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Exploring the future low-carbon electricity system: impacts of nuclear power and demand patterns

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Abstract

To achieve the climate goals set by the Paris Agreement, the global electricity system is expected to transition towards a low-carbon electricity system. The future low-carbon electricity system is uncertain regarding both generation and demand. First, the cost of variable renewable energy (VRE) technologies, such as wind and solar, has been decreasing over the past decade and the share of VRE in the electricity system is increasing. This trend is likely to continue for the foreseeable future. However, there is no consensus as to whether the goal of deep decarbonization of the electricity system can be accomplished without large cost escalation if nuclear power and fossil fuel plus carbon capture and storage (CCS) are excluded. Second, the future electricity demand is highly uncertain due to economic growth, e-mobility, electric heating, electric cooling, etc. These factors affect not only the volume of annual electricity demand, but also the inter-temporal electricity demand pattern. The change in demand pattern may affect a low-carbon electricity system with a high penetration level of wind and solar, as such a system is less capable of load following, as compared with the conventional electricity system based on dispatchable thermal power plants.

This thesis investigates the impacts of nuclear power and demand patterns on the future low-carbon electricity system, and addresses the following research questions: *What is the cost of a future low-carbon electricity system without nuclear power for Sweden*?; and *How will the electricity demand pattern affect the electricity system cost and the electricity supply mix?* A greenfield techno-economic cost optimization model with a high temporal resolution for the electricity system is developed and used to answer these questions.

The results of this work reveal that including nuclear power in the electricity system reduces the nodal net average system cost by 4% for Sweden. This implies that the economic rationale for Sweden as a country to invest in nuclear power is limited if there is a transition towards a low-carbon electricity system in Europe. In addition, we find that varied electricity demand patterns (seasonal and diurnal variations) affect only slightly the electricity system cost, except for the case of summer peak, where the system cost may increase by up to 8%. The demand pattern may have a stronger impact on the electricity supply mix, especially solar and storage capacities, than on the electricity system cost.

This thesis contributes to a better understanding of the potential future low-carbon electricity system. The results are beneficial in identifying the implications for the planning of the future electricity system, policy support for low-carbon technologies, and demand profile treatment for modeling studies.

Keywords: Low-carbon electricity system, energy system modeling, variable renewable energy, nuclear power, net system cost, demand pattern, electricity system cost, electricity supply mix

Appended publications

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

I. Kan, X., Hedenus, F., & Reichenberg, L. (2020). The cost of a future low-carbon electricity system without nuclear power–the case of Sweden. *Energy*, *195*, 117015. DOI: 10.1016/j.energy.2020.117015

II. Kan, X., Reichenberg, L., & Hedenus, F. (2020). The impacts of the electricity demand pattern on electricity system cost and the electricity supply mix: a comprehensive modeling analysis. Submitted to journal.

Paper I: HF and RL conceived the study, with contribution from XK. XK developed the model, analyzed the results. XK, HF and LR wrote the paper. All authors edited and approved the final version of the manuscript.

Paper II: HF and RL conceived the study, with contribution from XK. XK developed the model, analyzed the results. XK and LR wrote the paper with contribution from HF. All authors edited and approved the final version of the manuscript.

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Xiaoming Kan

Gothenburg, January 2021

Contents

Introduction

Currently, the electricity system is the largest emitter of CO_2 worldwide [1]. Meeting the ambitious goals of restricting the global temperature rise to well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C set by the Paris Agreement, would likely require reducing the CO_2 emissions from the global electricity system in the coming decades [2]. Various low-carbon technologies, such as wind and solar power, carbon capture and storage (CCS) and nuclear power, are possible options for decarbonizing the electricity sector. The wide availability of wind and solar power and the decrease in associated costs seen in the past decades make wind and solar promising generation technologies for the future low-carbon electricity system [3]. A low-carbon electricity system based on variable renewable energy (VRE) differs from the conventional electricity system based on dispatchable thermal power plants. The chief difference is that an electricity system with a high penetration of VRE is less capable of load following, due to the intermittency of VRE resources [4]. Dispatchable electricity generation resources, such as hydropower, biomass, and biogas, are constrained by regional resource endowments and environmental regulations. Variation management strategies (VMSs), such as transmission and storage, are potential options to deal with the variable generation of wind and solar power [5-7]. Several studies have shown that a future low-carbon electricity system based on VRE in combination with transmission and storage is technically feasible [5-10] and the average electricity cost is comparable to the cost of the current system [6, 11-14]. However, some other studies argued that a low-carbon electricity system based on VRE plus transmission and storage may face large cost escalations if firm low-carbon technologies, such as nuclear power and fossil fuel-firing plus CCS, are excluded [15-17]. For the case of Sweden, nuclear power generated 41% of the annual electricity supply in 2014 [18], but the nuclear fleet is aging and decommissioning is planned in the coming decades for economic reasons. Therefore, it is important to understand how the exclusion of nuclear power may affect the Swedish electricity system, especially the electricity system cost.

Apart from the technology options for electricity generation, the future low-carbon electricity system faces uncertainties and challenges related to the evolution of electricity demand. In reality, economic growth, climate change, e-mobility, electric heating, electric cooling and technological innovation may exert strong influences on the future electricity demand, affecting not only the annual electricity consumption but also the demand pattern [19-28]. Some studies have presumed that radical changes in the electricity demand pattern may strongly affect the electricity system [19, 23, 27, 29]. These effects might be more evident in a low-carbon electricity system with a high penetration of VRE, given that it is less capable of load following due to the intermittency of VRE resources, as compared with the conventional electricity system based on dispatchable thermal power plants [4]. However, the potential change in demand pattern is not considered in many energy system modeling studies [6, 30-37]. In those studies, rather historical demand profiles are directly used or linearly scaled up to a new value for the future electricity demand. Although the change in volume of the annul electricity demand might be considered, the inter-temporal pattern of the demand profile remains almost the same. Thus, regarding the large uncertainty of the future electricity demand pattern, it is important to understand the impacts of the electricity demand pattern on electricity system cost and the electricity supply mix.

Aims

This thesis focus mainly on the above issues surrounding the generation and demand sides of the future low-carbon electricity system. Two papers are included, and the specific aims are to:

1. Investigate the cost of a future low-carbon electricity system without nuclear power for Sweden, under conditions with different levels of interconnecting transmission grids within Sweden and between Sweden and neighboring countries;
2. Evaluate the effects on the system cost and the electricity supply mix of applying different demand patterns in energy system models.

Contributions

Paper I identifies the generation and variation management technologies that are cost-effective to invest in for the future low-carbon Swedish electricity system. It introduces a new method to quantify the nodal net average system cost (NNASC) for a country or region in an interconnected electricity system. This concept incorporates the system-wide capital and operational costs of generation and transmission, profit of trade (revenue from exporting electricity minus the cost of importing electricity), and congestion rent. Compared with studies [16, 38, 39] investigating the focused country in isolation, assuming no cross-border electricity trade or following historical electricity trade pattern, the NNASC approach can reflect the impact of electricity trade on the system cost for a specific country or region in an interconnected electricity system. Through investigating the cost difference for Sweden with nuclear power relative to a system without nuclear power, the economic benefits of including nuclear power for the future low-carbon Swedish electricity system is analyzed.

Paper II evaluates the impacts of different electricity demand patterns on the electricity system cost and electricity supply mix. The conditions under which the choice of demand pattern is influential are identified. This provides useful information to energy system modelers as to whether or not misleading results will be produced if they continue to employ historical electricity demand profiles as inputs to the model.

Background

This chapter gives a brief background of the transition of electricity system. In Section 2, the different low-carbon generation technologies included in this study are introduced and their pros and cons are presented. Section 3 reviews the VMSs. Finally, Section 4 describes the evolution of the electricity demand pattern.

Transition towards a low-carbon electricity system

In 2018, electricity and heat production accounted for 41% of global CO_2 emissions, being the largest CO_2 emitter [40]. The demand for electricity is expected to grow with increases in GDP and population, and with extensive coupling with other sectors. If the increased electricity demand is met by generation using conventional fossil energy, there will be a substantial increase in CO_2 emissions. Thus, decarbonizing the electricity sector has a pivotal role to play in achieving the global CO_2 emissions reduction target. Currently, there are several mature low-carbon electricity generation technologies, e.g., nuclear power and wind and solar power. In addition, decarbonizing the electricity sector is generally regarded as being less expensive compared with other sectors such as transport and energy-intensive heavy industries[41]. According to the 5th IPCC report, to limit the rise in average global temperatures this century to 2°C above pre-industrial levels, the electricity sector needs to be deeply decarbonized towards the second half of the 21st Century [1]. This implies significant investments in low-carbon generation technologies.

For Europe, the European Commission has presented its strategic long-term vision for a climate-neutral economy by Year 2050 [42]. To achieve this goal, more and more wind and solar power are invested in Europe for electricity supply. Apart from wind and solar power facilities, new nuclear power plants are being constructed in Europe. Other low-carbon electricity generation technologies include hydropower, biomass and biogas. In the following section, these technologies are briefly introduced.

Low-carbon electricity generation technologies

Wind and solar power exhibits a large global technical potential and the associated costs have been decreasing over the past decades [3], see Fig. 1. The reduction in cost is estimated to continue in the coming decade due to economies of scale and learning by doing [3, 43]. According to the International Renewable Energy Agency (IRENA), more than half of the commissioned projects for onshore wind and solar PV in Year 2020 will produce cheaper electricity (lower expected levelized cost of electricity; LCOE) than new fossil fuel-fired power plants without subsidies [43]. Wind and solar power accounted for 8.2% of global electricity generation in Year 2019, while the corresponding share in Year 2013 was only 3.4% [40]. Given the resource availability, technological maturity, and economic competitiveness, wind and solar are likely to be widely deployed globally. However, wind and solar power has limitations. The power outputs of wind and solar change throughout the course of a day, season and year, depending on the weather conditions. Solar power, in particular, has a natural diurnal variation, as there is no solar radiation at night. The output of wind power also has a diurnal variation, with relatively more wind energy produced at night than during the day in many locations [44]. However, the diurnal variation of wind power is less pronounced than that of solar power. In addition, both wind and solar power outputs vary over large geographic areas, albeit the variation is usually larger for wind due to different wind conditions resulting from geographic diversities [44]. Due to the fluctuation of weather conditions, there may be periods when wind and solar produce more electricity than is actually demanded, which will lead to curtailment.

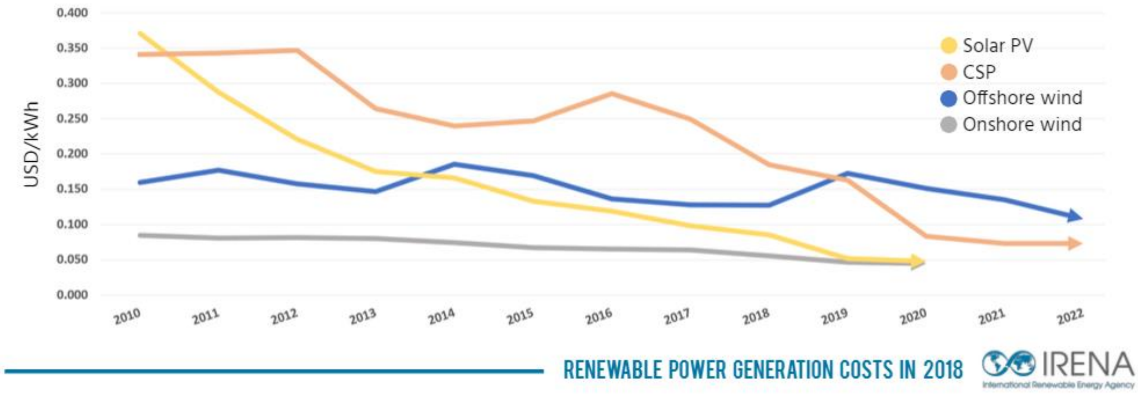

Fig. 1. The development of LCOE for renewable generation technologies (IRENA, 2019).

The future of nuclear power in Europe is uncertain. Germany, Belgium, and Switzerland have decided to phase out nuclear power, while Finland, France, UK and Slovakia are building new nuclear power plants. Apart from the problem of social acceptance linked to perceptions of radiation risks, the current investment cost for the third-generation nuclear power is very high. The investment cost of the two nuclear power plants (Olkiluoto 3 and Flamanville 3) currently under construction in Europe is estimated to be as high as 10000 $/kW [45]. This cost could probably be decreased through international standardization and the massive construction of new nuclear power plants. Similar to the case of Europe, the investment cost of nuclear power plant remains high in USA [45]. The situation is more optimistic for nuclear power plants in Russia and in Asian countries, where the investment costs for on-going projects are estimated at around 4000 $/kW [45]. The cost escalation for nuclear power plant in Europe and USA is mainly driven by the project delay and regulations regarding large-scale construction projects set by strict nuclear standards [45, 46]. As for the operation of nuclear power, it usually runs as the base load. To integrate more effectively nuclear power with VRE, flexible operation of nuclear power has been proposed to provide flexibility to the future low-carbon electricity system [47, 48]. However, this will reduce the utilization time for nuclear power, leading to a higher LCOE for nuclear power.

Reservoir hydropower (hydro reservoir) and run-of-river hydropower (hydro RoR) are conventional renewable energy technologies that are used worldwide. Hydro reservoir is considered to be a flexible power source, as it is quick to react and is capable of providing full capacity within a timeframe of seconds to several minutes [49, 50]. For hydro reservoir, water can be stored for days, months or even years, depending on the reservoir size, and released whenever electricity is needed [51]. The resource availability for hydro power varies from one geographic region to another. In Europe, due to environmental regulations, the capacities of hydro reservoir and hydro RoR are not likely to increase in the future. One important environmental regulation related to hydro reservoir is the minimum environmental flow [52, 53], which mandates that a certain proportion of the mean annual inflow be released to satisfy the downstream ecosystem and human needs for water.

As for biomass, it might be used as the source material for other sectors, such as transport and industry. Thus, the price for biomass might remain high due to scarcity of supply. In addition, large yields of biomass require a lot of land, which may cause external problems such as the security of food supply and deforestation [54]. Biogas can be produced from wood, manure, agricultural residues and waste. However, due to the scarcity of the biomass primary resource, the fuel supply for biogas is limited.

Variation management strategies

Although the output from wind and solar power fluctuates over time depending on the prevailing weather conditions, there are several ways to provide the flexibility needed to handle the variable generation associated with wind and solar on different time-scales of hours, days and seasons [5-7, 44]. These solutions, which are termed *variation management strategies* (VMSs), need to be able to: shift electricity generation temporally (storage); move electricity generation spatially (trade through transmission grids); shift or curtail electricity demand to adapt to the variable generation of VRE (demand-side management; DSM); and curtail generated electricity when it is not needed. The main VMSs considered in this thesis are shown in Fig. 2.

First, energy storage can shift the production of VRE over time. Energy storage can save wind- and solar-generated electricity from periods when there is overproduction to periods when the power output of VRE is lower than the demand. For this purpose, there are several mature storage technologies, such as different battery technologies and pumped hydropower. In addition, the surplus electricity can be applied to produce hydrogen as long-term storage.

Second, the variation of VRE can be smoothed through the exploitation of a diversity of geographic locations when selecting the VRE generation sites and connecting these sites with transmission grids. The transmission grids enable the transfer of electricity from regions where

VRE generators are currently producing electricity to areas where the demand is currently not satisfied.

Third, DSM technologies can shift or shed electricity demand so as to fit the fluctuating generation profile of VRE. The potential of DSM can be further increased when there is large-scale sector coupling, as this provides new flexible demand, such as electric vehicle charging and electric heating in the integrated energy system.

Last but not least, the excessive production of VRE can be curtailed when the level of electricity generation is higher than the demand for electricity.

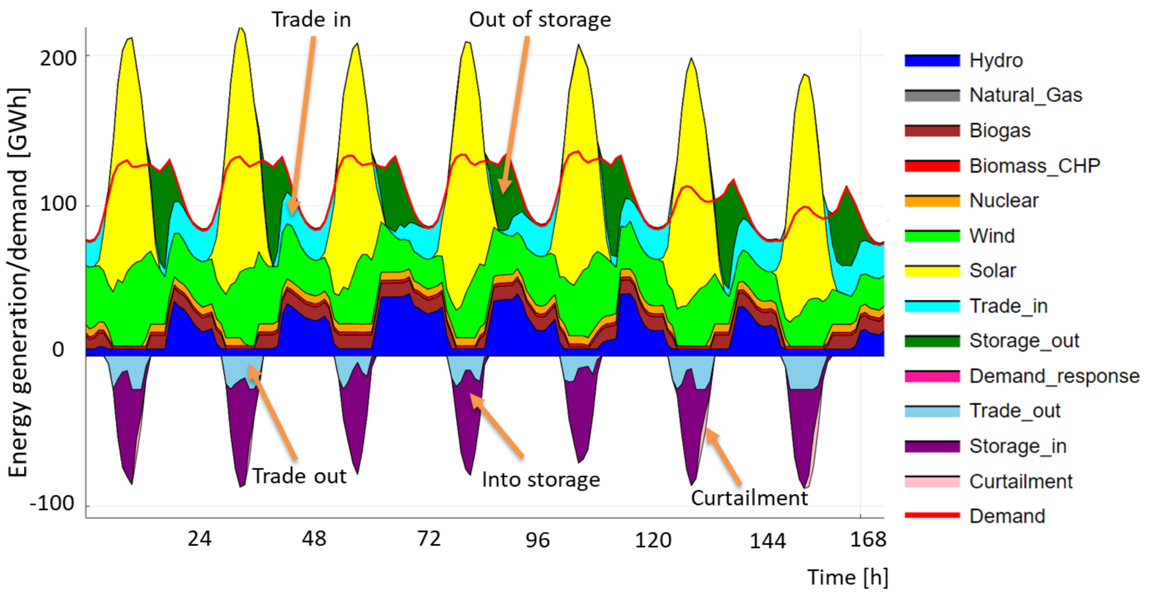

Fig. 2. Variation management strategies used in the electricity system, including storage, trade and curtailment. Electricity is stored and traded out during the daytime when the level of generation exceeds the demand. When the output of solar power ramps down sharply in the late afternoon, electricity is released from storage. During the night, there is both electricity release from storage and electricity trade-in.

Electricity demand pattern

The electricity demand pattern is reflected on the inter-temporal shape of the electricity demand profile. Electricity demand may be heavily affected by some important factors, such as economic growth, climate change, sector coupling (e-mobility and electric heating), electric cooling and technological developments. These factors influence not only the volume of the electricity demand, but also the electricity demand pattern. If there is massive diffusion of electric vehicles (EVs), the daily peak demand may change significantly depending on the charging strategies used [19]. Fig. 3 shows how different charging strategies for EVs could affect the potential demand patterns for Germany and the UK in Year 2050. Direct charging after work may lead to a very high evening peak, while the smart charging strategy may alter substantially the diurnal demand pattern through shifting the peak demand towards midday hours when there is a high output from solar PV.

As for the seasonal demand pattern, the widespread adoption of electric heating may drive up the winter peak demand, while the large-scale use of electric cooling may result in a higher peak demand in summer. This implies different seasonal demand patterns. Fig. 4 shows the historical and the simulated future seasonal electricity demand patterns for the UK [23]. The demand in summer remains almost constant, while the winter demand increases over time, creating a more pronounced seasonal variation in the demand profile. The increased winter demand is mainly driven by the estimated substantial increase in residential heat pumps. Similar to the case of electric heating, Kannan [28] estimated that the increased use of air conditioners (ACs) may increase the summer peak in Switzerland by 2%–23% in Year 2050.

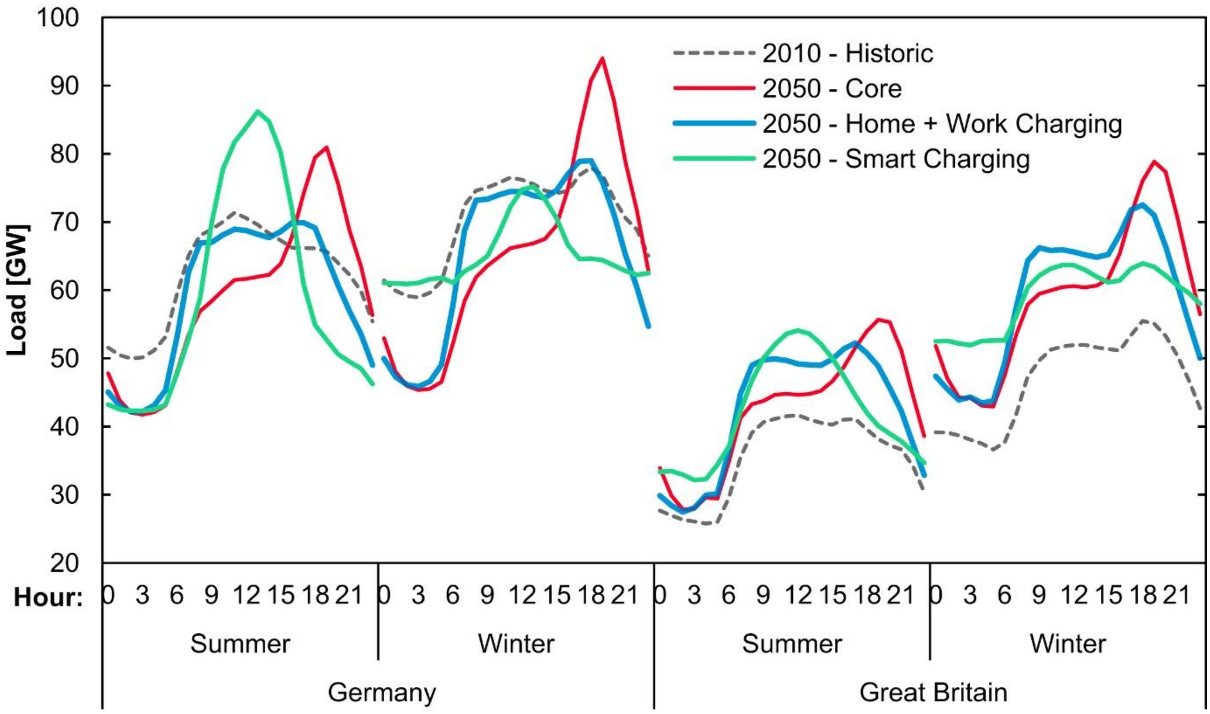

Fig. 3. Potential electricity demand profiles on weekdays under different charging strategies for electric vehicles in Year 2050 for Germany and the UK (Boßmann and Staffell, 2015).

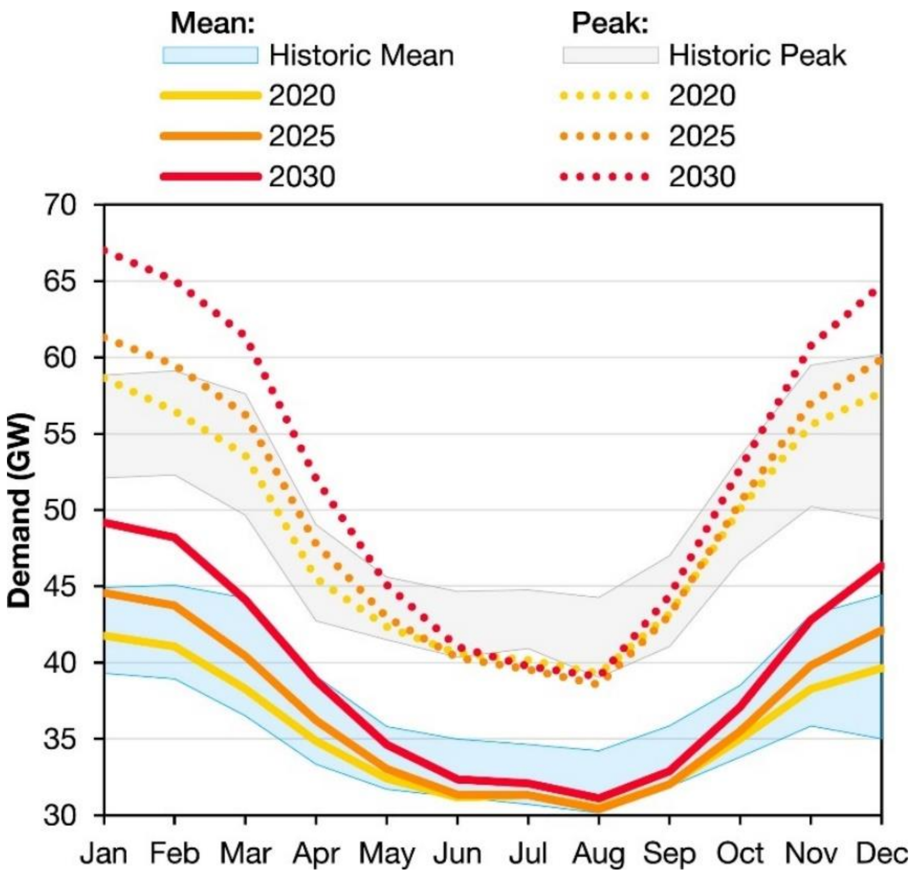

Fig. 4. The seasonal variations in the historic and simulated future demands. The shaded areas indicate the historic range from 2005 to 2015, while the lines show the simulation results for 2020, 2025, and 2030. The dotted lines indicate the peak demand within each month, and the solid lines represent the mean value (Staffell and Pfenninger, 2015).

Methodology

The principal method used in this thesis is the energy system optimization model for long-term investment planning. Energy system optimization model is widely used to generate insights for policy analysis and decision making for the electricity system. This chapter starts with a general introduction to energy system models. It is followed in Section 2 by a detailed description of the model developed in this thesis. The input data are summarized in Section 3. In Section 4, some reflections on the model and data are presented.

Energy system models

The energy system is a complex socio-technical system, such that the function and mechanism of the whole system are difficult to test and evaluate [55]. Energy system models are usually adopted to explore such a system [56, 57]. These models can show the potential energy system portfolios under different scenarios, considering resource availability, technology costs and developments, demand growth, and different energy and environmental policies [58-60]. For this thesis, we want to investigate how different generation technology options and different demand patterns may affect investments in the future low-carbon electricity system, and the corresponding system cost and electricity supply mix. To address these issues, we adopt the energy system optimization model with the focus on capacity investment as the investigation tool. The optimization model minimizes the electricity system cost, and the outcome is equivalent to that of a perfect market in which rational agents maximize their profits, even though our focus in this thesis is neither on the electricity market nor on agent behaviors.

An optimization model consists of three important parts: the goals to be met, the decisions to be made, and the constraints to be satisfied [61]. For the case of an energy system optimization model, a linear optimization approach is usually adopted to minimize the total system cost under resource, technology, environmental and policy constraints. The decision variables, which are the choices that need to be made, normally refer to the installed capacity for generation, storage, transmission, the amount of DSM, as well as the hourly dispatch. Some popular energy system optimization models include: MARKAL [62, 63], TIMES [64] and PyPSA [65].

Historically, energy system models were developed primarily for the conventional electricity system. When it comes to the modeling of an electricity system with a high penetration of VRE, several challenges arise, one of which is the representation of variability in electricity generation [60, 66]. Specifically, two important factors are related to the variability of generation: the temporal and spatial resolutions [60]. In addition, there might be extensive cooperation in the future electricity system to allow sharing of the VRE and dispatchable resources via cross-border transmission grids in a large spatial scope. Furthermore, the electricity system might be integrated with other energy sectors, to reduce the CO_2 emissions for the entire energy system. Last but not least, the transition pathway towards the future low-carbon electricity system is not yet clear and different transition pathways might result in different final configurations for the electricity system. The setups in energy system models regarding the five aspects (temporal resolution, spatial resolution, spatial scope, sectors included, and pathway) mentioned above can be influential on modeling results [59, 66], thus, affecting the system cost and capacity mix for the future electricity system. Therefore, in the following section, we characterize the energy system models along these five aspects.

Temporal resolution

Energy system models used to have a coarse temporal resolution, so as to ensure a reasonable solving time [60, 66]. Typically, these models use representative time-slices to represent a whole year [59, 60, 66, 67]. The representative time-slices might be sufficient for an energy system that is dominated by conventional thermal power plants, as the outputs of thermal power plants (e.g., coal and nuclear power plants) have little dependence upon fluctuating weather conditions [60]. An example of a model that uses representative time-slices is the TIMES model, in which 12 time-slices are used to represent the day, night and peak hours for four seasons in some studies [68, 69]. With this approach, the capacity factor of VRE follows the fixed temporal pattern of the representative days in a given time period (e.g., the same diurnal generation pattern for solar power in the summer). However, for an electricity system with a high penetration of VRE, the electricity generation varies over time depending on the weather conditions. The output of VRE (especially that of wind power) does not maintain the same temporal pattern. In this case, a small set of time-slices fails to capture the variation in generation for VRE, which may lead to an underestimation of the variability of VRE. Poncelet et al. [70] compared the impacts of different temporal resolutions on the energy system and showed that a low temporal resolution can lead to an overestimation of the share of VRE in the generation mix and an underestimation of the operational cost. Similarly, Haydt et al. [71] showed that a low temporal resolution may result in an overestimation of the penetration level for VRE and an underestimation of the installed generation capacity for VRE. Likewise, Ludig et al. [72] and Pina et al. [73] found that a low temporal resolution fails to represent the fluctuations of VRE generation, and may lead to an overestimation of the share for VRE in the generation mix. These studies [71-74] highlighted the importance of applying a high temporal resolution for the appropriate representation of VRE technologies. Therefore, an hourly temporal resolution is adopted for the studies included in this thesis.

Spatial resolution

Spatial resolution refers to the degree to which the modeled regions are spatially aggregated. It affects the representation of an electricity system with a high penetration of VRE in two ways: (i) the representation of transmission and distribution grids; and (ii) the representation of VRE resources. With a coarse spatial resolution, there may be an underestimation of the transmission and distribution cost if the subregions are treated as copper plates, and the transmission constraints inside each subregion cannot be adequately represented. However, Brown et al. [11] reported that the grid cost accounts for a relatively low share of the total electricity system cost. In addition, largely aggregated regions may fail to reflect the resource diversity for VRE, as the data for VRE resources are usually averaged over the subregion [75]. The supply potential and economic performance of VRE depend largely on the regional resource endowments. Moreover, the variations of VRE can be smoothed by locating the generation capacity in diverse geographic locations with different weather conditions and connecting them via transmission grids. Frew and Jacobson[75] compared the impact of different spatial resolutions on the electricity system and showed that, with a high spatial resolution, more generation capacity is installed on the sites with better output for VRE, which reduces the investment cost for generation capacity, as compared to the case with a coarse spatial resolution. Similarly, Hörsch and Brown [76] reported that a more detailed spatial resolution allows the model to allocate more generation capacity to the sites with better VRE resources. Therefore, it is clear that a high spatial resolution is essential for modeling generation infrastructure allocation and transmission grids.

Spatial scope

The spatial scope refers to the boundary of the electricity system covered in the model. The spatial scope is important for evaluating the impact of international electricity trade [66]. In particular, electricity can be traded from regions where VRE generators are currently producing to those areas where the demand is currently not satisfied, which indicates the share of VRE and dispatchable resources over a large geographic area. Schlachtberger et al. [6] compared the European electricity system with optimal interconnected transmission grids to a system in which all the countries are isolated from each other, and reported that isolating countries without international trade increases the electricity system cost by 30%. Similarly, Eriksen et al. [77] showed that the electricity system cost increases by 20% if cross-border electricity trade is not allowed. Likewise, Tröndle et al. [9] estimated that isolating countries for the sake of self-sufficiency in the national system increases the electricity system cost by 40%, as compared to a continent-wide electricity system in which both the VRE and dispatchable resources are shared. Pattupara and Kannan [78] incorporated international electricity trade revenue into the national electricity system cost and observed that international trade is important for the national system, as the trade revenue can offset the domestic investment cost. Therefore, it is important to reflect a large spatial scope in the model, given its influences on the electricity trade and system cost. One key implication that arises from this is the choice of spatial scope when investigating the national electricity system. One can look at the focused country in isolation, but this may underestimate the benefits of international cooperation for electricity trade via expanded transmission grids.

Sectors included

Electrification and electric fuels (power to fuel) are potential ways to decarbonize energy sectors other than the electricity system. These strategies can be achieved through, for example, replacing fossil fuel-powered infrastructures with electric ones (e.g., combustion engine vehicle vs. electric vehicle). Currently, more energy system models are investigating sector-coupled energy systems with high temporal resolution, such as PyPSA [65]. An integrated energy system, within which the electricity, heating, industrial and transport sectors are closely linked, can abate more CO_2 emissions and may provide greater flexibility from the demand side [79-81]. Brown et al. [8] investigated an integrated electricity, heating, and transport system for Europe, and showed that sector coupling may increase the electricity cost by 12% compared with an electricity system only; however, flexibilities accrued from the heating and transport sectors may reduce this cost by 17%. Similarly, Göransson et al. [82] estimated that the flexibilities obtained from the electrified steel industry and transport sector can reduce the electricity cost by 8% in Northern Europe, as compared to a case in which no flexibilities are provided. While these two studies [8, 82] assumed a certain level of sector coupling for the future energy system, it remains unclear as to what extent and in what way sector coupling will be implemented for the future energy system.

Pathway/No Pathway

In terms of the time horizon, energy system optimization models for capacity investment can analyze a single year (*No Pathway*) or a span of multiple years (*Pathway*) [59]. The *No Pathway* approach, also called the greenfield optimization approach, is widely used to investigate the optimal configuration for the future electricity system, although it does not provide insights into how to transition towards such a system [83, 84]. In contrast, the *Pathway* approach has the advantage that it analyzes the evolution of the energy system over a long time period. Specifically, the *Pathway* approach can be utilized to investigate mechanisms such as feedback effects, different learning rates for technologies, policies and regulations during the transition process, behavioral changes of the energy market participants, etc., as well as the corresponding impacts on the end-state of the energy system. Today's generation fleet and the decisions made in intermediate steps may affect the configuration of the future electricity system [83, 84]. However, given the long time horizon, if high temporal resolution is adopted, the computation time may escalate.

Regarding the transition pathway, it can be investigated through optimizing the entire transition process with perfect foresight or using the myopic optimization approach. With perfect foresight, it is possible to evaluate the cost-effective transition pathway, while the myopic optimization approach optimizes the energy system for each time-step based on the results from the former time-step. This does not necessarily yield either a cost-effective transition pathway or a cost-effective final configuration for the energy system.

Energy system model settings for this thesis regarding the five aspects

In the section above, the energy system models are characterized along five important aspects, i.e., temporal resolution, spatial resolution, spatial scope, sectors included, and pathway. For studies in this thesis, we develop a greenfield techno-economic cost optimization model REX (Renewable Energy eXpansion) for the future low-carbon electricity system. Instead of looking at the transitioning pathway or the system evolution, we focus on the static end-state of the future system. The rationale for this approach is that the *Pathway* approach introduces additional complexity and requires additional computation power and time commitment. Given the importance of temporal resolution, we use an hourly temporal resolution to represent the variability in generation of VRE, which is the core of this thesis. As for spatial scope, in **Paper I**, our focus is the Swedish electricity system, still we expand the system boundary to Europe to acquire a decent representation of cross-border electricity trade. In addition, we divide Sweden into four regions, Norway into five regions, and Finland into two regions. The other countries are modeled at the national level or are highly aggregated. We also analyze a scenario that entails an increased electricity demand, possibly due to sector coupling, although the potential flexibilities from the other sectors are not considered. For **Paper II**, we investigate the change in demand pattern (possibly due to electrification of transport, heating, etc.), and the corresponding impacts on the electricity system. In summary, we prioritize the temporal resolution to represent accurately the variability of VRE generation. As a trade-off, the spatial resolution is relatively coarse. In future studies, we hope to investigate further the spatial granularity (size of subregion) given the research aim.

The REX model

The REX model is a cost optimization modeling tool for capacity investment and the dispatch of electricity generation, transmission and storage. It employs an overnight investment approach to identify the minimum cost portfolio for the future electricity system. This entails a linear optimization problem with the objective to minimize the total annual electricity system cost, given the constraints of meeting the electricity demand, the renewable energy resource potentials, and a CO_2 emissions cap. The main decision variables in the model comprise: installed capacity for generation, storage, and transmission; the level of demand-response; and the hourly dispatch. An overview of the model and the associated generation technology options and variation management strategies are depicted in Fig. 5.

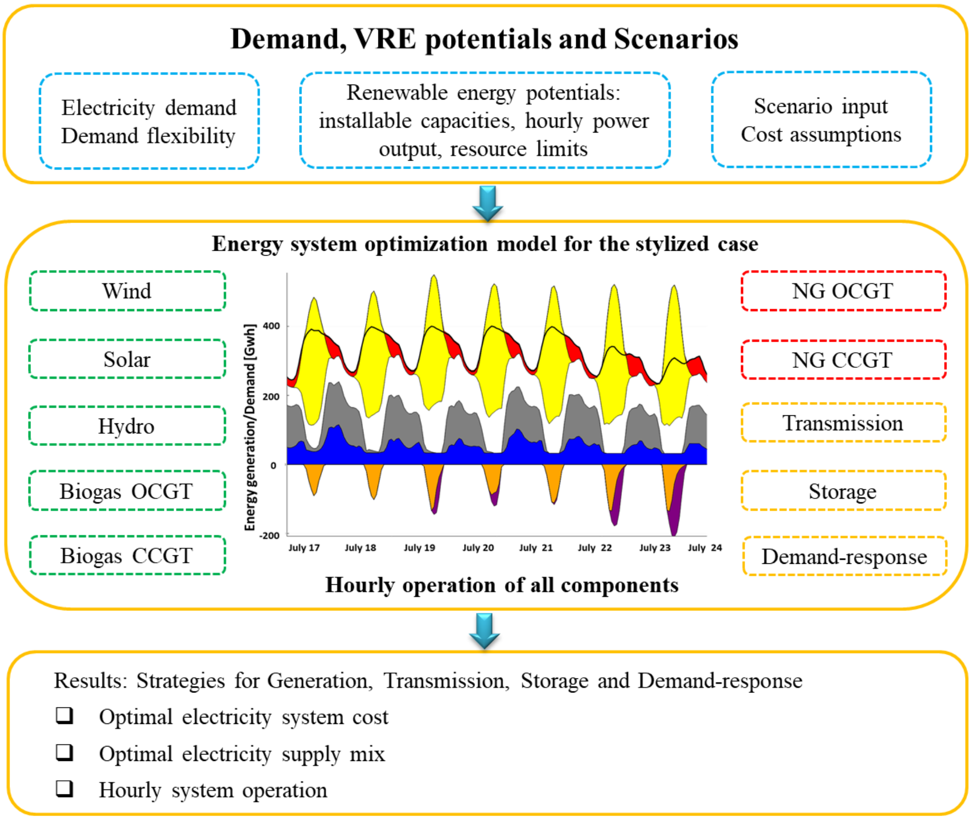

Fig. 5. Overview of the REX model. The dashed-line text boxes represent the: input data (blue); renewable generation technologies (green); fossil fuel-fired generation technologies (red); and variation management strategies (orange). OCGT, Open-cycle gas turbine; CCGT, combined-cycle gas turbine; NG, natural gas.

In the model, the nodes are labeled as *r*, *n* represents the electricity generation technology at the node, *m* represents the demand-response at the node, and *t* is the time of the year. The total annual system cost consists of the fixed annualized costs C_n for electricity generation capacity G_{rn}, fixed annualized costs $C^{storage}$ for storage S_r, fixed annualized costs $C_{rr'}$ for transmission capacity $Z_{rr'}$, variable costs R_n for electricity generation g_{rnt} and variable costs R_m for demand-response d_{rmt}. For storage and transmission, the variable cost is assumed to be zero. Therefore, the objective function of this linear optimization problem is formulated as follows:

$$Min \sum_{r,n} C_n G_{rn} + \sum_{r} C^{storage} S_r + \sum_{r,r'} 0.5 C_{rr'} Z_{rr'} + \sum_{r,n,t} R_n g_{rnt} + \sum_{r,m,t} R_m d_{rmt}. \quad (1)$$

Since $Z_{rr'}$ and $Z_{r'r}$ represent the capacity for the same transmission line rr', a coefficient of 0.5 is incorporated into the transmission cost formula to avoid double counting.

The electricity demand has to be satisfied through generation, demand-response, trade and storage.

$$\sum_{n} g_{rnt} + \sum_{m} d_{rmt} + \sum_{r'} (\eta_\gamma \gamma_{r'rt} - \gamma_{rr't}) + (\eta_s \alpha_{rt} - \beta_{rt}) \geq D_{rt}, \qquad (2)$$

where g_{rnt} is the electricity generation, d_{rmt} is the demand-response, $\gamma_{rr't}$ is the electricity traded from node r to node r', η_γ is the efficiency of transmission, α_{rt} is the discharge from storage, β_{rt} is the charge into storage, η_s is the round-trip efficiency of storage, and D_{rt} is the hourly electricity demand. The model was implemented in Julia using the framework JuMP [85] and was optimized using the Gurobi solver [86].

Input data

The geographic regions (**Papers I** and **II**) covered in the model are the EU-28 countries (excluding Cyprus and Malta) plus Switzerland, Norway, Serbia, Bosnia and Herzegovina, North Macedonia, and Montenegro. For **Paper II**, China is modeled as well. An example of a network topology for this model is shown in Fig. 6. The electricity demand is assumed to be inelastic and the data are taken from ENTSO-E [87] for Year 2014. For **Paper II**, the electricity demand data are treated to display typical seasonal and diurnal demand patterns, but the volume of the electricity demand remains constant. The CO_2 emission constraint is 10 g/kWh, which is equivalent to a 98% reduction in CO_2 emissions compared with the Year 1990 value for the electricity sector in Europe.

The input data for VRE is calculated based on the GIS model of Mattsson et al. [88]. The modeled subregions are divided into pixels (0.01° × 0.01°). To capture more effectively the weather conditions and represent the corresponding capacity factors for wind and solar power, the wind and solar technologies are divided into five classes based on resource quality. Solar irradiation is used to calculate the capacity factor profiles under the assumption that the PV technology is fixed latitude-tilted, and the wind speed is translated into capacity factors based on the power curve for a typical wind farm with Vestas 112 3.075 MW wind turbines. The capacity factors are calculated using solar irradiation and wind speed information from the ECMWF ERA5 database [89] and Global Wind Atlas [90]. The available land is given as a percentage of the suitable land, namely the total land less the areas which are not suitable for large-scale wind and solar power plants, e.g., areas with high population density, forest or protected area, too deep water (for offshore wind). For **Paper II**, a population density threshold of 150 persons/km^2 is adopted, the same as that in [88]. For **Paper I**, the population density threshold is scaled down to 75 persons/km^2 to represent a more conservative estimate on the potential contribution from VRE resources. All the data for VRE profiles are based on the data source in Year 2018. The assumptions about key technologies are listed in Table 2.

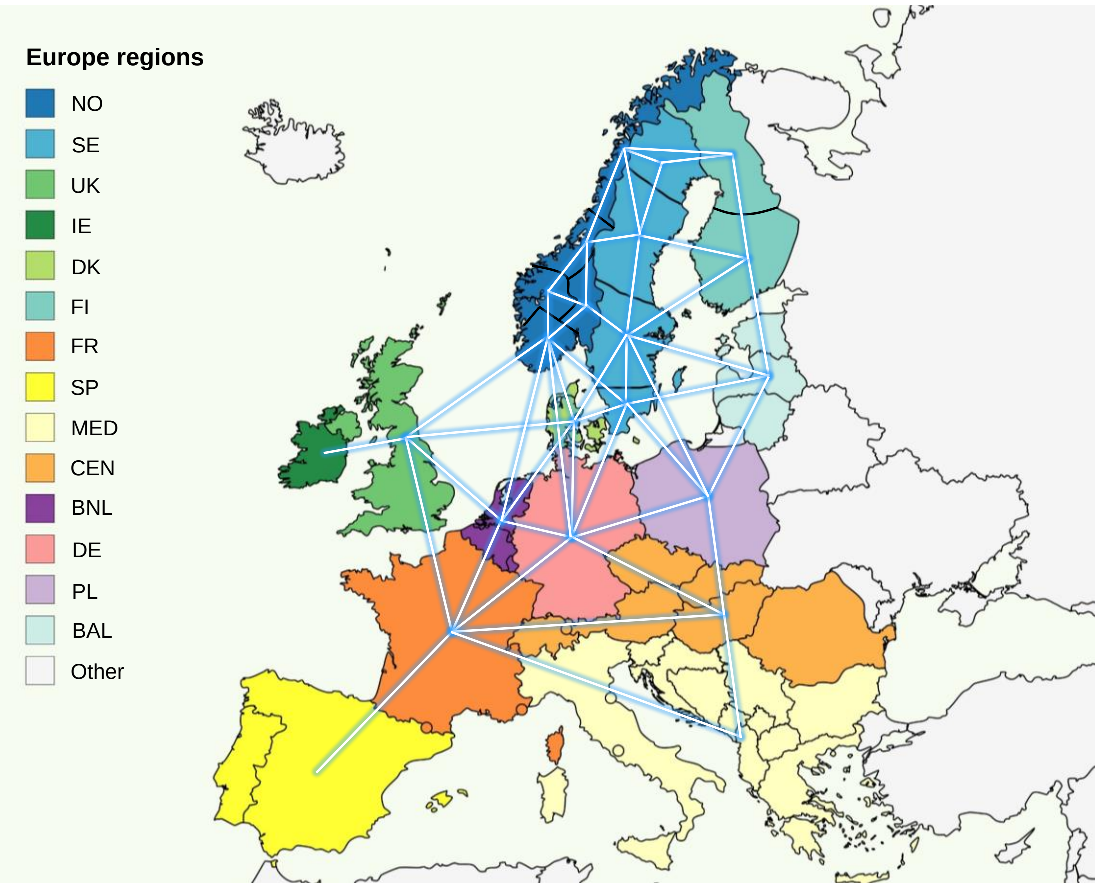

Fig. 6. An example of the regions and transmission network used in the REX model (**Paper I**).

Table 2 Assumptions made regarding the key technologies in the model.

Technology	**Assumptions**
Transmission	Transport model Copper plate for subregion
Biogas	Fuel supply: maximum 5% of the annual electricity consumption
Biomass	Fuel consumption and capacity keep at the current levels Electricity production follows the heat demand pattern in Year 2014
Storage	Battery cost is used as the reference
Hydropower	No pumped hydropower Capacity is kept at the current level Capacity data are taken from ENTSO-E statistics [91] Inflow for 2013 is taken from reference [6] Minimum environmental flow [52, 53] for hydro reservoir: hourly environmental flow is ≥5% of the average hourly inflow to the reservoir

Demand-response	In a given time period, the aggregated consumers can curtail up to 5% of the demand at a cost that lies in the range of 600–1000 $/MWh
Wind onshore	Density: 5 W/m^2 Available land[a]: 8% (**Paper I**), 10% (**Paper II**)
Wind offshore	Density: 8 W/m^2 Available land: 33% (**Papers I and II**)
Solar PV	Density: 45 W/m^2 Available land: 5% (**Paper I**), 6% (**Paper II**)

[a]The available land is given as a percentage of the suitable land, namely the total land minus the populated areas, natural parks, lakes, mountains, etc.

Reflection on the method and data

The REX model developed for this thesis has an hourly time resolution, which is important for revealing the variability of the VRE generation and electricity demand. However, it does have limitations related to spatial resolution and representation of technical operation constraints.

For **Paper I**, Sweden, Norway and Finland, respectively, are divided into several subregions, whereas the countries located far from Sweden are modeled at the national level or are highly aggregated. All the subregions are treated as "copper plates". This setup might lead to an underestimation of the transmission (and distribution) cost, as the transmission networks inside each subregion are not represented. Moreover, the transmission constraints inside each subregion are not taken into account in the present study. The bottlenecks of intra-country transmission networks may limit the amount of international electricity trade. As a result, more domestic generation capacity might be installed, which would drive up the cost for the national electricity system. Therefore, there might be an underestimation of the national electricity system cost for the present study, given that the transmission constraints inside each subregion are not considered.

As for the modeling of technical constraints, there are no operational constraints for thermal generation technologies, such as ramping rates for nuclear power. The ramping rate influences the speed with which a nuclear power plant responds to the load change in the power grid [47]. The lack of thermal constraints is likely to lead to an overestimation of the flexibility provided by nuclear power, thereby underestimating the cost for the electricity system. However, for a highly renewable power system, Cebulla et al. [92] found that the effect on cost of a unit commitment representation, as compared to a merit-order representation, is negligible.

In this thesis, we focus on the optimization of an electricity system that covers a large geographic area, whereby the VRE and dispatchable resources are shared and the variations are smoothed over the continental transmission network. A potential consequence of this approach is that the generation capacity is concentrated to several sites with the best VRE resource potentials. On the one hand, countries with good VRE resources might install large generation capacities and create job opportunities and revenues for the local community, while absorbing the land use and environmental impacts. On the other hand, countries with less resources might rely more on imports for the electricity supply and pay for the traded electricity but face potential energy security problems. The uneven deployment of renewable generation capacity in different countries may result in an uneven distribution of the associated regional impacts [93]. An alternative approach to optimizing the continental electricity system is to model the electricity system so as to include self-sufficiency for each country [9]. In this thesis, we do not impose additional constraints to represent self-sufficiency for each country, as we think that new renewable generation capacity is likely to be installed at the most profitable sites (best sites) in the future European electricity market.

Another limitation relates to uncertainties linked to the weather data for wind and solar power generation. For a low-carbon electricity system with a high share of VRE, the level of electricity generation depends strongly on the weather conditions. The weather data might be different for different years. For the purpose of this thesis, the data for wind and solar power are based on Year 2018. We have not investigated the resilience of the system in terms of different weather years. Höltinger et al. [94] investigated a highly renewable Swedish electricity system and showed that extreme climatic events, such as winter nights without wind, may result in a high residual load (electricity demand less the production of VRE), which requires more back-up capacity than the current balancing capacity in the system. To understand the extent to which extreme weather conditions could affect our results, we calculated the extra capacity required from a natural gas open-cycle gas turbine (OCGT) power plant to balance the system when there is no output from wind and solar power in Sweden, and no international electricity trade. The system without nuclear power requires 6.5 GW more of natural gas OCGT as back-up capacity, which increases the net average system cost by 4% for Sweden. If nuclear power is not included for Sweden, maintaining resilience within the system does not seem to change the results dramatically.

In this thesis, we investigate the electricity system only without modeling sector coupling, although we do consider electricity demand increases (**Paper I)** and pattern changes (**Paper II)** that might result from sector coupling. With sector coupling, both the volume and pattern of the electricity demand may change [19, 23]. Meanwhile, additional flexibilities could be provided by the other sectors [79-81]. The issue, therefore, is the extent to which sector coupling affects the results of this thesis. For **Paper I**, sector coupling is likely to increase the electricity demand. We do analyze one scenario with a higher electricity demand for Sweden in the sensitivity analysis and show that a higher electricity demand promotes the economic prospects for nuclear power investment in Sweden. Still, it is not clear which sector might be coupled to the electricity system, to what level the different energy sectors might be integrated by Year 2045, and how extensive the flexibilities provided by other sectors might be. For **Paper II**, we only consider the change in demand pattern while the volume of demand is kept the same. If the volume of the electricity demand is dramatically increased due to sector coupling the impacts of different demand patterns on the modeling results may be heavily influenced by the land availability constraints for VRE resources.

Present work

This chapter presents the main results from the appended papers. It begins with the impacts on the nodal net average system cost if nuclear power is excluded in the Swedish electricity system. Thereafter, the impacts of different demand patterns on the electricity system cost and the electricity supply mix are considered.

Impacts on the electricity system of excluding nuclear power for Sweden (Paper I)

Motivation and research question

Nuclear power accounts for 41% of the annual electricity production in Sweden [18], but the nuclear fleet is aging, and decommissioning is planned in the coming decades for economic reasons. Currently, there is an ongoing debate in Sweden as to whether new nuclear power plants should be installed after the decommissioning of existing ones. A key issue surrounding the debate is whether the electricity system cost will escalate if nuclear power is excluded from the future Swedish electricity system. Therefore, we develop a techno-economic cost optimization model (REX) with a high temporal resolution for the Swedish and European electricity systems, to investigate the cost of the future low-carbon electricity system without nuclear power for Sweden. The following research questions were addressed.

1) What is the cost of a future low-carbon electricity system without nuclear power for Sweden, given the present interconnecting transmission capacities within Sweden and between Sweden and neighboring countries?

2) How is the cost affected if additional investments in transmission within Sweden and to other countries are allowed?

Methods

In **Paper I**, we use the REX model to investigate the future interconnected European electricity system for Year 2045 with an hourly time resolution, assuming a CO_2 emissions constraint of 10 g/kWh of the electricity demand. The economic performance of the Swedish electricity system with and without nuclear power is evaluated based on the nodal net average system cost (NNASC).

The European electricity system covers a large geographic area with different VRE resource endowments for different locations. Using a techno-economic cost optimization model to investigate such a system may result in concentrating investments in renewable generation capacity to a few sites with the best harvests. Countries may then satisfy their domestic demands through importing electricity from neighboring countries with better outputs and paying for the imported electricity. The conventional system cost concept based on generation and transmission costs cannot represent the electricity system cost for an individual country, as the effect of trade is not considered. This problem can be solved by isolating a country and not allowing trade in electricity. However, this may generate misleading results, as electricity trade is important for electricity supply and variation management within a low-carbon electricity system with a high penetration of VRE [5, 6, 95]. To represent the system cost for an individual country in the interconnected European electricity system, we introduced the nodal net average system cost (NNASC) to incorporate trade profit and congestion rent [1], in addition to generation and transmission costs.

Main findings

The availability of nuclear power has limited impacts on the NNASC for Sweden in a future decarbonized European electricity system. The reduction in NNASC for Sweden due to the availability of nuclear power is less than 4.2%, and this holds true regardless of whether or not there is expansion of transmission capacity (Fix and Exp cases in Fig. 7a). As is evident in Fig. 7b, Sweden is a net importer in the current transmission case (case Fix), whereas when transmission is expanded optimally (case Exp) Sweden becomes a net exporter. In the optimal transmission cases (case Exp), Sweden receives high revenues from electricity exports. The main reason for this is that Sweden has a large volume of reservoir hydropower, which enables exportation when the supply of renewable power in Europe is scarce. When nuclear power is available (NUC-Exp), this effect is further enhanced, with higher net exports than in the case without nuclear power (NoNUC-Exp).

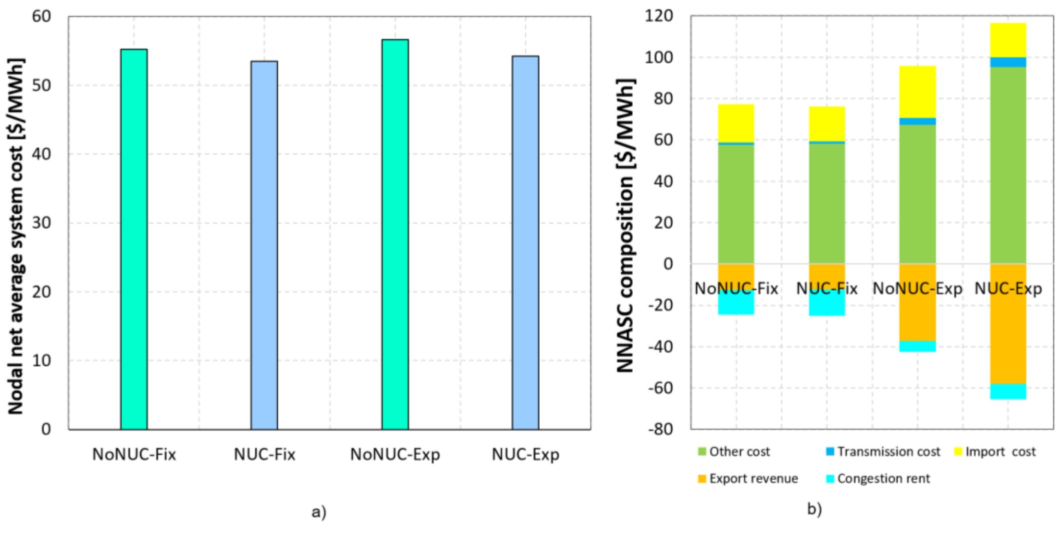

Fig. 7. Results for system cost from the modeling of the base scenarios. a) Nodal net average system cost for Sweden. b) Nodal net average system cost composition for Sweden. Since the costs of storage and demand-response are very low for Sweden, the 'Other cost' in (b) refers mainly to generation-related costs.

[1] *Congestion rent* is defined as the price difference times the power flow over a transmission network constraint.

We further conduct sensitivity analyses to uncover how nuclear power, storage and transmission costs affect the difference in NNASC for a system in Sweden with nuclear power relative to a system without nuclear power. With the present transmission capacity, the maximum economic benefit of nuclear power for Sweden is 10.2% (Fig. 8a). For the cases of optimal transmission, the cost differences between the nuclear power and non-nuclear power scenarios are in the range of 0% –16.5% (Fig. 8b). Unsurprisingly, the upper range of the cost reductions is obtained when the cost of nuclear power is low. Notably, the low investment cost for nuclear power, 3500 $/kW, is less than two-thirds of the projected value for Europe today [96]. Furthermore, the benefit of investing in nuclear power increases with higher storage costs, as more costly storage increases the cost of a highly renewable electricity system. However, investments in nuclear power in Sweden enable higher levels of electricity export from Sweden to smoothen the variations in the European electricity system and reduce the system-wide cost.

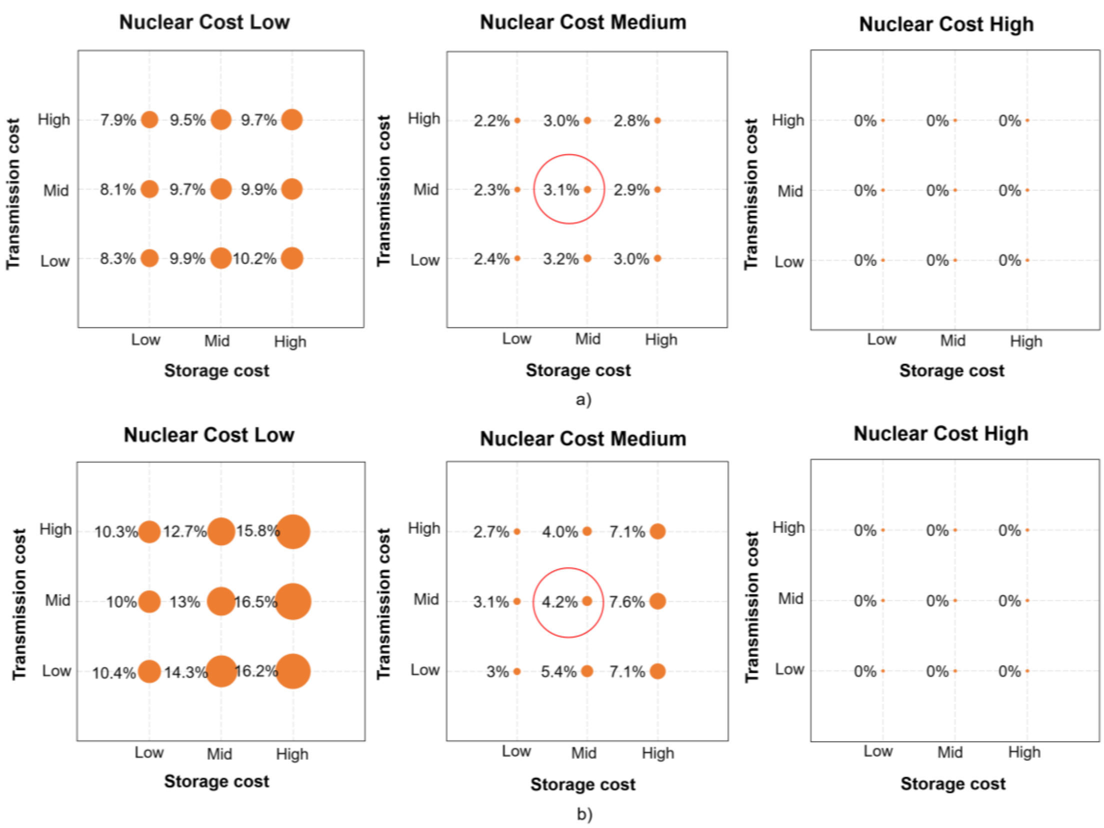

Fig. 8. The decrease in NNASC for Sweden with nuclear power compared to the case without nuclear power, using various assumptions related to the investment costs for nuclear power, storage and transmission. a) Cost difference between cases NUC-Fix and NoNUC-Fix. b) Cost difference between cases NUC-Exp and NoNUC-Exp. The results for the base scenarios are marked with red circles.

Conclusions

In **Paper I**, we model the European electricity system and analyze the nodal net average electricity system cost for Sweden. Our results show that:

- The economic rationale for Sweden as a country to invest in nuclear power if there is a transition towards a low-carbon electricity system in Europe is weak;
- The case with the best economic prospects for investment in nuclear power in Sweden is when the transmission capacity is optimal, in combination with a low cost for nuclear power and a high cost for storage. In this case, the inclusion of nuclear power reduces the NNASC for Sweden by 16.5%;
- In a highly renewable electricity system, allowing additional investment in transmission capacity would benefit Sweden through increased profits from electricity trading.

Impacts of the electricity demand pattern on the electricity system (Paper II)

Motivation and research question

Several studies in the literature have suggested that the future electricity demand patterns may entail large changes in both diurnal and seasonal variations as the results of economic development, climate change, massive adoption of electric vehicles, electric heating, electric cooling, etc. [19-28]. It remains unknown as how the potential electricity demand patterns will affect the cost and supply mix of the future electricity system. In particular, it is not known if misleading results will be produced if energy system modelers use historical electricity demand profiles or linearly scale them up as inputs to the energy system models.

Therefore, we evaluate the conditions under which a demand pattern is important for the modeling results. Specifically, we address the following research question: *What are the effects on the system cost and the electricity supply mix of applying different demand patterns in energy system models?*

2. Methods

To answer this question, we use a simple techno-economic cost optimization model with a high temporal resolution for the electricity system. The influences of different demand patterns are initially explored in a stylized case involving three interconnected regions with different VRE resource endowments in Europe (Fig. 9). The interconnected electricity system in the stylized case is modeled for 1 year with an hourly time resolution, under a cap on CO_2 emissions expressed in grams of CO_2 per kWh of electricity demand. The effects of different demand patterns on the system cost and the electricity supply mix are analyzed based on the modeling results. The REX model is then adopted to evaluate the European and Chinese electricity systems, to validate the results obtained from the stylized case. For both the stylized case and the cases of Europe and China, the electricity demand profiles are treated to display typical seasonal and diurnal demand patterns (Fig. 10). A summary of the method used in this study is presented in Fig. 11.

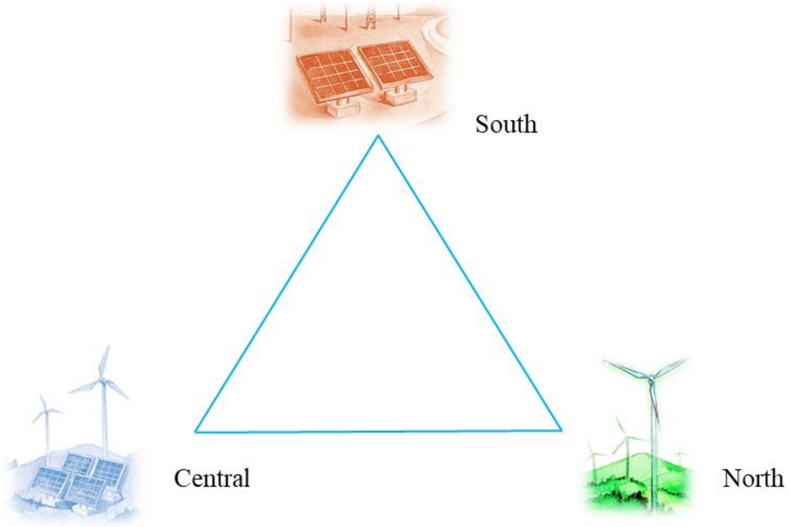

Fig. 9. Regions covered in the stylized case. We select three regions with typical VRE resource potentials and connect them with transmission grids to analyze the impacts of demand pattern on an interconnected electricity system. The three regions are located in the south, central and north of Europe, respectively, and they are accordingly labeled as South, Central and North. The data on VRE resources and the electricity demand pattern for Spain plus Portugal are assigned to region South. Similarly, data on VRE resources and the electricity demand patterns for Germany and Norway are assigned to regions Central and North, respectively.

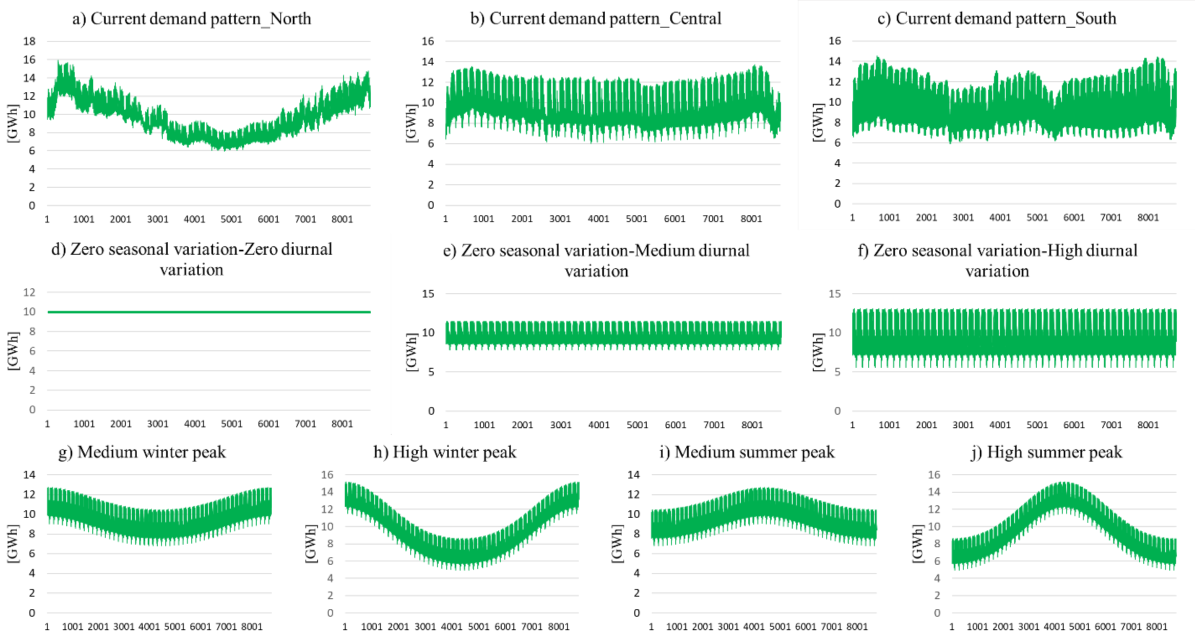

Fig. 10. Typical electricity demand patterns.

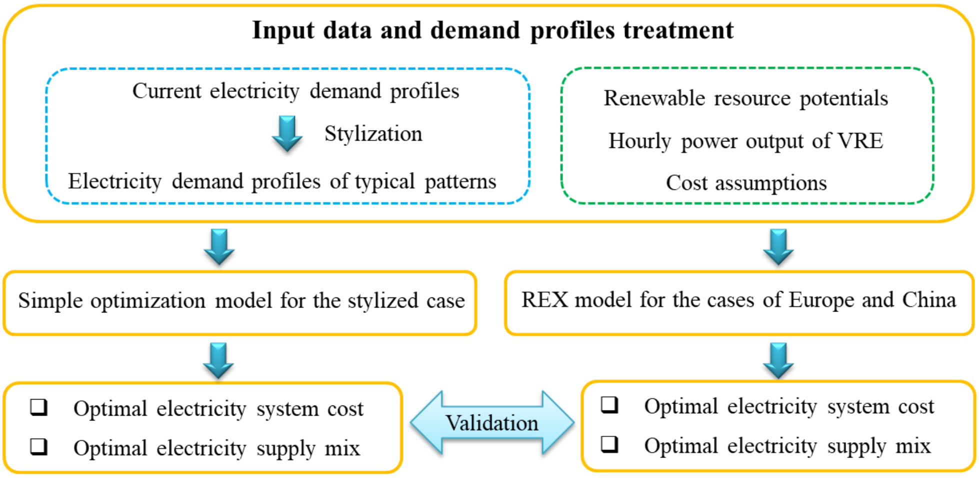

Fig. 11. Overview of the method. The input data for the electricity demand and the stylization of electricity demand profiles are shown in the blue dashed box. All the other input data are listed in the green dashed box.

Main findings

Results for the stylized case

Fig. 12 shows how the average electricity system cost increases for scenarios with different seasonal variations, as compared to the scenario of the current demand pattern. If the demand profile has no seasonal variation or a winter peak (possibly due to large-scale deployment of electric heating), the increase in system cost is small (<3%). In contrast, the increase in system cost is larger (3%–8%) if the annual peak is in the summer (possibly due to massive adoption of ACs). In the stylized case, onshore wind power is cheap to install, and wind power has a typical seasonality with higher output in the wintertime than in the summertime. In addition, the variation of large-scale wind power can be smoothed through the expansion of transmission grids. Therefore, when the annual peak of the electricity demand is during the winter, the seasonal variation of the demand profile is in line with the seasonal pattern of wind power, and the cheap wind resource is deployed. In contrast, if the annual peak demand is in summer when the output of wind power is lower, the optimal system configuration comprises more solar power and storage, which drives up the system cost. Correspondingly, there are large deviations in the capacity mix for the optimal electricity system portfolio, especially with respect to the solar and storage capacities (see Fig. 13). In the scenario with the highest summer peak, the increase in system cost is 8%, while the investments in solar power and storage capacities increase by 54% and 95%, respectively, as compared to the scenario of the current demand pattern. Similar phenomena are observed for other scenarios. Therefore, it is clear that a change in the seasonal demand pattern has a stronger impact on the electricity supply mix than on the system cost.

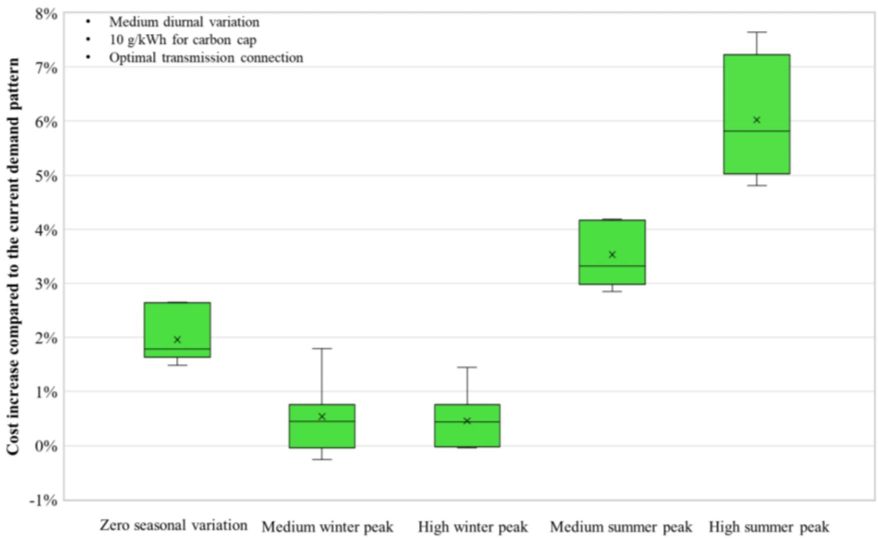

Fig. 12. Increases in the average electricity system cost for the scenarios of different seasonal variations, as compared to the scenario of the current demand pattern. Each seasonal demand pattern (label on the *x*-axis) represents a group of scenarios with the same or similar aggregated demand profiles. The ends of the box are the upper and lower quartiles, so the box spans the interquartile range. The bar in the box represents the median value and the cross represents the average value. The whiskers are the two lines outside the box that extend to the highest and lowest values.

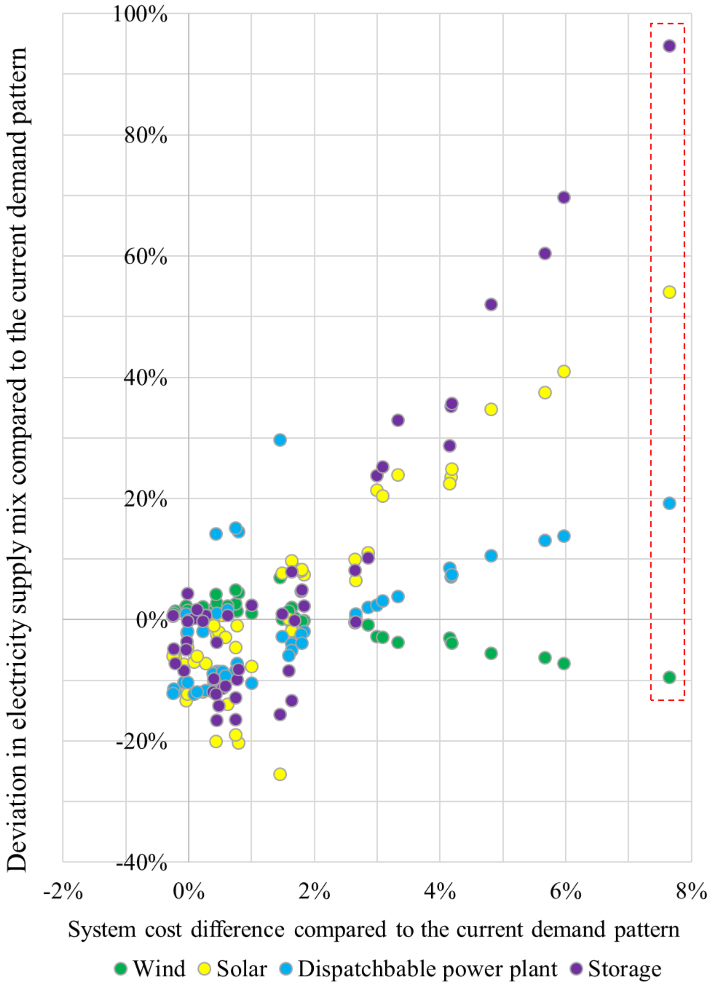

Fig. 13. Relationships between the differences in system cost and the deviations in the electricity supply mix for the scenarios of different seasonal variations, as compared to the scenario of the current demand pattern. The dots inside the red dashed rectangle represent the scenario with the highest summer peak, as described in the text.

The impacts of different diurnal demand patterns (the underlying causes of which may be various charging strategies for EVs) of the demand profile on the electricity system cost are depicted in Fig. 14. Across all the scenarios, a higher diurnal variation slightly increases the system cost, but the difference in system cost between the cases of medium- and high-diurnal variation is limited (<3%). Similar to the impact seen for the seasonal demand pattern, a higher diurnal variation has a more potent impact on the electricity supply mix than on the system cost.

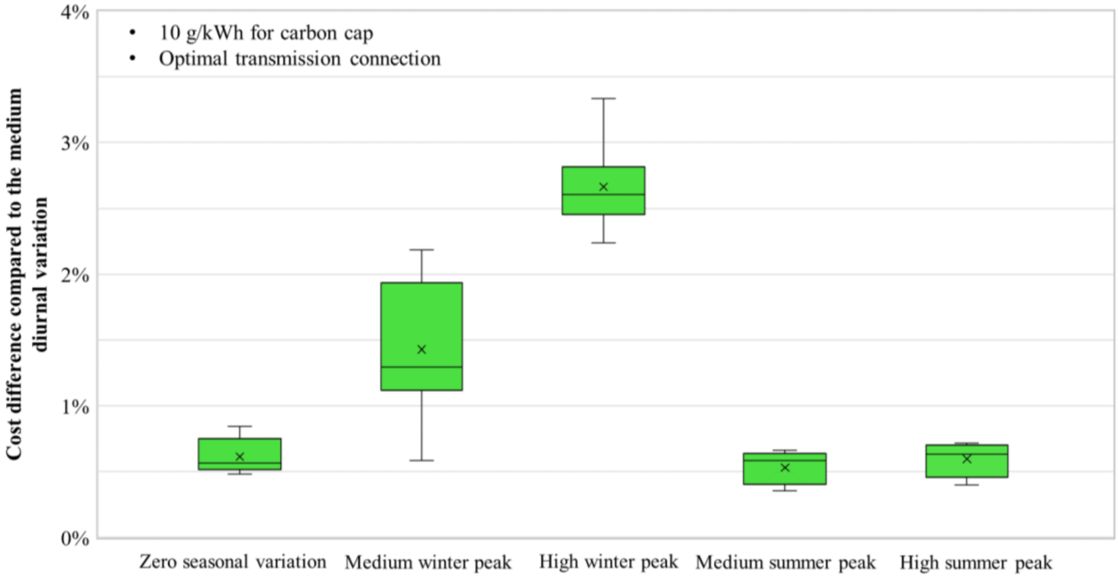

Fig. 14. Difference in the average electricity system cost for the case of high diurnal variation compared to the case of medium diurnal variation. Each seasonal demand pattern (label on the *x*-axis) represents a group of scenarios with the same or similar aggregated demand profiles. The ends of the box are the upper and lower quartiles, so the box spans the interquartile range. The bar in the box represents the median value and the cross represents the average value. The whiskers are the two lines outside the box that extend to the highest and lowest values.

Results for the cases of Europe and China

We also analyze the full-scale cases (Europe and China), to validate the results from the stylized case. As for the case of Europe, the system cost increase for scenarios with zero seasonal variation and a winter peak is less than 2%, while the summer peak increases the system cost by 5%. The cost deviation due to different seasonal demand patterns for Europe is in line with the results from the stylized case. In contrast, in the case of China, the system cost increases by 6% for the high winter peak and decreases for the summer peak. The chief reason for the discrepancy in the results for Europe and China is that hydro reservoirs in China are less capable of sequestering the water inflow as seasonal storage, as compared with the hydropower plants in Europe. Therefore, hydropower production in China is higher in the summertime when the water inflow is large, which offsets the impact of the summer peak for China. Therefore, our results regarding the impacts of different seasonal demand patterns based on the stylized case are only valid for Europe or regions with similar resource endowments.

Conclusions

Through investigating the impacts of different demand patterns on the modeling results for a stylized case and two applied cases, we show in **Paper II** how the demand pattern influences the electricity system cost and the electricity supply mix.

- In general, the seasonal demand pattern (zero seasonal variation, winter peak) has a limited impact on the system cost, except for the case of the summer peak, where the system cost may increase by up to 8%;
- A higher diurnal variation has minor impacts on the system cost (<3% increase in the system cost);
- The electricity demand pattern has a stronger influence on the electricity supply mix than on the system cost;
- The impacts of different seasonal demand patterns on a European, highly renewable electricity system are consistent with the results of the stylized case, but not for the case of China;
- In case the future electricity demand profile shifts from the current pattern to a summer peak, it is important for modelers to exercise caution regarding the assumptions made for the future electricity demand pattern.

Future work

Following the studies presented in this thesis, there are several interesting aspects that are worth investigating for the future low-carbon electricity system. In **Paper I**, the investment in nuclear power in Sweden enables greater export of electricity to the highly renewable European electricity system. The hydropower in Nordic countries is widely regarded as the "green battery" for Europe, as it can provide flexible hydropower to deal with the variations in the European electricity system. Apart from the uncertainty linked to nuclear power policy in Sweden, Germany has decided to phase out nuclear power, while the UK and Finland are planning new nuclear power plants. Therefore, it is interesting to discover *how the nuclear policy in the North Sea region could affect the "green battery" function of hydropower in the Nordic countries*.

In **Paper II**, a seasonal demand pattern with summer peak may increase the system cost by 8%, while the impact on solar capacity may be much larger (54%). One hypothesis is that there is a clear synergy between the high demand and good solar irradiation in the summer. Therefore, it is interesting to test this hypothesis and to explore the following questions:

1. *What is the impact of the increased cooling demand on the electricity system cost and the electricity supply mix, especially solar power, for the future low-carbon electricity system?*
2. *How is the effect contingent on geographic location (different latitudes)?*

Reference

1. Change, I.C., *Mitigation of climate change.* Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, 2014. **1454**.
2. Masson-Delmotte, V., et al., *Global Warming of 1.5 OC: An IPCC Special Report on the Impacts of Global Warming of 1.5° C Above Pre-industrial Levels and Related Global Greenhouse Gas Emission Pathways, in the Context of Strengthening the Global Response to the Threat of Climate Change, Sustainable Development, and Efforts to Eradicate Poverty*. 2018: World Meteorological Organization Geneva, Switzerland.
3. IRENA, *Renewable Power Generation Costs in 2019*. 2020, International Renewable Energy Agency: Abu Dhabi.
4. Newbery, D., et al., *Market design for a high-renewables European electricity system.* Renewable and Sustainable Energy Reviews, 2018. **91**: p. 695-707.
5. Reichenberg, L., et al., *The marginal system LCOE of variable renewables – Evaluating high penetration levels of wind and solar in Europe.* Energy, 2018. **152**: p. 914-924.
6. Schlachtberger, D.P., et al., *The benefits of cooperation in a highly renewable European electricity network.* Energy, 2017. **134**: p. 469-481.
7. Schlachtberger, D.P., et al., *Cost optimal scenarios of a future highly renewable European electricity system: Exploring the influence of weather data, cost parameters and policy constraints.* Energy, 2018. **163**: p. 100-114.
8. Brown, T., et al., *Synergies of sector coupling and transmission reinforcement in a cost-optimised, highly renewable European energy system.* Energy, 2018. **160**: p. 720-739.
9. Tröndle, T., et al., *Trade-offs between geographic scale, cost, and infrastructure requirements for fully renewable electricity in Europe.* Joule, 2020. **4**(9): p. 1929-1948.
10. Zappa, W., M. Junginger, and M. Van Den Broek, *Is a 100% renewable European power system feasible by 2050?* Applied Energy, 2019. **233-234**: p. 1027-1050.
11. Brown, T.W., et al., *Response to 'Burden of proof: A comprehensive review of the feasibility of 100% renewable-electricity systems'.* Renewable and sustainable energy reviews, 2018. **92**: p. 834-847.
12. Child, M., et al., *Flexible electricity generation, grid exchange and storage for the transition to a 100% renewable energy system in Europe.* Renewable Energy, 2019. **139**: p. 80-101.
13. Connolly, D., H. Lund, and B.V. Mathiesen, *Smart Energy Europe: The technical and economic impact of one potential 100% renewable energy scenario for the European Union.* Renewable and Sustainable Energy Reviews, 2016. **60**: p. 1634-1653.
14. Plessmann, G. and P. Blechinger, *How to meet EU GHG emission reduction targets? A model based decarbonization pathway for Europe's electricity supply system until 2050.* Energy Strategy Reviews, 2017. **15**: p. 19-32.
15. Buongiorno et al. *The future of nuclear energy in a carbon-constrained world*. 2018; Available from: http://energy.mit.edu/wp-content/uploads/2018/09/The-Future-of-Nuclear-Energy-in-a-Carbon-Constrained-World.pdf.
16. Hong, S., S. Qvist, and B.W. Brook, *Economic and environmental costs of replacing nuclear fission with solar and wind energy in Sweden.* Energy Policy, 2018. **112**: p. 56-66.
17. Sepulveda, N.A., et al., *The Role of Firm Low-Carbon Electricity Resources in Deep Decarbonization of Power Generation.* Joule, 2018. **2**(11): p. 2403-2420.
18. Swedish Energy Agency. *Energy in Sweden Fact and Figures 2016*. 2016; Available from: http://www.energimyndigheten.se/globalassets/statistik/energilaget/energy-in-sweden-2016_160218.xlsx.
19. Boßmann, T. and I. Staffell, *The shape of future electricity demand: Exploring load curves in 2050s Germany and Britain.* Energy, 2015. **90**: p. 1317-1333.
20. De Felice, M., A. Alessandri, and F. Catalano, *Seasonal climate forecasts for medium-term electricity demand forecasting.* 2015. **137**: p. 435-444.

21. Gallo Cassarino, T., E. Sharp, and M. Barrett, *The impact of social and weather drivers on the historical electricity demand in Europe.* Applied Energy, 2018. **229**: p. 176-185.
22. Miller, L. and R. Carriveau, *Energy demand curve variables – An overview of individual and systemic effects.* Sustainable Energy Technologies and Assessments, 2019. **35**: p. 172-179.
23. Staffell, I. and S. Pfenninger, *The increasing impact of weather on electricity supply and demand.* Energy, 2018. **145**: p. 65-78.
24. Van Ruijven, B.J., E. De Cian, and I. Sue Wing, *Amplification of future energy demand growth due to climate change.* Nature Communications, 2019. **10**(1).
25. Cooper, S.J.G., et al., *Detailed simulation of electrical demands due to nationwide adoption of heat pumps, taking account of renewable generation and mitigation.* 2016. **10**(3): p. 380-387.
26. David, F., et al., *Electric vehicles' impacts on residential electric local profiles – A stochastic modelling approach considering socio-economic, behavioural and spatial factors.* Applied Energy, 2019. **233**: p. 644-658.
27. Pudjianto, D., et al., *Smart control for minimizing distribution network reinforcement cost due to electrification.* Energy Policy, 2013. **52**: p. 76-84.
28. Ramachandran, K., *Dynamics of long-term electricity demand profile: Insights from the analysis of Swiss energy systems.* Energy strategy reviews, 2018. **22**: p. 410-425.
29. Santamouris, M., *Cooling the buildings–past, present and future.* Energy and Buildings, 2016. **128**: p. 617-638.
30. Climate-friendly, S., *reliable, affordable: 100% renewable electricity supply by 2050*. 2010, Technical report, German Advisory Council on the Environment (SRU).
31. DECC, G.B., *Electricity market reform: policy overview*. 2012, Department of Energy and Climate Change London.
32. Green, R., I. Staffell, and N. Vasilakos, *Divide and Conquer? ${k} $-Means Clustering of Demand Data Allows Rapid and Accurate Simulations of the British Electricity System.* IEEE Transactions on Engineering Management, 2014. **61**(2): p. 251-260.
33. Kan, X., F. Hedenus, and L. Reichenberg, *The cost of a future low-carbon electricity system without nuclear power–the case of Sweden.* Energy, 2020. **195**: p. 117015.
34. Reichenberg, L., et al., *The marginal system LCOE of variable renewables–Evaluating high penetration levels of wind and solar in Europe.* Energy, 2018. **152**: p. 914-924.
35. Schaber, K., F. Steinke, and T. Hamacher, *Transmission grid extensions for the integration of variable renewable energies in Europe: Who benefits where?* Energy Policy, 2012. **43**: p. 123-135.
36. Schill, W.-P. *Residual Load, Renewable Surplus and Storage Requirements for Renewable Integration in Germany*. in *Energy Economics of Phasing out Carbon and Uranium, 13th IAEE European Conference, August 18-21, 2013*. 2013. International Association for Energy Economics.
37. Staffell, I., R. Green, and K. Kendall, *Cost targets for domestic fuel cell CHP*. Journal of Power Sources, 2008. **181**(2): p. 339-349.
38. al., Q.e., *Kraftsamling elförsörjning långsiktig scenarioanalys*. 2020, Qvist Consulting Ltd: Sweden.
39. Söder, L. *På väg mot en elförsörjning baserad på enbart förnybar el i Sverige*. 2014; Available from: https://www.diva-portal.org/smash/get/diva2:727697/FULLTEXT01.pdf.
40. IEA, *Clobal Energy and CO2 Status Report*. 2019, International Energy Agency: Paris.
41. Williams, J.H., et al., *The technology path to deep greenhouse gas emissions cuts by 2050: the pivotal role of electricity.* science, 2012. **335**(6064): p. 53-59.
42. European Commission. *A Clean Planet for all - A European strategic long-term vision for a prosperous, modern, competitive and climate neutral economy*. 2018; Available from: https://ec.europa.eu/clima/sites/clima/files/docs/pages/com_2018_733_en.pdf.

43. IRENA. *Falling Renewable Power Costs Open Door to Greater Climate Ambition*. 2019; Available from: https://www.irena.org/newsroom/pressreleases/2019/May/Falling-Renewable-Power-Costs-Open-Door-to-Greater-Climate-Ambition.
44. Kroposki, B., et al., *Achieving a 100% renewable grid: Operating electric power systems with extremely high levels of variable renewable energy*. IEEE Power and Energy Magazine, 2017. **15**(2): p. 61-73.
45. Institute, E.T., *The ETI Nuclear Cost Drivers Project: Summary Report*. 2018.
46. Dawson, K. and P. Sabharwall, *A Review of Light Water Reactor Costs and Cost Drivers*. 2017, Idaho National Lab.(INL), Idaho Falls, ID (United States).
47. Jenkins, J.D., et al., *The benefits of nuclear flexibility in power system operations with renewable energy*. Applied Energy, 2018. **222**: p. 872-884.
48. Lazarev, G., V. Hrustalyov, and M. Garievskij, *1. Non-baseload Operation in Nuclear Power Plants: Load Following and Frequency Control Modes of Flexible Operation*. Nuclear Energy Series, 2018: p. 173.
49. Gonzalez-Salazar, M.A., T. Kirsten, and L. Prchlik, *Review of the operational flexibility and emissions of gas-and coal-fired power plants in a future with growing renewables*. Renewable and Sustainable Energy Reviews, 2018. **82**: p. 1497-1513.
50. O'connor, P., et al., *Hydropower Vision A New Chapter for America's 1st Renewable Electricity Source*. 2016, Oak Ridge National Lab.(ORNL), Oak Ridge, TN (United States).
51. Council, W.R.E., *Energy Resources, Hydropower*. 2016.
52. Efstratiadis, A., et al., *Assessment of environmental flows under limited data availability: case study of the Acheloos River, Greece*. Hydrological Sciences Journal, 2014. **59**(3-4): p. 731-750.
53. Renofalt, B.M., R. Jansson, and C. Nilsson, *Effects of hydropower generation and opportunities for environmental flow management in Swedish riverine ecosystems*. Freshwater Biology, 2010. **55**(1): p. 49-67.
54. Kauffman, J.B., R.F. Hughes, and C. Heider, *Carbon pool and biomass dynamics associated with deforestation, land use, and agricultural abandonment in the neotropics*. Ecological Applications, 2009. **19**(5): p. 1211-1222.
55. Sandén, B.A. and S. Harvey, *System analysis for energy transition-A mapping of methodologies, co-operation and critical issues in energy systems studies at Chalmers*. 2008, Chalmers University of Technology.
56. Hoffman, K.C. and D.O. Wood, *Energy system modeling and forecasting*. 1975.
57. Mirakyan, A. and R. De Guio, *Modelling and uncertainties in integrated energy planning*. Renewable and Sustainable Energy Reviews, 2015. **46**: p. 62-69.
58. DeCarolis, J., et al., *Formalizing best practice for energy system optimization modelling*. Applied energy, 2017. **194**: p. 184-198.
59. Lopion, P., et al., *A review of current challenges and trends in energy systems modeling*. Renewable and sustainable energy reviews, 2018. **96**: p. 156-166.
60. Pfenninger, S., A. Hawkes, and J. Keirstead, *Energy systems modeling for twenty-first century energy challenges*. Renewable and Sustainable Energy Reviews, 2014. **33**: p. 74-86.
61. Sterman, J.D., *A skeptic's guide to computer models*. Managing a nation: The microcomputer software catalog, 1991. **2**: p. 209-229.
62. Loulou, R., G. Goldstein, and K. Noble, *Documentation for the MARKAL Family of Models*. Energy Technology Systems Analysis Programme, 2004: p. 65-73.
63. Sarica, K. and W.E. Tyner, *Analysis of US renewable fuels policies using a modified MARKAL model*. Renewable Energy, 2013. **50**: p. 701-709.
64. Loulou, R., et al., *Documentation for the times model part ii*. Energy Technology Systems Analysis Programme, 2005.
65. Brown, T., *PyPSA documentation*. Renewable Energy Group, Emden, Germany, 2016.

66. Collins, S., et al., *Integrating short term variations of the power system into integrated energy system models: A methodological review.* Renewable and Sustainable Energy Reviews, 2017. **76**: p. 839-856.
67. Kotzur, L., et al., *Impact of different time series aggregation methods on optimal energy system design.* Renewable energy, 2018. **117**: p. 474-487.
68. Chiodi, A., *Climate and energy scenarios for Ireland to 2050 using the Irish TIMES energy systems model*. 2014, University College Cork.
69. GAGO, D., et al., *The JRC-EU-TIMES model-Assessing the long-term role of the SET Plan Energy technologies*. 2013, Publications Office of the European Union.
70. Poncelet, K., et al., *Impact of the level of temporal and operational detail in energy-system planning models.* Applied Energy, 2016. **162**: p. 631-643.
71. Haydt, G., et al., *The relevance of the energy resource dynamics in the mid/long-term energy planning models.* Renewable energy, 2011. **36**(11): p. 3068-3074.
72. Ludig, S., et al., *Fluctuating renewables in a long-term climate change mitigation strategy.* Energy, 2011. **36**(11): p. 6674-6685.
73. Pina, A., C. Silva, and P. Ferrão, *Modeling hourly electricity dynamics for policy making in long-term scenarios.* Energy Policy, 2011. **39**(9): p. 4692-4702.
74. Poncelet, K., et al., *The importance of integrating the variability of renewables in long-term energy planning models.* Rome, Italy, 2014.
75. Frew, B.A. and M.Z. Jacobson, *Temporal and spatial tradeoffs in power system modeling with assumptions about storage: An application of the POWER model.* Energy, 2016. **117**: p. 198-213.
76. Horsch, J. and T. Brown. *The role of spatial scale in joint optimisations of generation and transmission for European highly renewable scenarios*. 2017. IEEE.
77. Eriksen, E.H., et al., *Optimal heterogeneity in a simplified highly renewable European electricity system.* Energy, 2017. **133**: p. 913-928.
78. Pattupara, R. and R. Kannan, *Alternative low-carbon electricity pathways in Switzerland and it's neighbouring countries under a nuclear phase-out scenario.* Applied Energy, 2016. **172**: p. 152-168.
79. Connolly, D., et al., *The first step towards a 100% renewable energy-system for Ireland.* Applied Energy, 2011. **88**(2): p. 502-507.
80. Jacobson, M.Z., et al., *Low-cost solution to the grid reliability problem with 100% penetration of intermittent wind, water, and solar for all purposes.* Proceedings of the National Academy of Sciences, 2015. **112**(49): p. 15060-15065.
81. Mathiesen, B.V., et al., *Smart Energy Systems for coherent 100% renewable energy and transport solutions.* Applied Energy, 2015. **145**: p. 139-154.
82. Göransson, L., et al., *The Benefit of Collaboration in the North European Electricity System Transition—System and Sector Perspectives.* Energies, 2019. **12**(24): p. 4648.
83. Victoria, M., et al., *Early decarbonisation of the European energy system pays off.* Nature Communications, 2020. **11**(1): p. 6223.
84. Bolwig, S., et al., *Review of modelling energy transitions pathways with application to energy system flexibility.* Renewable and Sustainable Energy Reviews, 2019. **101**: p. 440-452.
85. JuMP. *Introduction to JuMP*. 2019; Available from: http://www.juliaopt.org/JuMP.jl/dev/.
86. Gurobi Optimization, I. *Gurobi Optimizer Reference Manual*. 2019; Available from: https://www.gurobi.com/documentation/8.1/refman/index.html.
87. ENTSO-E. *Consumption data: Hourly load values 2006–2015*. Available from: https://docstore.entsoe.eu/Documents/Publications/Statistics/Monthly-hourly-load-values_2006-2015.xlsx.
88. Niclas Mattsson, V.V., Fredrik Hedenus, Lina Reichenberg, *An Autopilot for Energy Models-Automatic Generation of Renewable Supply Curves, Hourly Capapcity Factors and Hourly Synthetic Electricity Demand for Arbitrary World Regions.* Submitted to Energy Strategy Review, 2019.

89. ECMWF. *Climate Data*. Available from: https://cds.climate.copernicus.eu/#!/home.
90. Global Wind Atlas. Available from: https://globalwindatlas.info/.
91. ENTSO-E. *Net Generating Capacity*. Available from: https://www.entsoe.eu/data/power-stats/net-gen-capacity/.
92. Cebulla, F. and T. Fichter, *Merit order or unit-commitment: How does thermal power plant modeling affect storage demand in energy system models?* Renewable Energy, 2017. **105**: p. 117-132.
93. Sasse, J.-P. and E. Trutnevyte, *Regional impacts of electricity system transition in Central Europe until 2035.* Nature Communications, 2020. **11**(1): p. 1-14.
94. Höltinger, S., et al., *The impact of climatic extreme events on the feasibility of fully renewable power systems: A case study for Sweden.* Energy, 2019. **178**: p. 695-713.
95. Gils, H.C., et al., *Integrated modelling of variable renewable energy-based power supply in Europe.* Energy, 2017. **123**: p. 173-188.
96. Houssin, D., et al., *Technology Road-map-Nuclear Energy*. 2015, Organisation for Economic Co-Operation and Development.