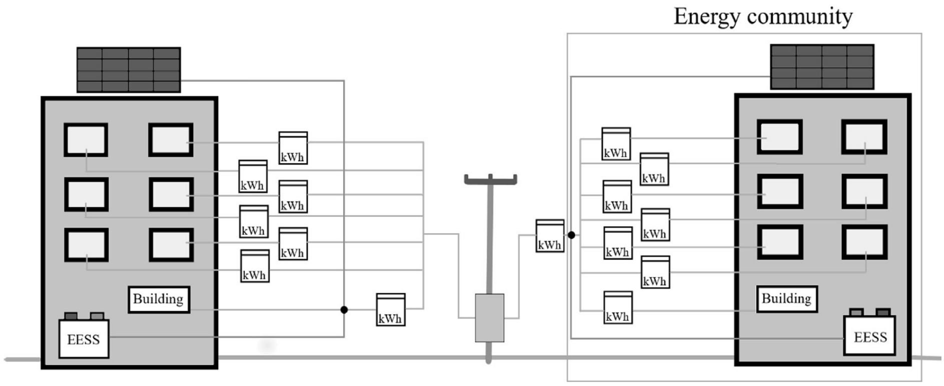


**Fig. 6.** Apartment building using the energy community model (right) and a typical model (left).

distribution tariff, which is typically only provided to small industrial customers. It includes a power-based charge component, which could increase the profitability of the EESS [9].

### 4.3. Electricity price data

In all calculations presented in this paper, the energy retailer tariff has been used, which is a dynamic market-price-based tariff based on day-ahead area prices for Finland in the Nordic electricity market [30]. The energy retailer margin used in the model is 0.25 c/kWh, which is typical in Finland.

The distribution tariff depends on the case type. For case study 1, the low-voltage power tariff was used. To study the benefits of the energy community model, the general tariff was also used. It is the simplest of distribution tariffs and includes only a basic charge and a constant volumetric charge. The low-voltage power tariff includes the basic charge and volumetric charge along with a two-time ToU structure and a power charge. To define the monthly power charge, the highest power peak in the previous 12 months was used, calculated as an average of the two highest monthly hourly power peaks. The charge components are introduced in Table 3.

Different tariff structures and prices were used in the detached houses case study (case study 2) because the houses were located in different DSO areas and power-based tariffs were not commonly used for domestic customers. Study prices were used here, as presented in [47] and [48], which were calculated for the same DSO area as the area in which the detached houses were located. Tariff components are shown in Table 4, including taxes. In the power-based tariff (simply termed "Power" hereafter), the power-based component is charged based on the highest hourly average power usage for the month. Weightings of the power charge component were calculated theoretically, and charge components of the power-based tariff represented total corresponding costs. If the DSO were to shift to power-based tariffs for small customers, in practice the power charge component might be lower and the other components higher.

**Table 4**
Alternatives for the distribution tariff in the detached houses case study (Case study 2) [47].

| Tariff | Basic charge €/Month | Volumetric charge c/kWh | Power charge €/kW/Month |
|---|---|---|---|
| General 3 × 25A | 13.66 | 6.09 | |
| Power | 4.74 | 3.51 | 7.23 |

### 4.4. Investment cost of BESS and PV

The actual investment cost of BESS depends on many things, such as the type of system, BESS manufacturer, and power retailers. Installation and maintenance also contribute to the costs, so accurate investment costs are difficult to estimate. The investment costs for Li-ion-based BESS were studied; the results in [22] state that in 2015, the LFP cell prices were in the 200–350 €/kWh range, and the projected price for 2020 ranged from 100 to 200 €/kWh. The cost of the required power electronics was in the 100–150 €/kW range in 2015, and it is assumed that it will reach approximately 80–110 €/kW in 2020 [49]. Power electronics can be partly combined with the PV system, so these costs could be divided between the PV and BESS. The total costs of the BESS can be roughly estimated, including investment and maintenance costs, ranging from 200 to 400 €/kWh. The calendrical lifetime of the LFP-based BESS is approximately 15 years, as presented in [50].

The investment costs for the PV system (€/kWp) strongly depend on its size. The relative costs of small-scale PV power plants are high in relation to larger systems. A PV system under 10 kWp can cost over 2000 €/kWp [4]. Over 40 kWp, the PV systems can cost approximately 1300 €/kWp in Finland [51]. The PV system costs used in this study included the costs of power electronics and some installation and maintenance costs and ranged from 1500 to 2100 €/kWp. The lifetime of a PV system is approximately 30 years (see [51]), and it is recommended that the power electronics be replaced or upgraded once in a PV system's lifetime.

**Table 3**
Alternatives for the distribution tariff in a case study of an apartment house (Case 1) [47].

| Tariff | Basic charge €/month | Volumetric charge c/kWh (7–22) | Volumetric charge c/kWh (22–7) | Power charge €/kW/month |
|---|---|---|---|---|
| General 3 × (25A–63A) | 3.98 | 5.98 | 5.98 | |
| General 3 × (> 63A) | 25.73 | 5.98 | 5.98 | |
| Low-voltage power | 213.18 | 4.52 | 3.97 | 2.58 |

**Table 5**
Distribution fees of the apartment building with different tariff structures.

| | 2013 | 2014 | 2015 | 2016 | Average |
|---|---|---|---|---|---|
| General | 10 431 | 11 373 | 13 121 | 13 984 | 12 227 |
| Low voltage power | 9206 | 10 097 | 11 569 | 12 360 | 10 808 |
| Annual savings | 1225 | 1275 | 1552 | 1623 | 1419 |

## 5. Simulation results for case studies

### 5.1. Case 1: apartment building

Table 5 shows a comparison of the annual electricity costs of an apartment building based on the distribution tariff using the energy community model with a low-voltage power tariff and with a general tariff. The comparison was made over four years (2013–2016). The building's electricity supply main fuse was 3 × 125A and each apartment's main fuse was 3 × 25A. In Table 4, *general* signifies general tariffs with typical contracts, where every apartment pays its own basic charges. The energy community model was used along with a low-voltage power tariff. The average annual saving in distribution fees was 1 419 €, and this together with the savings derived from not having to pay the energy retailer's basic charge, compensated for the extra costs associated with using the energy community model, e.g., billing.

Simulations using various sizes of PV system as show in Fig. 1 were performed for three years (2014–2016), with 50 different sizes of PV system modelled for each year. Based on these data points (results of simulations), lines *A* and *B* were fitted using linear regression. The results of the simulations and fitted lines are shown in Fig. 7. The optimal size *d* of the PV system (see Fig. 1) was approximately 31 kWp. This is a practical upper limit for the size of PV without incorporating BESS. The actual optimal size of the PV system was lower, caused by the curving cost line of the PV before the intersection point.

The same kind of simulation as shown in Fig. 7 was performed using various sizes of BESS, resulting in "optimal" PV system sizes (*d* in Fig. 1) for various sizes of BESS, and annual cost savings for the "optimal" PV system size (*i* in Fig. 1) using various sizes of BESS. These result points were fitted using linear regression, as presented in Fig. 8. The annual cost savings associated with the use of PV and the "optimal" size of the PV both increased when the capacity of the BESS increased. With the studied BESS sizes (0–99 kWh), the increase could be assumed to be linear, meaning that the PV system size could increase without limitations imposed by the increasing BESS capacity. When a customer purchases PV along with BESS, the BESS can be sized first, based on the available investment resources, and the PV can then be sized based on the size of the BESS.

In the following comparison, the BESS was assumed to be 25 kWh. When the energy community model was not used and the general tariff was applied, the annual profits from PV and BESS were low, as presented in Fig. 9. In all cases, the profit was higher without BESS than with it. The optimal PV size (*d* in Fig. 4) was between 13 and 27 kWp if BESS was not used. These values were slightly lower than the "optimal" sizes shown in Fig. 8, as theoretically predicted. Accurate optimal PV size depends on the investment prices for PV and BESS. Using BESS increased the optimal size of the PV system (*m* in Fig. 4) to a range of 20–41 kWp, but the annual profit dropped lower than without the BESS (*n* in Fig. 4 is lower than the cost of the BESS). However, the shapes of the profit curves agree with the theory discussed in Section 2, and the required characteristics can be found from the curves.

Fig. 10 shows the results from the energy community model when the low-voltage power tariff was applied. The profits generated using the energy community model in Fig. 10 were higher than without using it as shown in Fig. 9. Another notable difference was that the profits were higher with BESS than without it when the size of the PV system increased. However, the theory of PV sizing as presented in Section 2 remained valid when applying the energy community model and low-voltage power tariff. When the price of PV was 1500 €/kWp, the annual profit decreased very slowly as the size of the PV system rose above the optimal value. This indicated that this price was near the lower limit of the validity area of the theory. Further decreases to the PV price lead to increases to the annual profit together with increasing PV size. This is not the desired type of optimization.

The results from Figs. 9 and 10 are summarized in Table 6, which shows the optimal sizes of PV systems and the annual profits generated using these optimal sizes. From Table 6, it can be seen that PV was more profitable with the energy community model than without, and the profit increased when BESS was used, as long as the price of BESS was low. The price limit of BESS, in terms of its profitability, was 300–400 €/kWh depending on the price of PV. Additionally, the optimal PV size increased by 7–18 kWp while using BESS with the energy community model. The optimal size of PV increased by 21–39 kWp over the optimal PV size for the basic case.

The calculated values for the IRR are shown in Fig. 11. The very high values of IRR, noted in cases without a BESS and with only a small PV system, were caused by an assumed constant price component for PV. In real cases, a very small PV system size would be more expensive in terms of relative cost when compared with a larger PV system size. In this study, the price per kWp was assumed to be constant, which increased IRR for small PV system sizes. However, if the PV system sizing was performed using IRR, the optimal PV system size was slightly lower than in the profit study. In sizing PV and BESS, the customer must decide which of the following characteristics are more important: higher profits or higher IRR.

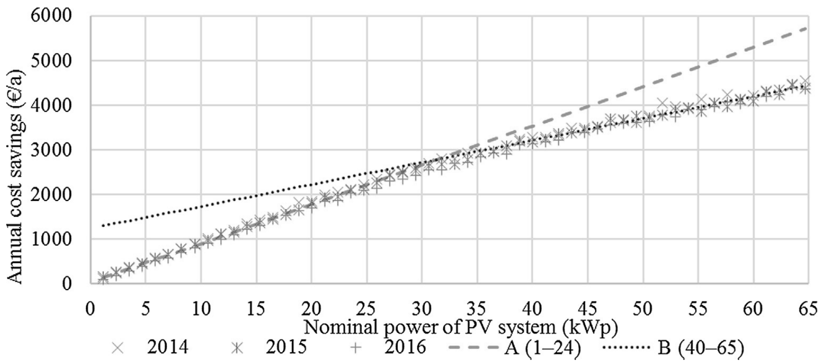


**Fig. 7.** Cost simulation for apartment building using various sizes of PV system (Fig. 1). Line *A* is the result of a linear regression performed on data points between 1 and 24 kWp nominal power of PV system and line *B* that of between 40 and 65 kWp.

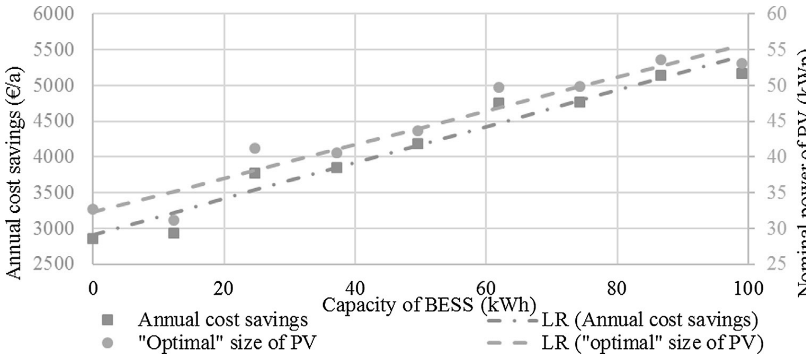


**Fig. 8.** Effect of BESS on annual cost savings from PV and "optimal" size of PV.

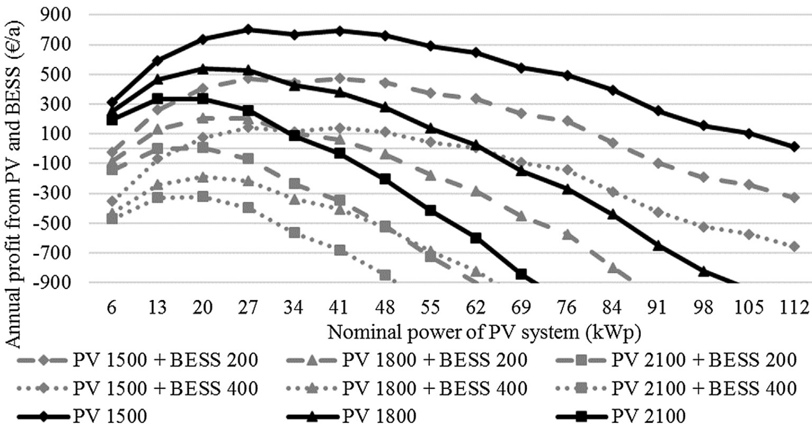


**Fig. 9.** Annual profit from various sizes of PV system both with and without 25 kWh BESS when the general tariff was applied. Three alternatives for PV investment prices (1500, 1800, and 2100 €/kWp) and two alternatives for BESS investment price (200 and 400 €/kWh) are presented.

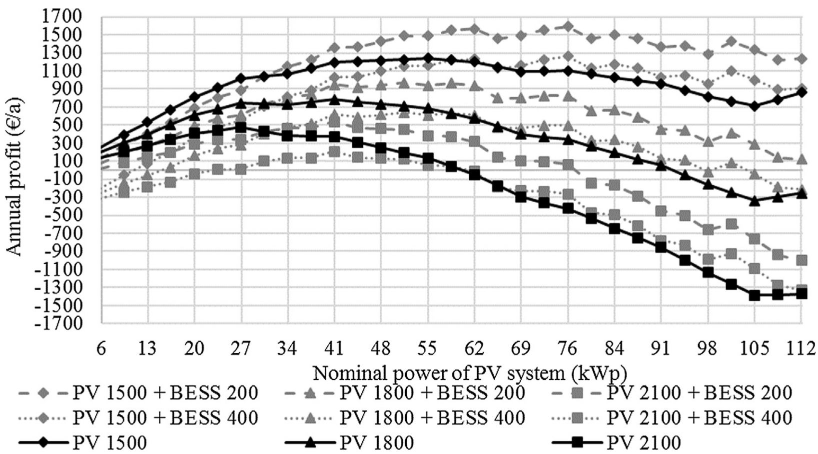


**Fig. 10.** Annual profit from various sizes of PV system both with and without 25 kWh BESS, when the energy community model with the low-voltage power tariff is applied. Three alternatives for the PV investment price (1500, 1800, and 2100 €/kWp) and two alternatives for the BESS investment price (200 and 400 €/kWh) are presented.

### 5.2. Case 2: detached houses

PV size optimization using various sizes of BESS was performed for detached house customers, as presented in Section 2. Evaluation was performed using two different tariff structures: power and general tariff. The results of the optimization are shown in Fig. 12, where the results were averaged over the study group of 12 customers. With a small BESS size (0–2 kWh), the "optimal" size of the PV system behaved contrary to the theory. The "optimal" size of the PV system decreased when the capacity of BESS increased. This was caused by chosen

**Table 6**
Optimal sizes of PV with various PV prices and annual profits.

| | Basic | | Energy community model | |
|---|---|---|---|---|
| | Optimal size of PV (kWp) | Annual profit (€/a) | Optimal size of PV (kWp) | Annual profit (€/a) |
| PV 1500 | 27 | 803.40 | 55 | 1240.69 |
| PV 1800 | 20 | 536.62 | 41 | 782.40 |
| PV 2100 | 20 | 336.62 | 27 | 474.16 |
| PV 1500 + BESS 200 | 27 | 473.40 | 62 | 1563.85 |
| PV 1800 + BESS 200 | 20 | 206.62 | 59 | 962.93 |
| PV 2100 + BESS 200 | 20 | 6.62 | 41 | 538.08 |
| PV 1500 + BESS 400 | 27 | 143.40 | 62 | 1233.85 |
| PV 1800 + BESS 400 | 20 | −190.04 | 59 | 632.93 |
| PV 2100 + BESS 400 | 20 | −323.38 | 41 | 208.08 |

simulation step size, which in this case was the PV step size of 3 kWp. When the "optimal" PV size was very low, as in this case, the fitting of line *A* was performed using only two or three points, which could cause this kind of error. However, after the BESS capacity reached 4 kWh, the behavior of the PV system size began to agree with the theory. While applying the power tariff, the "optimal" size of the PV system was 1–2 kWp higher than while applying the general tariff. When the BESS capacity increased over 6 kWh, the increase in annual cost savings began to demonstrate a decreasing trend. Thus, after this was identified, BESS sizes of only 4 and 6 kWh were used. Previously, the optimal size of a BESS for a detached house customer either with or without PV was optimized at approximately 4–6 kWh [8,9].

Annual profits were calculated using a 1500 €/kWp PV system price, because it was the highest price while still retaining a positive annual profit without using BESS. The price of BESS was chosen as 300 €/kWh in calculations because it was the median of the range, and the comparison was easier using a constant price. Calculated annual profits are shown in Fig. 13. The profitability while applying a power tariff and BESS was much higher than while applying the general tariff, even if the profitability of the PV alone was lower with the power tariff than with the general tariff.

The IRR while applying various investment prices for PV (1500–2100 €/kWh) and BESS (200–400 €/kWh), with the power tariff and a 6 kWh BESS, is shown in Fig. 14. Also shown are the IRR of a PV investment, with 1300 €/kWp of PV while applying a power and a general tariff for comparison. The results were averaged over the study group. The investment price of 1300 €/kWp was used because it was the highest investment price corresponding to a positive IRR. This indicated that the price of PV must decrease in the future so that PV without BESS becomes profitable for average customers without any subsidies, if the pricing remains the same in the future. Using power tariffs decreased the profitability compared with a general tariff if the BESS was not used, but with BESS, the profitability increased significantly. The IRR was highest with a small PV system (e.g., 3 kWp) and it decreased when the PV system size increased. The price of BESS had a more significant effect on IRR than that of PV.

## 6. Discussion

During the last few years, PV systems have been installed more often in apartment buildings. The pricing model and sizing, nowadays, leads to a very limited PV system size. Currently, with typical contracts and general distribution tariffs in the studied apartment building, the optimal PV size was found to be 20–27 kWp depending on the investment price for PV. This nominal power corresponded to about 30–40% of the building's annual maximum power usage. In practice, actual PV system size is lower because it was best to avoid generating surplus energy. Using EESS did not increase the profits using the present model. If the apartment building began to apply the energy community model and the low-voltage power tariff was selected, the optimal size of the PV system could increase by 21–39 kWp. This expansion of PV system would produce roughly an additional 19–35 MWh per year in Finland, which is all emission-free solar power. This amounts to approximately 8–21% of the annual consumption of the apartment building.

For detached house customers, PV profitability is very limited. A very small PV system size could be profitable if the investment price of PV is low. When the general distribution tariff is changed to the power-based tariff, the profitability of PV decreases. Photovoltaic production used for self-consumption becomes less profitable when the volumetric price of the tariff decreases. The power-based tariff incentivizes the use of BESS, increasing its profitability significantly. A decrease in power taken from the grid and stored surplus production are mutually exclusive operations for the BESS, so the same BESS can be used for both incentives. It is also possible to apply Market-price-based control to earn extra savings. This makes the combination of PV and BESS very profitable if they are sized correctly. Optimal PV size could be increased by using BESS, but in detached houses, the potential for this is much lower than in apartment buildings. This is caused by a higher basic consumption and different distribution tariff structures. In detached houses, the weight of the power-based component is higher and volumetric charges do not include a two-time ToU structure. However, the

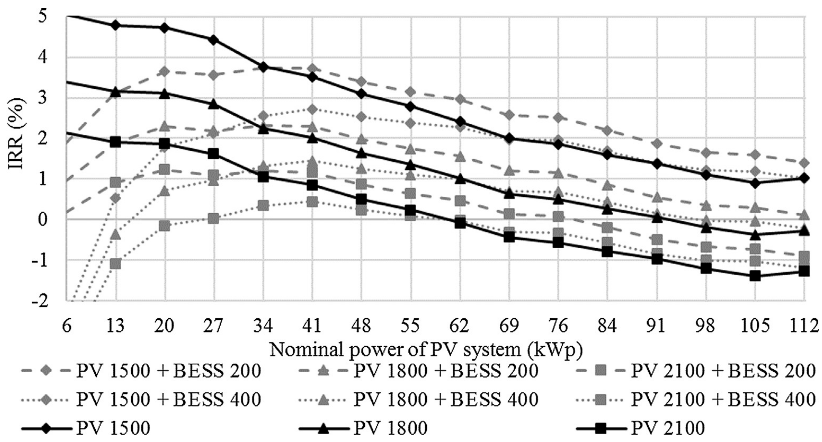


**Fig. 11.** IRR of PV and BESS investments. Three alternatives for the PV investment price (1500, 1800 and 2100 €/kWp) and two alternatives for the BESS investment price (200 and 400 €/kWh) are presented.

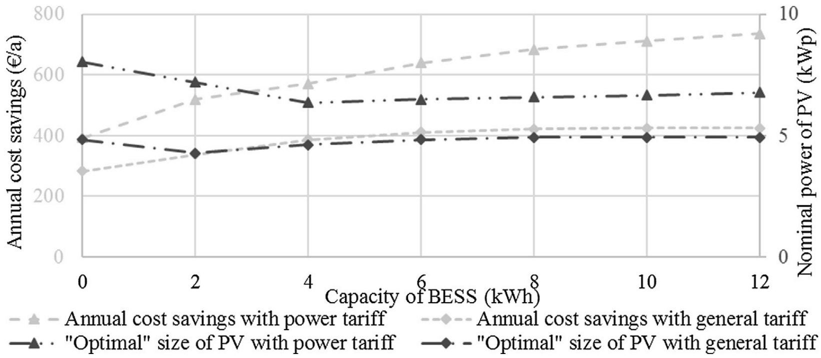


**Fig. 12.** Sizing of the PV system using various sizes of BESS.

potential for increasing the amount of BESS installed along with PV is very high, which could open new business opportunities for service providers.

In reality, the load and PV production forecasts for EESS control are not as ideal as shown in the simulations performed in this study. Forecasting errors can affect a decrease in annual savings. It is possible that the EESS is fully discharged when discharging is required to offset load increases that have not been forecasted, for instance. These problems could be avoided with accurate forecasts. Ideal forecasts were used in this study because the varying forecasting errors, the amount by which they could affect the results, and the effect itself were different for different customers. With ideal forecasts, the upper boundary of the results can be calculated. The effects of forecasting errors have been studied in [9], for example. In future, verification of the model and the results will be performed using a real battery system.

## 7. Conclusions

This paper introduces sizing methods for photovoltaic system and electrical energy storage system from an economic perspective. The most important result suggested that the sizing of the storage is profitable if performed first so that the photovoltaic sizing can be based on the chosen storage size. The electrical energy storage size depends mainly on variables other than the size of photovoltaic system (e.g., load profile and pricing structure), and the sizing of the photovoltaic system depends mainly on the size of the storage and the load profile. Verification of the sizing model was performed in Finland, but the same model can be utilized in other environments as long as the details of the local electricity pricing structures are accounted for. The main study object was an apartment building which has made several changes to improve its energy-efficiency. As a result, the maximum electrical load increased significantly even though the total amount of consumed energy decreased. Through the use of electrical energy storage, this could have been avoided.

A commonly-used photovoltaic sizing method which does not take into account the energy community model leads to a very limited sizing of the photovoltaic system. If the internal rate of return is used in the sizing, the size of the chosen photovoltaic panel array could be very small. In this paper, increasing the profitable size of the photovoltaic system has been investigated. The energy community model and low-voltage power tariff could increase the profitable size of the photovoltaic system. Using this model, the use of electrical energy storage along with a photovoltaic system also became profitable when the benefit from photovoltaic system and the storage system could be utilized simultaneously. Using electrical energy storage with a photovoltaic system can overcome the problematic effects on the power grid caused by increasing the number of grid-connected photovoltaic plants. In the long term, this could decrease the costs incurred by the distribution system operator and could lead to lower customer electricity prices.

A change to the power-based distribution tariff decreases the profitability of photovoltaic systems because the volumetric charge decreases. If a new incentive, which accounts for electrical energy storage control, is rolled out, the profitability of storage in conjunction with a photovoltaic system could increase significantly. This could increase the implementation of electrical EESS in detached houses.

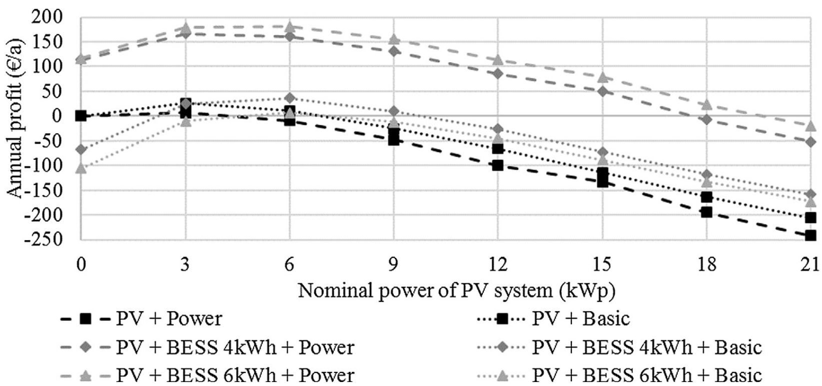


**Fig. 13.** Annual profit from PV and BESS with power or general tariff, with an investment cost of PV of 1500 €/kWp and an investment cost of BESS of 300 €/kWh.

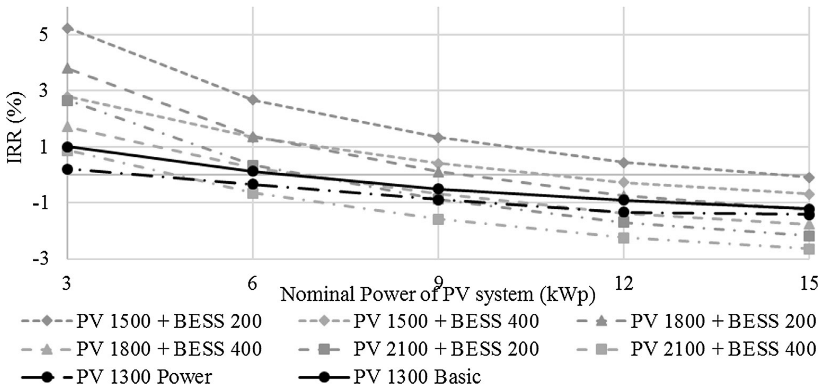


**Fig. 14.** IRR of PV and BESS investment for detached house customers with various investment prices of PV and BESS when power tariff is used, and IRR of PV investment with the power and general tariffs.

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# PUBLICATION 4

**Effect of the Electricity Metering Interval on the Profitability of Domestic Grid-Connected PV Systems and BESSs**

J. Koskela, A. Rautiainen, K. Kallioharju, P. Harsia, P. Järventausta

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Praise Worthy Prize

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# Effect of the Electricity Metering Interval on the Profitability of Domestic Grid-Connected PV Systems and BESSs

Juha Koskela, Antti Rautiainen, Kari Kallioharju, Pirkko Harsia, Pertti Järventausta

**Abstract** – *Installations of photovoltaic (PV) systems on residential buildings have increased over the last few years, and this trend will continue. PV systems can increase the production of sustainable energy. Many homeowners want to do something to decrease their emissions or increase their energy self-sufficiency. The most important issue in the decision to invest in a PV system is profitability. In the EU, electricity metering practices will be harmonized, and this will affect the profitability of PV systems and battery energy storage systems (BESSs). In many countries, electricity is metered by hourly intervals, but metering will be changed to 15-minute intervals. In this study, the effect of the metering interval on the profitability of PV systems and BESSs was studied has been studied in Tampere area in Finland. A shorter metering interval will decrease the profitability of photovoltaic systems, while the profitability of BESS will increase. However, the change is so minimal that the attractiveness of PV systems will only decrease slightly. Investment in BESSs in addition to PV systems will become more attractive and will benefit the evolution of smart grids, because batteries enable flexibility in the grid.* 

***Keywords***: *Solar Energy, Energy Storage, Batteries, Meter Reading, Simulation*

## Nomenclature

| | |
|---|---|
| $\beta_P$ | Temperature coefficient of the solar cell power |
| $\eta_c$ | Battery charging efficiency |
| $\eta_{dc}$ | DC-converters efficiency |
| $\eta_{inv}$ | Inverter efficiency |
| $B_t$ | Storage energy transmission during an hour $t$ |
| $B_{eff}$ | Efficiency of the storage energy transfer |
| $C_v$ | Verification coefficient |
| $D$ | Electricity consumption of building |
| $E_{\max}$ | Maximum capacity of storage |
| $E_t$ | Amount of stored energy at time $t$ |
| $G$ | Demand to power grid |
| $G_{b,i}$ | Beam component of solar irradiance |
| $G_{d,i}$ | Diffuse component of solar irradiance |
| $G_i$ | Global irradiance |
| $G_{r,i}$ | Reflected component of solar irradiance |
| $i$ | Discount rate |
| $I_c$ | Battery charging current |
| $n$ | Length of lifetime |
| $NPV$ | Net Present Value |
| $P_{dc}$ | Production after DC-converter |
| $P_{PV}$ | Production of photovoltaic system |
| $P_{STC}$ | Nominal power in standard test conditions |
| $R_b$ | Battery internal serial resistance |
| $R_y$ | Cost saving at the year $y$ |
| $SOC_t$ | State of charge at time $t$ |
| $T_c$ | Solar cell temperature |
| $T_{STC}$ | Standard solar cell test temperature |
| $V_b$ | Battery nominal voltage |

## I. Introduction

Electricity metering practices vary across the EU. The market time unit in balancing markets will be harmonized. In the Nordic electricity market, the balancing and metering period is one hour. Based on EU regulations (2017/2195) that establish guidelines for electricity balancing, all the Transmission System Operators (TSO) shall apply an Imbalance Settlement Period (ISP) of 15 minutes [1]. This change will happen gradually, and in Nordic countries, it will be implemented first in the intraday markets and then in the balancing settlement and balancing markets [2]. After some time, the 15-minute ISP will be implemented in day-ahead markets. ISP changes will set new requirements for electricity metering. Advanced metering infrastructure requires updating so that 15-minute measurements can be registered. The measurements are currently registered on an hourly basis (i.e., hourly energy).

When the time unit of electricity billing changes, this could affect the profitability of self-production and the Demand Response (DR) operations of customers. Self-production refers to electricity production by a customer (i.e., a prosumer), e.g., using solar energy and a photovoltaic (PV) system. Self-production can be used by an individual, but, in many cases, self-production exceeds an individual's consumption. Prosumers can sell surplus electricity to the grid, but the feed-in price of electricity is much lower than the purchase price [3]. It consists of the energy price, distribution price, and taxes,


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but the feed-in price consists only of the energy price.

The profitability of a PV system depends on the difference between the feed-in and purchase prices, the share of self-consumption and the investment price of the PV system [4]. Common sense says that probability for the same timing of consumption and production is higher when the time unit is an hour, opposed to 15 minutes. This hypothesis is under study in this paper. The share of self-consumption can be increased with a Battery Energy Storage System (BESS), so the change of market time unit can affect also the profitability of BESSs. The effect of changes to the market time unit on the profitability of PV systems and BESSs is the main research question of this study.

The profitability of a BESS can increase when different incentives from electricity billing structures are combined in the control of BESSs, as in [5] and [6].

These incentives of market-price-based control and peak cutting depend on the pricing structure, so the market time unit also affects these cost benefits. At the beginning, the time unit in day-ahead electricity markets remains an hour, and the 15-minute price for customers is the same during an hour. In this study, the market price is kept the same during an hour regardless of the metering interval. If the electricity distribution tariff from a Distribution System Operator (DSO) includes power-based fees, customers can get cost savings by peak cutting. The metering interval can affect the power-based charge because peak power can be very different in 15-minute increments compared to hourly increments.

Therefore, peak cutting with BESSs can also lead to very different results with different metering intervals. In this study, BESSs are used only to increase the self-consumption of PV production.

Although the general profitability of PV systems and BESSs has been studied thoroughly, the effect of the metering interval on the profitability of PV systems and BESSs has not been considered. Studies have used data from places such as Nordic countries where the hour metering interval is used. PV system and BESS profitability in Finland has been studied in [5]. In Germany, 15-minute data has been used in [7]. The profitability of grid-connected PV storage systems with five-minute data has been studied in [8]. Additionally, the profitability of battery energy storage alongside PV production has been studied in Greece in [9] and in Switzerland in [10].

Energy storages and effects of different control systems have been studied widely in many previous papers. The profitability of battery energy storage system connected to low voltage distribution network in case of Finland has been studied in [11]. Minimizing monthly peak powers in domestic real estate by using the control of BESS and charging of electric vehicle has been studied in [12]. Off-grid PV system in residential home with energy storage has been designed in [13]. Energy storage peak saving has been used for the optimization of a PV and energy storage system in [14].

This novel study is the first on where the effects of different metering intervals are compared. The results of this study are very important for the attractiveness of customers to participate smart grid via small scale PV production and DR with BESS. Previous studies do not compare different metering intervals and their effect on the profitability of PV and energy storage systems. In this study, three different metering intervals are compared: a one-hour interval, which is used in Nordic countries; a quarter-hour interval, which will be a common metering interval in the near future in the EU; and a one minute-interval because in the future the metering interval could be even shorter than a quarter-hour. In this study, the billing of electricity is based on metering when the interphase and time unit net metering are used. During every metering interval, only one measured value is used, and billing based on consumption differences between phases is not taken into account.

The paper is organized as follows. A simulation model that includes PV production and battery modeling is described in Section II. Section III presents the input data used in the simulations. The PV system and BESS are sized in Section IV. The simulations and their results are discussed in Section V. Section VI presents the conclusions of the study.

## II. Simulation Model

### *II.1. PV Production*

The PV production model is based on the global solar irradiance components of beam $G_{b,i}$, diffuse $G_{d,i}$ and reflected $G_{r,i}$. The model of the global solar irradiance based on the location on Earth has been introduced in [15]. Used panels are tilted and this is accounted in the model. In this study, the PV panels are tilted at a 45º angle facing south. Different irradiance components can be measured separately and global irradiance is the sum of these components $G_i = G_{b,i} + G_{d,i} + G_{r,i}$.

The production of a PV system ($P_{PV}$) can be calculated by equation (1), where $P_{STC}$ is the nominal power in Standard Test Conditions (STC), $\beta_P$ is the solar cell power temperature coefficient (0.006), $T_c$ is the solar cell temperature and $T_{STC}$ is the standard solar cell test temperature (25ºC) [16]. Theoretical PV production in real PV production is not same. For this reason, the verification coefficient $C_v$ is added to the equation:

$$P_{PV} = C_v P_{STC} G_i \left(1 - \beta_P (T_c - T_{STC})\right) \tag{1}$$

The simulation model of PV production has been verified with real measurements of PV systems in [5]. The result has been that the verification coefficient $C_v$ is 0.85. In modeling, the actual temperature of panel cannot know, so the outdoor temperature is used. In real situation, panel temperature rises higher than outdoor temperature because the panel absorbs solar radiation.

Wind speed affects also the panel temperature.

Additionally, the efficiency of the solar panels is decreased because of the aging of the cells and the type of solar cell affects this. The Effect of these error sources can be minimized by using verification. The verified simulation model gives realistic PV production data.

### II.2. BESS Modeling

In this study BESS simulator, which has been developed for research the profitability of BESS during long periods, is used. A model of a BESS simulator has been developed and presented previously in [4], [5] and [6]. The type of BESS used in the model includes a Li-ion battery with a lithium iron phosphate (LFP or $LiFePO_4$) cell-type and a graphite negative electrode.

LFP is good for domestic use because of its good safety features [17]. Its long cycle and calendar lifetime and high efficiency increase the profitability. The BESS system and its connection to the building's electricity network are shown in Fig. 1.

Modeling of the BESS state is based on the state of charge (SOC), as shown in equation (2):

$$SOC_t = 100\frac{E_t}{E_{max}} = 100\frac{B_{eff}B_t}{E_{max}} + SOC_{t-1} \quad (2)$$

where $E_t$ is the amount of stored energy at time $t$, and $E_{max}$ is the maximum capacity of the BESS. The SOC at time $t$ is $SOC_t$, and $SOC_{t-1}$ is the SOC of the previous time step.

Variable $B_t$ is the charged or discharged energy, and $B_{eff}$ is the efficiency of the charging and discharging. Efficiency depends on the SOC, charging or discharging powers and aging of BESS. The positive and negative directions of current flow, if they are possible, are shown in Fig. 1.

To simplify, the losses are assumed to be the same in charging and discharging. In actual losses are not same, but when the using of BESS is cyclic, the overall losses is in realistic level. In this study, the efficiency of the inverter $\eta_{inv}$ is 98%, and the converters' efficiency $\eta_{dc}$ is 99%.

Thus, the efficiency of charging battery from the grid is 97%, and the efficiency of charging overproduced energy from PV panels is 98%. BESS losses occur mainly in the converters and in the battery itself [17].

Very high or low SOC increase the losses [18].

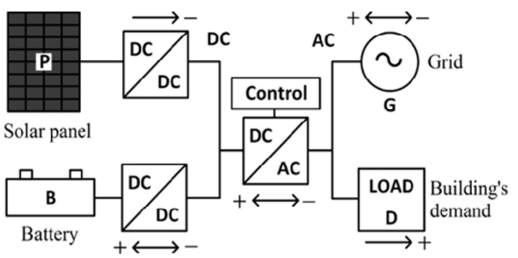


Fig. 1. BESS components and connections to building's electricity network [5]

For this reason, the SOC limits of the battery are set at 25-95%. Inside these limits, losses are almost linearly dependent on the charging current $I_c$, assuming that the internal serial resistance $R_b$ is constant [19]. In this case, the charging and the discharging efficiency $\eta_c$ can be calculated using equation (3):

$$\eta_c = 100\frac{V_b - I_c R_b}{V_b} \quad (3)$$

where $V_b$ is the nominal voltage of the battery. The efficiency $B_{eff}$ in (1) can be obtained by multiplying the efficiencies $\eta_{dc}$, $\eta_{inv}$, and $\eta_c$. The charged or discharged energy of battery $B_t$ is calculated by multiplying the charging current $I_c$ with the charging voltage $V_c$, which can be calculated using equation (4):

$$V_c = V_b - I_c R_b \quad (4)$$

The suitable voltage level of battery is constructed by connecting series battery cells. Battery capacity can increase, so the voltage level is kept stable by connecting these battery cell packages in parallel. In this paper, the internal serial resistance value of one modeled LFP cell has been 0.026 Ω, the cell voltage has been 3.3 V, and the capacity of one cell has been 2.5 Ah [20]. C-rate of battery tells the ratio of maximum power on capacity.

The C-rate 0.7 C has been the most profitable for the multi-incentive control type used in the study of [6], so this C-rate is also used in this study. The electricity demand of customers from the grid ($G$) perspective, so the effect of BESS and PV is accounted, can be modeled using equation (5):

$$G = \begin{cases} \eta_{inv}(-B_t - P_{dc}) + D, \| \eta_{inv}P_{dc} < D \\ -\eta_{inv}(P_{dc} - B_t) + D, \| \eta_{inv}P_{dc} \geq D \end{cases} \quad (5)$$

where $P_{dc}$ is the self-produced PV energy between the converter and the inverter, and $D$ is the electricity consumption of a building. From the grid perspective, the electricity demand of prosumers could be positive or negative. Negative demand means that the surplus energy is fed to the grid.

### II.3. BESS Control System

In this study, the BESS is used to store the overproduced solar energy. The BESS control strategy is described in Fig. 2, where the SOC of the battery varies between 25% and 95% as a result of the properties of Li-ion batteries [18]. Battery degeneration can be slowed by not completely discharging the battery or by completely charging it. A battery is charging if production is higher than demand, and the stored energy is designed to discharge immediately when the demand rises higher than production.

This leads to a situation in which the battery is completely empty most of the time if the BESS is too large with respect to the size of the PV system.

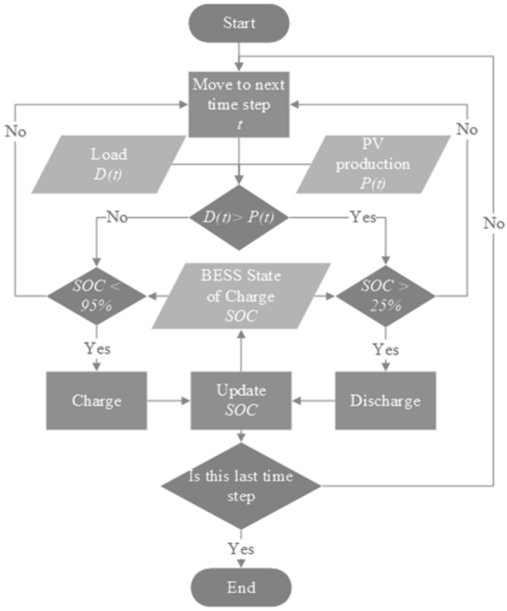


Fig. 2. BESS control process for increase the self-consumption of PV production

If the BESS is too small, the battery is fully charged most of the time. The price of electricity is not taken into account in the BESS control, because it is assumed to be same, when the metering interval change and the costs savings from electricity price control is same. The possible effects are taken into account in the discussion of this paper.

## III. Initial Data

### III.1. Load Profiles

The load data consist of the electricity consumption measurements from three detached houses in Finland.

These houses are located outside of Tampere city. Table I shows the detailed information of the houses. H1 and H2 were built in 2011 and 2012, respectively. The newest house is heated by a water boiler, and the second newest one is heated by a ground heat pump. The total consumption is much lower in the house with ground heating compared to the house where the water boiler is used even though the area of the former house is much higher. The third house (H3) was built in 1988, where underfloor heating resistors are used. The area of this house is much larger than the ones of the other houses, and the total consumption is also much higher. These three houses represent three kinds of typical detached houses in Finland, so the data include enough variations for this study.

Data have been measured with Efergy Engage online energy monitoring [21]. Measurements have been registered as the average power for a minute interval for the entire year of 2018. Five different channels have been used, which have made it possible to measure the total consumption and four other outputs at the same time.

One sensor has measured the total consumption of a house, and the other ones have measured four final circuits for which the consumption is assumed to be the highest, e.g., heating, electric sauna or kitchen stove. The entire year of minute-interval measurements consists of 525600 values, including short gaps when data have been missed because of connection breaks or other failures.

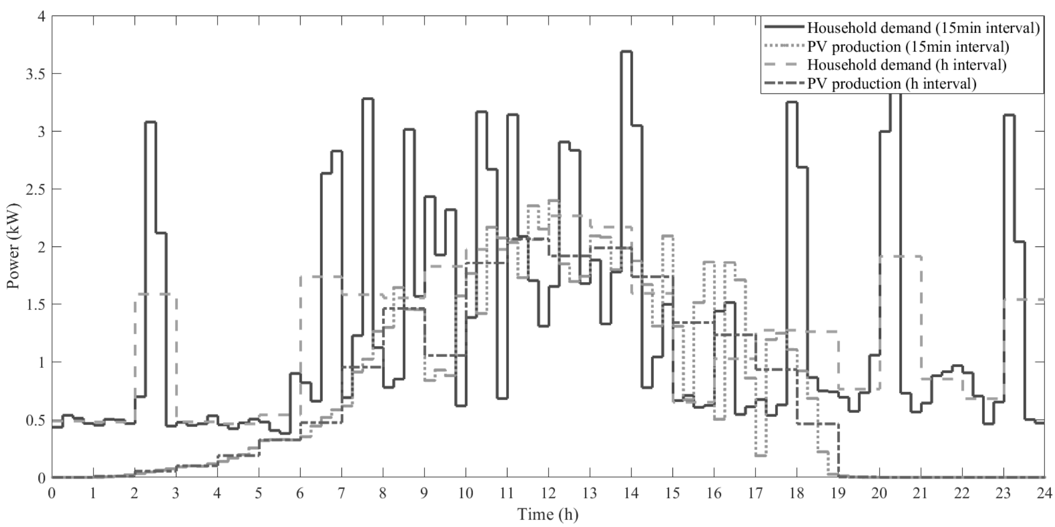


Fig. 3. An example of one day on a household customer's electricity demand and PV production (3 kWp) measured by 15-minute and hour metering interval

TABLE I
STUDY GROUP

| House | H1 | H2 | H3 |
|---|---|---|---|
| Construction year | 2012 | 2011 | 1988 |
| Area ($m^2$) | 152.5 | 190 | 220 |
| Warming (primary) | Water boiler | Ground heat pump | Underfloor heating resistors |
| Warming (secondary) | Electric heaters in garage + fireplace | Heat recovery + fireplace | Heat recovery + fireplaces |
| Yearly electricity consumption | 18.7 MWh | 13,2 MWh | 24,2 MWh |
| Heating power | 13 kW + (4.5kW water top up heater) | 13.5 kW | 14 kW + (4.5 kW water heater) |

These gaps in total consumption have been replaced by the sum of the measurements from the other sensors, which nearly corresponds to the total consumption. If there has been a gap in the other sensors, then it has been replaced by the value of the previous minute. However, the total number of gaps is so low that there is not a notable effect on the results of the study.

### *III.2. Solar Radiation Data and Weather Data*

The input data of PV production are based on a mathematical model of PV panel output, which is calculated from real one-minute solar radiation data.

Measurements of solar radiation were taken from the open data of the Finnish Meteorological Institute. The data have been measured at the weather station of Jokioinen, which is the nearest one to the studied houses.

The beam, the diffuse, and the reflected solar radiations for the entire year of 2018 have been measured in Jokioinen [22].

Fig. 3 shows an example of one day of household consumption and PV production metered by an hour interval and a 15-minute interval.

It can be seen that the variation of consumption is much higher for the 15-minute interval than the hour interval.

The variation of PV production is not so high in this example because this specific day was mostly sunny. During a day when cloudiness changes rapidly, the variation of PV production could be much higher.

### *III.3. Electricity Price Data*

In Finland, end-use electricity bills consist of the costs of electrical energy, distribution fees and taxes. A customer can sell surplus energy to the same energy retailer who is the seller of electrical energy. The price of energy is typically based on the market price of electricity in Nordic electricity markets [23]. Customers can tender out of retailers, and retailers can compete via margins, which are the amounts retailers add to the market price. When a retailer buys a customer's surplus energy, this margin is taken off from the market price. Energy selling contracts have typically been based on a constant price, but the average price is more inexpensive in market-price-based contracts than in constant-price contracts because the risks of retailers are lower. In this study, the margin of energy retailers is 0.25 c/kWh, which is typical in Finland. Market price changes for each hour, and if the metering interval is shorter than an hour, the price is constant during the entire hour.

Distribution System Operators (DSOs) have local monopolies, and they set the distribution prices under the control of public authority.

Customers have to pay electricity taxes based on the amount of used energy, which is charged with the distribution bill.

The value of the electricity tax is 2.79 c/kWh for household customers. In addition, there is a value tax (i.e., 24%), which is paid on all the cost components. In this study, the general distribution tariff of the local DSO has been used, and the volumetric charge is a constant 3.93 c/kWh [24].

The level of the volumetric charge affects the profitability of PV self-consumption because this price determines the difference between electricity purchase and feed-in prices, but it does not affect the differences between metering intervals because the costs increases in proportion with the price component.

## IV. Sizing of PV Systems and BESSs

### *IV.1. Sizing of BESSs*

In [4], it has been states that when PV systems and BESSs are sized based on electricity cost optimization, the suitable size of a BESS relative to the load profile of a customer has to be chosen first. After this, the PV system is sized relative to the size of the BESS. In this study, the sizing model from [4] is used. The same BESS can be used for several control targets. In this study, the increase of self-consumption is the only control target, so the size of the PV system affects the size of the BESS more than when other targets are involved.

In the sizing of the BESS, few potential sizes are selected at first, from 0 to 12 kWh, with an increment of 2 kWh. Then, we simulated the cost savings for each size have been when the size of the PV system varies between 0 and 6 kWp. After this, linear regression has been used to fit the lines for the first and last two result points. The intersection of the fitted lines indicates the optimal size for a PV system, as discussed in [4]. This has been done for all the three customers with all the three metering intervals.

Fig. 4 shows the average cost savings per 1 kWp of PV panels in the intersection of the fitted lines. At the beginning, the cost savings increase when the size of the BESS increases, but the growth slows down very quickly. The highest growth can be noticed for a 2-kWh BESS. For systems larger than 6 kWh, there is no increase in cost savings. The changes are similar with different metering intervals, but the differences are higher for small BESSs than for larger BESSs. For these three customers, 2 kWh is the best BESS size if the system is used only for increasing the self-consumption of PV energy.

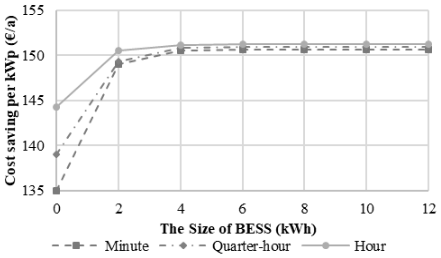


Fig. 4. Average annual cost saving per 1 kWp PV, with optimal sized PV for different BESS sizes and variable metering interval

Henceforth, a 2-kWh BESS is considered, and a 6-kWh system is used for comparison because it is largest size when cost savings still increase in the sizing simulations.

### IV.2. Sizing of PV System

Fig. 5 shows the optimal size of the PV system with the 2- and 6-kWh BESSs. They come from the intersection of fitted lines as in [4]. The PV array consists of panels with nominal powers of approximately 300 Wp. Thus, the potential sizes of the PV array are 2.1, 2.4, 2.7 and 3.0 kWp. With a 2-kWh BESS, suitable PV array sizes for customers H1, H2 and H3 are 2.1 kWp, 2.4 kWp and 2.1 kWp, respectively. In the simulations, the PV sizes are divided into 1-kWp intervals, and to maintain comparability for both BESS sizes, one PV size is chosen for all the customers. Thus, PV array sizes of 2 kWp and 3 kWp are chosen for 2-kWh and 6-kWh BESSs, respectively.

## V. Results

In order to compare different metering intervals, simulations have been completed for all the customers with the chosen PV system and BESS sizes and with the minute, quarter-hour and hour metering intervals. Fig. 6 shows the benefits of a 2-kWp PV system and a 2-kWh BESS. Fig. 7 shows the benefits of a 3-kWp PV system and a 6-kWh BESS. These benefits refer to the amount of yearly cost savings that customers can expect. The investment is not accounted for the benefits.

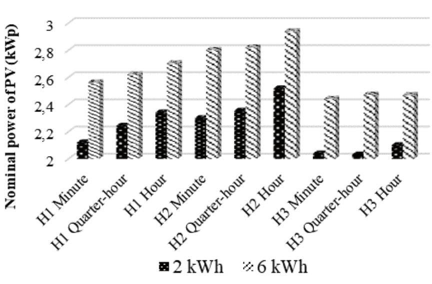


Fig. 5. Optimal size of PV with two different BESS size for three customers, when different metering intervals are used

The benefit of a PV system means the cost savings without a BESS, and the benefit of a BESS means the increase of cost savings when the BESS is involved. The total cost savings of a customer is the sum of these benefits. When considering money, the benefits of PV systems are much greater than the benefit of BESSs. For comparability, the axis of benefits of a PV system starts from 200 €/a in Fig. 6 and from 300 €/a in Fig. 7. With different y-axes, the levels of benefits in nearly similar conditions are obtained, and the differences of metering intervals can be considered. The effects of metering interval changes largely depends on a customer's load profile. Changes in money and percentage changes, in addition to the mean values, are shown in Table II for all customers separately. Changes in money are higher for the benefits of a PV system than the benefits of a BESS, but the percentage changes are much higher for BESSs. In Table II, the lowest values are shown by light blue, and the highest values are shown by red. Hour-to-quarter-hour and quarter-hour-to-minute changes reduce the benefits of PV systems but increase the benefits of BESSs. For many customers, the increasing benefits from BESSs nearly replace the losses from the decreasing benefits of PV systems. A shorter metering interval decreases the profitability of PV systems. Yearly cost savings decrease on average by 12.28 € for a 2-kWp PV system and by 14.68 € for a 3-kWp system if the metering interval changes from an hour to a quarter-hour, as shown in Table II.

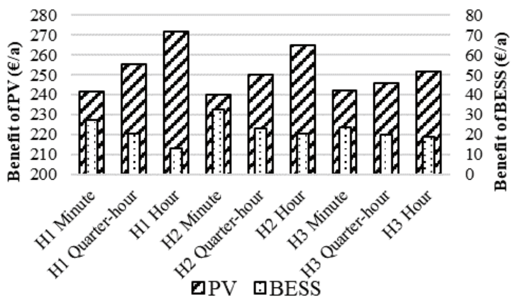


Fig. 6. Benefits of PV and BESS for three customers with different metering intervals, when 2 kWp PV and 2 kWh BESS is used

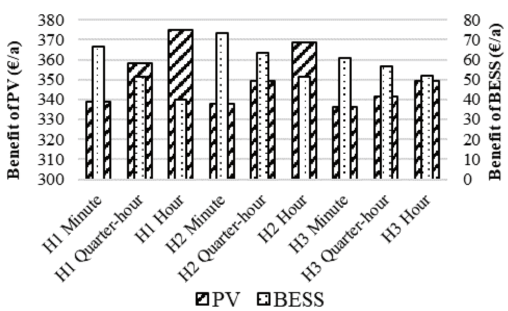


Fig. 7. Benefits of PV and BESS for three customers with different metering intervals, when 3 kWp PV and 6 kWh BESS is used

TABLE II
EFFECT OF METERING PERIOD CHANGE IN MONEY AND PERCENTAGE CHANGES

| | | PV: 2 kWp BESS: 2 kWh | | PV: 3 kWp BESS: 6 kWh | |
|---|---|---|---|---|---|
| | | PV | BESS | PV | BESS |
| Hour to Quarter-hour | H1 | -16.25 € | 7.57 € | -16.71 € | 11.64 € |
| | | -5.98 % | 58.46 % | -4.46 % | 29.16 % |
| | H2 | -14.73 € | 2.71 € | -19.25 € | 11.85 € |
| | | -5.57 % | 13.20 % | -5.22 % | 23.05 % |
| | H3 | -5.85 € | 1.18 € | -8.09 € | 4.54 € |
| | | -2.32 % | 6.29 % | -2.32 % | 8.70 % |
| | Mean | **-12.28 €** | **3.82 €** | **-14.68 €** | **9.34 €** |
| | | **-4.67 %** | **21.93 %** | **-4.03 %** | **19.53 %** |
| Quarter-hour to Minute | H1 | -13.72 € | 7.09 € | -19.27 € | 15.03 € |
| | | -5.37 % | 34.56 % | -5.38 % | 29.17 % |
| | H2 | -9.70 € | 9.34 € | -11.33 € | 9.91 € |
| | | -3.88 % | 40.12 % | -3.24 % | 15.66 % |
| | H3 | -3.95 € | 3.66 € | -5.08 € | 4.12 € |
| | | -1.61 % | 18.37 % | -1.49 % | 7.26 % |
| | Mean | **-9.12 €** | **6.70 €** | **-11.89 €** | **9.69 €** |
| | | **-3.64 %** | **31.53 %** | **-3.40 %** | **16.95 %** |

The change is slightly lower if the metering interval changes from a quarter-hour to one minute. The lifetime of a PV system can be 30 years [3]. If it is assume that the electricity prices, taxes, customer load profiles and the production of a PV system are similar over the entire lifetime of a PV system, the total effect of metering interval changes on the profitability of a PV system can be evaluated. Net present value (NPV) is a good tool to evaluate the profitability of an investment and it can be calculated using equation (6):

$$NPV = \sum_{y=1}^{n} \frac{R_y}{(1+i)^y} \tag{6}$$

where $R_y$ is the cost savings at the year $y$, $n$ is the length of lifetime and $i$ is the discount rate. Fig. 8 shows NPV calculations of cost savings over the lifetime of 2-kWp and 3-kWp PV systems with possible system lifetimes of 15 and 30 years and discount rates of 1% and 3%.

Calculations are made for hour, quarter-hour and one minute metering intervals.

### V.1. Effect of Metering Interval on the Profitability of PV Systems

Additionally, three possible investment prices for a PV system are shown by dashed lines. If the NPV is higher than the investment price, the investment is profitable and the part of the block that is over the investment price indicates the total profit of the investment, which comes over the required return. The results of Fig. 8 show that the change from an hour metering interval to a quarter-hour interval or the change from a quarter-hour interval to a minute interval affects the profitability of PV systems in approximately the same way as an increase of 100 €/kWp in the investment price of a PV system.

The profitability of the PV systems depends mainly on the lifetime of the system, the sizing of the system, the electricity prices, and the discount rate, but the investment costs and the metering interval are also significant. Additionally, how soon a prosumer wants the money back from the investment is important.

### V.2. Effect of Metering Interval on the Profitability of BESSs

In contrast to the profitability of PV systems, the one of BESSs increases when the metering interval becomes shorter. In Fig. 9, the calculated NPVs for the lifetime cost savings with a BESS are shown. The lifetime of an LFP Li-ion battery with good battery management is approximately 15 years [25]. Thus, a 15-year lifetime and a cautious estimate of an 8-year lifetime are used in the calculations. The discount rates are the same as those used in the PV calculations: 1% and 3%. Additionally, two investment costs for a BESS system are shown.

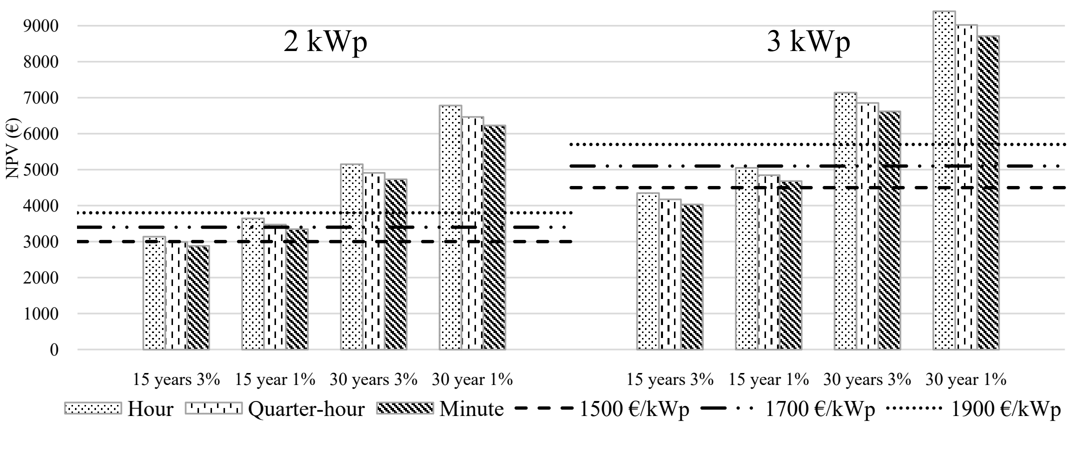


Fig. 8. Net present value of PV lifetime benefits with different metering intervals and three possible investment prices for 2 and 3 kWp PV systems. Two possible lifetimes (15 and 30 years) and two possible discount rates (1% and 3%) are used

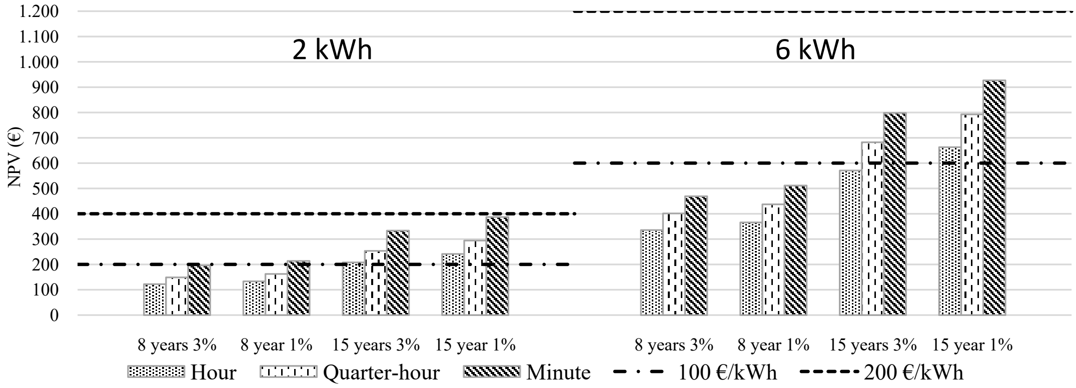


Fig. 9. Net present value of BESS lifetime benefits with different metering intervals and three possible investment prices for 2 and 6 kWh BESS. Two possible lifetimes (8 and 15 years) and two possible discount rates (1% and 3%) are used

The current investment price for Li-ion batteries is 200-400 €, as evaluated in [4] and based on [26] and [27].

Prices have decreased rapidly over the last decade, and development is expected to continue [28]. Power electronics increase the price of BESSs, but when a BESS is used together with a PV system, a portion of the costs are included in the price of the components of the PV system, e.g., a grid inverter. The presented investment prices are 200 €/kWh, which is the lowest possible price today, and 100 €/kWh, which is the expected price in the future as the volume of manufacturing grows. These optimistic prices are used because they are almost at the same level as the NPVs of the cost savings. This strengthens the perception that the use of BESSs with PV systems to increase self-consumption is not currently profitable.

The results of Fig. 9 show that the change from an hour metering interval to a minute metering interval results in the highest effect on the profitability of a 2-kWh BESS with a 15-year lifetime and a 1% discount rate. This change corresponds to a change of approximately 73 €/kWh in the BESS investment price.

A metering interval change from an hour to a quarter-hour corresponds to a change from 11 €/kWh to 26 €/kWh in the BESS investment price. Another observation is that the effect of a metering interval change on the profitability of a BESS is higher for an optimally sized BESS with 2 kWh as opposed to a slightly oversized 6-kWh BESS.

## VI. Discussion

In this study, data from three different households in area around of Tampere in Finland have been used. Even though the sample size of the study group is small, these houses represent current domestic houses in Finland, and the size of the houses is slightly larger than average. In all the houses, the primary heating system is different, and the systems are commonly used today and in the future. Two of the houses are quite new, while the other one is older. This leads to the variations in the total consumption of the houses. The results show that the benefits of PV systems and BESSs do not depend on the amount of total consumption. The differences between the houses are not large even though the load profiles vary substantially, confirming that the results are representative.

The benefits of BESSs are calculated when a BESS is used only for increasing the self-consumption of PV production. The same BESS can also be used for other control targets, but these ones are not studied in this paper because the metering interval does not directly affect them if the electricity prices remain constant in relation to the load profile. For this reason, the results of this study do not directly indicate the profitability of using BESSs in houses. A change in the metering interval will affect other control targets due to the changing price components or the changing peak power values. If power-based distribution tariffs are used, the peak power consumption values are higher with a shorter metering interval because when the metered load is averaged for a longer period, e.g., an hour, short high peaks are smoothed. When DSOs keep their revenue the same through a metering period change, the power-based price component will decrease. This means that the savings from peak-cutting will be almost at the same level. The differences between customers will increase, but the effects require additional research.

The savings from market-price-based control will also change when the time unit in the electricity market changes. The price change between quarter-hours could be higher than that between hours [29]. This will increase the profitability of market-price-based control. Second, when the time unit is shorter, BESSs will be used more frequently. This will affect the sizing of BESSs and their actual lifetime.

## VII. Conclusion

In a case of Tampere area in Finland, a shorter electricity metering interval decreases the profitability of grid-connected domestic PV systems but increases the profitability of BESSs associated with PV systems.

Currently, PV investment is profitable in the long term in Finland, and transitioning from an hour metering interval to a quarter-hour metering interval does not radically affect the situation. However, this shift increases payback time and notably decreases profits. If the metering interval is shortened to one minute from 15 minutes in the future, the effect of this change will be approximately similar to the change from an hour interval to a quarter-hour interval.

Using a BESS to increase the self-consumption of PV production is not yet profitable. A shorter metering interval will increase the cost savings notably but will not make BESSs profitable. Economically profitable use of BESSs requires other control targets, such as market-price-based control or peak cutting, when power-based distribution tariffs are used. In the long term, a shorter metering interval is a good thing for the future of smart grids because it has many positive effects. Increased profitability makes investments in BESSs, along with investments in PV systems, more attractive. Using BESSs can decrease the surplus energy feeding into the grid and smooth the demand from the grid to restrain the increasing distribution costs when the need to strengthen the grid decreases. Additionally, BESSs use larger PV systems profitable and can increase the total amount of PV production. Without BESSs, the attractiveness of PV investment will decrease when the metering interval becomes shorter.

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## Authors' information


**Juha Koskela** received his M.Sc. in electrical engineering from the Tampere University of Technology in 2016. At present, he works as a doctoral student in the Unit of Electrical Engineering at the Tampere University. His research focuses on electrical energy storages and their impacts on technical and economical points of view.

**Antti Rautiainen** received his M.Sc. and Dr.Tech. degrees in electrical engineering from the Tampere University of Technology in 2008 and 2015, respectively. At present, he works as a post-doctoral researcher fellow in the Unit of Electrical Engineering at the Tampere University. His research focuses on various topics related to electricity grids and the electricity market.

**Kari Kallioharju** received his B.Eng. degree in electrical engineering from Tampere University of Applied Sciences in 2007 and M.Sc degree in electrical engineering from Tampere University of Technology in 2012. At present, he is a senior lecturer in the Unit of Building Services Engineering at Tampere University of Applied Sciences. His research focuses on various topics related to smart buildings as a part of energy system.

Principal Lecturer **Pirkko Harsia** received her M. Sc. and Licentiate of Technology degrees in electrical engineering from Helsinki University of Technology in 1982 and 2003 respectively. At present, she is a principal lecturer in the Unit of Building Services Engineering at Tampere University of Applied Sciences. The main interest focuses on the issues of smart buildings from the electrical building services point of view.

Prof **Pertti Järventausta** received his M.Sc. and Licentiate of Technology degrees in electrical engineering from Tampere University of Technology in 1990 and 1992 respectively. He received the degree of Dr.Tech. in electrical engineering from Lappeenranta University of Technology in 1995. At present he is a professor in the Unit of Electrical Engineering at Tampere University. The main interest focuses on the issues of Smart Grids from the grid and electricity market point of view.

# PUBLICATION
# 5

**Using Load Forecasting to Control Domestic Battery Energy Storage Systems**

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Article

# Using Load Forecasting to Control Domestic Battery Energy Storage Systems

**Juha Koskela *, Antti Mutanen and Pertti Järventausta**

Unit of Electrical Engineering, Tampere University, FI-33014 Tampere, Finland; antti.mutanen@tuni.fi (A.M.); pertti.jarventausta@tuni.fi (P.J.)

* Correspondence: juha.j.koskela@tuni.fi

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**Abstract:** The profitability of domestic battery energy storage systems has been poor and this is the main barrier to their general use. It is possible to increase profitability by using multiple control targets. Market price-based electricity contracts and power-based distribution tariffs alongside storage of surplus photovoltaic energy make it possible to have multiple control targets in domestic use. The battery control system needs accurate load forecasting so that its capacity can be utilized in an optimally economical way. This study shows how the accuracy of short-term load forecasting affects cost savings by using batteries. The study was conducted by simulating actual customers' load profiles with batteries utilized for different control targets. The results of the study show that knowledge of customers' load profiles (i.e., when high and low peaks happen) is more important that actual forecast accuracy, as measured by error criteria. In many cases, the load forecast based on customers' historical load data and the outdoor temperature is sufficient to be used in the control system, but in some cases a more accurate forecast can give better cost savings.

**Keywords:** battery energy storage system; load forecast; control system

## 1. Introduction

Decentralized electricity generation and self-production is increasing very fast, because it allows local production of much emission-free electricity and decreases the need to transfer high amounts of electric energy over long distances. This will decrease the amount of electricity customers' purchase, lowering the cost of electricity from energy retailers (ERs) and distribution system operators (DSOs). Customers can sell over-produced electricity to the grid and obtain some revenue. Nevertheless, in the market environment of Finland, electricity self-production is profitable only for self-consumption [1]. Self-production by using photovoltaic (PV) panels is becoming very popular, because the equipment for PV production is easy to purchase, the profit is sufficient in many cases, and it has been studied in much research (e.g., [2–4]). Optimal sizing of PV panels is based on maximizing the savings on the electricity bill [2]. With the optimal panel size, some production can be sold to the grid, but the production is mostly used for self-consumption. The rate of self-consumption can be increased by using a battery energy storage system (BESS). Using a BESS increases the capacity of self-consumption, which means that the optimal size of PV panels also increases.

In residential buildings, BESSs can also be utilized for functions other than storing over-produced electricity. An uninterrupted power source is one application, but a BESS could also be used to minimize the cost of electricity with different pricing structures. Customers can have a contract with an ER, and the retail price will be based on the market price of electricity. With this kind of contract, the BESS could be charged when the price is low and discharged when the price is high [5]. During the last few years in Finland, there has been a lot of discussion around power-based distribution tariffs (e.g., [6,7]). With a power-based distribution tariff, some of the cost depends on the customer's highest power. The highest power can be decreased by discharging the BESS during the peak, when the cost from the distribution tariff decreases and the customer can obtain cost savings [8].

The effects of load forecasting for the profitability of household level BESS have not been widely studied before. However, many studies focusing on energy storage at the household level have been published. The effects of load forecast errors were studied in [9] by Koponen et al., where different error criteria were compared. The profitability of BESSs in residential use with PV has been studied (e.g., [10–12]). Sizing of the BESS is very important when aiming for the highest possible profit and high profitability; sizing from an economic perspective has been studied (e.g., [2,13–16]). To increase the benefits of BESSs, multiple control targets can be used, as in [17] by Litjens et al. Predictive control strategies for BESSs have been studied previously (e.g., [18,19]). The lifetime of a BESS affects total profitability, so it is important to take care of the health of the battery during control operations. The lifetime expectation of batteries in residential use is studied in [20] by Beltran et al.

Control of BESSs can be very simple when it is used for only one control target. When it is used to store surplus PV production, BESS can be discharged empty before the high production of midday. Alternatively, if the BESS is used to decrease maximum peak power, it is fully charged to await possible high peaks. These simple controls can work well if the customer's load profile is suitable and the BESS is sized well. If the BESS is used for market price-based control or the same BESS is used for multiple control targets and its utilization is optimized, the control system must be based on load forecast. Optimal control of BESSs is based on the predicted state-of-charge (SOC) behavior. Changes in SOC during the optimization period can be calculated based on the load and PV production forecast. Predicted SOC levels make it possible to control SOC at the right level for different control targets all the time. Errors in these forecasts cause situations where the SOC levels are not optimal, e.g., the battery is full when a lot of surplus energy is available for storage. For this reason, high accuracy of forecasts is important in the control of BESSs. The main objective of this paper is to study how much forecast errors affect the use of BESSs. This study researches the current level of forecast errors sufficient for use in the control of domestic BESS and how it is affected if BESS is used for different control targets, which make possible to cost savings for the customers. The level of cost savings and profitability of BESS depends on many factors other than error level of load forecast e.g., prices of electricity and BESS system, customer's load profile and technical details of system, but this study focuses on the effect of load forecast, so the results do not present the actual profitability of system.

The results of this study will help to improve the control of BESSs, which leads to an increase in their profitability. Profitability has been the basic reason why residential BESSs did not become more common earlier, and is the main problem with BESSs nowadays. Increasing the profitability could make BESSs more common in the future, and then all of their benefits can be implemented for the system, such as flexibility and higher electricity self-production. This kind of study has not been conducted, so its novelty is very high.

The remainder of this paper is divided into four sections. Section 2 introduces the simulation model and used data. Section 3 presents the results of simulations, and the discussion is presented in Section 4.

## 2. Materials and Methods

### *2.1. Battery Energy Storage System (BESS) Control Targets*

In this study, several control targets of BESS were studied. BESS can be used for different control targets individually or in combination. In this subsection, the different control targets and their requirements are introduced. Electricity pricing structures are based on the market environment of Finland.

#### 2.1.1. Storing Surplus Photovoltaic (PV) Production

In Finland, prosumers can sell surplus electricity to ERs, but the selling price is approximately only a third of the purchase price, because customers have to pay distribution prices and electricity taxes on purchased energy. It is profitable to avoid buying electricity from the grid by using PV self-production. If production is higher than consumption at some times, surplus energy has to be sold to the grid. Self-consumption of PV production can be increased by using BESS. The cost benefit of using BESS to increase PV self-consumption $EB_{BESS,pv}$ comes from the price difference between total selling price $C_{t,s}$ and total purchase price $C_{t,p}$ of electricity, which can be described by Equation (1):

$$EB_{BESS,pv} = C_{t,p}\, B_{eff}^2\, E_{s,pv} - C_{t,s}\, E_{s,pv} \quad (1)$$

where $E_{s,pv}$ is the amount of stored surplus energy and $B_{eff}$ is the battery efficiency during charging or discharging. Actually, the efficiency is not the same during charging and discharging, and calculating accurate values depends on many factors, such as charging and discharging power, but in these calculations efficiency is assumed to be the same. This assumption is valid when the efficiency represents the estimated average efficiency during a cycle. Because the utilization of stored surplus energy needs two actions (charging and discharging), the efficiency is square, which corresponds to the round-trip efficiency of the battery.

Using BESS to store surplus PV production is a simple process, but control could be challenging. Before midday, when the surplus PV production is usually the highest, the battery should be empty enough and ready to receive energy. Control can be implemented very simply; e.g., the battery is discharged empty during the evening for consumption and charged during daytime, when surplus energy is available. This kind of simple control does not utilize BESS optimally. Production and consumption vary from day to day, and BESS is sized using some kind of average values. With accurate load and production forecasts, BESS can be utilized optimally.

The northern location of Finland means that PV production is high in summer and very low in winter. Long days in summer means that PV production is widely available during the day. In winter, days are very short and PV production is negligible. Usually electricity consumption is higher in winter than summer. As a result, available surplus energy varies a lot throughout the year. BESS is needed mostly in summer and very little at other times. Using BESS to increase self-consumption of PV production allows BESS to also be used for other control targets.

#### 2.1.2. Decrease Maximum Peak Power

Distribution tariffs can include a power-based component. This means that customers can obtain cost savings by discharging BESSs during peak power. Control of BESS can be implemented so that the battery is fully charged the whole time to await peak power. When the power increases above the selected level, the BESS is discharged to decrease consumption. This could work if customers have only a few individual peaks in consumption and power levels are very stable. Optimal utilization of BESS requires accurate load forecasts so that power levels can be optimized and the BESS can prepare for situations when the power peak lasts longer than an hour. One hour is the commercial unit for determining the peak power in power-based tariffs (i.e., highest average hourly power calculated by measured hourly energy). Cost savings from using BESS to decrease maximum peak power $EB_{BESS,p}$ can be calculated with Equation (2):

$$EB_{BESS,p} = C_{p,p}\, P_{BESS} \quad (2)$$

where $C_{p,p}$ is the price of the power-based component in distribution tariffs and $P_{BESS}$ is decreased maximum power by BESS. In this equation it is assumed that the cost from charging the BESS is negligible compared with the benefits, so it is assumed to be zero. This assumption is valid, because usually only a few cycles can save up to tens of euros, but charging in these cycles costs only few cents [8]. Decreasing power peaks by BESS includes a high risk that control failure will affect cost savings. If several high peaks are close together and the control system is not prepared for this, during the highest peak the BESS can already be empty. Therefore, very accurate load forecasting, especially forecasting of high peaks, is very important in this kind of utilization of BESS.

In Finland, a lot of electricity is used to heat buildings. The highest power peaks usually occur in the coldest time of winter. Electric saunas usually cause the highest peaks among individual electric devices in buildings. Without any special devices, cold weather and electric saunas require BESSs to decrease power in typical Finnish residential buildings. Weather-dependent loads can be forecast using weather forecasts, but the load of heating a sauna depends on the customer's choice, so it can be difficult to forecast.

#### 2.1.3. Market Price-Based Control

The third control target of BESS is market price-based control. The basic idea is to charge the BESS at hours when the electricity price is low and discharge when the price is high for one's own electricity demand. In Finland, a customer's contract with an ER can be based on the electricity market prices in Nord Pool day-ahead spot markets [21]. Nord Pool publish the prices for the next day between 13:00 and 14:00 CET, so in Finland the prices for next day will be available at 15:00 local time at the latest. Electricity prices are known for the next 10 to 33 h. The control system can optimize the utilization of the BESS for the period when prices are known, or an optimization period can be chosen. Unknown hourly prices in the optimization period can be forecasted. The cost savings from market price-based control $EB_{BESS,mc}$ can be calculated by Equation (3):

$$EB_{BESS,p} = \sum C_{spot,t1}\, B_{eff}\, E_{sc,t1} - \sum C_{spot,t2}\, (E_{sc,t2}/B_{eff}) \quad (3)$$

where $C_{spot,t1}$ is the electricity price when the price is high, $C_{spot,t2}$ is the price when it is low, $E_{sc,t1}$ is discharged energy, and $E_{sc,t2}$ is charged energy. Summations are in Equation (3) because the BESS can be charged or discharged over several hours and the prices and amounts of charged and discharged energy can be different.

Both charging and discharging cause energy loss, as Equation (3) shows. Using BESS for market price-based control can be profitable only if the difference between low and high price is so large the benefits outweigh the losses. Additionally, using the BESS decreases the lifetime of the battery, so the benefits must also compensate for this. The benefit from market price-based control is the least of the control targets in this study, relative to the used BESS cycles. Therefore, the control system must be careful that the BESS is used for market-price control only when it is profitable.

#### 2.1.4. Combination of Control Targets

Different control targets can be utilized by the BESS. When optimizing its utilization with different control targets, the control system must know which target is most profitable at any given moment. Usually this is not difficult, because the BESS is needed to store surplus PV production at midday in the summer and to decrease maximum peak power in coldest winter. Additionally, the profitability of market price-based control is usually much lower than that of other control targets [2,5]. If there is a situation where the BESS is needed to both decrease peak power and store surplus PV production, it is better to first decrease peak power, because even at only one hour the power decrease could fail. These situations are still very rare, so the basic rules for combining different control targets can be formed easily.

With ideal load forecasting, it is easy to optimize the utilization of BESS, but errors in load forecasting can cause failure in optimal control, e.g., BESS is empty when energy is needed to decrease peak power. This kind of situation is possible when the power peak cannot be predicted in the load forecast and just before the peak the price of electricity was high and the BESS was discharged empty. Accuracy of load forecasting is very important when control targets are combined.

### 2.2. Simulation Model

This study is based on simulations using ordinary household customers' demand data, with BESS added to the households' electricity system. The simulation model is presented in Figure 1, which shows the directions of power flow and information data flow with red and green arrows, respectively. In the basic situation, PV power flows through the metering to the inverter, where it can go straight to the household to meet demand or to the BESS, and if the amount of produced energy is higher than the demand and the storage capacity is full, it can be fed to the grid and measured by automatic meter reading (AMR). If PV production cannot meet the energy need, it can be taken from the grid to meet the demand or to the BESS.

Decision-making for battery charging and discharging occurs in the BESS control system. It controls the inverter/charger, which gives feedback on the battery conditions. Additionally, the control system includes a battery management system (BMS), which takes care of battery health. In the decision-making process, the control system uses the information from load and production forecast, upcoming electricity prices, and feedback from the charge controller and AMR. Load and production forecasts are based on weather forecasts and mathematical models, but these can be corrected based on PV production metering and data from AMR.

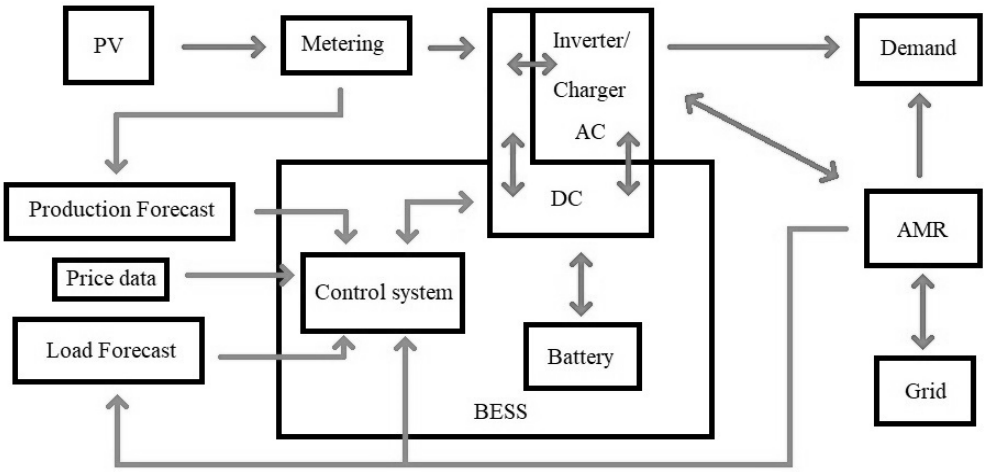


**Figure 1.** Structure of household power system in simulation. Power flow is indicated by red arrows and information data flow by green arrows.

#### 2.2.1. Household Electric System Model

In simulations, calculations are based on the initial household demand $D$, which is taken from measured data of actual electricity customers. The efficiency of inverter/charger $\eta_{inv}$ affects the amount of energy, which is converted from direct current (DC) to alternating current (AC) or from AC to DC in an inverter/charger. In this study, the inverter efficiency and charger efficiency are assumed to be equal, and were both 98%. Additionally, battery charging and discharging causes losses on the DC side, but this is taken into account in the BESS model. PV production before the inverter/charger $P_{dc}$ can go straight to the BESS, when inverter or charger efficiency does not affect it. Charger efficiency affects when the BESS is charged from the grid. The customer's electricity bill is based on the measurements of AMR. Therefore, it is important to calculate the total demand measured by AMR, i.e., the demand from the grid perspective $D_g$, which is shown in Equation (4) [5]:

$$D_g = \begin{cases} \dfrac{B_t - P_{dc}}{\eta_{inv}} + D & \| if\ B_t > P_{dc}\ \&\ B_t \geq 0 \\ -\eta_{inv}(P_{dc} - B_t) + D & \| if\ B_t \leq P_{dc}\ \&\ B_t \geq 0 \\ \eta_{inv}(-B_t - P_{dc}) + D & \| if\ B_t < 0 \end{cases} \quad (4)$$

where $B_t$ is power flow to or from the BESS at time $t$. There are three equations for $D_g$ because the equation is different if the battery is charged or discharged; additionally, if the battery is charged, the equation is different when charged energy is from PV or from the grid.

### 2.2.2. PV Model and Production Forecast

PV production $P_{pv}$ is simulated by using a solar panel model, which is based on the nominal power of panels in standard test conditions $P_{STC}$ and modeled global solar irradiance $G_i$. Differences in solar panel conditions are taken into account in Equation (5), which can be utilized in PV calculations [22]:

$$P_{pv} = C_v P_{STC} G_i \big(1 - \beta_P (T_c - T_{STC})\big) \quad (5)$$

where $T_c$ is the solar cell temperature, $T_{STC}$ is the standard test temperature (25 °C) and $\beta_P$ is the solar cell power temperature coefficient (0.006). This model was verified in [5] with actual data from solar panels and the verification coefficient $C_v$ was added (0.85). In the verification, polycrystalline silicon PV cells were used. This because the temperature of the solar panel cannot be known in simulations and outdoor temperature has to be used instead. Lower temperatures in Equation (5) increase production, so a coefficient is needed.

Solar irradiance modeling is based on the Reindl model [23], which is a suitable model for diffuse irradiance with south-tilted solar panels in the conditions of Finland [22]. In the model, global irradiance $G_i$ is the sum of beam irradiance $G_{b,i}$, diffuse irradiance $G_{d,i}$ and reflected irradiance $G_{r,i}$. In modeling, it is most important to find out the time series of solar irradiation. How strong is the solar irradiation on solar panels at different times? Solar irradiance depends on the location on the Earth and the angles of tilted PV panels. In this study, modeled solar panels are tilted at a 45° angle to face south.

The amount of PV production depends on the cloudiness. In the Reindl model, cloudiness is modeled by a brightening factor. In [24], a model for cloudiness probability in Finland is presented, and it is based on cloudiness changing randomly, but based on probability. The same time series of solar radiation was utilized in all simulations so that the circumstances are stable. In actual systems, production forecasting has been utilized in control systems. In this paper, where load forecast is under study, the production forecast is assumed as ideal so that this does not affect the results of load-forecasting effects.

### 2.2.3. BESS Model and Control System

In simulations, modeling of BESS is based on controlling the battery's state of charge (SOC), which is the percentage of full battery $E_{max}$. In every moment when the battery is charged or discharged, the SOC changes, and it depends on the SOC at the previous moment. This can be formed with Equation (6) [5]:

$$SOC_t = 100 \frac{B_{eff} B_t}{E_{max}} + SOC_{t-1} \quad (6)$$

where $SOC_t$ is the SOC at time $t$ and $SOC_{t-1}$ is the SOC of the previous time step.

Modeling of the battery type is undertaken via the efficiency of BESS $B_{eff}$, which is a combination of battery efficiency and power electronics efficiency, i.e., inverter/charger DC side in Figure 1. In this study, the efficiency of power electronics on the inverter/charger DC side $\eta_{dc}$ was 99%. The battery type was a lithium iron phosphate (LFP, $LiFePO_4$) cathode with a graphite anode. A lithium-ion (Li-ion) battery was chosen because it is currently the best commercial solution for residential use, with high efficiency, developed technology, and long lifetime. The LFP cell type was chosen because it has good safety features and a very long lifetime, and the specific energy is not as high as other Li-ion batteries. It is a good choice for use in stationary home systems [25]. Battery loss modeling was presented previously (e.g., in [8] by Koskela et al.). Loss depends on SOC and charging or discharging current. Very high or low SOC increases the loss and decreases the lifetime of the battery [26]. For this reason, the SOC limits of the battery were set at 25–95%. In Li-ion batteries, the internal serial resistance $R_b$ is approximately constant between these SOC limits [27]. Therefore, the modeling of battery loss can be implemented with constant serial resistance of 0.026 Ω, which was studied for LFP cell type in [28] by Weniger et al. Charging and discharging losses are not equal, but when the battery use is cyclic, we can use average values for both processes. Charging and discharging efficiency $\eta_c$ can be calculated with Equation (7):

$$\eta_c = 100\frac{V_b - I_c R_b}{V_b} \tag{7}$$

where $V_b$ is the nominal voltage of the battery and $I_c$ is the charging or discharging current. The value of $B_t$ can be calculated by multiplying charging or discharging current by charging or discharging voltage $V_b$, which can be calculated by using Equation (8):

$$V_c = V_b - I_c R_b \tag{8}$$

The control system in this paper makes it possible to combine multiple control targets, and it is a novel structure. The basic operation of the control system is that it tells the inverter/charger when to charge the battery and when to discharge. Optimization of the BESS for control targets based on minimizing customers' electricity cost and its rules are described in Section 2.1. Firstly, if customers' electricity cost depends on peak power, BESS is used to decrease maximum peak power. This is implemented via an algorithm which is presented in [8]. Based on the load forecasting, the control system calculates the power level that is possible to keep below by using BESS. If average power during a pricing period goes over this limit, the battery is discharged. Errors in load forecast can cause failure. Based on the amount of failure, a new target power level is determined.

Secondly, if customers have their own PV production, maximizing self-consumption is the next target. If the battery is not used to decrease maximum peak power, it is discharged empty before the high production hours of midday. When it is necessary to do this depends on the production forecast and load forecast. Control systems estimate the potential needs of SOC levels in the battery based on the forecasts. The BESS stores the surplus energy from PV, which is used later when it is needed. Stored energy can be used immediately when consumption increases higher than production, but this can be delayed for other control targets.

Thirdly, if customers' electricity cost depends on the market price of electricity, the control system charges the battery during low prices and discharges during high prices. Controlling is based on pairs of hours when electricity prices are different, as in [5]. Charging and discharging operations must follow one another, because the capacity of the BESS is limited, so with a reasonably sized BESS, typically charging and discharging cycles will be once a day. If other control targets are involved, other operations can be done, e.g., the BESS is charged from surplus PV production and discharging is timed for high price, or the BESS is discharged to decrease peak power and charged during low price. For these reasons, the control system uses some rules for market price control: the BESS is charged full at least during the three hours before the forecast power peak and is not charged during three hours before forecast surplus production. These rules are valid only if these control targets are involved. If there are any other restrictions, the control system finds the lowest and highest prices of the day and calculates whether it is profitable to use the BESS. The price difference must be so large that loss of storage will be exceeded.

### *2.3. Load Forecast*

Load forecasting is used in the BESS control system. Because the use of load forecasting is the main study object in this paper, it is described in its own subsection. To compare the benefits of BESS caused by forecast-based control and errors in forecasts, forecast errors between 0% and 200% are studied. Ideal load forecasting corresponds to a forecast error level of 0%. When the load is forecast by using a load forecasting algorithm, the error level is 100% (i.e., the 100% error level corresponds to the actual load forecast). The range 0–200% is divided into 20% steps, and the absolute value of forecast error in every hour increases linearly from 0% to 200%.

In this study, forecasting error is modelled with two different methods: the basic method, where 100% forecast error is formed by using the load forecast algorithm, and the random method, where forecast error is formed randomly. For comparability, we try to keep the effectiveness at the same level as much as possible.

The basic load forecast is formed separately for every customer. The load forecast algorithm is based on the customer's historical consumption data and the effect of outdoor temperature variation. The method was initially presented in [29] and was utilized in [8]. In load forecasting, the load profile of the day is formed from the average consumption of historical data from similar days, and the data are corrected with outdoor temperatures. Different types of days are weekdays, Saturday, Sunday and weekdays with public holidays. Additionally, days are divided for the four seasons throughout the year.

Mean absolute error (MAE) and root mean squared error (RMSE) are the best criteria for comparing the validity of the load forecast, and are used in the control of residential BESS [9]. In the random method, forecast errors are made by the random function in MATLAB® R2018a by Matworks, so MAE and RMSE increase linearly, similar to the basic method. For ideal forecasting, normally distributed random errors are added, whose mean is zero and standard deviation increases 0.25 kW per 20%. With these parameters, RMSE is the same as in the basic method and MAE is also very close, as we can see from Figure 2.

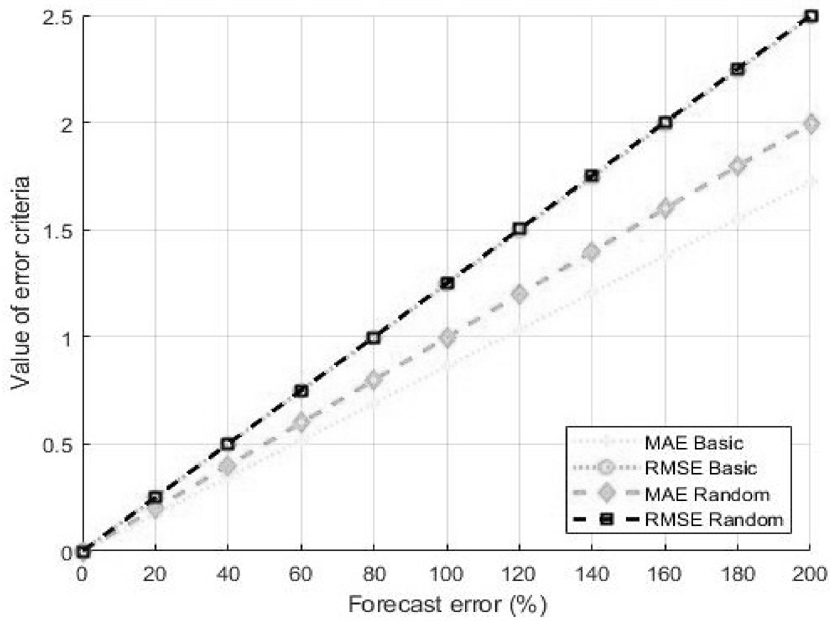


**Figure 2.** Error criteria with basic and random load forecast error models.

## 2.4. Initial Data

This study used large datasets from different sources. The simulations need consumption data from customers and many kinds of electricity price data. Additionally, forecasting and PV production models need measured weather data. This subsection presents the data used in this study.

### 2.4.1. Consumption Data

Customers' consumption data were collected from actual customers between January 2014 and August 2016. The data were measured using customers' AMR measurements from the area of one DSO in Finland. The total number of customers is 1525, but for the simulations 100 customers were selected randomly. These are basic household customers who live in detached houses, which mainly use electric heating, but the heating method can vary. The study group also included a few larger customers, such as farms. Data from 2015 were used for simulating the effects and the other data were used in load forecasting.

#### 2.4.2. Electricity Prices

A customer's electricity bill in Finland consists of three parts: the ER part, the DSO part and taxes. Both the ER and DSO parts typically include basic charges (€/month), but customers cannot affect this by using the BESS, and for this reason basic charges are not included in the calculations in this study. The ER pricing used here is typical market prices based on tariffs in Finland, where hourly price is based on the day-ahead spot prices of the Nord Pool (Finland area prices) [21]. ERs add a 0.25 c/kWh margin to the market price, and if surplus energy from PV production is fed into the grid, ERs buy this energy for the same market price, but the margin is taken off. The margin forms the income of ERs.

In this study, two distribution tariffs of a DSO are used. One is the power-based tariff, which is calculated for the same area where the group under study lives [7]. The power-based tariff includes an energy charge (0.72 c/kWh) and a power charge (7.23 €/kW/month). The power charge is based on the highest hourly average power of the month. The power-based tariff is used so that all possible BESS control targets are available. Because the power-based tariff is not yet widespread, the general distribution tariff in the same area is also used. The general tariff is widely used in Finland; it includes only an energy charge (5.21 c/kWh) [30]. All prices in this study include a 24% value added tax. In Finland, customers have to pay an electricity tax (2.79 €/kWh) on purchased energy. In this study, customers do not need to pay the DSO for surplus energy that is fed into the grid, and this is the typical situation in Finland.

#### 2.4.3. Weather Data

Load forecasting is based on outside temperature. Additionally, temperature and solar radiation data are used in the PV model. All weather data were taken from the open data of the Finnish Meteorological Institute [31]. Temperature data are measured hourly, and were measured at the Juupajoki weather station, which is the closest station to customers in the study group.

### *2.5. Study Cases*

The effect of load forecasting was studied with different cases. There are three control targets, and all combinations of them were studied. The study cases are presented in Figure 3. The three basic control targets form study cases 1–3. These three basic targets are introduced earlier in Section 2.1., and in more detail: the case 1 in subsection 2.1.1., the case 2 in subsection 2.1.2., and the case 3 in subsection 2.1.3. Cases 4–6 are the combinations of two of the basic targets and study case 7 is the combination of all targets. Combining of cases are introduces in Section 2.1.4. These seven cases are selected, because cases include all combinations, which make it possible to obtain cost savings for customers.

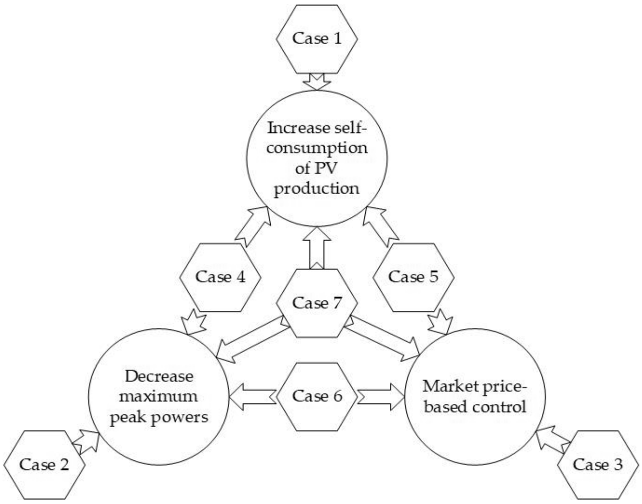


**Figure 3.** Study cases.

In every case, load forecast error varies between 0% and 200%. The ideal forecast corresponds to an error of 0%, and calculated forecast (i.e., load forecast, which is calculated as described in SubSection 2.3.) corresponds to an error of 100%. The load forecast for every customer was formed based on earlier consumption data and temperature. Absolute value and direction (forecasted value higher or lower than actual value) were calculated every hour. For every customer 11 load forecasts were formed, with error increasing from 0% to 200% with 20% steps. Simulations were made with all of these load forecasts. Based on the results of the simulations, it is possible to study the effect of the accuracy of load forecasts.

## 3. Results

### *3.1. Simulations with Power-Based Distribution Tariff*

In simulations, every customer had the added production of 3 kWp solar panels. The results are shown as average cost savings in the study group. Cost savings are presented as the function of forecast error. The results were calculated with the basic and random methods of modeling forecast errors. First, simulations were made with the power-based distribution tariff, where all possible cases (control targets) are meaningful.

#### 3.1.1. Basic Method

The results of the simulations are presented in Figures 4–6. Figure 4 presents the cost savings from total electricity costs per year. The cost savings from the distribution tariff and electricity tax are presented in Figure 5. Figure 6 shows the savings from market price-based cost paid to ERs.

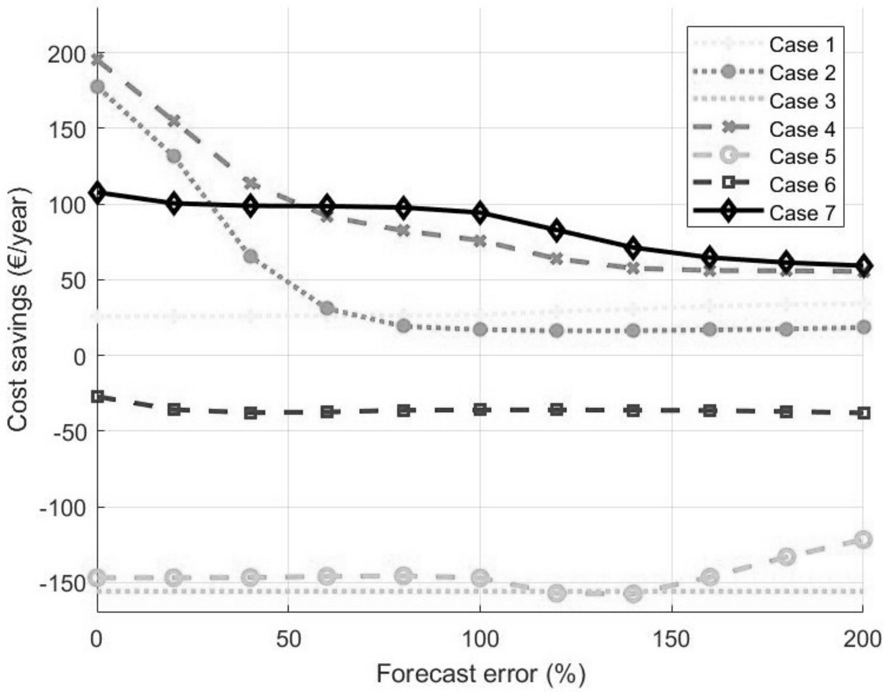


**Figure 4.** Total cost savings in function of forecast error in cases with basic method for modeling forecast error.

In case 1, the total cost savings increase marginally around the 100% forecast error, when the forecast error increases. This effect is caused by control inaccuracy. In the basic method of load forecasting, the direction of the error is the same at all error levels. Therefore, when the error increases, the control system increases its preparedness to store surplus energy. The same effect can be seen in case 5, which combines market price-based control (case 3) with case 1. In case 2, improved load forecasting strongly increases the cost savings when the forecast is very accurate. When the forecast error is over 80%, cost savings are almost constant. In case 3, the curve is flat. The negative number is leading from the increasing maximum peak power in market price-based control. Additionally, forecast errors do not notably affect the cost savings from market price-based control if decreased maximum peak power is not involved. The control system knows the whole time when high and low prices occur, so it uses BESS capacity maximally to shift the load from high price to low price, and it does not care about the load forecast.

When cases 1 and 2 were combined in case 4, the accuracy of the load forecast had a strong effect on the cost savings. Improving the load forecast increases cost savings significantly. In case 6, the load forecast must be very accurate after the improvement increases the cost savings. When all control targets are involved in case 7, the accuracy of the load forecast is very important around the 100% forecast error, but below 60% or over 140% the cost savings are stable. It is an important observation that with the current load forecast (100% forecast error), case 7, using all control targets, gives the highest cost savings.

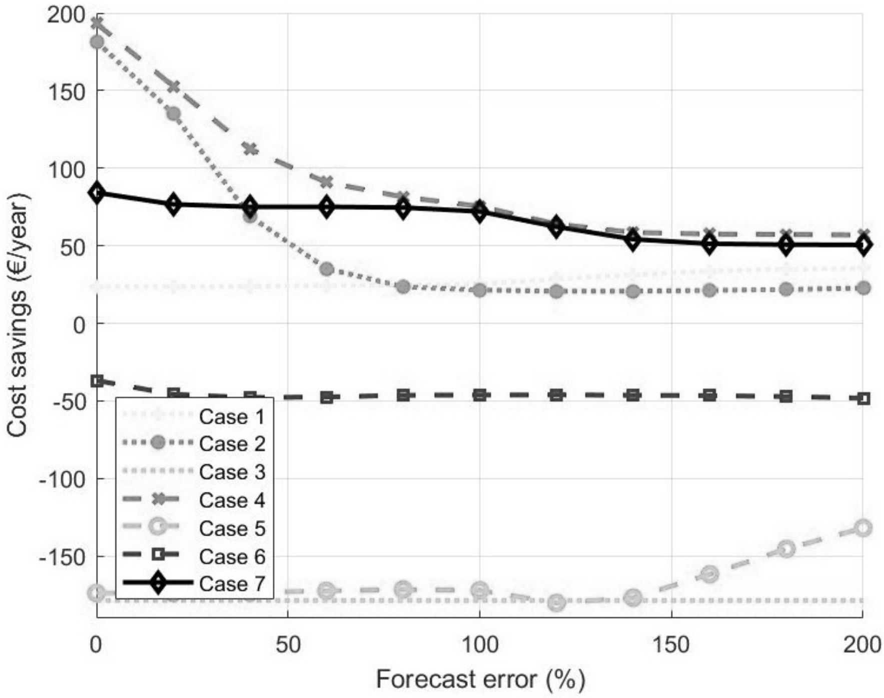


**Figure 5.** Cost savings from distribution tariff in function of forecast error in cases with basic method of modeling forecast error.

Cost savings from the distribution tariff and electricity tax mostly affect total cost savings, as shown by the similar shape of curves in Figures 4 and 5. Cost savings from the distribution tariff in cases where market price-based control is involved are lower than total cost savings. Additionally, in cases where decreased maximum peak power is involved, cost savings are higher.

The cost savings from ER contracts (Figure 6) shows that when the load forecast accuracy is increased from the current level, cost savings increase only marginally. Instead of a decreased load forecast, accurate cost savings are decreased dramatically in cases 5 and 7. These two cases give even higher cost savings from ER contracts than the clean market price control in case 3. The reason is that in case 3, control does not care when electricity is purchased and fed into the grid. In cases 5 and 7, feeding into the grid is limited when it is possible, because surplus energy is stored and grid feeding is not profitable. This makes it possible to obtain even higher cost savings when total electricity consumption is lower. Nevertheless, this needs very accurate load forecasting, and with bad load forecasts, cost savings drop lower.

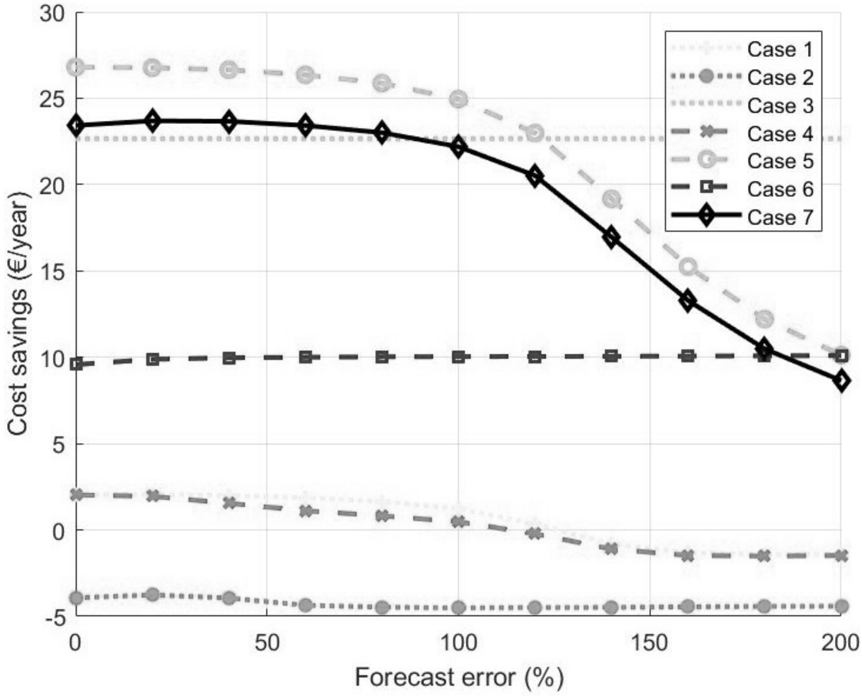


**Figure 6.** Cost savings from energy retailer (ER) contracts in function of forecast error in cases with basic method of modeling forecast error.

### 3.1.2. Random Method

The results of the simulations with the random method of modeling forecast error are presented in Figures 7–9. In the random method, the knowledge of high and low peaks in the load profile disappears when the forecast error increases. This can be seen when comparing the results in Figures 4–9. With the random method the decrease of cost savings is smoother and continues almost the same throughout the whole forecast error range.

There are differences in how the forecast error modeling method affects the control targets. In case 2 with 100% error level, the random method gives higher cost saving than the basic method, and the same effect can be seen in case 4. This is because in the basic method, the same control errors repeat, because the forecast is based on historical data and temperature. In the random method, control errors also happen randomly, so the errors do not have as significant an effect. In case 7, which uses all control targets, almost all cost savings are lost with the random method at the 100% error level, and with the basic method, the cost savings are almost the same at the 0% error level.

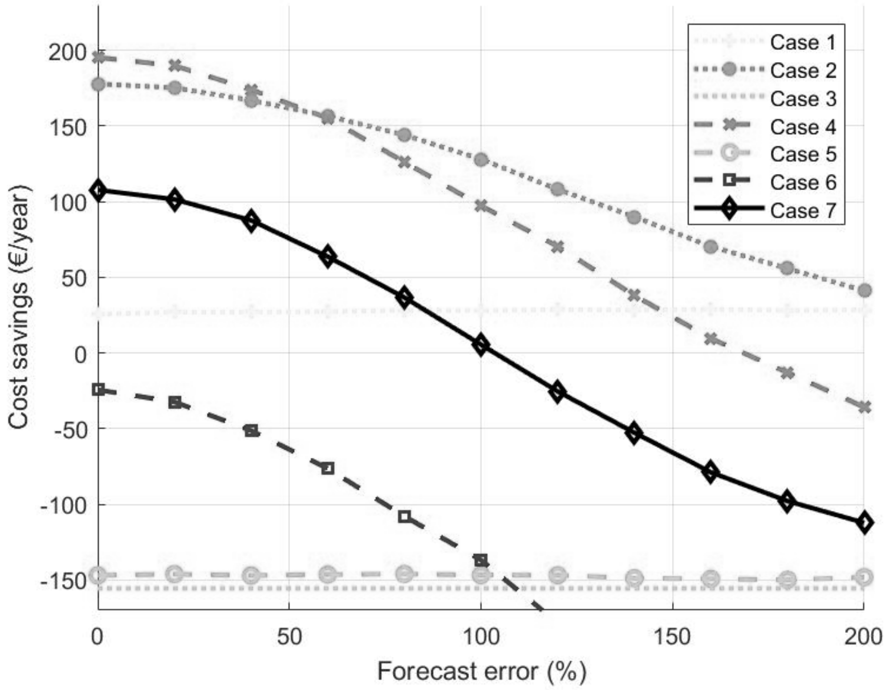


**Figure 7.** Total cost savings in function of forecast error in cases with random method for modeling forecast error.

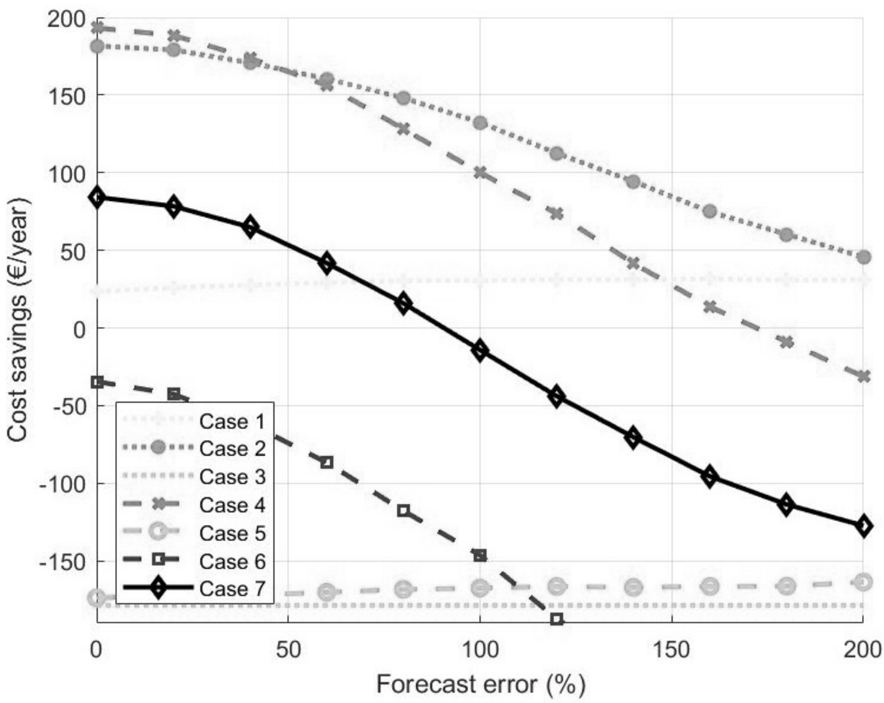


**Figure 8.** Cost savings from distribution tariff in function of forecast error in cases with random method for modeling forecast error.

For cost savings from ER contracts (Figures 6 and 9) clear differences can be seen between forecast error modeling methods. The decrease of cost savings is smoother with the random method, but with the basic method higher cost savings can be reached at the 100% error level.

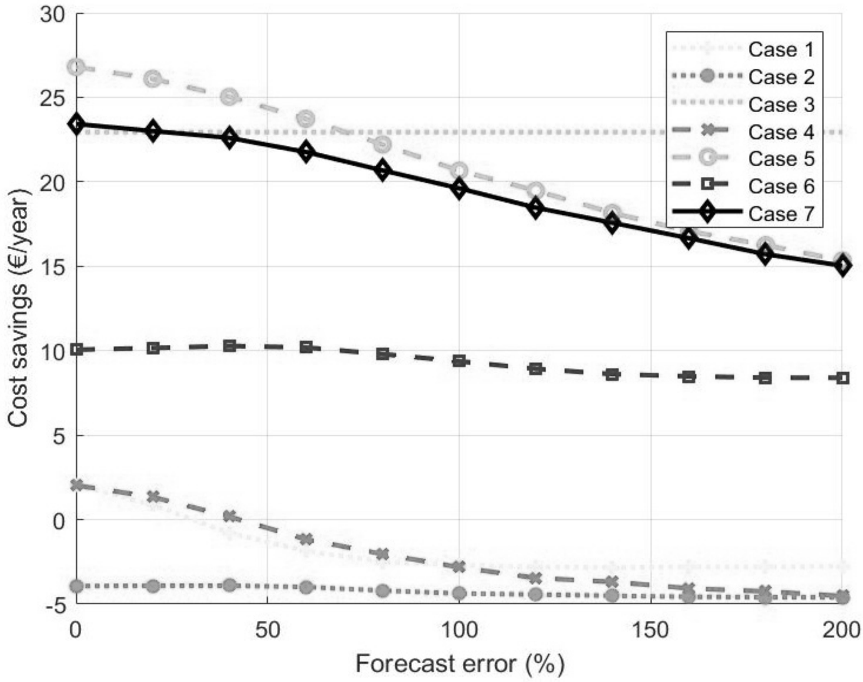


**Figure 9.** Cost savings from ER contracts in function of forecast error in cases with random method of modeling forecast error.

### 3.2. Simulations with General Distribution Tariff

In this subsection, the general distribution tariff is used. The power-based component of the tariff is not involved in the general distribution tariff, so it is meaningful to study only cases 1, 3 and 5, where decreased maximum peak power is not the target for control.

#### 3.2.1. Basic Method

When the basic method for modeling the error of load forecast is used, case 5 gives the highest cost savings before the error level of 120%. The results of this is shown in Figure 10. After that, as with the power-based tariff, the cost savings in case 1 increase and rise higher than in case 5. This is caused by the inaccuracy of the control system and the knowledge of the load profile in the basic method. The total cost savings in case 3 is not as negative as it is with the power-based tariff, but is still negative. This is because the control in case 3 does not care about the grid feeding from storage during high prices. This feature is involved in case 5, when the rise in cost savings is strongly positive. The main finding is that the effect of forecast error is not significant with the general distribution tariff and the differences between error levels are only marginal.

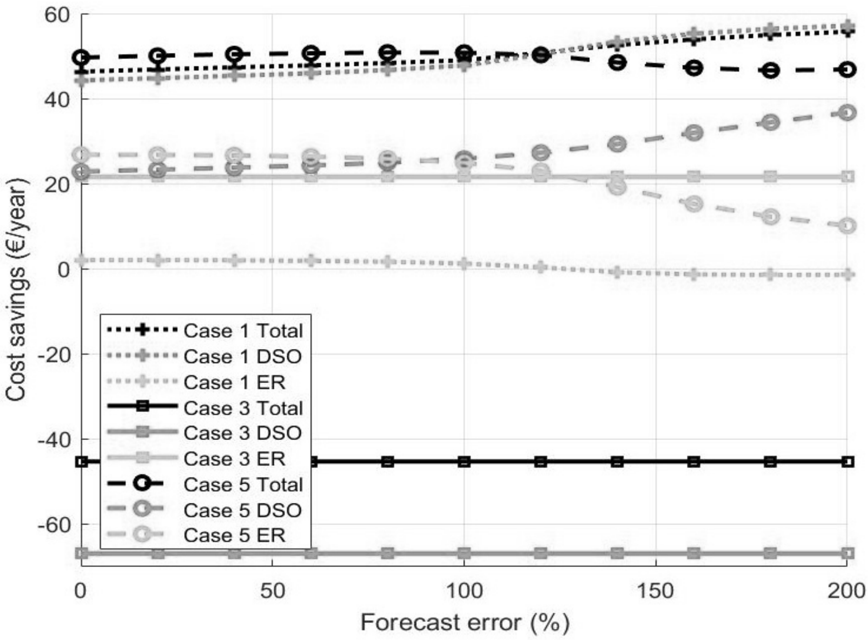


**Figure 10.** Cost savings in function of forecast error with general distribution tariff using basic method of load forecast error modeling in cases 1, 3 and 5.

#### 3.2.2. Random Method

When the random method is used, the levels of cost savings are very similar to the basic method and the differences between error levels are only marginal. The results with the random method is shown in Figure 11. The biggest difference between basic and random methods is that the changes that happen after the 100% error level with basic the method happen before the 60% error level with the random method. When the random method is used, it seems that with current load forecast accuracy (100%), it is not profitable to use the combination of control targets (case 5) instead of case 1. However, when the basic method is used, the combination of control targets is the most profitable.

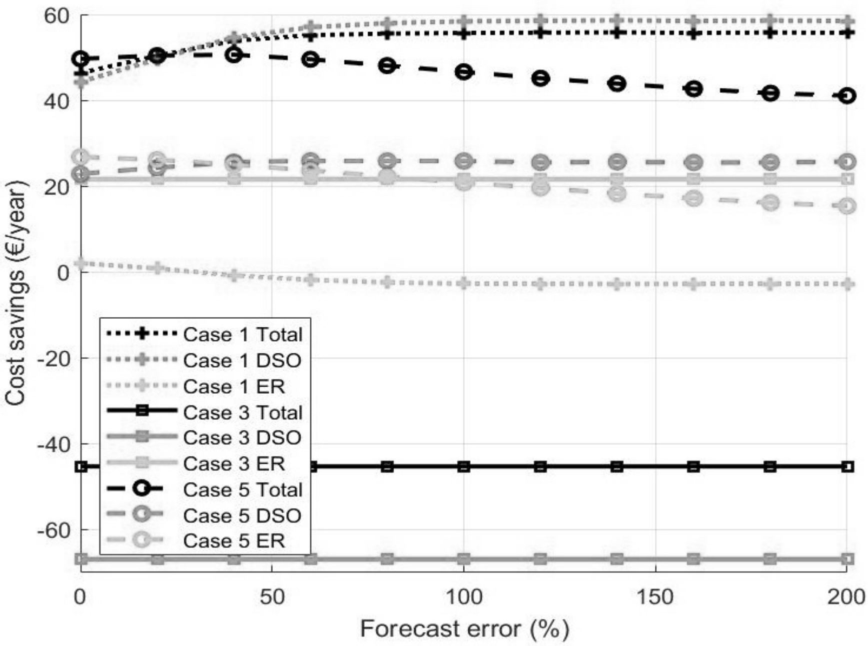


**Figure 11.** Cost savings in function of forecast error with general distribution tariff using random method of load forecast error modeling in cases 1, 3 and 5.

## 4. Discussion

The results of this study correspond with the expectations. Load forecasting is an important part of BESS control in domestic use when multiple control targets are used. Power-based distribution tariffs and market price-based ER contracts make it possible to use BESS for multiple control targets. When a general distribution tariff is used, the load forecast is not necessary. In simulations, it can be difficult to model the effect of load forecast errors. The modeling of forecast errors can be implemented by adding random errors to actual data. Forecast validity can be evaluated with error criteria such as MAE, RMSE or mean absolute percentage error (MAPE). However, this method does not correspond with real cases of load forecasting, which is done before BESS control. As the results of this study show, real load forecasts include information from the load profile, even if the error criteria are high. Therefore, the error criteria do not directly show the validity of the load forecast when it is used in the BESS control system.

Using BESS for only one control target can give some cost benefits, but using it for multiple targets can give even higher cost savings. In some cases, this also needs accurate load forecasting. This study shows that load forecasting is important, especially in cases 2, 4 and 7. In these cases, decreasing maximum peak power is involved. When both decreasing maximum peak power and storing surplus PV production are used, accurate load forecasting is very important. The profitability of BESS has been a barrier to its generalized domestic use. Higher cost savings from smart control systems makes it possible to increase profitability.

The results of this study are presented as average values of the study group. There are differences in cost savings between different customers, but average values show how this phenomenon behaves. When designing the control system of BESS for commercial application, this is expected to work with average customers. Even the load forecast is reasonable to individualize for different customers; it can be done by using the same principles. The results of this study show that it is more important for the load forecast to predict the load profile (i.e., when high and low peaks happen) than the actual accuracy of the forecast measured by error criteria.

The used optimization method was used partly before in [2,5,8], but all combinations are not used before. The benefits of this method are e.g., good functionality with different control targets, fast response with decent computation time and sensitivity for accuracy of load forecast. The used battery model corresponds to the modern Li-ion battery, which are available nowadays. Results of simulations are simulated in the Finnish electricity market environment, so the specifics of markets could cause the restrictions for the results. In other market environment, the cases and price levels could be different. There could be also other benefits from using BESS, e.g., the quality of electricity could improve, if BESS is also used for avoid black outs or stabilize the voltage level.

Simulations are made by using selected values in variables of modeling equations. The results of the study depends on the selected values. These values have been selected to correspond to the typical situation in a chosen environment. A small variation in these values causes only minimal effects on the results, when comparing these with the effect of load forecast error level. The results are not very sensitive for individual changes in these variables.

In the future, it will be worthwhile repeating the study with multiple ways of doing load forecasting. This study was conducted in the market environment of Finland, so future studies may be needed in different market environments. The results show that in many cases, the actual level of load forecasting is sufficient, but more accurate load forecasting could give even better cost savings and increase the profitability of BESS. More accurate load forecast is needed, when multiple control targets is used. In the future, there could be even more control targets which are studied in this paper and then the even more accurate load forecast could be useful. These are the focus of future studies.

**Author Contributions:** Conceptualization, J.K. and A.M.; methodology, J.K.; software, J.K.; validation, J.K. and A.M.; formal analysis, J.K.; investigation, J.K.; resources, J.K.; data curation, J.K. and A.M.; writing—original draft preparation, J.K.; writing—review and editing, J.K. and P.J.; visualization, J.K.; supervision, P.J. All authors have read and agreed to the published version of the manuscript.

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# PUBLICATION
# 6

**Demand Response Possibilities of Electrical Heating in Detached Houses in Finland and Comparison with Battery Energy Storage Systems**

J. Koskela, P. Järventausta

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# Demand Response with Electrical Heating in Detached Houses in Finland and Comparison with BESS for Increasing PV Self-Consumption

**Juha Koskela *** and **Pertti Järventausta**

Unit of Electrical Engineering, Tampere University, Korkeakoulunkatu 7, FI-33720 Tampere, Finland
* Correspondence: juha.j.koskela@tuni.fi

**Abstract:** Distributed electric power production by small-scale customers is increasing continuously. Photovoltaic production is a popular method of producing self-energy for customers. Additionally, power systems require more flexibility when weather-dependent renewable energy production increases. Small-scale customers can increase the self-consumption of self-produced energy by using batteries or a demand response operation. However, batteries require high investment, and demand response operations induce a loss of comfort. Customers who heat their buildings using electric heaters are a good target for demand response operations because their heating can be controlled with limited changes in the indoor temperature. The demand response potential of a building can be defined by simply using customer load profiles and knowledge of the outdoor temperature. Any other information is not required in the proposed novel method. A tolerable variation in indoor temperature corresponds to considerably smaller battery capacity, though it is still a significant amount. With an optimally sized photovoltaic system, it is possible to use both methods simultaneously to increase self-consumption. Maximal benefits can be attained from both methods if the battery system is used as a primary control and the demand response is used as a secondary control. The defined novel method for determining the demand response potential of small-scale customers can also be used when estimating the flexibility of a large customer group. Small-scale customers together can provide significant flexible capacity when their electrical heating is centrally controlled.

**Keywords:** demand response; battery; buildings; photovoltaic

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## 1. Introduction

Flexibility will have a key role in future power systems as electrification and 100% renewable energy production are being pursued [1]. In power systems, flexibility can be implemented through many applications and at various scales. One method is to use demand response (DR) operations in which the consumption flexes when production changes. Flexible loads can be of various sizes, and a large number of small loads can form a larger group of flexible loads. Flexible loads can be controlled for the direct benefit of customers using their own control system, or they can be centrally controlled to benefit the system such that all customers benefit [2]. A customer self-control system can be called a price-based DR program, in which customers make load changes by responding to economic signals. A centrally controlled system can be called an incentive-based DR program, in which customers are offered payments for reducing their specific loads over a given period. The grid contains many detached houses, which are considerably small loads from the power system perspective but together create a significant flexible load. This paper focuses on DR with electric heaters in a Nordic area where there are a lot of electrically heated detached houses. A high number of small-scale customers from Finland were studied.

In the future, small-scale energy production will increase when it becomes economically more attractive to domestic customers [3]. Household-level customers typically use a small photovoltaic (PV) system; thus, the production is mostly used in self-consumption, because the economic value of the produced energy for self-consumption is significantly higher than the value of produced energy for selling to the market [4]. Flexibility, for example through the use of battery systems, enables fixed-sized PV panels to better react and adjust to self-consumption increases [5]. Historically, power transfer in the power lines is conveyed from power plants to customers. Multiple small-scale power plants (e.g., household small-scale PV systems) around the grid can reform the grid and energy flows bidirectionally. Increasing weather-dependent energy production and distributed energy resources (DER) set new requirements for power systems [1]. The grid must be redesigned toward bidirectional function, and the power system requires more flexibility for efficient operation in the future. High flexibility will decrease the negative effects of increasing DER, e.g., the requirement to reinforce the grid. Child et al. demonstrated that customers who have PV production systems with battery storage can reduce the requirement for transmission interconnections by 6% [1].

The benefits of using flexibility to increase self-consumption have been examined in many papers. Merei et al. presented a techno-economic analysis of a PV–battery system, and the results indicated that increasing self-consumption through the use of batteries has cost problems associated because of high battery investment costs [6]. The results of Ref. [7] show that low discount rates and debt financing may significantly increase the profitability of battery investment. The potential of battery use with PV systems also increases if the lifetime of the battery increases. Angenendt et al. presented a forecast-based operation strategy for this [8]. Puranen et al. focused on a case study from Finland for a techno-economic analysis of energy storage concepts with residential PV systems [9]. The profitability of battery systems with PV production under different retail tariffs was studied in Ref. [10]. A comparative study of different control strategies for PV–battery systems is presented in Ref. [11] for an office building environment.

DR operations are effective for increasing distributed PV penetration [12]. The effectiveness of DR operations depends on the operation algorithms, and Sivaneasan et al. [13] presented one option for using such algorithms. Nyholm et al. [14] presented an economic assessment of PV production in Sweden with a special focus on the impacts of DR. Additionally, in many papers, batteries and DR have been combined [15,16].

However, earlier studies did not publish a wide comparison of battery storage and heating power DR with long-period simulations and did not explore the effects the battery and DR operation have on each other. In this novel research, we studied the possibility of using batteries and DR in parallel and the potential of using both. Earlier studies, such as the study conducted by Lorenzi et al., compared battery storage and water boiler DR from an economic perspective, and the results demonstrated the high potential of DR operations compared to batteries [17].

Heating power DR has rarely been studied even though it has high potential. One reason for this is that every building is different, and the features of buildings are difficult to approximate. Generally, studies require a building model that considers the insulation and ventilation of the building. Bashir et al. formed a building model based on Finnish construction requirements, and it was used to evaluate the storing of PV production as heat for the building [18]. This method aids in evaluating the possible power of DR operations and the changes in indoor temperature that occur in a building during operation. This paper presents a novel method of evaluating the DR potentials of buildings from electricity load profiles without any other knowledge of the building. In previous studies, values from typical buildings and calculations based on theoretical features were used, though real building data were used in Ref. [19]. For evaluating the DR potential of space heating, Nyholm et al. used constant effective heat capacity, which was taken from previous studies [20]. The model presented in this paper calculates accurate thermal storage features for every customer. Additionally, as an improvement on previous studies, the number of customers in the study group was large and the study period was long. For example, while this paper uses a year-long study period, Zhang and Guéquen used a 24 h period [21].

In earlier papers, the number of studied buildings was low and buildings features were usually from some form of test house [22] or were based on the average features used in the studied area [23].

Naturally, the potential of DR is limited and depends on the customers' load profile. Possible DR devices should be high-load devices whose time of use can be flexible. Electrical heating is appropriate for DR because houses include thermal storage capacities. Short breaks in heating do not dramatically decrease the indoor temperature, and in controlled systems, breaks can be prepared by overheating the house before the breaks. If heating is used for DR, the DR capacity depends on the outdoor temperature and limits set for indoor temperature. DR should cause only a minimal loss of comfort for the customer, but it always causes some effects. With the use of a battery, a customer's load profile can be modified without any loss of comfort. The capacity of the battery and charging and discharging power are the only limits of its use. Even if the DR and battery are used for the same purpose, their basic principles in how benefits are formed are different. Therefore, comparison between DR and batteries is very difficult.

Indoor temperature limits varied significantly in earlier research [24]. Many people do not notice an indoor temperature change of $\pm 0.5$ °C over the course of an hour, but a $\pm 2$ °C change can affect the comfort of most people [25]. Additionally, the law sets limits. In Finland, the terms of electricity supply define that an electrical heater can be switched off for a maximum of 1.5 h when continuously controlled by an aggregator, and the total switch-off time should be 5 h in a day [26]. This paper compares the use of DR and a battery by comparing 1 and 2 °C flexibility in indoor temperature to the corresponding size of the battery. This novel information provides knowledge about the possibilities of DR and battery use. The most significant problem relating to battery use has often been high investment costs and how those costs compare to the potential benefits. The comparison method used in this paper is very extensive because it enables systems to be compared even if the investment costs or electricity prices change over time.

The objective of the developed novel method for evaluating the flexibility of building heating is to determine a simple method of comparing heating demand usage for DR with a battery. Additionally, the method provides the possibility of evaluating DR potential in larger groups. The results of this study can be utilized in many applications. Small-scale customers can use the results when making future investment decisions on whether it is better to invest in a DR control system or energy storage system and whether there may be problems if both are used. Service providers can develop their products to sell to customers. Additionally, aggregators who sell incentive-based DR programs to customers can estimate potential DR capacity. The method also provides the possibility of estimating the DR potential of all local electric heating customers within the grid.

For small-scale customers, the possibility of storing surplus PV energy is most important; therefore, the research focus was on this control target. The same flexible capacity can be used for other control targets, e.g., market price-based control or decreasing maximum power with power-based distribution tariffs. The results of this paper can be used to estimate the potential of decreasing the maximum power. Market price-based control is a potential topic for future research because its economic potential is currently very low, particularly with a battery system [27].

Storing surplus PV energy in a building's heat means that the indoor temperature increases temporarily. The thermal features of buildings operate similarly in both directions; therefore, DR operation can be upshifting (e.g., surplus PV energy storing) or downshifting (e.g., decrease in maximum power). Downshifting operations can be effective in scenarios in which consumption is very high owing to very cold outdoor temperatures, and also when maximum power should be limited to avoid local grid reinforcements. This paper also investigates the DR potential of a large local customer group.

This study utilizes simulations. New load profiles for customers were modeled in a simulator and PV production and flexibility options added. Simulations are a good way to study phenomena involving a large number of customers with minimal time and cost. Self-coded simulators provide the possibility of studying novel methods of evaluating DR potential with the minimum amount of information from customers. Modeling simulators for commercial buildings need much more specific information in terms of buildings features.

The remainder of this paper is divided into six sections. Section 2 presents the theoretical background of simulation models and calculations. Section 3 includes the initial input data and introduces the study on customers' DR capacity, and examples are presented for how the coefficients are solved and their effect on DR capacity. Section 4 presents the results of simulations and a comparison between a DR operation and battery system in regard to storing surplus PV energy. Section 5 presents the results of a DR capacity study with a large local customer group. A discussion is presented in Section 6, and the conclusions of the paper are shared in Section 7.

## 2. Components of the Simulation Model

### *2.1. Small-Scale Electrical Energy Self-Production with Solar Panels*

In the simulations in this study, we assumed that detached house customers had small-scale PV energy production systems. PV production depends on geographical location, weather conditions, and time of day and year. Owing to many variables, the momentary power of PV production varies significantly. In this study, PV production was modeled with a mathematical model for the same area in which the studied detached house customers were located and included realistic weather data. A similar PV model was presented earlier in Ref. [4].

#### 2.1.1. Solar Irradiance Model for Tilted Panels

The model of PV production is based on the solar irradiance of a tilted panel in a known location on Earth. Global solar irradiance can be mathematically modeled and it can be divided into three components: the direct beam ($G_{b,i}$), the diffuse component ($G_{d,i}$), and the reflected component ($G_{r,i}$) [28]. Global irradiance is the sum of the irradiance components, i.e., $G_i = G_{b,i} + G_{d,i} + G_{r,i}$. In this paper, the azimuth angle of modeled solar panels is assumed to be 0°, i.e., panels are tilted straight to the south and the angle of inclination β is 45°. Beam irradiance can be modeled accurately if the conditions of the sun are assumed to be constant, and it can be calculated using $G_{b,i} = G_b (\cos \theta_i \;/\; \sin \alpha_s)$, where $G_b$ is horizontal beam irradiance, $\theta_i$ is the angle of incidence onto the surface based on the azimuth angle of the sun, and $\alpha_s$ is solar elevation [29]. Diffuse irradiance on a tilted surface can be calculated using $G_{d,i} = G_d (1 + \cos \beta)/2$, where $G_d$ is the horizontal diffuse irradiance. The reflected irradiance can be calculated using $G_{r,i} = \rho_g\, G\, (1 - \cos \beta)/2$, where $\rho_g$ is the average reflectance of the reflecting surface and G is horizontal global irradiance, which is used because both the beam and diffuse irradiance are assumed to reflect isotropically.

Different irradiance components are modeled with mathematical methods and several competing decent models are available. The Perez All-Weather Sky model was observed to be the overall best model for modeling diffuse irradiance involving Finnish conditions; however, when solar panels were tilted to the south, the Reindl model was better [29]. The Reindl model was used in this paper. The Perez model is introduced in [30] and the Reindl model in [31]. Additionally, in Ref. [32], the Reindl model is considered one of the best diffuse solar irradiance models. The brightening factor ($k_T$) models the cloudiness of the sky, and in the Reindl model, it is modeled using the ratio of horizontal diffuse irradiance to horizontal global irradiance. In this paper, a brightening factor based on cloudiness probability in Finland was used [33].

Reflectance values are used to model reflecting irradiance. Average reflectance has two constant values in year-long simulations. During the winter season (December–April), the average reflectance is set to $\rho_g = 0.58$, which corresponds to the reflectance of snow, because snow is typically on the ground during this period in Finland. At other times of the year, it is set to $\rho_g = 0.24$, which corresponds to the reflectance of dark roofing materials and deciduous trees, which are the materials assumed to be directly adjacent to the solar panels.

#### 2.1.2. PV Production Model

The power of PV production ($P_{PV}$) can be calculated using Equation (1), where $P_{STC}$ is the nominal power in standard test conditions (STC), $\beta_P$ is the solar cell power temperature coefficient (0.006), $T_c$ is solar cell temperature, and $T_{STC}$ is the standard solar cell test temperature (25 °C) [29]. Different types of solar panels provide slightly different power with the same solar irradiation; therefore, the verification coefficient ($C_v$) is included in the equation.

$$P_{PV} = C_v P_{STC} G_i (1 - \beta_P (T_c - T_{STC})). \quad (1)$$

This PV production simulation model was used previously in [27], where it was verified by comparing model values to actual values obtained from polycrystalline silicon PV cells. Modeled PV power was systematically slightly higher than measured power; therefore, $C_v$ is set to 0.85.

#### 2.1.3. Economic Benefits of PV Production

In Finland, the price of electricity includes the price of electrical energy, the cost of distribution, and taxes. When a prosumer sells electricity to the grid, the total price of selling electricity ($C_{s,t}$) is based only on the price of electrical energy. Frequently, the selling price of an energy retailer is slightly lower than the purchase price because the margin of the energy retailer is included in the purchase price, and it is thus removed from the selling price. The total purchase price of electricity ($C_{p,t}$) includes the selling price of the energy retailer, distribution fees, and taxes. The main benefits of PV self-consumption result from differences in the selling and purchase prices, because the selling price is significantly lower than the price that would be paid for electricity if the self-consumed electricity ($E_{PV,sc}$) were to be purchased from the grid. The economic benefits of PV production ($EB_{PV}$) can be formed using Equation (2), where $E_{PV,fg}$ is the PV production fed to the grid:

$$EB_{PV} = C_{p,t} E_{PV,sc} + C_{s,t} E_{PV,fg}. \quad (2)$$

The aim of using flexibility to increase self-consumption is to enhance the economic benefits of PV production. The sum of PV production ($E_{PV,sc}$ + $E_{PV,fg}$) remains the same, but moving the maximal amount of grid feeding ($E_{PV,fg}$) toward self-consumption ($E_{PV,sc}$) increases total benefits. The economic benefits depend strongly on electricity prices and pricing structures. These benefits are not calculated in this paper, but Equation (2) explains the motivation to increase self-consumption.

### *2.2. Energy Storage*

A battery energy storage system (BESS) is a suitable energy storage solution for residential buildings. A BESS is the most flexible method of shifting loads because it can be controlled without depending on any other variable. Only the features and size of the battery affect charging and discharging power and the amount of energy. A high investment cost and poor profitability are the main problems that have hindered the implementation of residential BESSs [27]. The price of lithium-ion (Li-ion) batteries has decreased rapidly, and this trend is expected to continue [34]. The trend of increasing variability in electricity prices will increase the profitability of BESSs in the future [27]. Because the prices of batteries are still high, the other method of shifting loads (DR) will be a good option, whether used alone or with a BESS.

#### 2.2.1. Battery Model

The modeled battery is a Li-ion battery with a lithium iron phosphate (LFP, LiFePO4) positive electron and a graphite negative electrode. This type of battery is excellent for domestic use because of its good safety features, and it has a long cycle and calendar lifetime [35]. The BESS includes a control system, which is implemented via an inverter that requires information from all other components of the system. The battery converter includes a charge controller.

The state of charge (SOC) of the BESS is modeled in Equation (3):

$$SOC_t = 100\frac{E_t}{E_{max}} = 100\frac{B_{eff}B_t}{E_{max}} + SOC_{t-1}, \quad (3)$$

where $E_t$ is the amount of stored energy at time $t$ and $E_{max}$ is the maximum capacity of the BESS. The variable $SOC_t$ is the SOC at time $t$, and $SOC_{t-1}$ is the SOC for the previous time step. Additionally, $B_t$ is the energy transfer to or from energy storage, and $B_{eff}$ is the efficiency of the transfer.

The modeling of BESS losses is a very important aspect in simulations. The efficiency of components affects the losses of the BESS. In this study, the efficiency of the inverter ($\eta_{inv}$) was 98%, and DC converter efficiency ($\eta_{dc}$) was 99%. The losses of the BESS primarily occur in the converters and the chemical reactions of the battery [35]. In this study, the SOC limits of the battery were set at 25%–95%, because losses increase when the SOC is near extreme values [36]. The behavior of battery losses is nearly linear with a limited charge range; therefore, in battery loss modeling, the losses can be assumed to linearly depend on the charging current ($I_c$), assuming that the internal serial resistance ($R_b$) is constant [36]. In this case, charging efficiency ($\eta_c$) can be calculated using Equation (4):

$$\eta_c = 100\frac{V_b - I_c R_b}{V_b}, \quad (4)$$

where $V_b$ is the nominal voltage of the battery. The efficiency $B_{eff}$ in (3) can be obtained by multiplying the efficiencies $\eta_{dc}$, $\eta_{inv}$, and $\eta_c$. The energy transfer to or from storage ($B_t$) is calculated by multiplying the charging current ($I_c$) by the charging voltage ($V_c$), which can be calculated using Equation (5):

$$V_c = V_b - I_c \cdot R_b \quad (5)$$

The battery used in the simulations consisted of cells. A suitable battery capacity and voltage level can be attained by connecting cells in series or parallel. The values used in the simulations of this study were an internal serial resistance of 0.026 Ω, a cell voltage of 3.3 V, and capacity for one cell of 2.5 Ah [37]. The C-rate of a battery describes the ratio of maximum power to capacity. The C-rate in this study was 0.7 C. The effect of the BESS and PV production on the customer's electricity load was modeled using equations from the grid perspective. The energy transition between the grid and customer ($G$) was determined using a model based on the energy transfer to and from the BESS, the building's demand ($D$), and the amount of self-produced PV energy ($P_{dc}$). When the battery was charged, the energy transfer between the customer and the grid could be represented using Equation (6):

$$G = -\eta_{inv}(P_{dc} - B_t) + D, \quad (6)$$

where the value of self-produced PV energy is defined before the inverter. BESS discharge can be calculated using Equation (7):

$$G = \eta_{inv}(-B_t - P_{dc}) + D \quad (7)$$

### 2.2.2. Control of the Battery

When the BESS is used only to increase self-consumption of PV energy, controlling it is very simple. When surplus energy is available and the SOC is under the upper limit, the BESS is charging until either the SOC is at the maximum level or surplus energy is no longer available. It is better to discharge the BESS instantaneously so that the BESS can be ready to receive possible surplus energy in the future. Therefore, if the SOC is higher than the minimum limit and the demand of the customer is higher than PV production, the BESS discharges until either it is empty or PV production becomes higher than the demand.

### 2.3. Demand Response Operation

In this study, DR was implemented via a building's electric heating. The heat of electrical heaters can be stored in the mass of buildings and the air in rooms. Modern houses are better insulated, and they include heat storage, e.g., in concrete floors. If surplus PV production is available, the indoor temperature can be temporarily increased. Alternatively, if total consumption is required to be cut down, the indoor temperature can be temporarily decreased by interrupting the heating load. There are set values for the maximum changes in indoor temperature. Actual exact indoor temperatures cannot be known; therefore, they are modeled. Although this paper's focus is on electrical heating, the same method can be used when studying cooling systems or heating provided by heat pumps, but the efficiency of these other systems must be studied separately.

#### 2.3.1. Electrical Heating Systems and Theoretical Indoor Temperature

The load of electrical heaters depends on the outdoor temperature ($T_{out}$), the value set for the indoor temperature ($T_{set}$), and the stored thermal energy of the building. The building itself is similar to a form of energy storage, where the energy is stored as thermal energy. When $T_{out}$ is lower than the indoor temperature ($T_{in}$), the insulation of the building resists the self-discharge of the storage. Better insulation means lower self-discharge. The quality of insulation is represented by the total heat loss coefficient ($c_f$, W/K) of the building, which is the sum of the heat loss coefficients of different components of the building (roof, floor, etc.). The heat loss coefficient of the building's components can be calculated by multiplying the area ($m^2$) of the components by the thermal transmittance (also known as U-value) of the material ($W/m^2K$). The total heat loss coefficient of the building is defined by how much heating power is required to maintain a stable indoor temperature. A low heat loss coefficient is a valuable feature when pursuing low energy consumption. From the perspective of DR, a low heat loss coefficient means that the necessary flexibility must be obtained elsewhere because the ability to respond to demand is also low.

Buildings have a large mass that can store thermal energy. Heat can be stored in components such as concrete floors; however, all mass in insulations can store thermal energy. When the indoor temperature is constant, the energy stored in the mass does not change and it does not affect heating demand; however, when the indoor temperature changes, this stored energy strongly affects how fast heating demand changes. Every material has its own specific heat capacity (J/kg·K or Wh/kg·K), and when we multiply it by the mass of the material, we obtain the heat capacity of the material. The sum of all heat capacities in a building is the total heat capacity ($c_p$, Wh/K) of the building. A large total heat capacity means that the indoor temperature changes gradually, e.g., after $T_{set}$ changes or during heating power breaks, which are basic operations in DR. Total heat capacity is defined as the capacity to store thermal energy.

Changes in the theoretical indoor temperature can be calculated as follows using a building's total heat loss coefficient and total heat capacity [38]:

$$c_p \frac{dT_{in}}{dt} = E_h - c_f(T_{in} - T_{out}), \tag{8}$$

where $E_h$ is heating power. This equation is derived from Newton's law of cooling. From Equation (8), we can solve the indoor temperature after the DR operation as

$$T_{in}(t) = T_{in}(t-1) + \frac{\Delta t}{C_p}[E_h(t-1) - c_f(T_{in}(t-1) - T_{out}(t-1))]. \tag{9}$$

Equation (9) can be used when modeling indoor temperature in scenarios in which heating power changes. Additionally, Equation (8) can be used when solving total heat capacity ($c_p$) and the total heat loss coefficient ($c_f$). When we have data regarding customer consumption and outdoor temperature, we can calculate $c_f$ when we assume that indoor temperature is constant. Heating temperature ($T_h$) is calculated using $T_h$ = $T_{in}$ − $T_{out}$

$-$ $T_{self}$, where $T_{self}$ is the endogenous temperature from inside the building. It is typical that $T_{set}$ = $T_{in}$ = 21 °C, but the building is required to be heated only when $T_{out}$ < 16 °C, which can be observed when comparing outdoor temperatures and heating demands. This difference results from small heat sources in the building. All electric devices incur heat losses when used, and people inside the building produce heat. $c_f$ is defined using the measurement points $E_h$ and $T_h$, where $T_h > 0$. $c_f$ can be solved using the average value of heating power, which is divided by the heating temperature ($c_f = \Sigma(E_h/T_h)/N$), where $N$ is the number of measurement points. When we do not have exact measurements for heating power ($E_h$), we use measurements of customers' total electricity consumption, though consumption which is in addition to that incurred from heating demand must be considered.

The other coefficient, $c_p$, can be solved similarly to $c_f$, but the difference is that now the change in temperature and heating power is studied over time. In DR operations, it is important to know how fast the indoor temperature changes when we modify heating power. Total heat capacity defines how fast this change is. If we do not have measurements for changes in indoor temperature, we can obtain total heat capacity when we know when and by how much the outdoor temperature changes. The same is applicable for changes in $T_h$ if the changing component is $T_{in}$ or $T_{out}$. $c_p$ can be solved using the equation $c_p = \Sigma(\Delta E_h/\Delta T_h)/N$. The change in temperature and heating power can be increasing or decreasing. For the calculation, we selected hours when $\Delta T_h$ > 0.5 °C. Hours where the change was very small were ignored because this causes more errors than the amount of extra value gained for approximations. Other consumption causes random errors, but the error is minimal when using average values obtained with a high $N$ value. Another reason is that the hysteresis curve for a thermostat, which controls the electric heaters, suffers from a higher amount of error with low temperature changes.

### 2.3.2. Simulation Model for Demand Response in a Heating System

In a DR operation, the indoor temperature is under control. In the simulations, the $T_{set}$ of the building was 21 °C, and the approximation for $T_{self}$ was 5 °C. This was an approximation based on consumption data, in which we noticed that heating demand frequently started to increase when the outdoor temperature decreased to under 16 °C. Additionally, we observed that average daily temperature ($T_{Dave}$) affects heating demand. Even cold nights did not affect heating demand if $T_{Dave}$ was over approximately 10 °C. In the simulations, heating began when $T_{Dave}$ decreased below the building's daily average temperature limit for heating ($T_{Dself}$). This $T_{Dself}$ value varied significantly between customers; thus, it was calculated separately for every customer. The value of $T_{Dself}$ can be determined by adjusting the value such that the amount of decreasing surplus energy is approximately the same as that in increasing self-consumption. With the wrong value, the simulation model does not work, and the simulated heating demand does not follow actual consumption data.

Stored heat is used and thus promptly restores the indoor temperature to the set value for two reasons. First, the system is again ready to receive surplus energy, and second, a higher indoor temperature causes slightly higher heat losses. In simulations, when a customer had a heating demand that was higher than the amount of PV production, the indoor temperature was promptly returned to the set value. Naturally, the total demand must not decrease below zero; therefore, heating demand can only decrease the amount of total load. In some cases, it will require several hours to reach the set value for indoor temperature after the DR operation.

The simulation model calculated the building's $T_{in}$ every hour based on Equation (9) and coefficients $c_p$ and $c_f$. The indoor temperature is assumed to be constant when either DR operations are not used or the outdoor temperature does not increase significantly. In summer, the outdoor temperature can become high even for long periods, which increases the indoor temperature. This is problematic for DR operations when they are used for storing surplus energy. High solar power production and high outdoor temperatures are timed similarly, and there is naturally no heating demand where the surplus energy can be stored. When outdoor temperature increases to such a high value that $T_h$ is negative, the indoor temperature increases based on Equation (9), and it can increase to very high values in simulations. In practice, customers may have cooling systems that decrease indoor temperatures and thus use some of the surplus energy in the process. These considerations are not involved in DR simulations because this demand can already be observed from the load profile and using the surplus energy to heat the building at the same time it is being cooled by the cooling system is pointless. Thus, the indoor temperature during the hot season demonstrates the building's potential to store heat more than it does the actual indoor temperature that customers can experience. Without the cooling system, the simulated indoor temperature corresponds to the actual indoor temperature, and when it is high, there is the potential to increase PV self-consumption with a cooling system.

### *2.4. Combination of Demand Response and Battery Energy Storage Systems*

In simulations, DR operation and a BESS can be combined. These systems compete for the same surplus PV energy; therefore, it is assumed that these decrease each other's benefits. The combination is performed in two ways. First, DR is the primary operation, and if surplus energy remains, the BESS functions as a secondary operation. The other version is the opposite, where the BESS is the primary operation and DR is the secondary operation. In combined control simulations, the secondary operation does not affect the primary operation.

### *2.5. Calculations with the Simulation Model*

The simulation model was formed by using MATLAB® code. Simulations utilized real hourly consumption data from customers and simulated new consumption profiles with the used components. The simulation period was an entire year. For the DR model, the total heat loss coefficient and total heat capacity were calculated separately for each customer. These coefficients were utilized in DR simulations where new customer consumption profiles were simulated with limited indoor temperature changes by using Equation (9). In BESS simulations, the new customer consumption profile was simulated by utilizing SOC changes in the BESS via Equation (3). Modeled PV production in simulations was calculated in hourly resolution from the results of Equation (1). The simulation model consists of many components which are modeled by using several references. Used methodologies are verified in the references. The code used for the simulator was carefully checked and tested before simulations.

## 3. Initial Data and Heating Coefficients

### *3.1. Electricity Consumption Data*

The study group consisted of 1525 customers in Finland. Customers were selected from a larger group (8078 customers) of one distribution system operator (DSO)'s customer base who had temperature-dependent loads, which means that they used electric heating systems. Temperature dependency is an important component that ensures these customers are suitable for studies involving the simulation of DR operation with electric heating. K-means clustering was used to select customers for this study group [39].

Consumption data were measured using the DSO's smart meters, and the same data were used when invoicing customer consumption. The data were measured in 2015, and consumption was metered hourly. We obtained 8760 data points from every customer, which were values for energy consumption per hour (kWh). Measurement accuracy was 0.01 kWh. The customers were located in rural areas or small towns in inner Finland. To protect the privacy of customers, the data are not being made public.

Additionally, data from one Finnish electrical heated detached house includes measurements for model validation that were made in 2022. Hourly measurements from the DSO's smart meters were used. For validation, indoor temperature was measured for a short time period.

### 3.2. Weather Data

Openly available data from the Finnish Meteorological Institute (FMI) were used for outdoor temperature data [40]. Temperature measurements were obtained for the area where the study group customers resided. Measurement accuracy was 0.1 °C. When the temperature is not measured immediately around the building, this causes an error in the results as there could be differences in temperature between locations even when they are very near to others. Nevertheless, the very accurate measurements of the FMI provided useful information about the temperature in the studied area.

### 3.3. Total Heat Loss Coefficient

Coefficients (total heat loss coefficient and total heat capacity) were defined separately for every customer. Figure 1 shows energy consumption per heating temperature throughout a year for one random customer. We can observe that the value was within a very narrow range in the heating season. There was no heating demand in the summer; therefore, the value decreased to zero. In spring and autumn, when the heating temperature was low, the range was higher because the weight of other consumptions increased. Consumption other than heating and daily changes in the load profile explain variations in the heating season. Consumption other than heating led to systematically higher total heat loss coefficient values. In Figure 1, the green line indicates the average value of the entire year, and the red line indicates the average of the heating season. The average value of the entire year was used in simulations because it better represents a base level of heating consumption. The load profiles of customers included all forms of consumption; therefore, other demands can be considered in addition to basic heating load, and from the perspective of this study, they are positive errors. For example, the total heat loss coefficient of 0.1 kW/K means that a 10 °C heating temperature causes an approximately 1 kW heating demand on average.

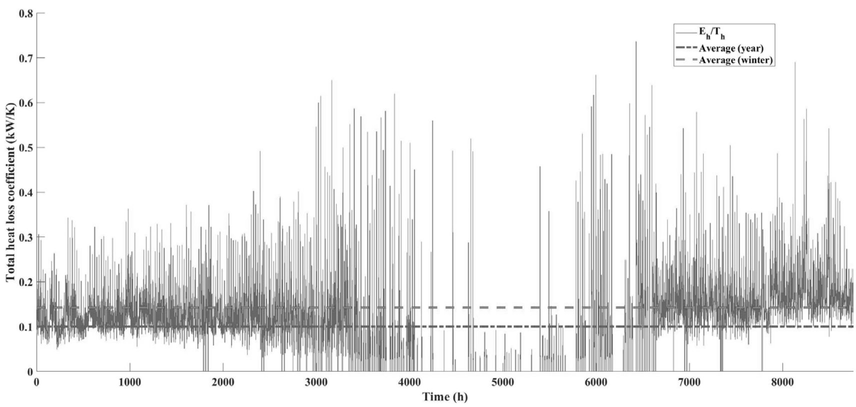


**Figure 1.** Total heat loss coefficient of a random customer. Heating time (winter) is outside of the June–August period (hours 3624–5808).

Figure 2 shows the calculated total heat loss coefficients for all customers. A few customers had a total heat loss coefficient that was very high or very low, but the value was approximately 0.1 kW/K for most customers. The average value of the total heat loss coefficient was 0.0937 kW/K for the entire group. Frequently, the heat loss of a building is calculated separately for each component. The size and materials of a building affect total heat loss. A very high total heat loss coefficient can be the result of a very large building or poor insulation. Some households in the study group could have had large sheds with poor insulation that were heated electrically. A very low total heat loss coefficient can mean that a building is very small with very good insulation and can also be the result of some buildings having their basic heating implemented in a manner that does not rely on electrical heating (though they may have some extra electrical heating). Extremes are rare and approximately 91.5% of customers' total heat loss coefficients were in the range of 0.03–0.16 kW/K.

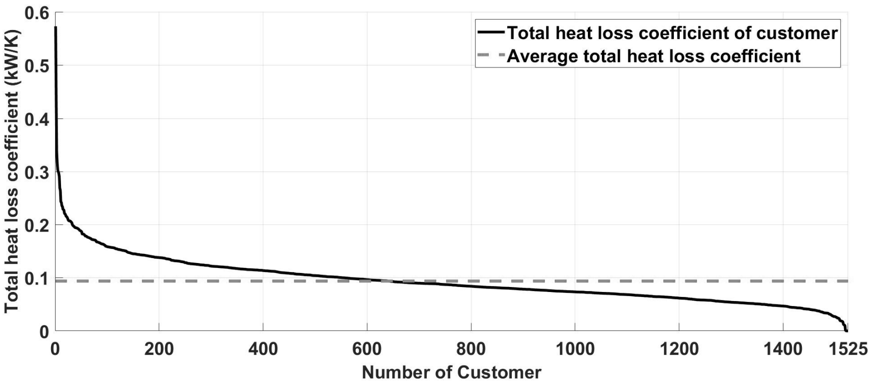


**Figure 2.** Total heat loss coefficients of customers in the study group.

### 3.4. Total Heat Capacity

Figure 3 shows the distribution of total heat capacity for a random customer. Every data point represents the change in consumption divided by the change in temperature over the same hour. Blue marks indicate a negative change, when consumption increased owing to decreasing outdoor temperature, and red marks indicate a positive change when consumption decreased due to increased outdoor temperature. Additionally, Figure 3 shows the average values of negative and positive changes and the average value of all changes, which were used as the total heat capacity of a customer in simulations. The variation was observed to be high. In summer, many low values caused high temperature changes with low heating demand. High values for the entire year were the result of changes in other forms of consumption with low outdoor temperature changes. The average value of the positive changes was slightly higher than the average value of negative changes because the increasing heating load caused higher heat loss. The average value of both changes provided a good estimate of the customer's total heat capacity. A total heat capacity of 1 kWh/K meant that the building could store as much heat as approximately 4800 kg of concrete.

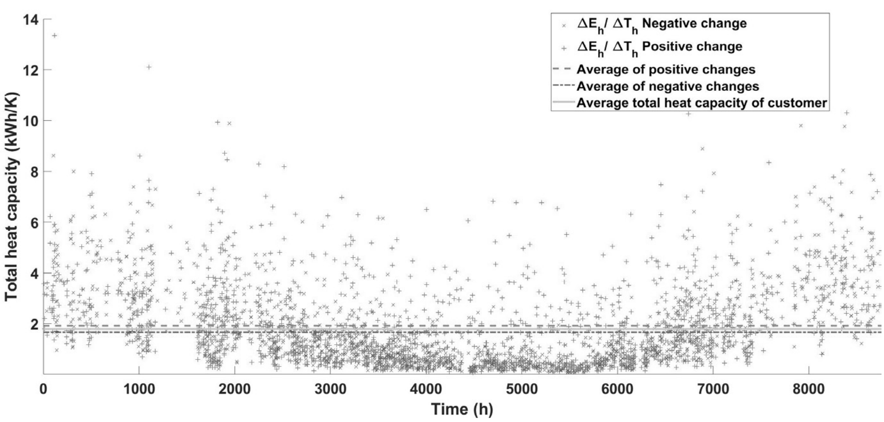


**Figure 3.** Distribution of total heat capacity for a random customer.

The total heat capacities of all customers in the study group are shown in Figure 4. The average total heat capacity of all customers was 1.7184 kWh/K. A few customers had very high total heat capacity and a few customers had very low total heat capacity. The majority, approximately 91.5% of customers, had a total heat capacity between 0.6 and 3.0 kWh/K. Total heat capacity values primarily depended on the size of the building and the construction materials used.

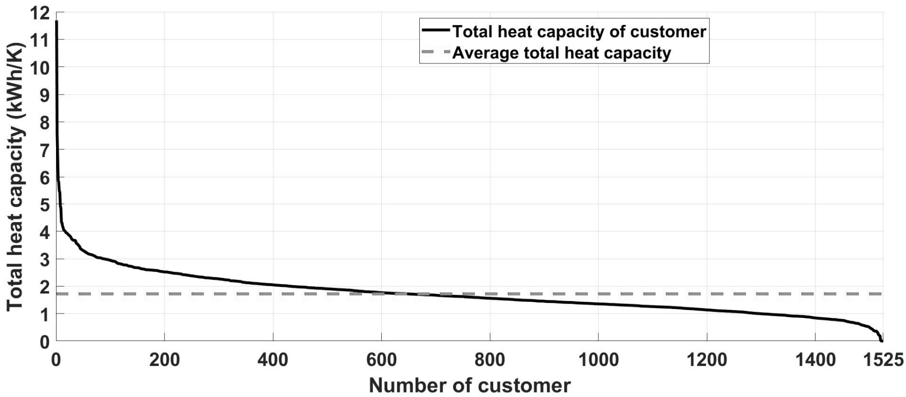


**Figure 4.** Total heat capacity for customers in the study group.

A building's total heat capacity depends strongly on its total heat loss coefficient, as shown in Figure 5. In most cases, both coefficients changed by the same proportion. In Figure 5, the linear regression line is indicated, which intersects the average total heat capacity line and average total heat loss coefficient line at the same point. Customers whose points are above the regression line had higher heat capacity in proportion to heat loss than average, e.g., modern well-insulated buildings have very low heat losses as they have a large mass that can store heat. A couple of surprising observation were that the calculated points were near the linear regression line and variation was very low, although the study group included buildings of different ages. The calculations indicate that all buildings with electrical heating have DR potential despite age or building type.

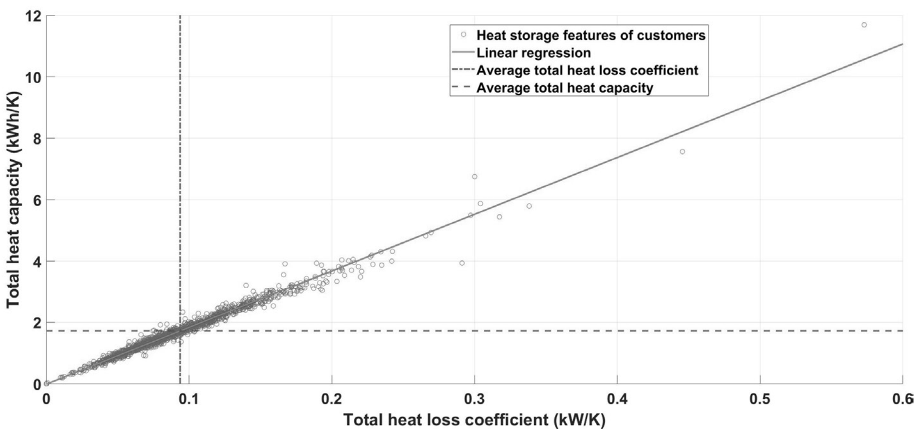


**Figure 5.** Customer heat storage features for demand response operations.

### 3.5. Example Case for Storing Surplus Energy in a Building

To demonstrate DR operation, we simulated a week's data (2–8 March) for a random customer with a 3 kWp PV system, and the results are shown in Figure 6. The blue line shows the customer's electricity consumption, and the red line shows PV production, which was negative because it has a decreasing effect in terms of total load from the grid's perspective. The yellow line is the total load, taken from the sum of consumption and production. We observed that the grid was fed for six days of the week, and this should be avoided for economic reasons. The outdoor temperature varied between −1.2 and 6 °C during the week. The random customer's total heat loss coefficient was 0.1 kW/K and total heat capacity was 1.7859 kWh/K, i.e., very close to average values. The green line shows total load after the DR operation when all surplus energy was stored in the building's indoor heat. During this period, the indoor temperature varied between 21.00 and 21.76 °C, i.e., all surplus energy could be stored with a maximum increase in indoor temperature of only 0.76 °C. During this week, 6.59 kWh of surplus energy moved from grid feeding to self-consumption.

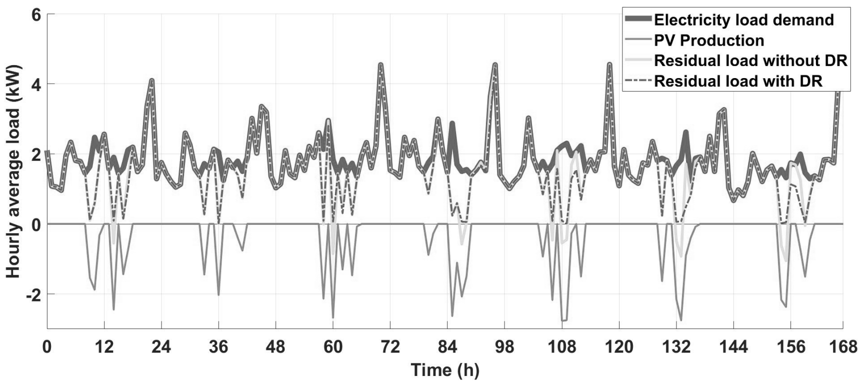


**Figure 6.** Storage of a random customer's surplus energy within the building over the course of a week.

### 3.6. Validation of the DR Model

Indoor temperature changes in DR operations were calculated as presented above. For validation, the changes in indoor temperature were measured in one typical electrically heated detached house in Finland. From the electricity consumption of this customer, the total heat loss coefficient was defined as 0.1273 kW/K and total heat capacity was defined as 2.4559 kWh/K. These values are slightly higher than in average buildings but are still close to the values of the main group of customers, as seen in Figure 5. The validation test was performed two times. In day 1, the test was timed so that electric heating was interrupted between 18:00 and 19:00, and in day 2 the period was 14:00–15:00. Indoor temperature was measured an hour before the interruption and two hours afterwards in 10 min intervals. Figure 7 presents the modeled and measured indoor and outdoor temperatures during the test period, so the interruption is timed between 1:00 and 2:00. In day 1, the outdoor temperature was about −6 °C, and in day 2 it was around 0.5 °C. During these periods, there was a lot of other electric consumption that may have led to errors in modeling, and there were also other possible error sources such as outdoor openings which could thus affect indoor temperatures. Considering these error sources, the measured indoor temperatures follow the modeled indoor temperatures very well. This validation proves that the introduced simulation model also works in practice.

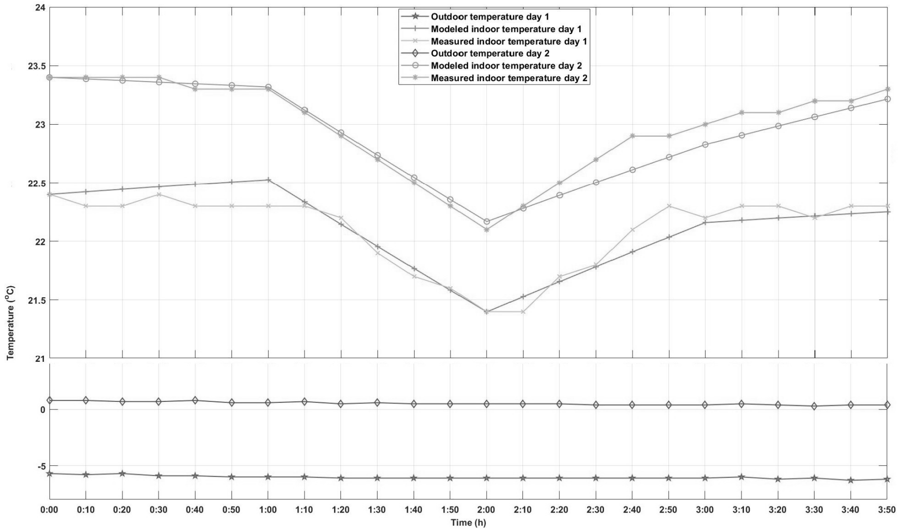


**Figure 7.** Validation of the DR model with temperature measurements. Scaling of the y-axis is divided in two different areas to show changes in values.

## 4. Simulations of Increasing PV Self-Consumption

### *4.1. Variable: Increase in Self-Consumption*

With simulations, we studied the benefits that could be obtained with DR operations and the size of the BESS required for the same level of benefits. Additionally, we studied the possibility of using DR and a BESS together in the same building. The important question is whether the two technologies are competing against each other. To compare these technologies and their benefits, the increase in self-consumption (kWh) per year was a key variable. This was calculated as the average value of the decreased energy sold to the markets and the decreased energy purchased from the markets. Not all decreased energy sold to markets decreases the energy purchased from markets, as some of the energy is lost in heat losses in the DR operation. Therefore, the average value was the studied variable.

The increase in self-production is also a useful variable for studying BESS operations. The use of a BESS results in losses; therefore, the average value must be used, similar to DR. Because this variable is similar for both technologies, it can be used for comparison. We can first calculate the increase in self-consumption for DR operation and then determine the size of the BESS when the increase in self-consumption is similar.

### *4.2. Demand Response for Increasing Solar Power Self-Consumption*

DR operations were studied with two different sizes of PV systems, which were 3 and 6 kWp. These sizes correspond to the typical sizes of PV systems in detached houses [4]. The smaller 3 kWp system is a traditional size in which grid feeding is avoided, and the larger 6 kWp system is an economically optimal size for PV systems. The exact optimal size must be determined separately for every customer using an electricity pricing model, but a constant size was used to make the results comparable. Two different levels of DR operations were studied: the indoor temperature could increase by a maximum of either 1 or 2 °C from a basic level of 21 °C. The results are presented in Figure 8, where customers are arranged in order of size according to the increase in the self-consumption. A few customers had a much higher increase in self-consumption than others, but the majority of the study group had very similar results.

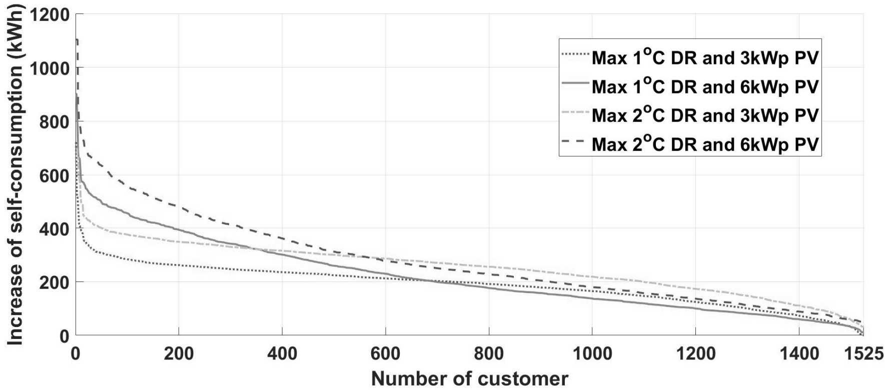


**Figure 8.** Effect of total heat capacity on customers' increased self-consumption at two different levels of DR operation and with two different PV panel sizes.

The average yearly increase in self-consumption with 3 kWp PV panels was 187.5 kWh with a maximum DR of 1 °C and 252.5 kWh with a maximum DR of 2 °C. When a 6 kWp PV system was used, the average values were 217.6 kWh with a maximum DR of 1 °C and 273.4 kWh with a maximum DR of 2 °C. The shapes of the curves in Figure 8 show that a group of customers (approximately 600 customers) received higher benefits from the DR operation with the 6 kWp PV system than with the 3 kWp PV system. These customers' load profiles facilitated the storage of surplus energy from the larger PV system as heat in the building. Other customers could not receive higher benefits from DR with a larger PV system. The increase in self-consumption for these customers was lower with the 6 kWp PV system than with the 3 kWp PV system because the larger PV system resulted in lower consumption in the load profile, which could thus be fulfilled from the stored heat. For clarification, Figure 9 shows annual PV production with 3 kWp and 6 kWp systems and customers' total consumption when they are ordered similarly to how they are in Figure 8. Total consumption affects the increase in self-consumption, but there is also a lot of variation because the customers' thermal coefficients and load profile affect the results.

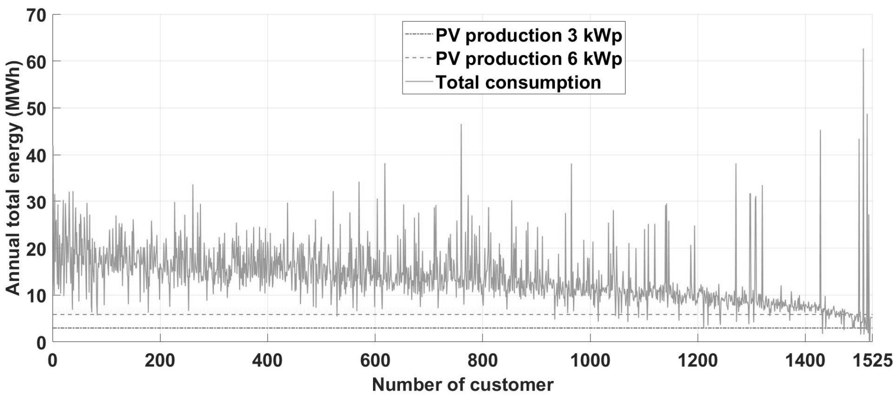


**Figure 9.** Annual PV production with 3 kWp and 6 kWp systems and the total consumption of customers. Customers are in the same order as they are in Figure 8.

When the DR limit increased from 1 to 2 °C, all customers gained more benefits with both PV sizes, but the increase due to a 2 °C increase was much lower than that of a 1 °C increase. The increase in self-consumption from the 2 °C increase was only 0.35% with the

3 kWp PV system and 0.26% with the 6 kWp PV system when compared to the increase in self-consumption that resulted from a 1 °C increase. When indoor temperature variation increased, it caused more discomfort for customers and the increase in benefits decreased; therefore, the limits for indoor temperature variation must be selected wisely.

We studied the effects of the features of customers' buildings on the increase in self-consumption. Figures 10 and 11 show the same results, but the x-axis shows the customer's total heat loss coefficient in Figure 10 and the customer's total heat capacity in Figure 11. Both features affected increases in self-consumption in a similar manner. An approximately 0.1 kW/K total heat loss coefficient and 2 kWh/K total heat capacity were the limit values that divided customers into those who received higher benefits from DR operation with the larger PV system and those who did not. The results indicated that the higher total heat loss coefficient and higher total heat capacity provided customers with higher benefits from the DR operation, though limits existed at which benefits no longer increased. A small group of customers obtained clearly higher benefits from the DR operation with a low total heat loss coefficient and low total heat capacity. These customers had low base consumption but repeated high load peaks, which caused systematic errors in the simulation results.

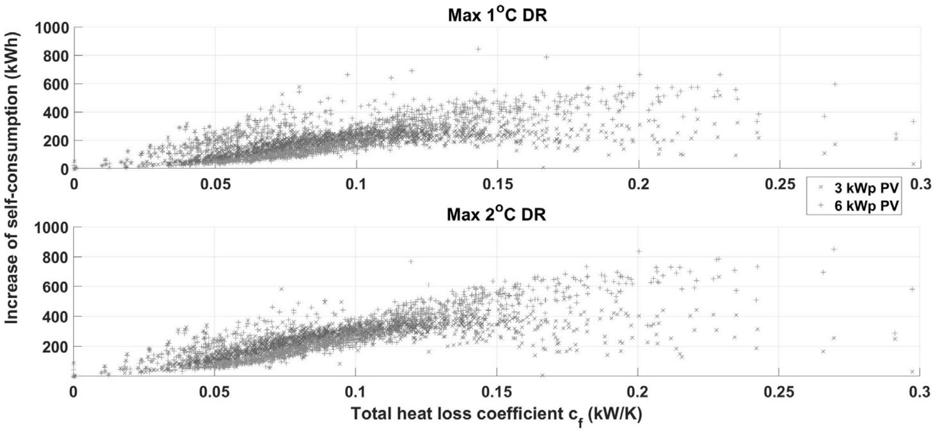


**Figure 10.** Effect of total heat loss coefficient on customers' increase in self-consumption at two different DR operation levels and with two different sizes of PV panels.

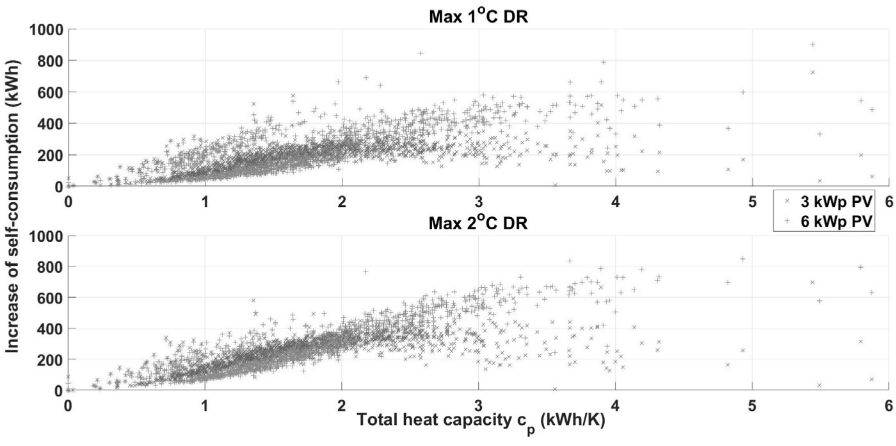


**Figure 11.** Effect of total heat capacity on customers' increase in self-consumption at two different DR operation levels and with two different sizes of PV panels.

### 4.3. Comparison of Demand Response and Battery Energy Storage

The results of the DR operations indicated the value of the increase in self-consumption, and the aim of the BESS simulations was to determine the size of the battery when the increase in self-consumption was similar to that of the DR operation. The initial battery size was set to 100 Wh and if the increase in self-consumption was lower than that of the DR operation, the size of the battery was increased in 10 Wh increments until the increase in self-consumption was a maximum distance of 5 kWh away from the value of the DR operation. The results for all four cases are shown in Figure 12. A few customers required a higher storage capacity to reach a similar increase in self-consumption to that of the DR operation, but the main research group required only a very small storage capacity in this regard. The average values for battery sizes corresponding to DR operations were a maximum of 1 °C DR and 0.83 kWh when the PV system size was 3 kWp and 0.65 kWh when the PV system size was 6 kWp. Under DR operations, the indoor temperature could increase by a maximum of 2 °C, and the average values were 1.67 kWh with the 3 kWp PV system and 0.91 kWh with the 6 kWp PV system. The smaller PV system required a higher BESS capacity on average to reach a similar increase in self-consumption to that achieved with DR. The reason for this is that the BESS must use a large amount of energy with the 3 kWp PV system to reach the set increase in self-consumption because the amount of surplus energy isa low. With the 6 kWp PV system, the amount of surplus energy is large, and the BESS could thus be used efficiently.

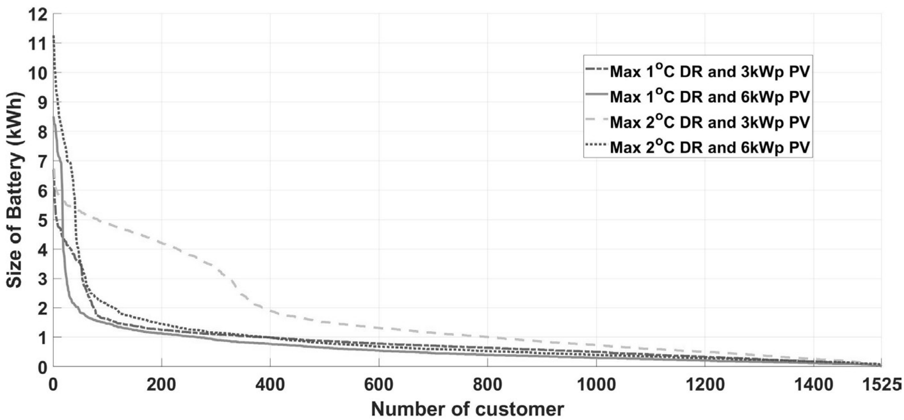


**Figure 12.** Battery sizes required to provide the same increase in self-consumption to that of DR operations at two different DR levels and with two different PV panel sizes.

The curves of these cases appear to be very similar, except in the case of a maximum of 2 °C DR with the 3 kWp PV system, which is quite different to the others. This inconsistency required further close study. Therefore, Figure 13 shows the results for battery size (x-axis) and increases in self-consumption (y-axis), which was used to define the battery size. We can observe that with a maximum of 2 °C DR and a 3 kWp PV system, a large group of customers required high battery capacity (3–6 kWh) to reach an approximately 300–400 kWh increase in self-consumption. These values representing increases in self-consumption were the maximum values for these customers that could be reached with the BESS or DR, and this value was more difficult to attain with BESSs because BESSs cause more losses than DR. In simulations, DR caused only negligible losses with a maximum 1 °C and maximum 2 °C indoor temperature change, while BESSs caused significant losses. These customers were not valid for the comparison study between DR and BESSs with the 3 kWp PV system, but this result indicated the importance of sizing the PV system and the BESS correctly for the load profiles of customers. Additionally, Figure 13 shows that the increase in self-consumption increased rapidly when the size of the battery increased, but there was a clear limit at which the increase stopped. With the 3 kWp PV system, this limit was approximately 200–400 kWh, and with the 6 kWp PV system, it was approximately 500–700 kWh. Most customers could reach this limit with a very small BESS size. With the 3 and 6 kWp PV systems, the BESS size was approximately 1 and 2 kWh, respectively. These results show that, for sizing the BESS, the 2 kWh capacity is suitable in most cases.

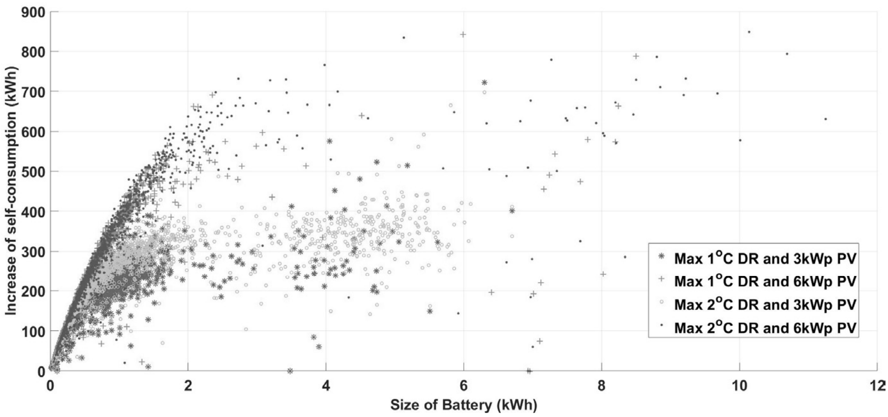


**Figure 13.** Battery sizes which provide the same increase in self-consumption as DR operations at two different DR levels and with two different PV panel sizes.

*4.4. Using Demand Response and Battery Energy Storage Together*

One of the main research questions in this study was whether the DR and BESS operations compete against each other. Is it possible to use both controls simultaneously such that one does not impair the other's potential? The use of DR and BESS together was studied with a 2 kWh BESS and a DR operation in which the indoor temperature could change by a maximum of 1 or 2 °C. This combination can be implemented by using the DR operation as the primary control and then using the BESS under surplus energy as the secondary control, or vice versa. The potential of DR depends on the demand for heating power; therefore, the DR is only rarely available. If the BESS is the primary control, the amount of time slots where DR can be used can decrease, and if the DR operation is primary, the possibilities for using the BESS can decrease. It is very interesting to compare which primary control is more disadvantageous than the other. The results of these combination simulations can be compared to the sum of results from separate simulations of DR and BESS operations.

The results of the comparison are presented in Figures 14 and 15, which show the results for a maximum 1 and 2 °C DR, respectively. Two different PV system sizes (3 and 6 kWp) were used; therefore, the initial settings formed four different variations (two DR levels and two PV sizes). With every variation in settings, we simulated four different cases: primary controls with DR and a BESS and the secondary controls of both. The secondary controls were simulated using the results of primary controls as the initial load profile. Thus, in the results, the combination controls were the sums of the results from the primary and secondary controls. The case in which DR was primary and the BESS secondary is denoted as DR&BESS, and the case in which the BESS was primary and DR secondary is denoted as BESS&DR. For comparison, the sum of both primary controls DR+BESS, which represents the theoretical maximum, is also shown.

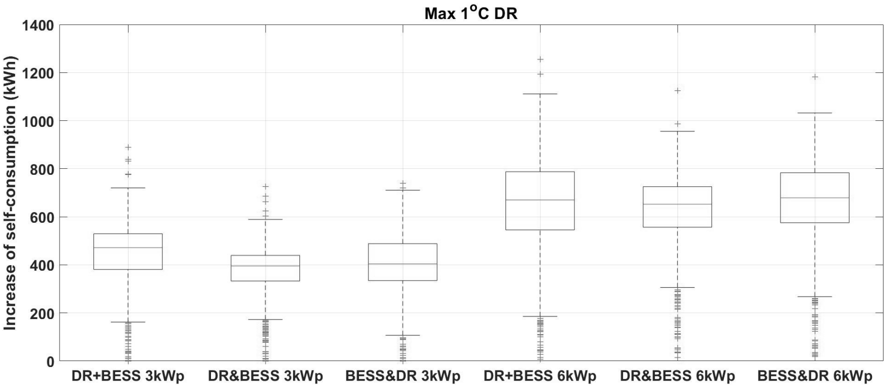


**Figure 14.** Comparison boxplot of customers' increase in self-consumption with a maximum 1 °C DR and a 3 or 6 kWp PV system. The results from both (BESS and DR) separate controls are summarized as DR+BESS, combined controls where the DR is the primary control and the BESS is the secondary control are summarized as DR&BESS, and combined controls where the BESS is the primary control and DR is the secondary control are summarized as BESS&DR. The boxplot shows the median, and the bottom and top edges of the box indicate the 25th and 75th percentiles, respectively.

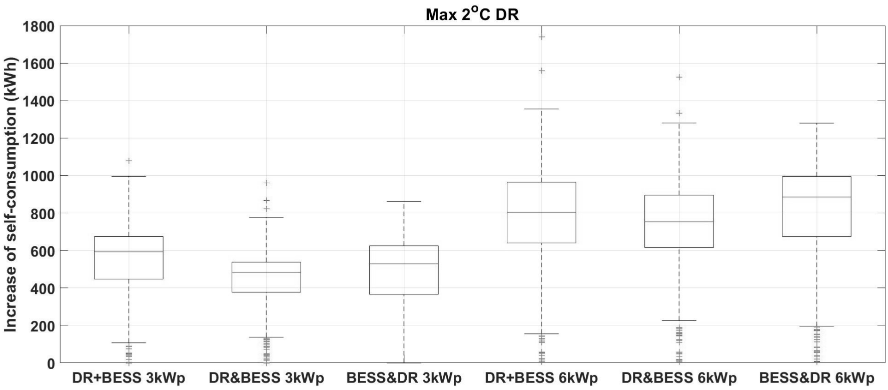


**Figure 15.** Comparison boxplot of customers' increase in self-consumption with a maximum 2 °C DR and a 3 kWp or 6 kWp PV system. The results from both (BESS and DR) separate controls are summarized as DR+BESS, combined controls where the DR is the primary control and the BESS is the secondary control are summarized as DR&BESS, and combined controls where the BESS is the primary control and the DR is the secondary control are summarized as BESS&DR. The boxplot shows the median, and the bottom and top edges of the box indicate the 25th and 75th percentiles, respectively.

The results from all cases and variations in settings clearly show that DR and BESS operations can be used together. When the PV system size was 3 kWp, the combination controls produced a lower increase in self-consumption than the sum of separate controls, but the difference was very low. When the size of the PV system doubled to 6 kWh, the differences were even lower because more surplus energy was then available. A surprising result was that with a maximum 2 °C DR level and 6 kWp PV system size, the combination BESS&DR had an even higher median value than the sum of separate controls. The reason for this was the limitations placed upon the DR operation. The capacity and requirement for DR operation was constantly changing when the outdoor temperature and PV production changed continually. The same fluctuation in indoor temperature resulted in different increases in self-consumption when the BESS operation was performed first and a large amount of surplus energy remained, and the required DR operations may be more suitable from the perspective of increasing self-consumption than cases without the BESS. This enables some cases of the BESS&DR combination to produce a higher increase in self-consumption than the theoretical summation of both controls (DR+BESS). Even the exact increase in self-consumption depends on the load profile of the customer; these results show clearly that if DR and BESS operation are used simultaneously, it is better to use the BESS as the primary control and DR as the secondary control.

## 5. Analysis of Demand Response Potential in the Grid

In the simulations, we studied individual customers' potential to store surplus PV production through DR or BESS operations. Additionally, the presented method enables us to evaluate DR possibilities in large groups of customers. If customers' DR potential were centrally controlled, it could be utilized for everyone's benefit, e.g., a DSO could avoid high peaks or an energy retailer could shift load to cheaper hours. There are two main questions for the DR potential of the customer group. First, how much flexible power is available? Second, how long can the load flex? The heating power of flexible buildings depends on the outdoor temperature; thus, it varies significantly. Figure 16 shows the total hourly heating power of the entire 1525 customer group, which is the flexible power that can be cut in a centrally controlled DR operation if required. This depends on the outdoor temperature; therefore, the temperature limits are presented in Figure 16. In the geographical area where the studied customers lived in 2015, there were 1960 h where the outdoor temperature was below 0 °C, and the heating power of the study group was at least 2.3 MW. This is the power that can be cut by interrupting electric heating in these buildings. For the coldest hour of the year, heating power was 5.7 MW, which was the maximum DR capacity.

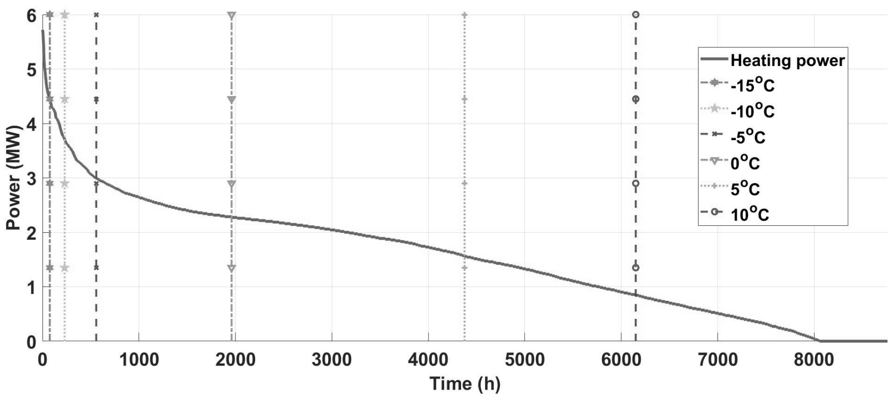


**Figure 16.** Total heating power of all 1525 customers in the study group for every hour of the year in descending order with six dashed lines corresponding to different outdoor temperatures.

The question of how long the heating load could be interrupted also needed to be answered. This question was answered by studying the decreasing indoor temperatures in the studied buildings. The initial temperature was set to 21 °C in all buildings, and the heating was then interrupted for an hour. Figure 17 shows the percentage of customers that could allow their heating power to be interrupted without the indoor temperature decreasing by more than the DR limit at any hour of the year. There were four DR limits, which were 2, 1.5, 1, and 0.5 °C. If indoor temperature decreased by a maximum of 2 °C, there were 8535 h of the year where 100% of customers could tolerate a maximum of an hour of heating power interruption. This also means that only 225 h in 2015 were very cold (under −15 °C), and that only some customers' indoor temperature decreased by more than

2 °C during the hour-long heating power interruption. If the DR limit is tighter, the amount of hours where all customers can tolerate heating power interruption is much lower.

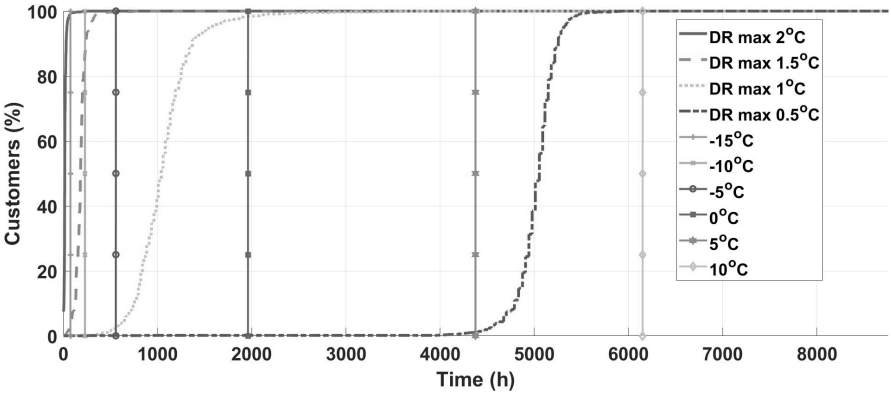


**Figure 17.** Percentage of customers whose indoor temperatures do not decrease by more than the DR limit (2, 1.5, 1, and 0.5 °C) during an hour-long heating power interruption. The hours of the year are sorted in ascending order by outdoor temperature and the six vertical lines correspond to different outdoor temperatures.

Figure 17 shows that when the outdoor temperature is very cold, a customer's indoor temperature can decrease rapidly. However, approximately 7% of customers were able to tolerate an hour-long heating power interruption (less than a 2 °C decrease in indoor temperature) during the coldest hour of the year. When the results in Figures 16 and 17 are examined together, we can observe when flexibility is available with different DR limits. If the DR limit is a maximum of 1 °C for an outdoor temperature of 0 °C, approximately 2.3 MW of flexibility is available; however, when the outdoor temperature decreases, the amount of flexibility decreases rapidly (even when heating load increases), as customers do not tolerate any more interruption to heating power.

## 6. Discussion

The motivation for this study was a comparison between DR operations and battery operations. The approach toward studying DR operations implies that studies with few modeled buildings are insufficient in terms of sample size. In battery operations, the load profile of the customer is strongly affected; therefore, variations in load profiles must be widened in research. This approach provides a novel method for studying the DR potential of a large study group. This method requires only weather and consumption data, which makes it very useful. Knowledge of customers' heating systems or building sizes or types is not required. Aggregators who offer DR operation services can approximate the DR potential of customers using this method. This method is also very useful for researchers because it facilitates many future studies, e.g., coefficients of customers' heating features could be used to form load forecasting models or approximations of the DR potential of all buildings in a studied area. Coefficients defined from historical data can be used for forecasting customers' heating load with forecasted temperatures.

In this study, the comparison of DR and battery operations focused only on increasing PV self-consumption, and only heating demand was used in the DR operation. These two selections were made for multiple reasons. Increasing PV consumption is the most used control target for batteries and is available to most customers, while also being more profitable in most cases [41]. Additionally, the combination of different control targets causes a loss of benefits due to inaccurate load forecasts. The use of different control targets is a topic that could be explored in future research.

DR operations have multiple load types that can be used. In many studies, domestic hot water boilers have been controlled by DR operations, e.g., in [17]. It is a natural target for DR operations because it includes thermal storage with a known capacity, and heating requirements can therefore be modeled. It is widely studied, and this possible DR capacity must be remembered when analyzing the results of this study. However, only the total consumption of customers is widely metered, and the load of a hot water boiler is one part of these measurements. These loads do not follow the outdoor temperature and depend on the customer's behavior, such as the use of other devices, washing machines, or electric saunas, which are also good objects for a DR operation. Therefore, the electric heating of a building is the only target for a DR operation that can be directly detected from total consumption measurements, which is achieved by comparing consumption and temperature measurements.

Only customers whose consumption followed the outdoor temperature were selected in the study group because these customers were known to use electric heaters. No exact knowledge was derived regarding customers' heating systems; therefore, this group could also include customers with electric heaters that are used as secondary heating systems, e.g., heated floors in wet rooms. This could result in a scenario where, if secondary heating is under DR operation, the primary heating system compensates for it. Additionally, customers with electric heaters as their primary system could have a secondary system, e.g., a fireplace. These can cause errors in results, but because the proposed method examines the load profile of an entire year, the effect of these errors is minimal. If a customer systematically uses another heating source when the outdoor temperature is very low, the method observes this, and the coefficient of heat loss decreases; thus, it is indicated in DR capacity approximations.

The indoor temperature of buildings is modeled and does not correspond exactly to the actual indoor temperature. Many behaviors by customers affect indoor temperatures (e.g., door openings), and not every customer sets their indoor temperature to 21 °C. Therefore, these factors cause errors in the results. In DR simulations, the changes in customers' heating loads are adjusted such that their measured load profile follows the changes in indoor and outdoor temperature. Hence, the modeled indoor temperature is only a variable in simulations, and it does not correspond exactly with the actual indoor temperature level. Only the changes in indoor temperature are relevant. When the number of measurement points is high (8760 per year) and errors occur in both directions, the errors can be minimized in the long term by using mean values.

The proposed method is based on direct electric heaters where heating load depends linearly on the outdoor temperature. Direct electric heaters are controlled by a thermostat. The hysteresis curve of thermostats causes lag for heaters reacting to changing temperature. This lag causes errors when defining the total heat capacity of a building because the response of electric heaters is slow. This error is minimized by using only hours where temperature change is high, because then the effect of lag is negligible with a simulation time step of one hour. If customers have heat pumps, dependency between outdoor temperature and heating load is no longer linear because of heat pumps' temperature-dependent efficiency. If this method is used with heat pump customers, the heating load indicates the direct thermal heat energy demand of the customer, and the efficiency of the heat pump must be considered as a correlation coefficient.

On a large scale, DR capacity is an interesting aspect when high flexibility is required, e.g., when large power plants rapidly disconnect from the power grid. The use of reserve power plants can be avoided if customers can be flexible in these scenarios and decrease their consumption. The present study demonstrates how long 1525 customers were able to be flexible in these scenarios and the degree of flexibility they had. These customers were grouped in an area containing a total of 8078 customers. This means that approximately 19% of the customers in this area were able to implement this flexibility. In the heating period, DR potential varies hourly from 15% to 30% of the total consumption of all customers (average of approximately 20%), i.e., the DR potential of electric heaters can rapidly cut approximately 20% of the total consumption of all customers. The percentage varies hourly owing to changes in the outdoor temperature and total consumption. The statistics from 2020 show that Finland has 589,106 electrically heated buildings, which means approximately 38% of all buildings [42]. Therefore, small-scale customers can develop high DR potential in Finland.

Although this study was conducted with Finnish data, the results are applicable anywhere electric heaters are used to heat buildings. Additionally, the method for obtaining the heating coefficients of buildings can be used with cooling systems. If electricity load follows the outdoor temperature, this method can be used to approximate a building's capacity for storing energy in cold as well as hot conditions.

## 7. Conclusions

The DR features of electrical heating systems in small-scale residential buildings can be determined from electricity consumption data. The total heat loss coefficient and total heat capacity are the key coefficients when studying the effect of heating load DR on a building's indoor temperature. These coefficients can be estimated by comparing outdoor temperature and a building's consumption data. Without knowledge of a building's actual indoor temperature, the coefficients can be estimated by comparing changes in outdoor temperature and customers' load profiles. This novel method uses changes in loads and outdoor temperatures over time as they are the same for mathematical models of thermal features with changing variables for indoor or outdoor temperatures (the effective variable is the difference between them).

The presented novel method for evaluating the DR possibility of electric heating fulfils the outlined objectives. The advantages of the method are that it is simple and requires only minimal information. It is suitable for quickly evaluating the DR potential of large customer groups. Earlier methods need specific information about the thermal features of a building's materials, and these methods provide a rough estimate which should verified afterwards. These methods are well suited to new buildings. The presented novel method is not suitable for new buildings because history consumption data are needed. This novel method is very effective with old buildings and makes it possible to evaluate the existing building stock.

The DR operation of an electrical heating load or a battery can be used to increase PV self-consumption. The capacity of a DR operation is quite low for individual small-scale customers, and its effectiveness corresponds to battery capacity. Most of the benefits can be obtained from the flexibility acquired with one degree temperature changes, and when the indoor temperature fluctuates by more than one degree, the benefits do not increase as rapidly as comfort is lost. Thus, for increasing PV self-consumption, it is effective to use low flexibility limits.

With an effectively sized DR operation and battery system, both can be used simultaneously without much of the benefit being lost. Both methods compete to utilize the same surplus PV energy; however, with an optimally sized PV system, surplus energy remains for both methods. When combining both methods, it is more profitable to use battery systems as the primary control and DR operation as a secondary control.

Customers' heating loads can be used in centrally controlled DR operations when it is possible to temporarily decrease the total consumption of customers by a significant amount. This type of operation can aid the power system in scenarios in which production rapidly decreases or high consumption peaks in the grid need to be avoided locally. The problem is that during very cold outdoor temperatures when consumption is typically highest, the indoor temperature of residences decreases rapidly during heating load interruptions, which limits the amount of time that customers can be flexible.

The results of this study will benefit many future studies. The method of defining the DR potential of small-scale customers can be used when studying the DR potential of larger areas involving higher numbers of customers. Future research should investigate different control targets for comparison to the proposed DR and battery system. Electricity market price levels and variation have been increasing significantly since autumn 2021 because of difficulties in energy markets. There could therefore be significant potential in market price-based control, which should be researched more in future. Additionally, different loads as the target of DR operation will be the object of future research.

**Author Contributions:** Conceptualization, J.K.; methodology, J.K.; software, J.K.; validation, J.K.; formal analysis, J.K.; investigation, J.K.; resources, J.K. and P.J.; data curation, J.K.; writing—original draft preparation, J.K.; writing—review and editing, J.K. and P.J.; visualization, J.K.; supervision, P.J.; project administration, P.J.; funding acquisition, P.J. All authors have read and agreed to the published version of the manuscript.

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**Conflicts of Interest:** The authors declare no conflict of interest.

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