THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

The role of Swedish single-family dwellings in the electricity system

-The importance and impacts of solar photovoltaics, demand response, and energy storage

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Abstract

This thesis investigates the role Swedish single-family dwellings can play in the electricity system. Both through becoming electricity producers through the use of solar photovoltaic (PV) systems, and the possibilities of demand response (DR) and energy storage in combination with this, and through the DR of electric space heating in the dwellings. The methodology used builds on the use of optimization models, which describe the relevant parts of the dwellings and technical systems, measured household load profiles, and modeled space heating demand. The developed models are linked to an existing model that performs a cost optimal dispatch of the electricity generation system. Thereby, allowing for co-optimization of the dispatch of supply side electricity generation and DR, and the evaluation of impacts on the supply side of the system from actions taken on the demand side and *vice versa*.

The results indicate that given that there is added value in self-consumption of PV generated electricity, i.e., not paying taxes and variable grid fees on self-consumed PV generated electricity, an expansion of household PV systems in Sweden that is driven by economic incentives appears to be robust with regards to the composition of a future electricity system. The households' economic potential for battery investments is found to be dependent to a large degree upon the economic value of utilizing them for arbitrage and in the economic value of increased self-consumption of PV generated electricity. Furthermore, a practical limit on the ability of batteries to increase the self-consumption of PV generated electricity in Swedish households is identified. For the DR of household loads the economic value provided to a household's investment in a PV system is small, except in the case of hydronic heating loads. It is also shown that for future evaluations of large scale investments of household PV-battery systems there is a need to include feedback mechanisms between the supply and demand sides of the electricity system.

A significant DR potential is identified for the electric space heating in the dwellings. The economic value of the DR is found to depend on the future electricity system composition. In a future system that is dominated by variable wind power, DR offers economic value through decreasing the number of start-ups, obviating the need for part-load operation of thermal power plants, and avoiding the operation of peaking gas power plants. In an electricity system less dominated by wind power the value of DR is low. The DR is found be used to a large extent for valley filling, increasing load during low load hours, and peak shaving, decreasing load during high load hours.

Keywords: Demand side management, Demand response, Distributed generation, Solar photovoltaics, Batteries, Single-family dwellings, Electricity system models, Optimization, Electric space heating

List of publications

This thesis is based on the following appended papers:

I. Nyholm, E., Odenberger, M. and Johnsson, F. An economic assessment of distributed solar photovoltaics in Sweden - the impact of demand response. Submitted for publication to *Renewable Energy*, 2016

II. Nyholm, E., Goop, J., Odenberger, M. and Johnsson, F. Solar photovoltaic-battery systems in Swedish households–Self-consumption and self-sufficiency. *Applied Energy* 183 (2016): 148-159.

III. Goop, J., Nyholm, E., Odenberger, M. and Johnsson, F. Impact from electricity market feedback on PV and battery investments in Swedish single-family dwellings. To be submitted for publication.

IV. Nyholm, E., Puranik, S., Mata, E., Odenberger, M. and Johnsson, F. Demand response potential of electrical space heating in Swedish single-family dwellings. *Building and Environment* 96 (2016): 270-282.

V. Nyholm, E., Goop, J., Odenberger, M. and Johnsson, F. System benefits of demand response of electric space heating in Swedish single family dwellings. To be submitted for publication.

Emil Nyholm is the principal author of **Papers I**, **II**, **IV**, and **V**. Joel Goop is the principal author of **Paper III**, to which Emil Nyholm (as co-author) contributed with method development, discussions, and editing. Joel Goop contributed with method development, discussions, and editing to **Paper V** and with discussions and editing to **Paper II**. Professor Filip Johnsson, who is the main academic supervisor, contributed with discussions and editing to all five papers. Mikael Odenberger contributed with discussions and editing to all five papers. Érika Mata contributed with discussions and editing of **Paper IV**. Sanket Puranik contributed with method development, discussions, and editing to **Paper IV**.

Additional publications not included in this thesis:

Norwood, Z., Nyholm, E., Otanicar, T. and Johnsson, F. A Geospatial Comparison of Distributed Solar Heat and Power in Europe and the US. *PLoS One* 2014; 9(12): e112442.

Nyholm, E; Steen, D., Can Demand Response Mitigate the Impact of Intermittent Supply? *System Perspectives on Renewable Power* (2014), Chalmers University of Technology, ISBN: 978-91-980974-0-5

Carlson, O.; Hammar, L.; Norwood, Z. et al. Harnessing energy flows: technologies for renewable power production. *Systems Perspectives on Renewable Power* (2014): s.32-45. Chalmers University of Technology. ISBN/ISSN: 978-91-980974-0-5

Kjärstad, J.; Bisaillon, M. ; Harvey, S. et al. Transforming the energy system in Västra Götaland and Halland – linking short term actions to long term goals (2015). Göteborg: Chalmers University of Technology. ISBN/ISSN: 978-91-980974-6-7

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1. Introduction

The harnessing of energy is to an increasing extent one of the main drivers of the development of human civilization. Since the 19th Century, a key supplier of this energy has been, and still is, fossil fuels. Since fossil fuels are abundant and cheap, they drive technological progress at an increasingly rapid pace. However, the burning of fossil fuels has brought with it environmental costs, in that it constitutes the largest source of anthropogenic greenhouse gas emissions and, consequently, is the main cause of climate change.

The Paris Agreement reached at the COP21 meeting established the long-term goal of keeping the global long-term average temperature increase well below 2°C relative to pre-industrial levels, and it aims to limit the increase to 1.5°C. To reach the 2°C target with a *likely* degree of certainty, greenhouse gas emissions will need to be reduced by 40%–70% by Year 2050, as compared to the Year 2010 levels [1]. As the global energy system is currently dominated by fossil fuels, achieving these reductions requires a rapid transformation of the energy system. A major part of this transformation concerns the electricity system due to its high share of fossil fuels.

In all the conceivable scenarios for this transformation, the demand side, which is the main focus of this thesis, plays important roles in decreasing energy use, creating efficiency improvements, generating electricity, and helping to balance supply and demand within the system. The concepts of prosumers (producing consumers) and demand-side management (DSM) have become popular recently [2]. In addition, the increase in information and expansion of the communication infrastructure pave the way for a more system-beneficial utilization of distributed resources, which was not possible previously. Figure 1 gives an overview of the impacts of DSM and prosumers on the remaining electricity system. The value of more consumers engaging in renewable generation of energy is clear, i.e., the possibilities to reduce fossil-based energy generation. The usefulness of DSM, however, can be more diverse. Since demand can be used both to optimize the use of the existing infrastructure and to avoid the need for new investments, DSM can play various roles in the different pathways proposed for a more sustainable energy system. In scenarios that have high levels of variable renewable electricity generation, e.g., those proposed by Delucchi and Jacobson [3] and Lund and Mathiesen [4], DSM could help to avoid curtailment of generated electricity through shifting demand or reducing the amount of needed generation by introducing efficiency measures. Furthermore, DSM could play similar roles in scenarios that propose massive expansion of the electricity grid so as to harvest remote renewable energy sources, as discussed by Chatzivasileiadis et al. [5], or in the development of the Smart grid [6]. Scenarios that involve extensive deployment of carbon capture and storage technologies, as investigated by Odenberger and Johnsson [7], could benefit from DSM through more efficient operation of power plants.

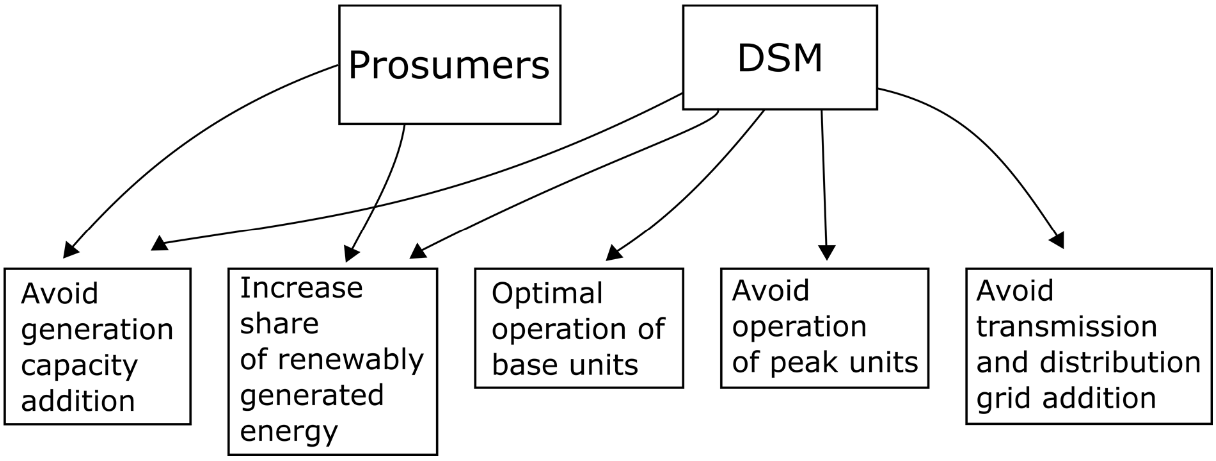


Figure 1. Different ways in which demand-side management and prosumers can help to manage the energy system. Adopted from [8].

Given the multiple benefits that can be derived from DSM and distributed generation, it is highly likely that the demand sector of the energy system will play an important role in a future, more-sustainable energy system. Therefore, it is important to investigate the actual potentials and limitations of DSM and distributed generation.

1.1 Aim and Scope

As mentioned in the *Introduction*, the demand side of the electricity system is likely to play a more active role in the future electricity system than has been the case historically. This is likely to have consequences for the evolution of the surrounding system. Therefore, it is useful to assess the technical and economic potentials and limitations for the participation of different demand sectors. This thesis and the appended papers do this for Swedish single-family dwellings. The dwellings are investigated with regard to their roles as prosumers, i.e., producers of electricity, and the use of their loads for the purpose of demand response (DR). The aim is to evaluate this from both the perspective of individual dwellings and the perspective of the surrounding electricity generation system. More specifically, the overall aim can be divided into two objectives:

- Investigate the technical and economic potentials of Swedish single-family dwellings becoming prosumers through the use of solar photovoltaic (PV) systems, taking into account possibilities for flexibility in consumption patterns through DR and energy storage, and investigate how such systems might interact with the surrounding electricity generation system.
- Identify the technical potential of DR of electric space heating in Swedish single-family dwellings, and investigate the value of this potential for the surrounding electricity generation system, as well as for the individual dwelling.

Special emphasis is placed on the interactions between households and the electricity system, including the feedback dynamics that influence the benefits of large-scale employment. The inclusion of feedback, so that it is not only a reactive evaluation of a given situation, fills a knowledge gap in the literature and is the major contribution from this work. The geographic scope with regards to the description of DR and households is limited to Sweden. However, the electricity system implications of the households' behaviors are evaluated in terms of the European electricity system. The questions are addressed with regard to both current conditions and future conditions. The two objectives specified above are investigated through modeling of the relevant parts of the energy system. The modeling is in the form of optimization models. The results from the models are not geared towards simulating current reality or predicting an exact outcome of the future, but rather exploring the dynamics and responsiveness of the interactions between households and the general electricity generation system given certain constraints.

1.2 Overview of the appended papers

In accordance with the objectives, the thesis can be divided into two themes: 1) the interaction between household PV installations and the possibility to increase the value of such installations through DR and batteries, as covered in the appended **Papers I**, **II**, and **III**; and 2) the possible value and usefulness of the DR of single-family electric space heating, which is covered in **Papers IV** and **V**. Here follows a short summary of each paper.

Paper I investigates the extent to which the DR of household appliances and hydronic space heating can help to increase the economic value of investments in PV in Swedish households. Furthermore, the impacts of DR measures are compared to the impacts of different electricity pricing schemes, subsidies, and changes in economic factors. In the paper, a model for the DR of household load is developed.

Paper II investigates the technical limitations of household PV-battery installations in terms of their abilities to increase the self-consumption of PV-generated electricity and thereby, also their abilities to increase the electricity self-sufficiency of the household. The investigation is made in the context of Swedish households, i.e., using PV electricity generation profiles valid for Northern European conditions. Several different combinations of PV-panel sizes and battery capacities are investigated for 2,103 different households.

Paper III investigates the impacts of household PV-battery investments on the surrounding electricity system and *vice versa*. This is done through iteratively optimizing two optimization models: one PV and battery investment model for households, and one electricity system dispatch model. The models are dependent upon each other in that the hourly electricity price generated by the electricity system dispatch model will influence the investment in PV panels and batteries by the households. In turn, the level of investments made by the households will influence the electricity load profile and the overall electricity demand, which will have an impact on the dispatch of the electricity system.

Paper IV aims to identify the technical and short-term economic potentials for DR of electric space heating in Swedish single-family dwellings. The DR is modeled by describing the heat balance across the dwellings, thereby allowing for variations in indoor temperature and the storage of energy in the building mass. In total, 571 dwellings are modeled, and these are subsequently scaled up to represent the entire Swedish single-family dwelling building stock.

Paper V investigates the system-optimal way of utilizing the DR of electric space heating identified in **Paper IV**. This is done through integrating an updated version of the electric space heating model introduced in **Paper IV** and using an electricity system dispatch model. This integration allows the operation of the DR to be co-optimized with the dispatch of the electricity system and thereby be utilized in a system-optimal manner. The paper investigates the extent to which the DR can help lower system running costs depending on future electricity system compositions and the value of engaging in this DR for individual dwellings. Furthermore, it introduces a new method for controlling the indoor temperature of dwellings in a system optimization model.

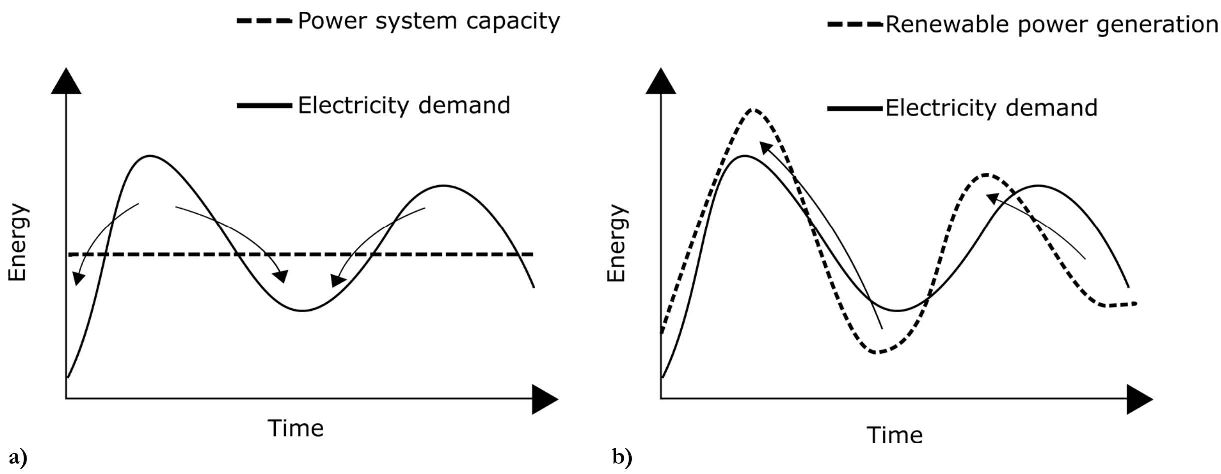
1.3 Outline

The thesis is organized as follows. Chapter 2 gives an introduction to the concepts of DR, distributed generation, and distributed resources, with the focus on their applications in the residential sector. Chapter 3 gives a literature overview of the methods used for modeling residential energy demand. Furthermore, a review of the current literature in the field of modeling DR is presented, with a focus on residential demand response, and the modeling of residential PV-battery systems. Chapter 4 presents the methodology used in the papers presented in this thesis, giving the model descriptions and definitions of the concepts used. Chapter 5 gives a description of the data applied. Chapter 6 provides an overview and a discussion of the results from the appended papers. Chapter 7 discusses the methods and data applied. Chapter 8 presents the conclusions reached with regards to the research questions posed. Chapter 9 proposes some future work.

2. Distributed resources

Distributed resources can be defined as all the demand-side and supply-side resources that can be deployed throughout an electric distribution system [9]. Thus, it encompasses all the technologies investigated in this thesis, i.e., distributed electricity generation, demand response, and distributed energy storage. A definition of these sub-categories for distributed resources is given below.

The idea of DR, which is applied in **Papers I**, **IV** and **V**, is part of the broader concept of DSM. DSM encompasses a broad set of measures that can be applied to the demand side of the energy system. The objective here is to diminish, increase or reshape the electricity/energy demand according to a specific goal. Included in the concept are: 1) energy efficiency measures, involving decreasing total load/demand either through technical or behavioral changes, and fuel-switching measures, such as replacement of oil boilers with heat pumps; and 2) demand response measures, which aim at reshaping the demand without necessarily changing the total demand [10]. While the idea of influencing demand has been around since the 1970s, it is only recently, owing to the increased availability of variable renewable energy sources and the emergence of an information communication technology infrastructure, that interest in DSM has grown. Traditionally, DSM, and particularly DR, has had the goal of increasing the efficiency of the existing generation capacity, through increasing its load factor, as well as increasing utilization of the grid infrastructure, thereby alleviating the need for additional investments in peak generation facilities and grid reinforcements [11]. This has been achieved through reducing the load during peak hours, known as 'peak clipping', which decreases the need for peaking capacity, and building load during off-peak hours, known as 'valley filling', thereby increasing the load factor of base-load generation. Therefore, the main aim of DR is to reduce peak demand (Fig. 2a). However, as more variable generation is introduced into the power system, a reduction in peak demand is not necessarily the desired outcome of DR. Depending on the generation profile of the variable source, a buildup of higher peak demand might be desirable (Fig. 2b).



a) b)

Figure 2. Difference between demand response strategies in a traditional electricity system (a) and one with a considerable level of variable generation (b) [12]. The arrows represents the moving of demand.

The concept of distributed generation is generally not included in definitions of the DSM concept, as it is not a consumer load. It is defined by Ackermann et al. [13] as:

"Distributed generation is an electric power source connected directly to the distribution network or on the customer side of the meter."

Thus, it is not to be assumed that distributed generation is owned and operated by consumers. The distributed solar generation investigated in **Papers I**, **II,** and **III** should thus be more accurately defined as consumer-based distributed generation.

Although distributed energy storage does not fall within the concept of distributed generation, as it does not generate any surplus energy in and of itself, the definition used for distributed generation can also be applied to distributed energy storage. Similarly to distributed generation, the definition of the energy storage used in this thesis and in **Papers II** and **III** should be narrowed to 'consumer-based energy storage'.

2.1 The use of demand response and energy storage coupled with variable generation

As mentioned in the *Introduction* section, DR and energy storage can contribute to the resolution of several issues within the power system.

On a time-scale of milliseconds to minutes, stability issues concerning frequency and voltage can occur. The possibility of using DR to modulate such instabilities is outside the scope of this thesis, although it has been investigated by others, e.g., Short et al. [14], who looked at frequency control. Short et al. [14] concluded that allowing refrigerators to react to frequency fluctuations created the potential to confer frequency stability in cases that involved sudden increases/decrease in demand or generation and during fluctuations related to wind power generation. The benefit of batteries for frequency regulation has also been covered in the literature, e.g., Oudalov et al. [15].

On longer time-scales, i.e., extending from minutes to days, the problem is that scheduled/predicted generation must meet the predicted demand. Increased variable generation introduces two issues concerning this requirement: uncertainty; and the shortage or surplus of available generation capacity. Uncertainty arises from the need to predict scheduled generation from variable sources through the use of forecasts. Any errors in the forecast will result in a discrepancy between scheduled generation and actual generation. This will increase the need for generation that is traded on intra-day and intra-hour markets. In such situations, DR could be used to handle the issue rather than activating additional generation. The possibility of using DR for managing forecast errors is also beyond the scope of this thesis, although it has been investigated by Madaeni and Sioshansi [16] and others. Madaeni and Sioshansi [16] concluded that DR in the form of real-time pricing could reduce the cost of wind uncertainty in the Texas electricity system (in which wind power accounts for 18% of installed capacity) by $0.20–2.27/MWh of wind power generation, depending on the level of uncertainty and the responsiveness of the demand.

There is also the issue of low or high levels of predicted generation. As the scheduling of generation from the variable sources is dependent upon uncontrollable weather patterns, it cannot be based on predicted demand. As a consequence of this, and assuming that there is sufficient variable generation in the system, the level of generated electricity can be higher than the demand for electricity. By the same token, when generation from variable sources is low there is a substantial need for dispatchable generation. The difference between demand and variable generation, i.e., the demand for electricity minus the level of variable electricity generation, is often referred to as the 'net load'. The load and net load for the Danish system during Year 2014 (with 40% of electricity supply coming from wind power) are shown in Figure 3. It is clear that the net demand takes on a negative value during parts of the year, indicating that generation is higher than demand, necessitating curtailment of that excess generation. In the case of Denmark, although excess generation can sometimes be exported to neighboring countries, there are still hours of curtailed generation.

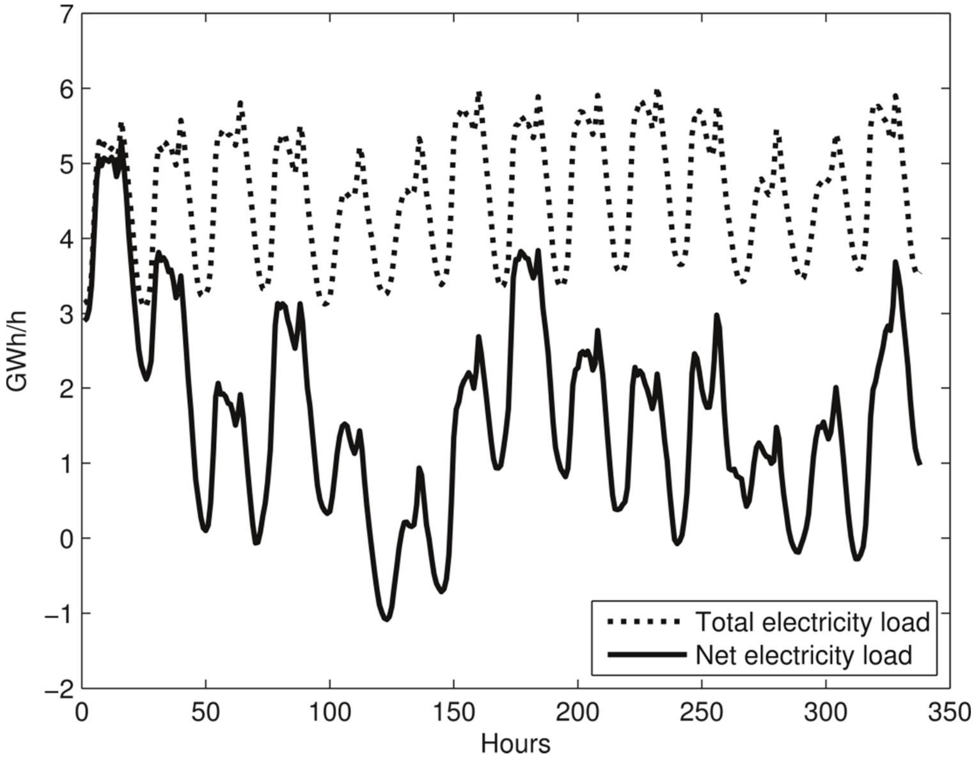


Figure 3. The total and net electricity loads in Denmark for two winter weeks in Year 2014.

Similarly, there are periods during which the net load is almost equal to the total demand. In these situations, DR can be used to shift load to hours with curtailment and away from hours with lack of generation, yielding a higher utilization/capacity factor for the variable generation and reducing the need for back-up generation. The impact on utilization times has been investigated by Hedegaard et al. [17], who concluded that DR could help to reduce fuel costs and CO_2 emissions in the Danish energy system, which contains 50% wind power (on an energy basis), through increasing the utilization of wind power and thereby, decreasing the need for fossil fuel plant operation.

In **Papers I**, **IV**, and **V**, the DR of energy, and in **Papers II** and **III,** the use of energy storage on an hourly basis are investigated. **Paper I** investigates the DR from the consumer perspective in terms of increased value of self-generated electricity, which means that system aspects are not investigated. In **Paper IV**, the system implications of DR given a static supply side, as well as the benefits to consumers of individual consumers acting in their own best interests are investigated. **Paper V** investigates the system-optimal use of DR. Likewise, batteries are investigated from the consumer perspective in **Paper II**, and from a combined system and consumer perspective in **Paper III**.

2.2 Demand response programs

DR can be implemented through several different methods or programs, depending on the intended purpose and the time-frame. On a broad scale, DR can be divided into *price-based* programs and *incentive-based* programs [18, 19]. The difference between these two programs is the way in which consumers are incentivized towards shifting or reducing load. In price-based programs, the instantaneous underlying cost of generating electricity is to varying degrees passed on to the end-consumer. The end-consumer is thereafter free to react to the price by shifting or reducing load. However, since acting on the price signal is entirely voluntary, consumer involvement is not guaranteed, i.e., consumers can choose to pay the higher price rather than reducing/shifting load. Thus, the precise magnitude of the load reduction is not known when using price-based programs. In contrast, incentive-based programs are based on contractual arrangements between consumers and other actors in the electricity market (e.g., grid operators and utilities), so they can be regarded as dispatchable. Consumers who are enrolled in an incentive-based program are paid for either contract-agreed or measured load reductions. Although participation in an incentive-based program is voluntary, if pre-contracted consumers fail to respond when asked they usually are penalized. An additional difference between the two DR types is that price-based programs can be applied to affect demand either continuously or only during critical periods for the power system, whereas incentive-based programs are only used during critical periods. The two programs also diverge with regard to the time-scales and electricity market segments in which they operate (see below).

The United States Department of Energy [20] defines the following DR programs:
A. *Incentive-based* DR programs

- *Direct load control (DLC)*, whereby the utility or distribution system operator can control remotely the costumers' loads and use them as it sees fit. In return for making their load available, the costumers receive a fixed payment or electricity rate discounts, regardless of whether or not the load is used. The load is primarily used on short time-scales (>15 min).
- *Interruptible/Curtailable (IC) programs* are related to DLC, with the difference being that the utility or DSO does not have direct control over the consumers' loads. Instead, the customers are asked to reduce their load to an agreed-upon level. If the customers fail to comply they face penalties. These programs operate on an hourly time-scale.
- *Capacity programs* work in the same way as IC programs, i.e., customers offer load curtailments in the form of system capacity to replace conventional generation or delivery resources. However, the customers only receive payment for load that is actually curtailed. Customers typically receive one day of notice of events.
- *Ancillary services programs* are similar to capacity programs, except that the load is used on the reserve market and customers must thus be ready to reduce load at short notice.
- In *Demand bidding/buyback programs*, end-users can offer their load curtailment at a desired price on the day-ahead market, which is analogous to bidding on generation capacity.

B. *Price-based* programs

- For *Time-of-Use (TOU) pricing*, electricity prices are set at different levels during a given time period, corresponding to diurnal variations, off-peak and peak hours, and even seasonal variations. These prices are generally fixed months in advance to reflect the average generation cost during the specified period.

- *Critical peak pricing* applies the same pricing structure as TOU pricing, with the added possibility to change prices during extreme peak hours at short notice.
- *Real-time pricing* is a system in which the customers are charged an hourly fluctuating electricity price. The final electricity price can be set on a day-ahead basis or on a real-time (hour-ahead) basis, and it is supposed to reflect the actual hourly cost of electricity generation.

In **Papers I** and **IV**, DR through *real-time pricing* is applied. **Paper III** also applies *real-time pricing*, this as the operation of a household's battery is also influenced by the choice of DR program. This tool was chosen because it is commonly regarded as the primary way to activate DR in residential demand, given that the "instantaneous" cost of generating electricity is passed on to the consumer [21-24]. Furthermore, following the installation of smart meters in Swedish households, it is possible for consumers to take advantage of real-time pricing. In **Paper V**, the system-optimal way of operating DR is investigated. In this case, the operation of DR constitutes a form of *direct load control*, whereby the utility has direct control over the operation of the DR.

2.3 Distributed generation in the residential sector

Distributed generation in the residential sector has existed since the dawn of electricity generation, with one of the first hydroelectric power stations being built in the country house of Cragside in England in 1870 [25]. However, residential electricity generation is nowadays dominated, in terms of installed capacity, by solar power. The value of distributed generation can be higher for consumers in the residential sector, as compared to other actors in the electricity system. The reason for this is that in addition to the wholesale price of electricity, residential consumers pay fees and taxes on the electricity that they purchase from the grid. In the case of distributed generation in Sweden, which is considered in **Papers I** and **III**, an energy tax, a value added tax, and a markup are all added to the wholesale price. Furthermore, a grid fee per unit of bought electricity has to be paid to the grid owner. Thus, electricity that is generated "behind the meter" can side-step the need to buy electricity, which means that it has a higher value than if the generated electricity is sold on the spot market. This difference also increases the residential consumers' incentive to engage in DR and invest in batteries, as increasing the self-consumption of generated electricity can be more lucrative than simply shifting between high-price and low-price hours.

There are several different pricing schemes for compensating residential solar PV owners for the electricity that they feed into the grid:

- An hourly RTP scheme: in similarity to the RTP scheme described in Chapter 2.2, electricity is sold and bought by the hour.
- Monthly electricity price: electricity is still sold and bought by the hour, albeit at a fixed monthly electricity price.
- Net metering scheme, whereby a bill/payment is received for the monthly net consumption/generation.
- Tax reduction: as currently available in Sweden, for each kWh fed into the grid a fixed amount is added to the price the prosumer receives for selling the electricity.
- Feed-in tariffs, whereby consumers receive a guaranteed price for their generated electricity.

- Net billing, which is similar to net metering, except that instead of paying for net consumption a discount is received on the following electricity bill. In this scheme, the consumer still has to pay taxes and fees on all the electricity drawn from the grid.

In **Paper I**, the first four schemes are investigated. Feed-in tariffs are not included, as they are only dependent upon electricity generated from PV-panels, which means that there is no interplay with demand. In **Paper III**, the RTP scheme is applied.

2.4 Batteries as energy storage in the residential sector

The use of batteries in the residential sector has traditionally served the purpose of backup power in case of power outages or has been used to enable off-grid operation. Historically, lead acid batteries have been the dominant battery technology, as they have been cheaper than competing batteries. However, different forms of lithium ion batteries have recently become more popular due to considerable price reductions [26]. The batteries investigated in **Papers II** and **III** are assumed to have the characteristics of lithium ion batteries. In addition to the added benefit of increasing self-sufficiency and thereby reducing electricity costs, as discussed in Section 2.3, batteries can be used for arbitrage in the electricity market. This arbitrage is accomplished through charging the battery with electricity from the grid during hours with low electricity prices and discharging the batteries during high-price hours to avoid buying electricity or to sell electricity to the grid. However, it should be noted that in the case of selling electricity to the grid, the price received is the market price for electricity, while the price paid for the electricity when charging the battery includes V.A.T., energy tax, and distribution grid fees. Thus, the price difference between the charging and discharging hours needs to be sufficiently large to make up for this additional cost of purchased electricity.

2.5 Demand response in the residential sector

The residential sector comprises numerous loads of various magnitudes, both in terms of specific load size and the overall level of energy used. In relation to these loads, different potentials can be specified. In **Papers I** and **IV**, the *technical potential* is identified and the *economic potential* for DR is investigated. The technical potential constitutes the actual physical potential that is present, e.g., the load of space heating and the maximum time-frame within which it can be shifted. The economic potential is the share of the technical potential that can be utilized in an economically optimal way. This potential can be viewed from a system perspective, i.e., minimizing total system costs, as is done in **Paper V**. However, in **Papers I** and **IV**, the economic potential is investigated only in part, as the supply side of the electricity system is considered to be static. Since the economic potentials are seldom reached, a third type of potential needs to be introduced: *achievable potential*. This potential constitutes the share of the economic potential that is actually utilized. The size of this potential is dependent upon several factors. For the residential sector, the factors may include whether the consumer is informed of the possibility of achieving economic savings through DR or if they feel that the eventual inconvenience of using DR outweighs the savings. Defining the achievable potential for DR is outside the scope of this thesis, as any investigation of this potential would require a behavioral analysis. Such an analysis has not been performed. Nevertheless, identifying the achievable potential is useful for identifying the gap between the achievable and economic potentials, as well as the measures that must be taken to close this gap. However, the achievable potential should not be regarded as an upper limit as to what can be attained by implementing DR [27].

As previously stated, the residential sector consists of a myriad of different loads, ranging from home entertainment systems to heat pumps. Theoretically, almost all of these loads are flexible if the price of electricity is sufficiently high, thus making the total technical potential for DR substantial (residential electricity demand constitutes 23% of the total Swedish electricity demand). However, it is difficult to distinguish those residential loads that are actually suitable for DR and to discern to what extent these loads are available for DR. As residential consumers, compared to industrial or commercial consumers, are to a lesser extent rational cost-minimizing entities, they do not necessarily follow financial logic. Furthermore, the utility that one consumer extracts from a certain load might be totally different than that obtained by another consumer, i.e., one person may be happy to postpone starting the dishwasher for 12 hours, whilst another individual is always in dire need of clean cups and runs the dishwasher as soon as it is full. The selection of loads used for the DR in **Papers I**, **IV**, and **V** is based on an evaluation of the literature regarding the DR potential of residential loads, in terms of energy and power, but also in terms of acceptance among consumers.

Mert et al. [28] investigated consumer attitudes concerning smart appliances, i.e., appliances that have the possibility to communicate and can thus be used for DR, in five EU countries (Austria, Germany, Italy, Slovenia, and the United Kingdom). They found that consumer acceptance of smart appliances was high, i.e., consumers were willing to adopt smart appliances as long as they had control over the finishing time of the appliance. The study investigated only those loads that could be shifted without having a strong impact on the service that they provided; thus, loads (such as cooking appliances and televisions) that require more extensive behavioral changes were omitted. Paetz et al. [29] conducted a study of consumer acceptance of smart meters, variable tariffs, and smart appliances, which included all residential loads. Similar to the findings of Mert et al. [28], consumers in the study were generally positively inclined to adopt smart technologies, listing monetary savings and environmental benefits as the primary motivations for doing so. However, the need to change ones routine and the experience of decreased personal flexibility limited the willingness of the subjects to engage with smart technologies. Thus, loads that must be serviced instantly, such as lighting, cooking, and entertainment, were often seen as non-shiftable by consumers. Several other studies that investigated consumer acceptance, such as Hargreaves et al. [30], Stragier et al. [31], and Fell et al. [32], have reached the same general conclusion, that consumers are not willing to make major behavioral changes. Other obstacles/fears perceived by consumers included misuse of the measured data. Assessing the impacts of such concerns is not within the scope of the present work but obviously needs to be addressed if the potential for DR is to be realized.

Based on the work of Mert et al. [28], Seebach et al. [33] assigned residential appliance loads to four qualitative classifications with respect to their suitability for DR: 1) specific load during operation; 2) availability; 3) shifting flexibility; and 4) convenience for consumers. Where *the specific load during operation* relates to the size of the shiftable appliance load, a larger load is obviously better for DR. *Availability* relates to how often the load can be accessed for DR. *Shifting flexibility* relates to how far ahead in time the load can be shifted, where the possibility to shift the load for a long period of time obviously is beneficial. *Convenience for consumers* reflects the degree to which the DR operation of the appliance is likely to avoid causing inconvenience to the costumer. Table 1 shows the resulting indicators for nine different appliances. The indicators range from low (red color), indicating that the specific load performs poorly in relation to the classification, to very high (dark green), indicating that the load performs well in relation to the classification. One further classification that is important but that is not explicitly shown is the total shiftable energy, although it can be extrapolated by combining the *specific load during operation* and *availability* classifications.

Electric heating (EH; investigated in **Papers I**, **IV** and **V**) and water heating (WH; investigated in **Paper I**) are the most promising candidates. The remaining loads studied in **Paper I** have both pros and cons, with dishwashers (DW), washing machines (WM), and driers (TD) allowing for a high load to be shifted, although they have low availability. For refrigerators/freezers, the opposite is true.

Table 1. Classification of nine different residential loads in relation to four different aspects that are important for DR potential. The colors indicate how well the different loads perform in relation to the different classifications, ranging from red (poorly) to dark green (very well). Adopted from Seebach et al. [33].

	WM	TD	DW	RF	FR	AC	WH	EH	CP
Specific load during operation	high	high	high	low	low	mod.	high	very high	low
Availability	low	low	low	high	high	low	mod.	mod.	mod.
Shifting flexibility	mod.	mod.	high	low	low	low	mod.	high	mod.
Convenience for consumers	low	low	mod.	high	high	low	mod.	high	mod.

Abbreviations: WM, Washing machine; TD, tumble dryer; DW, dishwasher; RF, refrigerator; FR, freezer; AC, air conditioner; WH: water heating; EH, electric heating; CP, circulation pump; mod., moderate.

It is clear from these studies that washing machines, dryers, dishwashers, refrigerators, freezers, tap-water heating, and space heating are the loads that are the most accepted by consumers for use in DR, as well as being among the largest loads in the residential sector. Therefore, the initial modeling and analysis of DR in the residential sector focused on these loads.

The demand side of the energy system could be used as a tool to address several different issues that can arise as the energy system is transformed, ranging from frequency regulation on the millisecond scale to the shifting of energy demand over days. As shown, there are several ways to incentivize DR, distributed generation, and energy storage in the residential sector. The combination of DR or energy storage with distributed generation could also generate additional benefits for consumers through increasing the value of the distributed generation. **Papers I**, **II**, and **III** shed light on the possibilities for this combination. Furthermore, it is shown that electric heating (space heating and hot tap-water heating) has the largest potential for DR in terms of energy, load, convenience, and flexibility. Thus, it is of interest to investigate the potential for DR of electric space heating and how it can be used (**Papers IV** and **V**).

3. Related research

This chapter presents research that is related to the work presented in this thesis. The chapter is divided into two sections. In the first section, an overview of residential electricity demand models and their applicability to DR and energy storage modeling is presented. The second section comprises an overview of the literature related to the research described in the appended papers.

3.1 Modeling of residential electricity demand for energy system models

Electricity demand models have been reviewed in several publications [34-37]. However, the utility of these different models in terms of DR modeling has not been studied. When modeling electricity demand for DR purposes, some requirements that are not essential for traditional demand modeling have to be met. First, a time resolution that is sufficiently high to address the intended purpose of the DR is required, i.e., if the purpose is to model frequency response a resolution of milliseconds is needed, whereas for energy balances in, for example, the Nordic electricity market an hourly resolution is adequate. Second, the method should ideally be able to generate specific load profiles for different end-uses. However, it is not required to know these profiles in order to model DR. Third, if the storage of energy is to be included, e.g., through thermal inertia of buildings, hydronic heating systems or a battery, a description of the characteristics of that storage needs to be represented. Fourth, if a country/region-wide potential is desired the model needs to be scalable. This chapter gives a brief overview of residential electricity demand models and their suitabilities for DR modeling with respect to these requirements. Concerning demand modeling for the purpose of operation of household battery systems, the requirements are less strict. There is no need to have load profiles for specific end-uses. Instead, load profiles representative of the location of the electricity storage are required, i.e., at the household level for household installations and at the system level for system installations. Below, the most common approaches to demand modeling and their applicabilities to DR will be presented briefly.

There are two overarching forms of modeling frameworks used in demand modeling: top-down and bottom-up. Top-down approaches make use of macroscopic data, such as GDP, appliance prevalence, floor area, and other factors that can influence electricity demand, so as to create econometric models. Such models are not suitable for modeling DR, as they do not allow for a sufficiently high temporal resolution, and so they are not covered in this overview.

Bottom-up models can be broadly divided into statistical models and engineering models. These models have in common that they, in contrast to top-down models, model the electricity demand and profile based on individual houses/households and thereafter scale up/extrapolate to represent the entire building stock or a targeted type of consumer. For statistical models, such house/household load profiles are created through regression analysis, more specifically *conditional demand analysis* (CDA) [38] in the case of individual loads, or through evolutionary or supervised learning algorithms. Such algorithms can be *artificial neural network* models (ANNs) [39] and *support vector machines* for supervised learning or *genetic algorithms* in the case of evolutionary algorithms. Other types of algorithms have also been used in conjunction with those mentioned above. As ANNs are the most commonly used, they are the only models covered here. Engineering models work by modeling each end-use separately using data that describe the end-use. The behaviors of occupants can also be included. The different approaches used in engineering models include *probabilistic* models [40] and *archetype/sample* models [41].

The CDA method was first developed by Parti and Parti [38]. In contrast to other regression model approaches used for demand prediction, CDA breaks down the contributions of the individual loads to the total household load. Here, selected appliances are used as some of the independent variables to explain the total demand, which is set as the dependent variable. The minimum requirement in terms of data is the total electricity demand curve for individual households and the existence or non-existence of appliances. A disadvantage of CDA is that appliances with a high penetration rate cannot be distinguished from the remaining load due to multicollinearity. This is a drawback because these appliances include a large share of appliances that are considered suitable for DR. The time resolution that can be achieved is dependent upon the available data. New loads cannot be introduced, as the profiles are extracted from existing data. Furthermore, there is no possibility to represent energy storage possibilities.

An ANN employs statistics to reveal the relationship between the input values and desired output values, without relying on an actual physical description of the loads. Park et al. [39] were the first to use this method to describe electricity demand. The method uses several layers of what are called neurons, where the layers are classified as the input layer, hidden layers, and output layer. The signal/information, which can be the time of day or flows from the input layer that continue through the hidden layers and arrive at the output layer, e.g., electricity consumption for dishwashers. The output from each neuron, with the exception of the input neurons, is generated by passing through a function the weighted output values from all the neurons in the previous layer. The values of the weights in each layer are determined by a learning/training algorithm, which adapts the weights using an input set and a target output set. The weights are changed until the error between the output and the target output becomes sufficiently small. The target/training output set may comprise the actual measured load curves, and the input could be the temperature or time of day. With this method, a sufficiently high time resolution is achievable, given that consumption data are available. Similar to CDA, new loads cannot be introduced because the profiles are extracted from existing data. Furthermore, to represent the storage input, data that describe the storage, e.g., indoor temperature or water storage temperature, need to be collected.

In engineering modeling approaches, synthetic load profiles are created based on appliance and/or building data, e.g., cycle times and power demands of appliances or the thermal behaviors of buildings. These models can also be coupled with functions that describe the behaviors of the household inhabitants. Models that incorporate inhabitant behavior for an individual household level can be classified as *probabilistic models*. These probabilistic models aim to mimic the behaviors of household inhabitants, e.g., the time when they leave the house or the time when they use the dishwasher, and thereby construct load curves for different end-uses. This is accomplished by assigning probabilities to occupancy and occupant behaviors. The level of detail used to describe the behaviors varies between models. Paatero and Lund [42] used a random factor to determine occupancy level. Others have based their behavior analyses on so-called 'use of time' surveys where participants are asked to keep a diary of their daily activities, together with information on where the activities were performed and with whom [40, 43-45]. These data are then used to create a model of occupancy behavior. To create descriptions for a specific region, all the households in the region are modeled and then aggregated into a single load curve. The models allow for very detailed DR modeling, as the actions of individual occupants are considered, and given that the data for appliance behaviors are available, a high time resolution is possible. New loads can be introduced to the model if the corresponding technical data are available. Since the occupant behavior for the new specific load cannot be modeled, it must instead be based on assumptions. In a similar way, storage can be added. However, if the DR in an electricity system on a country scale is to be investigated, resolution at the individual occupant level is not feasible.

Models that use archetypes or samples include a limited number of households, which are supposedly representative of the diversity within the region being modeled. These parameters are then weighted so that the total load for the region is calculated. In the case of archetypes, this is achieved through creating a set of typical representations for the load that is to be modeled. For the samples approach, a sample of the existing demand composition is selected to be representative of the total and subsequently assessed, in the form of either measuring the actual load or a physical description of the buildings. **Papers IV** and **V** are based on this concept and use a physical building model, i.e., an energy balance model, developed by Mata et al. [41]. Occupancy behavior in the form of probabilistic models for archetype households can be incorporated into archetype models. Shimoda et al. [46] applied a *use of time* study to specify 460 archetypes composed of 23 household types and 20 dwelling types. The model was used to describe the load profiles of end-uses and the total load for the city of Osaka, Japan. The time resolution can be high given that appliance data are available. However, if weather-dependent loads, such as space heating, are modeled the resolution of the available weather data would also limit the time resolution. Storage can also be included. Scaling up the results is easy, as the archetypes/samples are selected to represent the region being modeled. In **Papers I**, **II**, and **III,** samples in the form of measured household loads are used; the samples have not been selected to be representative of a region.

Table 2 summarizes the presented modeling approaches, as well as their suitability for DR modeling. All these approaches, with the exception of the top-down macroeconomic approach, can be used in DR modeling. However, if some form of energy storage or new load is to be introduced engineering approaches are the most suitable choice. Furthermore, the use of CDA or learning algorithms requires extensive measured data in order be useful for modeling in a larger context. Therefore, an archetype engineering or sample approach seems to be the most suitable for modeling large systems.

Table 2. Overview of the suitability of different electricity demand modeling approaches for system-scale DR and energy storage modeling.

Modeling approach	Time resolution	Load resolution	Storage representation	Scalability	Suitability for DR
Top-down macroeconomic	Low	High	No	Yes	Not suitable
CDA/regression [38]	High	Medium	No	Yes, given that data are representati ve	Suitable, requires extensive data
Learning/genetic algorithms [39]	High	High	Yes	Yes, given that data are representati ve	Suitable, requires extensive data
Engineering probabilistic [40]	High	High	Yes	Low/High if coupled with archetypes	Suitable for small-scale or in combinatio n with archetypes
Engineering archetype/sampl e [41]	High	High	Yes	High	Suitable

3.2 Overview of related research

The choice of demand representation is dictated by the chosen method for modeling the DR. Depending on the potential that is to be investigated, the approach to DR modeling varies. In a comprehensive literature review of model-based assessments of DR, Boßmann and Eser [47] proposed six main features that can be used when classifying DR models: thematic; methodologic; temporal; spatial; technological; and practical. These features are useful for classifying the numerous DR studies that have been published. Here follows a classification of the appended papers in line with their thematic features. The thematic features concern the research focus of the paper, which the authors divide into four main groups: 1) *pricing schemes*, which is an economic analysis of the different pricing schemes presented in Section 2.2 and the impacts of these on different actors; 2) *electricity system*, which investigates the economic and technical use of DR in a system context; 3) *specific end-uses*, which investigates specific end-uses accounting for technical constraints; and 4) *control strategies*, which investigates specific control algorithms for controlling the dispatch of DR end-uses given signals from a DR program. The different groups can also be combined, for example to represent specific end-uses (group 3) in the context of an electricity system model (group 2). The DR-focused papers appended to this thesis can be categorized as follows: **Papers I** and **IV** are a combination of groups 1 and 3, investigating specific end-uses under a specific pricing scheme (RTP). **Paper V** is a combination of groups 2 and 3, investigating electric space heating in a system context. In the literature overview presented below, papers that deal exclusively with group 1 or 4 will not be covered as these are outside the scope of this thesis.

The classification system used for DR modeling can to a large extent also be used for describing the PV-battery modeling papers. While **Paper II** can be categorized as group 3, focusing solely on the technical limitations of PV-battery systems in Swedish households, **Paper III** is a combination of group 2 and group 4, as it investigates the impacts on the system of investments in PV-battery systems in Swedish households.

Presented below is an overview of the studies in the literature that fall within the same categories as the appended papers.

Demand response with a household focus

Several studies have investigated the DR of specific end-use technologies in the context of different pricing schemes, i.e., combinations of thematic categories 1 and 3 presented above. For the residential sector, the main focus has been primarily on the loads presented in Section 2.3, although some groups, e.g., Setlhaolo et al. [48], have investigated the DR scheduling of every appliance load in a typical South African household under a TOU pricing scheme. They showed that savings of up to 25% of the households electricity cost could be achieved. However, the level of savings was highly dependent upon the flexibility demonstrated by the consumer. Similar studies conducted by Zheng et al. [49] and Setlhaolo and Xia [50] utilized measured load profiles in their DR modeling. There are also several papers that have used probabilistic models to investigate DR. Paatero and Lund [42] used load curves created from their probabilistic model (based on a random factor for occupancy), to investigate the possibility of cutting the peak load. This was achieved by generating 10,000 household load curves and thereafter applying predefined shifting schemes. Gottwalt et al. [51] used hourly variable electricity prices together with a probabilistic model to apply DR to household loads. Widén et al. [44] introduced a different DR modeling approach, in which the probability of a load being activated was to some degree governed by the electricity price, resulting in more loads being initiated during low-price periods and *vice versa*. This allows the model to capture the actual potential, as not all the loads are moved and the behavior is not deterministic.

All of the above-described studies have focused on the DR as the sole activity in which the households engage. DR in conjunction with other end-user engagements, such as investment in PV-panels (investigated in **Paper I**), has been studied to a lesser extent. Castillo-Cagigal et al. [52] studied the DR of a washing machine, dryer, and dishwasher coupled with PV in a self-sufficient solar house in Spain. The aim was to increase self-consumption of the electricity generated by a 5.5-kW_p installation, with no investigation of any economic benefits derived from engaging in DR. The DR was shown to increase the self-consumption of electricity by 15 percentage points. Based on the measured load profiles of households in Sydney, Australia, Oliva H and MacGill [53] modeled the DR in combination with household PV installations. The economic benefits of this combination were investigated with regards to one time-invariant and one time-dependent feed-in tariff, as well as a TOU-type electricity price scheme. The DR was not modeled at an appliance level; instead, fixed percentages of the load were considered shiftable. These authors concluded that the economic savings for households were modest. For Swedish conditions, i.e., seasonally skewed household load profiles and PV electricity generation profiles, Widén et al. [54] investigated the technical ability of DR, among other things, to increase the self-sufficiency of households with PV-panels. They showed that for small PV installations, DR had a relatively low impact irrespective of the share of the load considered for DR, increasing self-sufficiency by at most 2 percentage points. This was because most of the generated electricity was already consumed in-house. For large PV installations, the impact was more pronounced, with an increase in self-sufficiency of up to 13 percentage points. Widén [55] investigated the economic potentials of DRs in terms of increasing self-consumption of PV-generated electricity in Swedish single-family buildings. Widén investigated the DR scheduling of washing machines, clothes dryers, and dishwashers, together with PV-panels that ranged in size from 3 kW_p to 9 kW_p in 200 buildings. The DR was governed through a RTP scheme that used historic electricity prices for Sweden and optimized using a heuristic approach. The economic benefits of DR were found to be small, maximally €20 per year and household. The increase in PV-self consumption was also small, with increases of a few percentage points of the total generated electricity from the investigated PV-panels.

Paper I appended in this thesis investigates further the economic value of DR coupled with PV-panel investments for Swedish households. The paper includes hydronic heating loads in conjunction with the DR loads investigated by Widén [55]. The study described in **Paper I** further compares the impact of DR to other factors that can influence the economic value of a households PV-installation, such as electricity pricing schemes, interest rates, and PV-panel prices.

System-level demand response

All of the above-mentioned papers have focused primarily on the consumer and the benefits they might be achieved through engaging in DR. Studies investigating the system impacts of the DR of specific end-uses are also available albeit fewer in number. Patteeuw et al. have published extensively regarding the DR of single-family dwelling space heating in a system context [56-60]. In similarity to the work regarding DR of space heating presented in this thesis, they employed an energy balance model over the dwellings as a way to limit the behavior of DR. This approach is combined with the archetype approach (presented in Section 3.1) to scale up the DR to a system level. The energy balance model is then integrated with an electricity system dispatch model so as to capture the feedback between the two components. The geographic scope of the papers published by Patteeuw and colleagues [56-60] is Belgium, i.e., the building stock modeled is aimed at describing the future Belgian building stock and the electricity system is inspired by the Belgian system. In Patteeuw et al. [60], the CO_2 abatement cost for heat pumps (HPs) was investigated: they compared the investment cost of HPs, which is higher than the cost of the commonly used condensing gas boiler, versus the potential lower CO_2 emissions and operational costs that result from replacing the boilers with HPs. They investigated different HP types, the impact of the degree of renovation of the buildings, whereby a higher degree of renovation meant better insulation, and the impact of DR. They found that the most effective approach to lowering the abatement cost for air-source HP was to engage in DR. The lowest abatement cost was found for thoroughly renovated buildings with air-source HP coupled with floor heating and DR. From the system perspective, replacing the gas-fired boilers with HP increases the electricity demand and the amount of electricity generated by gas-fired power plants. The reason that the use of HPs reduces CO_2 emissions is thus the higher overall efficiency that results from the shift to HPs. If the HPs also engage in DR, a small fraction of the increased electricity demand can be covered through reducing the curtailment of variable RES. In Arteconi et al. [56], using the same modeling framework as was used by [58], the impact of the market penetration of DR was investigated by examining how the number of dwellings engaging in DR influences the system benefits and the cost savings per participant. They found that the annual cost saving per dwelling decreased with increasing DR penetration; this was the case because the amount of load shifted per household decreased. As a consequence of this there was also lower thermal losses per dwelling. The cost savings for the household range from €35 to €112 per customer per year for 100% and 5% participation, respectively. These savings can be tripled if one accounts for deferred investment costs resulting from reductions in peak demand. They also show that increased usage of variable renewables in the system increases the value of the DR, with an increase from a 30% RES penetration level to a 50% RES penetration level generating an increase in savings of around €30 per dwelling. It should be noted here that no start-up costs for the power plants is included in the modeling.

Archetype models have been used by Hedegaard and Balyk [61] to model the DR of space heating/HP and investments in different heat storage options, such as accumulation tanks and control systems for the DR of the HP, in Denmark. The system model used represents Denmark in Year 2030 with a wind penetration of around 60% and also includes a representation of the surrounding countries' electricity systems. The paper concluded that investment in a control system for DR was profitable in 34% of the households with HP installations. However, investment in additional accumulation tanks was shown to be not feasible economically. They concluded that while an advantage of DR is that it can reduce the need for peak and reserve capacity investments, the model does not account for the start-up costs, minimum load requirements or part-load efficiencies of the power plants. Hedegaard et al. [17] and Papaefthymiou et al. [62] investigated the economic potential of the DR of HPs in two future German electricity systems with RES penetrations of 36% and 47%. This was achieved by incorporating the HPs into a mixed-integer stochastic optimization model, which dispatches electricity generation and includes uncertainty related to the wind forecast. They did not include the investment cost for the HPs, but instead evaluated the value of the HPs in terms of their ability to reduce the system cost. The authors concluded that at a penetration level of 47%, DR could achieve a system cost reduction of up to €50 million, corresponding to 0.5% of the total system costs.

There have also been studies of the system impacts of DR of electric space heating, among other loads, without utilizing a physical description of the building stock. Gils [63] performed an extensive evaluation of the technical potential of DR in Europe, which included all the demand sectors and appropriate loads within each sector. Each load was assigned a characteristic load profile based on metering data or characteristic load profiles taken from other sources. Gils concluded that there was a minimum load reduction potential of 61 GW and a maximum load increase potential of 68 GW in the European electricity system for every hour of the year. The potential identified by Gils was evaluated from a system perspective in the study of Gils [64] for the case of Germany, and in the study of Brouwer et al. [65] for the case of Western Europe. Brouwer et al. [65] showed that in a system with 60% RES, DR reduced the total system costs by 1.7%–2.5%, given that 47 GW of DR was available. The savings arose from deferred investments in peak power plants and decreased running costs that resulted from a shift from peak power plants to base-load power plants. These publications give good indications of the potential of DR. However, the simplified descriptions of the space heating loads disregard the increase in electricity demand that might result from the DR operation, as well as the constraints linked to weather conditions, i.e., outdoor temperature and solar irradiation levels.

The system-scale modeling of DR of electric space heating through the use of energy balance models has, as shown above, been investigated for a number of different countries. However, studies of the Swedish building stock are lacking, a deficit that is addressed in the appended **Papers IV** and **V**. Furthermore, most studies have been confined to investigating the interactions between supply and demand for a single country, thereby ignoring the impacts of interconnections with neighboring countries and regions. In **Paper V**, the dispatch of DR of electric space heating in Swedish single-family dwellings is investigated in a multiregional model that represents parts of central and northern Europe. For system-scale models, there is also a need for models that can handle both upward and downward regulation of the indoor temperature. Current optimization models predominantly utilize a method that only allows for upward regulation of the indoor temperature. **Paper V** introduces a modeling approach that allows for both upward and downward regulation of the indoor temperature.

Household PV-battery installations

The potential of batteries to increase the self-consumption and self-sufficiency levels of the PV-generated electricity of a household and the households benefits of such an arrangement have been investigated in numerus studies [52, 66-71]. The focus in the papers is either on the technical potentials of the batteries for increasing self-consumption / self-sufficiency (i.e., the degree to which the batteries reduce the need to purchase electricity from the grid) or on the economic potential (i.e., under which circumstances is investment in batteries profitable). The appended **Paper II** investigates the technical potential of a large sample of Swedish households.

With regards to the technical potential of batteries to increase the degree of self-sufficiency under Swedish irradiation conditions, Widén et al. [54] investigated the technical potentials of PV and batteries in Swedish households. For smaller-size PV installations, they concluded that the inclusion of a battery has a negligible impact, as all the generated electricity is already consumed in-house. For larger-size PV installations, they showed that self-sufficiency can be improved by up to 28 percentage points given a battery size of 2 Wh/W_p. Thygesen and Karlsson [72] investigated battery installations with capacities in the range of 5–24 kWh (actual usable energy capacity), together with a PV installation of 5.2 kW_p in a Swedish building. For the batteries with capacities of 5 kWh and 24 kWh, PV electricity self-consumption increased by 18 percentage points and 33 percentage points, respectively, relative to a case in which a battery is not used, indicating a reduced marginal benefit of the additional increase in battery capacity. Widén and Munkhammar [73] studied several battery and PV combinations for a Swedish household. They found that a 5-kW_p PV installation coupled with a 3-kWh battery (actual usable energy capacity) increased PV electricity self-consumption by 614 kWh/year. Furthermore, they showed that doubling the battery size increased PV electricity self-consumption by only an additional 358 kWh/year. There are also studies of the impacts of batteries under non-Swedish conditions [52, 66-71]. The results of these studies suggest that the potential for self-consumption of generated PV electricity is higher in regions that lie closer to the equator.

While numerous studies have examined the potentials of batteries to increase the amount of PV-generated electricity that is self-consumed, a systematic approach that uses a sufficiently large sample of buildings to give a reasonable representation of a true building stock is lacking. There are also considerable differences between the levels of self-consumption and self-sufficiency achieved for different geographic locations, which suggests that studies that relate to different latitudes and climates are warranted. These concerns are also put forward in the review paper concerning PV electricity consumption authored by Luthander et al. [74]. **Paper II** appended to this thesis gives such an overview for Swedish conditions.

Household PV-battery installations in an electricity system context

Investigations of the interactions that occur between household PV-battery systems and the surrounding electricity system have not been published to date. Studies regarding investments in household PV-battery systems have focused primarily on the views of the households and have assumed a static supply side. Some studies have made assumptions as to future electricity prices. For example, Mulder et al. [75] investigated investment in PV-battery systems for Belgian households taking into account changes in future electricity prices through an assumed price increase relative to Year 2012 prices. However, there were no interactions between the demand side, i.e., the households, and the supply side. This analysis also assumes a time-invariant electricity price during the year. Given this assumption, Mulder et al. [75] concluded that for batteries to become a valid option without any form of subsidy, the general electricity price level would have to increase by at least 4%. A similar approach for Germany was adopted by Hoppmann et al. [76], who performed a modeling exercise to identify the cost-optimal combination of investments for PV and batteries, using one standard load profile from a utility and an electricity tariff that was constant over the year, but that developed from year to year over the life-time of the investments. Thus, they showed that there already exists (Year 2014) an economic rationale for small residential PV systems. They also pointed out that if households were not allowed to sell excess electricity on the wholesale market, the economic viability of storage for residential PV would be particularly high. However, they did not consider any feedback between the households and the supply side.

If large-scale implementation of household PV systems occurs, it will in all likelihood have an impact on the supply side of the electricity system and *vice versa*. The incentives for a household to purchase PV panels and batteries, as well as the way in which the householder operates the battery are dependent upon the price they have to pay for electricity. However, if a sufficiently high percentage of the households invest in PV panels and batteries, their investments will have a significant impact on the overall demand for electricity. A change in demand will lead to a change in the dispatch of the system, which may promote a change in the electricity price. This might in turn affect the incentive to invest in PV panels and batteries. Therefore, approaches that incorporate the feedback mechanisms between these two sides of the electricity system are needed. **Paper III** introduces the idea of such a mechanism between Swedish households and the dispatch of parts of the central and northern European electricity system.

4. Methodology

The research questions and aims listed in Section 1.1 are addressed by means of models, which represent the relevant technical and economic parts of the systems. The following four models are developed: Electric Space Heating Dispatch; Demand Response Appliance; PV-battery; and Solar Heat and Power. In addition, two models that were not developed by the author are used: the ELectricity INvestment (ELIN) model; and the Electric POwer Dispatch (EPOD) model. The solar heat and power model is a simulation model, whereas the remaining five models are optimization models. The simulation model is implemented in Matlab and the optimization models are implemented in the General Algebraic Modeling System (GAMS). All the optimization models have perfect foresight. Furthermore, the Demand Response Appliance model is a mixed integer model and the remaining four models are linear optimization models. In brief, the developed models entail:

- *Electric space heating dispatch*, which models the energy balance over building envelopes and optimizes the dispatch of space heating equipment. For this model a one zone and two zone version is developed (**Papers IV** and **V**).
- *DR appliance,* which optimizes the dispatch of different household appliance loads, e.g., dishwashers and washing machines (**Paper I**).
- *PV-battery*, which is essentially an extension of the DR appliance model that optimizes the dispatch of batteries in households. In addition to the dispatch of batteries, investments in PV-panels and batteries for the households can also be modeled (**Papers II** and **III**).
- *Solar heat and power model*, which simulates the electricity generation and/or heat generation for eight solar energy technologies (**Papers I**, **II**, **III**, **IV**, and **V**).

As mentioned above, two additional models that where not developed by the author are used:

- *ELIN,* which is a partial equilibrium optimization model that optimizes the investments in electricity generation and infrastructure in Europe up to Year 2050.
- *EPOD,* which is an electricity generation dispatch model that optimizes the dispatch of power plants in a given energy system.

The models presented above are used separately or in combination in the appended papers. Figure 4 shows which model is used in which paper, with the different types of boundaries representing the different papers.

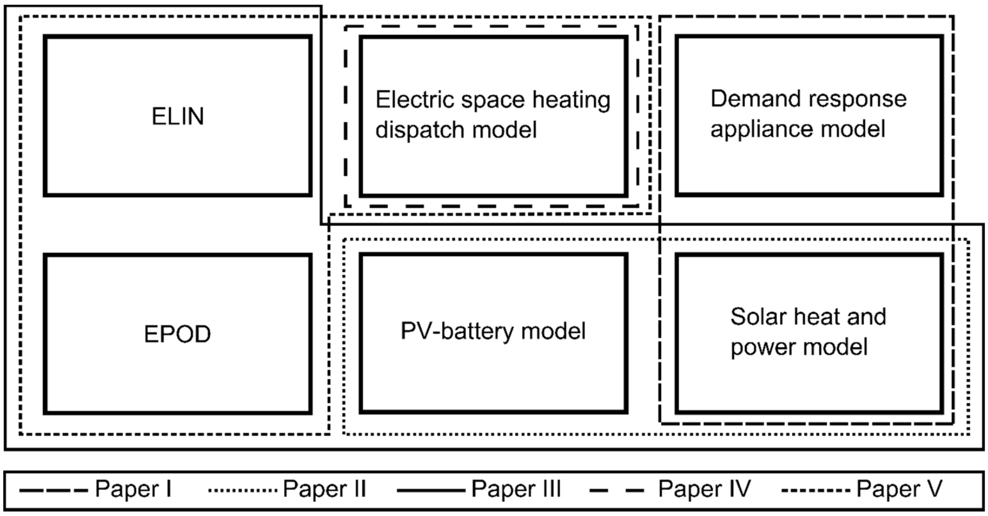


Figure 4. Connections between the six models and the five appended papers.

The one-zone version of the electric space heating dispatch model is used in **Paper IV**, while in **Paper V** the two-zone version is used.

The optimization objectives differ between the papers. **Paper I** and **Paper IV** minimize the annual electricity costs of the individual households/dwellings through the dispatch of DR loads, given a static supply side. **Paper II** maximizes the self-consumption of household-generated PV electricity through the dispatch of batteries. **Paper III** iteratively optimizes initially the dispatch of the electricity system through minimizing the total system cost and subsequently, the household investment in PV-panels and batteries, as well as the dispatch of said batteries through minimizing the household electricity cost; the results from each optimization influence the inputs to the other optimization. **Paper V** minimizes the total electricity system dispatch cost with the inclusion of the dispatch of the electric space heating equipment. All the modeling, except for the investment model ELIN, are performed over a time horizon of 1 year and with a temporal resolution of 1 hour.

There follows a definition of the indicators used in this work, a description of the above-mentioned models, and a description of the connections between the models and the appended papers.

4.1 Definitions of indicators

A number of different indicators are used for the sizing of PV-panels (**Papers I**, **II**, and **III**) and batteries (**Papers II** and **III**). Furthermore, the concepts of self-sufficiency and self-consumption used with regards to PV installations in households are defined (**Papers II** and **III**).

Sizing of PV-panels and batteries

The sizes of PV-panels for household use are often measured in kilowatt peak (kW_p) units, as this results in panel sizes of single- or double-digit numbers. For the same reason, battery sizes for household use are usually measured in kWh. However, as households vary widely in terms of annual electricity consumption, comparing the absolute sizes of PV-panels and batteries between households can be problematic, especially when trying to discern trends within a large set of households. For instance, the self-sufficiency of a household with an annual electricity consumption of 25,000 kWh and a 4-kW_p PV-panel is significantly lower than a household with an annual electricity consumption of 6,000 kWh and a 4-kW_p PV-panel. To allow for more comparable sizing of the PV-panels, the concept of Array-to-Load ratio (ALR) is used [54]. The ALR of a PV installation is the size of the PV-panel in kW_p divided by the average load over a chosen time period of the household/consumer in kW. The result is a dimensionless number that correlates the size of the PV-panel to the size of the household's annual load, thereby allowing for a comparison between households with different magnitudes of electricity demand. The definition of ALR is as follows:

$$ALR = \frac{array\ size\ (W_p)}{average\ annual\ load\ (W)} \tag{1}$$

The choice of time period over which the average load is calculated is dependent upon the purpose of the installed PV-panel. If the PV-panel is installed to cover electricity demand for a specific time period, e.g., for a month during which a summer home is used, then that month would be a suitable time period to use. In this work, the focus is on permanent households and the time period used is 1 year, as this captures all the seasonal variations in household demand.

Analogous to the sizing of PV-panels, the sizing of batteries in absolute numbers can pose a problem when comparing different households due to the variability of electricity demand across households. Thus, there is a need for a sizing parameter for batteries that allows for comparison between households. As the batteries in this thesis are only investigated in the context of an existing PV-panel, the batteries presented in the results are related to the ALR of the PV-panels installed. The PV-panels and the batteries are related to each other through the Relative Battery Capacity (RBC), which is a concept/indicator that was previously used by Luthander et al. [74], [69] and Mulder et al. [68] (although not termed as RBC in those studies). The RBC is the size of the installed battery in kWh divided by the annual amount of electricity generated by the installed PV-panel in MWh. It can be written as:

$$RBC = \frac{battery\ energy\ capacity\ (Wh) \times 1000}{annual\ generated\ PV\ electricity\ (Wh)} \tag{2}$$

The use of the amount of electricity generated in the denominator ensures that the variations in electricity generated by geographic location or placement of the PV-panel are taken into account when sizing the battery in relation to the size of the PV-panel.

Self-consumption and self-sufficiency

The formulations for self-consumption and self-sufficiency applied in this thesis are those formulated by Luthander et al. [74]. Self-consumption and self-sufficiency are concepts that are used in relation to distributed generation that occurs on the consumer side of the meter. Self-consumption of electricity generated by a distributed electricity source is a measure of the share of generated electricity that is consumed by the consumer at whose residence the source is installed. Self-sufficiency, which is closely related to self-consumption, is the share of the electricity demand of the consumer that is supplied by the distributed generation source. Figure 5 shows curves that represent the electricity load profile of the consumer and the electricity generation profile for the distributed electricity source. The load profiles are divided into three regions: region A is the part of the electricity load profile in which electricity has to be supplied from the grid; region B is the part in which generated electricity is consumed locally by the consumer; and region C is the part of the electricity generation profile in which electricity is fed to the grid. The self-consumption is then

$$\varphi_{sc} = \frac{B}{B + C} \tag{3}$$

From Figure 5 it is also possible to deduce the level of self-sufficiency:

$$\varphi_{ss} = \frac{B}{A + B} \tag{4}$$

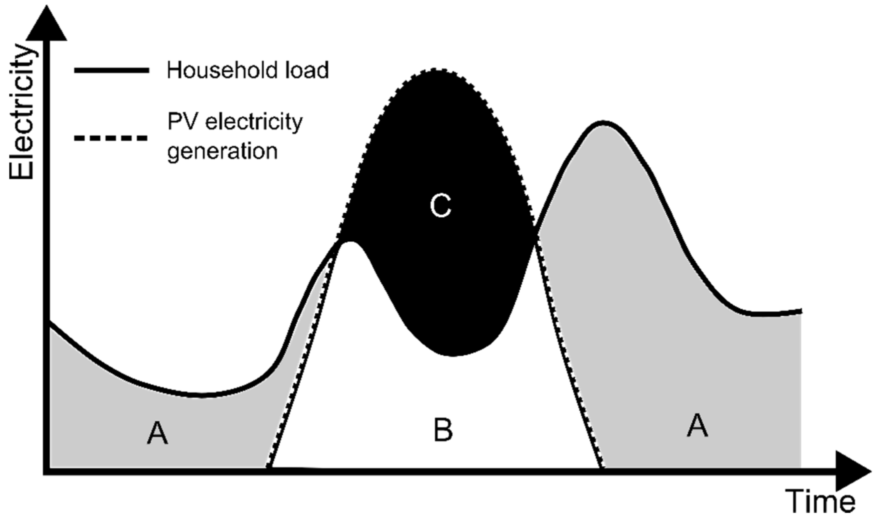


Figure 5. Conceptual description of a household load and PV electricity generation profile. A, The household load supplied by grid electricity; B, the household electricity supplied by PV-generated electricity; and C, PV-generated electricity fed to the grid.

The timeframe used when calculating the two indicators is arbitrary and should be determined by the context of the question one is trying to answer. However, as both the electricity load for the consumer and the generation of many distributed generation sources are weather-dependent, which in turn is correlated to the earth's rotation around the sun, an annual timeframe should be sufficient for capturing the overall picture of the interactions between the consumer and generation source.

For a more precise mathematical formulation of the definitions of self-consumption and self-sufficiency used, see **Paper II**.

4.2 Electric space heating dispatch model

The one-zone energy balance model used in **Paper IV** is the same as that described by Mata et al. [41] with one zone representing the entire dwelling. For the two-zone model used in **Paper V**, the described approach is extended, with one zone representing the building envelope and one zone representing the internal parts of the dwelling. Figure 6 shows the two approaches, with the left panel depicting the one-zone model, in which the entire building is the zone, and the right panel illustrating the two-zone model, in which the indoor and envelope are separated (the arrows indicate energy flows). Obviously, both zone descriptions are simplifications of the energy transport that occurs within a building, e.g., different rooms in the building and the differentiation of different parts of the envelope could also be included. The model can either be used by its own with a static supply side (**Paper IV**) or integrated into the EPOD model (**Paper V**).

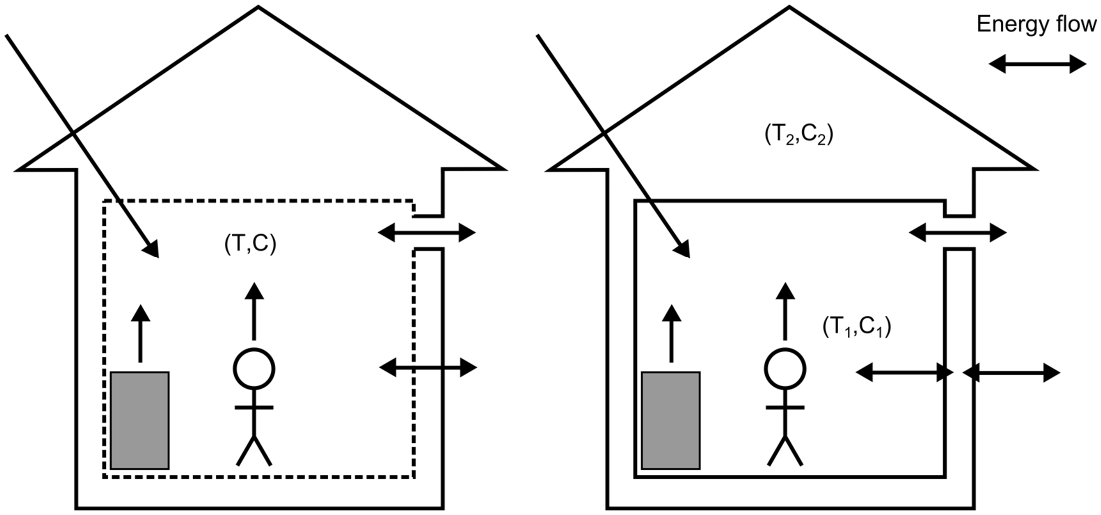


Figure 6. Conceptual description of the one-zone (left panel) and two-zone (right panel) energy balance models for a building. The arrows represent the different energy flows.

The formal description of the electric space heating dispatch model is as follows (variables in the optimization are bolded). When used with a static supply side as in **Paper IV** the model minimizes the total cost of purchasing electricity:

$$C_{tot} = \sum_{h \in H^A} \sum_{t \in T} \left(p_t^{buy} \times \boldsymbol{e}_{h,t}^{bot}\right) \tag{5}$$

where H^A is the set of all modeled sample dwellings, and T is the set of all time-steps. Furthermore, p_t^{buy} is the price for purchasing electricity at time-step t. The price includes the electricity market spot price per unit of electricity, an energy tax per unit of electricity, a surcharge, a renewable energy certificate charge, and a distribution grid charge. All of these items are also subject to value added tax. The amount of electricity purchased by dwelling h at time-step t is represented by $\boldsymbol{e}_{h,t}^{bot}$.

The amount of electricity purchased is determined by the heating demand for each dwelling and is subject to:

$$\boldsymbol{e}_{h,t}^{bot} = \boldsymbol{q}_{h,t}^{heat} \times tsl \times \sum_{w \in W} \frac{\gamma_{h,w}}{\eta_{w,t}} \qquad \forall\ h \in H^A, t \in T \tag{6}$$

where $\boldsymbol{q}_{h,t}^{heat}$ is the energy transfer in W from the heating equipment in dwelling h at time-step t. This is multiplied by the time-step length, tsl, to get the energy for heating at time-step t. The set W is the set of all types of heating equipment. The conversion from demand for energy for heating to demand for electricity is dependent upon the type of heating equipment available in the dwelling, and $\gamma_{h,w}$ is the share of heating equipment w in dwelling h. Each heating equipment type w has an associated efficiency, $\eta_{w,t}$ (or the reciprocal of the coefficient of performance in the case of heat pumps).

The energy demand for heating is in turn governed by the need to maintain the indoor temperature at a predefined level or within a predefined temperature interval. For this reason, the model is subject to the intertemporal energy balance:

$$\boldsymbol{T}_{h,t}^{in} = \boldsymbol{T}_{h,t-1}^{in} + \frac{\left(\boldsymbol{q}_{h,t}^{heat} + \boldsymbol{q}_{h,t}^{vent} + \boldsymbol{q}_{h,t}^{tran} + q_{h,t}^{int} + q_{h,t}^{r} + \boldsymbol{q}_{h,t}^{cool}\right) \times tsl}{TC_h^{tot}} \qquad \forall\ h \in H^A,\ t \in T \tag{7}$$

where $\boldsymbol{T}_{h,t}^{in}$ is the indoor temperature in dwelling h at time-step t. The energy balance also contains the variables $\boldsymbol{q}_{h,t}^{vent}$, which is the energy transfer through the ventilation system, $\boldsymbol{q}_{h,t}^{tran}$, which is the energy transfer through the building envelope, and $\boldsymbol{q}_{h,t}^{cool}$, which is the energy transfer due to natural cooling, i.e., opening a window, for each dwelling h at time-step t. The remaining two parameters are $q_{h,t}^{int}$, which represents the internal energy gains, i.e., the energy from people and machines in the dwelling, and $q_{h,t}^{r}$, which is the energy derived from solar irradiation. TC_h^{tot} is the total thermal mass of dwelling h.

Each energy transfer term is subject to an energy balance, with $\boldsymbol{q}_{h,t}^{tran}$ being subject to:

$$\boldsymbol{q}_{h,t}^{tran} = U_h^{tot} \times sa_h\left(T_{h,t}^{out} - \boldsymbol{T}_{h,t}^{in}\right) \qquad \forall\ h \in H^A, t \in T \qquad (8)$$

where U_h^{tot} is the overall heat transfer coefficient, and sa_h is the building envelope surface area for dwelling h. Furthermore, $t_{h,t}^{out}$ is the outside temperature for dwelling h at time-step t.

The energy transfer through the ventilation differs depending on whether or not the dwelling has a heat recovery ventilation system. If the dwelling has a recovery system it is subject to:

$$\boldsymbol{q}_{h,t}^{vent} = vc \times cp^{air} \times ar_h\left(\boldsymbol{T}_{h,t}^{vent} - \boldsymbol{T}_{h,t}^{in}\right) \qquad \forall\ h \in H^{Aftx},\ t \in T \qquad (9)$$

where $H^{Aftx} \subset H^A$ is the set of all dwellings with a heat recovery system. All dwellings are assumed to have the same ventilation air flow per m^2, vc, and cp^{air}, which is the volumetric heat capacity of air. In addition, ar_h is the heated floor area of dwelling h, and $\boldsymbol{T}_{h,t}^{vent}$ is the ventilation temperature in dwelling h at time-step t.

The ventilation temperature is dependent upon the outside temperature according to:

$$\boldsymbol{t}_{h,t}^{vent} = t_{h,t}^{out} + \eta^{rec} \times \left(\boldsymbol{T}_{h,t}^{in} - T_{h,t}^{out}\right) \qquad \forall\ h \in H^{Aftx},\ t \in T^{ftx} \qquad (10)$$

where η^{rec} is the heat recovery efficiency. However, Eq. (10) is only applied for the time-steps in set $T^{ftx} \subset T$, which contains the time-steps for which $T_{h,t}^{out}$ is ≤15°C.

For all the time-steps in which $T_{h,t}^{out}$ is >15°C, the set $T^{noftx} \subset T$, $\boldsymbol{T}_{h,t}^{vent}$ is simply expressed as:

$$\boldsymbol{T}_{h,t}^{vent} = T_{h,t}^{out} \qquad \forall\ h \in H^{Aftx},\ t \in T^{noftx} \qquad (11)$$

Thus, for outdoor temperatures >15°C, it is assumed that the heat recovery system does not operate.

For all dwellings that do not have a heat recovery system, the set of dwellings $H^{Anoftx} \subset H^A$, the energy transfer through the ventilation system is:

$$\boldsymbol{q}_{h,t}^{vent} = vc \times cp^{air} \times ar_h\left(T_{h,t}^{out} - \boldsymbol{T}_{h,t}^{in}\right) \qquad \forall\ h \in H^{Anoftx},\ t \in T \qquad (12)$$

The possible energy transfer from the heating system is subject to:

$$\boldsymbol{q}_{h,t}^{heat} \leq sh_h \qquad \forall\ h \in H^A, t \in T \quad (13)$$

where sh_h is the maximum heating capacity in dwelling h.

The ability of a dwelling to store energy is dependent upon the allowed variation in the indoor temperature $\boldsymbol{T}_{h,t}^{in}$. This allowed variation is limited by:

$$\boldsymbol{T}_{h,t}^{in} \leq T_t^{max} \qquad \forall\ h \in H^A, t \in T \quad (14)$$

$$\boldsymbol{T}_{h,t}^{in} \geq T_t^{min} \qquad \forall\ h \in H^A, t \in T \quad (15)$$

where T_t^{max} is the maximum allowed indoor temperature, and T_t^{min} is the minimum allowed indoor temperature at time-step t. This approach to limiting the indoor temperature variations is named the *fixed interval* method.

The internal heat gains are defined as:

$$q_{h,t}^{int} = q_{h,t}^{app} + q_{h,t}^{occ} + q_{h,t}^{light} + q_h^{buis} \qquad \forall\ h \in H^A, t \in T \quad (16)$$

where $q_{h,t}^{app}$ is the heat from appliances, $q_{h,t}^{occ}$ is the heat from occupants, $q_{h,t}^{light}$ is the heat from lighting, and q_h^{buis} is the heat from the ventilation fan in dwelling h at time-step t.

These four sources of energy are in turn defined as follows:

$$q_{h,t}^{app} = app_t \times Ac \times ar_h \qquad \forall\ h \in H^A, t \in T \quad (17)$$

$$q_{h,t}^{occ} = occ_t \times Oc \times ar_h \qquad \forall\ h \in H^A, t \in T \quad (18)$$

$$q_{h,t}^{light} = light_t \times Lc \times ar_h \qquad \forall\ h \in H^A, t \in T \quad (19)$$

$$q_h^{buis} = Pfh_h \times ar_h \qquad \forall\ h \in H^A, t \in T \quad (20)$$

where app_t, occ_t, and $light_t$ are the profiles for the appliances, occupation, and lighting, respectively. The parameters Ac, Oc, Lc and Pfh_h are given in units of W/m^2 for appliances, occupation, lighting, and fan heat, respectively.

The solar energy gains are:

$$q_{h,t}^{r} = Ts_h \times Wc_h \times Wf_h \times Sw_h \times Ir_{h,t} \times 0.65 \qquad \forall\ h \in H^A, t \in T \quad (21)$$

where Ts_h, Wc_h, Wf_h, Sw_h and $Ir_{h,t}$ are the window solar transmittance, solar shading coefficient for a window, the frame coefficient of the window, the total surface area of the windows of the building, and the global irradiation on a horizontal surface, respectively.

Here follows a description of the two-zone extension of the model presented above. In addition, an alternative to the *fixed interval* method for limiting the variation in indoor temperature is introduced. In this alternative to the temperature interval, the indoor temperature is allowed to vary without limitation; instead there is a penalty cost associated with deviating from an indoor set-point temperature. This method is called *deviation cost* method.

The modification of the energy balance model involves replacing Eq. (7) with the following:

$$\boldsymbol{T}_{h,t}^{in} = \boldsymbol{T}_{h,t-1}^{in} + \frac{\left(\boldsymbol{q}_{h,t}^{heat} + \boldsymbol{q}_{h,t}^{vent} + \boldsymbol{q}_{h,t}^{stran} + q_{h,t}^{int} + q_{h,t}^{r} + \boldsymbol{q}_{h,t}^{cool}\right) \times tsl}{TC_h^{in}} \qquad \forall\ h \in H^A,\ t \in T \qquad (22)$$

The change from Eq. (7) is the removal of $\boldsymbol{q}_{h,t}^{tran}$ and the introduction of $\boldsymbol{q}_{h,t}^{stran}$. The new variable $\boldsymbol{q}_{h,t}^{stran}$ represents the energy transfer between the newly introduced temperature zone and the indoor air for dwelling h at time-step t. The newly introduced zone represents the entirety of the building envelope. Furthermore, the thermal mass of the building is divided among the two zones of the dwelling, such that the TC_h^{in} value represents the thermal mass of the indoor temperature zone.

An intertemporal energy balance is introduced for the new temperature zone:

$$\boldsymbol{T}_{h,t}^{env} = \boldsymbol{T}_{h,t-1}^{env} + \frac{\left(\boldsymbol{q}_{h,t}^{tran} - \boldsymbol{q}_{h,t}^{stran}\right) \times tsl}{TC_h^{env}} \qquad \forall\ h \in H^A, t \in T \qquad (23)$$

where $\boldsymbol{T}_{h,t}^{env}$ is the temperature of the building envelope for dwelling h at time-step t, and TC_h^{env} is the thermal mass of the building envelope in dwelling h.

Equation (8), which represents the energy transfer between the dwelling and the outside, is altered to give:

$$\boldsymbol{q}_{h,t}^{tran} = U_h^{tot} \times sa_h\left(T_{h,t}^{out} - \boldsymbol{T}_{h,t}^{env}\right) \qquad \forall\ h \in H^A, t \in T \qquad (24)$$

where $\boldsymbol{T}_{h,t}^{env}$ replaces $\boldsymbol{T}_{h,t}^{in}$, as it is assumed that only the building envelope is in contact with the outside.

The transfer of energy between the building envelope temperature zone and the indoor air temperature zone is governed by:

$$\boldsymbol{q}_{h,t}^{stran} = h_h^{as} \times su_h\left(\boldsymbol{T}_{h,t}^{env} - \boldsymbol{T}_{h,t}^{in}\right) \qquad \forall\ h \in H^A, t \in T \qquad (25)$$

where $h_h^{as}$is the heat transfer coefficient between the indoor zone and the building envelope.

The alternative to having a fixed interval for the temperature variation, i.e., Eq. (14) and Eq. (15), involves a change in the objective function, as in Eq. (5), to the following:

$$C_{tot} = \sum_{h\in H^A}\sum_{t\in T}\left(p_t^{buy} \times \boldsymbol{e}_{h,t}^{bot} + \boldsymbol{T}_{h,t}^{upl} \times c^{upl} + \boldsymbol{T}_{h,t}^{uph} \times c^{uph} + \boldsymbol{T}_{h,t}^{dl} \times c^{dl} + \boldsymbol{T}_{h,t}^{dh} \times c^{dh}\right) \qquad (26)$$

where $\boldsymbol{T}_{h,t}^{upl}$ is the low-cost temperature increase, $\boldsymbol{T}_{h,t}^{uph}$ is the high-cost temperature increase, $\boldsymbol{T}_{h,t}^{dl}$ is the low-cost temperature decrease, and $\boldsymbol{T}_{h,t}^{dh}$ is the high-cost temperature decrease for dwelling h at time-step t. Furthermore, c^{upl}, c^{uph}, c^{dl}, and c^{dh} are the costs for the low-cost temperature increase, high-cost temperature increase, low-cost temperature decrease, and high-cost temperature decrease, respectively.

For those cases in which this alternative objective function is used, the indoor temperature, $\boldsymbol{T}_{h,t}^{in}$, is calculated as follows:

$$\boldsymbol{T}_{h,t}^{in} = \boldsymbol{T}_{h,t}^{ina} + \boldsymbol{T}_{h,t}^{upl} + \boldsymbol{T}_{h,t}^{uph} - \boldsymbol{T}_{h,t}^{dl} - \boldsymbol{T}_{h,t}^{dh} \qquad \forall\ h \in H^A, t \in T \qquad (27)$$

where $\boldsymbol{T}_{h,t}^{ina}$ is the setpoint temperature from which the increase and decrease in temperatures are allowed to vary for dwelling h at time-step t. Furthermore, $\boldsymbol{T}_{h,t}^{ina}$ can also be allowed to vary within a temperature range without the dwelling incurring any additional penalty costs.

The allowed temperature interval for $\boldsymbol{T}_{h,t}^{ina}$ is governed by:

$$\boldsymbol{T}_{h,t}^{ina} \leq T_t^{max,ina} \qquad \forall\ h \in H^A, t \in T \qquad (28)$$

$$\boldsymbol{T}_{h,t}^{ina} \geq T_t^{min,ina} \qquad \forall\ h \in H^A, t \in T \qquad (29)$$

where $T_t^{max,ina}$ is the maximum allowed temperature, and $T_t^{min,ina}$ is the minimum allowed temperature for $\boldsymbol{T}_{h,t}^{ina}$ at time-step t.

The low-cost temperature increase, $\boldsymbol{T}_{h,t}^{upl}$, and the low-cost temperature decrease, $\boldsymbol{T}_{h,t}^{dl}$, are subject to:

$$\boldsymbol{T}_{h,t}^{upl} \leq T_t^{max,upl} \qquad \forall\ h \in H^A, t \in T \qquad (30)$$

$$\boldsymbol{T}_{h,t}^{dl} \leq T_t^{max,dl} \qquad \forall\ h \in H^A, t \in T \qquad (31)$$

where $T_t^{max,upl}$ and $T_t^{max,dl}$ are the maximum values for the low-cost temperature increase and low-cost temperature decrease at time-step t, respectively.

The following variables can only have positive values:

$$\boldsymbol{T}_{h,t}^{in}, \boldsymbol{T}_{h,t}^{ina}, \boldsymbol{T}_{h,t}^{upl}, \boldsymbol{T}_{h,t}^{uph}. \boldsymbol{T}_{h,t}^{dl}, \boldsymbol{T}_{h,t}^{dh}, \boldsymbol{T}_{h,t}^{vent}, \boldsymbol{T}_{h,t}^{env}, \boldsymbol{e}_{h,t}^{bot}, \boldsymbol{q}_{h,t}^{heat}, \boldsymbol{q}_{h,t}^{cool} \geq 0 \quad \forall\ h \in H^A, t \in T \qquad (32)$$

The following variables can take on both positive and negative values:

$$\boldsymbol{q}_{h,t}^{tran}, \boldsymbol{q}_{h,t}^{stran}, \boldsymbol{q}_{h,t}^{vent}\ free \qquad \forall\ h \in H^A, t \in T \qquad (33)$$

To obtain the system-level impact of dispatching the electric space heating, each dwelling h is scaled up according to:

$$E_t^{tot} = \sum_{h \in H^A} \left(\boldsymbol{e}_{h,t}^{bot} \times w_h \right) \qquad \forall\ t \in T \qquad (34)$$

where E_t^{tot} is the total electric space heating demand at time-step t , and w_h is the weighting of the dwelling h, i.e., the extent to which the specific dwelling represents part of the total number of dwellings in the Swedish single-family dwelling building stock.

4.3 Demand response appliance model

The DR appliance model used in **Paper I** optimizes the dispatch of household loads subject to certain constraints. The loads can be divided into appliance loads and thermal loads. Appliance loads include dishwashers, washing machines, and dryers. For these loads, a timeframe for shifting is set. However, if there is a need to operate the load earlier than the end of the shifting timeframe then that takes precedence, i.e., if the allowed shifting timeframe for a dishwasher is 24 hours but there is a need in the household to run the dishwasher again after just 12 hours, the shifting time becomes 12 hours. The thermal loads include refrigerators, freezers, hot tap-water heating, and hydronic heating. For the cold appliances, the load can be shifted by 1 hour, either to a preceding or a succeeding hour, signifying a change in temperature inside the appliance. For the hydronic space heating and hot-water demands, there is the possibility to store heat, meaning that the shifting time variable is only limited by the size of the storage.

The model minimizes the total cost of electricity as follows:

$$\min C_{tot}^{DR} = \sum_{h \in H^{DR}} \sum_{t \in T} \left(p_t^{buy} \times \boldsymbol{e}_{h,t}^{bot} - p_t^{sell} \times \boldsymbol{e}_{h,t}^{sold} + pn_h \times c^{PV} \times a^{PV} + in_h \times c^{inv} \times a^{inv} + om \times pn_h \right) \tag{35}$$

where H^{DR} is the set of all households modeled. The electricity purchasing price, p_t^{buy} is the electricity market spot price per unit of electricity, an energy tax per unit of electricity, a surcharge, a certificate charge and a distribution grid charge. All of these values are also subject to value added tax. While p_t^{sell} is the price received for selling electricity to the grid (the wholesale price of electricity and a reimbursement from the distribution grid owner) at time-step t. The electricity bought from the grid is as previously stated $\boldsymbol{e}_{h,t}^{bot}$, and $\boldsymbol{e}_{h,t}^{sold}$ is the electricity sold to the grid by household h at time-step t. The households also have to pay the cost of investing in a PV-panel, where pn_h denotes the size of the PV-panel investment made by household h. As it is assumed that the inverter has a shorter lifespan than the rest of the system, in_h represents the size of the investment in the inverter made by household h. Furthermore, om is the maintenance cost, c^{PV} is the cost of the PV-panel, c^{inv} is the cost of the inverter, and a^{PV} and a^{inv} are the annuity factors for the PV-panel and inverter, respectively. The annuity factor is defined as:

$$a = \frac{r}{1 - (1 + r)^{-n}} \tag{36}$$

where r is the interest rate, and n is the lifetime of the investment.

The dispatch of the DR loads and the charging of the hot-water storage are subject to:

$$d_{h,t}^{rest} + \boldsymbol{e}_{h,t}^{sold} + \boldsymbol{s}_{h,t}^{add} + \sum_{x \in X} \left(\boldsymbol{m}_{h,x,t}^{fst} + \boldsymbol{m}_{h,x,t}^{sec} \right) = \boldsymbol{e}_{h,t}^{bot} + PV_{h,t} + \boldsymbol{s}_{h,t}^{rem} \qquad \forall\, h \in H^{DR}, t \in T \tag{37}$$

where X is the set of all DR loads, with the exception of hot-water storage. The parameter $d_{h,t}^{rest}$ is the electricity demand from all non-DR loads in household h at time-step t. Furthermore, $\boldsymbol{s}_{h,t}^{add}$ is the energy added to the hot-water storage, and $\boldsymbol{s}_{h,t}^{rem}$ is the energy removed from the hot-water storage in household h at time-step t. The DR loads are represented by $\boldsymbol{m}_{h,x,t}^{fst}$ and $\boldsymbol{m}_{h,x,t}^{sec}$, where $\boldsymbol{m}_{h,x,t}^{fst}$ is the electricity demand from DR load x in household h at time-step t. The second variable, $\boldsymbol{m}_{h,x,t}^{sec}$, is the additional demand for loads that operate for two time-steps. Each $\boldsymbol{m}$ variable is binary and can thus only attain the value 0 or the load size of the load x that it is representing. The parameter $PV_{h,t}$ is the electricity generated by the PV panel in household h at time-step t.

To ensure the DR loads are dispatched within the allowed shifting timeframe, the dispatch of the DR loads is subject to:

$$\boldsymbol{m}_{h,x,t}^{fst} + \boldsymbol{m}_{h,x,t+1}^{fst} + \cdots + \boldsymbol{m}_{h,x,t+n}^{fst} = d_{h,x}^{app} \qquad \forall\ h \in H^{DR}, t \in L_{h,x}, x \in R \tag{38}$$

where $L_{h,x} \subset T$ is the set of time-steps t that are DR starting hours for household h and DR load x, i.e., these are time-steps within which the load must be dispatched. $R \subset X$ is the set of DR loads that have a running time of one time-step. The DR loads are summed until time-step $t + n$, where n is the number of time-steps for the given shifting timeframe, and must equal $d_{h,x}^{app}$, which is the electricity demand for DR load x in household h.

DR loads that have a running time of two time-steps, the set $S \subset X$, are subject to:

$$\boldsymbol{m}_{h,x,t}^{fst} + \boldsymbol{m}_{h,x,t+1}^{fst} + \cdots + \boldsymbol{m}_{h,x,t+(n-1)}^{fst} = d_{h,x}^{app} \qquad \forall\ h \in H^{DR}, t \in L_{h,x}, x \in S \tag{39}$$

where the only change from Eq. (38) is that the shifting timeframe is now $n - 1$. This is necessary, as otherwise there is a risk that the load in the second time-step coincides with the load in a new shifting timeframe.

The additional demand is subject to:

$$\boldsymbol{m}_{h,x,t}^{fst} = \boldsymbol{m}_{h,x,t+1}^{sec} \qquad \forall\ h \in H^{DR}, t \in L_{h,x}, x \in S \tag{40}$$

thereby ensuring that the loads are consecutive.

The fridge and freezer DR loads, the set $F \subset X$, are treated differently, as follows:

$$\boldsymbol{l}_{h,x,t}^{frid} = \boldsymbol{m}_{h,x,t}^{fst} - d_{h,x}^{frid} \qquad \forall\ h \in H^{DR}, t \in T, x \in F \tag{41}$$

where $\boldsymbol{l}_{h,x,t}^{frid}$ is the storage level of the fridge or freezer x in household h at time-step t , and $d_{h,x}^{frid}$ is the per time-step electricity demand for fridge or freezer x in household h.

To ensure that the storage level is not too low for longer than the allowed timeframe, it is subject to:

$$\boldsymbol{l}_{h,x,t}^{frid} + \boldsymbol{l}_{h,x,t+1}^{frid} \geq -d_{h,x}^{frid} \qquad \forall\ h \in H^{DR}, t \in T, x \in F \tag{42}$$

where Eq. (42) ensures that the fridge or freezer storage level cannot remain at a low level for more than one time-step.

Furthermore, the storage level is subject to:

$$\boldsymbol{l}_{h,x,t}^{frid} \geq -d_{h,x}^{frid} \qquad \forall\ h \in H^{DR}, t \in T, x \in F \tag{43}$$

$$\boldsymbol{l}_{h,x,t}^{frid} \leq d_{h,x}^{frid} \qquad \forall\ h \in H^{DR}, t \in T, x \in F \tag{44}$$

which ensures that the level is maximally one per time-step demand down or up.

The total electricity demand for the fridge or freezer needs to be the same as the total per time-step demand during the modeled period:

$$\sum_{t\in T} \boldsymbol{m}_{h,x,t}^{fst} = d_{h,x}^{frid} \times |T| \qquad \forall\ h \in H^{DR}, x \in F \tag{45}$$

The hot-water storage level is subject to:

$$\boldsymbol{l}_{h,t}^{wat} = \boldsymbol{l}_{h,t-1}^{wat} \times \eta^{wat} - \boldsymbol{s}_{h,t}^{rem} + \boldsymbol{s}_{h,t}^{add} \qquad \forall\, h \in H^{DR}, t \in T \tag{46}$$

where $\boldsymbol{l}_{h,t}^{wat}$ is the storage level of the hot-water storage in household h at time-step t. For each time-step, some of the energy in the storage is lost; the amount lost is governed by the per time-step efficiency of the hot-water storage, η^{wat}.

The energy removed from the storage is subject to:

$$\boldsymbol{s}_{h,t}^{rem} \leq d_{h,t}^{wat} \qquad \forall\, h \in H^{DR}, t \in T \tag{47}$$

where $d_{h,t}^{wat}$ is the demand for hot water (either for hydronic or tap-water purposes, or both) in household h at time-step t. The equation ensures that the stored hot water is not used for anything other than hydronic heating or hot tap-water.

The storage operation is also limited by the maximum power capacity of the heating system according to:

$$\boldsymbol{s}_{h,t}^{add} + d_{h,t}^{wat} - \boldsymbol{s}_{h,t}^{rem} \leq y_{h}^{wat} \qquad \forall\, h \in H^{DR}, t \in T \tag{48}$$

where y_{h}^{wat} is the maximum power capacity per time-step of the heating system in household h.

The possible storage level is limited according to:

$$\boldsymbol{l}_{h,t}^{wat} \leq b_{h}^{wat} \qquad \forall\, h \in H^{DR}, t \in T \tag{49}$$

where b_{h}^{wat} is the maximum amount of energy that can stored in household h.

The following variables can only take on positive values:

$$\boldsymbol{s}_{h,t}^{add}, \boldsymbol{s}_{h,t}^{rem}, \boldsymbol{l}_{h,t}^{wat}, \boldsymbol{e}_{h,t}^{bot}, \boldsymbol{e}_{h,t}^{sold} \geq 0 \qquad \forall\, h \in H^{DR}, t \in T \tag{50}$$

4.4 PV-battery model

The PV-battery model can be regarded as an extension of the DR appliance model and is used in **Papers II** and **III**. The battery is modeled using a simplified representation of a lithium-ion battery system, similar to the descriptions used in Weniger et al. [69] and Mulder et al. [68]. The simplifications imposed are that the battery is assumed not to self-discharge and that the efficiency of charge and discharge of the battery is assumed to be constant. Moreover, there is no accounting for degradation of the battery due to its operation. Furthermore, no depth of discharge is taken into account, i.e., the modeled battery only represents the usable part of the battery. The battery-PV system is assumed to be to be AC/DC-coupled. The detailed model description follows below.

The PV-battery model can be used to maximize self-consumption of PV-generated electricity, which is equivalent to maximizing the self-sufficiency of a household, i.e., minimizing the amount of purchased electricity, this is done in **Paper II**. Thus, the optimization model minimizes the total amount of purchased electricity according to:

$$min\, \boldsymbol{E_{tot}} = \sum_{h \in H^{bat}} \sum_{t \in T} \boldsymbol{e}_{h,t}^{bot} \tag{51}$$

where the set H^{bat} is the set of all households h , and T is the set of all time-steps t. As previously noted, $\boldsymbol{e}_{h,t}^{bot}$ is the electricity purchased by household h at time-step t.

To ensure that the electricity demand is met for each household, the optimization is subject to:

$$d_{h,t}^{tot} + \boldsymbol{e}_{h,t}^{sold} + \boldsymbol{s}_{h,t}^{add} = \boldsymbol{e}_{h,t}^{bot} + PV_{h,t} + \boldsymbol{s}_{h,t}^{rem} \times \eta^{bat} \qquad \forall\, h \in H^{bat}, t \in T \tag{52}$$

where $d_{h,t}$ is the electricity demand from household h at time t. Furthermore, $s_{h,t}^{add}$ is the energy added to the battery, and $s_{h,t}^{rem}$ is the energy removed from the battery for household h at time t. The removed energy is multiplied by the battery discharge efficiency, η^{bat}, to capture energy losses from operating the battery. In addition, $PV_{h,t}$ is the electricity generated by a PV-panel that belongs to household h at time t.

The energy storage level of the battery is defined as:

$$\boldsymbol{l}_{h,t} = \boldsymbol{l}_{h,t-1} - \boldsymbol{s}_{h,t}^{rem} + \boldsymbol{s}_{h,t}^{add} \times \eta^{bat} \qquad \forall\, h \in H^{bat}, t \in T \tag{53}$$

where $l_{h,t}$ is the storage level of a battery that belongs to household h at time t.

The possible storage level and the capacity for charge and discharge are subject to:

$$\boldsymbol{s}_{h,t}^{rem} \leq y_h^{bat} \qquad \forall\, h \in H^{bat}, t \in T \tag{54}$$

$$\boldsymbol{s}_{h,t}^{add} \leq y_h^{bat} \qquad \forall\, h \in H^{bat}, t \in T \tag{55}$$

$$\boldsymbol{l}_{h,t}^{bat} \leq b_h^{bat} \qquad \forall\, h \in H^{bat}, t \in T \tag{56}$$

where y_h^{bat} is the power capacity per time-step of the battery, and b_h^{bat} is the energy capacity of the battery in household h.

All of the variables can only assume positive values:

$$\boldsymbol{e}_{h,t}^{bot};\ \boldsymbol{e}_{h,t}^{sold}; \boldsymbol{s}_{h,t}^{add}; \boldsymbol{s}_{h,t}^{rem}; \boldsymbol{l}_{h,t}^{bat} \geq 0 \qquad \forall\, h \in H^{bat}, t \in T \tag{57}$$

The objective function of the model can be changed to minimize the household electricity cost which is done in **Paper III**. The new objective minimizes the total electricity cost for all households according to:

$$\min C_{tot} = \sum_{i \in N} \sum_{h \in H_i^{bat}} \sum_{t \in T} \big(p_{i,t}^{buy} \times \boldsymbol{e}_{i,h,t}^{bot} - p_{i,t}^{sell} \times \boldsymbol{e}_{i,h,t}^{sold} + \boldsymbol{b}_{i,h} \times c^{bat} \times a^{bat} + \boldsymbol{pn}_{i,h} \times c^{PV} \times a^{PV} + \boldsymbol{in}_{i,h} \times c^{inv} \times a^{inv} \big) \tag{58}$$

where $N \subset I$ represents the set of regions of all regions I that contain household load profiles, and H_i^{bat} is the set of households in region i. Similar to Eq. (35), $p_{i,t}^{buy}$ is the price for purchasing electricity from the grid (i.e., the electricity price, V.A.T., energy tax, distribution grid fee), and $p_{i,t}^{sell}$ is the price for selling electricity to the grid (the electricity price plus reimbursement from the distribution grid owner) in region i at time t. Furthermore, $\boldsymbol{e}_{i,h,t}^{bot}$ is the amount of electricity purchased from the grid, and $\boldsymbol{e}_{i,h,t}^{sold}$ is the amount of electricity sold to the grid in region i by household h at time t. For the investments, $\boldsymbol{b}_{i,h}$ is the size of the battery investment, $\boldsymbol{pn}_{i,h}$ is the size of the PV-panel investment, and $\boldsymbol{in}_{i,h}$ is the size of the inverter investment in region i made by household h. In addition, c^{bat} is the cost of the battery, c^{PV} is the cost of the PV-panel, c^{inv} is the cost of the inverter, and a^{bat} , a^{PV} , and a^{inv} are the annuity factors for the battery, PV-panel, and inverter, respectively. The annuity factor is defined according to Eq. (36). The variables and parameters in Eqs. (52–57) now also operate over the set N.

4.5 Energy system models

Two energy system models are used in conjunction with the models presented above, both of which are partial equilibrium optimization models, in that they only model the electricity sector of the economy. The ELIN model is a bottom up, long-term, dynamic optimization model that optimizes the investments in the power sector for the EU-27 countries, as well as Norway and Switzerland. The modeled countries are divided into 50 regions (Fig. 6). This division is based on the current bottlenecks in the European electricity system. The model has a time horizon of Years 2010–2050, with investment decisions being made each year. For each year, there is an intra-annual time resolution of 16 time-steps, representing day and night for weekdays and weekends for four seasons. For a more detailed description of the ELIN model, see Odenberger et al. [77] and Göransson et al. [78]. The results for a given scenario from the ELIN model are used as the input to the electricity system dispatch model EPOD. EPOD takes the description of the power system from a selected ELIN year and carries out optimization, in order to find the least-cost hourly dispatch of the system over 1 year for all regions in Figure 7. For a more detailed description of EPOD, see Unger and Odenberger [79], Göransson et al. [78], and Goop et al. [80]. Both the electric space heating dispatch model and the PV-battery model are connected to EPOD. The Electric space heating dispatch model operates over the Swedish regions SE1, SE2, SE3, and SE4 and the PV-battery model operates over regions SE1 and SE2. The modifications applied to the EPOD model arising from these connections are described below.

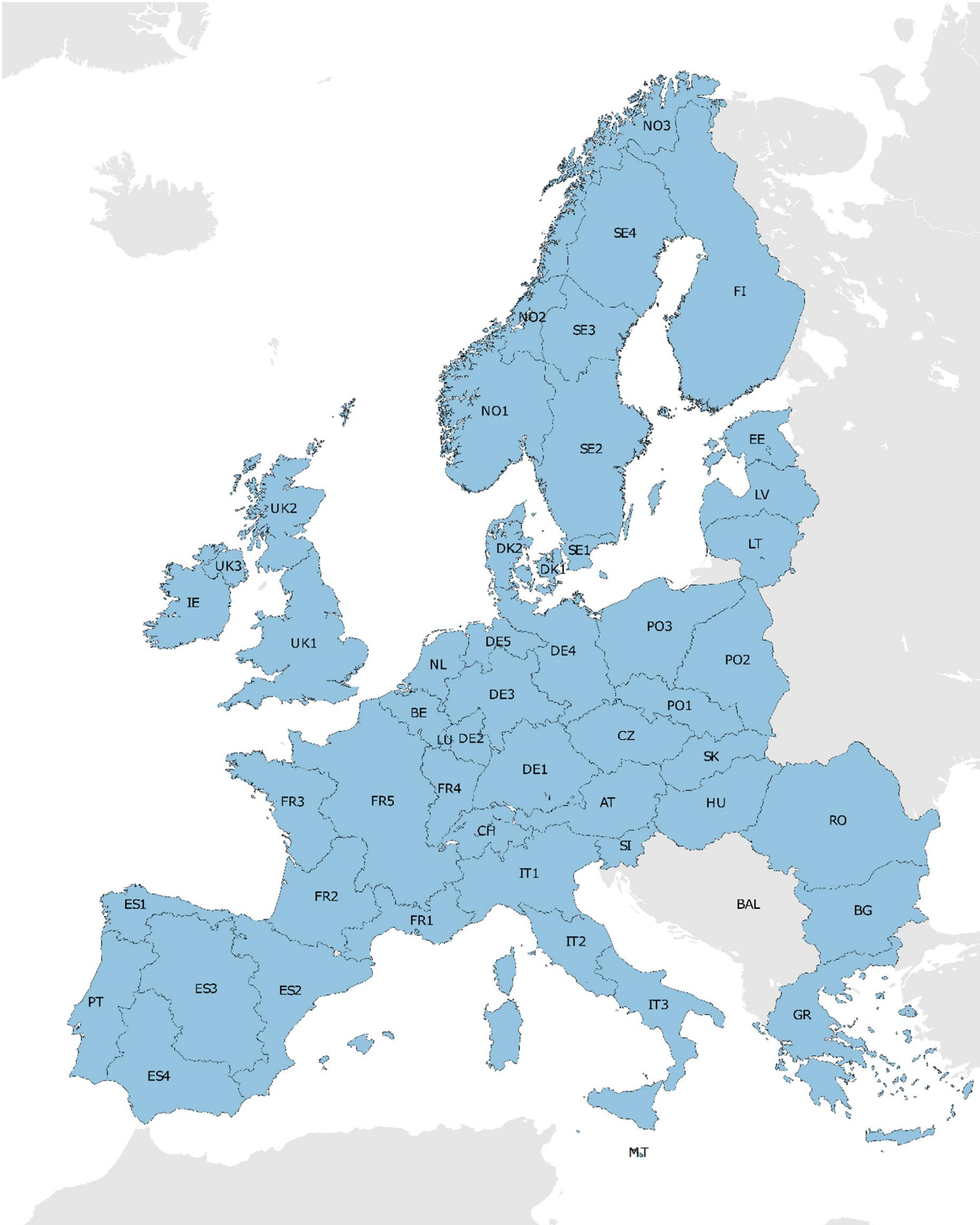


Figure 7. Regional divisions used in the EPOD and ELIN models.

The two-zone electric space heating dispatch model is included in the system for which EPOD optimizes the dispatch, i.e., EPOD has control over the operation of the heating equipment in the dwellings (**Paper V**). As a consequence of the inclusion of the electric space heating model, some of the equations and input data in EPOD are modified. The energy balance constraint is changed to:

$$d_{i,t}^{EPOD} + \sum_{h \in H_i^A} \left(\boldsymbol{e}_{h,t}^{bot} \times w_h \right) \leq \sum_{p \in P_i} \boldsymbol{g}_{p,t} + \sum_{\substack{j \in I \\ j \neq i}} \boldsymbol{f}_{i,j,t} \qquad \forall \ i \in I, t \in T \qquad (59)$$

where $d_{i,t}^{EPOD}$ is the electricity demand in region i at time-step t , excluding the electric space heating demand in $V \subset I$, where V is the set of Swedish regions. In addition, $\boldsymbol{g}_{p,t}$ is the power generated in plant p at time-step t, and $\boldsymbol{f}_{i,j,t}$ is the electricity traded between regions i and j at time-step t. The set P_i is all power plants in region i, and H_i^A is the set of all dwellings in region i. To capture the impact on the overall electricity demand of changes in the dispatch of the heating equipment, a baseline electric space heating demand is defined. Once calculated, it is scaled up and subtracted from the electricity demand profile in EPOD, i.e., as stated, the parameter $d_{i,t}^{EPOD}$ is the electricity demand with the baseline electric space heating demand subtracted in region i at time-step t for the set V.

The extent of the modification of the objective function in EPOD is dependent on whether the *fixed interval* method is used for the allowed indoor temperature change in the dwellings, as in Eqs. (14) and (15), or on whether the *deviation cost* method is used, as in Eqs. (27–31). If the *fixed interval* method is used there is no change to the objective function, as the change in total cost is captured by changes in the demand and thereby, changes in the electricity generation. For the case in which the *deviation cost* method is introduced, this penalty cost must be included in the objective function, as follows:

$$\min C_{tot}^{EPOD} = \sum_{i \in I} \sum_{h \in H_i^A} \sum_{p \in P_i} \sum_{t \in T} \left(c_{p,t}^{run} \times \boldsymbol{g}_{p,t} + \boldsymbol{c}_{p,t}^{cycl} + \boldsymbol{k}_{h,t} \times w_h \right) \qquad (60)$$

where $c_{p,t}^{run}$ is the running costs, and $\boldsymbol{c}_{p,t}^{cycl}$ is the cycling costs (the sum of the start-up and part-load costs) for plant p at time-step t. The introduced variable $\boldsymbol{k}_{h,t}$, is the cost penalty for deviating from the set-point temperature for dwelling h at time-step t.

The variable $\boldsymbol{k}_{h,t}$ is in turn subject to:

$$\boldsymbol{k}_{h,t} = \left(\boldsymbol{T}_{h,t}^{upl} \times c^{upl} + \boldsymbol{T}_{h,t}^{uph} \times c^{uph} + \boldsymbol{T}_{h,t}^{dl} \times c^{dl} + \boldsymbol{T}_{h,t}^{dh} \times c^{dh} \right) \qquad \forall \ h \in H_i^A, t \in T \qquad (61)$$

The PV-battery model, Eqs. (52–58), is iteratively optimized together with EPOD (**Paper III**). This approach is used so as to capture the feedback effect between the households that are optimizing their investments and EPOD. The iterative procedure is as follows:

1. The electricity system composition is generated in ELIN. The system composition for 1 year is extracted from ELIN and fed into EPOD.
2. EPOD optimizes the dispatch of the system over 1 year, generating a marginal cost of electricity (market price of electricity) for each region and time-step.
3. The marginal cost of electricity is used as electricity prices in the PV-battery investment model. This model then optimizes the investment levels of PV-panels and batteries for each household, as well as the dispatch of the batteries.

4. The new household net loads [see Eq. (62)] are scaled up to represent all households in the regions.
5. The demand/load curve in EPOD is changed with regard to the new household net load.
6. Steps 2 to 5 are repeated until the convergence criteria or the maximum number of iterations are reached.

The households' net load is:

$$d_{i,t}^{net} = \sum_{h \in H_i^{bat}} \left(\left[d_{h,t}^{tot} - p_{h,t} + \boldsymbol{s}_{h,t}^{add} - \boldsymbol{s}_{h,t}^{rem} \times \eta^{bat} \right] \times w_h^{bat} \right) \qquad \forall\ i \in N, t \in T \tag{62}$$

which is simply the households' total load, $\boldsymbol{d}_{h,t}^{tot}$, minus the PV-generated electricity plus the energy added to the energy storage minus the energy removed from storage multiplied by the weighting of each household.

4.6 Solar heat and power model

In Norwood et al. [81], an extensive modeling framework is presented that incorporates the following different solar energy systems: non-tracking photovoltaics (four different PV technologies are included: poly-Si, mono-Si, CdTe, and CIGS); 2D-tracking photovoltaics; high-concentration photovoltaics; flat-plate thermal; evacuated tube thermal; concentrating trough thermal; concentrating solar combined heat and power; and hybrid concentrating photovoltaic/thermal. In the modeling, empirically verified models are used for thermal and PV collectors. The empirical models for the PV technologies are taken from the studies of King et al. [82] and Huld et al. [83]. The models are not presented here but can be found in the sources presented above, as well as in the detailed description provided by Norwood et al. [81].

5. Data

The data used in this thesis and in the appended papers primarily concern either household/dwelling loads or weather. The data concerning household/dwelling loads comes in two categories;1) measured loads from actual households, which in turn comes from two different sources, Zimmermann [84] and E.ON. [85]; and 2) data describing the building envelope and other physical characteristics of dwellings, enabling modeling of the space heating demand. Weather data also comes in two categories; Typical Meteorological Year (TMY) data and year specific data.

Additional data that are required is the composition of the surrounding energy system, i.e. the results from the ELIN model, and economic and technical data for all papers. The ELIN scenarios used are presented below and technical and economic parameters used in all papers are presented in appendix A.

5.1 BETSI

The data used as input to the electric space heating dispatch model is a dataset called BETSI (Byggnaders Energi, Tekniska Status och Inomhusmiljö) [86]. BETSI contains data describing the building envelope, other building data (e.g. size), the geographical location, and weighting (reflecting the share of the total building stock represented by the dwelling) of 826 Swedish single-family dwellings as well as a number of multi-family dwellings and locales. The dwellings have been selected to be representative of the Swedish buildings stock. From this data all single-family dwellings with some form of electric space heating are extracted and used as input for the papers, resulting in a total of 571 dwellings. Thus, the representation of the electric space heating is only included in regions SE1-SE4 (Sweden, see Figure 7), as these are the regions for which there is available data. The data contains most parameters presented in the model description in section 4.2 except the power capacity of the heating equipment, coefficient of performance (COP) values for the heat pumps, profiles for the internal heat gains, thermal mass of the indoor air zone, and weather data.

For the methods used for assigning the missing data and validation of the data see **Papers IV** and **V**.

5.2 Appliance loads

For the DR appliance model, load profiles measured on an appliance basis are used as input data. The load profiles are taken from a measurement study performed by the Swedish energy agency [84]. The aim of the study was to investigate energy efficiency potentials in Swedish households. In the study 40 single-family households and apartment households were measured for a period of one year and 360 single-family households and apartment households were measured for one month. From the measured households the single-family households with a measurement period of one year where selected as input to the model, i.e., 21 households are modeled. The loads have been measured with a temporal resolution of 10 minutes which are aggregated to the 1 hour temporal resolution used in the model.

The loads that are used for DR are dishwashers, washing machines, dryers, fridges, freezers, hot tap water, and hydronic space heating. The washing machine and dryer are treated as one machine, i.e., it is assumed that there is no need to transfer laundry between the two machines. For each household and each appliance the set $L_{h,x}$ is created indicating the starting time step from which it is possible to shift the load forward in time. The starting time is based on the load profile of the appliance, with each indication of a load start on the measured load profile translating to a starting time for the DR of the load. The size of the shiftable appliance loads are set to the average size of the appliance load for each household, the resulting load sizes can be seen in Appendix A. For the cold appliance loads, i.e., the fridge and the freezer, the hourly load is set to the average load as well. For the hot tap water and hydronic space hearting the measured demand needs to be fulfilled in each time step. The maximum power that can be used for hot water purposes is set to either 9 kW, for households with hydronic space heating and hot tap water heating, or 3 kW, for households with only hot tap water heating. For each household with hot water storage possibilities the storage size is assumed to be either 10.2 kWh, for households with hydronic space heating, or 5.8 kWh, for households with hot tap water heating.

5.3 Household loads

For the PV-battery model, the input data is measured household load profiles. The measurement dataset comes from a measuring campaign performed by E.ON in Sweden [85]. The original dataset consists of 10,086 household measured over a 1-year period (February 1, 2012 to January 31, 2013) with a 1 hour resolution. In addition to the load profiles there are data concerning geographical location, heating system, and number of inhabitants. Of the 10,086 measured household loads 2,104 are used in the modeling. The reduced number of households used is due to lack of supplementary data and missing measurements. Households that did not include supplementary data are removed since this information is required in order to assign solar PV generation profiles to the households and in the scale up. With regards to the missing measurements all households missing ≥ 5 % of the data points are removed from the dataset. For a complete description of the data treatment see **Paper II**.

The households in EPOD regions SE3 and SE4 are scaled up to represent all single-family households in the two regions. The scaled up done through assigning weightings to each household in the used dataset. The weighting of each household is calculated using geographical location and heating technology data included in the dataset and statistics for the number of households with specific heating technologies in the two regions modeled. For further detail on the scale up and the validation of it see **Paper III**.

5.4 Weather data

Weather data is used for both the creation of PV electricity generation profiles as well as for outdoor temperatures used in the modeling of space heating demand. As mentioned two different type of datasets are used depending on the modeling purpose, TMY data and year specific data.

TMY datasets are created to, as the name indicates, represent a typical meteorological year. The TMY (more precisely TMY3 standard) dataset used consists of data for Europe with a spatial resolution of 0.25°×0.25° and a temporal resolution of 1 hour [87]. The data set consist of direct normal radiation, diffuse horizontal radiation, outdoor temperature, wind speed, albedo, and the suns position.

Year specific data is taken from the MERRA-2 dataset from NASA [88]. The MERRA-2 dataset has a spatial resolution of 0.5°×0.625° and a temporal resolution of 1 hour. Most the parameters available in the TMY dataset are available in the MERR-2 data, except for direct normal radiation, diffuse normal radiation, and sun position. For the solar radiation the dataset instead contains global horizontal radiation. However, as the direct normal and diffuse horizontal radiation is required for the modeling framework developed in Norwood et al. [81], the global horizontal radiation is split into these two parts using the method proposed by Ridley et al. [89]. The suns position is also calculated for each location and time-step using the methods described in Iqbal [90].

5.5 ELIN scenarios

A description of the European electricity system is needed in order to model the dispatch of said system. The systems are created through the use of the ELIN model. Three different scenarios are modeled; Green Policy (GP), Climate Market (CM), and Regional Policy (RP). The scenarios reach a decrease in CO_2 emissions from the electricity sector of 95% (GP and CM) or 99% (RP) relative to 1990 levels. The different scenarios have different driving forces with regards to the development of the electricity system. The GP scenario is driven by a tightening cap on CO_2 emissions but also includes targets on RES based electricity, not allowing for nuclear or fossil fuel (even if equipped with CCS) by Year 2050 and a moderate electricity demand increase. For the CM scenario the driving forces are an increased cap on CO_2 emissions and a high electricity demand increase. The RP scenario is driven by an increased cap on CO_2 emissions, targets on RES based electricity and no electricity demand increase. Figure 8 shows the development of the technology mix in total European electricity generation from Year 2010 to Year 2050 for a) the GP scenario, b) the CM scenario, and c) the RP scenario. As can be seen the system compositions vary considerably. GP is dominated by wind power, RP has relative large amounts of wind power, and CM showing a more diverse composition.

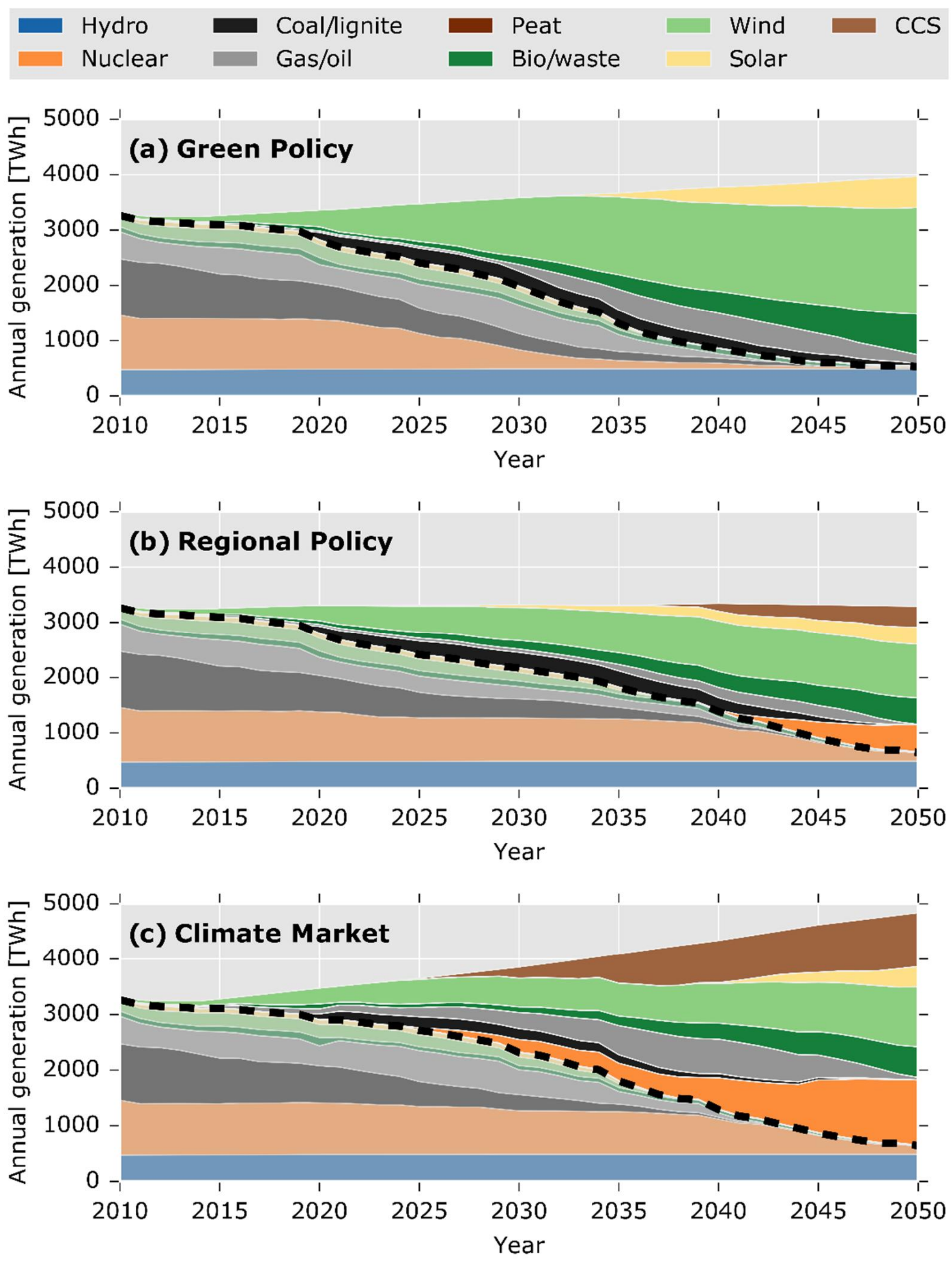


Figure 8. The development of the European electricity generation mix in the two scenarios: (a) Green Policy, (b) Regional Policy and (c) Climate Market. Faded colors represent contribution from existing power plants whereas clear colors describe contribution from new investments.

5.6 Use of the data in appended papers

The use of different data sources is motivated by the data characteristics required in order to answer the questions posed in the different papers. Table 3 shows which dataset that is used in which paper, a gray box indicates that the data has been used in the paper. For the weather data TMY is used in **Paper II** as the paper aim to give an average picture of what the expected power generated from the PV panels will be. Furthermore, the households investigated in this paper are investigated in isolation, i.e., there is no surrounding system whose description needs to be correlated with the data. For **Papers I**, **III**, **IV**, and **V** year specific weather data are used as other parameters which works as input to the models, e.g., electricity prices and system load curve, are year specific.

Through using the same time period for the different datasets possible correlations between data are hopefully preserved. All three scenarios are used in **Paper III** while GP and CM are used in **Paper V**. From each scenario the system composition for the year 2032 is selected and used for the dispatch modeling in EPOD. The scaled up household loads used in **Paper III** cover regions SE1 and SE2 and the dwellings in **Paper V** represent the whole of Sweden (SE1-SE4).

Table 3. The datasets used in each of the appended papers, a grey box indicates that the data has been used in the paper.

	BETSI	Appliance loads	Household loads	TMY weather data	Year specific weather data	ELIN scenarios
Paper I		■			■	
Paper II			■	■		
Paper III			■		■	■
Paper IV	■				■	
Paper V	■				■	■

6. Overview and discussion of the results

In this chapter, the key results from the appended papers are presented and discussed. The chapter is divided into two sections. Section 6.1 concerns household PV-systems and the technical and economic impacts that the DR and batteries can have on such systems. Section 6.2 concerns the technical potential and system value of DR of electric space heating in the Swedish single-family dwelling stock. The presented results are an overview and should not be viewed as exhaustive.

6.1 Solar photovoltaics in Swedish single-family dwellings

As mentioned in Section 2.3, the value of the PV installation of a household is dependent upon the degree of self-consumption of PV-generated electricity, as self-consumption implies that no taxes or fees are paid on the consumed electricity. Furthermore, if the electricity sold by prosumers is subject to the market price for electricity during the period of selling, i.e., through an RTP scheme, there may be additional incentives to increase self-consumption in the case of low electricity prices or to decrease self-consumption when electricity prices during hours with electricity generation are sufficiently high. A change in self-consumption can be accomplished by: 1) moving loads to or from the hours of excess PV electricity generation; or 2) charging or discharging energy storage units (batteries or hot-water tanks) during hours of excess electricity generation. Here follows the results from **Papers I–III** concerning the technical capability for and economic value of changing the level of self-consumption in Swedish single-family households. First, the technical potentials in terms of self-consumption of PV-generated electricity and self-sufficiency of PV-battery systems in Swedish households are presented. Second, the techno-economic potentials for DR and PV are presented, assuming a fixed supply side. Third, the techno-economic potential of PV-battery systems and the possible feedback with the surrounding electricity system arising from such investment are presented. The results are shown for the sizing of the PV-panels in terms of ALR and for the sizing of the batteries in terms of RBC. For a clarification of the concepts, see Section 4.1.

The technical potential of batteries

The combination of PV panels and batteries allows for the storage of excess electricity generated during daytime, which can be used subsequently to meet in-house electricity demand during evening, night-time or cloudy hours. Described below are the results concerning the technical limitations of batteries with regards to increasing the self-sufficiency and self-consumption of PV-generated electricity in Swedish single-family households, taken from **Paper II**. The PV-panel sizes in parentheses represent the ranges for the investigated households.

Figure 9 shows the resulting absolute values for self-sufficiency for ALRs of 0.5 (0.07–2.55 kW_p), 1.5 (0.21–7.65 kW_p), 3 (0.42–15.3 kW_p), and 6 (0.85–30.6 kW_p), with each dot representing one of the 2,104 modeled households and the lines representing the median household in terms of self-sufficiency. For the ALRs studied, self-sufficiency of up to 60% can be achieved. However, for higher ALRs, there is a difference between households of up to 30 percentage points for a given RBC. As shown in the figure, in the absence of a battery (values for the median household at an RBC of 0), the difference in the degree of self-sufficiency between ALRs becomes smaller with increasing ALR, e.g., an increase in ALR from 3 to 4.5 increases self-sufficiency by 2 percentage points (19% to 21%), while an increase in ALR from 1.5 to 3 results in an increase in self-sufficiency of 7 percentage points. This phenomenon is explained by the concentrated electricity generation profiles of the PV-panels for Swedish conditions; as the PV panel size is increased, most of the new generation occurs during hours with excess generation. Although an increased battery size helps to exacerbate the difference in self-sufficiency between the ALRs relative to having no battery, the difference between the median values for a given RBC still becomes smaller with increasing ALR, i.e., increasing the ALR for a given RBC gives diminishing returns in terms of increased self-sufficiency.

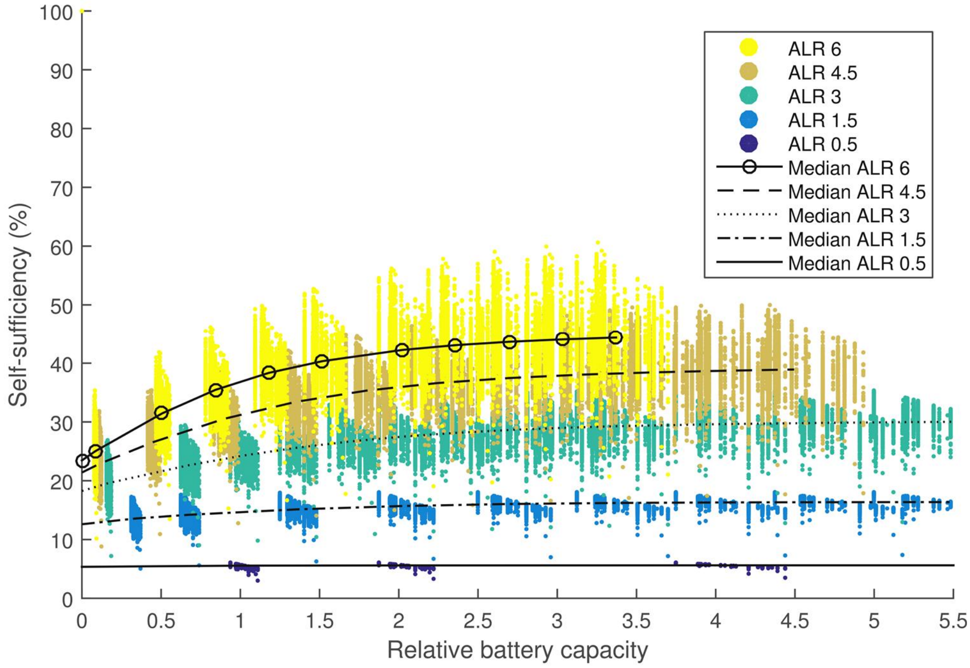


Figure 9. Self-sufficiency (in percent) for four different ALRs, plotted against the relative battery capacity. Each point represents a modeled household and the lines give the median value for the given ALR. Figure taken from Paper II.

The resulting absolute values for the self-consumption of PV-generated electricity for ALRs of 0.5, 1.5, 3, and 6 are shown in Figure 10, with each dot representing one of the modeled households and the lines representing the median household in terms of self-consumption of PV electricity. For the median household, the practical maximum PV electricity self-consumption ranges from 65% to almost 100%, depending on the ALR. Self-consumption of electricity can obviously be limited either by the attainment of 100% self-consumption or by limitations as to the available battery capacity (It should be noted that 100% PV electricity self-consumption cannot be reached through the help of a battery, as there are energy losses associated with operating the battery). For most of the investigated setups, it is the battery that is limiting, i.e., few households reach their practical (accounting for energy losses) maximum level of self-consumption. For ALRs ≥4.5, the practical maximum level of self-consumption of PV-generated electricity is never reached for any household, i.e., for all households with ALRs ≥4.5, PV electricity self-consumption is limited by the battery capacity, given the battery capacities investigated here. The ALRs for which the median household is limited due to reaching the practical maximum level of self-consumption are ≤1.5. However, even for ALRs of 1.5, batteries with an RBC of up to 2 to 3 are required by most of the households, i.e., batteries of considerable size compared to the PV installation (e.g., 5–7 kWh for a 2.5-kW$_p$ installation).

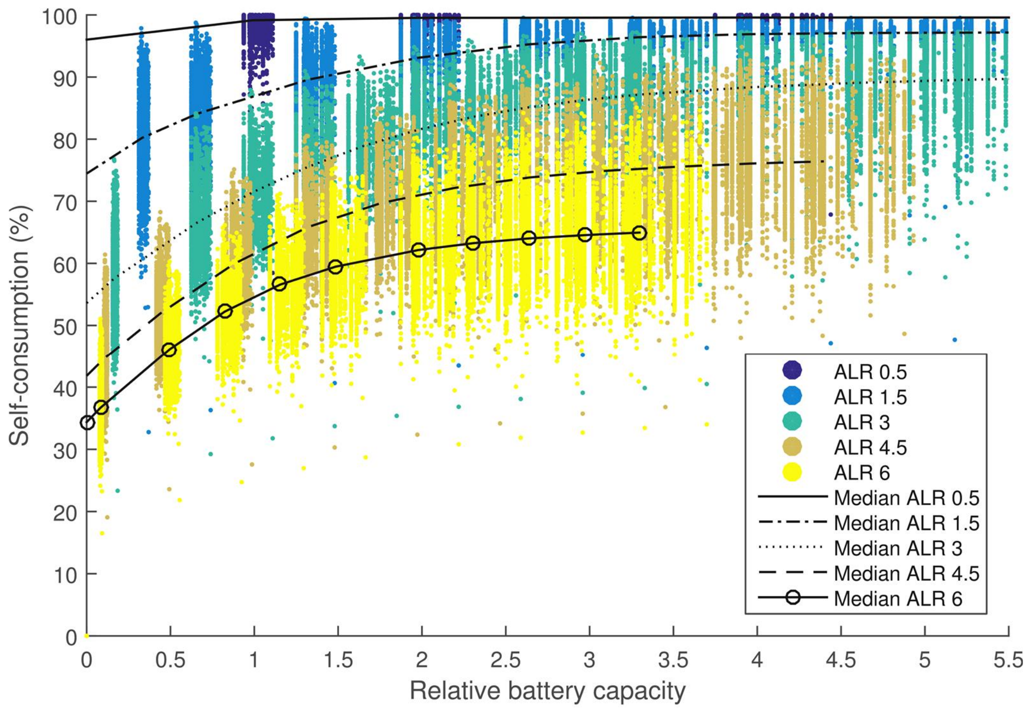


Figure 10. PV electricity self-consumption (in percent) for four different ALRs, plotted against relative battery capacity. Each data-point represents a modeled household and the lines indicate the median value for the given ALR. Figure taken from Paper II.

The explanation for the decrease in marginal benefit seen with increasing battery capacity seen in Figures 9 and 10 is down to two factors concerning the relationship between the electricity load profile and the PV electricity generation profile.

- The first factor that reduces the marginal benefit of adding battery capacity is that it is likely that there will be fewer occasions on which energy has to be moved from a period of excess generation to a period without excess generation, i.e., on some days, the existing battery can handle all the excess PV generation, rendering the extra battery capacity redundant during these periods.
- The second factor is that for sufficiently high ALRs, a further increase in battery capacity will eventually result in a battery that can store more than enough energy to meet the night-time demand during days in which daytime excess PV generation is higher than the night-time demand. As a result, the battery will not be completely discharged before the next period of charging. As a consequence of the battery not being fully discharged, some of the excess PV electricity generated during the following day may not be stored, thereby decreasing the utilization of the battery.

Both these factors are enhanced for Swedish conditions due to that both load and PV generation profiles are skewed, i.e., the electricity demand is highest during winter and the PV electricity generation is highest during summer.

Overall, it can be seen that the marginal benefit of additional battery capacity becomes smaller and smaller as battery size increases. Which RBC is economically optimal is obviously dependent upon the cost of the PV-battery system and the value of additional self-consumption. This value is in turn dependent upon the composition of the surrounding electricity system, as well as the policies regarding self-consumption that are put in place. However, given the behavior displayed in Figure

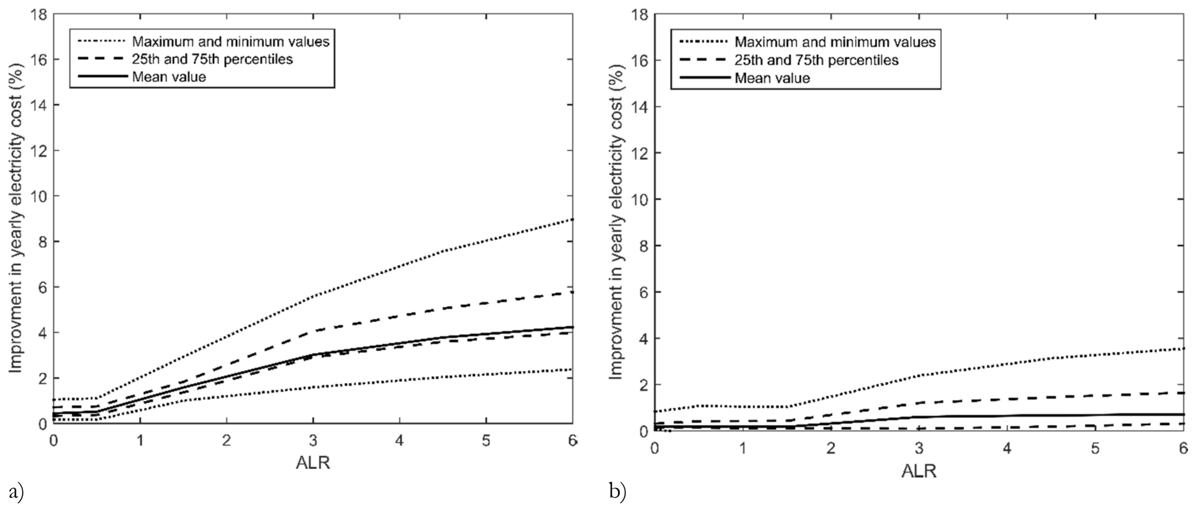
9, it seems unlikely that batteries with RBCs >2–3 will be installed for any purpose related to PV, be it economical or with the aim of maximizing self-sufficiency.

The values of demand response and hydronic storage for PV investments

As previously stated, engaging in DR is one possible way of increasing the value of a households PV installation. Figure 11a shows the improvement in annual electricity cost that can be achieved by combining the DR of hydronic loads and solar PV for the households investigated in **Paper I**. The improvements are compared to having an hourly RTP scheme without DR at the given ALR, i.e., assuming that the investment in a PV-panel has already been made. The maximum, minimum, and the 25th and 75th percentiles, as well as the mean value for the investigated households are shown. Figure 11b shows the corresponding data for the DR of appliances assuming a potential shifting time of 24 hours. As shown in Figure 11a, as the ALR increases the DR exhibits an *s*-curve with regard to its ability to improve the yearly electricity costs. The impact of combining PV and DR is negligible up to an ALR value of 0.5, owing to the absence of excess electricity generation from the PV panels. As all the electricity is already being used in-house, there is no additional gain to be derived from shifting loads. For all the households, diminishing returns for the benefit of DR are apparent at an ALR of 3. This happens even though the available shiftable load is considerably larger than the total PV electricity generation at this ALR value, with an average of 8,100 kWh/year of available hydronic DR compared to an average of approximately 4,000 kWh/year of electricity generated. Thus, the observed *s*-curve indicates that most of the new solar electricity generation at an ALR >3 occurs during hours in which there is no possibility to utilize the additional available DR loads.

There is a noticeable spread in the values among the investigated households, which increases with increasing ALR. The spread can be explained by the share of the shiftable load compared to the total annual load, as well as the initial match between the load and PV electricity generation. However, they all show the same *s*-curve.

For the appliance loads shown in Figure 12b, an *s*-shaped curve is also observed, showing the same properties as the hydronic DR. In addition, the improvements in annual electricity cost essentially level off for ALR values ≥3. This leveling off of the improvements shows that the technical limitations of the synergetic effects of appliance DR and solar generation are reached even when a generous shifting time of 24 hours is applied. However, it should be noted that the largest appliance loads, those for refrigerators and freezers, are not as flexible (±1 hour), which reduces their usefulness. Furthermore, the synergetic effects of appliance DR and solar PV are less pronounced than those of the DR of hydronic loads, with improvements in electricity cost of <1% compared to 4.5% for the hydronic loads. However, the maximum value shows a considerably higher increase with increasing ALR. This is attributed to one single household and is explained by the fact that the appliance load constitutes a relatively large part of the total load of that household. Thus, it exhibits a lower ratio for generated electricity to shiftable load, as compared to the other households.



a) b)

Figure 11. Improvements in annual electricity costs compared to an hourly pricing scheme for different ALRs for: a) DR of hydronic loads; and b) DR of appliance loads. Adopted from Paper I.

The impact of the DR measures can be compared to other factors that can affect the value of a households PV investment. Figure 12, a and b shows the impacts that a net metering scheme (a) and the current Swedish tax reduction scheme (b) have on improvements in annual electricity cost, compared to having an hourly RTP without DR. Figure 12, c and d shows the impact that a PV-panel price reduction of €290/kW_p (c) and a lower discount rate (moving from 2.5% to 0%) for the PV investment (d) have on the improvement in annual electricity cost, assuming an hourly RTP scheme.

The use of subsidy schemes has a considerably stronger impact than either DR approach at ALRs >2. The monthly net metering scheme shows a behavior similar to the DR, i.e., the marginal benefit tapers off at higher ALRs. This behavior is due to the fact that at higher ALRs the monthly level of PV electricity generation during summer months is higher than the monthly demand, effectively eliminating the benefit of net metering for these months. The spread in values between households reflects the differences in the monthly match between PV electricity generation and electricity demand. Households with a low seasonal match will benefit less for a given ALR. The tax reduction scheme does not show this type of behavior, as it effectively works as an annual net metering scheme.

Both the reduction in PV-panel price and the discount rate show a linear trend with increasing ALR, as they only affect the investment cost. The effect of the reductions in both cases is stronger improvements in annual electricity cost than are accomplished by the DR measures. It should be noted that the price of PV panels has previously dropped at twice the rate shown in Figure 12c in a single year, although the price has stagnated in recent years [91].

The impacts of the above-mentioned factors significantly outweigh those achieved through the use of appliance DR, while the impact of using hydronic DR is comparable at lower ALRs. However, a direct comparison between the impact of DR and the impacts of the other factors is not entirely fair, as the net metering and tax reduction schemes are subsidies and DR is not. Nevertheless, the comparison is interesting in the sense that it shows the relative strength of DR as a possible factor in the decision of a household to purchase a PV-installation. For instance, it can be seen that the discount rate that the household applies can have a considerable impact. As this value can fluctuate considerably depending on the household (see Harrison et al. [92]), reducing this value for households will have a strong impact, whereas attempting to incentivize DR of appliance loads will have only a minor effect.

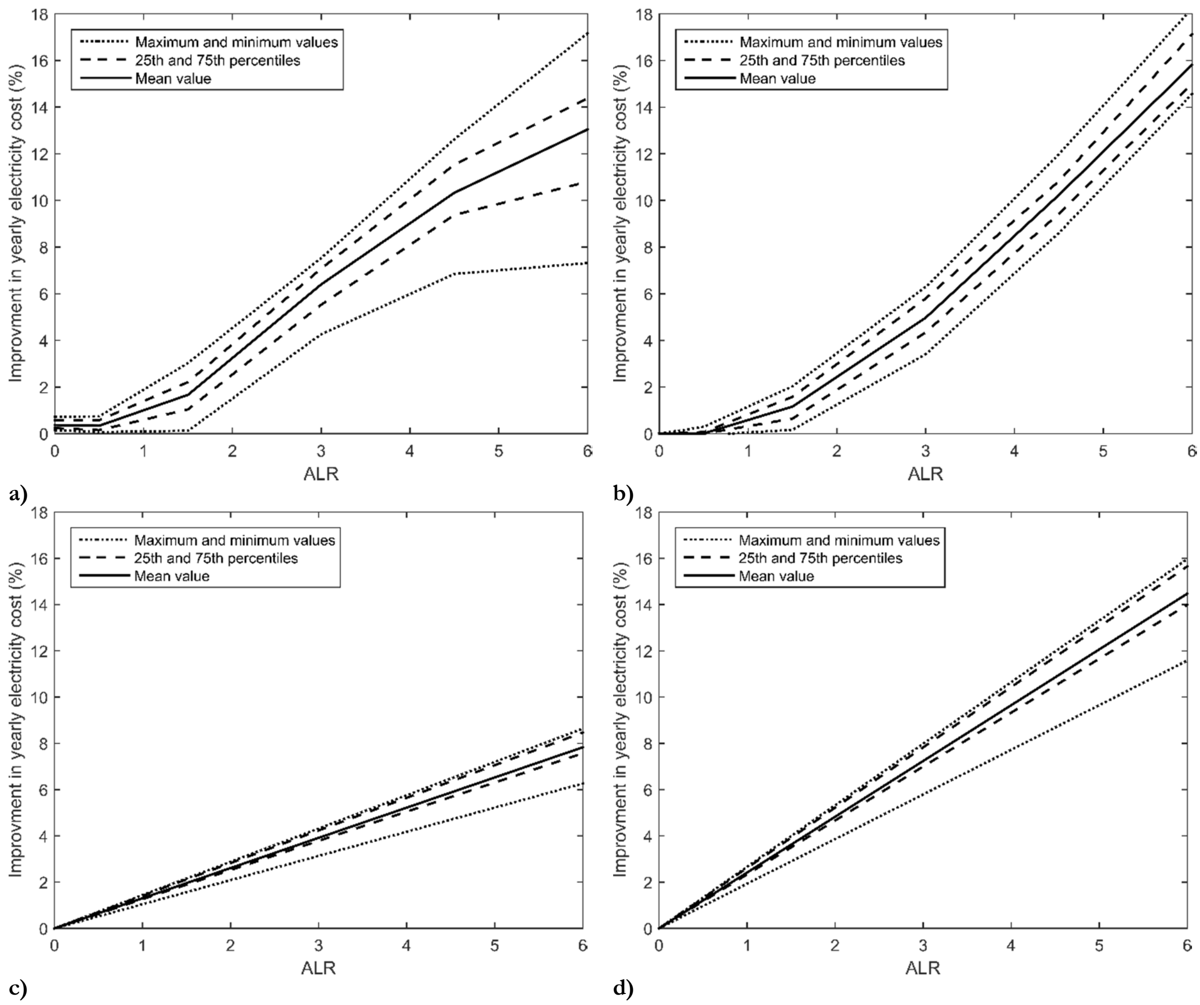


Figure 12. Improvements in annual electricity costs compared to an hourly RTP for different ALRs for: (a) a net metering scheme; (b) a tax reduction scheme; (c) a reduction in PV-panel price; and (d) a reduction in the interest rate for ALRs in the range of 0–6. Adapted from Paper I.

The techno-economic potential of PV-battery systems

A major expansion of PV or PV-battery systems in Swedish single-family households is likely to have an impact on the surrounding electricity system. Presented below are the results from **Paper III** showing the investment levels in PV panels and battery systems for households based on the iterative method presented in Section 4.5, which accounts for such feedback. The results are shown for the three electricity systems scenarios presented in Section 5.5: Green Policy (GP); Climate Market (CM); and Regional Policy (RP). It should also be noted that the only benefit of increased self-consumption for the households here is the avoidance of taxes and distribution grid fees. In order to investigate the sensitivity of the investments to changes in grid fees or taxes, a GP scenario with the variable grid fee removed is also investigated. This case is denoted as 'Fixed grid'. The households shown are based on the scale-up of the 2,104 households presented in Section 5.3. For cost assumptions regarding the PV and batteries, see Appendix A.

The resulting hourly electricity price profiles (i.e., the marginal electricity generation cost from EPOD) for the Swedish regions vary considerably across the different scenarios. As the price signal is the only feedback that the households receive from the system, these will influence their desire to invest in PV panels and batteries. Figure 13 shows the resulting electricity price duration curve for the SE1 region before the first iteration step, i.e., before any investments by the households. The price curve can broadly be categorized into: "High and stable" for the CM scenario; "Low and stable" for the RP scenario; and "High and variable" for the GP scenario. The very stable prices seen in the RP and CM scenarios are due to Nordic hydropower. Figure 14 shows the aggregate levels of PV and battery investments (i.e., the investments made by all the households in both regions) after convergence of the iterations for the four cases. All cases result in some form of investment by the households. However, the level of investment differs significantly. In addition to that, the following can be concluded:

- The largest investment in both PV panels and batteries is seen for the GP case, 8 GW_p and 8 GWh respectively. The relatively high electricity price level, as well as the strong variations in electricity price help to drive these investments. The large variations in electricity price allow for the use of the batteries for arbitrage, i.e., purchasing electricity from the grid at an hour with a low electricity price for charging the battery, and thereafter discharging the battery during an hour with a high electricity price, in order to avoid purchasing electricity from the grid at that hour. This helps to increase the value of the battery investment. Such operation of the battery is prevalent and has a significant impact on the surrounding system in that it helps to reduce the number of hours with high marginal generation cost. For more details, see **Paper III**.
- While the CM case shows almost the same level of PV investment as the GP case, the level of investments in batteries is 75% lower. This indicates that the level of investment in batteries is highly dependent upon the variations in electricity price seen in the GP case. The stability of the PV investments indicates that PV investments are more dependent upon the actual level of the electricity price than its variability.
- The RP scenario shows a considerably lower level of PV investments, 62% lower than the GP and CM cases, and there is basically no investment in batteries. The low and stable prices seen in this scenario reduce the incentives for PV investments. The lower amount of excess PV electricity generation, due to the small PV installation, and the stable electricity price entirely removes the incentives for battery investments.
- The removal of the variable grid fee (the Fixed grid case) has a considerable impact, decreasing investments in PV panels by 25% and investments in batteries by 70% relative to the GP case. The significant reduction in battery investments indicates that much of the value of the battery investment arises from the possibility to increase self-consumption. As the value of arbitrage also is of importance, as evidenced by the difference between the CM and GP cases, it can be concluded that both drivers are needed for large investments in batteries. The reduction in the value of self-consumption need not come from a change in the grid fees. A decision to tax self-consumed electricity with an energy tax in a manner similar to that imposed on purchased electricity will have the same impact, i.e., future policy decisions in this field are expected to have considerable impacts.

It should be noted that the investment levels shown in Figure 14 are not reached after the first iteration loop, i.e., the household investments in PV will affect the surrounding system. For instance, the first iteration in the GP case gives an investment of 16 GW_p and 15 GWh, i.e., twice the investment levels seen in the final iteration in Figure 14. This demonstrates the need for feedback between the electricity system and household investments when analyzing potential large-scale investments PV panels and batteries in the residential sector. For further results related to this topic, see **Paper III**.

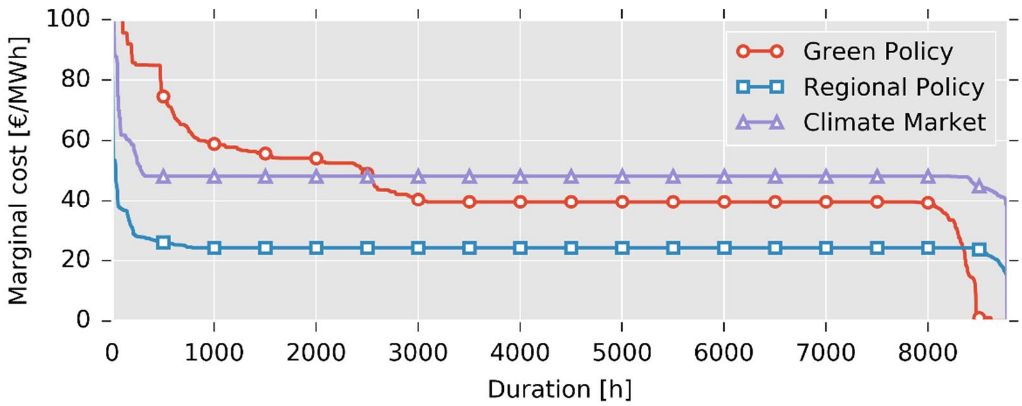


Figure 13. Duration curve for the marginal cost of electricity (which is the same as the electricity price seen by the households) for region SE1 before any household investments in PV panels or batteries have been made. Figure taken from Paper III.

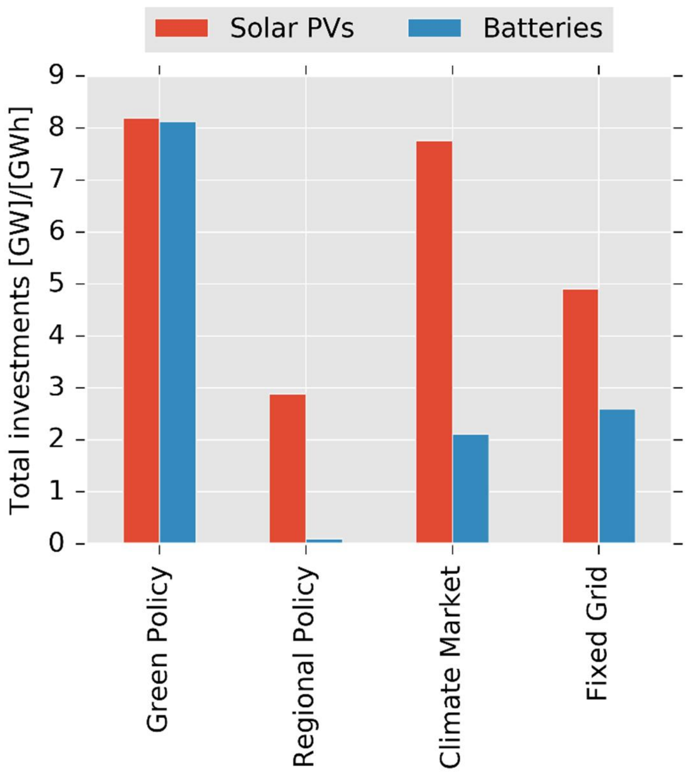


Figure 14. The households' levels of investment in PV panels and batteries after 15 iterations in the Green Policy case and 10 iterations for the remaining three cases. Adapted from Paper III.

Figure 15 shows the resulting investments in PV panels in terms of ALR, and Figure 16 shows the resulting battery investments in terms of RBC for all the households after scale-up, i.e., all household in the SE1 and SE2 regions are represented. It can be seen that the southernmost region, SE1, on average shows a higher ALR than the SE2 region. The difference in investment incentives could be due to both the better solar irradiation conditions and the lower electricity consumption for heating, due to warmer climate, in the SE1 region. In the GP cases, the average ALR in the SE2 region is around 3, and the average RBC is slightly less than 1. For an average Swedish household (annual electricity consumption of 15,000 kWh), this would correspond to a PV installation of 5.2 kW_p and a battery size of 5.2 kWh. One can compare the results shown in Figures 15 and 16 with the results concerning levels of self-sufficiency and self-consumption for a given

ALR and RBC in Figures 9 and 10. The combinations of ALR and RBC seen for the GP case result in a self-sufficiency level in the range of 15%–30% for the households in SE2 and 20%–35% for the households in SE1.

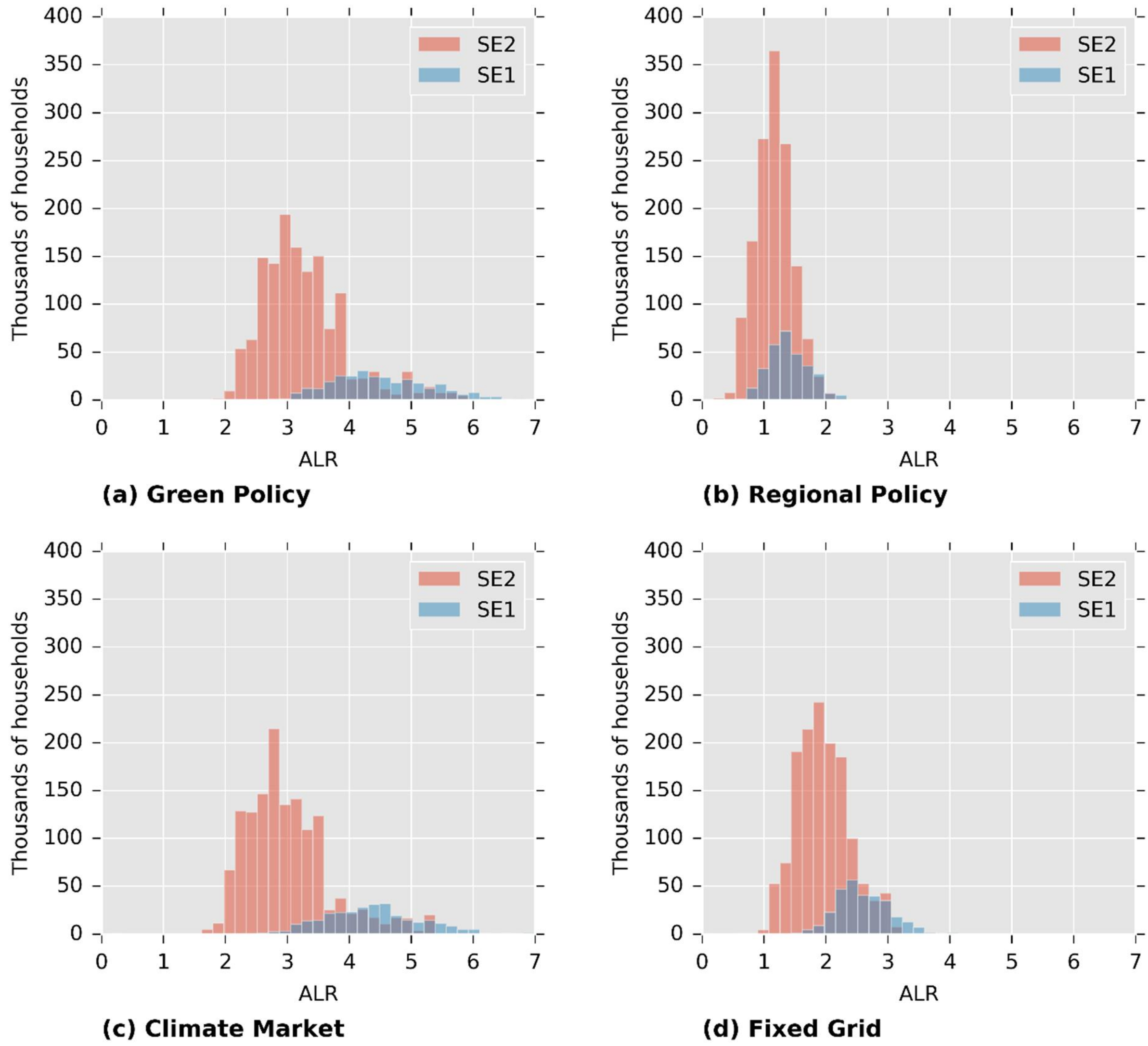


Figure 15. Levels of investment in PV panels per household in terms of ALR in the two SE regions modeled, SE1 and SE2, for: (a) the Green Policy scenario; (b) the Regional Policy scenario; (c) the Climate Market scenario; and (d) the Fixed Grid version of the Green Policy scenario. Figure taken from Paper III.

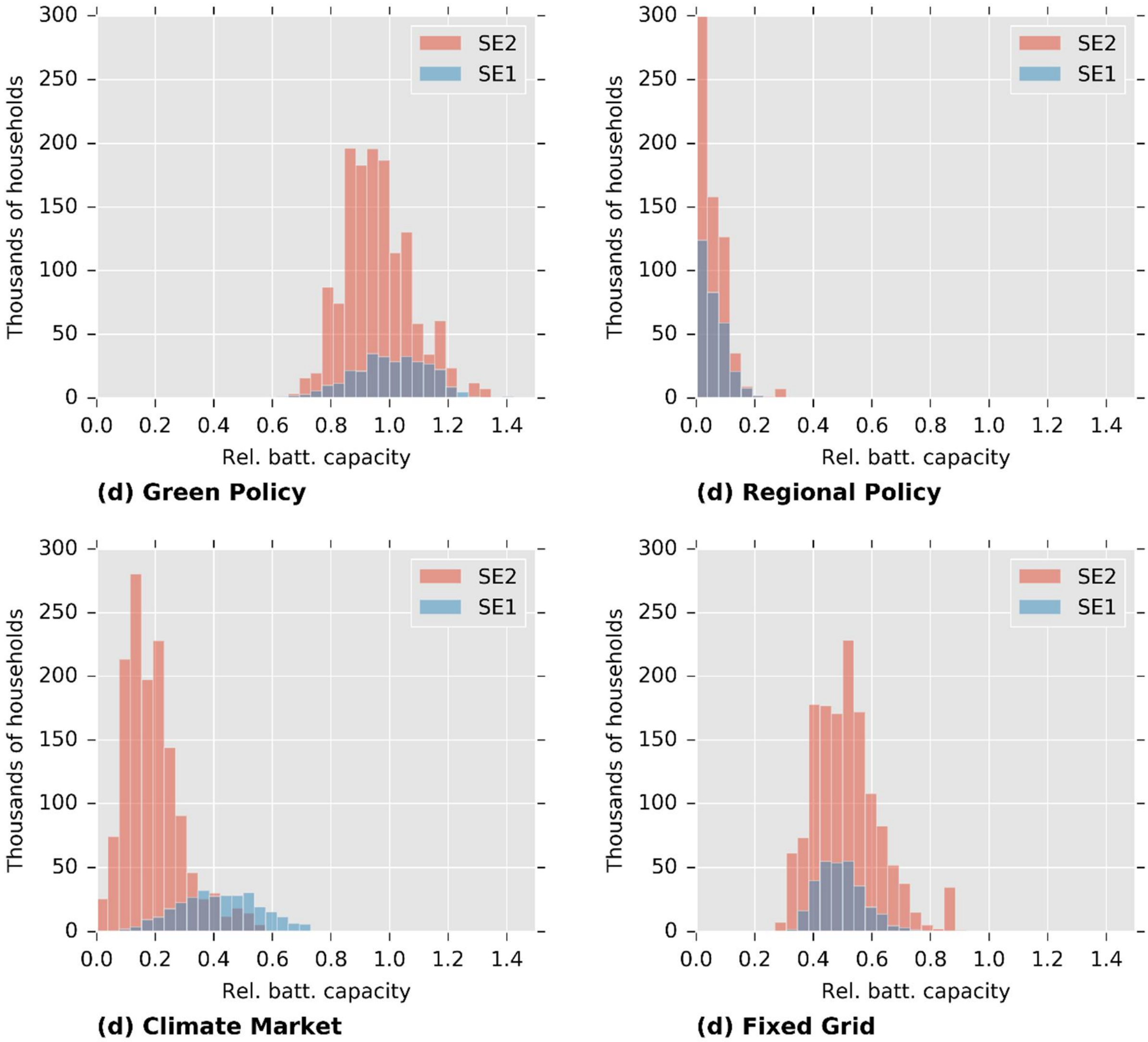


Figure 16. Levels of investment in batteries per household in terms of RBC in the two SE regions modeled, SE1 and SE2, for: (a) the Green Policy scenario; (b) the Regional Policy scenario; (c) the Climate Market scenario; and (d) the Fixed Grid version of the Green Policy scenario. Figure taken from Paper III.

Discussion

From the results presented in **Paper III** it can be seen that the economic value of the battery is highly dependent upon the additional value of self-consumption of PV-generated electricity. It is reasonable to assume that this is also true for the economic value of DR in **Paper I**. A significant fraction of this value is attributable to the avoidance of grid fees. Thus, a high penetration of household PV in the distribution grid could result in a considerable loss of income for distribution grid owners. In such a situation, it is possible that the price structure of the grid fees would be pushed towards a structure with higher fixed price and lower variable price or there might be a transition from using power tariffs to using energy tariffs. Sweco [93] has shown that the variable cost, i.e., the cost linked to energy losses when transferring the electricity, constitutes only a minor part of the total distribution grid cost, indicating that a move to grid fees that are less dependent upon the amount of electricity transferred could be justifiable. If such a move implies the introduction of power tariffs, batteries and DR could still play important roles in terms of limiting power spikes from the households. The value of DR in combination with power tariffs has been shown by for instance Steen [94]. However, a move towards a larger fixed price share would be detrimental for PV, battery, and DR household investments, as it would decrease the value of self-consumption.

The results for the DR and battery presented above aim to increase the value of a households PV investment and thus, in a sense, these two systems are competing with each other. A battery effectively works as an intermediate DR, i.e., instead of temporally moving the load to the generated electricity, the generated electricity is moved to the load. In other words, the occupants of the household can pay for a battery so as to avoid the inconvenience of DR. If batteries become sufficiently cheap for households to invest in them, the households' incentives to engage in any form of inconvenient DR will diminish considerably, as the marginal benefit of engaging in DR will decrease. Thus, there is the risk that the two paths towards increasing the value of a PV investment investigated here are to an extent mutually exclusive.

As both the Swedish PV electricity generation profile and the electricity demand profiles are very specific to northern latitudes, the results presented cannot readily be transferred to other electricity systems, other than countries at similar latitudes. Moreover, the availability of large amounts of hydropower in the Nordic power system has a dampening impact on the electricity price, which was shown to be detrimental to battery investments. For systems with less hydropower, the value of batteries is probably higher.

6.2 Demand response of electric space heating in Swedish single-family dwellings

This section presents the results concerning the demand response of electric space heating in Swedish single-family dwellings. First, the technical potentials identified in **Paper IV** are presented and thereafter, the system and dwelling values from **Paper V**. The system values from **Paper V** are shown for the GP and CM scenarios presented in Section 5.5. For each of the scenarios, three cases are presented. The first case is DR, which allows for variations around the set-point temperature using the temperature deviation cost method presented in Section 4.2. The remaining two cases incorporate energy savings measures in the form of decreasing the indoor temperature of the dwellings during night-time hours (18°C) and daytime working hours (15°C). The two cases that incorporate this are the D15N18DR case, which allows for both the DR and the temperature decrease, and the D15N18Fix case, which only allows for the indoor temperature to decrease. For further details of the cases, see Appendix A, Table A.4. The changes for the three cases are compared to a baseline case in which the electric space heating demand is calculated for a fixed temperature of 21.2°C. The cases are only modeled for the period extending from the 15th of September to the 15th of May.

Technical potentials

In **Paper IV**, the calculated available electric heating capacity is found to be 7.3 GW (assuming fixed COPs for the available heat pumps). This value should be seen as the upper limit, given that it is based on the current recommendations regarding the sizing of heating equipment from The Swedish National Board of Housing Building and Planning [95]. As a large part of the building stock is of advanced age, it is possible that the sizes of the heating equipment are different than the recommended sizes. For further details, see **Paper IV**. The amount of energy that can be shifted varies depending on the variations in indoor temperature that the occupants of the dwellings are willing to accept. In **Paper IV**, where temperatures are allowed to increase by up to 3°C relative to a baseline temperature of 21.2°C, up to 8 GWh of energy are shifted in each shifting segment, which here refers to the period between an increase in load and a subsequent decrease in load. Similar values are shown in **Paper V**, which applies the deviation cost method.

System value of DR of electric space heating

The system value of the DR investigated is the lowering of system dispatch cost, i.e., the running costs for generating electricity and the cycling cost that arises from ramping and part-load operation of power plants. Figure 17 shows the decrease in total system cost (gray bars), the share of this decrease that accrues from reductions in running costs (black bars), and the share of this decrease that is derived from cycling costs (white bars) (all in millions of Euros). As a fraction of the total system costs, the reductions in system cost observed for the DR case correspond to 0.12% in the GP scenario and 0.02% in the CM scenario. However, as a share of annual system electricity demand, the shiftable load only constitutes 0.9%, and of this share only a fraction is actually shiftable given the indoor temperature constraints.

The economic value of pure DR, i.e., in the DR cases, is higher for the GP scenario than for the CM scenario. This is due to the higher penetration of wind power in the GP scenario, especially considering that the levels of wind power Sweden and the regions closest to Sweden are considerably higher. More specifically, the increased economic value of DR can be ascribed to the following:

- The need for part-load operation and start-ups of dispatchable power plants is higher in the GP scenario due to the higher level of variable power in the form of wind. The availability of DR reduces these costs. The lower frequency of such events in the CM scenario removes part of the costs that DR can mitigate.
- For the GP scenario, the high variability in electricity generation linked to the higher share of wind power requires the use of fast-responding gas power plants. The DR enables decreased use of some of the gas power plants, instead increasing the use of CHP. As the variable operational cost is lower for CHP power plants, the DR helps to lower the running cost of the system. This occurs to a much lesser extent in the CM scenario.
- In the GP scenario, there are more instances of wind being curtailed that can be exploited using DR. Thereby, decreasing the operation of power plants with higher variable costs.
- In the GP scenario, DR also helps to reduce congestion in the transmission grid, allowing for better utilization of hydropower, which was previously curtailed. Thereby, decreasing the operation of power plants with higher variable costs. These congestion issues are not as prevalent in the CM scenario.
- The use of DR results in an increase in electricity demand due to an increase in the indoor temperature from the DR.

For more details of the changes in dispatch, see **Paper V**.

In the D15N18DR case, in which the night-time and daytime temperatures are allowed to drop to 18°C and 15°C, respectively, while still allowing for system-optimal DR dispatch, the annual system savings increase in both scenarios, see Figure 17. The increases in savings are almost exclusively derived from reductions in running costs. In both scenarios, the decrease in demand, as obtained from the reduced set-point temperature, results in altered dispatch of hydropower, enabling more long term storage of hydropower. For the GP scenario, this hydropower is used to replace the use of gas power, primarily during the summer months. In contrast, in the CM scenario, the stored hydropower is utilized primarily to reduce CHP operation during the autumn months.

When the possibility for DR is removed, as in the D15N18Fix case, the system savings decrease (compared to the D15N18DR case) in both scenarios. The impact on the CM scenario is minor, indicating that efficiency measures in the form of reducing temperatures without any feedback from the system result in an operation that is similar to the system-optimal situation. However, the GP scenario entails a considerably larger decrease in savings. The removal of DR in the GP scenario results in an increase in the amount of wind that is curtailed in the system. The level of wind power in the system is sufficiently high that the reductions in demand linked to the fixed temperature decrease occasionally, leading to hours during which the level of wind power generation is higher than the load.

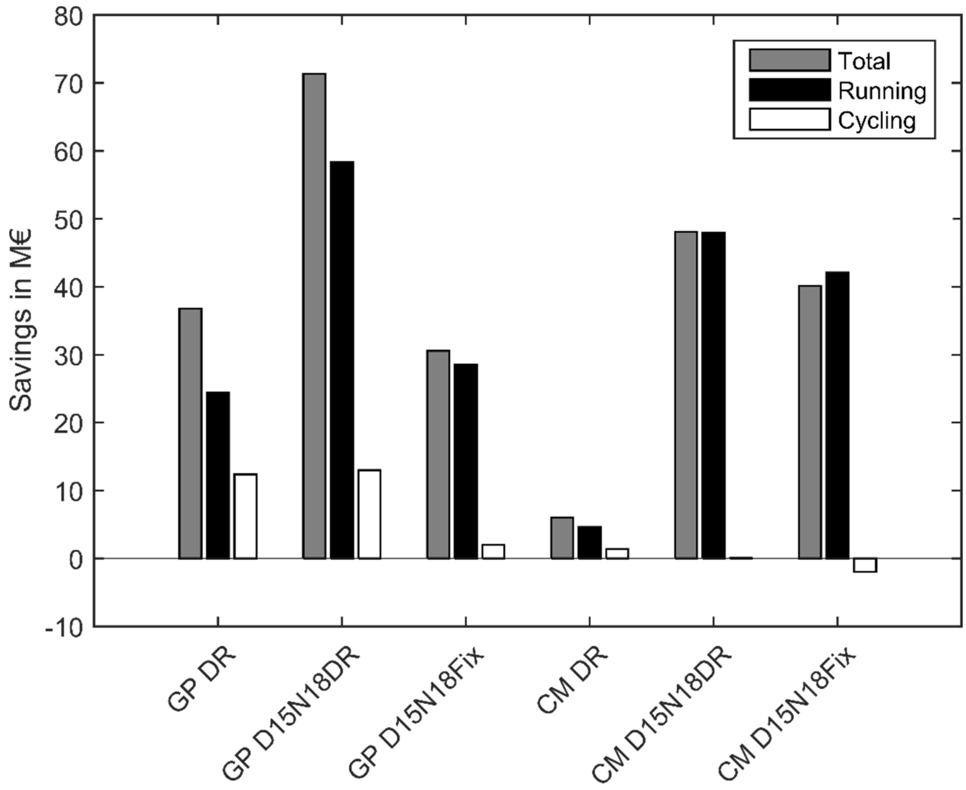


Figure 17. The annual system cost reductions (positive values) for the entire modeled system (in M€) relative to a base case, resulting from the different DRs and temperature-lowering cases. The different bars represent the total cost reductions (gray), running cost reductions (black), and cycling cost reductions (white). Adopted from Paper V.

Changes to the load curve

Figure 18 shows the hourly operation of the DR in Swedish region SE2 (see map in Figure 6), which is the region with the highest space heating load, for the DR case in the GP scenario. Shown on the *x*-axis are hours of the day, and on the *y*-axis are the days of the year; the colors represent the GWh/h operation of the DR, where a darker blue color indicates a decrease in load and a brighter yellow color indicates an increase in load relative to the base case. Two types of patterns can be discerned:

- A daily pattern with an increase in load during night-time and early mornings (00-6) and a subsequent decrease in load during the late morning and noon hours (8-12). Thus, the DR is engaging in valley filling and peak clipping, increasing the load during low-load night-time hours and decreasing the load in the subsequent higher-load morning hours.
- A pattern in which there are increases in load during the afternoon hours (14-17) and decreases in load during the early evening hours (18-20). This behavior also corresponds

to the shape of the diurnal system load curve, which has its peak in the early-evening hours, i.e., during hours when the load is reduced.

It can be concluded that even in a system dominated by wind power, the operation of DR is to a large extent governed by the system load curve. However, there are occasional hours where the availability of cheap electricity is high, i.e. high wind power generation, where new system peaks can be created.

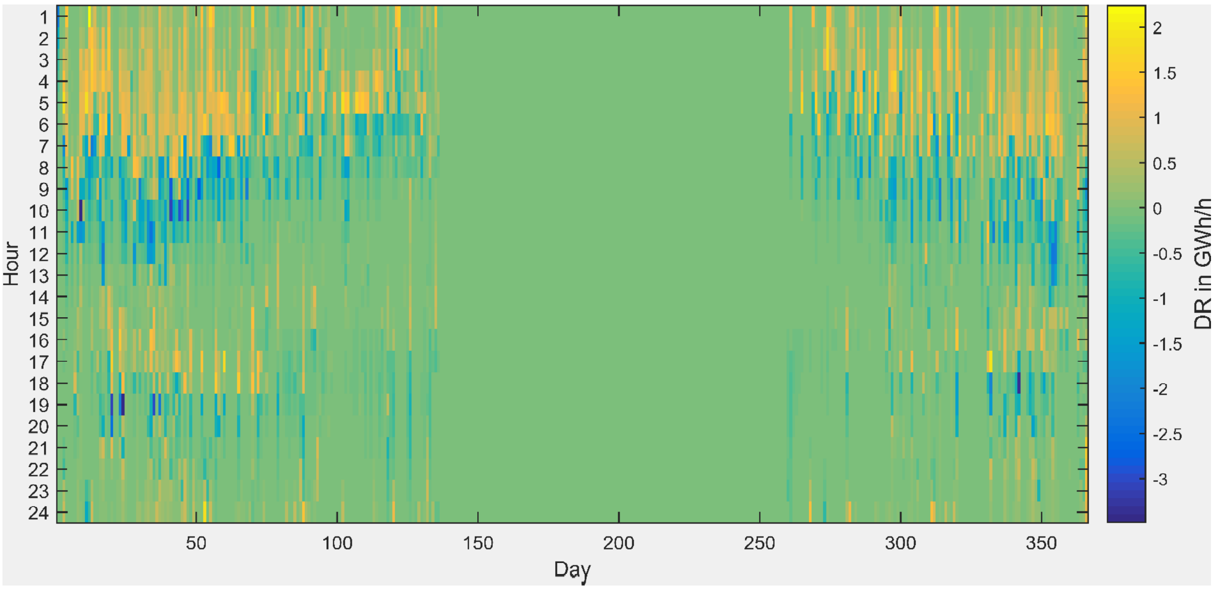


Figure 18. The hourly operation of DR for region SE2 in the DR case for the Green Policy scenario. The yellow coloration indicates an increase in load relative to the base case, and the blue coloration indicates a decrease in load relative to the base case. Adopted from Paper V

The consequences for the dwellings

The annual system cost reduction per dwelling based on their DR participation (here considered as the amount of down-regulation in load relative to the base case) is in the range of €1–€205, with most dwellings in the €20–€75 range. The range of cost reductions per dwelling depends on the absolute amount of DR in which each dwelling has engaged. The absolute amount of DR depends on a combination of the following factors: the DR suitability of the dwelling, i.e., a low U-value and high thermal mass per m^2; the size of the building, i.e., the heated floor area of the dwelling; the region in which the dwelling is situated, i.e., northern regions with large amount of hydropower engage in less DR due to the dampening effect of the hydropower; and the electric heating power available, i.e., the dwellings ability to increase or decrease its electricity consumption in at a given moment. For more details, see **Papers IV and V**.

The DR results in indoor temperature fluctuations in the dwellings. Figure 19 shows the mean indoor temperature for all dwellings (adjusted for the weighting of the dwellings in terms of representing the building stock), ranked from lowest to highest, resulting from the DR for the modeled period of the 15th of September to the 15th of May. As can be seen, there are roughly 2000 hours during which the temperature is increased and only 300 hours during which it is decreased. Overall, it can be said that the DR exerts a clear impact on the indoor temperature. Figure 20 shows for the modeled period of 15th of September to the 15th of May: (a) the mean indoor temperature; and (b) the variance of the indoor temperature for all dwellings. The mean temperature is above the baseline temperature of 21.2°C for all the dwellings, indicating that no dwelling is constantly at a low indoor temperature. The variance can give an indication of the extent of the fluctuations in indoor temperature, which is fairly low for most of the dwellings. However, the variance does not say anything about the rate of change of temperature fluctuations that the dwellings have to endure. During the most intense DR periods, the DR setup modeled here results in temperature changes of up to 3.8°C (23.15°C down to 19.5°C), within a few hours for the dwellings that are most intensively engaged in DR.

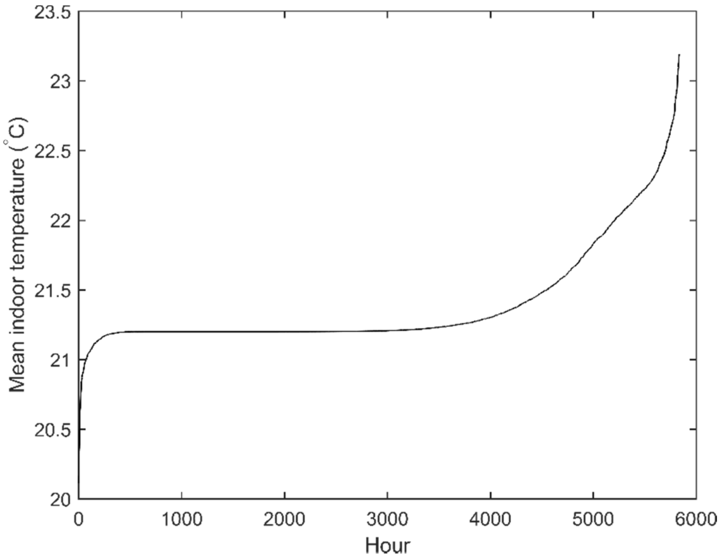
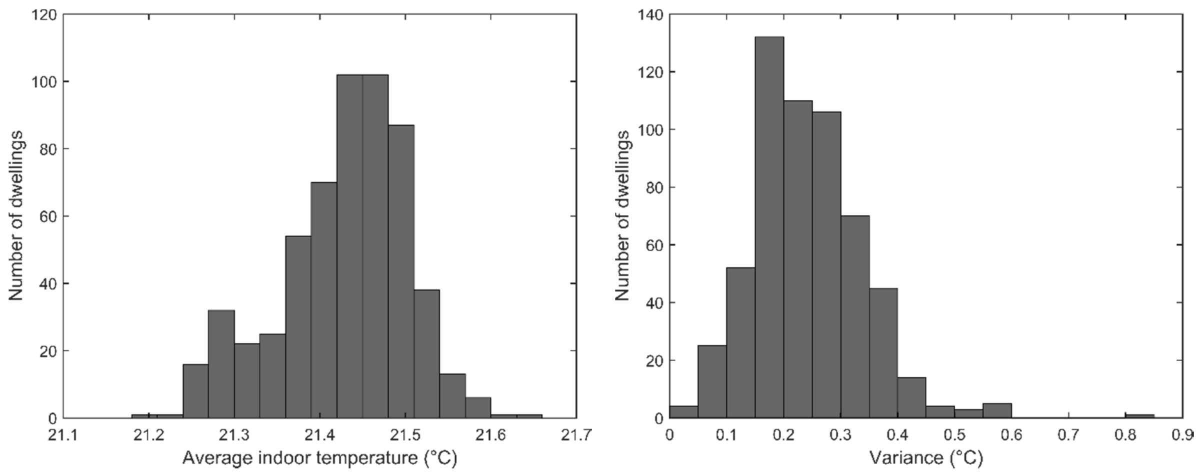


Figure 19. The mean indoor temperature duration curve for all dwellings (accounting for the share of the total building stock that each dwelling represents) for the DR case in the GP scenario. Only the hours modeled are shown, i.e., for the period from the 15th of September to the 15th of May. Adopted from Paper V.



a) b)

Figure 20. (a) Average indoor temperatures for all the modeled dwellings; and (b) the variance in indoor temperature for all the modeled dwellings for the DR case in the Green Policy scenario. Adopted from Paper V.

Discussion

As the cost reduction per dwelling is fairly low – the annual €20–€75 is equivalent to 0.07%–0.3% of the median per-person disposable income for people living in Swedish single-family dwellings – the willingness to accept DR in the form of direct load control of space heating could be limited. Broberg and Persson [96] investigated the willingness of Swedish households to accept different scenarios for direct load control of their space heating and concluded that the households demand annual reimbursements in the range of €66–€280 to partake in DR. Thus, attitudes to DR need to change if the DR potentials identified in the GP DR case are to be realized. However, the cases that include reductions in electricity demand, D15N18DR and D15N18Fix, could prove more attractive to these households. The households pay taxes, both energy tax and VAT, and variable grid fees on each unit of purchased electricity, i.e., in addition to the reduced system costs there is additional value for the households in reducing electricity consumption. If actors interested in utilizing the DR capabilities of the electric space heating also offered to ensure reduced electricity consumption for the households, resulting in an increased economic compensation, the households' willingness to partake in DR programs could increase.

The influences of Nordic hydropower on the Swedish electricity system, as well as the northern latitudes make it difficult to extrapolate the results presented here to other systems. However, since hydropower can act in the same manner as DR, its presence has a dampening impact on the system value of DR. Thus, DR is likely to have a greater contribution in systems that lack hydropower.

7. Reflections on the methods and data used

The methods and data used in this thesis obviously have some restrictions, which are considered in this section.

Even though the feedback from the traditional supply side of electricity system is captured in the modeling performed in **Paper III**, other sectors of society have drivers similar to those of the single-family dwelling sector in terms of becoming active electricity producers. An expansion of PV installations in the tertiary sector or in the multi-family dwelling sector is likely to be sufficiently large to influence the electricity system. Such an expansion would thus dampen the effects seen in **Paper III**. However, as the results relate to all-out expansion from all households, which is improbable, the expansion of PV-battery systems should be seen as an indication of the limitations of all sectors that are subject to the same benefits of self-consumption as single-family dwellings. Furthermore, as the DR in **Paper I** is evaluated by assuming a static supply side, the results presented therein should be regarded as being valid for households that are early adopters, i.e., there is no relevant feedback due to DR between the demand and supply sides. Analogous to the results described for batteries in **Paper III**, the value of DR in **Paper I** is likely to depend on the composition of the future electricity system. The composition of the electricity system assumed in **Paper I** is that for Year 2007 (with sensitivity analysis for Year 2010, see **Paper I**). Thus, an investigation of DR under a GP scenario could increase its economic value as such a scenario entails considerably higher variations in the electricity price. However, the observed difference in value between the use of hydronic loads and appliance loads is unlikely to change.

The system chosen for modeling the dynamics of the energy flow in buildings will have an impact on the outcomes. In **Paper IV**, the whole building is represented by one temperature, whereas **Paper V** separates the building envelope and the interior of the building. Both Harb et al. [97] and Reynders et al. [98] have investigated the use of gray-box models for predicting the thermal behaviors of buildings. They have concluded that a one-zone model is likely to dampen changes in indoor temperature variations caused by changes in the energy flow within the building. A consequence of dampened temperature variations is overestimation of the utilization of DR, i.e., the rate at which the limits set on the indoor temperature are reached is lower, allowing for more energy to be stored in the building. The adoption of a two-zone model improves the model behavior in this regard. However, as pointed out by both Harb et al. [97] and Reynders et al. [98], a two-zone model still suffers from some level of underestimation of the temperature variations, such that a three-zone model might be preferred. Thus, the results described in **Papers IV** and **V** may represent overestimations. However, it should be noted that increasing the number of temperature zones carries a computational cost, as it increases both the number of variables and the number of equations in the model, i.e., there is a trade-off between the accuracy of the model and reasonable modeling times.

The connection with the surrounding system of the household PV-battery systems described in **Paper III** and the DR of electric space heating described in **Paper V** allow for the capturing of feedback between the supply and demand sides. However, to capture the full value of DR, there is a need to investigate how these parameters also influence investments. As indicated by both Brouwer et al. [65] and Patteeuw et al. [60], possibilities exist to reduce the need for investments in peak power plants through the help of DR. Furthermore, an expansion of DR or demand-side PV-battery systems in the surrounding countries could also influence the results, potentially decreasing the value of DR.

The use of an hourly temporal resolution for the modeling could have an impact on the PV results presented above. The temporal resolution used in the discretization can influence the values for self-consumption and self-sufficiency, thereby affecting indirectly the levels of investments in PV panels and batteries. A too-coarse resolution can result in overestimation of both self-consumption and self-sufficiency, as variations in the electricity generation and consumption at a higher frequency than the temporal resolution used are filtered out. The impact of the choice of temporal resolution has been investigated by Widén et al. [99], Cao and Sirén [100], and Beck et al. [67]. The general conclusion is that hourly averaging can lead to significant errors with regards to the maximum load of the household load curve, while the impact on PV output is less significant. For the combination of load and PV output errors occur primarily with small PV sizes, where the load and the PV generation profile are of similar magnitudes. However, for sizing household PV-battery systems, Beck et al. [67] have concluded that an hourly resolution is sufficient. The consequences for the results presented above related to the use of hourly data should be most pronounced for the appliance DR results. The appliance loads used have load curves with peaks in demand, which is filtered out by hourly averaging. However, the hydronic heating load should be able to operate in a fashion similar to that used in the modeling, e.g., through the use of a stepless heater. This means that the impact of the DR of appliance loads is overestimated, especially at lower ALRs. As the potential value of DR of appliances was found to be low, the indication that it is overestimated further decreases its potential value. For the results presented in **Paper II** and **Paper III**, the largest errors should occur for those cases with no PV installation or a small PV installation, e.g., the value that the households derive from the PV installations seen in the RP scenario could be exaggerated.

The BETSI dataset used in **Papers IV** and **V** is representative of the current composition of the Swedish single-family dwelling building stock. However, as any large-scale implementation of DR lies in the future, the characteristics of the building stock are expected to change. The degree of transformation will depend on the rate of new construction, as well as on incentives to retrofit the current building stock. Energy efficiency measures will probably lower the U-values, the capacity of the heating equipment, and the overall demand, all of which will have impacts on the DR potential.

A significant fraction of the dwellings with electric space heating have hydronic systems. In the present work, these been modeled without any buffering capacity for such systems. The inclusion of water storage tanks in the systems in the model would increase the potential for DR in these households. Moreover, the use of storage tanks would avoid the indoor temperature fluctuations to which the dwellings are exposed.

The household load data used in **Paper I**, which cover 21 actual household demand profiles with appliance-level resolution, vary considerably in terms of electricity demand and should therefore give a reliable picture of how electricity is used in Swedish households. However, this is a rather small sample size, so the results presented may not be representative of the Swedish household sector as a whole.

8. The contribution of this thesis

As the development of the future electricity system moves forward, it seems likely that we will see more active participation of actors on the demand side of the system. This thesis aimed at investigating specific aspects of such a development. The overall aims set out for this thesis were to:

- Investigate the technical and economic potentials of Swedish single-family dwellings becoming prosumers through the use of solar photovoltaic (PV) systems, taking into account possibilities for flexibility in consumption patterns through DR and energy storage, and investigate how such systems might interact with the surrounding electricity generation system.
- Identify the technical potential of DR of electric space heating in Swedish single-family dwellings, and investigate the value of this potential for the surrounding electricity generation system, as well as for the individual dwelling.

With regards to the first aim, the following can be concluded. The technical capacity of a battery to increase both the self-sufficiency and self-consumption of PV-generated electricity in Swedish single-family dwellings shows a diminishing return with increasing battery size. These limitations are due to the skewed generation profile of PV electricity generation under Swedish conditions. Thus, it is unlikely that batteries with RBC values >2–3, approximately corresponding to 10–15 kWh for a 5-kW$_p$ PV panel, will be installed in Swedish households for any purpose related to PV, whether that purpose is economical gain or is designed to maximize self-sufficiency.

Regarding the economic potential of household PV-battery systems, it is clear that all the investigated future electricity system compositions result in the households investing in PV-systems. This indicates that given that the added value conditions for self-consumption are preserved, i.e., not having to pay taxes and variable grid fees on self-consumed electricity, an expansion of household PV systems in Sweden that is driven by economic incentives appears to be robust with regards to the composition of a future electricity system. However, the level of PV investments and potential investments in batteries are shown to depend on both the electricity system composition and the additional value of self-consumption. A relatively high and stable electricity price and an electricity price that is more variable both result in substantial PV investments, up to 8 GW$_p$ for the assumed costs for PVs and batteries in this work. A future in which electricity prices remain stable and low results in a 60% reduction in the installed level of PV. The economic potential of battery investments is found to be dependent to a large degree upon both large variations in electricity price, enabling the use of batteries for arbitrage, and upon the economic value of increased self-consumption of PV-generated electricity. If both conditions are present investments up to 8 GWh are seen in this work.

The DR of hydronic heating and hot tap-water are found to yield the highest economic value for household investment in PV of all the household loads investigated, due to its relatively large size in terms of energy, and the fact that it can act as an energy storage system. In contrast, for the DR of appliance loads, e.g., dishwashers and washing machines, the economic value provided to a household investment in PV is small, even when generous shifting timeframes are employed. The skewed generation profile of PV electricity generation results in diminishing returns for DR as the ALR exceeds 3, as excess electricity generation will primarily occur during hours in which the possibility for DR has been exhausted. This effect is especially pronounced for the DR of appliance loads, where essentially no increase in economic value is seen from combining DR and PV for ALR values >3 for most households.

It can also be concluded that in future evaluations of large-scale investments of household PV-battery systems that are driven by a dynamic electricity price, i.e., an RTP scheme, there is a need to include mechanisms of feedback between the supply and demand sides. If such a feedback mechanism is excluded there is a risk of overestimating the households' potential investments in PV-battery systems.

Concerning the second aim listed above, it can be concluded that there is a technical potential for DR of electric space heating in Swedish single-family dwellings that corresponds to 7.3 GW (assuming fixed COP values). The amount of energy that is available for DR depends on the willingness of the household to accept variations in the indoor temperature; in the modeling performed in this work, up to 8 GWh of energy were shifted. The value of DR through direct load control is found to be highly dependent upon the composition of the future electricity system. In a future system that is dominated by variable wind power, DR offers economic value through decreasing the number of start-ups, obviating the need for part-load operation of thermal power plants, and avoiding the operation of peaking gas power plants. In a future electricity system that is dominated by wind power to a lesser extent, the value of DR is small. Furthermore, in a scenario in which households engage in energy efficiency measurers through decreasing the indoor temperature during periods of the day, there is a risk of increased curtailment of wind power; this risk can be mitigated by the use of DR. It can also be concluded that the large share of hydropower in Nordic electricity systems helps to mitigate some of the need for DR, as it can fulfill the same role.

Although DR to a large extent helps to decrease costs associated with wind power variations, the operational pattern of DR is found to be governed by the shape of the system load curve. The DR is mainly used for valley filling, increasing the load during low-load hours, and for peak shaving, decreasing the load during high-load hours. The system cost reduction per dwelling for participation in DR is found to be low, in the range of €1–€200 per year, even in the electricity system composition that has the highest value for DR.

9. Further research

The work presented in this thesis is by no means an end point but rather opens up new pathways for research. For example, the representation of an active demand side in energy system models should be of interest.

The modeling framework presented in **Paper V,** which connects the dispatch of electric space heating and the dispatch of the electricity system, should be extended with data that are representative for other countries present in the EPOD model. In this context, the work of Mata et al. [101] has produced archetype building stock descriptions for France, Germany, Spain, and the UK. The implementation of these descriptions in the EPOD modeling framework would allow for the modeling of DR electric space heating and air-conditioning loads in the listed countries. The inclusion of DR in other countries would enable evaluations of DR in systems that are not as heavily influenced by high levels of hydropower. As hydropower is shown to have a dampening effect on the value of DR, such investigations of DR might show a higher value for DR. This would also allow for investigations into how the value of DR is affected by a more system-wide implementation of DR. Moreover, as the diurnal variations in PV electricity generation are more in line with the timeframe within which DR can operate, the inclusion of DR of space cooling loads might reveal both a higher system value and a higher value for the individual household than the contributions observed from space heating loads in **Papers I**, **IV** and **V**. The building stock is also likely to evolve, through retrofitting of existing buildings, as well as new construction. Understanding the effects of this evolution on the potential for DR should be of interest. A good basis for studies of possible future retrofits and energy efficiency measures is the work of Mata [102], which investigates potential routes to energy conservation in building stocks.

In this thesis and in the appended **Papers IV** and **V**, only the electric space heating in Swedish single-family dwellings is investigated. However, a considerable part of the heating demand in Sweden is met using district heating, especially for multi-family dwellings. The generation of this energy is linked to the electricity system through both CHP power plants and the operation of large-scale heat pumps. There are possibilities for longer-term storage in such systems. Thus, variation management through the use of non-electric heating could prove to be an important source of DR. In this regard, the work of Kensby [103] is seminal, in that it demonstrates the possibility of utilizing thermal energy storage in multi-family dwellings in Gothenburg for flattening the heat demand profile in Gothenburg's district heating system.

While the impacts of DR on the dispatch of the electricity system have been investigated in this thesis, additional value might be derived from DR in relation to its potential to defer investments in electricity generation and transmission infrastructure. Addressing such questions would require the implementation of a representation of the DR in electricity system investment models similar to ELIN (presented in Section 5.5). Such an implementation would also enable a comparison to be made between DR and other variation management strategies, such as transmission grid expansions, energy storage investments, and electricity generation investments. Such evaluations are needed in order to fully understand the system value that DR can supply.

There is also a need to develop models and data that allow in a meaningful way for the upscaling of loads to an electricity system level, facilitating studies similar to the one conducted in **Paper III**. The possibility to generate and assess data that would allow for the creation of sample households that are statistically representative of different demand segments would be of major value for energy systems modeling. As an example of this, Sandels [104] has developed a bottom-up modeling approach to modeling electricity consumption profiles in the Northern European building stock, accounting for end-user behavior.

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Gothenburg, October 2016

Nomenclature

a	Annuity factor (-)
Ac	Average appliance heat (W/m^2)
app	Profile for appliances (-)
ar	Heated floor area (m^2)
b	Storage capacity (Wh)
c	Costs (€)
C	Objective value for cost (€)
cp	Volumetric heat capacity of air ($J/(m^3\ K)$)
d	Energy demand (Wh)
e	Electricity purchased or sold (Wh)
f	Electricity trade (Wh)
g	Generated electricity (Wh)
h	Heat transfer coefficient indoor zone to building envelope ($W/(m^2\ K)$)
in	Inverter size (W)
Ir	Global irradiation on a horizontal surface (W/m^2)
k	Cost of temperature variation (€)
l	Fridge/freezer/battery storage level (Wh)
Lc	Average lighting heat (W/m^2)
light	Profile for lighting (-)
m	DR loads (Wh)
n	Lifetime (years)
Oc	Average occupancy heat (W/m^2)
occ	Profile for occupancy (-)
om	Operational and maintenance share (-)
p	Electricity price (€/Wh)
Pfh	Average fan heat (W/m^2)
pn	PV panel size (W)
PV	Electricity generated by PV panel (Wh)
q	Energy flow (W)
r	Interest rate (-)
s	Charge/discharge energy (Wh)
sh	Installed heating capacity (W_{heat})
sa	Surface area of building (m^2)
Sw	Total window surface area (m^2)
T	Temperature (K)
TC	Thermal mass (Wh/K)
Ts	Window solar transmittance (-)
U	Overall heat transfer coefficient ($W/(m^2\ K)$)
w	Weighting (-)
vc	Ventilation rate ($m^3/(s\ m^2)$)
Wc	Solar shading coefficient (-)
Wf	Frame coefficient of the window (-)
y	Power capacity of batteries or water heater (Wh/time-step)
γ	Share of heating equipment type (-)
η	Efficiency (-)

Appendix A

Table A1. The different combinations of pricing scheme, DR measures, pricing structure, PV system investment cost, discount rate, and REC price used Paper I and the result section in this thesis.

Pricing scheme	DR measure	Price structure	PV investment cost, €/kWp	Discount rate, %	REC price, €/MWh
Hourly	Appliance	Sweden, 2007	2300	2.5	29
		Sweden, 2010	2300	2.5	29
		Germany, 2010	2300	2.5	29
	Hydronic	Sweden, 2007	2300	2.5	29
	Hydronic and Appliance	Sweden, 2007	2300	2.5	29
		Sweden, 2010	2300	2.5	29
		Germany, 2010	2300	2.5	29
	None	Sweden, 2007	2300	0.1	29
				2.5	29
					19
					10
					0
				5.0	29
				7.5	29
			2010	2.5	29
			1720	2.5	29
			1430	2.5	29
		Sweden, 2010	2300	2.5	29
		Germany, 2010	2300	2.5	29
Tax Reduction	Hydronic	Sweden, 2007	2300	2.5	29
	None	Sweden, 2007	2300	2.5	29
		Sweden, 2010	2300	2.5	29
		Germany, 2010	2300	2.5	29
Monthly	None	Sweden, 2007	2300	2.5	29
		Sweden, 2010	2300	2.5	29
		German, 2010	2300	2.5	29
Net metering	None	Sweden, 2007	2300	2.5	29
		Sweden, 2010	2300	2.5	29
		Germany, 2010	2300	2.5	29

Table A2. Cycle demands, durations, and yearly available energy levels of DR loads used in Paper I. The indicated ranges represent the differences between different households.

Load	Cycle demand, kWh	Cycle duration time, hours	Yearly electricity demand, kWh
Dishwasher	0.67–1.77	2	70-720
Washing machine	0.71–1.64	1	62-350
Dryer	0.89–2.09	1	50-310
Fridge and Freezer (Aggregated)	0.04–0.31(hourly load)	1	400-1400
Hydronic space heating	Continuous	Continuous	8000-17500
Tap-water heating	Continuous	Continuous	1600-3100

Table A.3 shows the values used for V.A.T., energy tax, distribution grid fees, used in Paper I. The taxes and distribution fees are also used in Paper V.

Parameter	
Total investment cost of PV system	€2300/kW$_p$
Investment cost of Inverter	13% of total investment cost
Panel, BoS, and installation Cost	87% of total investment cost
Yearly operation and maintenance cost	0.17% of investment cost per year
Lifetime of PV panel	25 years
Lifetime of inverter	15 years
Heat storage efficiency	99% per hour
Discount rate	2.5%
VAT rate	25%
Electricity tax	€0.0417/kWh
Maximum heating power	9 kW (SH), 3 kW(HW)
Size of heat storage	10.2 kWh (SH), 5.8 kWh (HW)
Distribution fee	€0.0345/kWh
Renewable electricity certificate	€0.029/kWh
Deduction from selling price	€0.0046/kWh
Network income	€0.0064/kWh
Price add-on	€0.0046/kWh
Tax reduction	€0.069/kWh

Table A.4 The allowed temperature ranges for the D15H18DR cases and the minimum allowed temperature for the D15H18Fix case for different segments of the day and week in the modeled cases.

Cases	Weekday (5:00-9:00 15:00-23:00)	Weekday (9:00-15:00)	Weekday (23:00-05:00)	Weekend (05:00-23:00)	Weekend (23:00-05:00)
D15H18DR	21.2-24°C	15-24°C	18-24°C	21.2-24°C	18-24°C
D15H18Fix	21.2°C- n/a	15°C- n/a	18°C- n/a	21.2°C- n/a	18°C- n/a

Table A.5 shows the different penalty costs applied for deviating from the set point temperature in Eq. 26.

Case	Low cost temperature increase	High cost temperature increase	Low cost temperature decrease	High cost temperature decrease
DR	0.0005	0.005	0.0025	0.025

Table A.6 Key assumptions for the investment options in the household model in Paper III.

Technology	Inv. cost	Lifetime [years]
Battery	€150-300/kWh	12.5
PV	€1200-1600/kWp	30
Inverter	€100/kWp	15

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