THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Modelling interactions between distributed energy technologies and the centralised electricity supply system

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ABSTRACT

Renewable electricity generators, such as solar photovoltaics (PVs), and variation management technologies, such as battery storage and demand response (DR) systems, can be deployed in a distributed fashion, which can benefit the overall system. Such distributed energy technologies interact with and influence the centralised generation and transmission systems. This thesis investigates these interactions using a cost-minimising investment model (ELIN) to generate scenarios for the future European electricity supply system and analysing the operation of the system in an economic dispatch model (EPOD).

Using the EPOD model to study congestion in the European transmission system, we show that while demand-related congestion can be reduced with DR, congestion related to wind power production cannot. Results also demonstrate that solar and wind power correlate with congestion on different time scales. Solar power cross-correlates with hourly congestion with a time displacement of 6–9 hours, whereas wind power correlates with congestion on a weekly time scale.

Two approaches are applied to model the effect of household-level phenomena on the centralised electricity supply system. First, a model for electric space heating load is integrated into EPOD, in order to study DR. The results show that DR in Swedish single-family dwellings (SFDs) primarily reduces the system running costs in neighbouring regions outside Sweden. Second, to capture market feedback, a cost-minimising investment model for PVs and batteries for individual households is iteratively linked to EPOD, yielding optimal capacities of up to around 8 GW_p of PVs and 8 GWh of batteries in total for Swedish SFDs. It is concluded that capturing market feedback is crucial for avoiding overestimations of the household investments.

Keywords: energy systems modelling, power systems, variable renewables, distributed generation, electricity storage, demand response

SAMMANFATTNING

Förnybar kraftproduktion i form av solceller samt utrustning för variationshantering, såsom batterilager och laststyrning, kan installeras i distribuerad form, vilket kan medföra fördelar för systemet. Sådan distribuerad energiutrustning interagerar med och påverkar de centraliserade systemen för elproduktion och transmission. Denna avhandling studerar dessa interaktioner genom att använda en kostnadsminimerande investeringsmodell (ELIN) för att generera scenarier för det framtida europeiska elsystemet, vilka sedan kan analyseras i en ekonomisk dipatchmodell (EPOD).

Genom att använda EPOD för att studera flaskhalsproblematik i det europeiska transmissionssystemet, visar vi att flaskhalssituationer som orsakas av hög efterfrågan kan avhjälpas genom lastförflyttning, medan detta inte är möjligt om flaskhalsproblematiken orsakas av vindkraftens produktionsmönster. Resultaten visar också att sol- och vindkraft korrelerar med flaskhalsproblematiken på olika tidsskalor. Solkraft korskorrelerar med flaskhalsproblematik på timbasis, med en tidsförskjutning på 6–9 timmar, medan vindkraft korrelerar med flaskhalsproblematik på veckobasis.

Två metoder tillämpas för att modellera den effekt som distribuerad energiutrustning på hushållsnivå har på det centraliserade elförsörjningssystemet. Den första metoden bygger på en modell för elvärmelast som integreras i EPOD för att studera laststyrning. Resultaten visar att laststyrning i svenska enfamiljshus framförallt minskar körkostnaderna i kraftverk i grannregioner utanför Sverige. Den andra metoden kopplar iterativt EPOD till en hushållsinvesteringsmodell för solceller och batterier, med avsikt att beskriva återkopplingseffekten mellan hushållens investeringar och elmarknaden. Enligt resultaten kan de optimala solcells- och batteriinvesteringarna i svenska enfamiljshus totalt uppgå till 8 GW_p solceller respektive 8 GWh batterikapacitet. Det är avgörande att hänsyn tas till marknadsåterkopplingen för att undvika att överskatta hushållens investeringar.

Appended publications

This thesis consists of an extended summary and the following appended papers, which are referred to the text by their Roman numerals:

Paper I L. Göransson, J. Goop, T. Unger, M. Odenberger and F. Johnsson (2014). 'Linkages between demand-side management and congestion in the European electricity transmission system'. *Energy* **69**, pp. 860–872. DOI: `10.1016/j.energy.2014.03.083`.

Paper II J. Goop, M. Odenberger and F. Johnsson (2016). 'Distributed solar and wind power – Impact on distribution losses'. *Energy* **112**, pp. 273–284. DOI: `10.1016/j.energy.2016.06.029`.

Paper III J. Goop, M. Odenberger and F. Johnsson (2017). 'The effect of high levels of solar generation on congestion in the European electricity transmission grid'. *Applied Energy* **205C**, pp. 1128–1140. DOI: `10.1016/j.apenergy.2017.08.143`.

Paper IV E. Nyholm, J. Goop, M. Odenberger and F. Johnsson (2017). 'Electricity system benefits derived from the demand response of electric space heating in Swedish single-family dwellings'. Submitted for publication.

Paper V J. Goop, E. Nyholm, M. Odenberger and F. Johnsson (2017a). 'Impact of electricity market feedback on investments in solar photovoltaic and battery systems in Swedish single-family dwellings'. Submitted for publication.

Paper VI J. Goop, E. Nyholm, M. Odenberger and F. Johnsson (2017b). 'Electricity grid tariffs as drivers of residential photovoltaic and battery investments'. To be submitted for publication.

Paper I is the result of collaboration with Lisa Göransson, whereby Joel Goop contributed with analysis and writing. Joel Goop is the principal author of Papers II and III, and is responsible for the modelling, analysis, and writing. Papers IV–VI are the result of joint work with Emil Nyholm, whereby the Joel Goop contributed with modelling, analysis, and writing. Joel Goop is the lead author of Papers V and VI.

Mikael Odenberger and Filip Johnsson have contributed with discussions and editing of all the papers. Thomas Unger has contributed with discussions and editing of Paper I.

Other publications

Other publications by the author not included in the thesis:

A L. Göransson, J. Goop, M. Odenberger and F. Johnsson (2013). 'The role of Nordic hydropower to handle variations in the future European electricity system'. In: *Proceedings of the 12th International Workshop on Large-Scale Integration of Wind Power into Power Systems as well as on Transmission Networks for Offshore Wind Power Plants (London, UK, 2013)*. Langen, Germany: Energynautics, pp. 293–297.

B L. Reichenberg, J. Goop, F. Johnsson and M. Odenberger (2012). 'Maximizing value of wind power allocation: a multi-objective optimization approach'. In: *Proceedings of the 11th International Workshop on Large-Scale Integration of Wind Power into Power Systems as well as on Transmission Networks for Offshore Wind Power Plants (Lisbon, Portugal, 2012)*. Langen, Germany: Energynautics, pp. 804–807.

C J. Kjärstad, J. Goop, M. Odenberger and F. Johnsson (2014). 'Development of a Methodology to Analyze the Geographical Distribution of CCS Plants and Ramp-up of CO2-flow Over Time'. *Energy Procedia* **63**, pp. 6871–6877. DOI: 10.1016/j.egypro.2014.11.721.

D J. Goop, L. Reichenberg and L. Göransson (2016). 'The sensitivity of system cost and wind power revenues to sub-optimal investment in wind power capacity'. In: *35th International Energy Workshop (Cork, Ireland, 2016)*.

E E. Nyholm, J. Goop, M. Odenberger and F. Johnsson (2016). 'Solar photovoltaic-battery systems in Swedish households – Self-consumption and self-sufficiency'. *Applied Energy* **183**, pp. 148–159. DOI: 10.1016/j.apenergy.2016.08.172.

F V. Johansson, L. Thorson, J. Goop, L. Göransson, M. Odenberger, L. Reichenberg, M. Taljegard and F. Johnsson (2017). 'Value of wind power – Implications from specific power'. *Energy* **126**, pp. 352–360. DOI: 10.1016/j.energy.2017.03.038.

G L. Göransson, J. Goop, M. Odenberger and F. Johnsson (2017). 'Impact of thermal plant cycling on the cost-optimal composition of a regional electricity generation system'. *Applied Energy* **197**, pp. 230–240. DOI: `10.1016/j.apenergy.2017.04.018`.

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Göteborg, September 2017
Joel Goop

Contents

CHAPTER 1

Introduction

Electricity is a necessity in modern society. Everything, from the computers that we use daily and the associated communications infrastructure to public transportation systems, depend on a continuous and reliable supply of electricity. This supply has traditionally been dominated by plants that burn fossil fuels to create steam, which is thereafter passed through a turbine to generate power. Coal, natural gas, and oil account for the vast majority of the primary energy use for electricity generation globally (International Energy Agency, 2016a). As a consequence, power generation plants emit large amounts of CO_2. According to the International Energy Agency (2016b), electricity and heat generation accounted for 42 % of global CO_2 emissions in 2014. To combat anthropogenic climate change, it is clear that the power sector will have to undergo a comprehensive overhaul to reduce significantly its emissions. In the IPCC Fifth Assessment Report, CO_2 emissions from electricity generation are reduced to zero or negative levels before Year 2100 in all scenarios in which the CO_2 concentration in the atmosphere is stabilised (Bruckner et al., 2014). More recent research shows that in order to reach the goals in the Paris Agreement, global net-zero emissions as early as Year 2050 may be required (Rockström et al., 2017).

However, climate change is not the only issue, and other environmental problems as well as other concerns, such as the security of supply, spur initiatives to reduce our dependence on fossil fuels and to develop renewable energy sources for electricity production. Fluctuating or variable renewable electricity generation, in the forms of wind and solar power, is a growing area and it will have to play an even greater role in the future, if emission targets are to be reached.

It is a fundamental property of electricity that there is always an equilibrium between the power that is fed into and taken out of the grid. Historically, demand has been the major unknown variable, and the operation of power plants has been adjusted to maintain equilibrium in the system. Every time a light is turned on somewhere a generator, which is connected to the same grid, has to increase its power output. With increasing amounts of electricity being generated from variable renewable energy sources, i.e., sources for which the dispatch is determined by weather conditions, this situation may be reversed and the supply side could become the main source of variability in the electricity system. Thus, whenever wind power generation increases or decreases, the surrounding system must adapt to maintain the balance.

There are several strategies for managing the variability introduced by variable generation. The traditional approach is to use dispatchable units that are already present in the system, such as hydropower or conventional fossil-fuelled power plants. An alternative is to use demand response (DR) techniques, whereby as a response to a price or control signal, electricity consumption is controlled, either by shedding load or shifting it in time. In some cases, such as the generation of district heat, electricity can be substituted for other energy sources, e.g., combustible fuels, and *vice versa*. The storage of electricity, e.g., in batteries or pumped hydro storage, is another strategy managing variations in electricity generation. Finally, variability can be smoothed using the electricity grids. The variations in the supply of, for example, wind power, can be reduced by trading across a geographic area that is sufficiently large to reduce the correlations between weather patterns. In some cases, this can be accomplished by expanding the transmission grid. One can also extend the transmission capacity to access existing flexible assets and, for example, use Nordic hydropower to manage variations in continental Europe. Distribution grids may also play an important role in integrating new renewable generating capacity. Since wind and solar power can be installed as relatively small units, they can be located in proximity to consumers, through distributed generation. This confers potential system benefits, such as reduced grid losses, and also enables close integration with DR systems and local storage.

With decreasing investment costs for small-scale solar power and battery systems, together with increasingly accessible technologies for automated DR, the traditionally passive household consumers can become active players in the future electricity system. It is therefore crucial to understand the interactions between the household-level phenomena and the operation of the centralised power generation capacity and the usage of transmission and distribution grids. The focus of this thesis is therefore on linking the deployment of distributed small-scale technologies, such as residential solar power and battery storage as well as DR in households, to changes in the large-scale, centralised generation and transmission system.

1.1 Aim and scope of this thesis

This work investigates the impacts of distributed residential solar power and battery storage, as well as DR in single-family dwellings, on the European electricity system. The overall aim of this thesis is to advance the current knowledge of the interactions that will occur between distributed technologies in the electricity system and the centralised grids, generation systems, and markets during the transition to a more sustainable energy system. The following important questions are studied in this thesis:

- How do distributed solar power and DR affect the usage of and congestion in the European transmission grid?
- How do distributed generation, storage, and DR influence the operation of centralised generation and the electricity market?
- How strong are the economic incentives for households to invest in PVs and batteries in the future and what are the factors that drive those incentives?
- To what extent would it be beneficial to deploy storage and renewable generation in a distributed, as opposed to centralised, form?
- What are the benefits and disadvantages of different approaches to incorporating distributed generation, storage, and DR into large-scale electricity system models?

As these are broad questions, this thesis cannot provide complete answers to all of them. Nevertheless, the work presented here improves our understanding of the underlying issues and clarifies some of the issues raised in these questions.

This work is not intended to focus on the technical details of electricity grids, distributed generation, storage, or DR. Instead, it aims to investigate the connections between the distributed and centralised parts of the electricity system from a techno-economic point of view. In essence, this means that the modelling attempts to describe the technical aspects of the electricity system in sufficient detail, while also capturing some of the important trade-offs in system operation by using total system cost as the objective to be minimised.

However, although some economic aspects are considered, the modelling is restricted to the technical energy system and does not include macroeconomic processes. This means that, for example, demand growth is exogenously given as an input to the models. The primary tools employed are an investment model, which is used to describe the evolution of the electricity supply system in different future scenarios and economic dispatch models, which are used to analyse the operational characteristics of the systems.

1.2 Related work

The work described in this thesis involves several different models and is therefore connected to a large body of previous work. The following sections summarize first the efforts made to model capacity expansion and dispatch in electricity systems, primarily the European system, and then present the literature relevant to household-level DR and the dimensioning of residential PV and battery systems.

1.2.1 Capacity expansion and dispatch models

There is a vast body of literature on future developments of the capacity mix in and the operation of the electricity system using techno-economic modelling tools related to the models used in this thesis. Table 1.1 gives an overview of the techno-economic optimisation models that cover all or parts of the European electricity system and that

Table 1.1: Examples of techno-economic optimisation models that cover the entirety or parts of the European electricity system. The models are classified as *CE, ED* for combined capacity expansion and dispatch models and *ED* for dispatch-only models, with *(S)* indicating that the model is stochastic.

Model	Type	References
Balmorel	CE, ED	Ravn et al. (2001)
URBS-EU	CE, ED	Schaber (2013) and Schaber et al. (2012a)
E2M2s	CE, ED (S)	Spiecker and Weber (2014) and Swider and Weber (2007)
WILMAR	ED (S)	Meibom et al. (2004) and Trepper et al. (2015)
EMMA	CE, ED	Hirth (2013, 2017)
LIMES-EU	CE, ED	Haller et al. (2012), Knopf et al. (2015) and Nahmmacher et al. (2016, 2014)
DISPA-SET	ED	Quoilin et al. (2017)
DIMENSION	CE, ED	Fürsch et al. (2013) and Nagl et al. (2013, 2012)
TIMES-PLEXOS	CE, ED	Collins, Deane and Ó Gallachóir (2017), Collins, Deane, Poncelet et al. (2017) and Deane et al. (2012)
REMix	CE, ED	Scholz (2012) and Stetter (2012)

CE: Capacity expansion, endogenous investments.
ED: Economic dispatch.
(S): Stochastic.

are similar in terms of methods and scope to the ELIN-EPOD models used in this thesis. Some of the models have been used to study specific issues, such as grid extensions (e.g., URBS-EU, see Schaber et al., 2012a,b) or links between variable renewables and electricity prices (e.g., EMMA, see Hirth, 2013, 2016).

Whereas many models treat power plant dispatch and capacity expansion as a single optimisation problem (e.g., LIMES-EU and URBS-EU, see Nahmmacher et al., 2014; Schaber, 2013), the ELIN-EPOD modelling package used in this thesis applies a stand-alone dispatch model (EPOD) to analyse the results from the capacity expansion model (ELIN) in greater detail. This approach is similar to, for example, the linked TIMES-PLEXOS models presented by Deane et al. (2012). There are, however, differences between the two model packages. For example, the ELIN model has a more narrow sectoral scope than the TIMES model and it is limited to the power sector.

There are also a multitude of models with other geographic scopes, such as SWITCH (Mileva et al., 2016; Nelson et al., 2012) and ReEDS (Eurek et al., 2016), which cover the US. Other similar models take a broader approach, by employing a global scope and including other sectors endogenously. Examples of such models, that have been used to study the power sector, include the REMIND model (Pietzcker et al., 2014) and the GET model (Lehtveer, 2016).

1.2.2 Household demand response and investment models

Papers V and VI deal with the dimensioning and dispatch of residential PV and battery systems, which are topics that have been extensively studied in the literature (e.g., Cucchiella et al., 2016; Hoppmann et al., 2014; Mulder et al., 2013). The majority of these studies have evaluated a number of combinations of PVs and batteries of given sizes by calculating some economic output parameter, most often the electricity cost for the households (Hoppmann et al., 2014).

Darghouth et al. (2016) investigated the feedback between PV penetration and the marginal cost of electricity and its effect on the penetration levels of distributed solar PVs with different electricity retail rate structures. They applied the calculated rate at which the compensation for PV electricity sold to the grid decreases with increasing PV penetration level. Their approach did not include any explicit modelling of the effect that the solar PVs have on the operation of the centralised generation system.

An iterative approach, which is similar in some respects to that presented in Paper IV, was used by Tapia-Ahumada et al. (2013). They iterated between an economic dispatch model that describes the centralised generation system and a household-level model. Their focus, however, was on the expansion of gas-fired micro-CHP units, and distributed PVs and battery storage were not studied.

1.3 Contribution of this work

The major contributions to the field from this thesis are two-fold: the development of methodology; and an improved understanding of the system. This section gives an overview of how the work contributes in each of these respects.

1.3.1 Methodology development

The present work explores new ways through which distributed resources such as residential PV and battery systems, as well as DR, can be integrated into techno-economic electricity system models. In Papers I–III, aggregated representations of DR in the form of load shifting (Paper I) and distributed solar power (Papers II and III) are applied, and more detailed descriptions are used in Papers IV–VI.

In Paper IV, a method is proposed for integrating the shifting of electric heating loads in single-family dwellings into an economic dispatch model. This method combines a physical energy balance over a detailed representation of the Swedish stock of single-family dwellings with the cost minimising model of the north European electricity system, thereby allowing the potential system benefits of DR using electric heating systems to be investigated. The system benefits can be analysed in detail with respect to, for example, how power plant dispatch is affected in different geographic regions, what effects there are on cross-border trade patterns, and whether the extent of power plant cycling can be reduced.

Paper IV also introduces a method for modelling space heating DR in which both upward and downward deviations from the set-point temperature are permitted. The method most commonly used to describe heating DR in this type of model only allows for the temperature to exceed the set-point temperature.

In Paper V, an iterative method is developed for combining locally optimised household investments in PV and battery systems with the economic dispatch model that describes the centralised electricity system. The iterative method allows one to consider the perspective of households as opposed to only the overall system perspective. Here, to account for the grid parity effect, households make investments to minimise their own electricity cost based on an electricity price that is calculated by the dispatch model. The new total net load of the households is fed back to the dispatch model which then calculates a new electricity price, thereby creating a feedback effect, and the procedure is repeated until the two models converge. This method allows one to study the strength of the incentives for households to invest in PVs and batteries and the extent to which those incentives are dampened by the feedback effect. The effects of household investments on the centralised power plant dispatch and system costs can also be investigated. The method presented in Paper V also facilitates the analysis described in Paper VI, where the household model is further developed to include additional grid tariff structures.

1.3.2 Understanding the system

Papers I–III contribute to the current picture of how distributed resources and variable renewables affect the usage of transmission and distribution grids. The usage of electricity grids is strongly influenced by the economics of generation and the location of the generating power plants. Using techno-economic modelling, the changes in the usage of the grid in different future scenarios can be studied, as well as how these changes are affected by the development of the electricity generation system. It also enables investigations of the competition between using the grid to manage variations and using other strategies, such as DR or the cycling of thermal power plants.

While many of the studies reported in the literature have investigated the operations of transmission and distribution grids in much greater technical detail, the models applied in the present work include a more developed description of the generation system. As more variable renewable sources enter the system, this thesis also investigates how different variation management techniques, such as thermal power plant cycling and DR, influence how the grids are used. Compared with other studies that have employed similar techno-economic modelling approaches, the focus of this thesis is on how the grids are used in different future scenarios, that is, how trade patterns change as well as when and why congestion occurs, rather than the extent to which grid investments are needed or which areas in the grid need to be strengthened.

Papers IV–V focus on integrating the household perspective with the system perspective. In comparison to other related studies, this work contributes by combining detailed household-level descriptions with a large-scale electricity system model. The results of these studies enable us to understand more clearly how centralised dispatch is affected by decisions made at the household level, as well as how the incentives and roles of households change when placed in context. The geographic scope of the dispatch model also makes it possible to show how Swedish households can affect dispatch of power plants in continental Europe. The inclusion of DR in an economic dispatch model also provides realistic assessments of the economic benefits of DR under different scenarios for the centralised electricity system.

In Paper VI, we examine the role that grid tariffs play as a policy instrument for driving household investments. We also apply the iterative method developed for Paper V to discover how the feedback effects differ across different tariff structures.

1.4 Disposition of the thesis

This thesis consists of six appended papers and this extended summary. The extended summary is divided into eight chapters, where this *Introduction* is the first. Chapter 2 explains some relevant background and provides a review of the relevant literature. Chapter 3 describes the main modelling techniques used in the papers upon which the thesis is based. The main input data, and the assumptions made in the modelling are described in Chapter 4. The evaluations of the main models are described in Chapter 5. Chapter 6 presents the main findings from the work and Chapter 7 discusses the validity and implications of the results. Finally, Chapter 8 summarises the conclusions from the work and suggests pathways for future research.

CHAPTER 2

Background

This chapter provides a short introduction to the concepts that are important for understanding the methods used and the results derived in this work.

2.1 Basic principles of electricity grids

The purpose of electricity transmission and distribution grids is to deliver power to those who want to consume it, at the locations and times required (demanded) by the consumers. Electricity must also be supplied in a form that is amenable to usage by the consumers, which, among other things, means that the voltage has to be that mandated by the consumers' appliances. While this utilisation voltage varies around the world, it has been chosen to be safe and practical, typically in the range of 100–250 V (Willis, 2004). However, losses in transmission lines are related to the current flowing in the line, and if one attempted to transmit large quantities of power at these low voltages, the currents (and, as a consequence, the losses) would be very high. Since the alternating current systems that we mainly use for power transmission allow for relatively easy transformation between voltages, we usually choose high voltages when moving large amounts of power over long distances. However, there is a trade-off here as well, since the equipment and lines used for high voltages are significantly more expensive than those employed for low voltages. All these factors in combination with the traditional modes for generating electricity (which is also much more economical if performed in large centralised plants), have created a system of hierarchical voltage levels (Willis, 2004). In this system, the centrally produced power is first transported in bulk at high (stepped-up) voltage. As the grid branches out to reach all the consumers, less and less power flows in each individual branch, and the voltage is stepped down.

2.2 Distributed energy technologies

As mentioned above, the existing electricity system was designed on the basis that power would be produced in large centralised facilities connected to the high-voltage grid and then distributed to consumers through transmission and distribution grids of stepwise decreasing voltages. In such a system, consumers, especially small-scale consumers, are generally assumed to be passive. However, with the development of new technologies for load management and the decreasing costs of solar PVs and battery systems, small-scale consumers have the opportunity to become active participants in the system. In this scenario, both generators and other important resources such as battery systems, can be connected in the form of smaller units that are spread out across distribution grids and often located behind the meter at the consumer site. We designate generation capacity of this type as *distributed generation* (DG), although for the purpose of this thesis, other technologies, such as storage and load management systems, are also relevant[1].

Both solar PVs and battery storage systems are highly modular with small economies of scale, as opposed to conventional generation and storage technologies, which makes them suitable for deployment on a small scale. Distributed deployment of generation and storage offers several advantages over centralised deployment, such as the potential to reduce losses and alleviate bottlenecks in distribution grids, as well as being located close to the load. There are, however, disadvantages in comparison with centralised generation and storage. For example, with distributed deployment, the market and control systems risk becoming highly complex, and maintenance becomes more costly. In addition, if the generated or stored electricity cannot be consumed locally, for it to be transported to another location it will have to travel a longer path to return to the high-voltage transmission

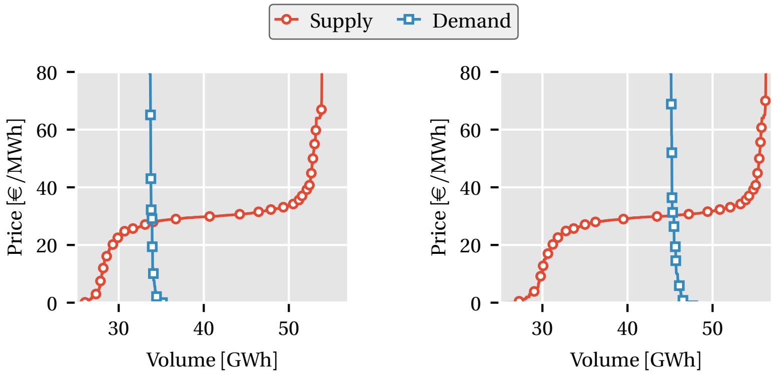
[1]For more formal definitions and discussion of the concept of DG and other distributed resources, see Ackermann et al. (2001).

grid, compared to a situation in which generation and storage units are connected at the transmission level.

2.3 The marginal cost of electricity

An important concept discussed throughout this work is the marginal cost of electricity or the marginal generation cost. In economics, the marginal cost of production of a commodity is the change (increase or decrease) in total production cost associated with producing one additional unit. A more formal definition is that the marginal cost is the derivative of the total production cost with respect to the produced quantity of the commodity in question. For electricity, this means that the marginal cost of generation is the change in the total cost of generating electricity that would result from an infinitesimal increase in demand. If we simplify this somewhat and assume that we use the plants with the lowest running costs first, we can construct a supply curve. If there remains some scope to increase the output of the last plant that is brought into operation, the marginal generation cost will be the running cost of that last, most expensive plant. We usually say that the unit that determines the marginal generation cost is the unit "on the margin".

Economic theory states that in a perfect market, the market price should equal the marginal production cost. In a spot market for electricity, such as the Nordic electricity market Nord Pool Spot, producers and consumers of electricity (often through companies acting as intermediaries) submit bids that state how much electricity they are prepared to buy or sell and at what price. These bids can be aggregated into supply and demand curves, and the intersection of these curves determines the market price and the volume that should be produced. However, both the demand for electricity and the conditions for producing it, for example the weather and fuel prices, can vary both spatially and temporally. In principle, the marginal cost of electricity could be different at every point in time, and if there are limitations within the grid, the marginal cost could be different at each grid node at which a consumer is connected. This type of temporal and spatial resolution cannot be handled in a practical way by a real market. Therefore, bidding on electricity spot markets is often



(a) Bids to Nord Pool Spot for 3 am. **(b)** Bids to Nord Pool Spot for 4 pm.

Figure 2.1: Supply and demand bids to the Nord Pool Spot market on December 20$^{\text{th}}$, 2014 for the hours of (a) 3 am and (b) 4 pm. While the supply bid curve changes slightly from the night to the afternoon, the main difference is seen for the demand, which is significantly higher in the afternoon. The price is therefore slightly higher in (b), although the supply curve is fairly flat at around 30 EUR/MWh for a wide range of volumes. Source: Nord Pool (2014).

aggregated to once per hour and aggregated within some geographic region, which is called a *bidding area*. As an example, Figure 2.1 shows the total supply and demand curves for all the bidding areas in the Nord Pool Spot market combined for two distinct time-points (3 am and 4 pm) on December 20$^{\text{th}}$, 2014. The main difference between the two time-points is that the demand is significantly lower during night-time, which leads to a lower price even though the price decrease is counteracted by the fact that the supply curve is slightly shifted to the left for the night-time hour compared with the day-time hour. It is noteworthy that the demand curve is very steep, indicating that the demand for electricity is inelastic, at least in the short term. It is also evident that the supply curve is fairly flat for the Nordic system in the interval within which the demand is varying here, which means that the variations in price between night and day are relatively small.

2.4 Variable renewable electricity generation

Electricity generation from the most of the commonly exploited renewable sources, i.e., wind and solar power, depends in real time on variations in wind speed or solar irradiation. Renewable generation technologies with such direct dependencies on changing weather conditions are referred to as *variable*, or sometimes termed *intermittent*. An important characteristic of variable renewable sources is that their associated running costs are close to zero. For this reason, it is usually preferable to utilise these sources when available. The near-zero running costs of the variable renewables place them in the left-most part of the supply curve. When electricity production from, for example, wind power is high, the supply curve shifts to the right and the price drops. With high shares of variable renewables in an electricity market, production can correlate negatively with the price. As the penetration levels of wind and solar power increase, there is a risk that the revenues for the owners of those plants will decrease.

Since variable renewable generation is prioritised in the dispatch, the flexible elements of the system have to adapt to the combined variations of demand and variable generation. The term *net demand* is therefore often used to denote the level of demand minus the level of production from variable renewables. In contrast to the demand, the net demand can have a negative value if the level of variable generation exceeds the demand.

2.5 Marginal cost and congestion

Congestion occurs when limitations in the grid prevent the electricity produced by the most desirable generating units from meeting demand. If we assume that the system is operated to provide electricity at the lowest possible cost (without risking safety, quality, or reliability), the most desirable generating units are those that have the lowest marginal costs. If a region that has a low marginal cost of electricity is connected *via* the transmission grid to a region that has a high marginal cost, from an economic perspective, electricity should be exported from the low-cost region until either the marginal cost is the same in the two regions or the grid no longer allows power to be transferred. If the grid is the limiting factor, the difference in marginal cost between the two regions will remain. The difference in marginal cost of electricity between the two regions is also equal to the marginal value of increased transfer capacity between the regions. Therefore, we consider the differences in marginal cost between regions to be an indicator of congestion.

As the electricity supply is transformed, the transmission grid may have to be used differently, for the following reasons:

- The locations of power plants can be changed. A wind power plant may, for example, be built at sites with good wind conditions or where it is possible to obtain planning permission, and solar cells may be placed on rooftops if they are installed by private homeowners. This could lead to both an increased need for transmission capacity, for example, if remote locations are used for building power plants, or reduced need for transmission if, for example, generating plants are located closer to the sites of consumption.

- When a large share of the generation is derived from variable sources, it may be beneficial to avoid the peaks and troughs of the variations. The grid can help to smoothen the variability of the generation by connecting different locations, as shown by Reichenberg et al. (2014).

- To utilise fully other resources for managing variations in generation, such as flexible hydropower in the Nordic countries, an increase in grid capacity may also be required.

CHAPTER 3

Methods and modelling

Several different modelling approaches are applied in this work to study different future scenarios for the European electricity system and the operation of systems with high penetration levels of variable generation, such as wind and solar power.

3.1 Investment modelling – future scenarios

To unveil the potential future developments of the electricity system in Europe, we construct, analyse, and compare different scenarios, for which we use the linear programming (LP) investment model ELIN, originally created by Odenberger (2009) and subsequently refined by Göransson (2014). ELIN is a cost-minimising, perfect-foresight model that focuses on the technical energy system, in a manner similar to that of commonly used energy systems models, such as MARKAL (Fishbone and Abilock, 1981) and TIMES (Loulou and Labriet, 2008). However, in contrast to most of the TIMES and MARKAL models, ELIN focuses exclusively on the power system and excludes other sectors, such as transport and industry. The limited sectoral scope of ELIN enables a more detailed representation of the power system, for example through detailed descriptions of power generation technologies and the present system, as well as a relatively high geographic resolution.

The ELIN model is fed input data on, for example, renewable resources, and is exogenously provided with some assumptions regarding the future, such as projections of electricity demand levels and fuel prices. Given these data, the model identifies investments in power generation and transmission that result in the lowest system cost, i.e., the sum of the running costs and investment costs, while meeting system-wide and national targets for CO_2 emission reductions and energy from renewable sources.

The ELIN model is multi-regional and maintains energy balances for each region while allowing trade between the regions. While the chosen regions can be entire countries, in this work, a more high-resolution geographic subdivision, which is more suitable for studying grid issues, is used. The EU-27 countries plus Norway and Switzerland (but excluding the electrically isolated islands of Malta and Cyprus) are divided into 50 regions based on transmission bottlenecks in the present and near-future European transmission grids, according to ENTSO-E (ENTSO-E, 2010; Göransson, 2014). Figure 3.2 shows the regional divisions used in the ELIN and EPOD models in the present work, together with the nodes that were used in the grid modelling, as described later in this chapter. The time-span investigated with the ELIN model in this work is from now up to Year 2050.

Given the long time horizon and computational limitations, the version of the ELIN model that is used in the studies described in the papers of this thesis has a relatively low time resolution of 16 time-steps within each year, corresponding to the days and nights of weekdays and weekends for each of the four seasons. The model contains only a simplified description of trade between the regions, which limits electricity trade to a specified maximum capacity for each interregional connection. Due to of these simplifications being made in the ELIN model, snapshots of the scenario results are studied in more detail with the EPOD dispatch model, which is described in the next section.

In most of the work of this thesis, however, the long-term development pathway of the system is not in focus. Instead, the ELIN model is used as a scenario generator and the emphasis is placed on analysing one or several future system compositions in the EPOD model. This work flow is illustrated in Figure 3.1.

An updated version of the ELIN model, which applies the "representative days" approach presented by Nahmmacher et al. (2016), is under development.

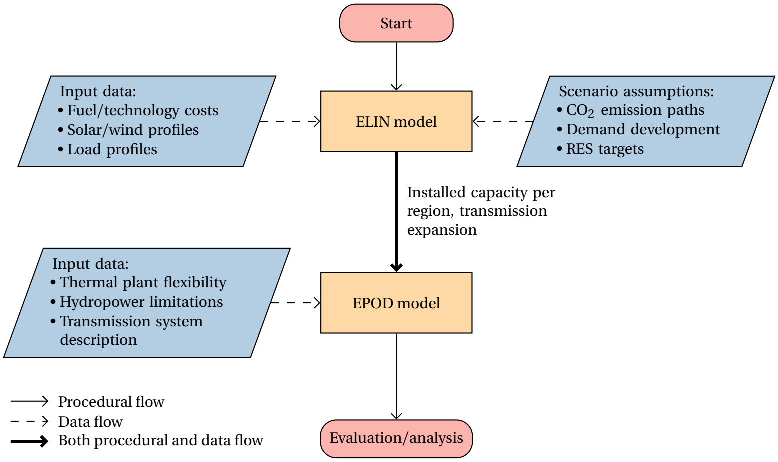


Figure 3.1: Flow chart illustrating the modelling work flow connecting the ELIN and EPOD models. The thin solid lines represent the procedural flow, the dashed lines represent the data flow, and the bold solid lines represent both the procedural and data flows.

3.2 Dispatch modelling – operation of power plants

Dispatch models typically determine how electricity generating units in a system are best operated so as to serve consumers at the lowest cost (Göransson, 2014). The time-span studied with dispatch models is typically up to 1 year, which is sufficiently short to permit the assumption that the system composition remains unaffected by new investments or the decommissioning of units. A relatively high time resolution, e.g., 1 hour, is usually chosen to capture more details of, for example, wind power variation and thermal power plant flexibility.

In this work, we apply two separate dispatch-type models. The first one is the EPOD model, which was designed within our research group (Unger and Odenberger, 2011) to be coupled with the ELIN model and was further developed by Göransson (2014), as well as within this work (see Papers I and III–VI). The second model is a single-region dispatch model that was developed in the present work and applied to western Denmark in Paper II.

The EPOD model, as used in this work, has the same geographic scope and resolution as the ELIN model, i.e., the same 50 regions covering the EU-27, Norway, and Switzerland but excluding Malta

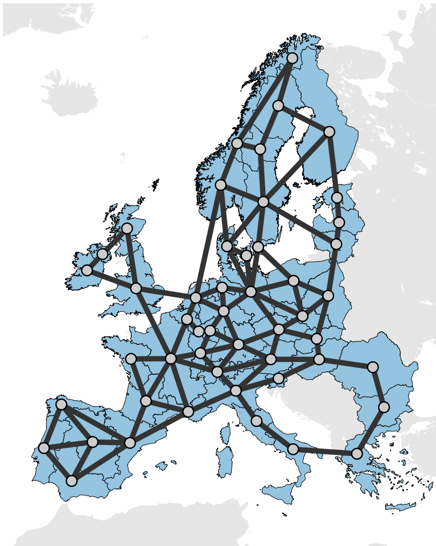


Figure 3.2: Map of the European transmission grid as described in the ELIN and EPOD models, and the regional divisions used in the models. Each point corresponds to a model region and a node in the grid model. Both AC and DC connections are included. A map with the names of the regions is provided in Appendix A.1.

and Cyprus (a map of the model regions and their names is shown in Appendix A.1). The regional division used in the EPOD model was developed through earlier work within the research group, and was designed to describe also the European transmission grid. Thus, the system of regional divisions used is not only based on the transmission bottlenecks described by the ENTSO-E (2010), but also defined so that each region consists of a set of NUTS2 regions, which are defined and used for the purpose of EU statistics (European Commission, 2015a), to enable the use of European statistics as input data. In the EPOD model, each region is used as a node in a transmission grid description that uses the DC load flow method (further described in Section 3.3). Figure 3.2 shows the nodes used in the grid modelling and the regions upon which they are based, together with the possible interconnections.

To study the electricity generation system in more detail than is possible with the ELIN model, the time resolution is much higher. In Papers IV–VI, the EPOD model is used with an hourly time resolution, whereas a time resolution of 3 hours is applied in Papers I and III, so as to match the European weather data used in these latter studies. For the chosen time resolution, the EPOD model calculates the cost-minimal dispatch over 1 year for a static system extracted for a selected year from the results of an ELIN run. Power plants are described as aggregates, whereby all the plants within a region that are similar with respect to fuel type, technology, and efficiency are described as a single unit.

The EPOD model also provides several methods for describing the limited flexibility of thermal power plants, i.e., in terms of start-up times and part-load limitations, and capturing the increased costs that arise from more flexible operation of these plants. The way in which the flexibility limitations of thermal power plants are included in the model is described in greater detail by Göransson (2014).

The single-region dispatch model developed and used for Paper II describes the dispatch of the power plant fleet in a single region, within which we assume that there are no grid bottlenecks. Having a narrower geographic scope than the EPOD model, other aspects are described in greater detail. In the single-region dispatch model, we represent three typical voltage levels with individual load profiles: low voltage (LV, typically $\leq 1\,\mathrm{kV}$); medium voltage (MV, typically up to 30 kV); and high voltage (HV, $\geq 100\,\mathrm{kV}$). This description is meant to capture the fact that different DG technologies connect at different voltage levels, both due to their typical sizes and the involvement of different actors, e.g., household consumers or utilities. The voltage levels have distinct load patterns, given that they serve different types of consumers, and consequently, the potential to consume electricity from DG locally will vary.

In the dispatch model described in Paper II, all large plants are represented individually with binary on-off variables. Smaller thermal plants, as well as solar and wind power plants, are aggregated, and for each aggregate, a continuous variable is used to represent the capacity that is currently online. For each plant (or aggregate), a start-up time and a minimum load level are specified, as well as the part-load efficiency. With binary variables, solving the optimisation problem can be time-consuming, so we have adopted a rolling horizon approach, in which smaller optimisation problems that span a shorter time interval are solved sequentially. The model moves the optimisation time window forward in small steps, while fixing the previously obtained solutions, until a solution for the entire year is obtained. This model also includes simplified dispatch optimisation of district heating (DH), to describe more accurately the marginal value of heat from CHP plants.

The results reported in Paper II are based on the application of this model to the system operating in western Denmark, albeit with load data from a German distribution system operator (DSO) and a DH load curve from Gothenburg, Sweden. Input data from different systems are mixed, mainly because of the limited availability of data from any one region. However, the systems were chosen to be similar in certain crucial aspects, such as climate conditions. The power system configuration, i.e., the technical and economic data for power plants, is based on the work of Göransson and Johnsson (2009) and updated with data from the power plant owners for Year 2012. Import and export prices to the neighbouring regions, as well as CO_2 emission allowance prices, are set to the historical values in Year 2012.

3.3 Transmission grid modelling – DC load flow

To describe the power flow between regions in the EPOD model, the so-called “DC load flow” (or DC power flow) method is applied for the AC network used in Papers I and III, in which the full European power system is modelled. DC load flow is a linearisation of the full AC power flow and we derive it by making the following assumptions: 1) that voltage differences between the nodes are negligible; 2) that the transmission line reactances are much larger than the line resistances ($X \gg R$); and 3) that the difference in voltage angle $\Delta\theta_{ij}$ between nodes i and j is small, so that $\sin\left(\Delta\theta_{ij}\right) \approx \Delta\theta_{ij}$. If we also choose to consider only real power flows, the full power flow equations can be simplified as: $P_{ij} = \Delta\theta_{ij}/X_{ij}$, where P_{ij} is the real power flow, and X_{ij} is the reactance between nodes i and j. This relationship can be included as a constraint in the LP description of the economic dispatch problem, which makes it possible to approximate the power flow as part of the dispatch optimisation.

For more information on DC load flow, Andersson (2008) describes the derivations of the DC load flow equations and places them in the context of general power systems analysis. In addition, van den Bergh et al. (2014) describe how the equations are obtained and how they can be used in unit commitment and dispatch models.

3.4 Measuring congestion

A central part of this work is to assess the levels of congestion in the European transmission system in future scenarios (Papers I and III). To accomplish this, we need to be able to identify and measure congestion both at individual connections between regions and at the overall systems level. In a perfect market and in a dispatch optimisation model, congestion at an individual connection can be identified as the difference in marginal generation cost between two connected nodes, which in our case corresponds to two connected regions. The rationale here is that if the transmission between the two regions is not constrained (by thermal limits or network constraints) and the marginal costs (or market prices) are different in the two regions, then the region with the higher marginal cost imports from the region with the lower marginal cost until either the marginal costs are the same in both regions or there is a transmission constraint that limits the trade, i.e., congestion. The marginal value of alleviating this congestion can thereafter be quantified as the magnitude of the marginal cost difference between the two regions or nodes. While this works well for our dispatch model results, it does not necessarily hold true for real markets, since prices do not necessarily reflect the local marginal cost and, in reality, different regions operate under different market conditions.

Measuring the overall system congestion, i.e., how congested the overall system is at any particular time-point, is not so straightforward. In Papers I and III, we argue that the existence of a wide range of marginal costs across all the individual regions in the system is an indication of congestion. Therefore, we chose to define a measure of system congestion sc_t at time t as the standard deviation of the marginal cost over all regions at time t, as follows:

$$\mathrm{sc}_t = \sqrt{\frac{1}{N}\sum_{i\in I}\left(\overline{\mathrm{mc}}_t - \mathrm{mc}_{i,t}\right)^2}\,, \tag{3.1}$$

where I is the set of all regions, N is the total number of regions, $\mathrm{mc}_{i,t}$ is the marginal cost in region i at time t, and $\overline{\mathrm{mc}}_t$ is the average marginal cost over all regions at time t.

3.5 Modelling electric heating demand response

In Paper IV, we integrate the shifting of electric heating loads in Swedish single-family dwellings into the EPOD model, to study the potential benefit the system. The integration is accomplished by adding constraints that describe the heating energy balances for a number of sample buildings representing the building stock. To represent all Swedish single-family dwellings that are at least partially heated by electricity, descriptions of 571 sample buildings are obtained from the report of the BETSI project (National Board of Housing, Building and Planning, 2011) (see Section 4.5).

The space heating model is a two-zone energy balance over each sample building and is based on the model presented by Nyholm, Puranik et al. (2016), which in turn is built on the work of Mata et al. (2013). The first zone represents the indoor air, furniture, and indoor walls, and the second zone represents the building envelope. Each zone is described in terms of a thermal mass and temperature. Heat gains are transferred to the indoor zone through heating equipment, other internal sources, and solar irradiation. Heat is also transferred from the indoor zone to both the outdoor environment (*via* ventilation) and the building envelope zone, which also exchanges heat with the environment. A schematic illustration of the zones and the energy flows between the zones is provided in Figure 3.3.

The inequalities that represent the space heating energy balances for each sample building are incorporated into the EPOD model as constraints that connect indoor temperature in the building stock to electricity consumption for each hour. In addition to these constraints, two different methods for representing the DR are applied: the conventional fixed interval method; and a new deviation cost

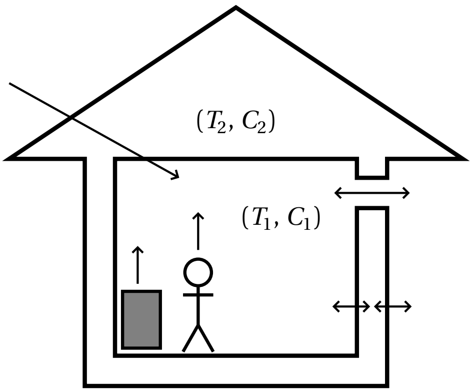


Figure 3.3: Illustration of the energy balance model used to describe indoor temperature in each of the sample buildings in the space heating model used to study DR. The building envelope and the indoor environment are treated as separate zones. Each zone is represented by a temperature and a thermal mass, where (T_1, C_1) represent the indoor zone and (T_2, C_2) represent the building envelope. The arrows indicate energy flows. The grey box is heating equipment and the stick figure (person) represents other internal heat gains.

method. The fixed interval method allows the indoor temperature to vary within a pre-determined range, i.e., allowing heating above the set-point temperature to an upper limit. The deviation cost method adds penalty costs for any deviation, either upwards or downwards, from the set-point temperature. In addition to the base temperature, the fixed interval method only requires setting an upper limit for the indoor temperature, whereas with the deviation cost method, four new cost coefficients are introduced that represent the willingness of the households to deviate from the set-point temperature. The set-point temperature chosen to be 21.2 °C, which corresponds to the average indoor temperature in Swedish single-family dwellings (Nyholm, Puranik et al., 2016).

The main benefit of the deviation cost method is that it allows the indoor temperature to drop below the set-point value if the system cost savings are sufficiently large. When using the fixed interval method, the temperature cannot be lower than the base temperature, and an optimisation model will often keep the temperature close to this level because it minimises the energy used for heating. Overheating is applied by the model when the savings from the stored heat outweigh the costs of the additional energy that is lost when heating the building to a higher temperature.

In addition to the DR methods, we also investigate using a set-point temperature that varies over time, so that a lower set-point temperature is used during night-time (11 pm–5 am) and during common working hours (weekdays 9 am–3 pm). During the night-time, the set-point temperature is changed to 18 °C and during working hours it is lowered to 15 °C.

3.6 Modelling residential PV and battery investments

Papers V and VI apply a separate model, which minimises the electricity costs for households with the possibility to invest in PV and battery systems. The model is based on the work of Nyholm, Goop et al. (2016), where, for each household, a PV system is simulated and the dispatch of an in-house battery system is optimised to maximise the self-sufficiency of the household. This original model is extended to also optimise the sizes of the PV and battery systems along with the dispatch, so as to minimise the total household electricity cost.

The household optimisation process is based on an hourly electricity price curve obtained from the EPOD model by extracting the shadow price from the load balance constraint in each model region. The net load profiles from all the sample households in each region are then aggregated using a weighted sum, where the weights are based on statistics obtained from the Swedish Energy Agency (2011). Figure 3.4 shows the iterative procedure and illustrates the respective roles of the ELIN, EPOD, and household investment models.

In the household model, households buy electricity from the grid at the hourly spot price, which is the marginal generation cost calculated by EPOD for each iteration. In addition to the spot price, each household is assumed to pay value added-tax (VAT), energy tax, and an energy-based distribution grid tariff.

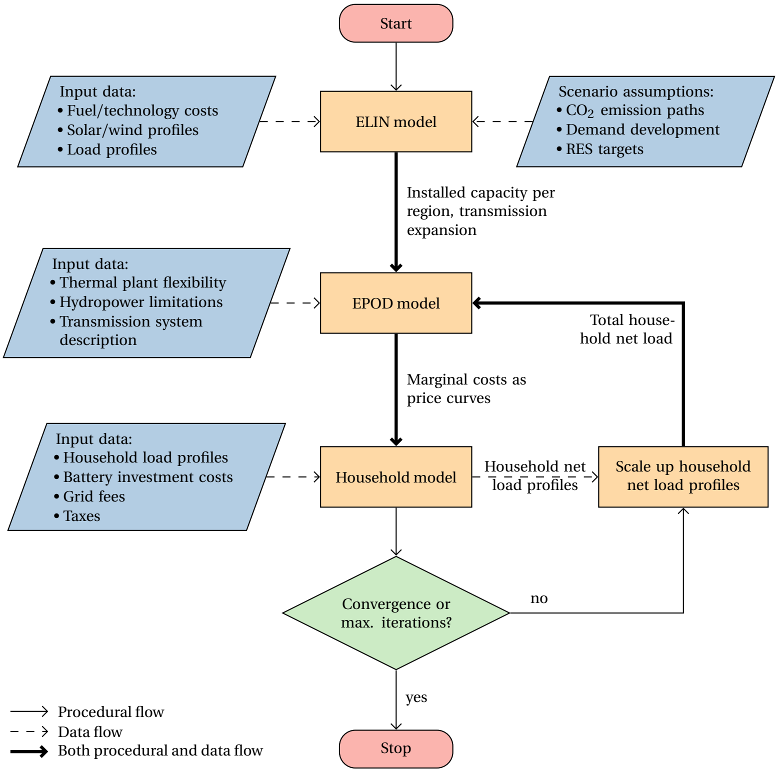


Figure 3.4: Flow chart illustrating the iterative modelling approach used in Paper V, and the respective roles of the ELIN, EPOD, and household investment models. The thin solid lines represent the procedural flow, the dashed lines represent the data flow, and the bold solid lines represent both the procedural and data flows.

3.7 Grid tariffs

For the analysis performed in Paper VI, several new types of grid tariffs are added to the household investment model. The following types of variable tariffs are included:

Energy-based tariff: Consumers are charged per kWh of total net consumption. This incentivises self-consumption of PV electricity (behind the meter). The cost for grid services for each household i is thus proportional to $\sum_{t \in T} d_{i,t}$, where $d_{i,t}$ is the electricity drawn from the grid by household i at time t.

Monthly power tariff: A fee is paid per kW of peak (hourly average) consumption during each month. Incentivises the use of batteries for lowering the monthly peak consumption. This is implemented in the model by adding a variable $p_{i,m}$ representing the power demand in household i during month m. It is controlled by the following set of constraints for each household i:

$$p_{i,m} \geq d_{i,t} \quad \forall t \in T_m, \tag{3.2}$$

where $d_{i,t}$ is the electricity drawn from the grid by household i at time t, and T_m is the set of hours in month m. The power demand is then added to the objective function to be minimised (total electricity cost for the household) with a coefficient that corresponds to the tariff level.

Annual power tariff: A fee is paid per kW of peak consumption during the entire year. This incentivises the use of batteries for lowering the annual peak consumption. Implementation in the model is similar to that of the monthly tariff. A variable p_i corresponding to the annual power demand for household i is introduced together with the set of constraints for each household i:

$$p_i \geq d_{i,t} \quad \forall t \in T, \tag{3.3}$$

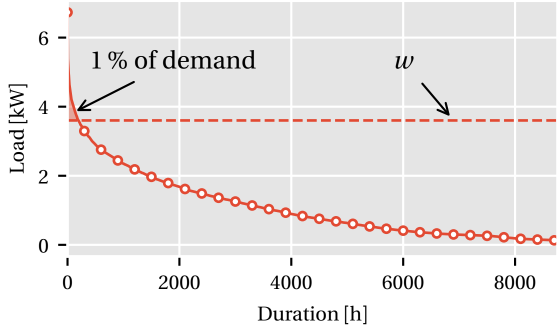
where $d_{i,t}$ is the electricity drawn from the grid by household i at time t, and T is the set of all the hours in the year. The cost is accounted for by adding p_i to the objective with a coefficient that corresponds to the tariff level.

Smoothed power tariff: The grid charges are proportional to the optimisation variable w, which represents the demand level, such that $\alpha = 1\,\%$ of the total annual demand is above this level. For the implementation of this tariff type, an additional variable $d_{i,t}^{\text{above}}$ is introduced, which represents the electricity drawn from the grid at levels above w by household i at time t. Two sets of constraints are also added to the model for each household i:

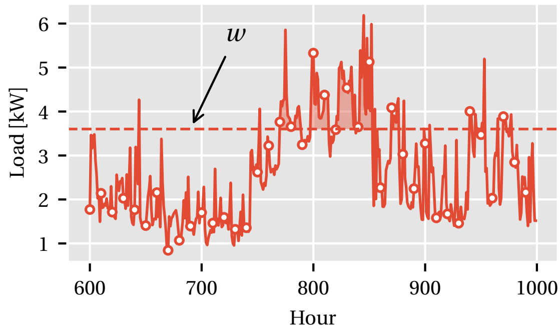
$$w + d_{i,t}^{\text{above}} \geq d_{i,t} \qquad \forall t \in T, \tag{3.4}$$

$$\sum_{t \in T} d_{i,t}^{\text{above}} \leq \alpha \cdot \sum_{t \in T} d_{i,t} \quad \forall i \in I, \tag{3.5}$$

where $d_{i,t}$ is the electricity drawn from the grid by household i at time t, I is the set of all households, and T is the set of all the hours in the year. Figure 3.5 illustrates how the level w, which represents the power demand with the smooth tariff, is calculated.



(a) Duration curve.



(b) Chronological curve for a selected example time interval.

Figure 3.5: Illustration of the concept of the smooth power tariff for a selected household. The fee is proportional to the level w, such that 1 % of the annual demand is above this level. Here, w is marked in: (a) a load duration curve over the entire year; and (b) a load curve for a selected time interval of 400 hours during the winter.

CHAPTER 4

Scenarios and input data

The models used in this thesis rely on multiple input data and assumptions. This chapter gives an overview of the different types of data used as inputs to the models, as well as the main assumptions and scenario set-ups used.

4.1 Three scenarios for the European electricity system

To model the development of the power system over a period of several decades, some variables that cannot be endogenously determined within the model have to be assumed or obtained from other sources. The nature of the variables that are exogenous depends on the type and scope of the model; in our case, they include the demand for electricity, the prices and availability of fuels, and implemented policy schemes. A set of consistent assumptions for all the exogenous variables, possibly together with additional constraints that represent specific conditions or policies, constitutes a *scenario*. The purpose of using different scenarios when modelling is often to perform a comparative analysis that highlights the range of potential pathways for the system and that reveals the differences in results stemming from uncertainties in the inputs.

There are three main scenarios used in the modelling on which this thesis is based: Green Policy, Regional Policy, and Climate Market. The basis for the scenarios was developed within the research programme "Pathways to Sustainable European Energy Systems" (see Johnsson, 2011; Johnsson et al., 2014). All the scenarios address the challenges of meeting stringent emission reduction targets for the European electricity system by Year 2050. Compared to the levels in Year 1990,

CO_2 emissions reductions by Year 2050 are in the range of 95 %–99 % in the three scenarios. All the scenarios implement the targets specified for each EU Member State in the National Renewable Energy Action Plans (European Commission, 2015b) up to Year 2020, after which the assumptions related to the type and level of renewables targets are specific to each scenario.

The main characteristics of the three scenarios are:

Green Policy A scenario with the aim of representing systems with very high penetration levels of renewable generation. In this case, such high levels are achieved by implementing a common European tradeable certificate scheme to attain targets for the share of renewable electricity. The electrification of certain other energy demands is also envisioned within this scenario, which is why demand grows by approximately 20 % relative to the present system up to Year 2050. A shorter life-time for existing nuclear power plants is also assumed here, as compared with the other scenarios. The Green Policy scenario is inspired by the scenario “High renewable energy sources” from the report “Energy Roadmap 2050” published by the European Commission (2012).

Regional Policy A multi-goal scenario that, in addition to CO_2 emissions reductions, aims to increase the share of renewable electricity generation and increase energy efficiency. Thus, the electricity demand remains relatively constant over the entire modelled period. Policy instruments are implemented at the national level rather than the European level. The Regional Policy scenario is based on the Roadmap scenario “High energy efficiency” (European Commission, 2012).

Climate Market A scenario in which the focus is only on reducing CO_2 emissions and no specific targets are set for either the shares of renewables or energy efficiency. The main policy instrument is a common European cap-and-trade system for emissions. In the Climate Market scenario, there is strong growth in the demand for electricity, as a consequence of a growing economy and electrification of other energy demands. The Climate Market scenario is loosely based on the Roadmap scenario “Diversified supply technologies" (European Commission, 2012) and the "Powerchoices reloaded" scenario analysis initiated by Eurelectric (2013).

4.2 Description of the present system

Modelling the evolution of the European power system for the coming decades requires a good description of the starting point, i.e., the system that is currently in place. The main building block of this description is the Chalmers Power Plant Database, as originally presented by Kjärstad and Johnsson (2007). The database contains detailed information on existing power plants, including location and capacity, and it is continuously updated. Some additional information, such as the time plans for the closing of nuclear plants, is also included in the database.

The description of current cross-border transmission line capacities is based on the "Yearly Statistics & Adequacy Retrospect 2014" from the ENTSO-E (2015a, 2015b). The transmission capacities between regions within the same country are primarily based on the transmission grid maps from the ENTSO-E (2014b, 2014c).

4.3 Technology data and cost projections

The input data regarding technologies in the ELIN model, with the exception of carbon capture and storage (CCS), as well as the development over time of investment costs are taken from the World Energy Outlook assumptions of the IEA from the 2011–2014 editions (International Energy Agency, 2011, 2012, 2013, 2014), and extrapolated for Year 2035 to Year 2050. Learning curves, i.e., cost reductions over time, are only assumed for variable renewables and CCS technologies. Costs for conventional technologies are assumed to remain constant throughout the entire modelled period.

The costs for CCS technologies are obtained from the Zero Emission Platform (2011), where the costs for coal and lignite CCS are based on the oxy-fuel technology, and the costs for natural gas CCS are based on the post-combustion capture technology. The investment costs and operational and maintenance costs, as well as the technical life-times for the key technologies are given in Appendix A.2.

4.4 Wind and solar power generation and load profiles

The hourly load profiles that are used in the models are retrieved for each country from the ENTSO-E (2017a). The model regions within a country share the same hourly profile but assigned a share of the total demand based on the region's share of the total GDP of that country.

The wind and solar power generation profiles are based on data from the "ERA-Interim" dataset, published by ECMWF (2017), and from the "MERRA2" dataset published by NASA (2017). The datasets are described in detail by Dee et al. (2011) and Rienecker et al. (2011), respectively. The ERA-Interim dataset has a finer spatial resolution than MERRA2 ($0.25° \times 0.25°$ and $0.5° \times 2/3°$ respectively), whereas MERRA2 has an hourly time resolution as opposed to the 3-hourly resolution of ERA-Interim.

The procedure for processing the wind and solar power data has been updated during this work. The most recent method used for onshore wind power divides the land area available for wind power in each region into 12 classes, depending on the average wind speed. For each class and region, the available land area and a wind power production profile are calculated. A function that cenverts a wind speed to electricity generation (as a fraction of installed capacity) is needed to create the required production profiles for the models. This function is called a *power curve*. We apply a power curve function as described by Johansson et al. (2017), with a specific power of 350 W/m^2, converted to represent farms of wind power plants rather than individual turbines. The applied power curve is shown in Figure 4.1.

The production profile is calculated in the following steps:

1. For each MERRA2 point: The wind speed is extrapolated to a height of 100 m, based on the wind speeds at 10 m and 50 m, as well as the displacement height.

2. For each ERA-Interim grid-point:

    a. The average wind speed is calculated.

    b. The point is assigned to one of the wind classes.

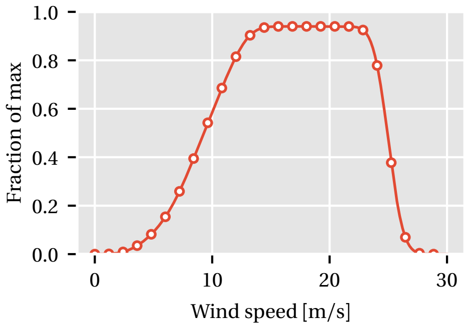


Figure 4.1: Power curve and assumed value of C_p as a function of wind speed.

c. The closest MERRA2 grid-point is located.

d. The MERRA2 profile is rescaled so that the average wind speed matches that of the ERA-Interim grid-point.

e. The power curve function is applied to create a generation profile that contains the fraction of installed capacity being generated for each time-step.

3. For each wind class and model region: A single production profile is calculated by averaging all the grid-points belonging to that class, weighted by the area available at each point.

Figure 4.2 shows a map of the calculated capacity factors for wind farms across Europe, using the power curve described above. For onshore wind power (the assumptions regarding offshore wind power are described below), the available land area at each grid-point was calculated in a GIS analysis by Nilsson and Unger (2014), excluding land areas unavailable for wind, such as densely populated areas, transportation infrastructure, waterways, seas and areas under environmental protection. If a grid-square (the square around surrounding a grid-point) overlaps with more than one region, the area is distributed across the regions according to the fraction of the grid-square that overlaps with each region. The resulting supply curves, which show the capacity factor as a function of the available area, are given for three different regions in Figure 4.3.

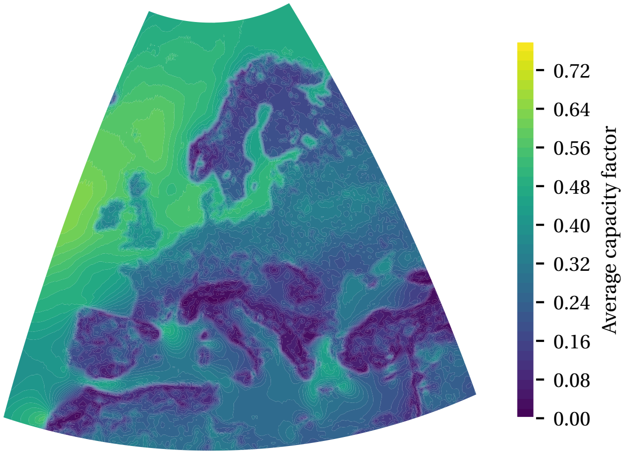


Figure 4.2: Map of calculated capacity factors of wind power across Europe, applying the power curve shown in Figure 4.1.

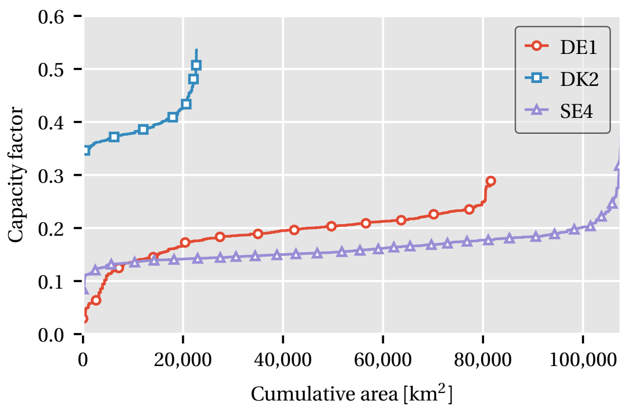


Figure 4.3: Supply curves for onshore wind power, showing the capacity factor as a function of the cumulative area, for three model regions: DE1 (southern Germany); DK2 (western Denmark); and SE4 (northern Sweden). Each step on the curve corresponds to a wind class, although not all classes are available in every region. A map of the model regions is presented in Appendix A.1.

For regions where offshore wind power is possible, deployment is assumed to be near-shore. The profile of the highest onshore wind class for the region in question is therefore applied, given that the windiest sites in coastal regions are usually those closest to the sea. For offshore wind power, the potential is assumed to be unlimited, although the investment cost is significantly higher than for onshore wind power.

The production profiles for solar power are calculated per technology and region. Four different solar power technologies are included in the models: cadmium telluride and crystalline silicon, each available with fixed (optimal) tilt or two-axis tracking. More details of the solar model are available in the paper by Norwood et al. (2014).

4.5 Building and household data

In Papers IV–VI, two different datasets were used to represent the Swedish stock of single-family dwellings. The first dataset, which is a collection of parameters that describe a set of sample buildings, is used for the space heating model in Paper IV. The second dataset, which consists of 2,104 measured hourly electricity consumption profiles, is used in Papers V and VI.

4.5.1 Sample buildings for the space heating model

The space heating model for the Swedish single-family dwellings, as used in Paper IV and described in Section 3.5, is based on data from the BETSI study conducted by the Swedish National Board of Housing, Building and Planning (2011). The stock of single-family dwellings in Sweden is represented by 571 sample buildings. Each sample building is described by a number of parameters used in the heating model, such as the U-value and the heated floor area, and is associated with a statistical scale factor. The thermal mass of the indoor temperature zone is assumed to be 30 kJ/K per m^2 of heated floor area.

The air-to-air, air-to-water, and exhaust air heat pumps used in some of the sample buildings are assumed to have a coefficient of performance (COP) that is dependent upon the outdoor temperature. The temperature dependencies for different types of heat pumps are based on measurement data from the Swedish Energy Agency (2017). For more details on the how the COPs are derived, see Paper IV.

4.5.2 Measured electricity consumption profiles

The household investment model used in Papers V and VI use hourly electricity consumption profiles for 2,104 Swedish single-family dwellings[1] measured by E.ON over 1 year between (February 1st, 2012 and January 31st, 2013). The measured households are mainly located in the southern parts of Sweden, and we therefore chose only to attempt to represent households in regions SE1 and SE2 (see Appendix A.1 for a map of the model regions). However, the vast majority of Swedish households are located in these two regions. For more details on the dataset and the treatment of missing data, see the paper of Nyholm, Goop et al. (2016).

In order for the sampled households to provide an accurate representation of the entire stock of single-family dwellings in regions SE1 and SE2, each household is assigned a statistical weight. To calculate the weights, the buildings are first divided into six categories based on the type of heating system used and then further sorted by geographic location, i.e., whether they are located in region SE1 or SE2. The number of sample buildings in each of the 12 categories is then matched to the total number of buildings in the corresponding category in the statistical data provided by the Swedish Energy Agency (2011)[2]. The scale factor is the total number of buildings divided by the number of sample buildings in each category. The calculated scale factors, as well as the total number of buildings and the number of sample buildings for each category, are given in Table 4.1.

The actual number of buildings represented is approximately 800 times higher than the number of buildings in the collected data. This means that if the scale factor of a category is greater than 800, the category is under-represented in the sampled data and vice versa. Table 4.1 shows that some categories, such as "oil" and "biofuels", are

[1] In all, 10,086 households participated in the original project, although those profiles with more than 5 % of the data-points missing or where crucial metadata were not present were dropped from the dataset.

[2] More information on the matching of the categories of the collected and statistical data can be found in Paper V.

Table 4.1: Numbers of buildings in the measured data and the statistical data, and the calculated scale factor for each combination of heating category and region. The statistical data are derived from the Swedish Energy Agency (2011).

		Number of buildings		
Heating	Region	Collected	Statistical	Scale factor
Electric[a]	SE2	620	384,807	620.7
	SE1	837	110,038	131.5
HP[b]	SE2	290	265,066	914.0
	SE1	132	36,616	277.4
Biofuels	SE2	60	433,616	7,226.9
	SE1	55	70,810	1,287.5
DH[c]	SE2	36	163,923	4,553.4
	SE1	39	37,311	956.7
Oil	SE2	0	17,814	—
	SE1	1	4,681	4,681.0
Others	SE2	30	127,531	4,251.0
	SE1	4	32,127	8,031.8

[a]Including direct electric, hydronic, and non-ground source heat pumps.
[b]Ground source heat pumps.
[c]District heating.

substantially under-represented. Since this study focuses on measuring electricity consumption, it is not surprising that the categories in which households are likely to have the highest electricity consumption, i.e., “electricity” and “HP”, are those that are best represented. However, the households that have the highest consumption of electricity are also the most interesting for our purposes.

The scale-up of the measured profiles is validated by comparing the total annual demand from households in each region with the historical data from Statistics Sweden (2016). The total consumption levels in regions SE1 and SE2 are within 0.3 % and 3.2 %, respectively. A possible explanation for why the scale-up is less accurate for region SE2 is that the collected data represent households in region SE1 significantly better, as seen in Table 4.1.

CHAPTER 5

Model evaluation

In this section we discuss the validity of the ELIN and EPOD models, the two main models used throughout the work. The numerical evaluation focuses primarily on the EPOD dispatch model on which most of the analyses in this thesis are built. Detailed validation of all the modelling tools used within this work is outside the scope of this thesis. The validity of the models and tools applied in the papers is dealt with in each paper.

5.1 The challenges associated validating models

Schwanitz (2013) has discussed the evaluation of integrated assessment models[1] and stated that model evaluation is "a continuous effort of testing whether the model can fulfill its purpose". The term "evaluation" is used instead of "validation", since it is unclear whether these types of models can actually be validated. Schwanitz has highlighted the fundamental issue: that while the models attempt to describe a future, empirical data are available only for historical conditions. This issue is highly relevant for the ELIN-EPOD package, which is designed to study possible future scenarios and situations for the European electricity system. Since there are no other data to validate against, we are forced to compare the outcomes of the models to historical statistics. This is also the method that is most commonly used for evaluating similar models in the literature (see, for example, Nahmmacher et al., 2014; Schaber, 2013).

[1]Although we are not working with integrated assessment models, much of the reasoning holds true for our models as well.

When validating the models against historical data, the evaluation runs the risk of being misleading as the very motivation for modelling the future system is that it will behave differently from that of today. If we push the models to fit the patterns found in historical observations, there is a risk that we will severely underestimate the adaptability of the system and miss new phenomena that we want the models to help us find. This phenomenon can be described as a type of overfitting, where there is a risk that improved validation performance is achieved at the cost of worsened performance for previously unseen settings.

Overfitting the models to historical data risks reinforcing old "truths" about how the system is supposed to work. One example is how base-load technologies, such as nuclear power, are treated in models. If the flexibility of such technologies is not limited in the models, the results easily become unrealistic, with nuclear power plants turning on and off every hour. Therefore, they have traditionally been described as "must-run technologies", i.e., without any flexibility to adapt to, for example, wind power variations. While this description usually works well in validations against historical data, it risks significantly underestimating the flexibility of nuclear power, in scenarios for the future. Thereby, it might also underestimate the competitiveness of nuclear power in systems where flexibility is of high value, for example in the presence of high levels of wind power.

Another example is the minimum flow restrictions for hydropower, which translates to minimum generation level constraints in the model. For example, the hourly production data for Norwegian hydropower for Year 2016 (ENTSO-E, 2017b) show that the minimum production level never drops below 6.6 GWh/h. However, when considering the minimum demand level of 9.2 GWh/h (Nord Pool, 2017a) in combination with the average import capacity of 4.5 GW (Nord Pool, 2017b) for the same year, it seems likely that the lowest observed production level is simply the lowest level that has been triggered by historical conditions, and not an actual lower limit. It is therefore important not to build such limitations into the models, even though this might also lead to results that do not reproduce historical patterns.

The evaluation process is also made more difficult by the fact that the models usually use input data that correspond to some type of normal or representative conditions. Examples of such inputs are:

demand, wind speed, and solar irradiation profiles, as well as hydropower inflow. In reality, however, this makes it difficult or even impossible to find a representative historical year for comparison, since all conditions are rarely representative at the same time.

Despite the challenges faced when evaluating the model, Schwanitz (2013) has stated that "transparency about its shortcomings and area of applicability, are integral to the evaluation process". Therefore, the following sections are devoted to investigating some of the results from the EPOD model for a system representing Year 2014, based on the data taken from the Chalmers Power Plant Database used in the ELIN model, and comparing the results with actual data from the same year. We will discuss some limitations of the model, as well as their explanations and consequences.

5.2 National electricity generation

For the purpose of comparison with historical data, the EPOD model is run with a system composition represents Year 2014, based on the description of the present system, as used in the ELIN model. Figure 5.1 compares the total electricity generation per country from the EPOD evaluation results for Year 2014 and from the historical data provided by Eurostat (2017). The generation technologies have been aggregated into categories to enable comparison. In general, there is sufficient agreement between the EPOD results and the historical data. However, some differences are apparent, such as an overestimation of the electricity production in France and an underestimation of that in Germany. A possible explanation for this is that the export potential for France is slightly exaggerated in the model, due to several factors, such as the assumptions of perfect foresight and fully cost-optimal cross-border trading, as well as a lack of detail in the description of transmission grid limitations (see the following section for a discussion of this issue). The deviations of the model results from the historical data can also, to some extent, be explained by the fact that the model uses input data, such as demand, wind, and solar profiles, which correspond to "representative" conditions.

Some generation categories do not match perfectly in the statistics and the EPOD results. Therefore, we have chosen to show a slightly more detailed classification of the EPOD generation technologies, whereby thermal generation (represented by the single category of "Combustible fuels" in the Eurostat data) is divided into the categories of "fossil" and "bio/waste". There also appears to be a difference with regard to the classification of CHP plants, whereby thermal capacity is more often classified as CHP in the Eurostat statistics than in EPOD, as can be seen in, for example, Italy and Poland. The comparison excludes countries for which no data is available from Eurostat.

5.3 Dispatch and operation

Figure 5.2 shows the results for nuclear power generation in Sweden from the EPOD evaluation, with and without the inclusion of cycling costs, and the historical data for Year 2014 from the Swedish TSO Svenska kraftnät (2017). As shown in the figure, the cycling costs are crucial for capturing the inflexibility of the nuclear power plants. Without cycling costs, the ramping of the nuclear capacity is much faster than what is realistic. However, with cycling costs, differences are apparent compared with the actual production pattern according to the historical data. In EPOD, the level of nuclear power generation varies more on shorter time scales, and less so on longer time scales. The short-term variations are explained by the fact that the model allows the nuclear capacity to run on part-load down to 80 % of the current started capacity. The literature supports the assumption that the load-following capabilities of nuclear power are greater than what is utilised today (see, for example, Gustavsson, 2014; Persson et al., 2011). The EPOD model does, however, ignore the need for refuelling, which may explain why there are no larger reductions in output over longer periods, as observed in the historical data.

The main benefit of including cycling costs in the model, is that the ramping of nuclear and other thermal capacity is not constrained beyond the technical limitations, although it can be limited for economic reasons. Figure 5.3 illustrates this phenomenon by showing the total electricity generation in Sweden during an 8-week period from the EPOD results for Year 2032 in the Green Policy scenario. Over a period of approximately 5 weeks with relatively high wind power production, part of the nuclear fleet is shut down. However, in order

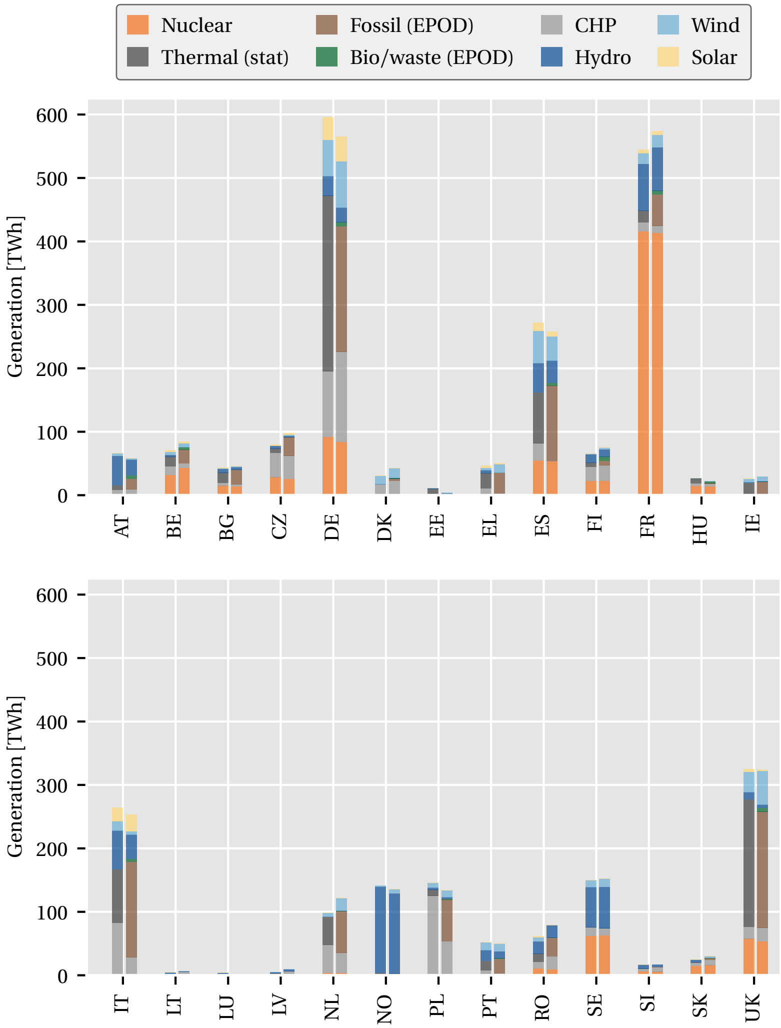


Figure 5.1: Electricity generation per country and source for Year 2014 from the Eurostat statistics (left bars) and from the EPOD model results (right bars).

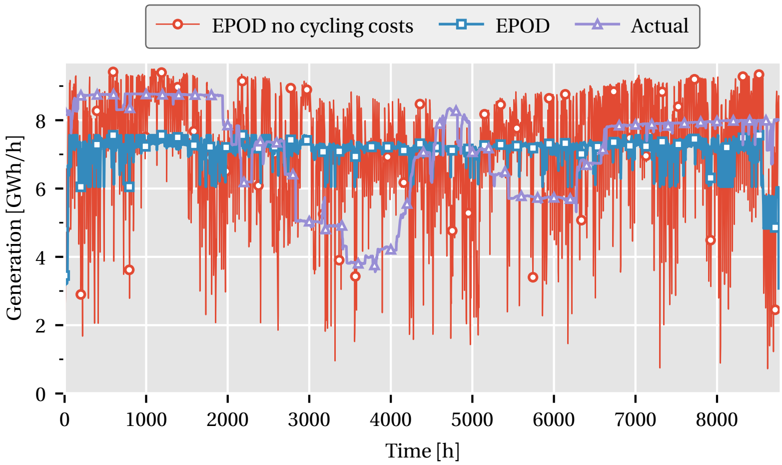


Figure 5.2: Hourly nuclear power generation in Sweden during Year 2014 from the EPOD results and from historical data from the Swedish TSO Svenska kraftnät (2017).

to meet demand during this period, even at times with lower wind power production, a large share of the nuclear capacity remains online, despite the fact that this leads to curtailment. The reason for this is that the avoided start-up costs are higher than the additional running costs paid to cover the curtailed power.

The hydropower generation levels in Sweden during Year 2014, as derived from the EPOD evaluation results and data from Svenska kraftnät (2017), are shown in Figure 5.4. It is clear from the data that hydropower is a highly flexible generation technology that is capable of rapid changes in output within short time-frames. Nevertheless, it is clear from the results that the EPOD model overestimates the flexibility of the Swedish hydropower. The explanation for this is that Swedish hydropower is part of a complex system, which is difficult to represent in a model of EPOD's size. In EPOD, all hydropower generating and storage capacity in one region is aggregated and described as a single plant. In reality, however, there are several large rivers in each region and many of the generating stations are often located along the same river, which links the production at one station to the inflow of those located downstream. Restrictions due to environmental legislation

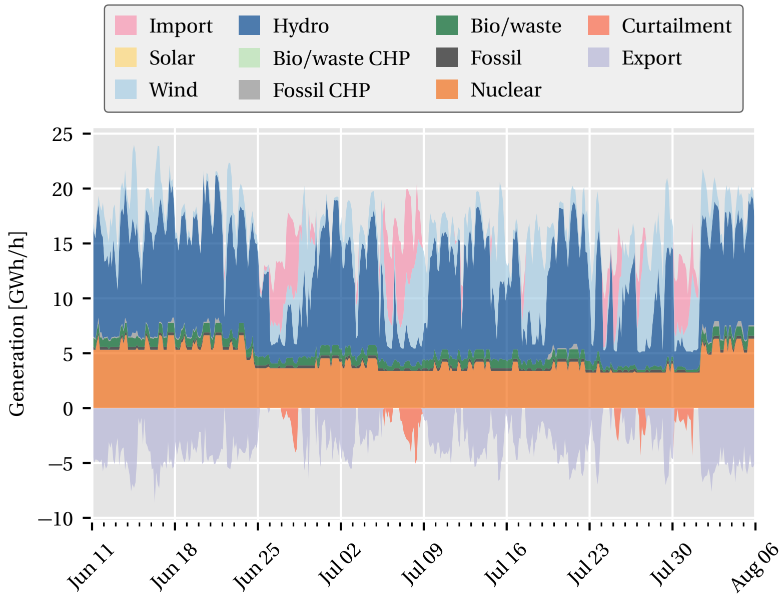


Figure 5.3: Electricity generation levels in Sweden during an 8-week period, as derived from EPOD results for Year 2032 in the Green Policy scenario.

also apply, both in terms of water levels in dams and lakes and in terms of the flows of rivers. Another aspect that limits the flexibility of hydropower is uncertainty regarding the future electricity demand and the inflow to the hydropower reservoirs. These uncertainties are also not addressed in EPOD, since perfect foresight is assumed.

5.4 Marginal costs and market prices

The marginal cost of electricity from the EPOD model plays an important role in the analyses conducted in this thesis, both as an indicator of congestion (Papers I and III) and as a representation of the spot price of electricity (Papers V and VI). We therefore compare the marginal cost from the EPOD evaluation results for Year 2014 to the historical spot market prices. Figure 5.5 shows the average marginal cost from the EPOD evaluation results for Year 2014 and the average spot mar-

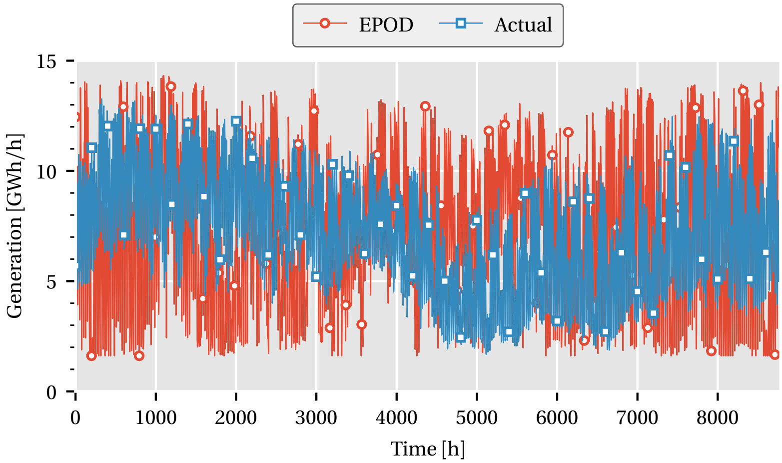


Figure 5.4: Hourly hydropower generation levels in Sweden during Year 2014, as derived from the EPOD results and from the historical data from the Swedish TSO Svenska kraftnät (2017).

ket prices for the Swedish and Danish model regions, as well as for Germany[2]. The average electricity prices are represented ably by the model and some trends observed in the historical data hold true for the model results as well. For example, the Swedish prices are higher in the south than in the north, while the Danish prices are higher in the east than in the west. However, it is clear that prices are generally underestimated, especially in the hydro-dominated northern parts of Sweden. The main reason for this is probably the overestimated flexibility of the hydropower, as mentioned above, although uncertainties related to demand and supply, as well as reserve requirements are also likely to contribute to higher prices in the real market.

A shortcoming of the model, attributable once again to the overflexible hydropower, is its inability to capture price volatility in general, and in hydro-dominated regions in particular. Figure 5.6 shows the standard deviation of the marginal costs obtained from EPOD and the spot prices from Nord Pool (2017c) and EXAA (2017). The standard deviation is generally underestimated by the model, and is extremely

[2]The EPOD marginal cost for Germany has been calculated as a demand-weighted average of the costs for the German model regions.

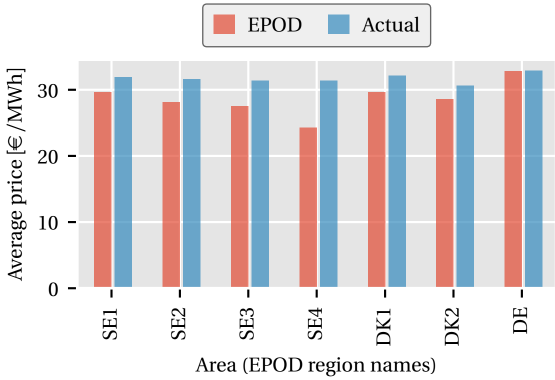


Figure 5.5: Average marginal generation costs obtained from the EPOD model evaluation results for Year 2014, as compared to the average spot market electricity prices. The EPOD marginal generation cost for Germany (DE) is the demand-weighted average of the results for the individual model regions. Note that the names of the Swedish and Danish regions are the model region names and not the Nord Pool bidding area names.

small for hydro-dominated regions SE3 and SE4. See Section 7.1 for a discussion of the impacts that this inability to model the Swedish price volatility have on the results and conclusions in Papers V and VI.

5.5 Electricity trade

In Figure 5.7, we evaluate the modelled representation of the electricity trade by comparing the total annual imports and exports of electricity by country. The model results fit well with the historical data and ably represent some important aspects, for example, countries that are mainly importers or exporters of electricity (e.g., Italy or France) or have large volumes of both imports and exports (e.g., Germany or Denmark) mostly play the same role in the model results.

As mentioned above, the levels of exports from France, which is the largest electricity exporter in Europe, are higher in the model than in the historical data. This overestimation is also connected to the relatively high levels of imports in Italy, Germany, and the UK. Some assumptions made in the EPOD model, such as centrally optimised

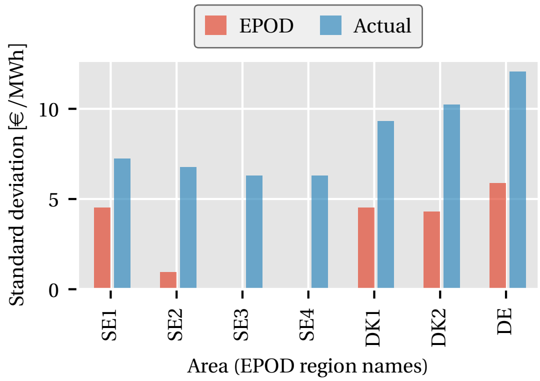


Figure 5.6: Standard deviations of the marginal generation costs obtained from the EPOD model evaluation results for Year 2014, as compared to the standard deviations of the spot market electricity prices. The EPOD marginal generation cost for Germany (DE) is the demand-weighted average of the results for the individual German model regions. Note that the names of the Swedish and Danish regions are the model region names and not the Nord Pool bidding area names.

cross-border exchange, or unconstrained intra-regional transmission, are known to generate exaggerated trade flows (Brancucci Martínez-Anido et al., 2013).

To evaluate the description of trade on shorter time scales, we compare the maximum electricity flows between the model regions in Sweden (where the model regions correspond approximately to the market bidding areas) to actual data from Nord Pool (2017d). Figure 5.8 shows the maximum hourly exchange between the model regions (or bidding areas) during Year 2014, as derived from the EPOD results and the historical data. As shown in the figure, flows from north to south (which is the main direction of flow in Sweden) are well represented, whereas the flows from south to north are not so well captured. However, it is likely that the underestimation of the flows to hydro-dominated regions SE3 and SE4 is due to the fact that the hydropower is less flexible in reality than in the model (see Section 5.3). Sometimes this inflexibility results in the need for imports, which cannot be captured by the model.

We also note that the differences in marginal cost between the

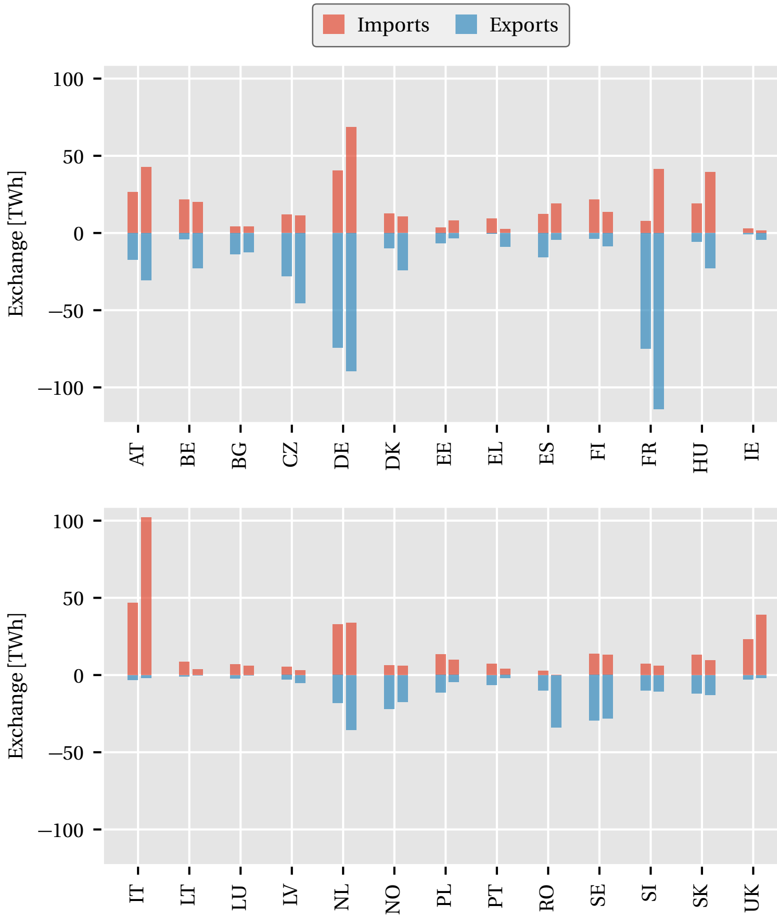


Figure 5.7: Imports and exports per country for Year 2014, as derived from the Eurostat statistics (left bars) and from the EPOD model results (right bars). Data source: Eurostat (2017).

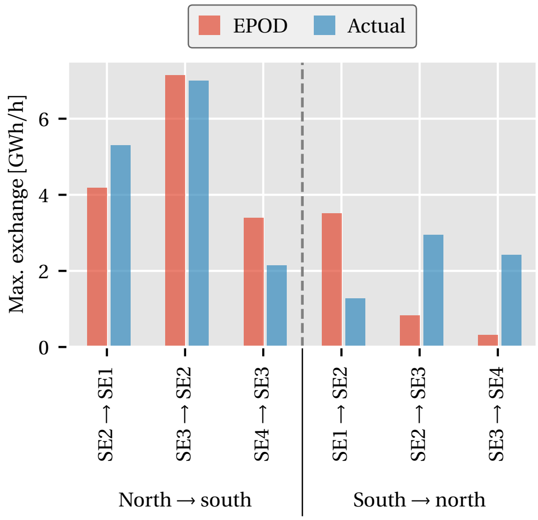


Figure 5.8: Comparison of the maximum hourly electricity exchange during Year 2014 between the Swedish regions, as derived from the EPOD results and the data from Nord Pool (2017d). Note that the names are the model region names and not the Nord Pool bidding area names.

Swedish regions are larger than the differences in spot prices, as shown in Figure 5.5, which may indicate that transmission between the Swedish regions is slightly over-constrained.

CHAPTER 6

Main results and findings

In this chapter, the most important findings of this work are summarised and reviewed.

6.1 Scenarios for the European electricity system

Papers I and III–VI all investigate the future European electricity generation systems obtained from the ELIN model. Therefore, we start by summarising results from the three scenarios used in the papers and described in Section 4.1: Green Policy; Regional Policy; and Climate Market. Due to the input data and assumptions being updated, some details for the scenarios differ between the papers. All the results shown in this section are obtained from the ELIN model, as used in Paper V.

Figure 6.1 shows how the ELIN model depicts the evolution of the European electricity generation up to Year 2050 for each of the three scenarios. The generation mix is clearly different for the different scenarios. In the Green Policy scenario, the high target set for the share of renewable electricity generation completely prevents CCS and nuclear power from entering the mix (and the existing nuclear capacity is phased out earlier due to the shorter assumed life-time, as mentioned in Section 4.1). Instead, by Year 2050 the mix is dominated by variable renewables, with 63 % of the total demand originating from wind and solar power.

The Regional Policy and Climate Market scenarios exhibit a more diversified technology mix, whereby both fossil-fuelled CCS and nuclear power play important roles in the Year 2050 system. In the Climate Market scenario, which has the strongest growth in demand, nuclear

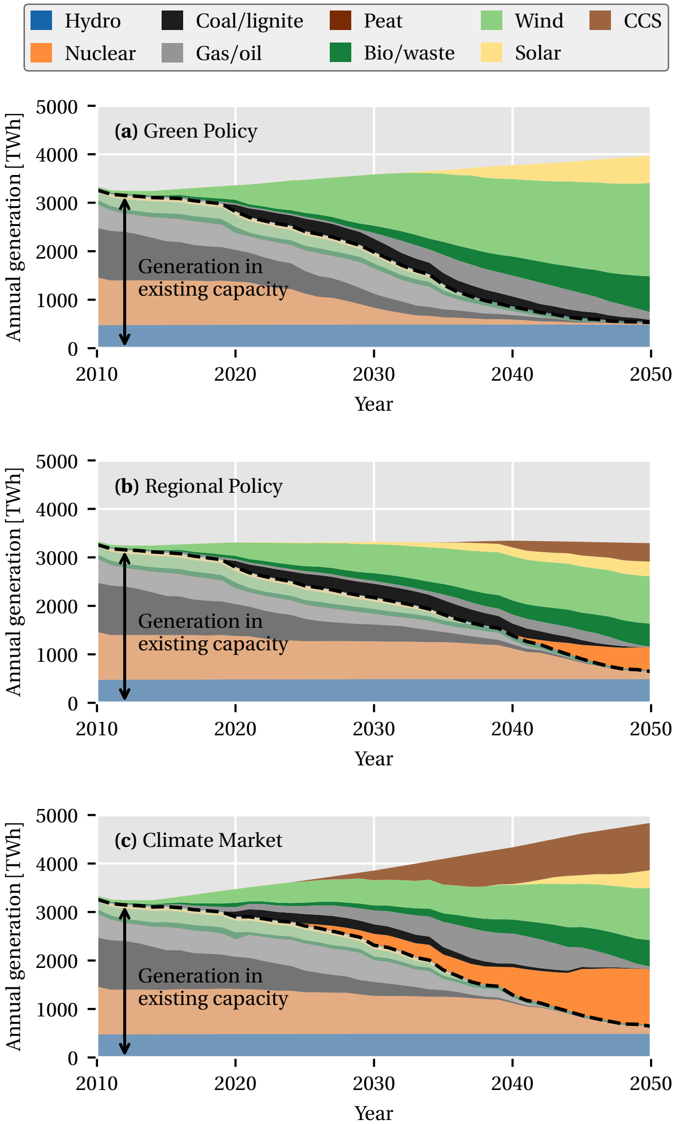
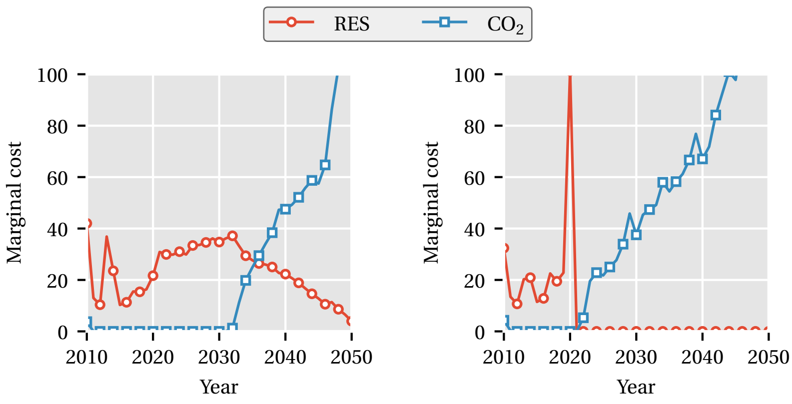


Figure 6.1: Evolution of the European electricity generation mix, as obtained from the ELIN model, for the scenarios: (a) Green Policy; (b) Regional Policy; and (c) Climate Market. The areas below the dashed line represent generation using currently existing capacity and the areas above the line represents new investments made by the ELIN model.



(a) Regional Policy

(b) Climate Market

Figure 6.2: The marginal costs for meeting the targets for renewables penetration and CO_2 emissions in €/MWh and €/t_{CO_2} respectively, are shown for: (a) the Regional Policy scenario; and (b) the Climate Market scenario.

power and CCS provide 27 % and 20 % of the total demand, respectively. The shares of both nuclear power and CCS are smaller in the Regional Policy scenario, in which 39 % of the demand is met by variable renewables.

The hydropower potential is assumed to be fully exploited and the capacity therefore remains at today's level throughout the modelled period in all three scenarios.

The different scenarios demonstrate the interactions between different kinds of policy instruments. Policy aimed at increasing the share of renewable energy sources and policy aimed at reducing CO_2 emissions will both to some extent affect the target of the other. If the share of renewables increases in the current system, for example, it is likely that at least partly, the new electricity replaces power from fossil sources, which reduces emissions. Correspondingly, if renewables offer a cost-effective means of reducing emissions, a decrease in emissions translates to an increased share of renewables. This phenomenon can lead to one of the measures having no effect, or in optimisation terms, that only one out of two constraints is binding. Only the binding constraint would have a non-zero shadow price. In an optimisation model, the shadow prices correspond to the marginal costs of meeting each target, which in reality would translate to, for example, a price on emission allowances or green certificates.

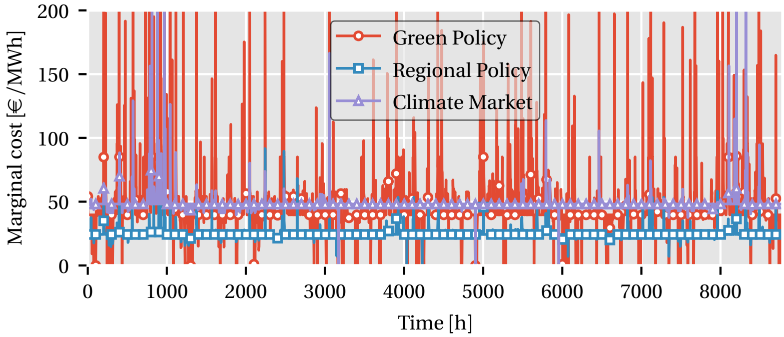
Figure 6.2 shows the marginal costs of meeting the targets for renewables and CO_2 emissions obtained from the ELIN model for the Regional Policy and the Climate Market scenarios. In both scenarios, up to Year 2020, the marginal cost for CO_2 emissions is zero, whereas the marginal cost for fulfilling the requirements related to renewables is a positive value. The reason for this is that the renewables targets are sufficiently high to fulfil also the emission targets. In the Climate Market scenario, the requirements for shares of renewables end after Year 2020, leaving the emission cap as the only policy measure in place. The peak observed for Year 2020 is most likely due to the targets for renewables being overly strict in relation to the CO_2 targets. This is supported by the fact that both marginal costs are zero for Year 2021. In the Regional Policy scenario, the national targets for renewables remain in place, thereby ensuring that the marginal CO_2 costs remain below those in the Climate Market scenario. Although the ELIN model only covers the power sector, these results illustrate how national targets for renewables can suppress the prices of emission allowances within the EU ETS.

Most of the analyses in the papers are based on analysing results from the EPOD dispatch model. The capacity mix fed to the EPOD model is extracted directly from the ELIN results for a specific scenario and year. From the EPOD model, we get hourly dispatch over the entire year, taking more detailed technical constraints into consideration. One of the important results extracted from EPOD is the hourly marginal cost of electricity, especially in Papers V and VI, where it is used as a proxy for the hourly spot market price.

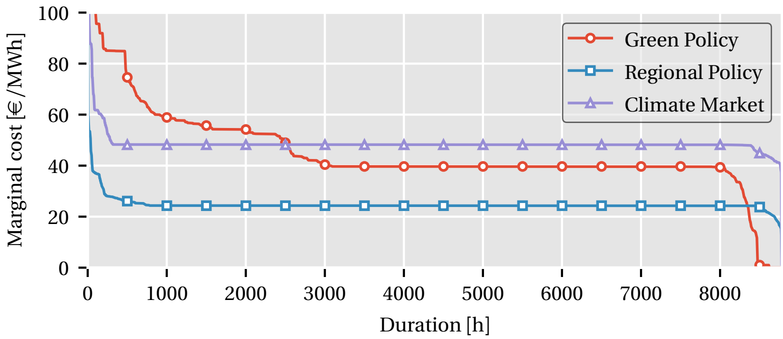
The differences between the scenarios in terms of the capacity mix obtained in ELIN (Figure 6.1) causes the hourly marginal cost of electricity to behave very differently in each scenario. The differences in the marginal costs are illustrated in Figure 6.3, which shows the duration curves and chronological curves for the marginal cost of electricity in region SE1 (southern Sweden) in Year 2032. The marginal cost is substantially more volatile in the Green Policy scenario than in either the Regional Policy scenario or the Climate Market scenario (see Figure 6.3a). One reason is that the growing demand is mainly satisfied with new investments in wind power, both in Sweden and the surrounding regions. Another reason is that, by Year 2032, all of the Swedish nuclear power has been phased out in the Green Policy scenario, whereas some nuclear capacity remains in operation in the other two scenarios. The duration curves (Figure 6.3b) show how flat the marginal costs are in the Regional Policy and Climate Market scenarios, and, for part of the year, even in the Green Policy scenario. This flatness is caused by the ability of Swedish hydropower to store energy throughout the year, a phenomenon which is exaggerated in the model (see the discussion in Section 7.1). We also note that the average marginal cost differs substantially between the scenarios; that of the Regional Policy scenario, in particular, is lower than the others. The reason for this is the limited demand growth assumed in the Regional Policy scenario, together with the fact that much of the Swedish nuclear power remains in operation.

6.2 Renewables and transmission expansion

The European electricity transmission system will most likely have to be significantly expanded to facilitate transformation of the system. Tröster et al. (2011) have studied the development of the European electricity transmission grid in scenarios with very high penetration levels of renewable sources, i.e., up to 99 % of total electricity generation in Year 2050. The shares of variable generation lie in the range of 49 %–64 % in the scenarios for Year 2050. Tröster and colleagues concluded that significant grid extensions, i.e., 258 GW of new transmission capacity by Year 2030 and up to 344 GW if optimised to avoid curtailment, would be needed to accommodate such high levels of renewables. They further stated that an important task is to strengthen capacity in "priority areas", such as the zones that extend from Spain *via* France to Central Europe and from Italy to Central Europe. The European Network of Transmission Operators for Electricity (ENTSO-E) also expects that the development of renewables will drive grid expansion (ENTSO-E, 2014a), stating that interconnection capacities must on average double to Year 2030 across Europe, and that a major concern will be to integrate more effectively the four main "electric



(a) Chronological curves



(b) Duration curves

Figure 6.3: Duration (b) and chronological (a) curves for the marginal cost of electricity for Year 2032 in region SE1 for each of the following three scenarios: Green Policy; Regional Policy; and Climate Market.

peninsulas" of Italy, the Iberian Peninsula, the British Isles, and the Baltic countries. Fürsch et al. (2013) have stated that increasing the total transmission line length by 76 % (relative to its current length) would be beneficial from a least-cost perspective in a scenario in which 80 % renewables is attained by Year 2050.

A large increase in transmission capacity as a result of the expansion of variable renewables is also consistent with our results from the ELIN model. Figure 6.4 shows the total transmission capacity between the model regions as a percentage of the capacity in Year

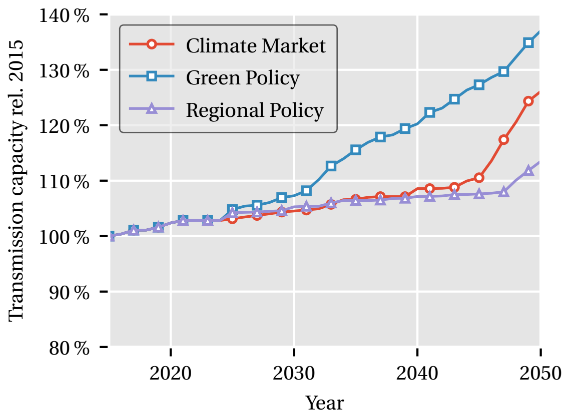
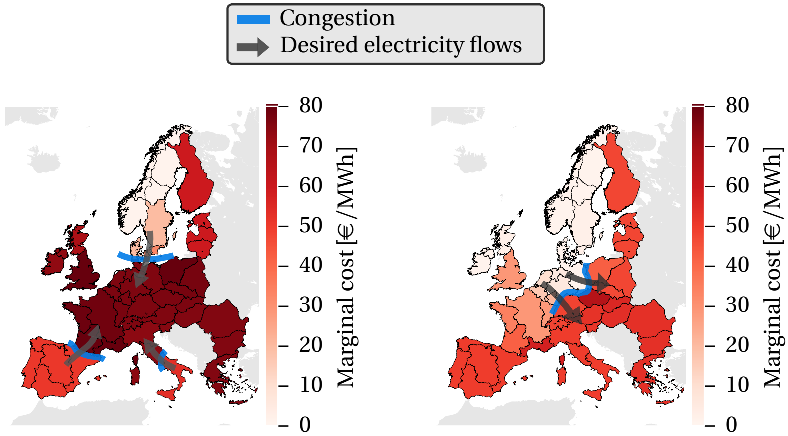


Figure 6.4: Total inter-regional transmission capacities up to Year 2050 from the ELIN model relative to the levels in Year 2015 for the three scenarios: Green Policy; Regional Policy; and Climate Market.

2015 for the three modelled scenarios: Green Policy; Regional Policy; and Climate Market. The Green Policy scenario, which entails both an increasing demand and high levels of renewables (predominantly wind power), expands the total transmission capacity by almost 40 % by Year 2050. This corresponds to a capacity of 234 GW, although it should be noted that the absolute capacity values are difficult to compare across different studies, since they depend on the resolution and level of detail inherent to the model. It is also likely that the limited temporal resolution of the ELIN model will lead to an underestimation of the transmission capacity, especially with high shares of variable renewable generation.

6.3 Congestion patterns in the transmission grid

Variable renewable generation substantially alters how and when congestion occurs in the European transmission grid. Using the ELIN and EPOD models (see Chapter 3), Papers I and III investigate the extent of congestion in scenarios that undergo strong wind and/or solar power expansion. The system setups for selected years are extracted from the ELIN investment model and analysed individually in greater detail



(a) Peak load congestion

(b) High wind congestion

Figure 6.5: Two congestion situations in the European transmission grid identified in the dispatch modelling: (a) during a time-step with peak load and low wind; and (b) during a time-step with high wind power generation. The colours indicate the marginal costs in each region, with white representing the lowest and dark-red representing the highest costs. Colour differences between neighbouring regions indicate congestion. Some examples of congested interconnections have been marked in the figure, together with the desired electricity flow directions.

in the EPOD dispatch model. EPOD calculates the cost-optimal power plant dispatch, including a DC load flow grid model, over 1 year with a time resolution of 3 hours.

By analysing the marginal cost differences between regions, we can observe new congestion patterns created by the increased penetration level of wind power. Figure 6.5 illustrates two different mechanisms, with respect to the direction of the electricity flow, that we have identified in our results—a “push” and a “pull” mechanism—that are implicated in congestion in the European transmission system. The figure shows the marginal cost in each region for two different time-steps, as derived from the dispatch model results for the Year 2020 scenario. The white colour indicates the lowest marginal cost and the dark-red colour indicates the highest marginal cost. Thus, colour differences between neighbouring regions indicate zones of congestion in the transmission grid. The first situation (Figure 6.5a) is a time-step with high load and generally low output from wind power, albeit with some solar generation, primarily in the Iberian Peninsula and Italy. While marginal costs are high in central Europe, the limited import capacity creates congestion between central continental Europe and the Nordic countries, the Iberian Peninsula, and southern Italy. This situation, where a deficit is driving up the marginal costs in central Europe and import is limited, can be described as "pull"-type congestion, and it is perhaps historically the more common of the two types of congestion. In the second situation (Figure 6.5b), even though surplus wind generation is available in a few regions, the limited export capacity leads to congestion, for example, between northern Germany and south-eastern Europe, as well as between Scotland and England and Wales. Congestion that is caused by a surplus of generation driving down the marginal cost and the existence of a limited export capacity can be described as "push"-type congestion. This type of congestion can only occur when penetration levels are sufficiently high to lower significantly the marginal costs at the local level.

6.4 Congestion and demand response

DR and grid expansion can both be seen as variation management strategies, i.e., ways to handle the increased variability that results from the expansion of variable renewable electricity generation. In Paper I, we analyse a Year 2020 scenario with the ELIN and EPOD modelling package, and use the congestion measure defined in Equation (3.1) to investigate how DR in the form of load shifting would affect congestion in the transmission system and thereby, the value of grid expansion. The scenario used in this study includes national subsidies for renewables and focuses on energy efficiency. In the Year 2020 system, this scenario entails high penetration levels of wind power locally. When running this system in the dispatch model, we allow a certain share of the hourly load to be delayed within a given time-span. In Paper I, we allow 5 %–20 % of the hourly demand to be moved within 6 or 24 hours.

Our results clearly show that load shifting could reduce congestion

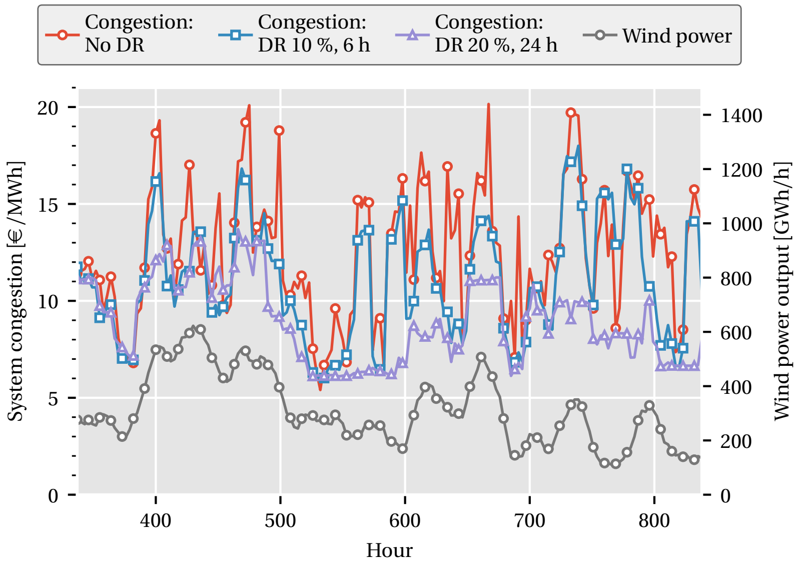


Figure 6.6: System congestion as a function of time over three winter weeks from the EPOD model results for the Year 2020 system (Paper I), shown without DR and with two different levels of load shifting. The aggregated European wind power output is also shown.

in the transmission system. Figure 6.6 shows the system congestion as a function of time over three winter weeks, as derived from our EPOD results for the Year 2020 system with different levels of load shifting being available, together with the aggregated European wind power output. The highest congestion level occurs at peak load, when no DR is available. With 10 % of the load being shiftable within 6 hours, some of the most severe congestion situations could be mitigated. With a high level of load shifting, when 20 % is shiftable within 24 hours, the congestion could be significantly reduced.

However, not all of the congestion is caused by demand variations, and even at the maximum level of load shifting investigated some congestion remains. We observe that the congestion in the highest load shifting case shown in Figure 6.6 follows quite well the variations in wind power output. The linkage between wind power output and congestion reflects the way in which congestion arises. In our results from Paper I, we identify three mechanisms that cause congestion at individual connections between regions:

- *Peak-load hour congestion* occurs when one of the two connected regions exhibits a steep supply curve, leading to high marginal costs during peak-load hours. This usually occurs via the pull-type mechanism described in the previous section.
- *Low-load hour congestion* occurs when one of the two connected regions has a high penetration of wind power, leading to a very low marginal cost, primarily during low-load hours.
- *All-hour congestion* occurs between two regions that have such different system structures and different supply curves that there are permanent differences in the marginal cost and, therefore, permanent congestion.

In many cases, load shifting can easily reduce the peak-load marginal costs and thus, peak-load hour congestion can often be mitigated with DR. The potential of DR to reduce all-hour congestion depends on the specifics of the systems in the connected regions, as well as on how the marginal costs respond to load shifting. However, typical low-load hour congestion is usually caused by high wind power output in combination with low load, and it generally cannot be reduced by load shifting. When only a small load is available for shifting and the wind power output is several times higher than the load, DR cannot significantly affect the marginal cost, so the congestion persists. This means that in some respects, grid expansion and DR play the same role in variation management, and in many cases they complement each other.

6.5 The impact of solar power on marginal costs

In Paper III, we investigate how high penetration levels of solar power would affect the European electricity system and compare two scenarios, in which very high shares of renewables are required. We run each scenario up to Year 2050 in the ELIN model and then extract the Year 2022 and Year 2032 systems for further analysis in the EPOD model. Both scenarios are built on the Green Policy scenario, and for the purpose of this study, they are designated as *Green Base* and *Net Metering*, respectively. The Green Base scenario is identical to the Green Policy scenario as described above. In the Net Metering scenario, we add a simplified representation of an annual net metering scheme, where the difference between the retail and wholesale electricity prices in each country (according to the current situation) is subtracted from the objective function for each unit of solar power production up to the residential demand.

At penetration levels of 20 %–30 %, solar power has a major effect on the daily variations in the marginal cost of electricity, compared with the current situation in which the daily variations are mainly determined by the load. Figure 6.7 shows the values for the production, import, and export of electricity in southern Germany (DE1) during 2 weeks in March, together with the marginal generation cost, as derived from the EPOD results for the Net Metering scenario for Year 2022. The marginal cost drops to almost zero every day at the point of peak solar production. The highest marginal cost occurs later in the evenings when solar production of electricity is low, even though demand remains high. The penetration level of solar power in DE1 is 31 %. Although Germany as a whole has a high level of wind power as well, this is mainly located in the other German regions.

The predictable and recurring marginal cost differences during the day create the potential for storage to be more profitable. If we assume that storage would allow shifting demand within each day from the hour with the highest marginal cost to the hour with the lowest marginal cost, we can obtain a simple estimate of the marginal storage value by summing the maximum marginal cost differences over all the days of the year. Figure 6.8 shows the distribution of the maximum daily marginal cost differences and the estimated marginal storage values for two German and two Swedish regions, calculated from the EPOD modelling for the Net Metering and Green Base scenarios for Year 2032. Solar power penetration is substantially higher in the Net Metering scenario, at around 30 % compared with $\leq$ 10 % in the Green Base scenario, in all four regions. As a consequence, the daily marginal cost differences increase and the marginal storage value is significantly higher. However, the figure shows that the effect is weaker in Sweden, especially in region SE2. The explanation for this is that the storage capacity that is already available in Swedish hydropower can partially smoothen the variations in the marginal cost.

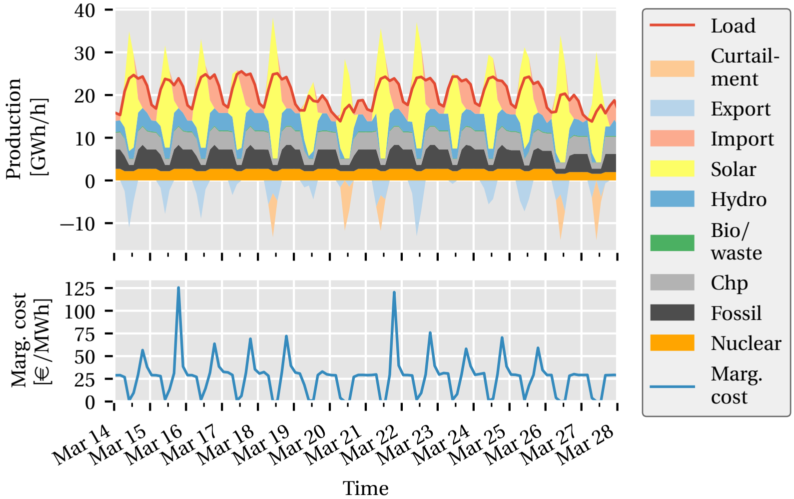
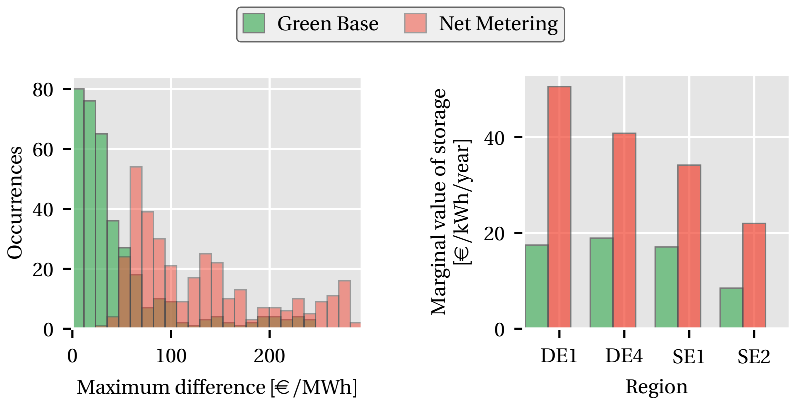


Figure 6.7: Production levels (top panel) and marginal costs of electricity (bottom panel) in the southern German region DE1, as derived from the EPOD results for Year 2022 for the Net Metering scenario presented in Paper III.

The main reason why solar power has a potent impact on the marginal cost of electricity is the nature of its production pattern. Solar power without storage can only produce electricity during the bright hours of the day, and production is also, at least in the northern parts of Europe, primarily during the spring and summer seasons. As a result, solar power produces much more of its output close to the rated power than does wind power. Figure 6.9 shows the distributions of solar and wind power outputs (Figure 6.9a) and the distributions of net load, i.e., load minus solar or wind power output (Figure 6.9b), for a wind-dominated region in northern Germany (DE4) and a solar-dominated region in southern Germany (DE1), as deduced from the EPOD modelling runs for Year 2022 in the Net Metering scenario. The data show that wind power is more potent than solar power at reducing the peak-load hours, since the peak-load hours occur during winter and wind power output is also higher in winter than in summer. It is also clear that solar power generates significantly more surplus hours, i.e., hours with a negative net load.



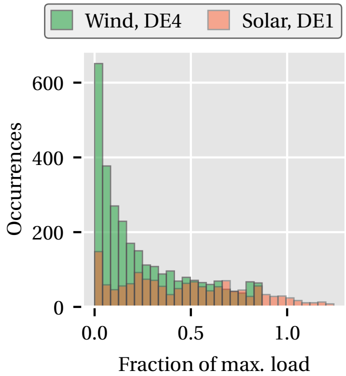
(a) Distributions of maximum daily marginal cost differences in region DE1.

(b) Marginal value of storage.

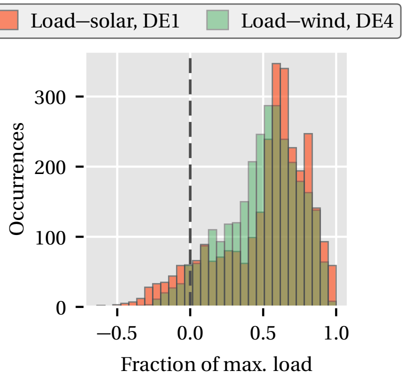
Figure 6.8: The value of storage with high levels of solar generation illustrated by (a) the distributions of maximum daily marginal cost differences in region DE1 and (b) the marginal value of daily electricity storage in two German and two Swedish regions calculated from the marginal costs from the EPOD modelling for the Net Metering and Green Base scenarios for Year 2032.

6.6 Solar power and congestion

In the analyses performed in Paper III, we investigate the effect that solar power has on congestion, by comparing the Net Metering scenario to the Green Base scenario. For this, we use the *system congestion* measure defined and presented in Paper I and described in Section 3.4. Figure 6.10 shows the average system congestion values for the periods of April–September (denoted as “summer”) and October–March (denoted as “winter”). We base these values on the EPOD results for the Year 2022 and Year 2032 systems from the Green Base and Net Metering scenarios. For the summer period, system congestion is higher in the Net Metering scenario, while the opposite is true for the winter period. This indicates that system congestion is related to solar and wind power production, given that solar power production is higher in the summer period and wind power production is higher during winter.



(a) Output distributions.



(b) Net load distributions.

Figure 6.9: Distributions of the: (b) wind power net load (load—wind) in the wind-dominated region DE4 in northern Germany and solar power net load (load—solar) in the solar-dominated region DE1 in southern Germany; and (a) outputs from wind power in region DE4 and solar power in region DE1. The results are from the EPOD modelling for the Year 2022 Net Metering scenario. In both figures, the output and net load values are normalised to the maximum load in each region. Zero-output hours have been excluded from the solar power output in (a).

However, we find that the total solar power output across Europe does not necessarily correlate directly with the levels of system congestion. Figure 6.11 shows the average rolling correlation, using a 1-week window, between the system congestion and each of the parameters of total demand, total wind power generation, and total solar power generation for the periods April–September (summer) and October–March (winter) for the years 2022 and 2032 in the investigated Green Base and Net Metering scenarios. Initially, in the Year 2022 system, the aggregated solar power output correlates positively with the level of system congestion during the summer period. The effect is seen in both scenarios, but is stronger in the Net Metering scenario. The reason for this is that solar power expands unevenly in the Net Metering scenario, fully utilising first the countries with the largest differences between the spot market price and the retail price. During the summer season in the Year 2022 system, one contribution to system

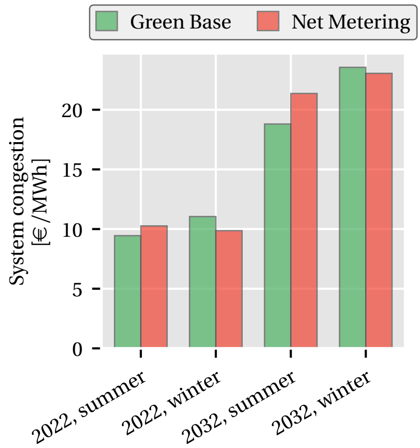


Figure 6.10: Average system congestion levels for the periods of April–September (denoted summer) and October–March (denoted winter) from the EPOD dispatch modelling results for the Green Base and Net Metering scenarios for Year 2022 and Year 2032.

congestion is that regions with high solar penetration levels experience low marginal costs at the solar power generation peak each day, whereas many of the neighbouring regions have high marginal costs at these same times. The levels of solar power penetration in the modelled regions for the Net Metering scenario in Year 2022 and Year 2032 are shown in Figure 6.12. In 2032, the solar power penetration levels are more even across most of the regions, which means that at the solar peaks, the marginal costs are low in most regions, which in turn leads to a lower level of system congestion. In contrast, hours with high system congestion often occur when there is little or no solar production of electricity and there is a scarcity of electricity in some regions. The total electricity demand exhibits a consistently positive, albeit relatively weak correlation with system congestion for all periods and for both scenarios.

To define the connection between solar power and congestion, we calculate the cross-correlation, i.e., where one of the time series is shifted in time. Figure 6.13 shows the average rolling window cross-correlation between system congestion and each of the parameters of total demand, total wind power generation, and total solar power

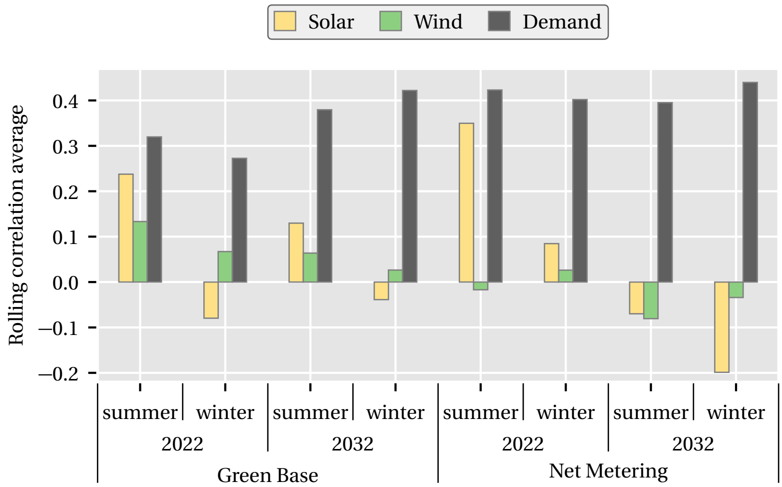
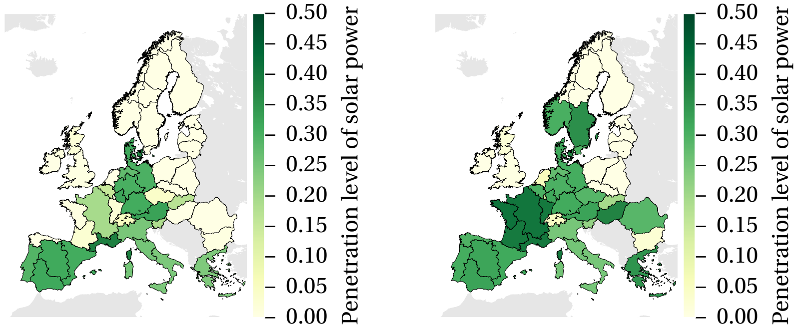


Figure 6.11: Average rolling correlation, using a 1-week window, between system congestion and each of the parameters of total demand, total wind power generation, and total solar power generation for the periods April–September (summer) and October–March (winter) for the years 2022 and 2032 in the investigated Green Base and Net Metering scenarios.

generation as a function of the time displacement, calculated for Year 2032 in the Net Metering scenario. Despite the initially negative correlation between solar power and system congestion, we find a relatively strong and positive correlation for time displacements of 6–9 hours. This indicates that in this system, congestion occurs mainly during the evenings when solar power generation is low but demand remains high. A possible explanation for this is that the ramping of power plants, which is required as the level of solar power production decreases, may incur start-up costs and induce marginal cost peaks in some regions. The correlation between system congestion and total demand is strongest in the absence of any time displacement.

In contrast, wind power correlates only weakly with system congestion, regardless of the time displacement. Instead, we find that wind power is connected to more slowly evolving variations in system congestion. In Year 2032 in the Green Policy scenario, a rolling 2-week average of system congestion and total wind power generation shows



(a) Year 2022. **(b)** Year 2032.

Figure 6.12: The regional penetration levels of solar power from the Net Metering scenario from Paper III for: (a) Year 2022; and (b) Year 2032. The expansion is initially uneven across Europe because the investments are initially taken up in the countries where the net metering benefits are the largest. As the potential is filled up, the expansion spreads.

a strong positive correlation of approximately 0.7, calculated as the average of a 6-week rolling correlation. The corresponding value for total solar power generation is negative and significantly weaker at approximately −0.2. In the Net Metering scenario the correlations for both wind and solar power on this time scale are weaker, although they have the same signs (positive or negative) as in the Green Policy scenario.

6.7 Distribution systems – hosting new generation

A hot topic in energy research over the last decade has concerned distributed generation (DG). While the definitions of DG listed in the literature vary, we focus on generating capacity that is connected to low or medium voltages, i.e., up to approximately 30 kV. A literature survey reveals that since distribution grids were not designed to host generators, significant adaptations may have to be made. The following technical factors limit the amount of capacity that can be integrated into the existing systems:

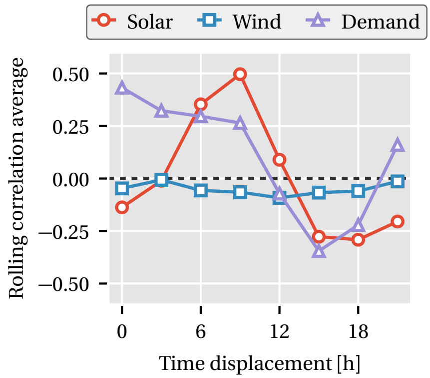


Figure 6.13: Cross-correlation between system congestion and total European solar power, wind power, and demand, as a function of the time displacement between the two correlated series for the Net Metering scenario, in Year 2032. A positive time displacement means that solar power, wind power or demand is shifted forward in time or that system congestion is shifted backward in time. The cross-correlation is calculated as the annual average of a rolling window correlation over 1-week windows calculated for each time-step.

- Maintaining the voltage within the allowed limits, can be difficult (Coster et al., 2011; Driesen and Belmans, 2006), mainly due to so-called *voltage rise* (Masters, 2002); and

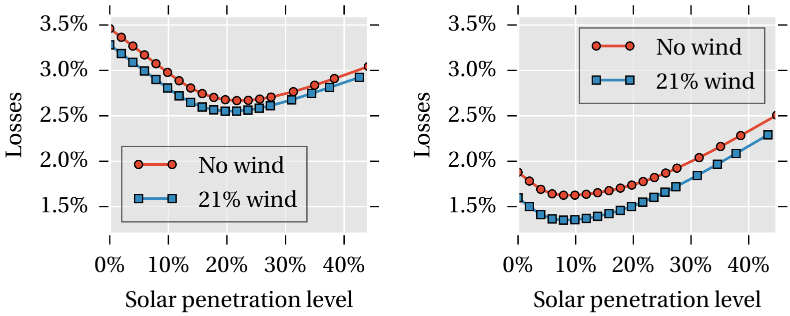
- The thermal capacities of lines and equipment may not be sufficient to cope with the new peaks generated by the distributed generators (Barker and de Mello, 2000; Masters, 2002).

However, some potential benefits are also mentioned in the literature:

- DG can reduce losses when it is placed close to the load (Barker and de Mello, 2000; Dondi et al., 2002; Pepermans et al., 2005); and

- When demand increases, DG can potentially abrogate the need for or delay investments in increased grid capacity (Driesen and Belmans, 2006; Harrison et al., 2007; Lopes et al., 2007).

Our modelling results, which are described further in Paper II, show that there exists the potential to reduce grid losses when the electricity

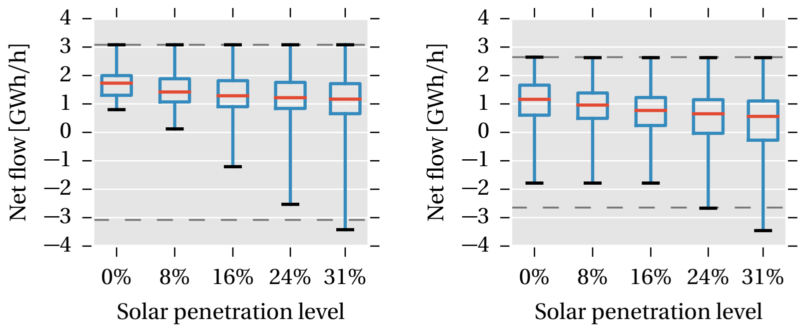


(a) Load mainly at low voltage. **(b)** Load mainly at medium voltage.

Figure 6.14: Annual energy losses from the dispatch modelling of the western Denmark system as a function of solar power penetration level, with: (a) the load concentrated mainly to the low-voltage level (70 % of total annual consumption); and (b) the load concentrated to the medium-voltage level (70 % of total annual consumption).

from DG is consumed locally and replaces electricity that is imported from higher voltage levels. We use a single-region dispatch model that describes western Denmark, where the typical voltage levels of the distribution grids are described separately with their own load curves and where each generating unit is connected to one of the voltage levels. Whenever power is exchanged between voltage levels a constant percentage is subtracted as a loss. We then sweep the penetration levels of wind power, which we assume is connected to the medium-voltage level, and of solar power, which we assume is connected to the low-voltage level. Figure 6.14 shows how the total annual energy losses change with the penetration level of solar power in the low-voltage grid. Initially, the losses decrease as all the generated solar electricity can be consumed locally in the low-voltage grid. However, as the penetration level reaches and then exceeds 15 % the rate of decrease in losses slows as more of the generated electricity has to be exported up to the higher voltage levels, incurring new losses in the process. Above a penetration level of approximately 20 %, the losses begin to increase above the minimum point.

From the same dispatch model results, we conclude that when solar power production and load show inverse seasonal variations,



(a) Medium voltage to low voltage. **(b)** High voltage to medium voltage.

Figure 6.15: Distributions of hourly power transfers between the voltage levels as a function of solar power penetration level for: (a) flows from the medium-voltage (MV) level to the low-voltage (LV) level; and (b) flows from the high-voltage (HV) level to the MV level. The upper and lower values mark the maximum and minimum flows, respectively, and the upper and lower borders of the box correspond to the upper and lower quartiles of the distribution, respectively. The red line indicates the median value.

solar PVs have a very limited potential to reduce the maximum flow of power between voltage levels in the distribution grid. Therefore, solar PVs have a limited potential to delay investments in increased grid capacity as the load grows. Figure 6.15 shows the distributions of hourly power transfer between the voltage levels as a function of the solar power penetration level. The figure clearly demonstrates how the peak downstream flows, both between the HV and MV levels and between the MV and LV levels, are entirely unaffected by increased penetration of solar PVs in the low-voltage grid. However, at relatively low penetration levels (around 10 %), negative flows, i.e., situations in which electricity is exported from the low-voltage level up to higher voltage levels, start to occur.

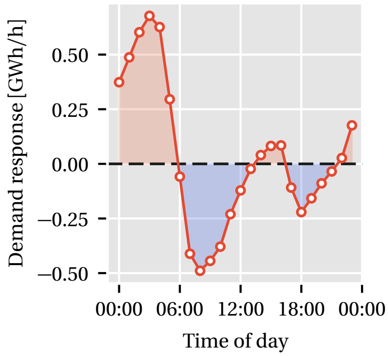
6.8 System effects of demand response

Paper IV investigates the benefits for the centralised electricity generation system of the integration of DR of electric heating loads in Swedish single-family dwellings. The capacity mix for the generation system is extracted from the results for Year 2032 from the ELIN model for two scenarios: Green Policy and Climate Market[1]. The capacity mix is then fed into the EPOD model, where the cost-optimal dispatch is calculated over 1 year with hourly resolution. The DR is modelled using the interval and deviation cost methods described in Section 3.5. We also investigate the effects of allowing the indoor temperature to be lowered during the night-time and during working hours. The temperature limits are set at 18 °C and 15 °C, respectively, and these saving measures are studied both on their own and in combination with DR.

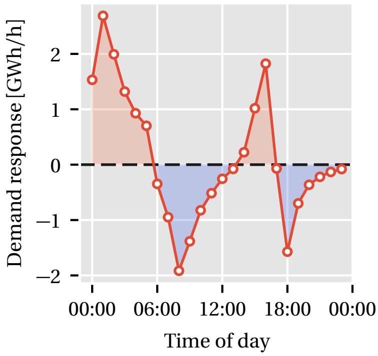
Our model results show that in order to minimise the system running costs, DR is used to shift the electric heating loads within the day. Figure 6.16 shows the changes in total demand, compared with a base case with no DR, together with the average indoor temperatures in the building stock for both the average day and an example day in February for the Green Policy scenario. A clear pattern emerges, in which demand is shifted from the morning and evening hours into the night-time and mid-daytime. This is accomplished by overheating the buildings during the night-time and mid-daytime, which increases the electricity demand, and then underheating the buildings and letting the temperature drop during the mornings and evenings, which decreases the electricity demand during those periods. The observed pattern indicates that the DR behaviour is mainly governed by the regularities of the total electricity demand curve, which generally has one peak in the morning and one in the evening, and not so much by the varying supply from, for example, wind power.

The results show that DR can produce significant operating cost savings in the electricity system. Figure 6.17 shows the total savings in operating costs, as well as the components in terms of the cycling (start-up and part-load) costs and other running costs. The cost savings are given for the fixed interval DR case (denoted as "DR"), the

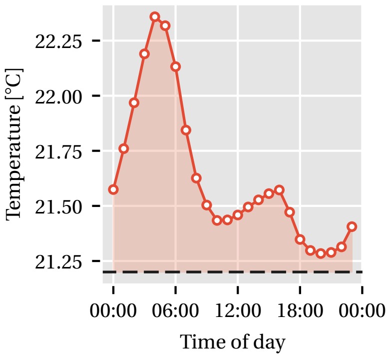
[1]The ELIN results are described in Section 6.1.



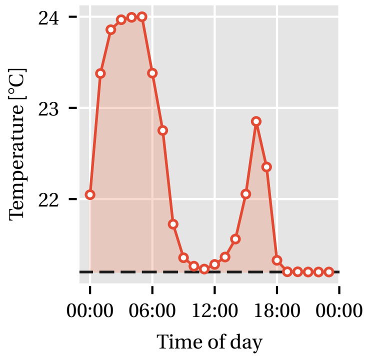
(a) DR, average day.



(b) DR, example winter day.



(c) Average temperature, average day.



(d) Average temperature, example winter day.

Figure 6.16: Top row: Shifting of electric heating load in Swedish households in the Green Policy scenario with the *interval* method for: (a) the average over 1 year for each hour of the day; and (b) one example winter day in February. Bottom row: Weighted average indoor temperature in Swedish households in the Green Policy scenario with the *interval* method for: (c) the average over 1 year for each hour of the day; and (d) one example of a winter day. Only the period of September 15th to May 15th, when the electric heating systems are active, is included in the average.

day-night temperature control case (denoted as “DN”), and the case with both temperature control and DR (denoted as “Both”), for each of the Green Policy and Climate Market scenarios. In the Green Policy scenario, there are significant cost savings in both the DR and DN cases, whereas in the Climate Market scenario, the savings accrued from DR are small compared with those from DN. The reason for this difference between the scenarios is the composition of the generation capacity mix. The Green Policy scenario has a substantially higher share of wind power in the mix, which leads to more variability in the marginal generation cost (see Figure 6.3a) and, thereby, a larger potential for savings from the short-term load shifting is possible with heat load DR. Due to the high penetration of wind power, the thermal plants will have to perform more start-ups and run more often on part-load in the Green Policy scenario than in the Climate Market scenario, which enables savings of cycling costs. In contrast, the Climate Market scenario has greater thermal capacity with relatively high running costs, which results in higher but less variable marginal generation costs. Therefore, the savings in running costs achieved for the DN case are higher in the Climate Market scenario than in the Green Policy scenario. These results lead to the conclusion that the benefits of DR are highly dependent upon the mix of generation capacity in the system.

Table 6.1 provides some insights into how the cost savings are realised in the different cases. The table shows, for each case, the changes, compared with a base case with a fixed set-point temperature and no DR, that occur in four types of generation, as well as in curtailment and demand. In the Green Policy scenario, the main savings in running costs arise from reduced curtailment (i.e., increased utilisation) of wind power and a shift from gas-fired and other thermal power plants to CHP plants and hydropower with lower running costs. We note that the demand increases when DR is active, which is unavoidable with the interval method, since it only allows increasing the temperature above the set-point value, which leads to higher losses and, thereby, higher consumption.

With the day-night temperature control, the savings mainly come from the reduced demand which, in the Green Policy scenario, leads to a lower level of production in gas-fired power plants. In the Climate

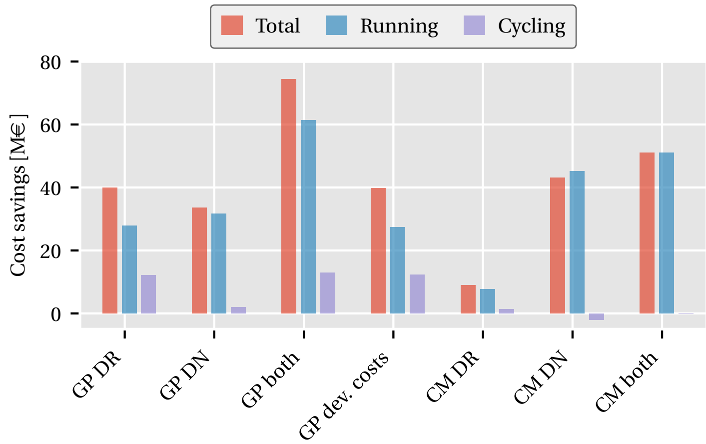


Figure 6.17: Savings in yearly operating cost accrued from applying DR in electric space heating in the Swedish building stock for four different cases for the Green Policy scenario (GP) and three cases for the Climate Market scenario (CM). The "DR" case corresponds to temperature DR described with the *interval* method. The "DN" case corresponds to lowering the temperatures during the days and nights. The case designated as "Both" combines the DR and DN cases. The "dev. costs" case represents DR using the *deviation costs* method.

Market scenario, however, it is mostly CHP plants that decrease their production levels. Although the DR is only modelled for Swedish households, we also see in the results that most of these changes occur in neighbouring countries. This shows the importance of considering a large geographic area in this type of modelling. It is also likely that Swedish hydropower plays an important role in maximising the cost savings from changes in the electric heating demand. By utilising the storage capacity of hydropower, the changes can be redistributed over time so that the decreases occur in those plants that have the highest running costs.

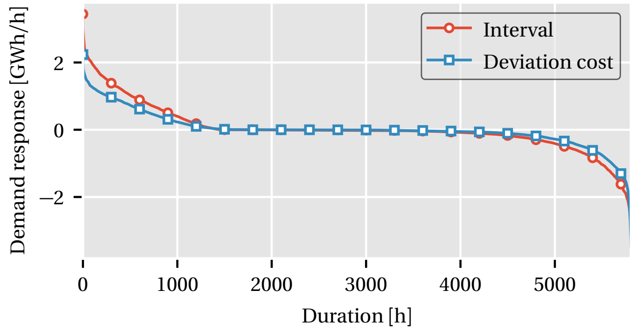
An interesting observation from Figure 6.17 is that the cost savings from DR and DN appear to be additive, i.e., the cost savings (when both are available) correspond approximately to the sum of the savings from the separate DR and DN cases. This additivity holds for both the Green Policy scenario and the Climate Market scenario. This is, however, not

Table 6.1: The annual changes in electricity generation for different generation technologies, together with the changes in wind power curtailment and electricity demand, as compared to the base case with no DR or indoor temperature reduction for the Green Policy and Climate Market scenarios, respectively. The "DR" case corresponds to temperature DR with a fixed interval. The "DN" case corresponds to the lowering of temperatures during days and nights, and the case designated as "Both" combines the DR and DN cases. Note that a negative change in curtailment corresponds to increased utilisation of renewables.

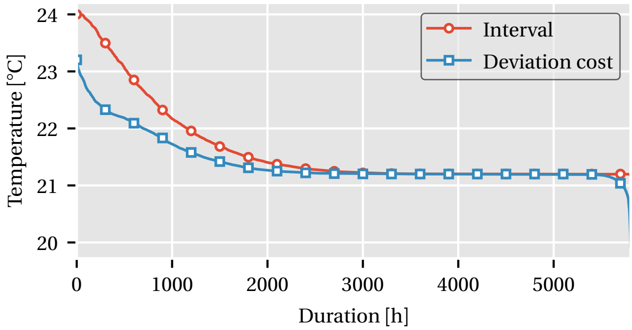
		Green Policy			Climate Market		
Category (GWh)		DR	DN	Both	DR	DN	Both
Prod.	CHP	290	−40	120	20	−920	−890
	Thermal	−140	−50	−200	−10	−40	−40
	Gas	−240	−680	−790	−40	−10	−40
	Hydro	80	−80	90	0	0	0
Curtailment		−210	120	−230	0	0	0
Demand		200	−970	−550	30	−970	−970

an obvious outcome. The DR-related savings are based on shifting the electricity consumption backwards in time by preheating the building. The preheating is often done during the night-time, to avoid using electricity during the morning consumption peak, or towards the end of the working day to avoid the evening consumption peak. While one might reasonably expect that this behaviour would reduce the potential for cost savings in the DN case, our results do not indicate any such phenomenon. These results show that both DR and smart temperature control can confer benefits upon the system without limiting one another.

In the case in which the deviation cost model is used for DR, the unknown cost coefficients are chosen so that the total savings approximately match those in the fixed interval case (see Figure 6.17). Even though the two methods give similar cost savings, the deviation cost method shows that the results can be achieved with overall lower levels of load shifting and significantly smaller variations in indoor temperature, at the cost of small dips below the set-point temperature. Figure 6.18 shows the duration curves for the total DR (Figure 6.18a) and the average indoor temperature (Figure 6.18b) for the interval



(a) DR



(b) Indoor temperature

Figure 6.18: Duration curves for: (a) the DR compared with the base case; and (b) the weighted average indoor temperature. Each figure shows two different DR cases: fixed interval; and deviation costs.

and the deviation cost methods for the Green Policy scenario. Overall, the average temperature with the deviation cost method is below the set-point value for 252 hours, although there are only 20 hours with an average temperature that is more than 0.5 °C lower than the set-point. The minimum value for the average temperature with the deviation cost method is 19.9 °C.

6.9 Residential PV and battery investments

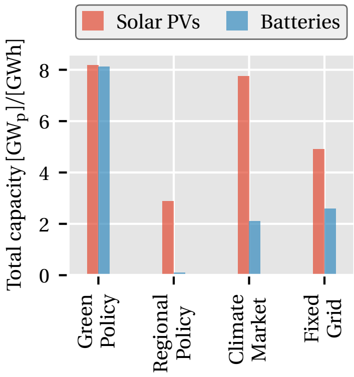
The results from the iterative modelling approach (see Section 3.6) show that in our scenarios for Year 2032, there are generally strong incentives for households to invest in PVs. Figure 6.19 shows the total installed capacities of PVs and batteries after the iterations (Figure 6.19a) and the changes in the total capacities from before to after the iterations (Figure 6.19b). The results are shown for each of the three scenarios, as well as for the "Fixed Grid" case, which uses the ELIN results for the Green Policy scenario but assumes that all grid fees for households are fixed, i.e., the variable grid fees are set to zero for all households. The large difference between the Green Policy and the Fixed Grid cases clearly shows how significant a role the grid tariff plays in the incentives for households to invest. This result serves to motivate Paper VI, which investigates different tariff structures and their effects on the incentives for residential PV and battery investments.

The differences in the total installed capacities of PVs and batteries between the three scenarios, as shown in Figure 6.19a, can be understood through the differences in the hourly electricity price curves to which they give rise. The hourly price and price duration curves depicted in Figure 6.3 show that the price curves for each scenario can be described, in simplified terms, as follows:

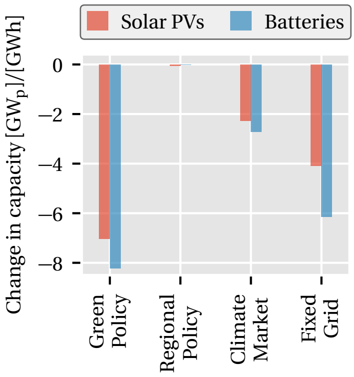
- Green Policy: High and variable prices
- Climate Market: High and stable prices
- Regional Policy: Low and stable prices

Not surprisingly, the highest levels of investment in both PVs and batteries are found in the Green Policy scenario. Although the Climate Market scenario reaches similar levels of PV investments, the stable prices do not stimulate as high a level of investment in battery capacity.

Figure 6.19b shows that the market feedback has a significant dampening effect on the residential investments in PVs and batteries. In the Green Policy scenario, the installed capacities of both PVs and batteries decrease by about 50 % after the iterations. We also observe that the feedback effect is strongest in the cases with the highest installed capacities, as could be expected, whereas the capacities in



(a) Total installed capacity.

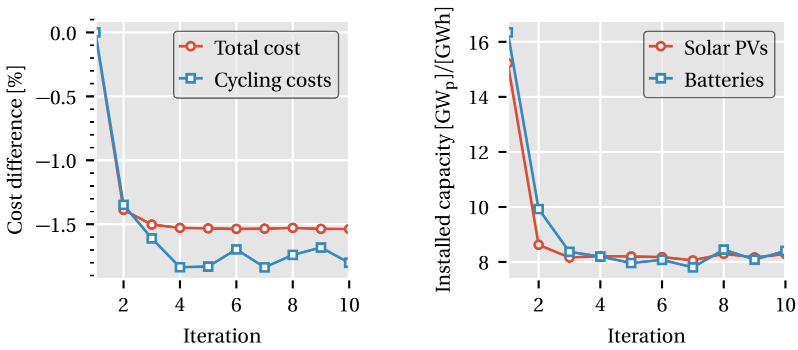


(b) Change in capacity after iteration.

Figure 6.19: Results from the iterative modelling of investments in PVs and batteries in Swedish households: (a) total installed capacities in solar PVs (in GW_p) and batteries, in GWh, after iterations; and (b) the changes in installed capacities compared with the first iteration. Each panel shows the results for the three modelled scenarios, and for the "Fixed Grid" case, which is identical to the Green Policy scenario except that the variable grid tariff has been set to zero for all the households.

the Regional Policy scenario are so small that there is no noticeable feedback effect. It is not clear from these results whether the PVs, the batteries, or a combination thereof is the primary reason for the limiting of the profitability of the investments. However, the results clearly demonstrate the importance of taking market feedback effects into consideration when modelling residential investments in PVs and batteries, at least for cases in which significant installations of both PVs and batteries are a possibility.

Additional insights into the iterative process can be found in Figure 6.20. The figure shows the differences in total running and cycling costs compared with the first iteration (Figure 6.20a) and the total installed capacities of residential PVs and batteries as functions of the number of iterations (Figure 6.20b). The most important effect of market feedback on the installed capacities of PVs and batteries in households occurs between the first and second iteration, when the capacities decrease dramatically. This is caused by households'



(a) Cost changes compared with the first iteration.

(b) Installed capacities.

Figure 6.20: Effects of the iterations between the EPOD model and the household investment model in the Green Policy scenario, in terms of: (a) the changes in total running costs and cycling costs compared with the first iteration; and (b) the installed capacities of PVs and batteries in households. Note that the costs are extracted from the EPOD model, which is run before the household model in each iteration and, therefore, includes the household capacities from the previous iteration (in the first iteration, no household PV or battery capacity is included).

reactions to the change in electricity prices that follows from the over-investments in the first iteration. After a few iterations the values stabilise, indicating that the model has converged.

The EPOD model is run before the household model in each iteration and, therefore, includes the household capacities from the previous iteration, which explains why the total running costs drop significantly between the first and second iteration (Figure 6.20a), since a substantial amount of “free” PV electricity is added to the system. In the Green Policy scenario, the cycling costs also decrease as the PV and battery capacities enter the system. This result, however, does not hold for the Climate Market scenario, where cycling costs increase after the first iteration. This difference can probably be attributed to the installed battery capacity, which is significantly larger in the Green Policy scenario (see Figure 6.19a). The larger battery capacity is used by households to respond to price signals, leading to a reduction in cycling costs.

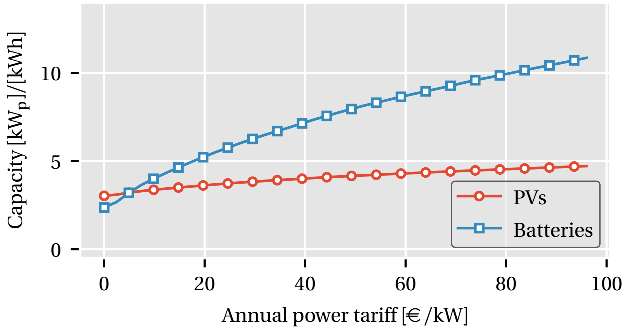
Interestingly, Figure 6.20a also shows that during iterations 2–4, the total cost and the cycling costs continue to decrease, despite the fact that PV and battery capacities are removed from the system (the costs are based on the household PV and battery capacities from iterations 1–3). This shows that the over-investment in the first iteration incurs unnecessary running costs in the centralised generation system, perhaps linked to how the household battery capacity is utilised.

6.10 Grid tariffs driving PV and battery investments

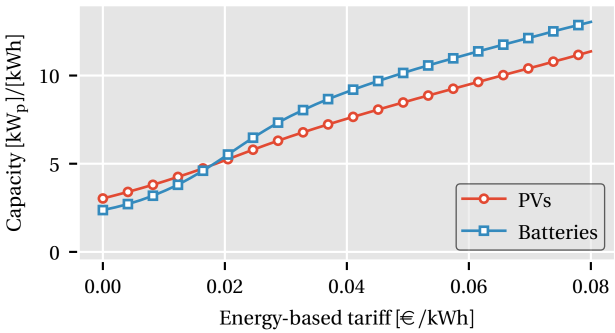
As mentioned in Section 6.9, the results from Paper V show that the inclusion or exclusion of an energy-based grid tariff at its current level would make a substantial difference to the profitability of residential PV and battery investments. In Paper VI, we expand the household investment model to include, in addition to the conventional energy-based tariff, several variations of power tariff schemes. In these schemes, the consumer pays a fee proportional to some measure of the power consumed. In this section, we explore the effects that the tariff levels have on the profitability of PV and battery investments in Swedish single-family dwellings, comparing an energy-based tariff to an annual power tariff, where the fee is proportional to the level of consumption during the peak hour of the year.

The results from Paper VI show that grid tariffs can potentially be strong drivers of residential investments in PV and battery systems. Figure 6.21 shows the weighted average installed capacities of PVs and batteries across the households as a function of tariff level for an annual power tariff and an energy-based tariff. The results shown in the figure are based on an electricity price curve extracted from EPOD for the Green Policy scenario. It is clear that both the power tariff and the energy-based tariff drive investments in residential PVs and batteries. However, the mechanisms that drive these investments differ between the two tariff types.

The power tariff (Figure 6.21a) stimulates investments in batteries, since batteries allow the household to redistribute their electricity consumption in time so as to lower their maximum consumption. As the power tariff increases, so does the value of storage capacity, which means that the optimal battery size for each household increases. The



(a) Annual power tariff.



(b) Energy-based tariff.

Figure 6.21: Weighted averages of the installed capacities of PVs (in kW$_p$) and batteries (in kWh) across the households as a function of the tariff level for: (a) an annual power tariff; and (b) an energy-based tariff. The results shown here are based on modelled electricity prices from the Green Policy scenario.

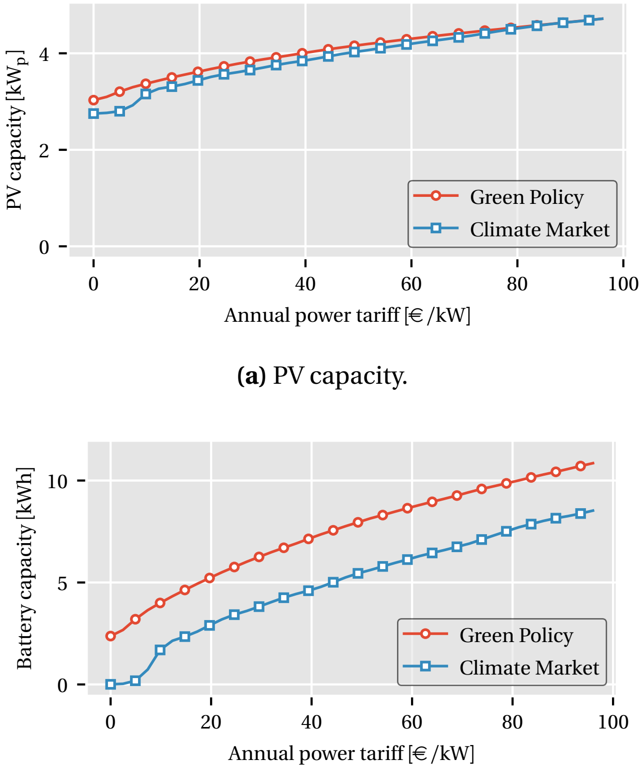
PV capacity also increases with increasing tariff level, even though the power tariff creates no direct incentive for investing in PVs. However, there is still an incentive for households to replace electricity from the grid with in-house PV electricity, so as to avoid the electricity tax. The available battery capacity makes it possible for some households to increase their self-consumption of PV electricity, which increases the optimal installed PV capacity. Thus, the PV capacity is "dragged along" as the battery capacity increases.

In contrast, the energy-based tariff (Figure 6.21b) strengthens the incentives for self-consumed PV electricity but provides no direct incentives for the acquisition of batteries. Indirectly, however, batteries have a value, since they allow larger quantities of PV electricity to be self-consumed. With the energy-based tariff (as opposed to the power tariff), it is therefore the PVs that drag the batteries along.

Figure 6.22 shows the average installed capacities of PVs and batteries, as a function of the level of annual power tariff, for electricity price curves from the Green Policy and Climate Market scenarios. The main difference between the two scenarios is that in the Green Policy scenario, both PVs and batteries are profitable without any variable grid tariff, whereas in the Climate Market scenario, batteries only become an attractive investment as the tariff levels go up. For high values of the power tariff, the installed PV capacity reaches similar levels in the two scenarios. In terms of the installed battery capacity, however, the Climate Market scenario is consistently lower than the Green Policy scenario. This result shows that the possibilities for using the batteries for market arbitrage, with the volatile electricity prices in the Green Policy scenario, contribute to increasing the profitability of the batteries for all values of the power tariff.

6.11 Power tariffs and the consumption profile

In Paper VI, we study the potential effects of a power tariff on the electricity consumption profile of Swedish single-family dwellings. Figure 6.23 shows the weighted average household peak loads as a function of the tariff level for an annual power tariff and an energy-based tariff. As expected, we observe in Figure 6.23a that a power tariff leads to a reduction in the peak load of households both in the

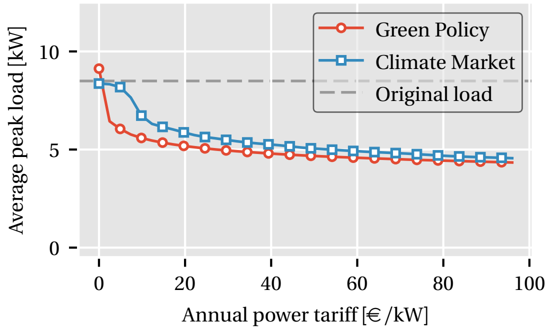


(a) PV capacity.

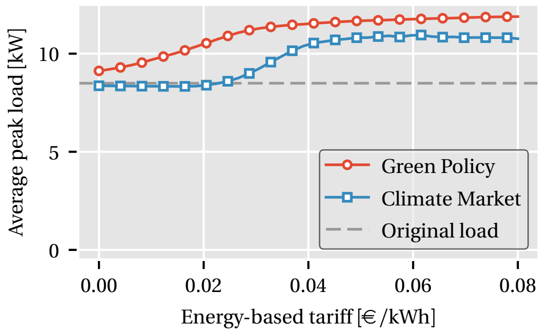
(b) Battery capacity.

Figure 6.22: Weighted averages, across all households, of the installed capacities of: (a) PVs; and (b) batteries. The results are shown for two electricity price scenarios: Green Policy, and Climate Market.

Green Policy scenario and the Climate Market scenario. As noted above, households invest in battery storage, so that they can shift their electricity consumption in time and thereby lower their annual peak demand and, consequently, reduce their expenditure on electricity. In the Green Policy scenario, the decrease in peak load occurs for lower levels of the power tariff, as compared with the Climate Market scenario. This effect is due to the fact that batteries are already present due to the market arbitrage opportunities provided by the volatile electricity price in the Green Policy scenario.



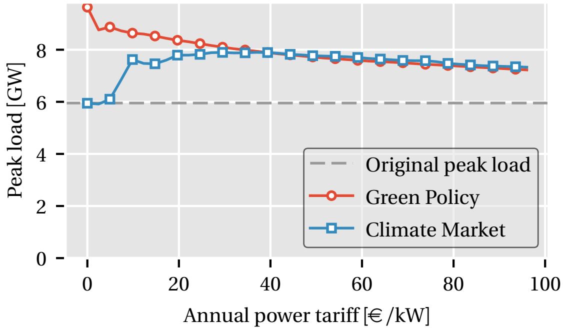
(a) Annual power tariff.



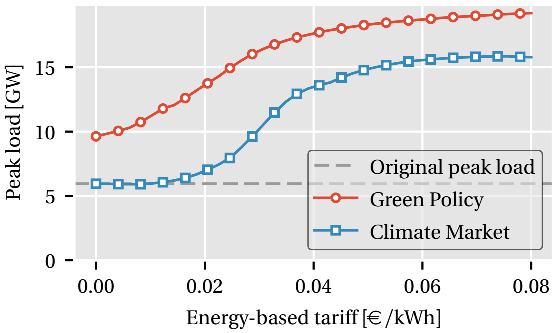
(b) Energy-based tariff.

Figure 6.23: Weighted average household peak loads as a function of the tariff level for: (a) an annual power tariff; and (b) an energy-based tariff.

With an energy-based tariff (Figure 6.23b), the average household peak load increases with an increasing tariff level. With this type of tariff, the primary role of the batteries is to increase the self-consumption of PVs. However, the available batteries can also be utilised for market arbitrage. If the battery capacity is sufficiently large, the level of electricity consumption during local price minima could surpass the original peak load of the household. In the Climate Market scenario, the effect is weaker and delayed compared with the Green Policy scenario. The Climate Market scenario, with its more stable prices, does not



(a) Annual power tariff.

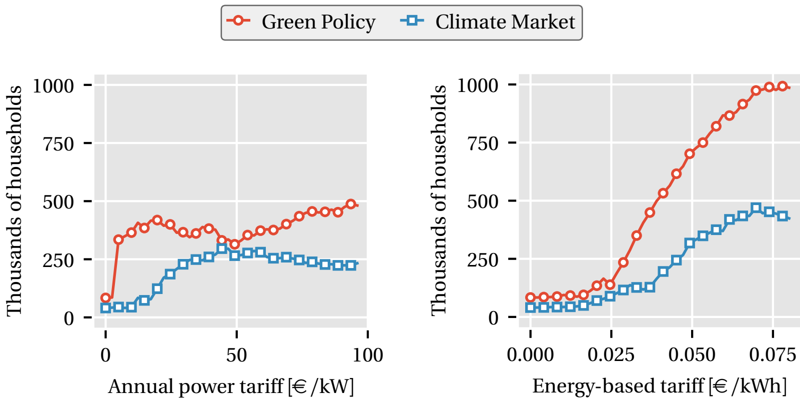


(b) Energy-based tariff.

Figure 6.24: Total (up-scaled) household peak load as a function of the tariff level for: (a) an annual power tariff; and (b) an energy-based tariff. Note the difference in the scales of the vertical axes between the two plots.

offer the same opportunities for market arbitrage and, therefore, has consistently lower installed battery capacities than the Green Policy scenario for the same tariff level.

The effects on the total household load curve are, however, a little more complex. Figure 6.24 shows the total household peak loads as a function of the tariff level for an annual power tariff and an energy-based tariff. A slightly unexpected result is that in the Climate Market scenario, the total peak load of households initially increases with



(a) Annual power tariff. **(b)** Energy-based tariff.

Figure 6.25: The maximum number of households with coinciding peak-load hours as a function of the tariff level for: (a) an annual power tariff; and (b) an energy-based tariff.

an increase in the power tariff (Figure 6.24a). This occurs because when the households are minimising their electricity cost, through the availability of batteries and a known electricity price, the peak loads of the households tend to become more concentrated towards the same, low-price hours. With the power tariff, this effect is counteracted by the incentive to keep peak consumption low, so as to avoid high tariffs. With the energy-based tariff, however, there is nothing to counterbalance the concentration of peak-load hours and the increase in the consumption during these hours, which is due to the larger installed battery capacities. This leads to a dramatic increase in total peak load (see Figure 6.24b, note the difference in the scales of the vertical axes between the panels). The peak-load hour concentration effect is illustrated in Figure 6.25, which shows the maximum number of households with coinciding peak-load hours as a function of tariff levels for an annual power tariff and an energy-based tariff.

6.12 A comparison of grid tariff structures

In Paper VI, we also investigate the differences between the energy-based tariff and the following types of power tariffs:

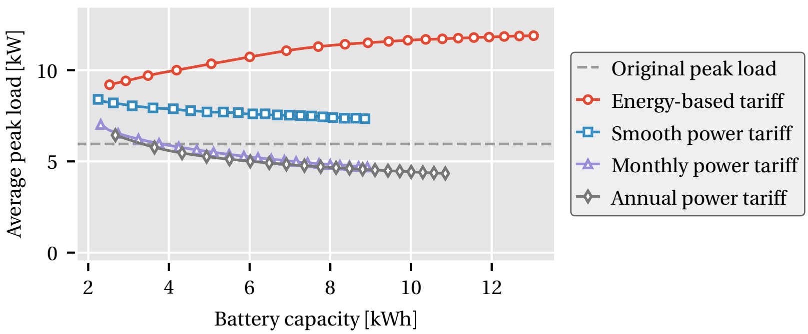


Figure 6.26: Weighted average household peak loads with electricity prices from the Green Policy scenario, as a function of the average installed battery capacity for the four investigated tariff structures.

- An annual power tariff, where the fee is proportional to the peak hourly consumption during the year for each household.
- A monthly power tariff, where the fee is proportional to the peak hourly consumption of each month for each household.
- A smoothed power tariff, where the fee is proportional to the load level, such that 1 % of the consumption is above that level (see Section 3.7 for a more detailed explanation).

Comparing the effects of different power tariff structures to each other and to those of the energy-based tariff is not entirely straightforward, since the levels of the tariffs are not directly comparable. In Figure 6.26, which looks at how the different tariff structures affect the average household peak load, we have chosen to show the peak load as a function of installed battery capacity. This demonstrates the different ways in which the tariff affects the households' usage of available battery capacity to decrease their peak consumption. The figure shows that the annual and monthly power tariffs have similar effects and significantly reduce the average household peak load. The smooth power tariff also noticeably decreases the average peak load with increasing battery capacity, albeit much more weakly. This is as expected, since the annual and monthly power tariffs directly penalise the peak consumption, whereas the smooth tariff only affects it indirectly. As noted above, the energy-based tariff substantially increases

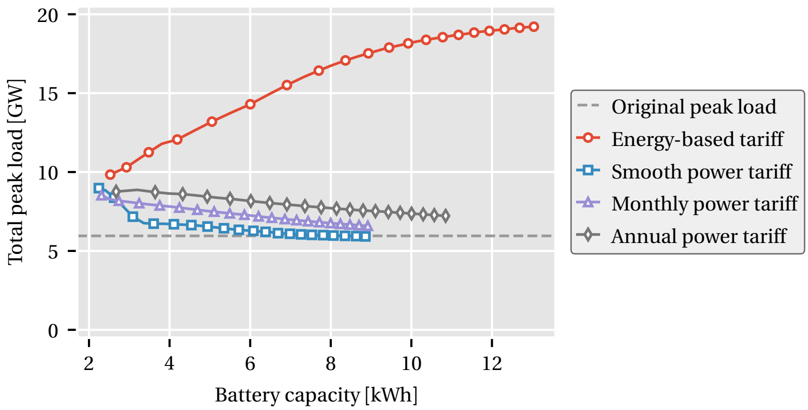


Figure 6.27: Total household peak loads with electricity prices from the Green Policy scenario, as a function of the average installed battery capacity for the four investigated tariff structures.

the average peak load with increasing battery capacity.

When we instead look at the total household peak load, as shown in Figure 6.27, we find that the smooth power tariff has a stronger impact on reducing the total peak load than the monthly and annual power tariffs at similar battery capacities, at least for average battery capacities above 3 kWh. It is also clear that the monthly power tariff has a stronger dampening effect on the total peak load than does the annual power tariff.

CHAPTER 7

Discussion

This chapter discusses the validity of the methods and the results obtained in the course of this work.

7.1 Methodological limitations

All the models applied in this work are cost-minimising optimisation models, which entail a certain set of assumptions. The cost-minimal solution corresponds to the outcome of a fully competitive and perfectly functioning market, in which all the actors have perfect information. Sometimes, it is described as a central planner perspective, since the solution also corresponds to what the outcome would be if the system was optimally controlled by a single entity, instead of being composed of many different actors with different goals and motivations. Given these assumptions, the models cannot be said to forecast or predict the future. Instead, we have to focus on comparative scenario analyses, and using the models to understand mechanisms that are important also in the real-world system.

In terms of electricity dispatch, the EPOD model can be regarded as being representative of a well-functioning, integrated European market. With the assumption of a perfectly functioning market, the results must be viewed as the best possible outcome, or as the technical upper limit to what can be achieved in a given system. In addition, there is currently no common European electricity market, although it is likely that the system will approach an integrated market in the future, since "A fully-integrated internal energy market" is a *Priority policy area* of the European Commission (2017).

Another general limitation of the models is the assumption of perfect foresight, whereby all information throughout the entire modelled time period[1] is known to the model. In reality, however, there exist several uncertainties, concerning everything from political decisions to fuel markets and weather patterns. This means that when it comes to variable generation, such as wind power, the EPOD model only considers the impact of the inherent variability of the supply. If uncertainty were also to be considered, this would likely increase curtailment and the use of expensive peak plants, since the dispatch of other, more inflexible plants cannot be optimally planned. A consequence could be that the variability in the electricity prices would be underestimated, as will be discussed further below.

The temporal resolutions in the ELIN and EPOD models are also a potential limitations. ELIN has a low time resolution, which is likely to favour variable generation in general and wind power in particular. The time slices in ELIN are primarily based on demand variations, which generally show a low correlation with wind power variations, which means that variations in the wind power profiles will be cancelled out by averaging. Therefore, the work of this thesis does not focus on finding cost-minimal capacity expansion scenarios but instead uses ELIN mainly as a scenario generator for the EPOD model and focuses on the mechanisms that can be identified therein. Improved time representations are currently being developed for the ELIN model, although no results are available at the time of writing.

The ELIN model, as used in this thesis, does not include investment in storage technologies or DR options. This primarily disadvantages solar power, in that storage or DR on the time scale of hours can significantly increase the possibilities to match solar power generation with demand. Wind power generally requires longer storage times, which makes storage more expensive than the alternatives, which include expansion of transmission or complementary generation capacities. Preliminary, and heretofore unpublished, results from ELIN modelling, in which storage is included in the model, seem to support the notion that storage is primarily used in combination with solar power, whereas wind power benefits more from substantial transmis-

[1] For ELIN, this means the entire period from Year 2010 to Year 2050, and for EPOD this means the entire modelled year.

sion expansion, or other strategies, such as using surplus power to produce electrofuels. In the Net Metering scenario studied in Paper III, post-optimisation calculations indicate that storage would be economically viable in the presence of high penetration levels of solar power. However, for the purpose of the study, which is to investigate how high levels of solar power might affect electricity trade and transmission congestion, the results are still useful.

In Paper III, we also chose a time resolution of 3 hours, in order to include all the model regions and constraints for cycling costs and DC load flow, while still ensuring reasonable computational times. Although a 3-hour time resolution appears to be sufficient to capture cycling in thermal power in combination with high levels of wind power, a higher time resolution might be needed to represent fully the variability of solar power. If so, it is likely that the variability in the marginal cost of electricity, and thereby congestion, caused by solar power in the system is underestimated when using a 3-hour resolution.

The time resolution in Papers V and VI, where solar power and batteries are in focus, was chosen to be 1 hour. For individual households, where there is no smoothing effect from a geographic spread of production facilities, there could be significant variability on even shorter time scales. However, we still deem the time resolution to be acceptable, considering that a relatively small battery capacity, which is present in most households in almost all the investigated cases, is sufficient to eliminate fluctuations on shorter time scales (see Nyholm, Goop et al., 2016, for a more detailed discussion).

The household modelling in Papers IV–VI also assumes that all household participate fully. Thus, the results must be interpreted as an upper limit of the potential for DR (Paper IV) and an upper limit for investment in residential PV and battery systems (Paper VI). The sensitivity analysis in Paper V indicates, however, that if only a fraction of the households invests in PVs and batteries, the optimal installed capacities per household will be larger due to the reduced feedback effect.

For households to respond to hourly price signals or control space heating loads in a system-optimal manner, some type of automatic control system would be required. Although we do not investigate how such a control system would be designed, technologies that perform this function are available on the market today. Therefore, it does not seem unreasonable to assume that such technologies would be accessible to households in a future scenario. However, it is possible that there would be an additional cost, which could reduce the profitability of PV and battery investments, as well as the profitability of DR participation.

The perfect foresight assumption made in the household investment optimisation in Papers V and VI allows the households to respond to a known price curve, without directly affecting the price. This is not an entirely realistic set-up and could lead to an overestimation of the economic benefits of market arbitrage using batteries.

Paper VI allows us to assess the effects of different grid tariff structures on the aggregated household load curve, although we are not able to investigate how loads change within the local distribution networks. While the literature suggests that power tariffs would be more cost-reflective than the current commonly used tariff systems, our method does not allow us to calculate the actual benefit in terms of cost reductions for DSOs. Instead, we are limited to studying how the revenues are affected by the different tariff structures.

The method applied in Paper II does not contain a grid model to represent the distribution grid. Thus, we ignore any effects due to grid topology and the actual power flows within the grid. Our method captures only the effects of energy exchanges, depending on how the different production profiles and the demand profiles of the different voltage levels vary in relation to each other. The main advantage of the model that we apply is that it enables us to model an entire year and that it allows the dispatch of the centralised power plants to adapt to changes in the level of distributed generation.

As discussed in Chapter 5, the EPOD model tends to exaggerate the ability of Nordic hydropower to dampen the variations in the marginal cost of electricity. The model also assumes perfect foresight and thereby disregards uncertainties on both the demand and supply sides. These issues result in the marginal cost from the EPOD model being significantly less volatile than actual spot prices are likely to be. The lack of uncertainty in the model (as mentioned above) probably also contributes to an underestimated price volatility. In Papers V and VI, the marginal cost represents the future electricity spot prices, and these limitations in the model are therefore likely to have an impact on the results. In part, we can observe the effects of price volatility in the analysis in Paper V, where the highly volatile Green Policy price curve is compared with the stable Climate Market and Regional Policy prices. The results show that the Green Policy price curve gives substantially higher investments in batteries than the Climate Market prices, despite similar levels of solar PVs. This means that a better representation of price volatility in the model would most likely increase the incentives for households to invest in batteries.

7.2 Generalisability of the results

The studies presented in this thesis are all based on case studies, in the sense that they describe a specific system under specific conditions. A relevant question is therefore how general are the conclusions that we draw from the results.

One example is that the household modelling in Papers IV–VI is limited to Swedish households. In some respects, Swedish conditions are rather uncommon. For example, the market share of electric space heating is relatively high in Sweden, leading to a comparatively high technical potential for DR as investigated in Paper IV. On the one hand, the potential for DR in other countries could be lower than that observed in our results. On the other hand, a possible strategy for decarbonisation of the heating sector is to increase the use of electricity for heating, especially as natural gas is currently a major energy source for heating. In a system that is more dominated by thermal power generation, the benefits of DR are also likely to be greater than in Sweden, where hydropower acts as a buffer and limits the usefulness of the added flexibility that DR provides.

The incentives for households to invest in PVs and batteries, found in Papers V and VI, might be even stronger at many other locations, since the conditions for solar PVs are not optimal in Sweden. Another reason why the incentives might be stronger under different conditions is that the storage capacity of Swedish hydropower dampens variations in the electricity price, which eliminates some of the potential benefits of battery storage. To understand more fully how the specific conditions affect the results, more case studies in different settings are needed for comparison, both for residential PV and battery investment and for space heating DR.

Papers IV–VI apply two different methods for incorporating household-level phenomena into a large-scale dispatch model. In Paper IV, we include the flexibility of DR in households in the total system optimisation, whereas in Papers V and VI, the households and the centralised system are optimised from different perspectives. These differences in perspective must be considered when interpreting the results. Including DR in the optimisation shows the potential for utilising that resource to benefit the system as a whole. However, a consideration of the optimal strategy to provide incentives for households to participate so that they can provide access to those benefits is beyond the scope of the present work. Nevertheless, the iterative modelling approach used in Papers V and VI focuses on the incentives for households to make investments and how such investments will affect the system.

In all the modelling performed for this thesis, there are several important factors that are unknown regarding the future systems that we investigate. When discussing the future of the European electricity system, the relevant unknowns include how the future markets will be designed, and whether there are any unexpected technological breakthroughs or sudden political turnabouts. Historically, such unknowns have made predictions about a system as complex as the energy system nearly impossible (Smil, 2000). Therefore, it is important that the results of this thesis are not interpreted as forecasts or predictions. The focus must instead be put on comparative analyses of different scenarios and what Schwanitz (2013) refers to as the "explanatory power" of the models. We interpret this as the ability of the models to illuminate mechanisms that are important for our understanding of how the system works.

7.3 Implications for policy and research

In Papers I–III, the focus is on the usage and role of the electricity grids in integrating variable generation. The studies demonstrate the importance of modelling congestion and other grid issues while including a description of an adaptable supply system. It is also clear from the results that distributed resources, such as DR or small-scale PVs and batteries, will influence trade patterns and congestion in the transmission grid.

With the iterative method that is applied in Papers V and VI, we show that the household investments in PVs and batteries have the potential to influence significantly the electricity market. This result is important for future research on the subject, as it means that the feedback that occurs between electricity market prices and investments in PVs and batteries at the household level cannot be ignored. This feedback is also important to consider in the design of the future electricity market, since the market has to be able to handle the participation of household consumers. If storage systems or DR are included, it is likely that this consumer participation will happen through automated "smart" systems. Avoiding potential problems with, for example, peak load concentration will probably require a market with real-time pricing or aggregators who optimise the utilisation of the available flexibility.

The results described in Papers V and VI also show that grid tariffs play an important role in determining how strong incentives the households have to invest in solar PVs and batteries. Moreover, the results in Paper VI show that energy-based grid tariffs might create opportunities for households to decrease significantly their costs for grid services by investing heavily in PVs and batteries, which would lead to a decrease in revenues for grid operators. However, a risk is that the grid operators' costs would not decrease correspondingly. Therefore, it will be necessary for grid operators to find tariff structures that improved reflect their own costs. Power tariffs, perhaps in combination with a partial shift to a higher fixed tariff, are likely to lead to better cost-recovery. The results in Paper VI demonstrate that a direct annual power tariff could be problematic, in that it would lead to a concentration of peak loads. A more indirect tariff, such as a monthly power tariff or a smoothing variant, could be more beneficial in terms of the aggregated household load. The distribution grid tariffs must therefore be carefully designed and evaluated bearing in mind how they affect the expansion of residential solar power, batteries, and DR.

CHAPTER 8

Conclusions and outlook

This chapter first gathers the main conclusions drawn from the work in this thesis under each of the research questions posed in Section 1.1, and then provides some suggestions for future work.

8.1 Main conclusions

How do distributed solar power and DR affect the usage of and congestion in the European transmission grid?

The results from Paper I demonstrate that variable renewable generation with near-zero marginal costs can give rise to congestion during production peaks, when generation exceeds local demand and the export capacity of the transmission grid becomes insufficient. This drives down the marginal cost of electricity and creates a marginal cost difference relative to the surrounding regions, which indicates that the system is congested. Surpluses of solar power, the output of which is concentrated to day-time, generally start occurring at lower penetration levels than for wind power, as observed in Paper III. In Paper III, with high penetration levels of solar power, the total solar generation in the system is found to cross-correlate with system congestion 6–9 hours later, i.e., congestion arises mainly in the evenings when the sun has set, although electricity demand remains high. In contrast, wind power correlates with more slowly evolving variations in congestion on a time scale of weeks.

In Paper I, we show that the potential of DR to reduce transmission congestion is highly dependent upon the mechanism through which the congestion arises. The study includes load shifting up to 24 hours, which is found to be sufficient to significantly reduce demand-related congestion. Congestion caused by wind power, however, can not be eliminated by DR, due to the difference in time scales between wind power variations and the load shifting, and because the wind power capacity is often located in regions with relatively low demand.

How do distributed generation, storage, and DR influence the operation of centralised generation and the electricity market?

Papers IV–VI show that household-level generation, storage, and DR can all significantly affect the centralised generation system. Automated DR in electric space heating has the potential to realise substantial savings in terms of the total running cost of the centralised electricity system. Smart temperature control, i.e., lowering the temperature at times when nobody is at home, can significantly lower the total system running cost. Load shifting can also contribute with considerable cost savings, although its potential is strongly dependent upon the generation mix in the centralised generation system, and we observe significant savings only in a scenario with very high levels of variable renewables. The effects of smart temperature control and load shifting are additive, i.e., the savings from automatic temperature control do not reduce the savings from load shifting and *vice versa*.

In Paper III, we observe that solar power has strong effects on the marginal cost of electricity at relatively low penetration levels, due to its output being concentrated to daylight hours. This characteristic production pattern plus the fact that it is not economically viable to shut down inflexible thermal power plants during a few hours every day, often drive the marginal cost to near-zero levels during solar peak production. There is also a risk of a peak in the marginal cost due to the ramping required every evening as the sun sets and the demand still remains high.

Partly due to the strong effects of solar power on the marginal costs of electricity, household investments in PVs and batteries also cause significant market feedback effects. This means that household investments in PVs and batteries have an impact on the marginal cost of electricity that is sufficiently strong to decrease significantly the profitability of the investments. The observed feedback shows that when investigating household investments in a future setting it is often not sufficient to use only a predetermined electricity price curve.

How strong are the economic incentives for households to invest in PVs and batteries in the future and what are the factors that drive those incentives?

Although the expansion of residential solar PVs has to date been driven to a large extent by subsidies, we show that with future investment costs and electricity prices, the economic incentives for households to invest in PVs and batteries are strong. The incentives are, however, highly dependent upon the volatility of the electricity prices, and thereby on the composition of the centralised generation system. The price volatility creates opportunities for using batteries for market arbitrage, which increases their profitability. The presence of battery capacity in a household also increases the value of solar PVs and *vice versa*, which creates a synergistic effect between battery and PV investments. Our sensitivity analysis shows that the profitability of batteries relies more strongly on the presence of PVs than the profitability of PVs relies on the presence of batteries.

As expected, the investment costs associated with PVs and batteries are also a determinant of the strength of the incentives for household investments. However, household-scale solar PVs are a proven technology and even using conservative estimates of the future investment costs, there are significant incentives for households to invest. Battery systems are, for these applications, a more immature technology, and the profitability of household investments in batteries is dependent upon the realisation of the expected investment cost reductions.

The grid parity effect also plays a major role in the incentives for household investments in solar PVs. The grid parity effect means that solar power placed behind the meter of private consumers usually does not compete with the wholesale price but with the retail price of electricity, including grid tariffs and taxes. As shown in Paper VI, the grid tariffs can be a powerful driver for household investments in PVs and batteries. The type of grid tariff, whether it is based on energy or power demand, determines whether it primarily drives PV investments or battery investments.

To what extent would it be beneficial to deploy storage and renewable generation in a distributed, as opposed to centralised, form?

Currently, distributed generation is expanding mainly with respect to solar PVs. Our results show that solar PVs in low-voltage distribution grids can reduce distribution losses by displacing energy imported from the higher-voltage levels. However, we observe that in the absence of storage or load shifting, the losses start to increase again at local penetration levels of around 15 %. This can be viewed as the upper limit for loss reduction benefits; taking local grid limitations into account would lower this value even further. We also see that the potential for solar PVs to reduce the maximum power flow between voltage levels is highly limited as long as the solar power peak and the demand peak occur during different seasons and no local storage is installed. However, the distributed form can confer other benefits, such as engaging the public in energy issues and spreading the ownership of generating capacity.

Turning passive household consumers into active participants in the transformation of the electricity system could be an important factor in speeding up the expansion of renewable energy sources. However, it is crucial that policy makers carefully consider the incentives that private consumers face. For example, a grid tariff structure with poor cost-reflection might stimulate over-investment in PVs and batteries and dispatch of storage, which is suboptimal from a systems perspective.

What are the benefits and disadvantages of different approaches to incorporating distributed generation, storage, and DR into large-scale electricity system models?

The methods adopted in this thesis for incorporating dispatch of storage technologies and DR into electricity system models can be considered to apply either a systems perspective (Papers I and IV) or an actor perspective (Papers V and VI). With the systems perspective, or central planner perspective, the usage of all resources in the system is optimised with respect to one common objective, to minimise the total system cost. In contrast, the actor perspective means that the usage of resources is optimised using different objectives, depending on which actor controls each resource.

In Papers I and IV, in which the systems perspective is used, the load shifting is optimised to give the lowest possible total system running cost. The advantage of the systems perspective is that the results show the potential benefits to the system, as well as how these benefits can be achieved in terms of load shifting patterns. A drawback of applying the systems perspective is that there is no representation of the mechanism through which the optimal behaviour is realised. There are several potential mechanisms, such as a system allowing household equipment to be controlled by an aggregator or to respond automatically to a price signal. However, each of these mechanisms must be studied further to assess its effectiveness and efficiency, as well as to avoid any unintended consequences for the system.

The iterative method used in Papers V and VI combines system cost minimisation for the centralised system with household consumers minimising their own individual electricity costs. This approach has the benefit of representing the actual economic incentives for households to invest in PVs and battery storage and to use these capacities to lower their own electricity cost. This method, however, is more complex and introduces several uncertainties, since it requires assumptions regarding the future taxes and fees that households will face, as well as regarding the mechanism through which households interact with the electricity market. In addition, the method does not reveal the potential for the household battery capacity to benefit the system if used in a system-optimal way.

8.2 Future research

There are several possible future directions for the work presented in this thesis. As Papers IV–VI only include Swedish households, a first step would be to expand the household description to other regions. In regions with a predominantly thermal power system, both the benefits of DR and the incentives for households to invest in battery storage are likely to be significantly greater. The studies conducted in this thesis focus exclusively on households, although the same technologies might be used by industries, which is an interesting topic for future studies.

It would also be interesting to further expand and improve the ELIN model to investigate the competition between different variation management techniques, such as battery storage, DR, and transmission grid expansion. Such an analysis would also provide a better understanding of the roles that distributed generation, storage, and DR could play in the long-term development of the electricity system.

More broadly speaking, further research and model development is needed to incorporate distribution grids in greater detail into large-scale electricity system models. The work conducted for this thesis has shown that it is highly likely that generation, storage, and DR in households connected to low-voltage distribution grids interact strongly with the centralised generation and transmission systems. Although the integration of these distributed technologies into distribution grids has been studied in isolation, more work is needed to link this to the dynamics and evolution of the centralised electricity system.

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Appendices

A Input data

A.1 Map of model regions

A.2 Technology input data

Technology	Life-time [years]	Inv. cost [€/kW] 2030	Inv. cost [€/kW] 2050	Fix O&M [€/kW,yr]	Var O&M [€/MWh]
Hard coal					
Condense	40	1,550	1,550	27.4	
CHP/BP	40	1,550	1,550	27.4	
CCS	40	2,390[a]	1,970[a]	47.9	1.55
CCS cofire	40	2,790[b]	2,370[b]	57.5	1.86
Lignite					
Condense	40	1,250	1,250	31.7	
CHP/BP	40	1,250	1,250	31.7	
CCS	40	2,190[a]	1,770[a]	44.9	1.36
CCS cofire	40	2,590[b]	2,170[b]	53.9	1.63
Natural gas					
GT	30	380	380	8	
CCGT	30	750	750	13	
CHP/BP	30	780	780	16.6	
CCS	30	1,170[a]	1,020[a]	41.2	2.8
Nuclear	45	4,200	4,200	57.6	
Bio & waste					
Condense	40	2,500	2,500	50	
Waste	40	9,060	9,060	443	
CHP/BP	40	2,900	2,900	57.6	
Intermittent					
Wind (land)	25	1,320	1,190	27.4	
Wind (sea)	25	2,190	1,880	72.7	
Solar PV	25	1,280	660	27.4	

Source: Assumptions from the World Energy Outlook by the IEA, 2011–2014 editions (International Energy Agency, 2011, 2012, 2013, 2014), extrapolated after Year 2035

[a] Costs for CCS from the Zero Emission Platform (ZEP) (2011)

[b] ZEP cost for CCS plus IEA cost for co-firing of biomass