THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Variability and variation management in a renewable electricity system

- large-scale wind- and solar power deployment in Europe

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ABSTRACT

The large-scale deployment of wind and solar power poses challenges to the electricity system by introducing variability on the generation side. To handle these variations, variation management strategies can be employed to ensure that generation meets demand. Such strategies include the deployment of storage and investments in wind and solar capacities in different regions connected by a network of transmission lines. This thesis investigates the interplay of such strategies, with special focus on the geographic distribution of wind power in Europe. The research questions addressed here include: To what extent can geographic distribution of wind power tailor aggregate output? What are the main characteristics of a cost-effective electricity system that is based on renewable energy? How does the system cost increase with the penetration levels of wind power and solar power? How should the time dimension be handled in electricity investment models that aim to design systems with a large share of variable renewable energy (VRE)?

Five optimization models, characterized by comparatively high temporal resolution, are developed to answer these questions. Two of the models apply multi-objective optimization, whereby Conditional Value-at-Risk is used as a measure of the variation in wind power output/residual demand. Two of the models are network models that specifically target the effect of optimizing the transmission network so as to make better use of wind and solar power capacities.

This thesis shows that the diverse weather patterns in Europe can be exploited to achieve effective smoothing of wind power, provided that there is sufficient transmission capacity to trade variations in generation and demand. Furthermore, it is shown that dispersing wind power and building transmission lines is the most cost-efficient strategy to design an electricity system with a large share of renewable generation. A system that contains a large share of variable renewables is also shown to be versatile, in the sense that it is possible to combine large-scale variable generation with considerable amounts of base-load generation, provided that the transmission network is enhanced. The marginal cost for generation from variable resources increases in an approximately linear fashion with the penetration level of such resources, up to a VRE penetration level of around 80%. The marginal cost for achieving a VRE penetration level of 80% is approximately 50% higher than the initial cost.

It is concluded that if wind- and solar power capacity is to be allocated over the entire area of Europe, at the same time as the transmission network is expanded, the cost for a future power system with a high (~80%) penetration of VRE will not be prohibitive.

Keywords: energy systems modelling, wind power, solar power, power systems, variability smoothing, VRE, renewable energy, marginal cost of electricity

SAMMANFATTNING

Storskalig användning av vind- och sol-el innebär utmaningar för elsystemet, på grund av att variationen på tillförselsidan ökar. För att tillse att elproduktionen tillfredsställer efterfrågan kan strategier för variationshantering användas. Dylika strategier innefattar bland annat investeringar i el-lager, t.ex. batterier, eller att sprida ut vind- och sol-kapacitet i regioner med varierande vädermönster, och binda ihop dessa med ett transmissionsnät. Den här avhandlingen undersöker hur sådana strategier samverkar, med särskilt fokus på betydelsen av geografisk spridning av vindkraft i Europa. Forskningen behandlar frågor som: Hur kan geografisk spridning av vindkraft påverka variationen i den samlade vindkraftsproduktionen? Vad karaktäriserar kostnadseffektiva system som domineras av sol och vind? Hur ser ökningen av systemkostnaden ut med stigande andel förnybar el i systemet? Hur bör variationen på tillförselsidan i elsystem med en hög förväntad andel sol- och vindel representeras i modeller?

Inom avhandlingsarbetet har fem optimeringsmodeller, som utmärks av en förhållandevis hög tidsupplösning, utvecklats. Två av dessa använder sig av flermålsoptimering, där bland andra måttet Conditional-Value-at-Risk används för att optimera för att undvika att den samlade produktionen från vind under vissa timmar blir låg, samt för att undvika att netto-efterfrågan av el under vissa timmar blir låg. Två av modellerna är nätverksmodeller, utformade för att optimera transmissionsnätverket för att bättre kunna utnyttja vind- och sol-resurserna.

Resultaten i avhandlingen visar att de varierande vädermönstren i Europa kan användas för att till viss del jämna ut vind-produktionen. Detta gäller om det finns tillräckligt med transmissionskapacitet för att handla med variationerna. Avhandlingen visar också att det att sprida ut vind och sol-kapacitet och binda ihop regioner med utökad transmission är det mest effektiva sättet att bygga ett förnybart elsystem. Det visas också att ett dylikt system är flexibelt, genom att det går att kombinera med en stor mängd baslast. När det gäller kostnaden för ett förnybart system i Europa, visas att marginalkostnaden för att öka mängden vind och sol ökar linjärt upp till en penetrationsgrad av 80%. Marginalkostnaden vid 80% penetrationsgrad är ungefär 50% högre än för de första procenten.

Slutsatsen från detta arbete är att om vind- och sol-kapacitet sprids över Europa och binds samman av ett kraftigt utökat transmissionsnät, så är kostnaden för ett framtida förnybart elsystem inte så mycket högre än för ett system baserat på termisk produktion.

LIST OF PUBLICATIONS

This thesis is based on the following appended papers (which are referred to in the text by their Roman numerals):

I. Reichenberg, L., F. Johnsson, and M. Odenberger, *Dampening variations in wind power generation - The effect of optimizing geographic location of generating sites*. Wind Energy, 2014. **17**(11): p. 1631-1643.

II. Reichenberg, L., A. Wojciechowski, F. Hedenus, and F. Johnsson, *Geographic aggregation of wind power—an optimization methodology for avoiding low outputs*. Wind Energy, 2017. **20**(1): p. 19-32.

III. Reichenberg, L., Wojciechowski, A. and Johnsson, F., 2013. *Wind power allocation strategies for Europe*. 12th Wind Integration Workshop, London, 2013.

IV. Reichenberg, L., F. Hedenus, M: Odenberger and F. Johnsson *Tailoring large-scale electricity production from variable renewable energy sources to accommodate baseload generation in Europe*. Submitted for publication 2016

V. Reichenberg, L., F. Hedenus, M: Odenberger and F. Johnsson *The marginal levelized cost of electricity (LCOE) for increasing shares of Variable Renewable Energy*. Submitted for publication 2017

VI. Reichenberg, L., S.Wogrin and A. Siddiqui *How should electricity investment models represent variability – Two methods to downscale the time dimension*. Submitted for publication 2017

Lina Reichenberg is the principal author of all the papers**.** The ideas for **Papers I-IV** and **Paper VI** were conceived by Lina Reichenberg. The idea for **Paper V** was conceived by Lina Reichenberg in collaboration with Fredrik Hedenus. Fredrik Hedenus contributed with continuous inspiration, discussions, and editing in the creation of **Papers II**, **IV** and **V**. Adam Wojciechowski contributed with method development and model implementation for **Papers II** and **III**. Professor Filip Johnsson, who is the main academic supervisor, contributed with discussions and editing to **Papers I-V**. Mikael Odenberger contributed with discussions and editing to **Papers I**, **IV** and **V**. Afzal Siddiqui contributed with discussions and editing, and Sonja Wogrin contributed with discussions to **Paper VI**.

Additional publications not included in this thesis:

Johansson, V., L. Thorson, J. Goop, L. Göransson, M. Odenberger, L. Reichenberg, . . . F. Johnsson, *Value of wind power – Implications from specific power*. Energy, 2017. **126**: p. 352-360.

Steen, D., Balram, P., Reichenberg, L., & Tjernberg, L. B. *Impact assessment of wind power and demand side management on day-ahead market prices*. In *Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), 2014 IEEE PES* (pp. 1-6). IEEE.

Goop, J., Reichenberg, L. and Göransson, L. *THe sensitivity of system cost and wind power revenues to sub-optimal investment in wind power capacity*. In *35th International Energy Workshop,* Corke, Ireland, 2016

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Göteborg, October 2017

Lina Reichenberg

TABLE OF CONTENTS

1. INTRODUCTION

This thesis is concerned with the extents to which it is possible and economically sound to cover the majority of the electricity demand using wind and solar power. The cost, feasibility, and design of such an electricity system is of great interest due to the crucial role assigned to the electricity system in CO_2 mitigation.

The importance of the electricity system in the transition to a CO_2-neutral world is reflected in the fact that the electricity system is a substantial greenhouse gas emitter (25% of global CO_2 emissions [1]), and that this may increase considerably [1] in line with population growth and the electrification of other sectors [2] . In addition, CO_2-emissions reductions are generally considered to be less expensive in the power sector than in other sectors [2]. In the electricity sector, even deep cuts in emissions have been shown to come at a lower cost than in other sectors, as evidenced by global pathways that result in deep emissions cuts [1]. Since the industrialized countries are likely to decarbonize their societies faster than the global average, the global mitigation pathway translates into even more stringent goals for the European electricity sector, where emission targets are set to be almost zero by Year 2050 [3] .

Thus, substantial reductions in emissions from the electricity system appear to be an essential part of a likely and cost-effective pathway to a low-carbon-emissions world [2], and, specifically, to a low-carbon Europe. There are, however, several options for CO_2-neutral electricity generation other than wind and solar power, including coal or gas with Carbon Capture and Storage (CCS), nuclear power, hydro power, geothermal power, and biomass-fired power plants. So, why is it interesting to investigate futures in which the electricity generation system is *based on* variable renewable energy, rather than one where generation using renewable resources is used as *an addition to* a predominantly thermal system, based on, for example, nuclear power and CCS? The reason is that the CO_2-neutral technologies all have their limitations and drawbacks, i.e., resources needed for geothermal power and hydro power are limited and restricted to certain geographic areas. It is assumed that hydro power will not within Europe, for reasons of resource scarcity, as well as environmental preservation issues [4]. The use of nuclear power is controversial, due to the associated costs [5] and risks. In addition to being perceived as risky by the public in much the same way as nuclear is regarded, CCS has not benefited from the same cost reductions linked to increased deployment as has solar PV (as an example), and is still an expensive technology. In addition, power plants with CCS (including transport and storage) do in fact emit CO_2, albeit less than coal or gas plants without CCS. Given that biomass is likely to be a resource for which there is a demand from other sectors, e.g., the industry and transport sectors, it may become expensive due to scarcity pricing. These issues motivate investigations into how wind and solar can function as generators of a large part of the demand, and how they may interact with other systems of generation, such as thermal and hydro, and storage technologies.

However, wind and solar power also have their drawbacks. Apart from the issues of public acceptance and land use, a significant challenge associated with both wind and solar power is the variability of generation, which lessens their suitability as electricity generation systems, in that generation has to meet the demand at all times. The risks and limitations linked to other CO_2-free generation technologies raises questions as to how an electricity system dominated by wind and solar would look. How costly would it be? To what extent can variability be mitigated, given the physical realities of weather patterns and diurnal and seasonal variations? To what extent can variable renewables be combined with thermal generation systems already in place, such as nuclear power? These are some of the questions that are addressed in the papers of this thesis.

This thesis consists of six papers (**Papers I-VI**). The first part of the thesis (**Papers I-III**) investigates wind power variability *per se*, and how it may be mitigated. There are undoubtedly differences in weather patterns, and these account for the aggregated output of wind power being considerably less variable than that of a single region. The first three papers quantify the extent to which aggregated variability can be reduced, and the trade-offs that occur with other parameters, such as high average output.

The second part of the thesis investigates the roles of wind power and solar power in electricity systems (**Papers IV-V**). The questions revolve around the extent to which it is possible to use variation management strategies, such as trading and storage, to reduce the system cost and to combine variable renewables with thermal (baseload) generation.

Paper VI is a methodological study of the time description in energy system models.

1.1. Aim

The objectives of this thesis are to gain insights into three overarching research questions:

- What are the possibilities to mitigate the variability of wind power through geographic distribution of the wind power capacity?
- To what extent and in what ways can a system that employs large-scale wind and solar still be flexible? (For example, in terms of being load-following at high penetration levels and being combined with different thermal capacity mixes).
- How does the variability of wind and solar power influence the total system cost at increasingly higher penetration levels of VRE, and how can variation management strategies be used in a cost-effective way?

More specifically, the main topics of the six papers are as follows:

Paper I employs a heuristic method to identify wind power sites in Northern Europe that minimizes the aggregate coefficient of variation, which is the standard deviation divided by the mean.

Paper II investigates the trade-off between three objectives for the aggregated wind power output in Europe: to avoid low outputs; to minimize the hour-to-hour variations (ramps); and to achieve as high an average output as possible.

Paper III investigates the trade-off between two objectives for the aggregated wind power output in Europe: to avoid low output; and to cover as much demand as possible locally, using the division of Europe into 50 regions.

Paper IV investigates the trade-off between two objectives for the electricity system: a high average output of variable renewables; and the possibility to combine variable renewables with baseload generation.

Paper V assesses the levelized cost of electricity (LCOE) for variable renewables at different penetration levels of the same.

Paper VI compares the performance, in terms of predicting optimal VRE capacity, of two methods to downscale the time dimension in electricity investment models.

1.2. Outline

The thesis is organized as follows. Chapter 2 provides a general background to variable renewables and the electricity system. Chapter 3 is a literature review that focuses on wind power variability, electricity investment models, and studies that involve a high share of variable renewables. Chapter 4 summarizes the methods used in the six papers, with special emphasis on the models. This chapter also discusses the methods and data used, limitations, and possible improvements. In Chapter 5, the results from the appended papers are compared and discussed. Chapter 6 outlines some ideas for future work.

2. VARIABLE RESOURCES AND VARIATION MANAGEMENT

This chapter describes the traditional/current electricity system, as well as a possible future system. The electricity system that is typically present in developed regions, herein termed the "traditional" system, consists mainly of thermal generation, whereas a future, renewable system may incorporate a large fraction of variable sources, such as wind power and solar power. The description of the contrasting systems highlights some of the problems, barriers, and possibilities associated with transitioning from one system to another.

The electricity system comprises generation (power plants), transmission and distribution (the transport infrastructure of electricity), and consumption. In addition, there are storage options, such as hydro dams, batteries, and storage built in to the grid.

Electricity differs from many other commodities in four main ways:

- In general, electricity, must be consumed as soon as it is generated.
- The demand for electricity varies over the day, as well as across seasons.
- It is costly to store electricity, even on short time-scales, such as hours.
- It requires a trading infrastructure (transmission lines), which cannot be used for anything else. (In contrast, many other goods are, for example, shipped, whereby the ships can be used for multiple goods and have a high utilization time).

2.1. The traditional electricity system

Generation in the traditional electricity system is thermal (nuclear, coal, gas etc.) and, in some regions, hydro power. Some of these technologies are less flexible due to their costly and slow ramp-up/down characteristics. Such generation is called 'base-load', examples of which are nuclear power and coal power. Base-load power plants have high investment costs and low running costs compared to the other two types of generation: intermediate-load plants; and peak-load power plants. Since demand is varying and it is costly to store electricity (e.g., in batteries), the electricity system typically comprises a mix of non-dispatchable (base-load) and dispatchable (intermediate-load and peak-load) generation (Figure 1).

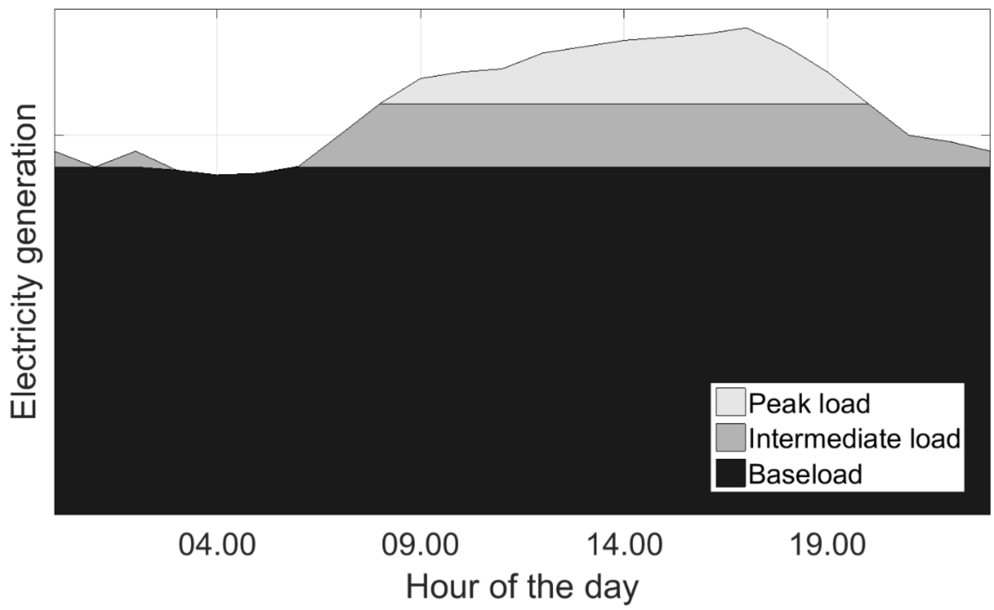


Figure 1 The traditional electricity system, with base-, intermediate- and peak-load generation.

2.2. Wind and solar resources

Wind and solar power are variable resources. The variation in wind and solar power of a site in Spain is shown in Figure 2, where it is apparent that the variations are both large and can occur within short time-spans. Apart from variability, another important feature of VRE is that the running cost is miniscule, with the consequence that the total cost is made up almost entirely of investment cost. This means that there is very little to gain from downregulating a plant, since, unlike the case for a gas plant (for example), this entails no fuel saving, i.e., no cost saving. Taken together, the variability and the high investment cost lead to a lack of flexibility, since upregulation us not possible. While downregulation is possible, this entails a decrease in yearly production and thus, an economic loss, due to the cost profile mentioned above.

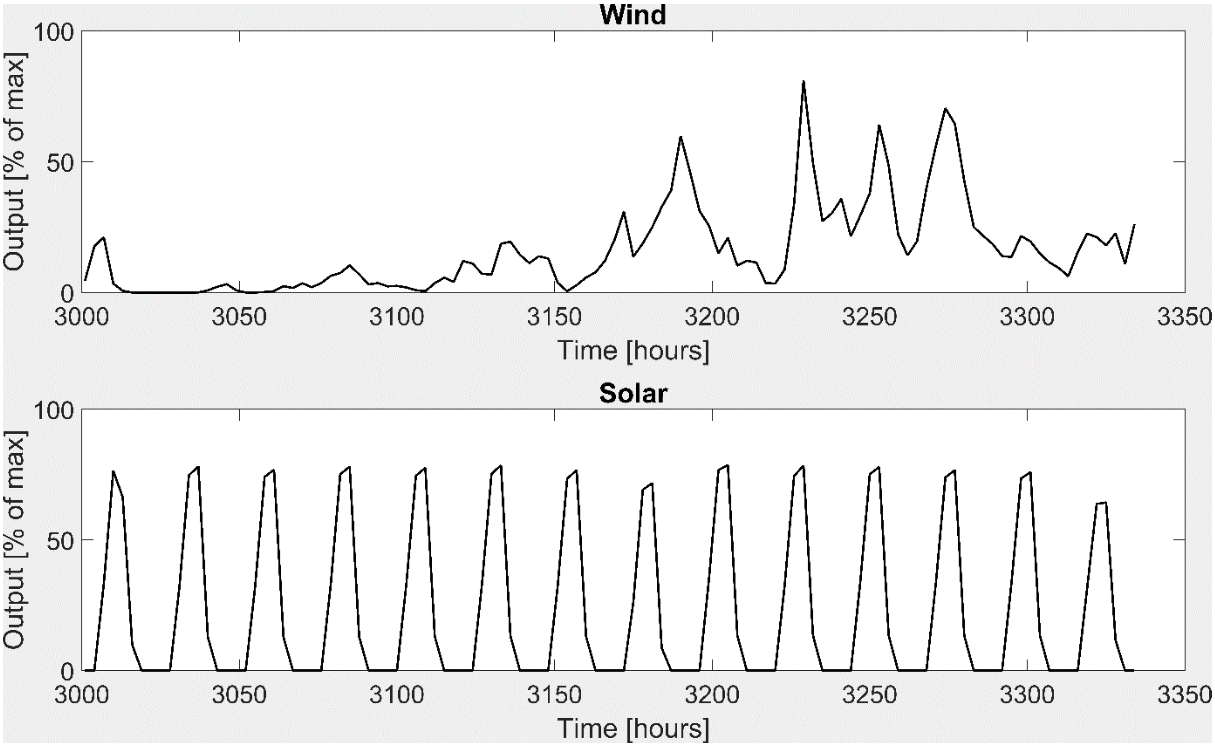


Figure 2 Wind power and solar power outputs for a site in central Spain. The upper panel shows the wind output, and the lower panel shows the solar output for 2 weeks in May 2007. (Based on weather data from [6]). The wind power data and the conversion from wind speed to wind power output are the same as in ***Paper IV****.*

2.3. A new system paradigm and variation management

As illustrated in the previous section, VRE resources are non-dispatchable and inflexible. Nuclear power is also inflexible, in the sense that it is costly to reduce its utilization time, due to high investment costs, and it is slow and costly to ramp, due to technical constraints. VRE sources are inflexible in a different way, and so their large-scale introduction into the electricity system is likely to drive a major re-design of the same. A new system in which electricity generation to a large extent is based on VRE is likely to require different tools than the base-mid-peak system depicted in Figure 1. The effect of increasing the levels of wind power is shown in Figure 3. It is clear from Figure 3a that two challenges arise: (i) there is an increasing level of excess generation that cannot be absorbed by the demand; and (ii) even when there is a lot of wind power in the system, there is still a need for almost the same capacity of flexible (gap-filling) power plants, which can be dispatched when it is not windy. The curtailment challenge reduces the yield from VRE capacity invested in, while the gap-filling challenge requires a substantial back-up capacity, which will have a low utilization time. The level of excess generation that may have to be curtailed is shown in Figure 3b. It increases dramatically once the level of wind power is at around the same capacity as the maximum demand. Thus, at first glance, an electricity system that consists mostly of variable generation is likely to have issues with cost efficiency.

Nevertheless, tools, other than adjusting generation, exist that can be deployed to integrate higher levels of VRE. These tools and strategies are herein termed *variation management strategies*. Variation management strategies are used to shift electricity generation in time (storage) or in space (trade) or to move the demand to fit variable generation (demand-side management; DSM). A schematic of two of the most important strategies for this thesis are shown in Figure 4. Figure 4a shows the principle underlying electricity storage, where the storage is filled during times of excess generation and emptied during times of low VRE output. Figure 4b shows how electricity can be traded between two regions, so that a region that momentarily experiences a high level of VRE generation can export its excess production to a region with a low level of VRE generation.

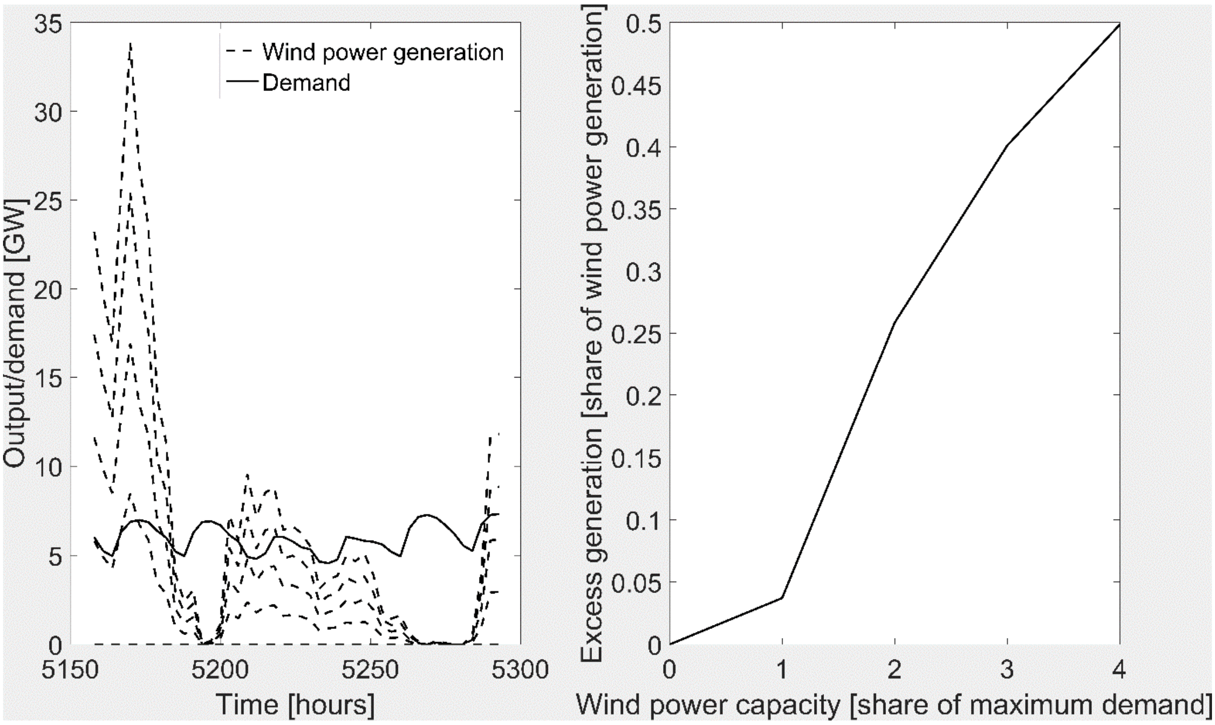


*Figure 3 The effect of increasing wind power generation. The left panel shows the time series for wind power output and demand. The dashed lines show an increasing wind power generation, where each line represents an increment of wind power capacity equivalent to the maximum demand during the year, ranging from zero to four-times the maximum demand. (Thus, if the maximum demand is 10 GW, the wind power output for the uppermost curve is for 40 GW of wind power capacity.) The right panel shows the excess generation resulting from increasing wind power output from zero to four-times the maximum demand. The wind power data, from ECMWF [6], and the conversion from wind speed to wind power output are the same as in **Paper IV**.*

a)

b)

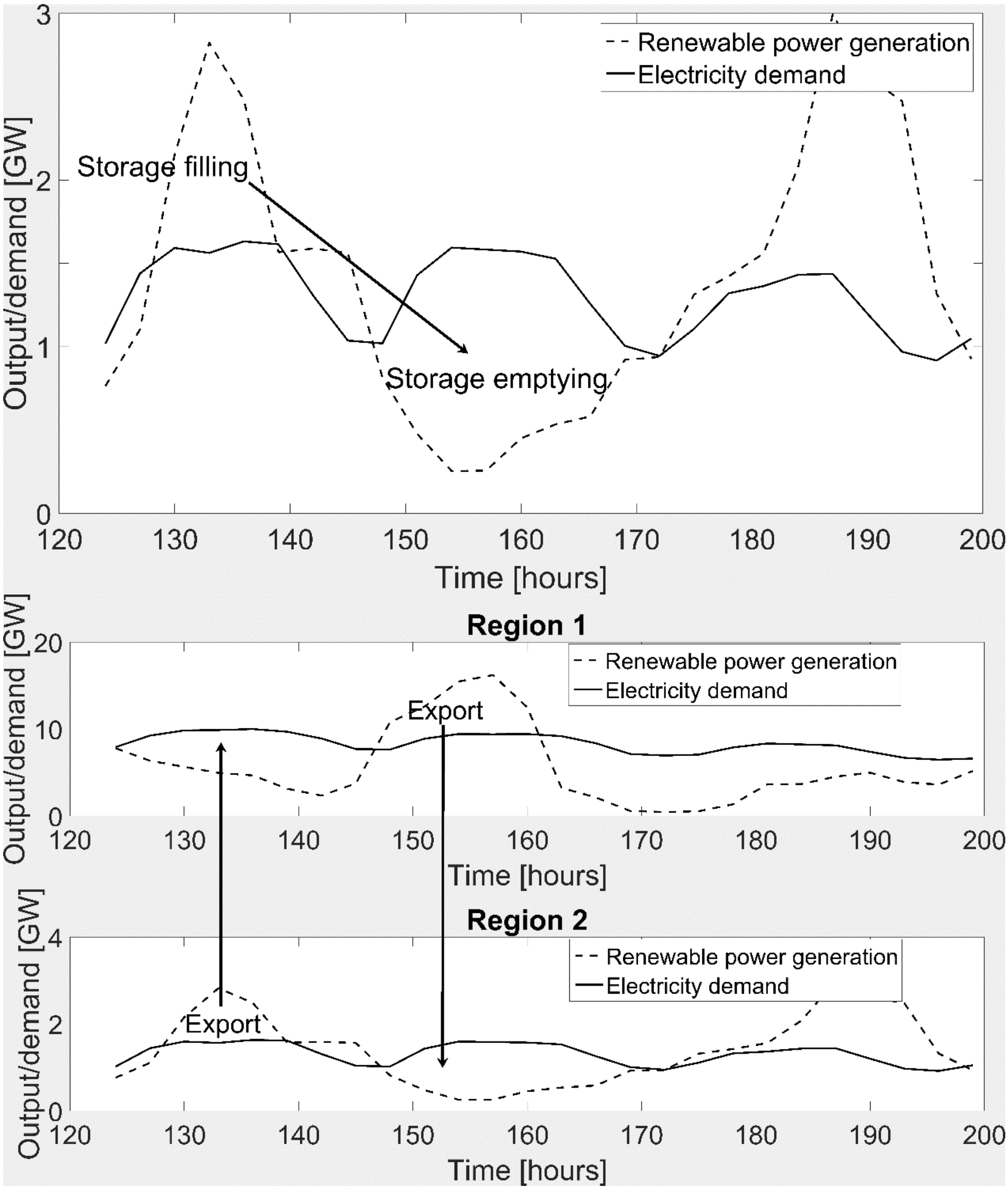


Figure 4 Schematic of the functions within the electricity system of: a) storage, enabling the movement of electricity in time to make the generation fit the demand. During Hours 130–150, there is excess generation and the storage is filled. The arrow indicates that this energy is then used during Hours 150–180, when storage is emptying; and b) electricity trade between regions with different patterns of renewable power generation. During Hours 130–150, Region 2 experiences excess generation and exports electricity to Region 1. During Hours 150–165, the export is in the opposite direction, i.e., Region 2 exports its excess electricity to Region 1.

The variation management strategies that are relevant for the electricity sector are (those in bold are considered in the present thesis):

- **Storage**, which may be in the form of batteries, pumped hydro, compressed air storage etc. Although there are different technical limitations pertaining to the different forms of storage, they are all characterized by moving electricity from periods of excess generation to periods in which there is a shortage of generation.

- **Curtailment**, which entails the shedding of excess generation. A variation management strategy associated with curtailment is to over-invest in VRE capacity, knowing that a certain share will have to be curtailed.
- **Transmission and trade**. Building transmission lines and trading electricity enables so-called 'smoothing', where net variations, which depend on demand and VRE output, can be traded between countries with different patterns of the same.
- Demand-Side Management (DSM). The function of DSM is to reduce demand at times when electricity is scarce and prices are high (this is called 'load-shedding') or to shift demand from times of scarcity to times when generation is more abundant. This last function resembles storage, except that there are no necessary losses (such as losses due to round-trip efficiency in, e.g., a battery).
- **Adapting the thermal technology mix**. Thermal technologies differ in terms of their flexibility and investment costs, which influence how well the different thermal technologies function in combination with VRE generation.
- **Complementarity between wind and solar**. The aggregated wind and solar power may have a dampening effect on variations, for instance in regions where it is more windy at night and (of course) sunny during the day. The mix between the two may thus be used as a tool in the integration of VRE.

In summary, the large-scale introduction of variable renewables (wind power and solar power) entails a shift in the electricity system paradigm to one in which variation management strategies are necessary to make the system feasible. In theory, some of the variation management strategies, e.g., storage, can by themselves "solve the problem". However, since they all interact with each other, a mixture of variation management strategies represents the most cost-efficient method to design a predominantly renewables-based power system. Therefore, the emphasis in this thesis is on the system aspects, i.e., the interplay between the nature of wind and solar power generation and the potential variation management strategies. This emphasis leads in to the areas of related research covered in the next section. The areas of related research cover the nature of wind power, as well as the system aspects of high-penetration power systems and how to model them.

3. RELATED RESEARCH

This thesis is about the variability in VRE (especially wind power) output, and the requirements that it imposes on the electricity system, in terms of the surrounding generation mix and variation management strategies. This complex, which we term *VRE-centered energy system studies*, draws on the literature in relation to energy system models, as well as on studies that focus more on wind variability in general.

Therefore, the chapter is divided into three sections. The first section covers research on variations in wind and solar outputs. The second section covers electricity investment models and how they may be designed to investigate variable renewables. The third section gives an overview of studies that have been performed with a high penetration (>50%) of variable renewables.

3.1. Wind variations and the smoothing effect

The commonly used term for the dampening effect that geographic dispersion of capacity has on the variability of aggregated VRE output is the *smoothing effect*. This term does not specify the nature of the smoothing, as it can refer to different time-scales, as well as to different measures of variation dampening, as described elsewhere [7]. We will here focus on studies of the wind smoothing effect. The smoothing effect for wind power has been studied in an energy systems context in various studies [7-9]. These studies show that hourly to sub-hourly variations in wind power output can be substantially reduced by spreading wind power over a sufficiently large area, such as the Nordic countries. However, the aforementioned studies did not perform optimization with respect to the geographic allocation of wind power capacity. Instead, they investigated the *consequences* of already existing allocations of wind power. With respect to the optimization of wind power allocation, fewer studies have been carried out. A study of the optimization of hourly changes carried out by Rombauts et al. [10] had a geographic scope of five countries in central Europe, and the effect of allocating capacity to several countries was compared to the effect of allocating capacity to only a few countries. That study quantified the trade-off between low variance of hourly changes and high average output, and showed that an optimal allocation across three countries could lower the standard deviation of intra-hour variations by about one-third, at the expense of a reduced average output.

Reducing the fluctuations in wind power output between longer periods of high and low outputs requires the use of larger geographic areas if a substantial reduction is to be achieved [11, 12]. This is because wind conditions are determined by weather systems, which can persist for a few days or for up to several weeks. Managing the variations in output over a longer time-scale, i.e., avoiding extreme highs and lows, would allow definition of part of wind power generation as the base load and reduce the cost for back-up generation. Kiss and Jánosi [11], Degeilh and Singh [13], Drake and Hubacek [14], and Grothe and Schnieders [15] have investigated the variation in aggregated wind power output, e.g., the variance and maximum and minimum, as opposed to *changes* in the variation between hours. Kiss and Janosí [11], using a Monte Carlo method for optimizing site location in Europe, have reported that the absolute minimum aggregated wind power output over the 30-year period covered by their data is 1% of the installed capacity. Grothe and Schnieders [15], who focused on the possibility of avoiding low output by optimizing the geographic allocation in Germany, have shown that when penalizing low outputs in the objective function there is a probability of 0.12 of achieving, for a given hour, an output of less than 5% of the installed nameplate capacity. These results reveal a discrepancy between the current and optimal allocations, whereby the optimal allocation performs about 50% better than the present allocation [15]. Drake and Hubacek [14] investigated reducing the variance of aggregated wind power output in the UK, and showed that there was a trade-off between variance and average output in the aggregated output at four sites in the UK, when the relative contributions of the sites were varied. Degeilh and Singh [13] investigated the variance of pooling wind farms using a methodology that allows for a convex, and thus computationally more manageable, formulation of the problem.

In summary, several aspects of the smoothing effect conferred by dispersed wind power have been investigated, although the majority of the published work in the field has focused on a single country or region, such as the UK, Germany or the Nordic countries. This means that the limitations that apply to the potential to provide variation management using geographic distribution of wind power are not fully understood.

3.2. Electricity investment models

The focus in the present review is on the representation of variability, both in generation and demand, as well as on variation management (transmission, storage, DSM, cycling of power plants). Variability and variation management are tightly connected: without a representation of variability there is no need for variation management.

The investment models that are of particular relevance for this thesis (**Papers IV-VI**), and which are therefore of primary interest for this review, should ideally have the following features. The arguments for limiting the literature review to those studies that have these features are given in italics.

- (i) Focus on, and are most often confined to, the electricity sector

The inclusion of sectors other than electricity sector typically makes the models either more approximate or confined to only one region (see below), which counteracts the focus on a detailed description of variability, which is the focus of this thesis.

- (ii) Describe the electricity system for a larger area, e.g., (part of) Europe or the US

One of the major variation management strategies discussed in this thesis is trade, where the pooling of output, as well as demand from different countries is important. The effect of pooling, the smoothing effect, attains importance for the system only when it is applied on larger geographic scale.

- (iii) Represent network models that enable trade between regions/nodes

Network models can assess the cost of exploiting the smoothing effect by investing in transmission system extensions, whereas single-region models collapse all demand and generation into a single node.

- (iv) Allow for *transformation* of the capacity mix, i.e., they determine investments, and not only dispatch

Since one of the main topics of the thesis is the system design of a VRE system, the main interest is in models that try to address that issue. In contrast, dispatch models investigate how to make best use of a plant fleet that is already in place.

- (v) Optimize, rather than simulate, the electricity system

The main purpose of the thesis is to assess the limitations that variability, i.e., the physical constraints, impose on the cost and feasibility of a VRE-based system. To assess such limitations, optimization models are necessary. Simulation models, on the other hand, are well adapted to evaluating already laid plans, or to assess a system in which the degrees of freedom, e.g., regarding where to place variable generation capacity, are small.

These models will be referred to as Capacity Expansion Models (CEMs), as proposed earlier [16], so as to highlight that it is not only generation capacity, but also potentially transmission, storage, and DSM capacities that are investment options for the models. While limitations (i) – (v) may appear to be obvious, other approaches are available to model power systems, e.g., by exogenously determining one or several of the investments and using a more dispatch-type model to evaluate them, as explained by others [17].

In addition to the features discussed above, CEMs may be *greenfield*, in that the power system is determined without taking into consideration any (or very little) of the existing capacity, or *pathway*, i.e., modeling the transition of the power system for the current form to that in (for example) Year 2050. The pathway approach, which is more prevalent than the greenfield approach (Table 1), introduces some additional complexity, and even more complexity is added if the model takes into account multiple pathways, e.g., by introducing stochastic programming, of which the EMPIRE model [18] is one example.

Some of the features of the models that are mentioned in this review are summarized in Table 1.

3.2.1. Variability and time description

The description of variability is tightly linked to the description of time in a model. Due to their technological, temporal and spatial details, electricity investment models are computationally demanding. They are therefore constrained in terms of their representation of time, and thereby, in relation to the description of variable generation. Many such models have been developed for the traditional electricity system (see the *Background* chapter of this thesis), where the main varying quantity is demand, and they are therefore equipped with a time description that averages over many time-steps [19]. Examples of such models are MARKAL [20], TIMES [21], and ReEDS [22]. These models have in common that they reduce the time dimension by averaging across time-steps that are identified using fluctuations in demand. Following Nahmmacher et al. [19], we will refer to the method to represent time by averages as *integral*, and we will refer to the methods that take into consideration only demand (and not wind and solar variability) when determining time slices as *demand-based integral*. The demand-based integral method underestimates the variability of VRE, and thus overestimates the value of VRE to the system, as shown previously [19, 23, 24]. Two strategies have recently been proposed to address the shortcomings of demand-based integral time reduction methods. The first approach is to couple investment models to a coarser time resolution, e.g., the models described above, in order to dispatch models that can rectify (or at least point to) the shortcomings of the investment model. One such study has been conducted by Pina et al. [25], where this approach is referred to as the *hybrid model* approach. The hybrid model approach thus couples two models with a feedback loop. This technique is a heuristic, and thus, there is no guarantee that the solution will be optimal. Essentially, the feedback loop ensures that the solution is *feasible*, but not *optimal*. One simple example of the effect that the heuristic may generate is that a low time resolution in the investment model underestimates the variability of wind power, and thus overestimates the optimal capacity of the same. When a dispatch model is run in conjunction with the investment model, the dispatch model may warn that there is not enough capacity to cover demand at all times, and signal that there is a need for more back-up/storage/transmission capacity. However, "fixing" this in the investment model may entail a more costly solution than the optimal solution.

The second approach is to define more accurately the variability on the generation side using new methods for down-scaling the time dimension, while maintaining a representation of the variability also on the generation side. Thus, the essential characteristics (mainly variability of wind and solar) that determine the optimal capacity mix are retained, while the number of time-steps needed to represent them is reduced. Such methods can be divided into different "families" of methods, two of which are compared in **Paper VI** of this thesis.

The *integral methods* [19] retain the idea of finding typical situations but base the identification of situations not only on demand, but also on wind and solar conditions. An intuitive and simple example is to identify occasions that have all the combinations of wind output and solar output, i.e., high wind-high solar, low wind-high solar, high wind-low solar, and low wind-low solar (Figure 5). Integral methods that involve wind and solar variability have been used for single-node models only [26-28], so their application to network models is still uncertain.

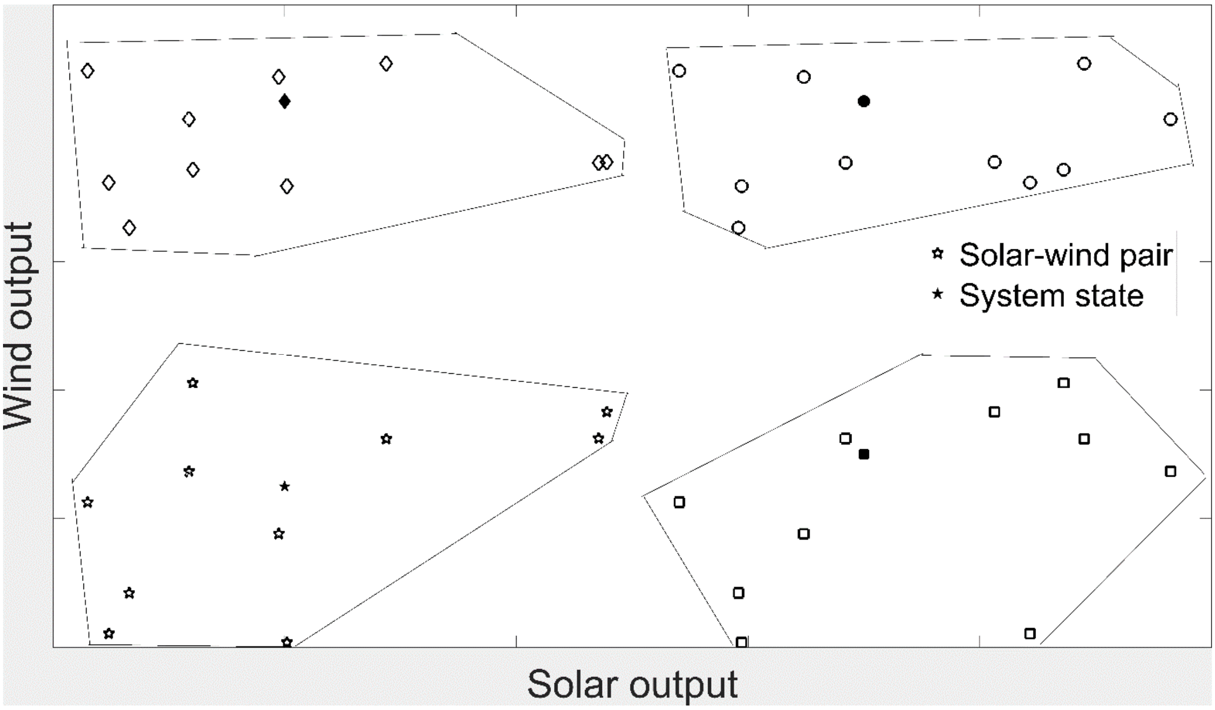


Figure 5 Schematic of the principle behind integral methods. The y-axis represents the wind power output and the x-axis the solar power output. Each point represents one time period (e.g., 1 hour). The time periods are characterized by a value-pair of wind power output and solar power output. The time periods are arranged into four clusters, where the circles represent high-wind, high-solar, the diamonds represent high-wind, low-solar etc. Each filled shape indicates the value pair (wind-solar) that would represent the cluster. The figure is adapted from Wogrin et al. [27].

The second family of methods uses representative days. The representative days method builds on the idea of using entire days, e.g., to use 4 days with each 24-hour time-step, to represent an entire year (Figure 6). This was done already before the development in recent years of the method, e.g., in the SWITCH model [29]. However, in earlier studies, the days were selected using a specific rationale, such as selecting 2 days per month [30]. Nahmmacher et al. [19] introduced a method to select *representative* days for network models and showed that, in the model Limes-EU+ [31], the use of 20–30 days was sufficient to predict correctly the system cost and VRE capacity. The method developed previously [19] is based on viewing each day as a vector of hourly outputs of wind, solar, and demand for all regions, and then clustering the vectors. The size of each cluster then becomes the weight on the representative day. Following Nahmmacher et al. [19], **Paper VI** confirms their results, and assesses the merits of the clustering selection method compared to the random selection of days. Merrick et al. [32] have also used representative days. However, they have shown that a period of ~300 days is necessary to obtain correct results. This discrepancy may reflect the fact that they were assessing a high number of variables, e.g., the dispatch, for correctness.

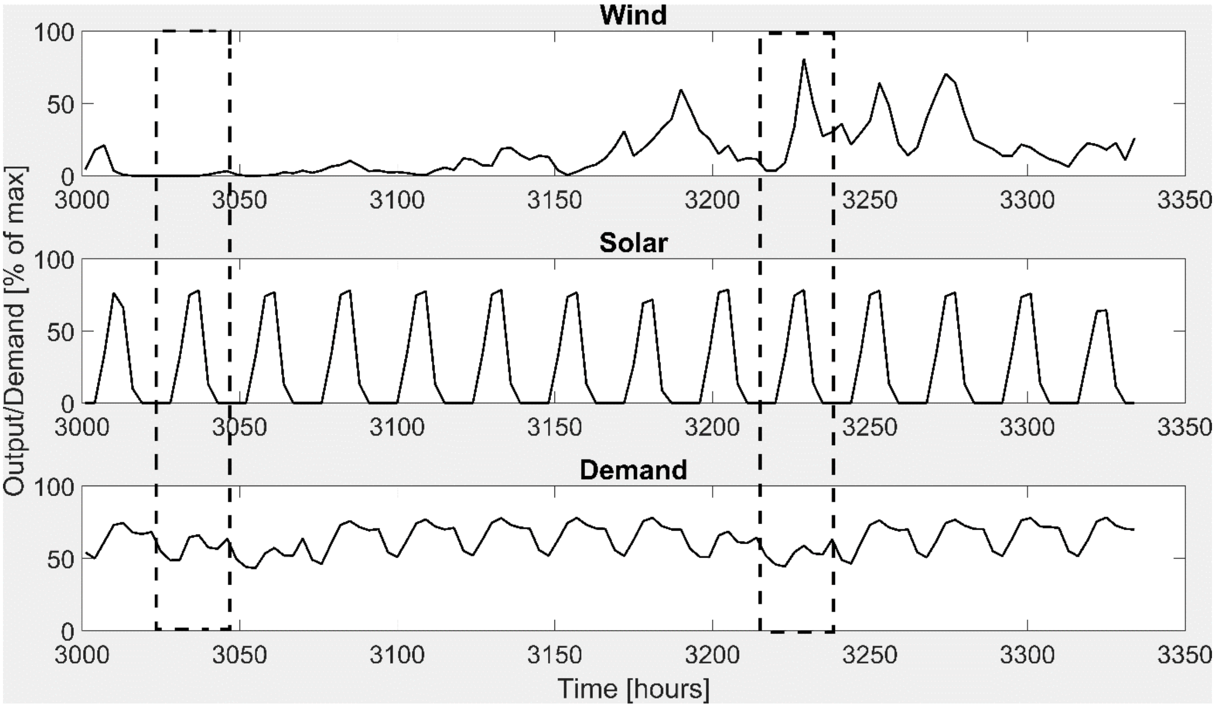


Figure 6 Schematic of the representative days approach. The panel show (from top to bottom) wind output, solar output and demand in % of maximum. The dashed lines enclose two representative days from this period of the year.

Another branch of the representative days family relates to the recent development of the time representation in the POWER model from Stanford [24]. The idea behind this method for the selection of days is to find the most extreme cases, e.g., when the wind power output attains its maximum value while simultaneously, the demand attains its minimum value. In the case of three dimensions (solar output, wind output and demand), the selection of such days can be regarded as the corners of a cube. Thus, this procedure includes 8 days, which depending on the time resolution, amount to 64 (3-hour resolution) to 192 (hourly resolution) time-steps. In addition to the eight extreme days, Frew et al. [24] incorporated random days to represent "normal" conditions.

For the CEMs with endogenous decision variables, the *elesplan-m* model [33] and the NEWS model [34] stand out as the models with the most detailed time representations (8,760 hours, which is here referred to as *full*). The *elesplan-m* model is designed so that the geographic allocation of VRE generation capacities and transmission capacity is done first, creating a net demand curve. The net demand curve is then filled using thermal generation and storage technologies. The advantage of using a full year of hourly resolution, i.e., not using any method to downscale the time dimension, is that it retains chronology, thereby ensuring that storage, including hydro power, can be evaluated without restriction as to the storage operation time. The representation of a storage investment option that is unlimited in its time scope may be important if one of the modeling objectives is to investigate the extent to which a future system with a high penetration of VRE will rely on storage/DSM or transmission as the major variation management strategy.

To summarize, the last few years have seen adaptation of CEMs to represent scenarios in which VRE sources constitute a larger fraction of the electricity generation. This thesis also emphasizes the more detailed description of VRE, especially regarding the time dimension, in the models. Thus, the models reviewed here can serve as a comparison, both in terms of methodology and results, to the papers in the thesis. The next section covers investigations of high-VRE scenarios, some of which are produced using the models reviewed here.

Table 1 Overview of sample CEMs, with the emphasis on more recent attempts at representing variability in a more detailed fashion.

Model	**Region**	**Time representation (hours/periods per year)**	**Time representation type**	**Approach**
NEWS [35]	US	8760	Full year	Greenfield
SWITCH [36, 37]	US	Up to 600	Representative days	Pathway
EMPIRE [18]	Europe	192	Representative days	Pathway
elesplan-m [33]	Europe	8760	Full year	Pathway
POWER [24, 38]	US	308	Representative days	Pathway
TIMES [21]	various	various	Demand-based integral	Pathway
MARKAL [20]	various	various	Demand-based integral	Pathway
ReEDS [22]	US	17	Demand-based integral	Pathway

3.3. Studies of high-penetration scenarios

There is no consensus in the literature regarding what constitutes “a high level” of penetration of VRE. On the one hand, some authors seem to suggest that “high” penetration is when challenges, e.g., those relating to over-production and reduced full-load hours in thermal generation, are becoming more pressing [39]. On the other hand, “high” may refer to the use of close to 100% renewables [40]. In this thesis, “high” refers to the *variable* renewable part exceeding 50% of the demand. While the exact value is arbitrary, it is somewhere around that point at which the penetration level of VRE, variation management strategies other than curtailment, and changes to the thermal power plant fleet can be assumed to become important. It is likely that systems with >50% VRE exhibit a design and dynamics that are quite different from those of the traditional electricity system.

The definition based on variable generation deviates from the commonly held notion of defining the system based on its renewable share (i.e., also including hydro power and geothermal power, and, possibly, biomass- or biogas-fired power plants). The definition based on the VRE share is chosen because there are electricity systems in which a renewable share close to 100% is easily achieved without much need for additional flexibility in the generation mix or storage. Examples of these are the hydro power-dominated systems of the Nordic countries and New Zealand. Therefore, the main challenges associated with a renewable system arise from the variable part.

Hohmeyer and Bohm [40] have provided a review of historical studies (from the 1970s to 2013) that consider electricity systems with near-100% renewable generation. Their review reveals a marked increase in the number of such studies, as well as in their level of detail, after 2009. The focus of the current review is studies in which the assessment required that the demand be fulfilled at every time-step. These are classified as 1st order studies by Hart et al.[41]. (In contrast, 0th order studies use annual averages of, for example, wind power output, to assess the potential of fulfilling the annual demand). In the present review of the literature, a distinction is made between studies with *endogenous optimization* of relevant quantities (geographic distribution of generation capacities, transmission capacities, and storage) and those where one or more of these categories are exogenously given. These types of studies are distinguished based on the assumption that the levels of cost effectiveness of, in particular, variation management strategies are strongly dependent upon each other. For example, the cost effectiveness of battery storage may strongly depend on the extent to which countries with different weather patterns are connected through transmission networks, since such connections enable the smoothing effect and thereby can reduce the variation in residual demand fluctuations. Therefore, if the transmission network is not optimized concomitant with the storage, it will not be clear to what extent the results (e.g., the system cost) are a consequence of this method, and thus to what extent it is suboptimal. It should be noted that endogenous optimization is often performed at the expense of temporal and/or spatial detail. Table 2 lists the high-penetration studies that are discussed here.

In the following section, three aspects of the results from high-penetration studies are discussed: the estimated system LCOE (system cost); the respective roles of solar and wind in these systems; and the roles of the variation management strategies for transmission extensions and storage.

3.3.1. System LCOE

The *average system LCOE*, which is simply the total annual system cost at a certain penetration level divided by the total annual demand for electricity, is here used as the comparative number for system cost. Minimizing the system cost is usually the objective of energy systems models.

To date, five studies have determined all the capacities endogenously (model in parenthesis): Plessman and Blechinger [33] (*elesplan-m*); Haller et al. [42] (*EU-Limes+*); Macdonald et al. [34] (*NEWS*); Mileva et al. [37] (*POWER*); and Frew et al. [38] (*POWER*). Referring to the discussion about the importance of representation of variability, and thus the relevance of the representation of time in CEMs, three of these studies stand out as having a time representation that exceeds the ~25 representative days that Nahmmacher et al. [19] found to be sufficient for modeling systems with high levels of VRE: Plessman and Blechinger [33]; Macdonald et al. [34]; and Mileva et al. [37].

Macdonald et al. [34] have evaluated systems with 80% CO_2 reduction, as compared to the Year 1990 levels in the US. Their scenarios are based on different cost combinations for VRE capacity and natural gas, and in one of their scenarios (the low-cost RE-high-cost NG scenario) the VRE part is 55% and the average system LCOE is ~100 $/MWh. Mileva et al. [37] have used the SWITCH model to evaluate systems with up to 75% VRE, based on 12 different cost scenarios. The resulting average system LCOE is close to 200 €/MWh for the case with 75% VRE. Plessman and Blechinger [33] have evaluated an optimal pathway through which Europe can achieve a 100% RE (80% VRE) system by Year 2050, with the average LCOE being estimated, depending on the cost scenario, to be within the range of 80–100 €/MWh.

Continuing with studies that look at endogenous optimization, albeit with less representation of variability, Haller et al. [42] have included Europe, as well as Northern Africa and Turkey. The endpoint system contains ~90% RE (75% VRE) and the system LCOE is estimated at approximately 100 €/MWh. Frew et al. [38] have investigated the situation in the US and shown that the LCOE is ~100 $/MWh for an 80% RE penetration level and ~200 $/MWh for a 100% RE penetration level.

Brouwer et al. [17] have simulated Western Europe with different scenarios for transmission expansion and with a rule of thumb for the distribution of VRE capacities. They have reported that the LCOE for a 0%–60% VRE system is in the range of 80–87 €/MWh. Since all the scenarios have a reduction in CO_2 emissions of 96%, as compared to the Year 1990 levels, the increase in cost from 80 €/MWh to 87 €/MWh that occurs when the VRE levels are increased from 0% to 60% is attributed to replacing thermal generation (mainly nuclear and gas with CCS) with VRE generation.

The estimated average system LCOE values from these nine studies are summarized in Figure 7. As can be seen, there is a large span of values, ranging from ~50 to ~200 € or $/MWh[1].The magnitude of the span may be attributed to differences in the methodologies used, as well as the assumptions that were made regarding costs and demand/system boundaries. However, as expected, the trend shows an increasing LCOE for increasing shares of VRE. Within the range of 75%–100% VRE (these systems are 100% or near-100% RE), the cost ranges from ~100 to ~200 € ($)/MWh, which is roughly 2–4-times the current cost for electricity.

The review of the modeling of system costs in high-VRE systems reveals a consensus that the system cost is increasing with the penetration level of VRE. However, the results differ as to the magnitude of the system cost increase that occurs with each increase in VRE penetration level. In other words, the impact on cost from the variable nature of wind and solar is unclear at high penetration levels. This is one of the topics in which this thesis (especially **Paper V**) contributes to the part of the field which deals with the cost of variability on hourly time-scales.

[1] The average system LCOE is assessed in €/MWh or $/MWh, depending on the area covered by the study. The values in the diagram have not been converted to the one or the other currency, since the difference between the Euro and US dollar is small compared to the differences in LCOE values between the different studies.

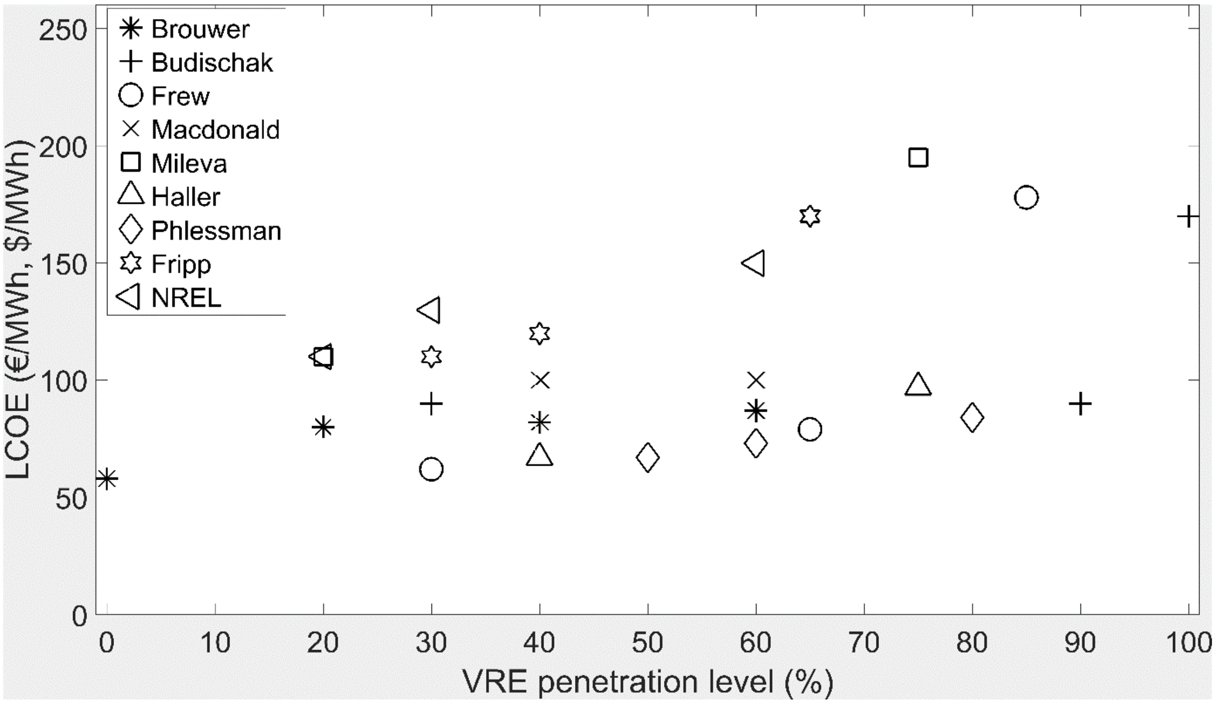


Figure 7 A Comparison of the average system LCOE values as a function of VRE penetration level for nine different studies of high-penetration systems in the US and Europe. The symbols refer to the following references: Brouwer et al. [17]; Budischak et al. [43]; Frew et al. [38]; Macdonald et al. [34]; Mileva et al. [37]; Haller et al. [42]; Plessman and Blechinger [33]; Fripp [36]; and NREL (Hand et al.) [44].

3.3.2. Solar-to-wind ratio

The mix of VRE technologies potentially includes several technologies, although with current costs, these are limited to solar and wind power, is in itself a variation management tool. The optimal mix of solar and wind power depends on several factors. The investment costs and the site conditions are of course important, while solar power and wind power also effect the system in different ways. The mechanisms that are in play for solar and wind power in the system include:

- Combining two or more outputs with different output patterns reduces the variation of the aggregate [39]. The outputs may be from different technologies (e.g., combining wind and solar) or from different geographic sites (e.g., combining wind output from sites with different weather patterns).
- Wind power variations are less well correlated spatially and temporally than are solar variations. Therefore, in a system with high capacity of transmission for import and export between regions, wind power is more valuable than in a system that has a lower transmission capacity (i.e., avoiding "locked-in" wind generation). The coupling of wind power and transmission also works in the opposite direction: a push towards more wind power, e.g., as a response to CO_2 constraints, makes transmission expansion more beneficial.
- The overproduction from solar, i.e., the amount of solar generation that exceeds demand, increases more with the penetration level than does the overproduction from wind. This is because wind power output is skewed, such that peak events are

rarer than for solar, for which the output is close to its nameplate capacity for the majority of the time when there is output at all [39].

- Related to the above, the presence of storage influences the optimal level of solar, since solar has a low marginal value after saturation [34]. This also works the other way around, in that the presence of high levels of solar makes storage more beneficial to the system.

The high-penetration studies with models that have endogenous capacity expansion and hourly time resolution both predict a solar-to-wind ratio of 1:4 on an energy basis[2] [33, 34] (see Table 2). Those that have endogenous capacity expansion, but with a less detailed time representation, display derived systems with more solar [36-38, 45]. Still, wind power is generally the dominating technology.

The studies that employ methods other than CEM network models show more heterogeneous results when it comes to solar penetration. Budischak et al. [43] found that the optimal share of solar is just 3%, while the results of Rodrigues et al. [46] shows a ~1:3 solar-to-wind energy ratio. Becker et al. [47] have optimized several objectives, whereby LCOE is minimized at 10% solar, while the amount of storage capacity is minimized at ~80% solar [48]. Rodrigues et al. [46] have optimized by minimizing the mismatch between generation and demand, thereby highlighting the profile qualities of the wind/solar mix, rather than the difference in cost. Their results indicate that wind contributes a larger fraction of the generation in the system due to its profile, and not only due to its lower technology-specific LCOE. The profile advantages of wind are mainly due to its irregular nature in time and space, producing a smoothed aggregate output when regions with sufficiently different weather patterns are aggregated.

In summary, wind power dominates VRE generation over solar power in high-penetration studies. Furthermore, the results suggest that the variation patterns of wind and solar, respectively, determine the roles that they play in systems with a high penetration of VRE.

3.3.3. Transmission versus storage

The representation of transmission requires a network model. Investments in transmission can be done either endogenously (as in [34, 42]) or exogenously (as in [17]), or by comparing a "copper plate" approach, in which electricity flows freely, with an approach that uses isolated countries (as in [46]). Several studies have compared the costs of systems that have higher levels of transmission to those of systems with transmission restrictions. The paper of Frew et al. [38] assesses the impact on system cost from the possibility to invest in transmission as being very high: isolated FERC regions in the US have a system cost that is 80% higher than that of an interconnected case. This large difference in system cost emerged in systems with 80%–100% penetration of VRE, while the lower penetration levels exhibited smaller differences in system cost. Plessman and Blechinger [33] have shown that restricting transmission expansion (to double that of existing lines) results in a 10% higher system cost, as compared to a case with optimal transmission extensions. Haller et al. [42], Plessman et al. [33], and Clack et al. [35] have all described optimal systems with transmission grid extensions of >300 GW for the EU and US, respectively, which corresponds to at least ~4-times the current transmission capacity. Skar et al. [49] have shown that restricting transmission expansion, instead relying on storage, increases the system cost by € 182 BN. When storage was not available, but transmission expansion was, the

[2] Since solar usually has a lower capacity factor, which is the average annual output as a share of nameplate capacity, than wind, the capacity relation is less relevant as a comparison.

system cost increases by a mere € 1 BN. They show that not only is increased transmission the most cost-effective way to manage variations in high-penetration systems, but that the alternative (investment in storage) is much more costly. Similar result have been reported by Frew et al. [38], where the system cost was nearly double for the high-penetration cases in which trade through transmission expansion was excluded as a variation management tool, and the local systems instead had to rely on storage and overproduction/curtailment.

In contrast to the above -mentioned studies, Brouwer et al. [17] have found that increasing the capacity of transmission lowered the system cost by only 1%–2%. They employed a method that relies on scenarios regarding expansion of capacities (generation, storage, transmission), rather than on co-optimization of these parameters, which may explain why their results differ so markedly from those of Skar et al. [49].

Table 2 List of studies conducted with a high level (>50%) of VRE penetration. The majority of these studies have focused on CO_2 emissions reductions or RE penetration levels, rather than VRE penetration levels. Here, the focus has been on extracting the VRE penetration level, since it is considered to be the source of the challenge associated with such systems.

Study	**Model**	**Maximum VRE penetration level [%]**	**Study area**	**Endogenous optimization?**	**Time resolution [time steps]**	**Solar [% of total VRE generation]**
Plessmann and Blechinger [33]	elesplan-m	80	Europe	yes	8,760	24
Macdonald et al. [34]	NEWS	55	US	yes	~27,000	27
Mileva et al. [37]	Switch	75	Western US	yes	600	33–56
Frew et al. [38]	POWER	85[3]	US	yes	336	46
Haller et al. [45]	LIMES-EU	75	Europe plus North Africa	yes	12	44
Fripp [36]	Switch	63	California	yes	“set of days” (?)	47
Hand et al. [44]	ReEDS	60	US	yes	17	3–22
Brouwer et al. [17]	PLEXOS	59	Europe	no	8,760	n/a
Budischak et al. [43]	RREEOM	99.9	Eastern US	no	8,760	0–3

Haller et al. [45] have used a conceptual model with three nodes and limited time representation to demonstrate that the absence of storage limits the RE penetration to ~80%. Their findings suggest that the possibility to invest in storage significantly affects the optimal penetration levels

[3] From the article, we were not able to discern the VRE contribution to annual load, so the value of 85% is based on the assumption that RE constitutes 100% of generation in one of their scenarios and that hydro and geothermal together were estimated (by us) to contribute to 15% of the US demand in that scenario.

of VRE, already at the 40% penetration level. Several other studies have suggested that storage is not vital, or that it may not even enter the cost optimal mix, until the VRE penetration levels reach 80% or higher [33-35, 38, 42]. Macdonald et al. [34] have employed a generous cost structure for the storage option (see supplementary material to [34]), although the optimal level of storage in their results with around 55% VRE was still very small, in fact smaller than the current US pumped hydro storage. Therefore, there is a discrepancy between the results from Haller et al. [45] and the results from other studies [33-35, 38, 42]. One possible explanation is that it is the physical reality of differing wind patterns (for which spatial heterogeneity is required in the model representation) that forms the basis of the benefits of transmission. Rather than displaying different profiles that may be used for variation trading, Haller et al. [45] estimated the benefit of interconnecting regions with high demand and lower-quality resources to those with high-quality resources.

3.4. Contribution of this thesis

This thesis contributes to the existing body of research in three main respects:

The review of the literature shows that research has been carried out on the nature of aggregated wind power output, and the effect of geographic distribution. However, those research efforts have either been non-optimizing, as in [9], or it has been confined to a smaller geographic area, as in [15]. The first part of this thesis contributes to the field with studies that investigate the possibility to mitigate the variation in aggregate wind power output. It does so by identifying *system-relevant measures,* such as minimizing the probability for low output in aggregated wind power output, and using *optimizing* methods to define the extents to which these measures can be improved.

The overview of the research shows that models and studies that investigate the feasibility and cost of providing electricity with predominantly renewable variables have become more advanced in the last few years. However, it remains unclear as to what extent it is possible to combine VRE with other CO_2-neutral base-load technologies, such as nuclear power. This thesis contributes by specifically addressing this issue and relating it to the lower average output of VRE (**Paper IV**).

The last few years have seen studies of cases in which the amount of variable generation is high (50%–100%). However, the cost increase for variability has not been investigated for consistently higher penetration levels of VRE. **Paper V** applies a theoretical framework to evaluate this cost increase, using a CEM for Europe.

4. METHODOLOGY

The research questions and aims listed in Section 1.1 are addressed by means of models. The models have a so-called *greenfield* approach, which means that no current investments in VRE generation or thermal generation are assumed. The reason for the greenfield approach is mainly that it alleviates computational constraints, but also that that it allows for a design that is not influenced by the current, predominantly thermal, system. The one exception to the greenfield approach is that the *Multi-objective model for net demand* in **Paper IV** and *Electricity investment model* in **Paper V** are applied with the current European hydro power capacities and annual power generation being fixed and exogenously given.

The input to the models is data on demand and wind and solar conditions (transformed using output functions), as well as a restriction imposed on the land available for VRE exploitation. In addition, the models in **Papers IV-VI** assume investment and running costs for generation, transmission, and storage.

4.1. Models

The following five models are developed: a heuristic optimization model for wind power siting (**Paper I**); a multi-objective model for wind power output (**Papers II** and **III**); a multi-objective model for net demand (**Paper IV**); an electricity investment model (**Paper V**); and a simple model with flexible time representation (**Paper VI**). Table 3 lists the factors that were taken into account in the different models.

Here follows a brief description of the models, grouped according to the three main research questions.

<u>What are the possibilities to mitigate variability of wind power by geographic distribution of the wind power capacity?</u>

- The *heuristic optimization model for wind power siting* is an optimization model with a heuristic that finds the next site (given all previous sites) that minimizes the variation (Coefficient of Variation) in the total output (**Paper I**).
- The *multi-objective model for wind power output* optimizes the joint wind power output, given four objectives that focus on high output, so as to mitigate variation (through Conditional Value at Risk and intra-hourly changes) and match the VRE capacity and regional demand (**Papers II and III**).

<u>How can variation management be used in a cost-effective way to increase VRE penetration?</u>

- The *multi-objective model for net demand* is similar to the *multi-objective model for wind power output*, except that the quantity that is optimized is the net demand (VRE generation subtracted from the demand) rather than only wind power. An additional feature of this model is that it is a network model (thus, it models transmission), so it also takes trade into account (**Paper IV**).

<u>How does the variability of wind and solar influence the system cost at increasingly higher penetration levels of VRE?</u>

- The *electricity investment model* is a cost-minimizing network optimization model that is aimed at finding the optimal configuration when there are high levels of variable renewables in the system (**Paper V**).
- The *simple model for flexible time representation* is a simple, single-region, electricity system model in which the time representation can be either a time-slicing type or a representative day type, with the time dimension having between 1 and 8,760 time-steps (**Paper VI**).

Table 3 Factors covered by the modeling in the papers of this thesis.

	Paper I	Paper II	Paper III	Paper IV	Paper V	Paper VI
WP variations	*	*	*	*	*	*
SP variations				*	*	*
Demand		*		*		*
Transmission bottle-necks				*		
Variation management by trade				*	*	
Variation management by storage					*	
Thermal generation				*	*	*
Costs					*	*

WP, wind power, SP, solar power.

4.1.1. Heuristic optimization model (Paper I)

This model deals exclusively with wind power output. The model is designed to identify combinations of wind power sites for which the aggregate output is high but less variable. This is done by means of the coefficient of variation (CoV), which is the standard deviation, σ, divided by the mean, μ.

$$min\ CoV = \frac{\sigma}{\mu} = \frac{\sqrt{\sum_t (X_t - \mu)^2}}{\sum_t X_t}$$

where $X_t, t = 1,2, \dots, T$ is the aggregate time series of output of all the sites, $X_t = \sum_i x_{it}$. This objective function is non-convex, so the optimization problem is "solved" heuristically, by starting at one point (the wind power site) and including the point that together with the first point minimizes the CoV of the aggregate of the two points. The aggregate of the two points is then taken as the starting time series and the procedure is repeated until the desired number of points is reached. The variables are the placements of wind power sites. Neither demand nor transmission constraints are represented. The method was applied to Northern Europe (Nordic countries plus Germany).

4.1.2. Multi-objective model for wind power output (Papers II and III)

This model is equipped with an objective function that consists of four parts, which are combined in the objective function as a weighted sum. The four objectives are to:

1) Maximize the average aggregate output $max \sum_t X_t$
2) Minimize the changes in the aggregate output between time-steps $min \sum_t (X_t - X_{t-1})^2$
3) Maximize the CVaR of the aggregate wind power output $max\ _{\alpha}CVaR(X)$

4) Minimize the residual demand of each region $min \sum_j \sum_t d_{jt} - \sum_{i \in J} x_{it}$

where $X_t, t = 1,2, \ldots, T$ is the aggregate time series of the outputs of all the sites x_{it}, $X_t = \sum_i x_{it}$, and d_{jt} is the demand of region *j*. Thus, the model treats primarily wind power output (objectives 1–3), but also contains a representation of the demand (objective 4). In **Paper II**, the model objective function consists of parts 1 and 4, and in **Paper III** the model objective function consists of parts 1, 2 and 3. In objective 3, the expression for CVaR is linearized, using the method outlined previously [50], such that the entire optimization problem is convex. The model yields Pareto optimal solutions, depending on the weight of the respective objective. There are no restrictions on transmission, so objectives 1–3 assume a copperplate area, while objective 4 assumes that there is no transfer of electricity between regions. The variables are installed wind power per "site". (Each site is the same size as the pixels in the dataset used.)

4.1.3. Multi-objective model for net demand (Paper IV)

The objective function of this model has some similarities to objectives 1 and 3 of the multi-objective model for wind power output, but instead of focusing on maximizing the wind power output, it minimizes the net demand. The net demand is defined as the used VRE output subtracted from the demand. The model seeks to design the net demand curve so as to accommodate better the base-load thermal generation, while at the same time maintaining a high average output. The model yields Pareto optimal solutions, depending on the weight of the respective objective in the weighted sum objective function. In contrast to the previous models, the transmission network is explicitly modeled, so the used VRE output may be the VRE generated in region *i* or the VRE generated in another region *j*, which is then exported and used in region *i*. The two parts of the objective function are to:

1) Minimize the average net demand $min \sum_t \sum_i (d_{it} - x_{it} - y_{it} + \sum_j (exp_{ijt} - imp_{ijt}))$
2) Maximize the CVaR of the net demand $max\ {}_{\alpha}CVaR(x, y, imp, exp)$

The expression for CVaR is linearized, which means that the entire optimization problem is linear. The variables are the distribution of a fixed amount of VRE and transmission capacity. The effects of the CVaR objective is to allocate capacities and to curtail VRE generation in a fashion that will create a more stable net demand curve, so that more base-load generation can be accommodated in the system.

4.1.4. Electricity investment model (Paper V)

The model in **Paper V** is a more classical Capacity Expansion Model (CEM), although it is tweaked to make it possible to run with considerably more time-steps than is usually the case for such models. In addition, it is simple in form, to allow the achievement of computation times in the order of 1 minute, making it convenient to run many times with different combinations of constraints and input data (e.g., constraints on VRE penetration level and investment costs for technologies). The variables in the model are the geographic distributions of capacities of solar, wind, transmission, storage, and thermal technologies, as well as the dispatch of the capacities. The existing hydro capacity and annual electricity generation are included in the model. The hydro capacity/annual generation levels are limited to the current values, since hydro power is limited by the hydro resources, similar to the limitations place on wind and solar conditions. The demand and thermal capacities are resolved into *regions*, while the wind and solar resources have a finer spatial description, such that there are several wind and solar *resource classes* within each region. The model takes a greenfield approach, and thus sketches an endpoint system. The objective function is to minimize the system cost (including the annualized investment costs and running costs). The generation must satisfy demand, which is inelastic. In the application used in **Paper V**, the amount of thermally generated electricity is exogenously constrained (which means that the remaining demand has to be covered by VRE generation, including the trade and storage). The model may be run with different time representations: in **Paper V**, with a full year of evenly dispersed (e.g., 3-hour) time-steps; or using the method with weighted representative days outlined previously [19].

4.1.5. Simple model for flexible time representation

This single-node model was designed for **Paper VI** as a test model for testing different time reduction methods for CEMs. It is formulated as a cost-minimizing investment model. Solar and wind resources are described by one time series each, and the decision variables are the investment in capacities (VRE plus four thermal capacities), as well as their dispatch. Generation is constrained to satisfy demand, which is assumed to be inelastic. The purpose of the model is to evaluate the performance of the different time reduction methods proposed in literature. The time dimension may thus be represented in four ways:

(i) Using a one-year representation on a 3-hour resolution, i.e., 2,920 periods with equal weighting.
(ii) Using representative days that are selected with a clustering method and weighted as in the previous report [19] (1–365 days)
(iii) Using random days (1365 days)
(iv) Using an integral method with states that are defined by wind, solar, and demand conditions (1–2920 states), as described previously [27]

4.2. Data

The inputs to the models are electricity demand, weather data, and data on hydro power (national capacities and levels of annual generation). Data on the demand and hydro power are taken from the statistical databases [51, 52]. The demand is always assumed to be inelastic and equal to that in the historic year used. Hydro power is assumed to have the same capacity and annual generation as today.

The wind and solar input data are generated with the method used for several CEMs (e.g.,elesplan-m [33]):

1) Weather data (time series for wind speed, solar insolation) are downloaded from one of the large meteorological organizations, in our case the European Center for ECMWF with a spatial resolution of 0.5×0.75 degrees.
2) The time series are filtered through a turbine function (wind) or a PV function (solar). (The wind power output data after this point are the input data to **Papers I** and **III**).
3) The time series pertaining to each transmission region (e.g., country) are identified (The wind power output data after this point are the input data to **Paper II**).
4) The wind and solar sites are grouped by aggregating, for example, the wind time series with similar average output. In the case of **Papers IV** and **V**, there are wind and solar power classes, such that each region is represented by around 10 wind and solar time series with different average outputs.

Special attention is paid to the treatment of wind speeds linked to the turbine function (point 2 above). The development of wind power turbines has been phenomenal during the past 10 years. This means that although the cost of constructing a wind power plant has not fallen dramatically, the average output has increased by approximately 50%, which of course affects the LCOE of the plant. In addition to the increase in average output, which has an impact on the cost, recent papers have shown that the design of wind power plants with higher *specific power*, i.e., a relatively high generator-to-turbine ratio, also affects the system impact of wind power [53, 54]. Thus, the choice of turbine may have important consequences for the outcome of an energy system study. The turbine functions used in the papers in this thesis are as follows:

- **Paper I:** A function similar to that of a single turbine that was in common use up to around 10 years ago [11]
- **Papers II and III:** A function developed to simulate future wind farm outputs [55]
- **Papers IV-VI:** A function developed to simulate wind power farm outputs from current state-of-the-art wind power plants with relatively high specific power outputs [56]

4.3. The VRE penetration level

The VRE penetration level intuitively refers to the share of demand that is covered by VRE generation. However, since there is spillage linked to curtailment (over-generation) and losses associated with transmission and storage operations, it is not straightforward to apply a stringent definition of this concept that is suitable for all purposes. In the present introduction to the thesis, three definitions are used:

- *Gross VRE penetration level* is defined as the electricity generated by VRE divided by the demand.

  $$p_g = \frac{\sum_t x_t}{\sum_t d_t}$$

  where p_g is the gross VRE penetration levels, x_t is the VRE generation, and d_t is the demand at time t.

  This concept includes electricity that is potentially curtailed or lost in transmission and during storage operations, and it is an upper estimate of the VRE penetration level.
- *Net VRE penetration level* is here defined as the share of electricity demand that does not originate from hydro or thermal generation.

  $$p_n = 1 - \frac{\sum_t h_t + b_t}{\sum_t d_t}$$

  where p_n is the net VRE penetration level, h_t is the hydro generation, b_t is the thermal generation, and d_t is the demand at time t.

  The net VRE penetration level assumes that all generation that emanates from hydro or thermal sources is used to cover the demand (and thus is not curtailed or lost during transmission and storage operations).
- *Net VRE penetration level less hydro* is a concept used in **Paper V** to define VRE penetration levels similar to p_n, only that the VRE penetration is expressed as the share of demand

minus the hydro generation. The reason for adopting this definition is that it reflects that the net VRE generation is unlikely to ever surpass the demand minus the generation from hydro. Covering all demand with hydro power generation (which is limited to its regional location) and VRE is thus the maximum level of VRE generation that is likely to be cost-efficient. Therefore, this point is defined as the 100% penetration level.

$$p_{nh} = 1 - \frac{\sum_t b_t}{\sum_t d_t - h_t}$$

where p_{nh} is the net VRE penetration level less hydro, h_t is the hydro generation, b_t is the thermal generation, and d_t is the demand at time t.

4.4. Reflections on the methods and data used

The methods used in the papers of this thesis are dictated by factors such as scope, data availability, computational resources etc. Here, some of the method choices are discussed and contrasted to other possible choices.

4.4.1. Data

As mentioned above, the input data in this thesis are the demand data, weather data, and hydro power data.

The demand data are assumed to be inelastic and equal to those of a historic year. The assumption that demand is inelastic reflects the more general limitation that DSM is not included in any of the present papers. (In addition, the inclusion of elastic demand would introduce non-convexity into the optimization models, creating a more challenging task). One could argue that the demand input should reflect a future demand, since the work of this thesis revolves around a large-scale penetration of VRE, which is not yet actual. However, due to energy efficiency measures, future electricity consumption in developed regions, such as Europe, is projected to grow at a slower pace than at present [57]. In addition, the main effects of VRE deployment are scale-insensitive, meaning that it is mainly the share of electricity from VRE that limits its deployment, rather than the absolute amount. Therefore, upscaling electricity demand by some percentage points is unlikely to affect the qualitative results. In addition to the issue of annual demand growth, the future demand *profile* may differ substantially from the present one, due to, for example, electric vehicle charging. However, the appearance of such a profile is still highly uncertain. Thus, using an historic demand curve (as is done in the present thesis) assumes that smaller changes in demand volume are less important for large-scale penetration of VRE, and that the regional demand profiles are similar to the present ones, i.e., they are governed by day-and-night activities and weather conditions.

In early integration studies, it was assumed that wind data were best collected from existing power plant outputs [9]. This is advocated in the well-cited article on the state-of-the-art for wind integration studies from Year 2011 [58]. From the perspective of investigating future electricity systems, there are two drawbacks to using real power plant output statistics: (i) there is a dependence on turbines that are already in place, which by definition are "old" compared to the future system and are fixed in space, so that the potential outputs of turbines in other locations cannot be investigated. Therefore, in this thesis, as well as in many other electricity system studies (e.g. [33, 38]), weather data from a meteorological model are used and filtered through a turbine function in order to derive time series for the outputs of the different sites. Such data (e.g., MERRA, ECMWF, NCAP/NCER) have the advantage of being available on a global scale, at increasingly finer spatial resolution, and (in a recent development) with an hourly resolution [59].

It has been shown that the procedure of using global weather data filtered through a turbine function produces accurate wind power output profiles [60]. However, a comparison carried out in this work of the annual averages of MERRA data and the annual averages from the Global Wind Atlas [61] reveals that the wind resource of a country is not well-represented using MERRA data. This is possibly because the resolution is too coarse [62]. The comparison was done using the Global Wind Atlas [61], which has a much finer resolution, as compared to the MERRA data. However, the Global Wind Atlas includes only annual averages. It was also found that the ECMWF data used in **Papers II-VI** more closely resembles the average output curve for a country than does the MERRA data. Nonetheless, a more thorough treatment of the input data is desirable and is being planned for future projects.

4.4.2. Temporal and spatial resolution

In optimization models, there is always a trade-off regarding the details of the different dimensions. While time and space are obvious dimensions, the technical description may also be viewed as a dimension. In this context, representing the cycling or ramping constraints of thermal power plants increases the complexity of the technical dimension. Adding more available technologies and specifying their features also adds to the technical dimension. The models developed within this thesis emphasize the time dimension, at the expense of the technical and spatial dimensions. The spatial and technical dimensions of a traditional CEM are usually more detailed than those in the models of this thesis, while the temporal dimension is less detailed.

The time dimension is emphasized because the function and dynamics of variable renewables are at the core of the present work. The time representation in the models in this thesis is at least 3-hourly for a full year. Recent work, e.g., that of Nahmmacher et al. [19], shows that in order to represent variability on the generation side, about 30 representative days (i.e., days with different weights in the objective function and constraints) represent a sufficient amount of time. This corresponds to 240 time -steps on a 3-hourly resolution, which is considerably less (by a factor of around 10) than what was used in this thesis. However, the representative days method removes chronology. Chronology is essential for storage, and thus if a model is intended to be used to investigate over-the-day storage or hydro power with reservoirs, it has not yet been shown whether it is possible to reduce the time dimension to fewer days than an entire year.

The relevance of the above discussion to the models in this thesis is that the time dimension of models that are created without any intention to compare long-term storage or hydro power, can most likely be reduced by a factor of around 10, without losing too much in terms of accuracy. This is the case for the models in **Papers I-IV**. Instead, the spatial or technical dimensions could be enhanced. However, for the Electricity investment model in **Paper V**, it is not clear whether, or to what extent, the time dimension could be reduced, without losing the interplay between transmission and storage. This is an important dynamic underpinning the results for system costs at different penetration levels in **Paper V**.

The spatial dimension in the models used here range from single-site to aggregated classes, in order to represent the resource and variability of wind and solar power. This spatial granularity is considerably finer than the regionalization, which ranges from smaller regions (50 in Europe, **Papers II** and **VI**) to the size of a large country (10 in Europe, **Papers IV** and **V**) to the entire continent of Europe (**Papers II** and **III**). The spatial granularity, e.g., the size of regions that is appropriate given the computational constraints and the aim of the investigation, is an issue that the author hopes to be able to explore further in the near future.

The emphasis on a high temporal resolution is the main reason for using a greenfield approach in the models in this thesis. The lack of representation of system evolution makes greenfield models computationally faster. For the models employed here, the simplicity of the models has yielded short computation times (in the order of minutes), which have been used for parameter sweeping. This has been used for multi-objective optimization to create Pareto fronts (**Papers II-IV**), so as to investigate several penetration levels and cost configurations (**Paper V**). The lack of evolutionary temporal dimension is thus replaced here by a larger "what-if" span than is commonly applied in energy system modeling studies.

5. OVERVIEW AND DISCUSSION OF THE RESULTS

In this chapter, examples of the results from the papers are presented in a way that allows the reader to follow and assess the design and performance of a VRE-dominated system. With the exception of **Paper I** (which is confined to Northern Europe) and **Paper VI** (in which geographic location is irrelevant), all the papers refer to the EU-27 countries plus Norway plus Switzerland.

5.1. Measures of performance: variation, average output, baseload and cost

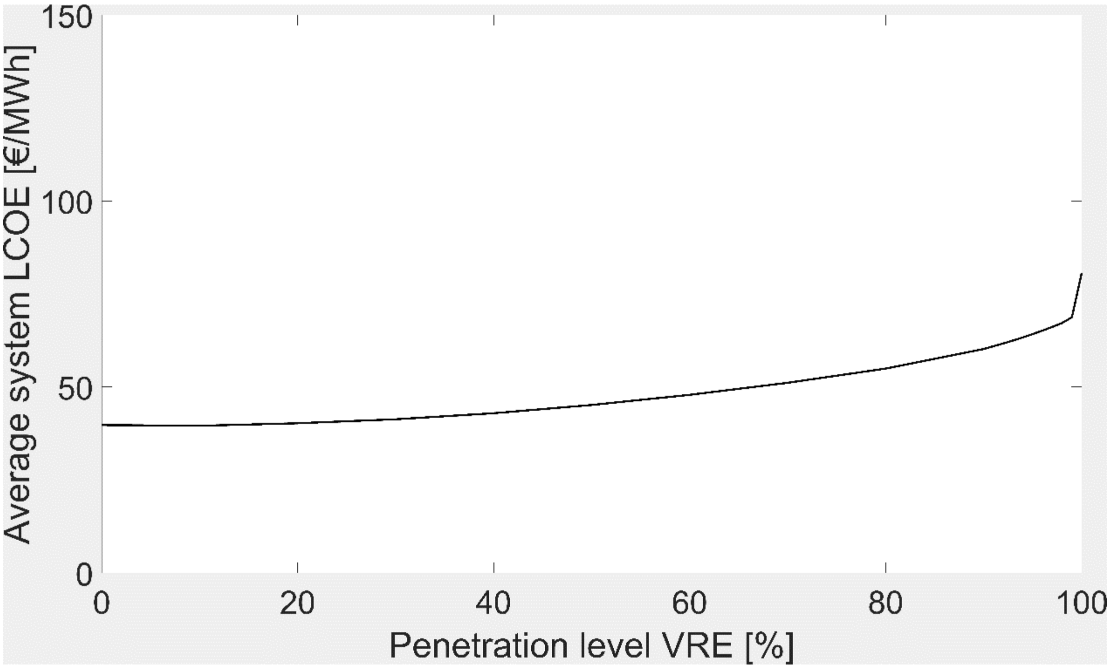
Each of the research papers in this thesis has a performance measure. System cost is the performance measure used in **Papers V** and **VI**. For **Papers I-IV**, the performance measures are the capacity factor[4] of wind power (**Papers I-III**) and the share of annual demand covered by VRE electricity (**Paper IV**). All the papers discuss the trade-off between the performance measure and one or two other parameters that are also considered important: less-varying wind power output (**Papers I-III**); proximity of wind power generation to demand (**Paper III**); accommodation of baseload generation (**Paper IV**); and VRE penetration level (**Paper V**).

The increase in cost with increasing penetration level of VRE (**Paper V**) is shown in Figure 8. Both Figure 8a and Figure 8b describe a case (the Base Case in **Paper V**) in which the thermal generation options are similar to those currently in use: coal and natural gas without any cost for emitting CO_2. Figure 8a shows the increase in *average system LCOE*, as discussed in the *Related research* section. As shown in Figure 8a, the average system LCOE is fairly constant or moderately increasing for VRE penetration levels up to 80%. The steep increase occurs for the last few percentage points, when there is a shortage of thermal back-up capacity to cover periods of low VRE output. The only back-up capacity that remains is in the form of batteries, which are expensive, hence the cost increase.

The average system LCOE depends to a large extent on assumptions made regarding the cost for VRE and the cost for thermal generation. While the cost for generation capacity is an important factor, it does not influence how *variability* in itself can incur increasing costs in a system. Therefore, the main topic of **Paper V** is the *marginal system LCOE of VRE*, which is the cost to increase the amount of VRE generation by 1 MWh, at a given penetration level of VRE. The increase in marginal system LCOE of VRE (Figure 8b) is attributable in part to penetration level of VRE increasing, as not all the electricity generated by wind and solar can be used directly to cover demand. The generated electricity that exceeds instantaneous demand may need to be (i) curtailed, (ii) stored or (iii) exported to another region, all of which measures add to the system cost. Another reason for the increase in marginal cost is that, as the best wind and solar resources get exploited, wind/solar sites that are less and less favorable need to be used to increase further the VRE penetration level. As can be seen in Figure 8b, the increase in VRE penetration level up to 80% is linear, revealing a doubling of the marginal LCOE for VRE compared to the first few percentage points of penetration. For penetration levels above 80%, the marginal LCOE of VRE increases more steeply.

[4] Capacity factor is the average annual output as a share of nameplate capacity and is usually measured in %.

a)



b)

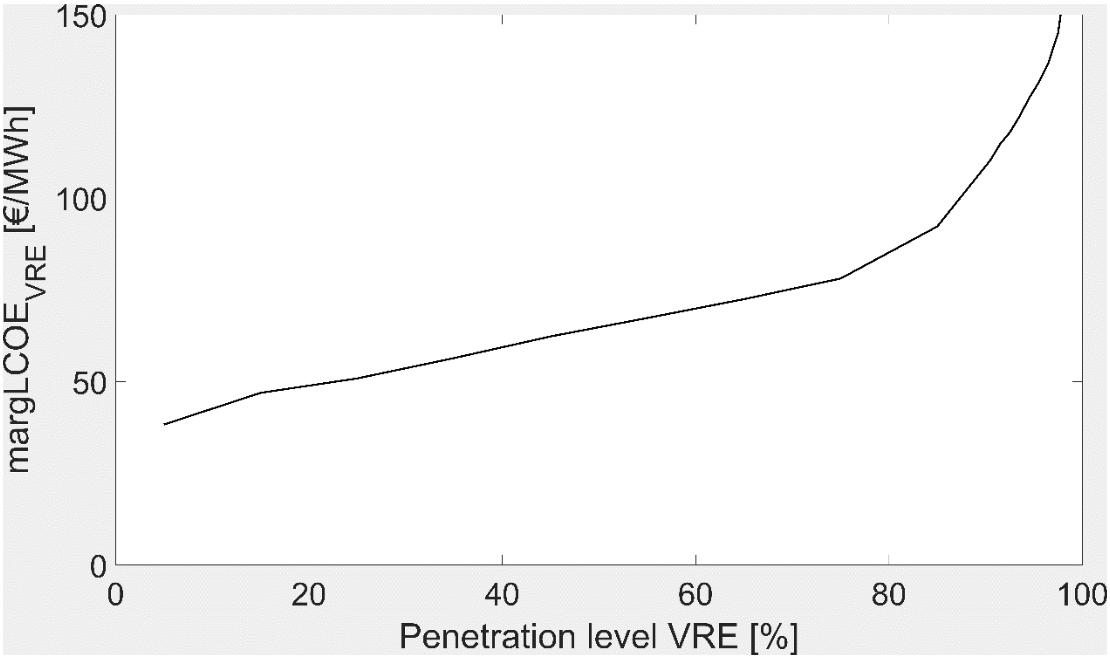


Figure 8 a) The average system LCOE and b) the marginal system LCOE of VRE ($margLCOE_{VRE}$) as a function of penetration level (based on the results for the Base Case in ***Paper V****). The penetration level is the net VRE penetration level, as discussed in the Methodology section, and thus VRE and hydro generate all the electricity at the VRE penetration value of 100%.*

The sensitivity analysis in **Paper V** suggests that there are many configurations (sets of variable values) that yield *near-optimal solutions*. Such near-optimal solutions may contribute additional value and can be found using different techniques. One way of finding such solutions is to apply multi-objective optimization, which allows examination of the trade-off, e.g., by showing the Pareto front between the performance measure and another quality. Multi-objective optimization is used in **Papers I-IV**.

One trade-off that is of paramount importance for the analysis in **Paper II** is that between a high average output of wind power and the avoidance of periods of low output of the aggregate wind power. The results regarding the trade-off between these two objectives are shown in Figure 9, where "VaR" (Value-at-Risk, see the *Methodology* section) refers to the measure for avoiding low outputs. The figure shows a steep Pareto front, where sacrificing 3% of the average output (capacity factor in the figure) would yield a VaR that is improved by more than 10%. The same wind power capacity configuration that is optimal for avoiding low output is also optimal for designing an output curve that is more smoothly varying. This is achieved by curtailing wind power so as to minimize the hour-to-hour variation. The figure also shows the value pairs (capacity factor and VaR) for the current (2010) geographic distribution of wind power (solid dot) and a case where wind power capacity is spread out evenly, and thus not optimized (circle). The distribution of wind power in 2010 displays a capacity factor of around 20%, which is less than 2/3 of the distributions on the Pareto front.

In Paper IV, the trade-off investigated is between the capacity factor and the possibility to combine VRE with baseload generation at a 50% VRE penetration level. As shown in Figure 10, the potential for baseload generation increases by more than three times, from 10% of annual demand to 35% of annual demand, for a 10% decrease in the capacity factor of the VRE system. This results entails that a 50% VRE share may be combined with a large share of baseload generation, provided that the geographic expanse of the system encompasses diverse enough weather patterns.

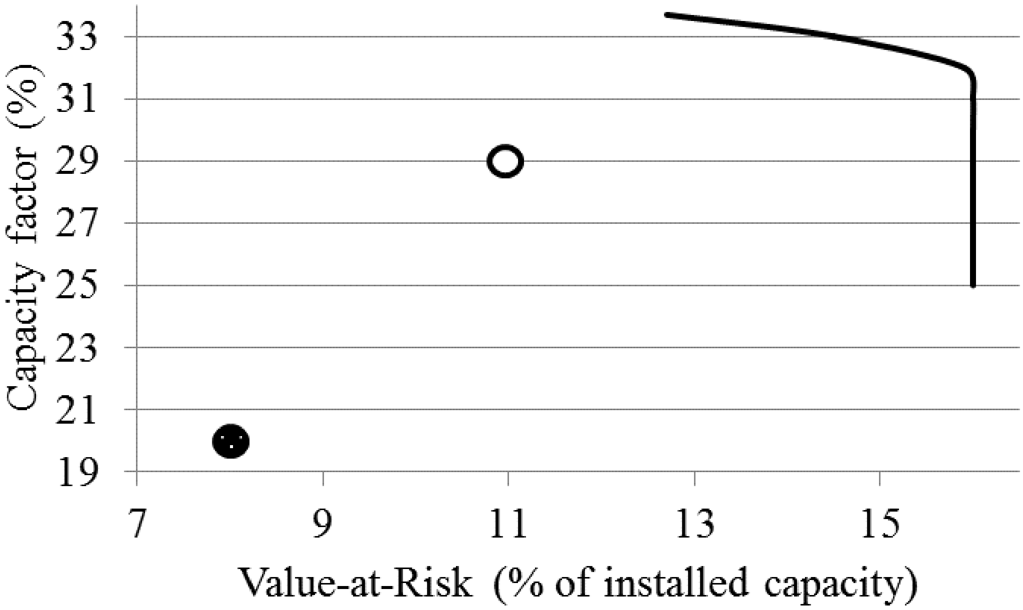


*Figure 9 The Pareto front shows the trade-off between two objectives: achieving a high average capacity factor (x-axis) and avoiding periods of low output (y-axis, measured as the Value-at-Risk, VaR), which is a measure of how well the aggregated output of an allocation avoids a low output. The allocations corresponding to the values on the Pareto front (solid line) are the results of the optimization processes described in Papers II. The solid dot represents the values of the present allocation and the circle represents the values of an allocation that is dispersed across Europe but that is not optimized (the Flat allocation reference case in **Paper II**). This allocation derives its smoothing effect from geographic dispersion without, however, optimizing it.*

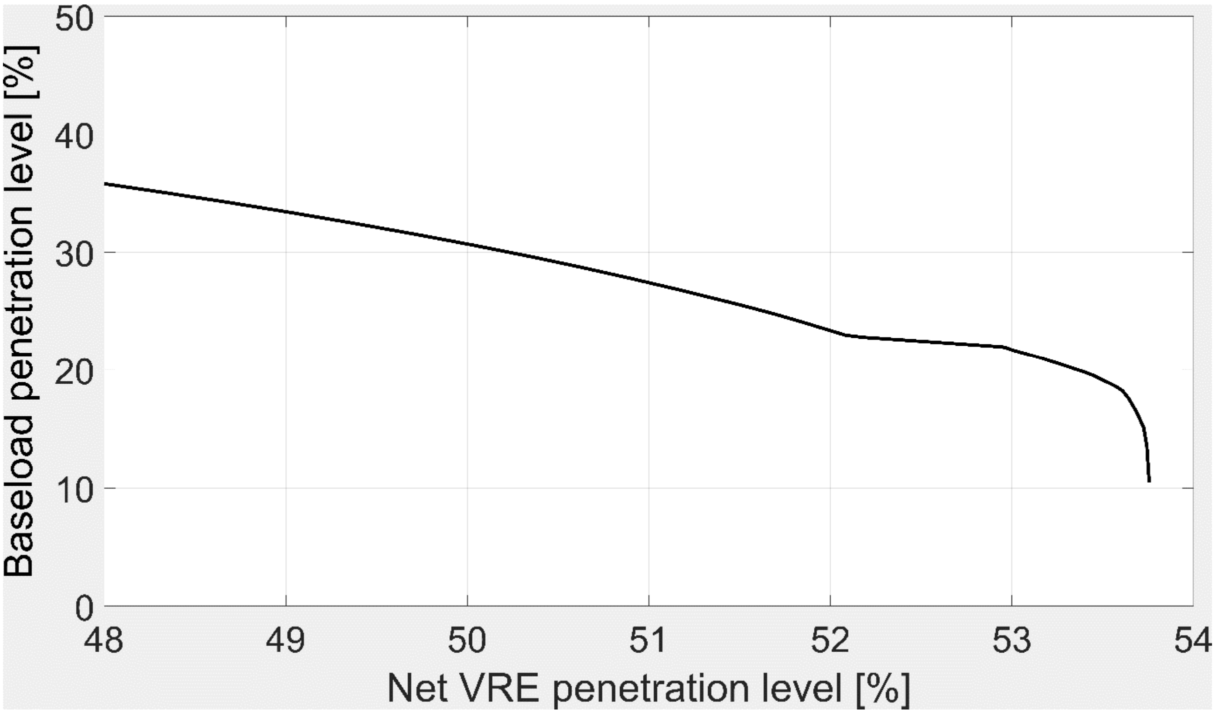


Figure 10 Electricity generation from base load as a function of net VRE penetration level (Paper IV).

This section shows that several system benefits can be delivered with little loss in terms of average output. These include:

- **Smoothing effect**: It is possible to significantly lower the variability as well as the occurrence of low outputs of aggregated wind power if its geographic distribution across Europe is optimized.
- **Accommodating base load**: for "mid"-level penetration systems (~50% VRE), the majority of the remaining thermal generation may be from base-load power plants, provided that there are transmission extensions between regions.
- **Raising the penetration level**: for high-penetration systems (~80% VRE), the marginal cost to cover the load with VRE is "only" about 50% higher than for the initial coverage (75 €/MWh vs. 45 €/MWh).

5.2. Wind and solar resources and the geographic distribution of VRE capacity

Wind and solar resources are unevenly dispersed across Europe (see Figure 11 and Figure 12 for wind and solar atlases). These figures show the average output of a wind or solar power plant, had they been placed at that specific site. For solar power, the southern part of Europe is naturally more advantageous, while wind power is highest in the north-western part of Europe. Wind and solar outputs also display differing temporal patterns, depending on geographic location. These differences facilitate the combining of sites to dampen the variation in the aggregate output.

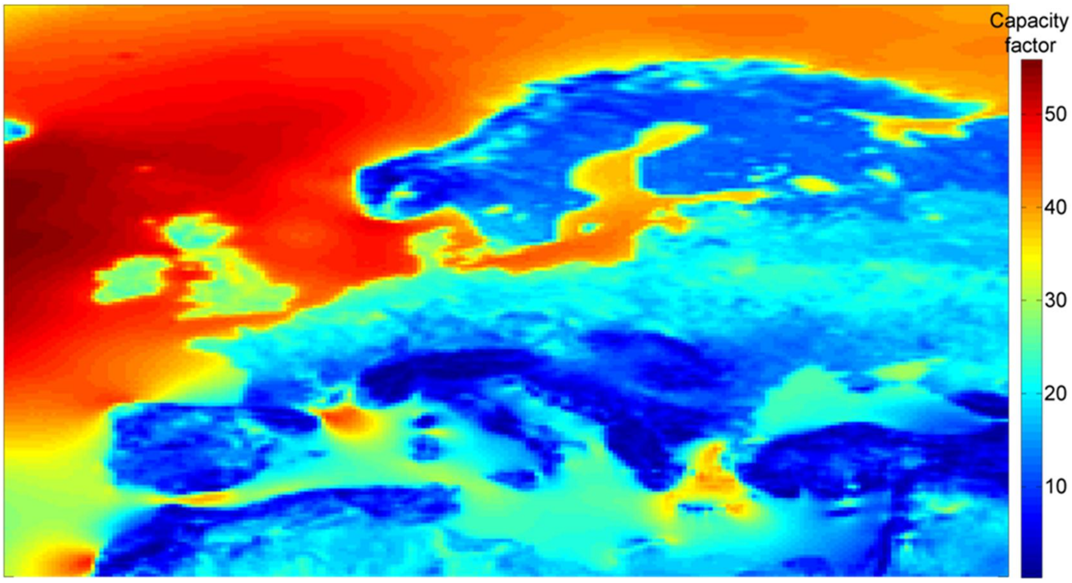


Figure 11 A wind power atlas of capacity factors, based on ERA-Interim data [3] for Years 2007–2009. The wind power output function is the same as that used in ***Paper II****. The color-scale shows capacity factors for the sites, where the best on-shore sites have capacity factors >40%.*

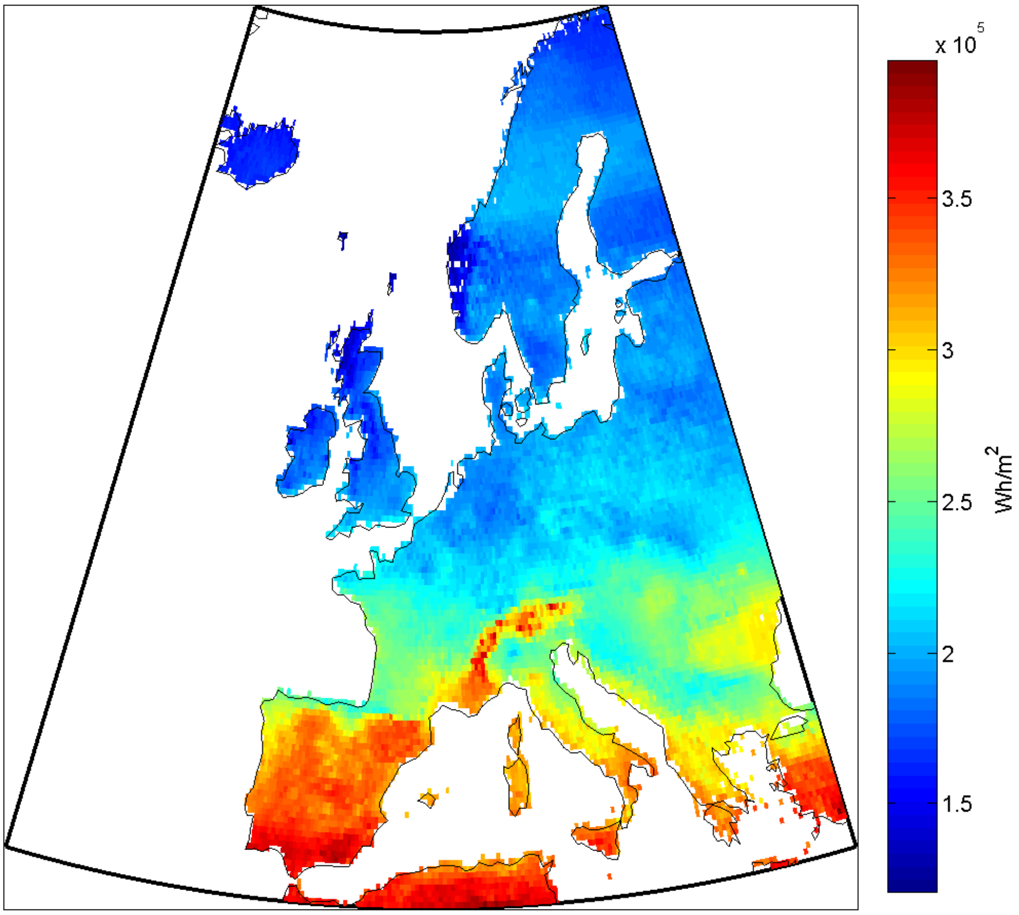


Figure 12 Average output of solar PV in Europe. The figure is taken from Norwood et al.[63].

Three strategies are used in this thesis to delineate how wind power can be dispersed in order to dampen the variation in the aggregated output (**Papers I-III**). The geographic distributions derived from these strategies define the boundaries of the area of study needed to obtain a comparatively large share of the capacity of wind power (see Figure 13 and 14). Figure 13 shows the resulting wind power distribution from **Paper I**. Note that while coastal sites predominate, the outskirts of the region, including non-coastal sites in Southern Germany, are exploited. Figure 14 shows the capacity distributions derived from the Avoid Lows and Short-term variation strategies (**Papers II and III**). These strategies also give rise to distributions where a large share of the capacity is located in regions far away from each other, such as Greece and northern Norway. Note that also for the Short-term variation strategy, it is optimal to exploit windy regions and curtail electricity, rather than to distribute capacity evenly.

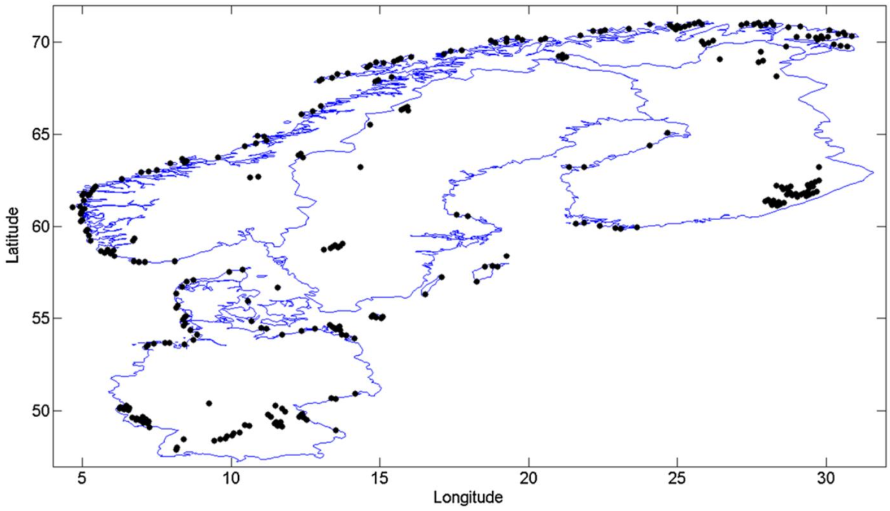


*Figure 13 Wind power capacity distribution in Nordic countries. Source: **Paper I**.*

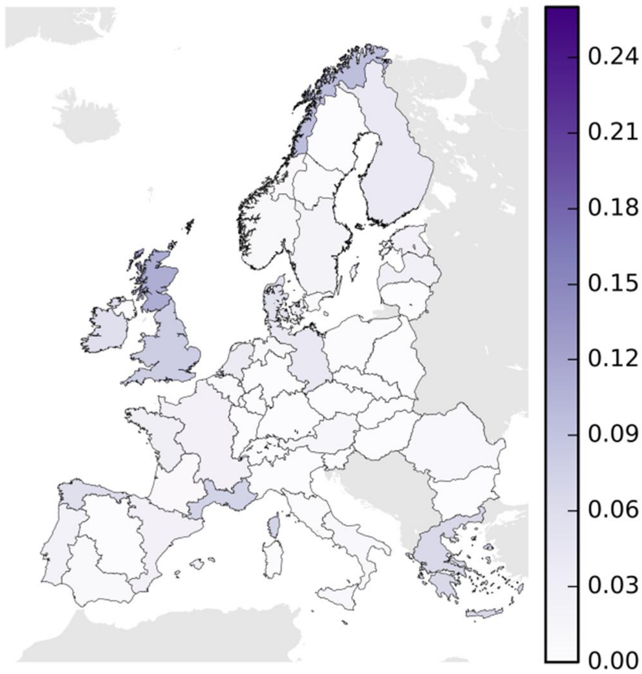


*Figure 14 Wind power capacity distribution (in terms of share of total European capacity) for the Avoid-Lows strategy in **Papers II** and **III**. The total wind power capacity in Europe is set at 500 GW. The capacity distribution is based on wind data for Year 2008. Source: **Paper II**.*

In **Papers IV and V**, the geographic distribution of VRE (wind and solar) capacity interacts with regional demand and the option to invest in transmission extensions. Figure 15 show these distributions for penetration levels of VRE of around 50%. In Figure 15a, the objective is to cover the maximum share of demand using a limited amount of VRE capacity. In Figure 15b the emphasis is more on accommodating base-load generation, and in Figure 15c is the focus is on minimizing the system cost. As can be seen from the figures, the distribution is almost identical for the three cases, even though the objectives are different. All three of these distributions have in common that that the regional gross VRE penetration level[5] varies between 10% and above 100%. For each of the three objectives (covering maximum demand, allowing for baseload and minimizing cost), it is thus “optimal” to distribute capacity so that regions with good wind conditions, such as the UK, may have annual VRE generation levels that exceed the annual demand, concomitant with less-windy regions, such as Italy, having low penetration levels of about 10%.

There are two reasons for the strongly differing penetration levels between regions. First, it may be more beneficial to install additional wind power capacity in a windy region and curtail electricity than to install in a less windy region. Second, the transmission network enables net export, e.g., from the UK to continental Europe, as well as variation management, e.g., by regulating UK wind power with the Nordic hydro power. This can also be seen in Figure 15, where the transmission networks are strongly enhanced compared to the present system, especially in north-western Europe.

The results regarding the different regional penetration levels of between 10% and 100% in the case of an overall European penetration level of 50% (Figure 16) raise the issue of whether a saturation effect of VRE electricity also appears in cases in which there are strong transmission extensions. As an example, we here show the results based on those in **Paper V**, where the transmission investments are optimal, given the objective to minimize system cost. Figure 16 shows the development of the gross VRE penetration level in the UK with increasing overall penetration level. It is clear that the UK gross VRE penetration level increases steeply at low overall VRE penetration levels, and then plateaus at around 120%. The maximum penetration level in the UK is 150% and this is reached in the system with close to 100% renewables in Europe. This demonstrates that the demand is indeed a moderating factor, where a regional generation of significantly more than 100% seems to be less cost-efficient, even in regions with very good wind conditions.

[5] Gross VRE penetration level is the ratio of domestic VRE generation to demand (see the *Methodology* section).

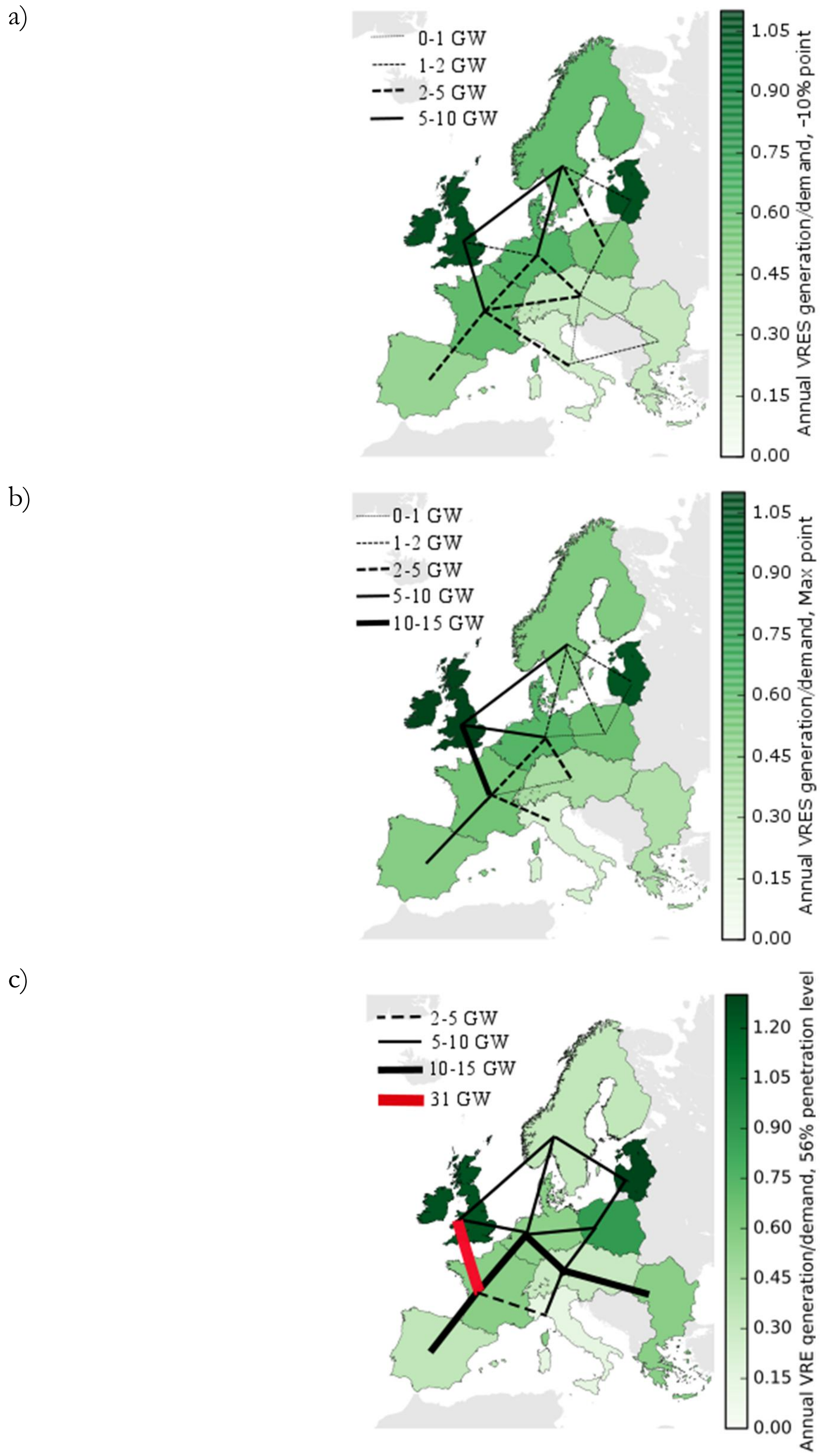


*Figure 15 VRE (wind plus solar) regional penetration level and transmission capacity for: a) the strategy (in **Paper IV**) in which 10% of VRE electricity is sacrificed to achieve a net demand that is more suitable for base-load generation, b) the strategy (in **Paper IV**) which minimizes annual net demand and c) the 56% gross penetration level from **Paper V**.*

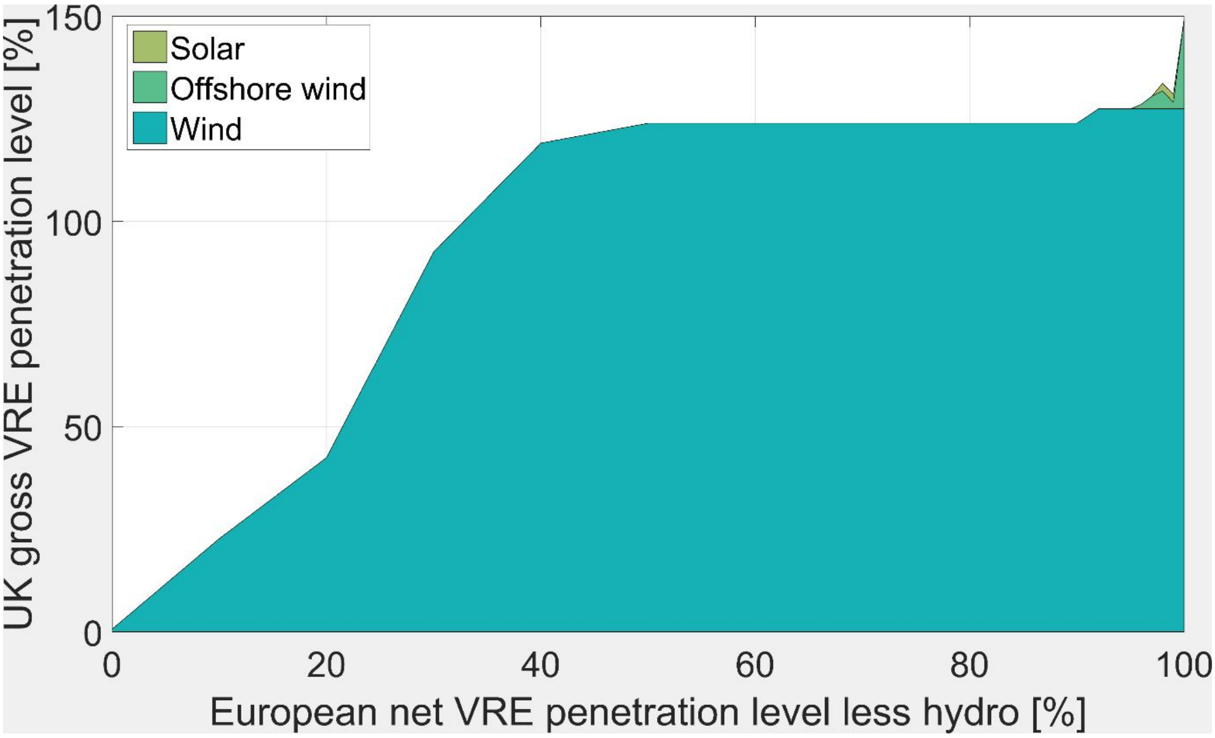


*Figure 16 The gross regional penetration level for the UK as a function of the net European VRE penetration level. The results are taken from the modelling in **Paper V**.*

In summary, system-optimal VRE capacity distributions in Europe are characterized by:

- concentration to the windy northern European region; and
- domestic generation being moderated by domestic demand, including cases in which there are large transmission extensions.

5.3. The capacity mix

The system capacity and energy mix is one of the topics of **Papers IV** and **V**. As outlined in the *Methodology* section, the models and scenarios that produce the results are different. The *Multi-objective model for net demand* (**Paper IV**) designs net demand curves at specific exogenously given levels of VRE and transmission capacity. The ratio of base load to flexible-load capacity is determined using a simple NRLDC (net residual load duration curve). The *Electricity investment* model (**Paper V**) is a purely cost-minimizing model, and it has a few constraints in relation to the optimal capacity mix. Despite the different models used, there are some similarities in the results regarding the energy mix, as can be seen by comparing the capacity mixes at a similar penetration level of ~50% (Figure 17). There are similarities between the solar-to-wind and base load-to-flexible load ratios: Wind dominates over solar, at a ratio of 9:1 (**Paper IV**) and 5:1 (**Paper V**) respectively (Figure 17). The degree of domination of wind over solar at this "mid" (~50%) VRE penetration level has to do with their relative costs: in **Paper IV**, the investment cost for solar power is slightly higher than in **Paper V**. At higher penetration levels, the presence and cost of storage as a variation management tool are vital to the potential penetration of solar. In fact, in the sensitivity analysis of the cost of VRE capacity and variation management capacity in **Paper V**, the only scenarios in which solar generation dominates over wind (by about 2:1) are those in which *both* solar and battery investment costs are set at levels that may be considered highly optimistic (75 €/MWh for batteries, and 300 €/MW for solar cells). Scenarios in which solar cell costs are at their lowest levels and battery costs are high do not display an energy mix that is dominated by solar. Thus, the domination of wind over solar is mainly attributed to the system-friendly property of smoothing out variations through geographic distribution, when there is a possibility to invest in transmission capacity.

The base load to flexible load ratio is about 6:1 on an energy basis for a net VRE penetration level of 50% in both **Papers IV** and **V** (see Figure 17). The cost-minimizing model (**Paper V**) thus finds an optimum similar to the optimization in **Paper IV**, which places the emphasis on the objective that designs net load curves to fit the base load. The finding that optimal capacity mixes contain a rather large share of base-load generation in a system that contains 66% RES (16% of which is hydro power) goes against "common sense" thinking. Such a logic, put forward previously [64], assumes that base-load and variable generation must be opposite to one another because of the way that VRE generation interferes with base-load generation when VRE is added to the capacity mix in a single region. The reason why this logic is not necessarily true in a larger geographic context, such as Europe, is that the base load may still be cost-effective in a system with high penetration of VRE if the smoothing effect of wind power is enabled by transmission extensions. This effect can also be seen in **Paper IV**, in which the *Multi-objective model for net demand* was run with isolated regions, and the amount of base-load generation was reduced by more than one-third, to ~20% of annual demand, see **Paper IV** appended in this thesis. Although the description of base load is simplified in both **Papers IV** and **V**, the analysis in **Paper IV** shows that it is likely that a more thorough analysis than a 'back-of-the-envelope' calculation using residual load duration curves (RLDCs) is needed to delineate the role of base load in a system with a high level of VRE penetration. This piece of information may be important in terms of achieving a better assessment of the potential of base-load technologies, such as CCS or nuclear, to play substantial roles in a future electricity system.

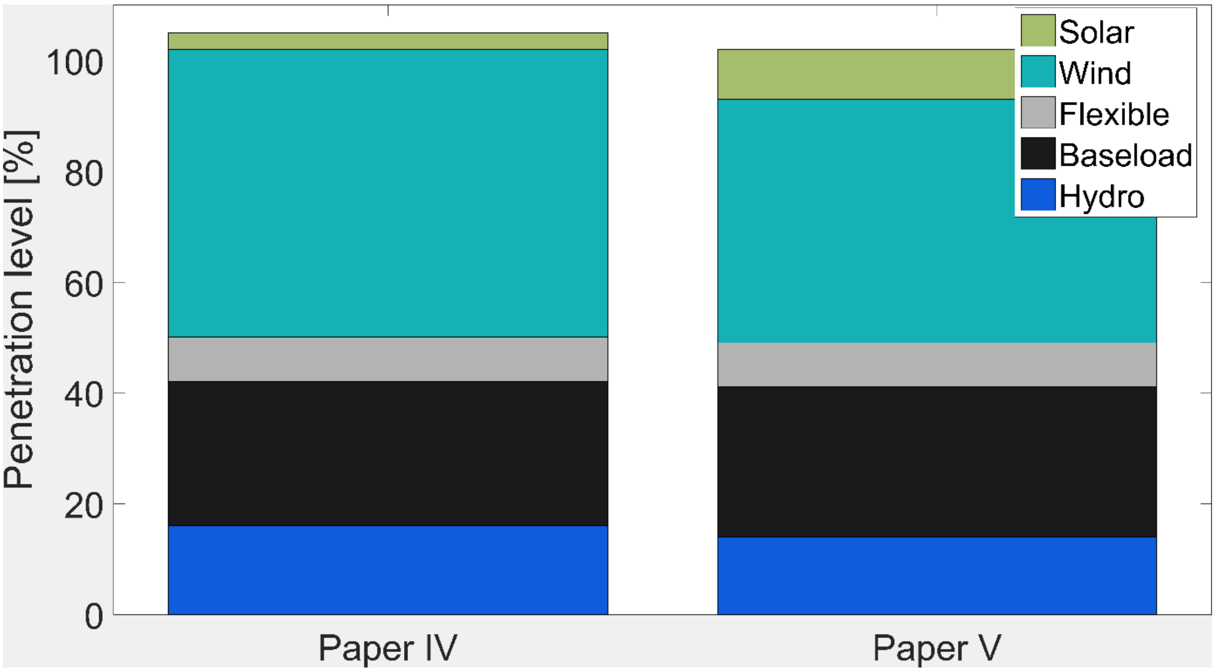


*Figure 17 The energy mixes at the net penetration level of VRE of 50% in **Paper IV** (left column) and **Paper V** (right column).*

In summary:

- A large amount of baseload (~30%) may be compatible with a large share of VRE (~50%) if there is sufficient expansion of the transmission network.

- Wind clearly dominates over solar, having 6-9-fold higher generation. This dominance is attributed to cost as well as system aspects, which favor wind that is dispersed across Europe, in combination with transmission expansion.

5.4. The importance of time representation

The importance of representing variability, and therefore time, in a more detailed way than is common practice in investment models (see the literature review in this thesis), is a cornerstone of this thesis. The developed models (**Papers I-V**) have been equipped with a high temporal resolution (>2,920 time-steps). The assumption underlying the deployment of this many time-steps is that a high temporal resolution is necessary to represent the possible system role of VRE[6]. However, the main body of this thesis (**Papers I-V**) does not *test* the time representation used, and thus it may be assumed that part of the time representation is superfluous given the aim. However, CEMs have historically been equipped with very few time-steps (see Chapter 2). **Paper VI** disambiguates the extent to which the time dimension in electricity investment models can be reduced, and two methods to downscale the time dimension are compared. Thus, **Paper VI** explicitly investigates the importance of the method and resolution of time in investment models, of which the models described in **Papers I-V** are examples.

The main[7] two methods investigated are *resource-based integral* and *representative days*. (These methods are described in the *Methodology* section). The results show that the number of time-steps needed to get within a 10% estimate of the VRE capacity obtained with a full resolution model is 16 for the resource-based integral method and ~200 for the representative days method (see Figure 18).

One may ask why then should one use the representative days method when the resource-based slicing seems to be very accurate in predicting the capacity? The resource-based integral method has some limitations, especially for cases in which it is anticipated that the share of variable generation will be high: it cannot be used for network models, i.e., models with explicit representations of transmission and trade, and it cannot incorporate storage. Thus, it is not readily adaptable to cases for which the goal is to investigate variation management strategies. However, it may be an option for large, global models, such as IAMs, where computational restraints leave little room for many time-steps.

The results from **Paper VI** confirm the previous findings [19] regarding the approximate number of representative days (~25) that is needed to represent variable generation. In addition, the results show that it is important to use a sound selection method (in this case, k-means clustering), rather than to select random days (see Figure 19). Figure 19 shows that the random selection of days may lead to large errors (~40%) for the estimate of VRE capacity, even for a high number of time-steps.

n summary, to represent variability on the generation side, the results in **Paper VI** show that:

- For network investment models, it is sufficient to use ~200 time-steps, using the representative days method with the days being selected using a clustering technique.
- For single-region investment models, it is sufficient to use ~30 time-steps, using a resource-based integral method.

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[6] In addition, finding the optimal mix when storage is present (**Paper V**) requires a chronologic time representation, since storage may, *a priori*, move energy from one point in time to *any other point* in time.

[7] In addition to these two, the type of integral method usually applied, demand-based integral (see the chapter on *Related research*), was investigated (see **Paper VI** for results).

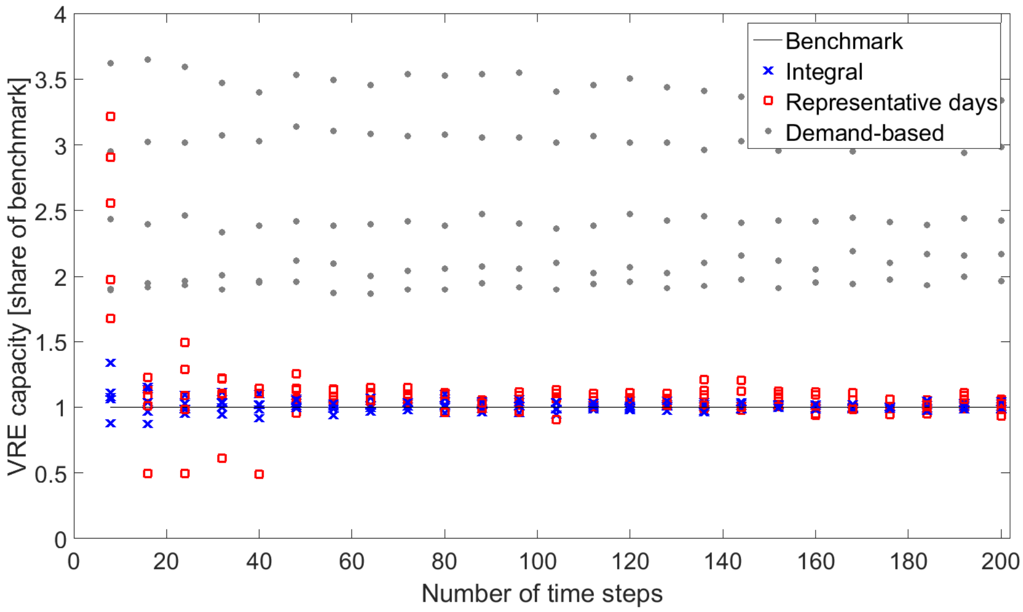

Figure 18 Performance levels of the three methods used to downscale the time dimension in electricity investment models: resource-based integral (blue); representative days (red); and demand-based integral (gray). The measure of performance (y-axis) is the prediction of VRE capacity compared to the results obtained from a benchmark model. Source: ***Paper VI****.*

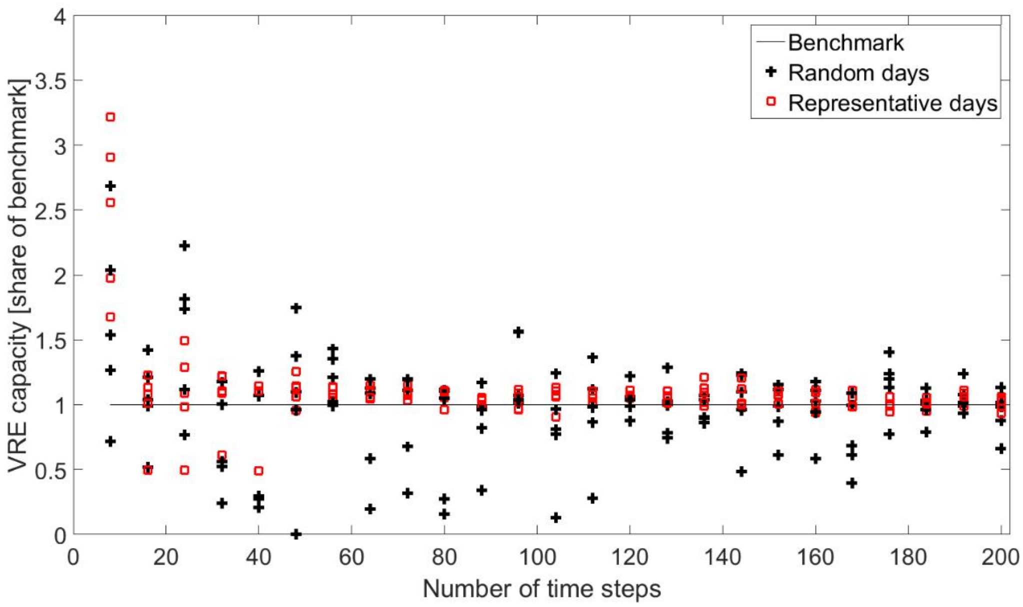

Figure 19 Performance of the representative days method (red) to downscale the time dimension, as compared to a method in which the days are randomly selected (black). The measure of performance (y-axis) is the prediction of VRE capacity compared to the results obtained from a benchmark model.

6. CONCLUSIONS

This thesis examines the possibility of creating an electricity system in which the majority of generation comes from wind and solar power. The thesis consists of method development and applied results, where the study region is Europe. Five optimization models, which are designed to capture electricity system dynamics with a large share of VRE, are developed. The time-scale is approximately hourly, and the geographic scope is that of a continent.

This thesis shows that (the overarching research questions posed in the *Introduction* are listed in italics):

- *What are the possibilities to mitigate the variability of wind power through geographic distribution of the same?*
    - The geographic distribution of wind power capacity in Europe, along with a matching transmisison network, may mitigate variability such that the span of wind power output (max–min) is halved, as compared to the output of a single small country.
- *To what extent and in what ways can a system hat employs large-scale wind and solar still be flexible? (For example, in terms of being load-following at high penetration levels and being combined with different thermal capacity mixes).*
    - Capacity mix: A system with around 50% variable generation may harbor a considerable share of base-load generation (the majority of the remaining thermal generation).
    - The possibility for a relatively low cost system does not depend on technology/cost leaps in the development of technologies such as batteries and solar power.
    - Geographic distribution: A system may contribute with additional benefits, such as a large share of domestic generation of VRE, with little loss in terms of the average output.
- *How does the variability of wind and solar power influence the system costs at increasingly higher penetration levels of VRE, and how can variation management strategies be used in a cost-effective way?*
    - The marginal cost for VRE generation is roughly doubled at a penetration level of 95%, as compared to low penetration levels.
    - Transmission dominates the variation management strategies at penetration levels up to ~85%.

7. FURTHER RESEARCH

There are several avenues of investigation that could be taken up in future research efforts. The following hypotheses, which are drawn from the findings described in **Paper V** of this thesis, as well as from the literature, could be tested using extensions of the models and applications presented here.

- Wind power dominates over solar power (at a ratio of ~3:1), except at very high penetration levels
    - Is this true in other areas of the world that are characterized by long distances between wind power resources and demand centers?
- Transmission dominates over storage as a variation management tool
    - Is this a model artifact of the spatial resolution being too low? Electricity system investment models assume that here is a “copperplate” within regions and that transmission investments are only needed between regions. This set-up makes it

difficult to assess how much additional transmission capacity within regions would be necessary to realize the trade streams between regions.

- Is this true also in other parts of the world? Other regions, such as the Middle East, may have less-favorable wind conditions while at the same time having better conditions for solar power.

Paper VI in this thesis is a methodological study that investigates methods to reduce the time dimension to represent variability on the generation side. However, the appropriate minimum temporal representation for storage and hydro power has not been investigated. Storage is important for scenarios that have a high penetration of VRE, since it represents a variation management method, which is likely to be essential in such scenarios. Electricity investment models are typically large and cumbersome to run, and therefore need a reduction in the time dimension in order to be tractable and practical. Thus, the precise benchmarking of a method to perform such a reduction warrants further investigation.

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Paper I

Paper II

Paper III

Paper IV

Paper V

Paper VI