

THESIS FOR THE DEGREE OF LICENTIATE OF ENGINEERING

Dampening Variation in the European Wind Energy System

A geographic allocation model using multi-objective optimization

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Cover:

A wind power atlas of Europe. The color coding indicates the scale of output of wind power farms at each location, whereby warmer colors designate higher outputs. See page 6 for further details about wind power variations.

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System benefits for the European wind energy system

The effect of optimizing geographic allocation

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ABSTRACT

In a future European electricity system, wind power and other variable renewables may constitute a large share of electricity production. This prospect calls for measures to manage the inherent variability of wind power, such as demand-side management, storage, and flexibility of other generation. Another way of managing variation is to take advantage of the weather patterns when allocating wind power over larger areas, so that the aggregated output of wind power displays lower variation than that of a single region. The extent to which aggregated wind variations can be managed depends on geographic scope and the limitations in transmission capacity between regions. Of great importance is the extent to which the aggregated wind power output can be smoothed through geographic allocation. Therefore, this thesis explores the limits of geographic smoothing, by optimizing the regional allocation of wind power in Europe.

This thesis first provides a description of the variability of geographically dispersed aggregated wind power, using a heuristic method to identify allocations with minimum variability while maintaining a high average output. The region in focus encompasses the Nordic countries and Germany. Then, the features of aggregated wind power that can provide system benefits are identified, and the optimal allocations of wind power capacity are explored with Europe as the geographic region. System benefits are formulated as objectives in optimization models, and the trade-offs between these benefits are analyzed. Allocations that yield the following system benefits are investigated:

- A high average output
- A smooth output, in which increments within the time-span of 3–24 hours have been minimized
- An output that avoids low output
- An output in which wind power covers the maximum load within the region where it is produced.

The only one of the system benefits that is explicitly in favor of windy spots is the one of high average output. However, the results presented in this thesis show that the allocations that result from optimizing the other system benefits tend to display a high capacity factor, of around 30%, given the assumptions applied. This should be compared to the highest possible capacity factor obtained (34%). Thus, considering that the present allocation has a capacity factor of 20%, there are potentially large benefits to be gained from optimizing geographic allocation. Furthermore, it is shown that avoiding low output and smoothing the output give rise to similar allocations, i.e., there is virtually no trade-off between these two goals. The objective of covering maximum load results in an allocation with high penetration levels of wind power, up to 60% of annual load, in windy regions.

Taken together, the results presented in this thesis highlight that wind power allocation can contribute to efficient use of wind power in a future Europe with a high share of variable renewables in the electricity system.

Key words: wind power; geographic allocation; variable renewables; electricity generation; large-scale penetration of wind power

List of publications

The thesis is based on the following appended papers:

- I. Reichenberg, L., Odenberger, M. and Johnsson, F., 2013. *Dampening variations in wind power generation-the effect of optimizing geographic location of generating sites*. Wind Energy, Vol. 22 No. 1, pp.18–32.
- II. Reichenberg, L., Wojciechowski, A., Hedenus, F. and Johnsson, F., 2014. *Geographic aggregation of wind power-and optimization methodology for avoiding low outputs*. Submitted for publication (2014).
- III. Reichenberg, L., Wojciechowski, A. and Johnsson, F., 2013. *Wind Power allocation strategies for Europe*. 12th Wind Integration Workshop, London, 2013.

Lina Reichenberg is the principal author of all the papers and has developed the ideas and the methodology for the model formulations upon which they are based. Adam Wojciechowski contributed to the development of the mathematical formulations in Papers II and III. Professor Filip Johnsson, who is the main academic supervisor, contributed with discussions and the editing of all the papers. Mikael Odenberger and Fredrik Hedenus are the co-supervisors and have contributed with discussions and the design of the studies.

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Contents

- 1. Introduction 1
 - 1.1 Background 1
 - 1.2 Aim and scope 2
 - 1.3 Outline of the thesis 3
 - 1.4 Contribution of this thesis 3
- 2. Wind speed and wind power variations in Europe 4
 - 2.1 Variation in time: hours to seasons 4
 - 2.2 Inter-annual variations 5
 - 2.3 Spatial variations 6
 - 2.4 Concluding remarks regarding the variation of WP 8
- 3. Modelling wind power allocation 9
- 4. Methodology 12
 - 4.1 Data 12
 - 4.2 Multi-objective optimization 12
 - 4.3 Objectives for the optimization 13
 - 4.4 Limitations 14
- 5. Results and Discussion 15
- 6. Future work 21
- References 22

1. Introduction

1.1 Background

The concept of global warming and the subsequent awareness of the need to reduce CO₂ emissions have increased interest in CO₂-free technologies for electricity generation. Climate mitigation scenarios project that the potential for mitigation is far larger in the electricity sector than in the transport, industrial, and housing sectors [1]. The future may also be geared towards a larger proportion of the *energy* being provided through electricity, e.g., through a shift to electric vehicles and increased electrification of industry. These circumstances highlight the need for specific investigations of the options available for transforming the electricity system into one that is close to CO₂-free. The options in terms of the production mix for the low-emitting, future electricity sector are dictated by various factors, such as carbon capture and storage (CCS), nuclear power, hydro power, interchanges between electricity and heat generation and varying renewable energy (VRE) sources, such as wind, solar, and wave/tidal power.

As wind power (WP) generation gives low CO₂ emissions and involves a relatively low investment per unit (thereby representing a low-risk investment), it already plays and is expected to play a substantial role in the renewable part of the energy system [2]. However, the electricity system was built during a time when production was mainly through thermal generation, such as in coal power plants, gas turbines, nuclear power and hydropower stations, which are all *dispatchable* systems, meaning that they can (within certain boundaries) be up- and down-regulated to meet variations in load. In contrast, WP and other renewable energy technologies, such as solar power, are *varying sources of energy*. Given the present structure of the electricity system (generation, transmission, and consumption of electricity), this characteristic of variance poses particular challenges, especially if the electricity system is to be transformed into a system in which a large fraction consists of variable generation. In the longer term, variable generation may become the corner-stone of generation, not merely an addition to a system that currently consists primarily of thermal generation. The nature of variable generation (wind, solar, wave, tidal) is profoundly different from other types of generation in that it exhibits large variations in output due to the varying “fuel” inputs of wind and solar energy and it is non-dispatchable. Regarding WP, the scale of the variations means that the output of a certain region may frequently vary between almost zero and the maximum output, which is close to the nameplate capacity, within the space of hours. Such rapid variations make large-scale integration of WP a challenge with respect to the ramp-up of online power plants, as well as the need for back-up capacity. The main difference between WP and thermal generation, which may also undergo interruptions or show variability of output, is that the variations cannot be regarded as a low-level risk, but it is rather part of everyday operation. The need for flexibility stems from the fact that electricity in general is not easily stored. Apart from hydropower, which in some regions constitutes natural low-cost storage, electricity storage, such as in batteries, is currently associated with high costs. Therefore, the lion’s share of electricity used by society is most cost-effectively generated at the same time as it is consumed, which requires a flexible electricity system. To date, this flexibility has been provided mainly by the generation side, i.e., the power plants have adjusted their generation levels according to momentary consumption demands. WP has limited potential to provide flexibility, since its output is upwardly limited by its “fuel”, namely the current wind conditions. Restricting output will entail spilling wind energy, either by curtailing, which provides down-regulation, or by restricting output so as to be able to provide upward regulation if required. Thus, given the current energy system architecture, the challenge of WP variation is three-fold. First, on a very short time-scale, of the order of seconds or less, the fluctuations are a problem mainly in terms of ensuring power quality. The

regulation of fluctuations is instead maintained by conventional power plants (e.g., so-called *spinning reserves*), although it can to some degree be performed by technologies within the wind turbines. Second, on a longer time-scale, on the order of minutes to hours, there is a need for flexibility in the surrounding system that allows one to adjust the supply, redistribute the electricity geographically to meet load (which requires increased transmission capacity) or adjust the load in time. At present, the flexibility is mainly provided on the supply side by thermal generation, with the plants adjusting their generation outputs according to how much wind there is. In a future, almost CO₂-free system, a significant part of the flexibility may be provided by redistribution of electricity in time using storage and by demand response measures. Third, on a time-scale of weeks, the flexibility need is likely to be fulfilled by large storage capacity: WP capacity will have to be combined with other types of generation or storage, which can be discharged when the wind is not blowing for a longer period of time. This may add to the cost of having large amounts of WP in the system. However, there is no strict delineation between how the two time-scales (hourly and weekly) can be handled; the best combination of variation management strategies is not known at present and will depend on how the system develops.

In total, several measures could be taken to incorporate a large amount of WP into the electricity generation system:

- Geographic allocation of WP, together with simultaneous transmission integration, so that the resulting output of WP would vary less.
- Adjusting the surrounding generation system through the dispatch of thermal or adjusting hydropower output.
- Extended Demand Side Management (DSM), with the aim of adjusting the demand to the current supply, also for the shifting of large amounts of electricity. This may involve industrial production being shifted to times with high WP production.
- Inclusion of Energy Storage (in whatever form, including already existing hydropower).
- Complementation of varying renewable sources of energy with different characteristics, so that there is decreased total variation.

These measures may be seen as either competing with each other, in the sense that the saving that comes from one measure may reduce the economic gain from employing another measure, or as complementing each other, since it is most likely that several measures will be required for cost-effective, large-scale integration of WP.

This thesis investigates *the first* of the above measures, i.e., geographic allocation of WP. In order to be able to benefit from the variation dampening achieved by spreading WP geographically, also called the *smoothing effect*, the transmission network will have to be enhanced so as to be able to transport WP electricity from one region to another. The topic of this licentiate thesis is how variations in aggregated WP output, on the time-scale of hours to weeks, can be dampened by spreading WP capacity over a larger geographic area, without considering limitations in transmission capacity or other limitations, such as regional demand.

1.2 Aim and scope

The aim of the work presented in this thesis is to understand how spatial allocation of WP plants can be used to maximize the benefits of WP, considering weather patterns on different time-scales. This is important to identify strategies for efficient large-scale integration of WP into the energy system.

Specifically, this thesis investigates how certain measures that are important for the performance of WP in the energy system are affected by optimizing allocation over larger areas, such as the continent of Europe.

The main questions addressed here are:

- How much can the variation of aggregated WP output be dampened using geographic allocation of WP capacity?
- Are there general characteristics, for the allocation patterns of such optimal allocations?
- What is the trade-off between a smooth output and a high average output?

1.3 Outline of the thesis

The thesis consists of an introductory essay (this part) and three appended papers. The introductory essay is intended to give a general introduction to the background of the work and to place the appended papers in a broader context.

The essay is divided into the following sections: Section 2 describes the characteristics of WP; Section 3 provides a literature review of the field; Section 4 discusses the choice of methodology; Section 5 summarizes and discusses some of the key findings of the thesis work; and in Section 6, ideas for future work are presented.

Paper I employs a heuristic method that minimizes the coefficient of variation, which is a measure of both average output and variability. The method is applied to the Nordic countries and Germany, a geographic area that may realistically be considered to be electrically integrated in the future.

In Paper II, a new methodology is developed which identifies allocations that provide system benefits for integrating WP into the energy system. Measures for variation that are relevant for the role of WP in the electricity system are defined and then used as objectives in a multi-objective optimization. The method is applied to the entire continent of Europe.

In Paper III, an objective that measures the proximity of WP to regions in Europe with high demand is introduced, and the trade-off with a high output and variation dampening is investigated.

1.4 Contribution of this thesis

This thesis reveals the variation dampening effects that can be achieved using geographic allocation of WP. The methodology developed herein is flexible in the sense that other variable resources, such as solar and wave power, can easily be incorporated. The methodologic advances also include the linkage of variability measures with the qualities of WP as part of the electricity system, as well as the convex formulation of an allocation model, which enhances computational feasibility.

The method developed during the course of the thesis has two major characteristics:

- It assesses both the volume of the resource (capacity factor) and the characteristics of the resource (variation and proximity to load centers).
- It assesses the role of WP in the electricity system by recognizing certain aspects of dampened variability and proximity to load as being tied to system benefits. By identifying these aspects and quantifying them as objectives in an optimization model, the method gives an indication as to the contribution that can be expected from WP output aggregated over a large region, such as Europe.

The present method may also be viewed as a complement to determining WP capacity allocation and assessing WP in traditional energy system models. Thus, the present method may be used for creating

alternative allocation strategies for future scenarios with large-scale penetration of variable renewables.

2. Wind speed and wind power variations in Europe

This section gives an overview of some of the characteristics of WP variations and briefly describes their impacts on the electricity system. We describe three types of variations and present one of them as the primary subject of the present work. As the sub-hourly time-scale is relevant mainly for power quality and primary reserve regulation, it is not discussed here. For an aggregation of sites (region), the WP output varies:

- from one hour to the next, between periods of high and low pressure (weeks) and between Winter and Summer (months)
- between years, since years are not equally windy¹
- spatially, whereby a region may be more or less correlated with other regions

2.1 Variation in time: hours to seasons

Short-term variation, in the order of hours, in WP output is characterized by the time-scale of changes in wind speed, as well as by the fact that the energy content of the wind is proportional to the third power of the wind speed. Thus, changes in WP output are more dramatic than changes in wind speed. Here, mainly the WP output is discussed, where a conversion function representing a specific wind turbine or an aggregation of WP plants has been applied to meteorologic weather data. Figure 1 shows the WP output for one year for one site in western Denmark, with the wind-speed data or Year 2007 [3] and the conversion function adapted from a previous study [4]. As shown in Figure 1, WP output varies greatly in a short period of a few hours. For instance, in the lower panel of Figure 1, on January 9th, the output fluctuates from 17% of nameplate capacity to the maximum output² within a period of a few hours. The hourly increments/decrements are important with respect to the demand for flexibility of the surrounding energy system, since they require ramp-up or ramp-down of other electricity-generating plants. Since weather systems, e.g., a high-pressure system, may dominate the weather for a much longer period, typically up to 2 weeks, very low output levels may persist during several weeks. In Europe, the winter is on average windier than the summer. This correlates well with electricity demand, which is higher during winter in most, but not all, countries of Europe. Figure 2 shows the output for one site in western Denmark over a period of 3 years (2007–2009), although the time series has been smoothed with a quadratic fit, to highlight the seasonal differences. It is apparent that winter-time is much windier than summer-time, with winter average wind power outputs of up to 70% of installed capacity. However, inter-annual variability is also visible, where the winters are not equally windy and 2009 stands out as a less-windy year.

¹ Just as there are wet and dry years for hydropower, there are windy and not-so-windy years for wind power.

² In this case (Figure 1), the maximum output is 94%, due to the power conversion curve used, which takes into account effects that do not allow for 100% of nameplate capacity output. For further explanation, see the *Methodology* section.

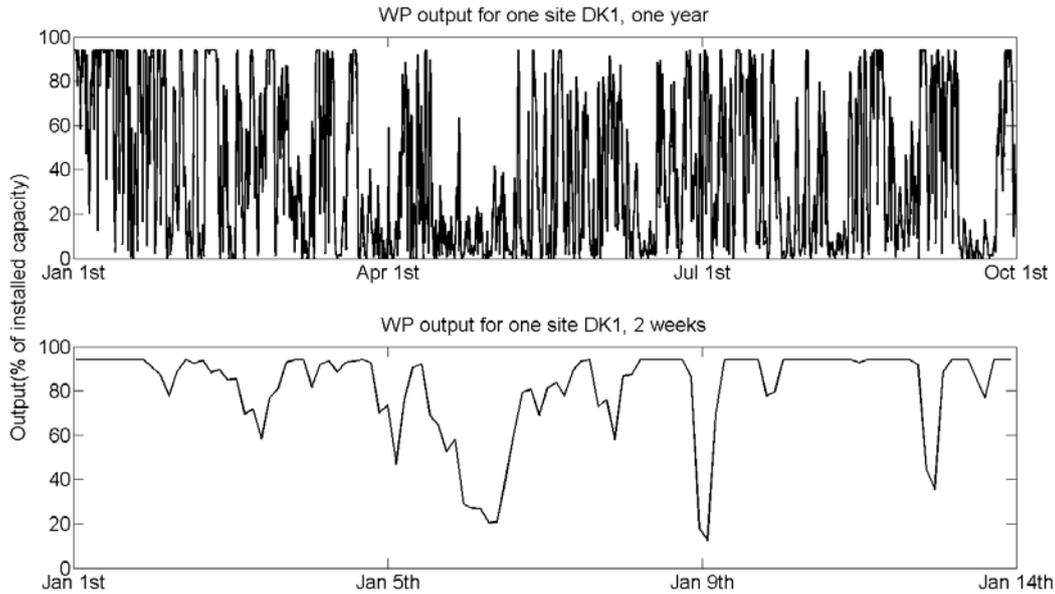


Figure 1 Wind power output for western Denmark. The upper panel shows the output for Year 2007, and the lower panel shows the output for the first 2 weeks of the same year. The wind power data and the conversion from wind speed to wind power output are the same as those used in Papers II and III; see the *Methodology* section for an explanation of the same.

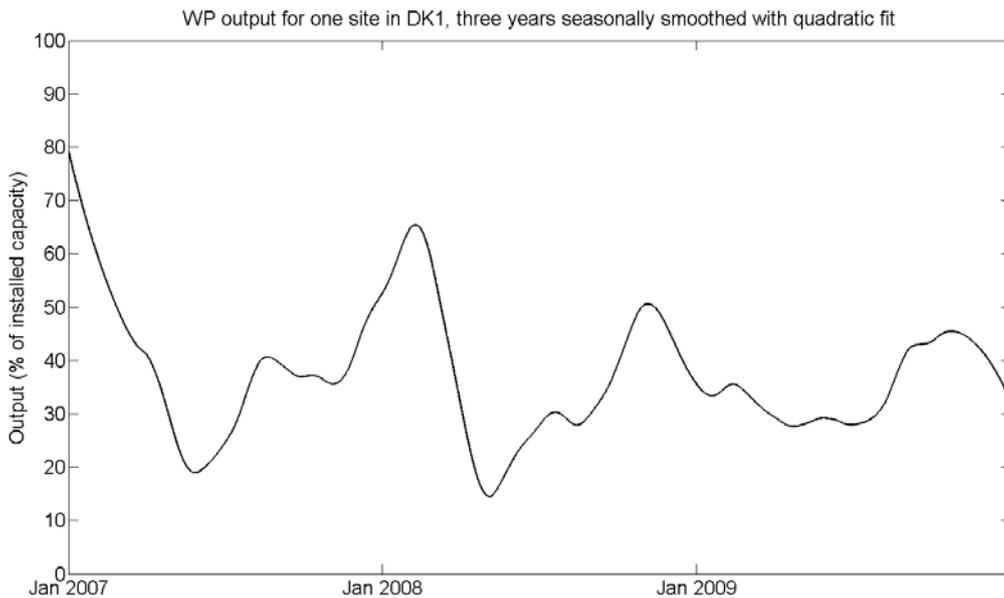


Figure 2 Wind power output for western Denmark over a period of 3 years (2007–2009). The output time series has been smoothed using a moving average of ~ 1 month, to ensure that the seasonal characteristics are visible.

2.2 Inter-annual variations

The variation in average WP output between years, the *inter-annual variability*, can be about 40%. This variability exists both for single sites [5] and for larger areas, such as countries [6]. The

variability also extends to cycles longer than just 1 year: the decade that started in 1990, for instance, was exceptionally windy in Northern Europe [6].

For WP planning purposes, the variability on the time-scale of years to decades entails that long time series of historic data are necessary to make accurate predictions regarding the expected capacity factor for WP at a certain site or region. There may also exist complementary relationships between different regions, so that a bad wind year in one part is likely to entail a good wind year in its counterpart region [6].

Figure 3 shows the inter-annual variability of one site in the Midwest of the USA, where the plant output is shown as shares of average output. This is called a wind index, where 100% represents the average for the normalization period of several years. This specific site has a wind index that varies between 0.82 and 1.13. (In Figure 3, the wind index is shown as percentage of the average farm output for the period.)

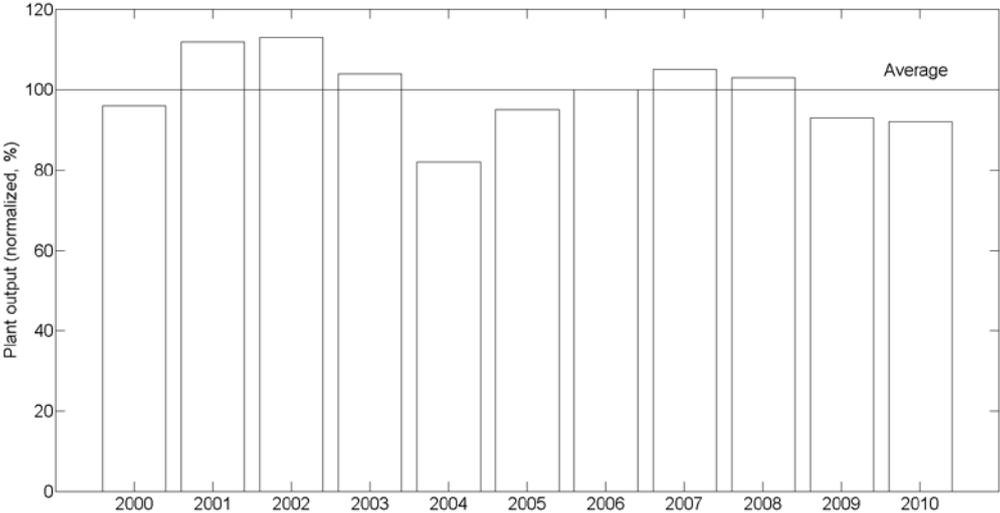


Figure 3 Inter-annual variability of wind power output at one wind farm at Lake Benton, Minnesota, USA. The output is normalized and the wind index is based on the average for the 11 years in the plot. The figure is adapted from [5].

2.3 Spatial variations

There is a spatial difference in how windy places are *on average*. This, in turn, gives rise to a corresponding average output from a wind turbine that is located on that site. The distribution of average values of wind speed for an area is typically visualized and quantified by means of a WP atlas. Average WP output is measured in terms of either a capacity factor (CF), which is the percentage of name-plate capacity (maximum) output, or full-load hours (FLH), which is the number of hours the WP plant would produce electricity during the year had it generated the nameplate capacity at all load hours. Figure 3 shows an example of a WP atlas, where the CF has been computed from the dataset used in Papers II and III.

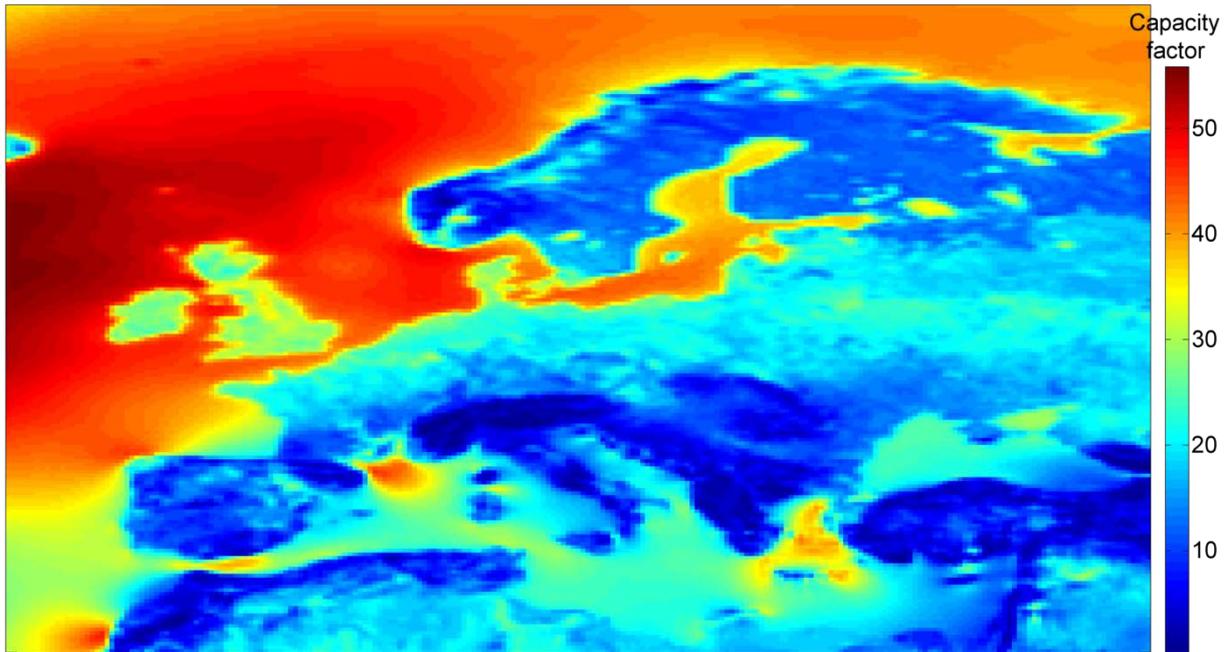


Figure 4 A wind power atlas of capacity factors, based on ERA-Interim data [3] for Years 2007–2009. The color-scale shows capacity factors for the sites, where the best on-shore sites have capacity factors >40%.

There is also spatial variation in *momentary* WP output. Since they experience the same weather pattern, there are stronger correlations between the outputs of WP plants that are situated in proximity to each other than those that are more distant from each other. The magnitude of the correlation depends on the time-scale: for time-scales on the order of seconds, the correlation between WP plant output is weak even for plants that are a few hundred meters apart. In contrast, for time-scales of the order of hours, days, and weeks, the correlations are stronger, also for larger distances. The latter simply reflects the typical size and duration of weather patterns.

One way of measuring the extent of similarity of WP output between two locations is to use correlation coefficients. A perfect correlation, which in this case means a perfect match of the output time-series profile, has a correlation coefficient of 1, whereas a correlation coefficient of 0 means that no information can be gained regarding the WP output at one location by examining the output at the other location. Table 1 lists the correlations for two pairs of plant locations: 1) northern Norway (NO in the table) and the Netherlands (NL); and 2) Ireland (IE) and eastern Poland (PL)³. The pairs were chosen on the basis that they lie at comparable latitudes (NO and NL) and longitudes (IE and PL). The computation of the correlation coefficients was based on the Year 2007 data used in Papers II and III. Time series representing a single site (chosen at random) and the entire region were compared in their original forms, at a 3-hour resolution and on a weekly average. Although the two pairs of geographic locations are equidistant from each other (around 2000 km), the correlation between IE and PL is significantly stronger than that between NO and NL, especially on a weekly time-scale (Table 1). In fact, NO and NL show a negligible correlation. The comparison shows that correlation of WP output is more specific than can be determined from geographic distance alone given that weather patterns typically follow a pathway across longitudes (“west to east”). The correlation was also stronger for the weekly average, where larger-scale weather patterns are more important, than for the 3-hour resolution, where smaller-scale phenomena also influence wind speed.

Table 1 Correlation coefficients for two pairs of sites: 1) northern Norway (NO)-Netherlands (NL); and 2) Ireland (IE)-eastern Poland (PL).

Correlation coefficient	Single site in NL-NO	Regional average for NL-NO	Single site in IE-PL	Regional average for IE-PL
Three-hour resolution	0.01	0.02	0.13	0.19
Weekly average	0.01	0.00	0.48	0.53

2.4 Concluding remarks regarding the variation of WP

From the above, it can be concluded that there are different aspects to wind variations. The three aspects treated in this thesis all have implications for the integration of WP into the energy system: 1) inter-annual variations influence the projected income for WP owners; 2) variations in time on different time-scales are important for the regulator; and 3) spatial variations (or the lack thereof) underpin the possibility of trading a WP surplus to neighboring countries. However, as the remainder of the thesis will show, knowledge of the basic facts about wind and wind speed correlations is not sufficient to foresee the role that geographic allocation of WP will have in the electricity system.

³ These regions correspond to regions NO3, NL, IE, and PO2 in Paper II.

3. Modelling wind power allocation

There follows a review of the literature related to the geographic allocation of WP. The review starts with how variability affects the market value of electricity production sources. Since market value can arguably be seen as an indicator of system benefit or social value, it is also an incentive for a deeper investigation of variability itself. As background, the integration of variable production into investment models for electricity generation is described. This is necessary because one of the major reasons for investigating the variability characteristics is to understand better the possibilities and limitations of large-scale integration of WP into energy systems. Thus, the review of electricity investment models, which (among other things) assign VRE capacities to geographic areas, is a backdrop to the literature of the core field of this study, namely, how variations in aggregated WP output depend on geographic dispersion.

Research has shown that variability in a source of energy imposes a lower value on that energy source, as compared with energy sources with less variability [7, 8]. This lower value is due to both the higher part-load and the start-up costs for the other plants in the system owing to hour-to-hour variation, as well as in a longer-time perspective, the need for extra capacity in the system, when part of the capacity is variable. The latter means that a larger part of the capacity remains idle for longer times during the year. Obersteiner [8] has linked WP variation to lower market value. This is true both in the short-term perspective, in which the surrounding energy system remains unchanged, and in the long-term perspective, in which VRE necessitates additional dispatchable capacity to ensure gap-filling. In a previous study [7], the linkage between a variability measure (the standard deviation) and the market value of VRE was quantified. The relationship is established for different penetration levels. It is shown that the lowered market value for sources with greater variability is more pronounced at higher penetration levels. In another study [9], it was shown that a strong correlation in wind output between two markets decreased the market value of WP. Combined, those two studies [7, 9] imply that the physical limits of variation dampening achieved *via* transmission integration are relevant also for assessing the market value of VRE at different penetration levels. They [7-9] also show that from the point-of-view of the value of WP in an energy system, it is valid to concentrate on the variational aspects of aggregated WP, as well as on the dependence on the penetration level of WP.

When optimizing the allocation of WP (and VRE in general) it is necessary to acknowledge the variable nature of WP, which means that the allocation strategies for WP differ from those for thermal power plants. Energy system models offer ways of allocating resources, amongst them WP capacity. For the electricity generation system, investment models can be used to investigate long-term (over decades) investments in plant and transmission capacity, and dispatch models can be used to investigate how a specific system can be operated on, for example, an hourly basis. While investment and dispatch modeling are sometimes integrated into a single model, as in a previous study [10], they are often performed in sequence, as in [11, 12]. An overview of the investment and dispatch models can be found elsewhere [13]. Electricity system investment models typically use time slicing, which means that they represent the variability of the energy system (for instance, day/night, winter/summer, weekend/weekday), albeit with a limited number of “typical” values. Time slicing is used in the ReEDS model [12] with 17 time slices, and the ELIN model [11] with 16 time slices. The reason for the simplified time dimension is the size of the input data and the high number of variables involved. The variability in an electricity system, based mainly on thermal generation and hydro power, is mostly due to variations in consumption, which can be described adequately using the time-slicing technique, since it then depends mainly on diurnal and seasonal patterns. However, the limited temporal resolutions of these models make it hard to capture the full consequences of the variability of WP (and other VRE). In order for the models to build sufficient capacity, including both production

and transmission capacities, the models use certain techniques to represent the variable nature, as well as the potentially complementary nature of WP in different regions. The ELIN model [11] takes into account some of the variability characteristics by mandating additional investment in dispatchable capacity for back-up purposes when an investment is made in variable capacity. The ReEDS model uses an approach that entails statistical treatment of correlations between wind and solar outputs and the loads in the respective regions [12], where the spatial correlation properties, as well as the correlation between load and wind and solar power, are captured. Thus, electricity system investment models are becoming more refined and can to some extent capture the characteristics of an energy system with high levels of VRE. However, it is not clear to what extent the techniques used to represent the characteristics of VRE compensate for the low temporal resolution, when it comes to valuing dampened variation in integrated transmission areas and investing in additional transmission capacity with the aim of reducing the variability. The field, of which this thesis is part, is rooted in the fact that dampening the variability of aggregated WP generation is beneficial, as epitomized in common-sense arguments and by model results, such as those reported previously [7], which show that the greater the variability of a production source, the lower the market value of that same source. Thus, the variability of aggregated WP generation is an important aspect of the value of an energy source within an energy system, and allocation and transmission integration are ways of managing that variability. At the same time, the aspect of allocating WP capacity so as to dampen variation is one with which energy system investment models experience difficulty, due to their low temporal resolution. Therefore, investigation of the variation itself is important in acquiring an understanding of the physical possibilities of variation dampening that can be realized with sufficient transmission capacity. This will also enhance our knowledge of the limitations of variability pooling in energy systems modeling with different geographic scopes.

The common term for the dampening effect of geographic dispersion of capacity on the variability of aggregated WP output is called the *smoothing effect*. This term does not specify the nature of the smoothing, as it can refer to different time-scales as well as different measures of variation dampening, as described earlier [14]. The smoothing effect has been studied in an energy systems context in various studies [14-16]. These studies show that hourly to sub-hourly variations in WP output can be substantially reduced by spreading WP over a sufficiently large area, such as the Nordic countries. However, the aforementioned studies did not perform any optimization with respect to the geographic allocation of WP capacity; instead, they investigated the *consequences* of already existing allocations of WP. With respect to the optimization of WP allocation, fewer studies have been carried out. A study of the optimization of hourly changes by Rombauts et al. [17] 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 reduction in average output.

Reducing the variability of WP output between longer periods of high and low outputs requires the use of larger geographic areas if a substantial reduction is to be achieved [18, 19]. This is due to the fact that 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 WP generation as the base load and reduce the cost for back-up generation. Kiss and Jánosi [18], Degeilh and Singh [20], Drake and Hubacek [21], and Grothe and Schnieders [22] have investigated the overall variation in aggregated WP output, as opposed to *changes* in the variation between hours. Kiss and Janosí [18], using a Monte Carlo method

for optimizing site location in Europe, reported that the absolute minimum aggregated WP output over the 30-year period covered by their data was 1% of the installed capacity. Grothe and Schnieders [22], who focused on the possibility of avoiding low output by optimizing geographic allocation in Germany, found that, when penalizing low outputs in the objective function, there was 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 performed about 50% better than the present allocation [22]. Drake and Hubacek [21] investigated reducing the variance of aggregated WP output in the UK. They 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 [20] 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, studies of the smoothing effect in itself are justified, since there is evidence that the variability of WP output needs to be addressed when considering a future with large-scale penetration of WP, and one of the tools that can achieve this is geographic allocation. Furthermore, electricity system investment models, owing to computational constraints, lack sufficient time resolution to capture fully the variability issue, and especially the benefits of geographic smoothing. Thus, there is a need to understand the characteristics of WP variability and how this variability depends on geographic allocation, in order to decide on its importance and how it can be included in energy systems models, such as the models of the electricity system mentioned above. Available studies on the potential of geographic allocation in terms of variation dampening in a future energy system, where Europe is substantially more integrated, have either a more limited geographic scope or lack optimization with respect to WP allocation. Moreover, the issue of avoiding low outputs of aggregated WP, as opposed to dampening short-term variation, has not been addressed with a multi-national geographic scope or with an optimization approach to WP allocation.

4. Methodology

One of the aims in this work was to develop a methodology that *optimizes* the placement of WP, as opposed to investigating the consequences of a certain configuration of WP sites. This goal requires data that can be mined to identify potential sites for WP, and not only sites that are already in use, for which production data are available. It also requires a methodology that allows for assessment of the degree of optimality of the configuration: the goal is that the methodology be designed so that it transcends mere exploration of *some scenarios* for WP placement. The emphasis has been on developing a method that is exhaustive, in the sense that it can find the physical limits for average output and geographic smoothing of aggregated WP, thus allowing it to be used to assess how distant different configurations, e.g., the present WP allocation in Europe, are from these limits. Alongside the development of the mathematical framing of the problem, this work progresses towards formulating goals (objectives) for the optimization that are linked to system benefits in a future energy system with large-scale penetration of WP.

4.1 Data

The work presented here is dependent upon wind data that are evenly dispersed with a sufficiently fine resolution, both spatially and temporally. This is a prerequisite for assessing potential WP sites, and not only those sites where WP plants happen to be located at present or where there is a weather station. In addition, the temporal resolution must be of the same order as the energy system-specific issues that are ultimately to be addressed with this research, i.e., the flexibility and capacity needs of the surrounding system. The above requirements led us to use the type of model data provided by meteorologic services, rather than using WP output data from existing plants or wind measurements from weather stations. (Weather model data have also been used in other renewable integration studies, see [23] for an overview of the data handling in the large integration studies performed by NREL). Such model data are used for weather forecasts and are provided as inputs from different measurements, such as satellite and weather station data. Examples of global datasets are: MERRA (from NASA); ERA-Interim (from ECMWF); and NCAR (from NCEP).

In Paper I, data for the period 2006–2009 from the meso-scale model HIRLAM were used [24]. The dataset consists of time series for wind speed with a spatial resolution of 11 km and a temporal resolution of 3 hours. The wind speed data were transformed to output using a single-turbine power curve adapted from a previous study [18].

In Papers II and III, ERA-Interim data from ECMWF [3] for the period 2007–2009 were used. The spatial resolution is 0.25 earth degrees. Each data-point is assigned a pixel size of $0.25 \times 0.25^\circ$, which means that the pixels range in size from 200 km² to 670 km². The temporal resolution is 3 hours. The wind speed data were transformed to WP output using the power curve for future land-based WP farms developed within the TradeWind project [4]. The main difference between this curve and the one used in Paper I is that since it represents a collection of wind turbines, it has a smoother cut-off speed and a maximum output of 94% of installed capacity (instead of 100%, as is the case for the single-turbine power curve).

4.2 Multi-objective optimization

Multi-objective optimization is a way of investigating problems where there is an *a priori* understanding that there are trade-offs between two or more goals (objectives). A common example in energy systems research is the assessment of systems with regards to emissions and cost, and to

explore the trade-off between them. Typically, the trade-off is explored at multiple points, so that intervals of special interest are identified. Such intervals may be where the value of one objective changes rapidly for only a slight change in another objective. The outcome of a multi-objective optimization is a collection of *Pareto optimal points*. Pareto optimality is when there can be no improvement of one objective without impairment of another, for instance, when there can be no further reduction in emissions without increasing the cost.

Multi-objective optimization is useful when it is appropriate to look at a problem from different points of view or when the actual cost or consequences are unknown. The cost, including the transition cost, for integrating a large share of renewables, is largely unknown, since it is highly system-dependent [25], and there is little empirical knowledge of such systems. Therefore, multi-objective optimization is a valid method to apply in this context, since it generates more than one solution that can be considered for the future WP allocation.

4.3 Objectives for the optimization

The objectives used in this work were chosen to reflect system benefits that might be achieved through the use of geographic allocation of WP capacity. The first attempt was to derive the *coefficient of variation* (Paper I). The aim of variation management was subsequently expanded in Papers II and III, where the variational objectives (*Short-term variation* and *Avoid-lows* objectives, see the explanation below) are convex, which allows for an exhaustive exploration of the objective space, i.e., to define the WP configurations that correspond with certainty to Pareto optimal points. In Paper III, an objective that covers the goal of placing WP in regions with large loads (*Load-match objective*) was added. In addition, the capacity factor of the aggregated WP output is discussed throughout the work. In Paper II, the objective of a high capacity factor is termed the *High-output objective*, while in Paper I it is part of the objective function of a low Coefficient of Variation (COV). The five objectives are presented briefly below, followed by a motivation as to why they are potentially important in an energy systems setting.

- 1) **The Coefficient of Variation (COV)** (Paper I): COV is the standard deviation divided by the mean, for the time series of the aggregated output.
- 2) **The Short-term variation objective** (Paper II): Aggregated WP output should be as smooth as possible, to enable other system components, such as consumption and thermal generation, to minimize ramp-ups. Since this objective allows for the curtailment of wind, which lowers the average output by cutting peaks, its value is highly dependent upon the capacity factor that is required.
- 3) **The Avoid-lows objective** (Papers II and III): Aggregated WP output should with some probability ensure a certain minimum level of output, so that the surrounding system can rely on WP providing at a minimal fraction of the load. This objective is connected, albeit not synonymous, with the concept of capacity credit.
- 4) **The High-output objective** (Paper II): Aggregated WP output should generate as much energy as possible.
- 5) **The Load-match objective** (Paper III): This objective states that *regional* WP should contribute as much as possible to covering the *regional* demand. Thus, this objective regards any regional wind production that exceeds the regional load as being curtailed and thereby not contributing to the covering of load. In contrast to the other objectives, which assume the removal of transmission bottlenecks, this objective assumes isolated regions with no transmission between them.

The **COV** was used as an objective in Paper I because it contains two important pieces of information about the time series of aggregated WP output: the standard deviation and the average. The standard deviation is the most common measure of variability. However, a low standard deviation of the time series alone is not a good measure of the appropriateness of a WP allocation, since it is generally lower for less-windy sites (and aggregations of sites). Therefore, the average function was also included in the objective function. The objective function is non-linear and non-convex, which is the reason for applying a heuristic method, rather than a strictly optimizing method. The method starts with one time series, which may represent one site or an aggregation of sites, and finds the next site that minimizes the COV of the aggregation of sites (old and new). Thereafter, this procedure is iterated until the desired number of sites is reached.

The **Short-term variation** objective is important because the hourly increments/decrements in output of the WP output determine the response required by the surrounding system (consumption, production, storage). Part of this feature has to do with forecasting and predictability, which are outside the scope of this study, although in general, large changes mean that a large part of the surrounding system has to ramp-up (or -down). This is costly, both on a shorter time horizon, where the capacity mix is fixed, and on a longer time horizon, where the surrounding capacity is geared towards ability to provide fast regulation. On a shorter time horizon, this may entail that plants that are not designed for frequent starting and stopping will have to do so regardless. On a longer time horizon, it directs the plant mix towards more flexible generation, which is generally more expensive per unit of produced electricity than less flexible generation.

The **Avoid-lows** objective is chosen to investigate how large a part of the WP capacity can be considered “firm”. This work argues that a WP output where the incidence of low output is lower (everything else being equal) provides a higher capacity credit from wind, which means that a lower back-up capacity is required. Other potential objectives are to *avoid high* outputs or to *avoid both high and low* outputs, thus squeezing the output curve towards the average output. Avoiding high outputs, while maintaining an average level (capacity factor) might entail lower costs being attached to start and stops of base-load generation.

The **High-output** objective is obviously a desirable characteristic of WP. It also sets a level for comparison of the capacity factors of the allocations attached to the other objectives.

The **Load-match** objective captures, albeit crudely, that WP is more valuable when it does not have to be exported to be of use. The variation aspect is not present in this objective; the Load-match objective instead emphasizes the extent to which the value of WP is associated with population density and wind conditions.

4.4 Limitations

This work focuses exclusively on the WP system, while other forms of electricity generation, transmission and consumption are omitted or are represented in a static fashion. Since the surrounding system is omitted, we are instead referred to look for measures of the aggregated WP output that are likely to be important in a system context.

Regarding the input data for the models, they are insufficient with respect to climatic parameters. Therefore, the results presented here cannot be used as a blueprint for policy actions regarding WP capacity allocation. Instead, this work mainly comprises the development of methodologies, although the geographic scope of this work is considerably larger than most of the previous studies in this research field.

5. Results and Discussion

This section highlights some of the most important results provided in Papers I–III, with the emphasis on Papers II and III, which represent methodological improvements compared to Paper I. The results are summarized with headline statements that are supported by the results in one or more of the papers. As a foundation for the results, we emphasize again that the results for variation dampening all assume a complete removal of transmission bottlenecks. Therefore, the results outline the *physical boundaries* for dampening using geographic allocation, without going into whether the necessary development of the transmission grid to realize this potential would be likely to occur or cost-effective. The exception to this is the case described in Paper III, where the possibility of covering as much load as possible regionally using regional WP generation is investigated. This case assumes that there is *no* inter-regional transmission that can help to dampen variation and thereby cover the additional load, and also that all instantaneous regional production that exceeds instantaneous regional demand is curtailed.

There is a possibility to avoid low outputs using pan-European allocation

The results presented in Papers II and III indicate that there exists significant potential to dampen variation if allocation occurs according to the Avoid-lows objective, which ensures a high probability of exceeding a certain output level. Optimization on the Avoid-lows objective gives rise to a configuration of WP capacity with an aggregated time series that has a low probability of low output, as well as an output with variation that occurs over a longer time-frame. In fact, this configuration also avoids *high* outputs, with the consequence that the time series is pushed towards the middle of the scale. This means that optimizing using the Avoid-lows objective, which is described in more detail in Paper II, produces an aggregated time series that is dampened in several ways. It exhibits variability in a longer time-scale and avoids both high and low outputs. Figure 5 shows the aggregated time series for the High-output (upper panel) and Avoid-lows (lower panel), respectively. The Value-at-Risk (VaR) for this time period, i.e., the level below which the output lies 10% of the time, is slightly higher for the Avoid-lows strategy (24% of installed capacity) than for the High-output strategy (22%) for the depicted time period (3 months of 2007). More striking is the shapes of the aggregated output, with the range between the high and low values for output being considerably narrower for the Avoid-lows strategy. Again, it is important to stress that the realization of the time series for aggregated output discussed here is dependent upon the complete removal of transmission bottlenecks.

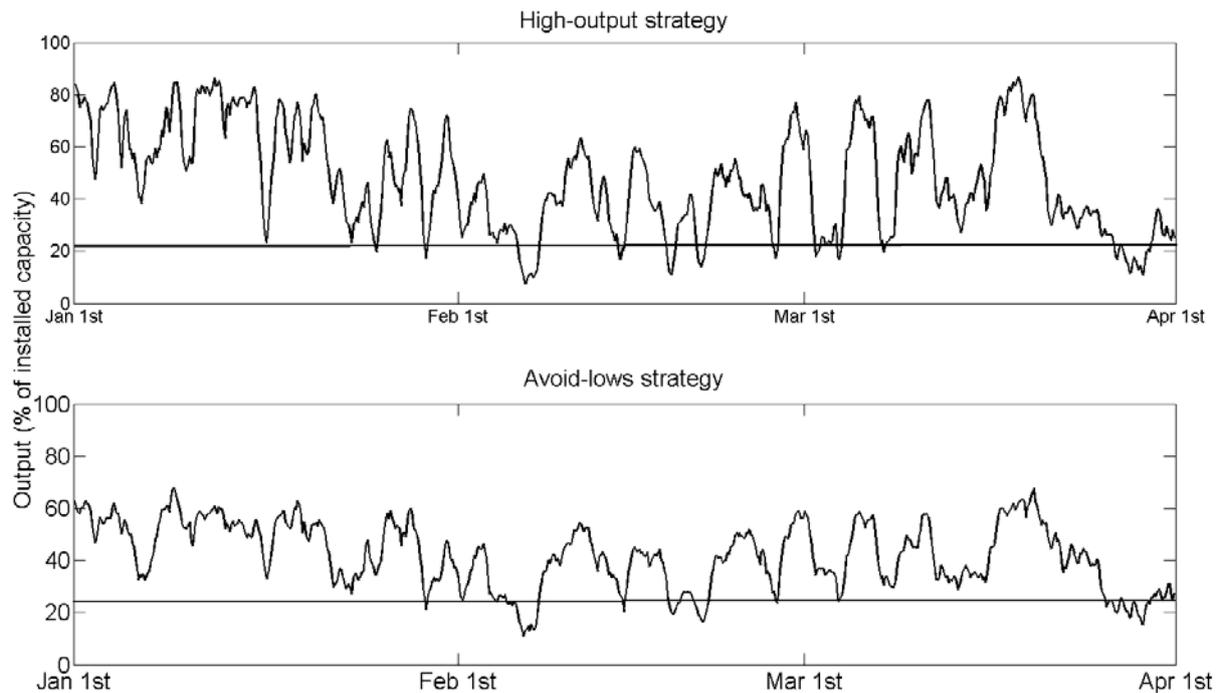


Figure 5 Aggregated time series resulting from the High-output (upper panel) and Avoid-lows (lower panel) strategies during the first 3 months of 2007. The line represents the VaR for this time period, i.e., the level below which the output lies 10% of the time. For the depicted time period, the VaR is 24% of installed capacity for the Avoid-lows strategy and 22% of installed capacity for the High-output strategy.

The present allocation of wind power is not based on wind conditions

The present allocation of WP in Europe is based not only on wind conditions but on a variety of factors, including national priorities for renewable energy, subsidy schemes, electricity production mixes involving other sources, and import possibilities. When compared to the allocations that result for the optimization criteria in Paper III, it is clear that the present allocation performs far from optimally in a Europe that is fully integrated with regards to electricity production. This is illustrated both by the differences in capacity allocation, as well as by statistics on the aggregated time series of the allocations. The difference in installed capacity for the present allocation and the High-output strategy (as investigated in Paper II) is shown in Figure 6. Clearly, WP installation is not first and foremost determined by where it is windy but the locations of WP plants are chosen based on a variety of constraints, such as the ones mentioned above (although wind conditions are obviously an important parameter in the sense that bad sites are not chosen). This is also evident when looking at the average capacity factor of the present allocation (20%), as compared with the optimal strategies in this work, in particular the High-output strategy, which displays a capacity factor of 34%.

The difference between the Avoid-lows strategy and the present allocation is shown for the capacity allocation in Figure 7. The allocation for the Avoid-lows strategy differs significantly from the present allocation; the UK, France and Norway get a substantially larger share of the total installed capacity in the Avoid-lows strategy, whereas Germany gets a smaller share. (This is one of the topics of Paper II).

Figure 8 shows a Pareto front, which is a way of illustrating the statistics of the aggregated time series. The distance between the present allocation and the Pareto optimal allocations that result from the modelling is substantial. This distance is one way of illustrating the fact that the present allocation is far from optimal, given the optimization objectives formulated in this thesis and in Paper II.

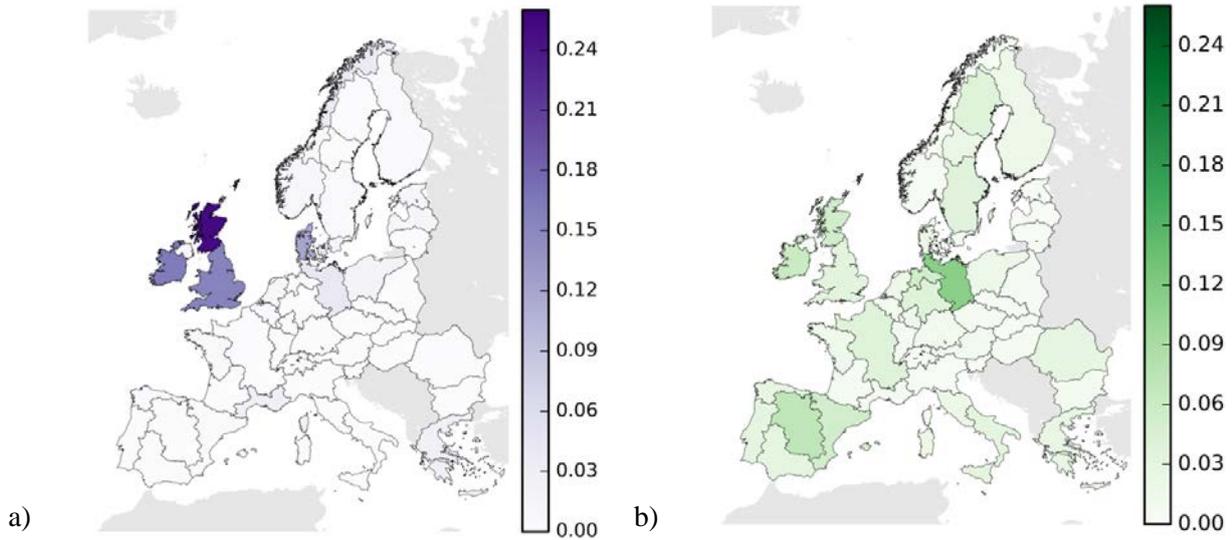


Figure 6 Shares of total installed capacity for: a) the High-output strategy; and b) the present allocation case. In a) the total installed capacity is 250 GW, while for the present allocation (b) the installed capacity of 136 GW is taken from the Chalmers Power Plant database [26].

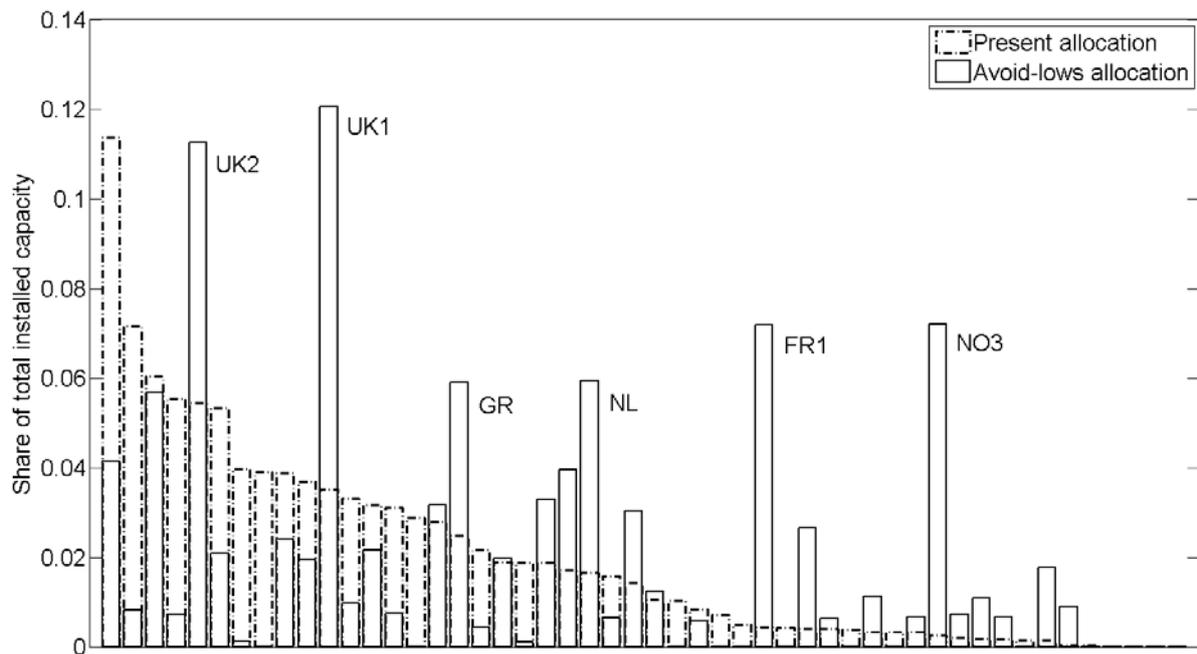


Figure 7 Shares of total installed capacity for the regions of Europe using the Avoid-lows allocation strategy compared to the present allocation strategy. The present allocation is taken from the Chalmers Power Plant database [26]. The regions where installation is particularly high under the Avoid-lows strategy are noted with the regional codes used in Papers II and III. The codes used here are: UK2, Scotland; UK1, England; GR, Greece; NL, The Netherlands; FR1, southern France; NO3, northern Norway.

Windy regions are preferred also for dampening variation

The results from Papers I–III show that *all* goals, including those that favor dampened variation and allocating in regions with high electricity consumption, favor windy regions. At first glance, this might seem surprising, since the preconception is that optimal smoothing can be achieved by also smoothing out capacity more or less evenly. However, this is not the case, since weather systems usually cover large areas, which means that the WP outputs for different regions in Europe are far from uncorrelated. In the optimization model results of Papers I–III, windy regions are very much favored at the expense of an even distribution of capacity. A consequence of this is that the trade-off between the system benefits (dampening variation and allocating in regions with high electricity consumption) and the average output is rather small (Papers II and III). For example, the configurations that are optimal and near-optimal when it comes to avoiding low output of aggregated WP display average outputs of around 30%, as compared with the highest possible output, which is 34%. A figure of 30% can be considered as being very high, especially compared to the present allocation, which has an average output of 20%. It should be noted that the absolute values rely on the assumptions made to convert wind data to WP output, as well as on the wind dataset used. However, the comparison is relevant, since the cases that are compared apply the same assumptions.

Furthermore, when optimizing by covering as much load as possible in each region using only regional WP capacity (the Load-match strategy of Paper III), the average output of WP is close to 30%. The reason for this is that the optimization tries to cover as much of the load as possible with a given amount of WP capacity and, since windy regions generate more electricity per installed unit of capacity, an allocation in which some regions get high penetration levels of wind (~60% of the demand), which entails momentary over-production and thus curtailment, is optimal.

Therefore, Papers II and III show that allocations that dampen variations (assuming the removal of inter-regional bottlenecks) and that cover maximum load (in the case of isolated regions) also have high average outputs, which is obviously an important factor in determining the economic feasibility of WP. This is shown in Figure 9, which depicts the trade-off between the Avoid-lows and Load-match objectives (the topic of Paper II). In Figure 8, the Avoid-lows objective is represented by the VaR measure and the Load-match objective is represented by how large a proportion of the European load is covered regionally. A large part of the Pareto front, i.e., the allocations that are optimal with respect to the aforementioned two system goals, display capacity factors >30% (encircled in Figure 8). Thus, the Pareto optimal allocations that result from an optimization process that only takes into account the Avoid-lows and Load-match objectives also yield high average outputs.

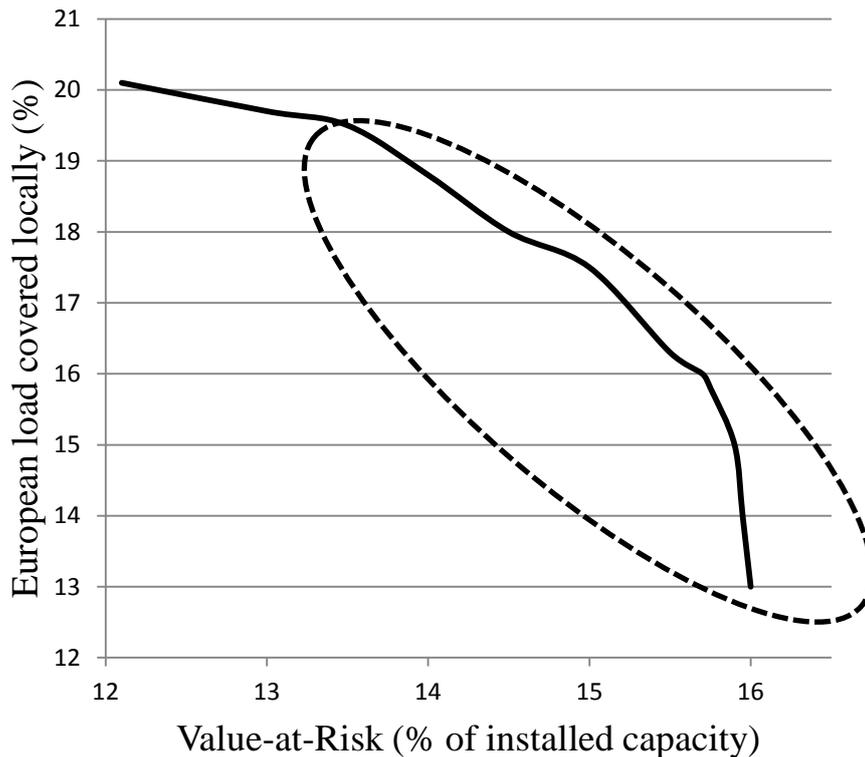


Figure 8 Trade-off between the Avoid-lows objective (represented by the Value-at-Risk measure) and the Load-match objective (represented by the measure of European load covered locally), which is the topic of Paper III. The encircled region of the Pareto optimal front corresponds to allocations with an average capacity factor of $\geq 30\%$.

Optimizing allocation adds to the smoothing effect

When optimizing using the variational objectives [COV (Paper I), Short-term variation (Paper II), and Avoid-lows (Papers II and III)], there is additional variation dampening, as compared to merely dispersing capacity over a larger geographic area. In Paper II, the effect of optimization, instead of using geographic dispersion alone, was investigated by comparing the Avoid-lows strategy to an allocation in which WP capacity was evenly spread over sites with a capacity factor of $\geq 25\%$. The results of this comparison show that there is an added value associated with optimizing, compared to the smoothing effect that is obtained when spreading WP over a sufficiently large area. For example, the even spread resulted in the output being $< 11\%$ of installed capacity one-tenth of the time and a capacity factor of 29%. The Avoid-lows strategy yielded an output of $< 16\%$ of installed capacity one-tenth of the time and a slightly higher capacity factor (30%). Figure 9 shows the Pareto front, i.e., the optimal allocations with respect to avoiding low output, while maintaining a high capacity factor for the aggregation. The dots show the locations of the present allocation and the evenly distributed allocation, respectively. The distances between the dots and the Pareto front are a measure of how far the present allocation (filled circle) and the evenly dispersed allocation (open circle) are from the optimal allocations. The reasons why the present allocation differs are numerous and are discussed briefly above. However, the distance between the evenly dispersed allocation and the Pareto front actually represents one measure of the power of optimization, as compared to the “rule-of-thumb” of allocating WP capacity to regions that are sufficiently windy all over Europe.

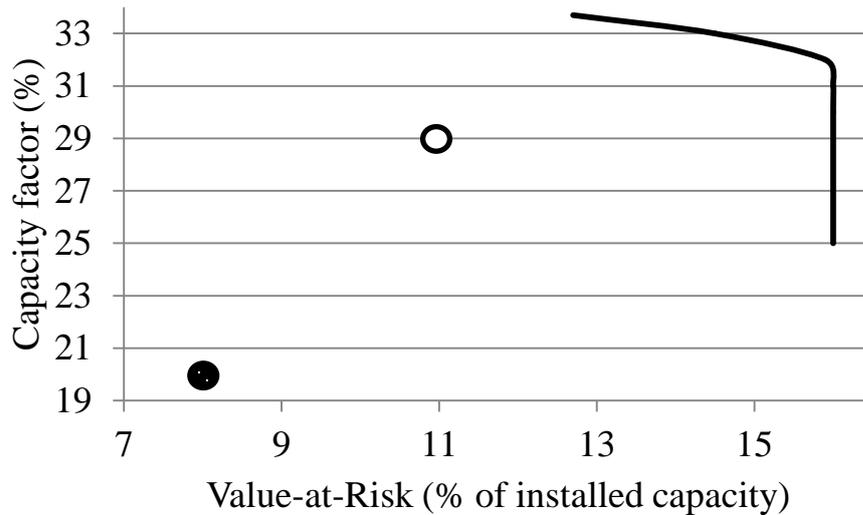


Figure 9 Trade-off between capacity factor and Value-at-Risk, which is a measure of how well the aggregated output of an allocation avoids a low output. The allocations corresponding to the values on the Pareto front (solid line) are the results of the optimization processes described in Papers II and III. 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.

Optimizing the avoidance of low output is sufficient for dampening variation

One of the main results from Paper II is that the Avoid-lows and Short-term variation strategies give rise to similar allocations. Figure 10 shows the Pareto front between the Avoid-lows and Short-term variation objectives. The measure on the y-axis is connected to short-term variation, and is to be minimized. The measure on the x-axis (VaR) is related to the Avoid-lows objective, and is to be maximized. The Pareto optimal points are thus those with a VaR of ~16%. The allocations that give rise to these points differ only by a few percent, so the essential difference between the points is the extent to which curtailment takes place. The explanation for this is that lowering short-term variation entails cutting peaks and avoiding low output. Curtailment can cut peaks but it cannot avoid low outputs. Avoiding low output is achievable only by allocating optimally, so that the difference in typical weather patterns can create the smoothing effect. Thus, the smoothing effect works both for lowering short-term variation and for avoiding low outputs. This result is not surprising in itself, although the quantification thereof, that there is almost no difference in optimal allocation for these two goals, has been used as an additional argument in favor of the Avoid-lows strategy in similar future studies. We conclude that, in terms of the choice between variation management strategies, finding aggregations of WP that display high minimum outputs is crucial for finding those outputs with low values with short-term variation. Short-term variation may be handled by applying flexible curtailment strategies that also take into account load variations and other available electricity generation, all of which are system-dependent and require a broader analysis than one that only considers wind conditions.

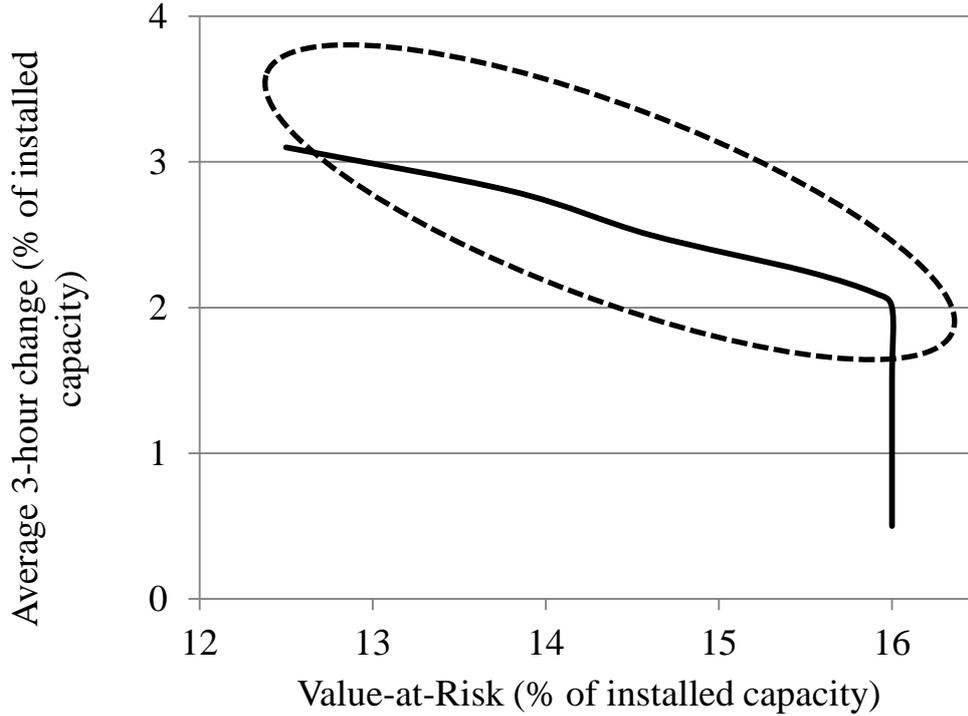


Figure 10 Trade-off between the Avoid-lows and Short-term variation objectives (Paper II). The average 3-hour change is a measure that is relevant for the Short-term variation, and the Value-at-Risk is a measure of relevance for the Avoid-lows objective. The encircled values are allocations with average capacity factors $\geq 30\%$. Note that the actual Pareto front between the Avoid-lows and Short-term variation objectives consists of only a few points in the right part of the diagram, since the desired characteristics are a *high* Value-at-Risk (x -axis) and a low average 3-hour change (y -axis).

6. Future work

The present work is largely methodological, with WP as the technology to which the methodology is applied. However, the methodology is in principle applicable to other types of variable generation (solar, tidal, wave power). Therefore, it is reasonable to incorporate these technologies into the analysis, thereby generalizing the methodology. As the variation characteristics of solar/wave/tidal power are different from those of wind, their inclusion would introduce an additional variation management strategy into the model, namely that of combining different VRE technologies, as discussed elsewhere [27].

In addition to the incorporation of additional VRE technologies, the modeling approach presented here, mainly described in Paper II, is being developed into a form that can be used to optimize the transmission grid extension that is necessary to achieve different levels of variation dampening. This relates to the concept of the European Super Grid. The quantification of grid extension also raises the questions as to the extents to which electricity storage and grid extension will complement, and compete with, each other. The knowledge of geographic WP allocation gained in the present work will be used as inputs to the investment and dispatch modeling performed in the research group, in order to understand the importance and sensitivity of wind power allocation in these models.

References

1. Edenhofer, O., R., Y.S. Pichs-Madruga, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J., and S.S. Savolainen, C. von Stechow, T. Zwickel and J.C. Minx (eds.), *IPCC, 2014: Summary for Policymakers. Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, 2014: Cambridge, United Kingdom and New York, NY, USA.
2. Capros, P., Mantzos, L., Tasios, N., De Vita, A., Kouvaritakis, N., *EU Energy Trends to 2030 - Update 2009*, 2010.
3. ECMWF. 2013; Available from: www.ecmwf.org.
4. McLean, J.R., *WP2.6 Equivalent Wind Power Curves in TradeWind2008*.
5. Wan, Y.H., *Long-term wind power variability*, 2012, NREL.
6. Pryor, S.C., R.J. Barthelmie, and J.T. Schoof, *Inter-annual variability of wind indices across Europe*. *Wind Energy*, 2006. **9**(1-2): p. 27-38.
7. Obersteiner, C. and M. Saguan, *Parameters influencing the market value of wind power - A model-based analysis of the Central European power market*. *European Transactions on Electrical Power*, 2011. **21**(6): p. 1856-1868.
8. Hirth, L., *The market value of variable renewables. The effect of solar wind power variability on their relative price*. *Energy Economics*, 2013. **38**: p. 218-236.
9. Obersteiner, C., *The Influence of interconnection capacity on the market value of wind power*. *Wiley Interdisciplinary Reviews: Energy and Environment*, 2012. **1**(2): p. 225-232.
10. Ravn, H., *BALMOREL: A Model for Analyses of the Electricity and CHP Markets in the Baltic Sea Region*, 2001.
11. Odenberger, M., T. Unger, and F. Johnsson, *Pathways for the North European electricity supply*. *Energy Policy*, 2009. **37**(5): p. 1660-1677.
12. Short, W., Sullivan, P., Mai, T., Mowers, M., Uriarte, C., Blair, N., Heimiller, D., Martinez, A., *Regional Energy Deployment System (ReEDS) 2011*.
13. Göransson, L., *The impact of wind power variability on the least-cost dispatch of units in the electricity generation system*, in *Department of Energy and Environment 2014*, Chalmers University of Technology.
14. Nanahara, T., Asari, M., Maejima, T, Sato, T., Yamaguchi, K., Shibata, M., *Smoothing effects of distributed wind turbines. Part 2. Coherence among power output of distant wind turbines*. *Wind Energy*, 2004. **7**(2): p. 75-85.
15. Hasche, B., *General statistics of geographically dispersed wind power*. *Wind Energy*, 2010. **13**(8): p. 773-784.
16. Holttinen, H., *Hourly wind power variations in the nordic countries*. *Wind Energy*, 2005. **8**(2): p. 173-195.
17. Rombauts, Y., E. Delarue, and W. D'Haeseleer, *Optimal portfolio-theory-based allocation of wind power: Taking into account cross-border transmission-capacity constraints*. *Renewable Energy*, 2011. **36**(9): p. 2374-2387.
18. Kiss, P. and I.M. János, *Limitations of wind power availability over Europe: A conceptual study*. *Nonlinear Processes in Geophysics*, 2008. **15**(6): p. 803-813.
19. 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.
20. Degeilh, Y. and C. Singh, *A quantitative approach to wind farm diversification and reliability*. *International Journal of Electrical Power and Energy Systems*, 2011. **33**(2): p. 303-314.
21. Drake, B. and K. Hubacek, *What to expect from a greater geographic dispersion of wind farms?-A risk portfolio approach*. *Energy Policy*, 2007. **35**(8): p. 3999-4008.

22. Grothe, O. and J. Schnieders, *Spatial dependence in wind and optimal wind power allocation: A copula-based analysis*. Energy Policy, 2011. **39**(9): p. 4742-4754.
23. Henson, W.L.W., J.G. McGowan, and J.F. Manwell, *Utilizing reanalysis and synthesis datasets in wind resource characterization for large-scale wind integration*. Wind Engineering, 2012. **36**(1): p. 97-110.
24. Per Undén, L.R., Heikki Järvinen, Peter Lynch,, et al., *HIRLAM-5 Scientific documentation*, 2002.
25. Holttinen, H., Milligan, M., Kirby, B., Acker, T., Neimane, V., Molinski, T., *Using standard deviation as a measure of increased operational reserve requirement for wind power*. Wind Engineering, 2008. **32**(4): p. 355-378.
26. Kjärstad, J. and F. Johnsson, *The European power plant infrastructure-Presentation of the Chalmers energy infrastructure database with applications*. Energy Policy, 2007. **35**(7): p. 3643-3664.
27. Lund, H., *Large-scale integration of optimal combinations of PV, wind and wave power into the electricity supply*. Renewable Energy, 2006. **31**(4): p. 503-515.