Article

Minute-Scale Forecasting of Wind Power - Results from the collaborative workshop of IEA Wind Task 32 and 36

Ines Würth [1*], Laura Valldecabres [2], Elliot Simon [3], Corinna Möhrlen [4], Bahri Uzunoǧlu [5], Ciaran Gilbert [6], Gregor Giebel [3], David Schlipf [7], and Anton Kaifel [8]

[1] Stuttgart Wind Energy, University of Stuttgart, Allmandring 5b, 70569 Stuttgart, Germany; wuerth@ifb.uni-stuttgart.de
[2] ForWind - University of Oldenburg, Institute of Physics, Küpkersweg 70, 26129 Oldenburg, Germany; laura.valldecabres@forwind.de
[3] DTU Wind Energy (Risø Campus), Technical University of Denmark, Frederiksborgvej 399, 4000 Roskilde, Denmark; ellsim@dtu.dk, grgi@dtu.dk
[4] WEPROG, Eschenweg 8, 71155 Altdorf/Böblingen, Germany, Willemoesgade 15B, 5610 Assens, Denmark; com@weprog.com
[5] Dept. of Engineering Sciences, Division of Electricity, Uppsala University, The Ångström Laboratory, Box 534, 751 21 Uppsala, Sweden; Dept. of Mathematics, Florida State University, Tallahassee, FL, USA, 32310; bahriuzunoglu@computationalrenewables.com
[6] Department of Electronic and Electrical Engineering, University of Strathclyde, 204 George St, Glasgow G11XW, UK; ciaran.gilbert@strath.ac.uk
[7] Wind Energy Technology Institute, Hochschule Flensburg, Kanzleistraße 91–93, 24943 Flensburg, Germany; david.schlipf@hs-flensburg.de
[8] Zentrum für Sonnenenergie- und Wasserstoff-Forschung Baden-Württemberg, Meitnerstraße 1, 70563 Stuttgart, Germany; anton.kaifel@zsw-bw.de
* Correspondence: wuerth@ifb.uni-stuttgart.de; Tel.: +49-711-685-68285

Academic Editor: Emanuele Ogliari, Sonia Leva
Version December 14, 2018 submitted to Energies

Abstract: The demand for minute-scale forecasts of wind power is continuously increasing with the growing penetration of renewable energy into the power grid, as grid operators need to ensure grid stability in the presence of variable power generation. For this reason, IEA Wind Tasks 32 and 36 together organized a workshop on "Very Short-Term Forecasting of Wind Power" in 2018 to discuss different approaches for the implementation of minute-scale forecasts into the power industry. IEA Wind Task 32 is an international platform for the research community and industry to identify and mitigate barriers to the use of lidars in wind energy applications. IEA Wind Task 36 focuses on improving the value of wind energy forecasts to the wind energy industry. The workshop identified three applications that need minute-scale forecasts: (1) wind turbine and wind farm control, (2) grid power balancing, (3) energy trading and ancillary services. The forecasting horizons for these applications range from around 1 s for turbine control to 60 minutes for energy market and grid control applications. The methods that can be applied to generate minute-scale forecasts rely on upstream data from remote sensing devices such as scanning lidars or radars, or are based on point measurements from met masts, turbines or profiling remote sensing devices. Upstream data needs to be propagated with advection models and point measurements can either be used in statistical time series models or assimilated into physical models. All methods have advantages but also shortcomings. The workshop's main conclusion was that there is a need for more research into new minute-scale forecasting techniques and how to enhance quality and reliability. Longer term, standards will help to support the adoption of these methods.

Keywords: wind energy; minute-scale forecasting; forecasting horizon; Doppler lidar; Doppler radar; numerical weather prediction models

1. Introduction

In the past years, minute-scale forecasting of wind power has become an important research topic in the wind energy community. Whereas traditional forecasting techniques provide a forecasting horizon in the hour or day range [1], new methods allow to predict the power output of wind turbines or wind farms on a minute scale. Due to the increasing penetration of renewable energy power systems into the grid, there is a demand for minute-scale wind power forecasts, as grid operators need to ensure grid stability in spite of the highly fluctuating power sources. The forecasts become even more important with increasing sizes of wind farms of several 100 MW and especially if those wind farms conglomerate geographically as it is the case for offshore sites. The objective of this paper is to provide a summary of the needs of minute-scale forecasting and an overview of the developed methods and the possible solutions to the barriers that prevent end users from adopting them.

The results presented in this paper are based on the outcome of the collaborative IEA Wind Task 32 and 36 workshop "Very Short-Term Forecasting of Wind Power" held in Roskilde, Denmark in June 2018. IEA Wind Task 32: "Wind Lidar Systems for Wind Energy Deployment" is an international open platform with the objective of bringing together experts from the academic and industrial communities to identify and mitigate barriers to the use of lidar for wind energy applications. IEA Wind Task 36: "Forecasting of Wind Power" is focused on improving the value of wind energy forecasts to the wind energy industry. During the workshop, participants from academia, forecasting service providers, wind farm operators as well as the lidar and wind turbine manufacturers discussed the future needs of minute-scale forecasting, the advantages and barriers of different forecasting techniques and strategies for overcoming those barriers.

This paper is organized as follows. Section 2 discusses the need for minute-scale forecasting and explains target forecasting horizons for different applications. In Section 3, different forecasting techniques are described. To that end, first a review of state-of-the art forecasting techniques and the gap that needs to be closed with new methods in order to achieve minute-scale forecasts is given. Then different approaches to close the gap are discussed and for each method barriers and possible solutions are given. In Section 4 challenges for the implementation and commercialization of the new methods are discussed and the paper is finalized with conclusions in Section 5.

2. The need for minute-scale forecasting

In 2017 Denmark was the country with the highest wind power penetration rate (44% of the annual consumption of electricity), followed by Portugal (24%) and Ireland (24%). In the case of Denmark, the maximum hourly penetration rate was over 140%. With a total net installed capacity of 169 GW, the power generation capacity of wind power in Europe increased by almost 300% in the last 10 years [2]. Given the expected rising penetration levels of wind power and the increasing size of on- and especially offshore wind farms feeding power into the grid at a single point [3], it becomes crucial to have forecasts of wind power generation with lead times of few minutes ahead and temporal resolutions of seconds or minutes.

When generating a forecast, one useful practice is to consider the power spectral density (PSD) of the measured physical process to understand which time frequencies contribute to the variance of the signal. Peaks in the spectra correspond to larger relative fluctuations which are traditionally more difficult to capture and predict. This type of analysis is demonstrated in Larsen et. al [4] using long term site measurements from Høvsøre test station and Horns Rev offshore wind farm in Denmark. Boundary layer wind spectra were resolved across cycles ranging from 0.1 seconds (10 Hz) to 1 year. Figure 1 presents a main result of that work which compares full scale wind PSDs at 50 m height both on- and offshore [4]. Apt [5] presents a similar PSD analysis of wind turbine output using 1-second power data for a single wind turbine as well as a 6-turbine wind farm. Attributes of the PSD signal

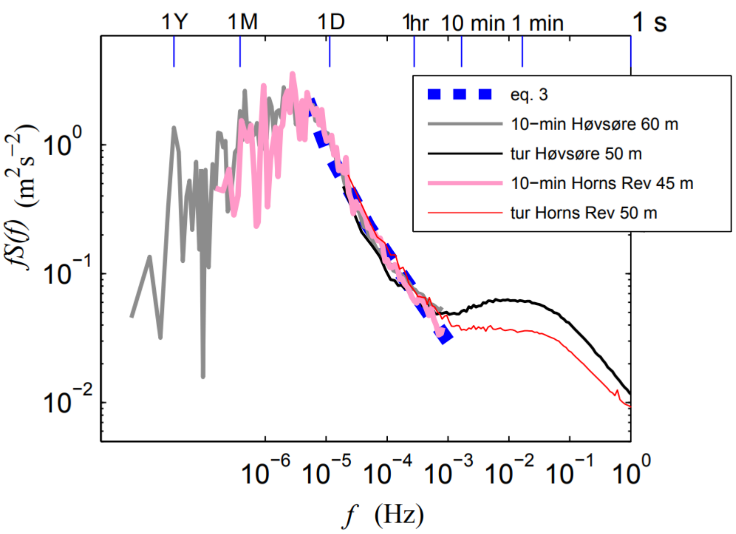

Figure 1. Power spectral density (PSD) of wind speed with corresponding timescales denoted atop. High frequency sonic measurements are used to devise the onshore (black) and offshore (red) lines. Reproduced with modifications from Larsen et. al [4] with permission from the Springer Nature publisher.

will vary by location, time, sensor type, and physical property being measured. Still, from the results in Figure 1, a strong peak can be detected around 1 min, indicating the strong variability of the wind at that temporal scale. This variability of the wind is associated to atmospheric phenomena like open cellular convection, gravity waves, sea breezes or low level jets, among others [6]. At frequencies f> 0.01 Hz (seconds to one minute) the PSD signal strongly decreases and, as reported in [7], wind power fluctuations of large wind farms are not considered an issue due to the smoothing effect of aggregated power.

Yet, the intra-hour variability of wind power not only depends on the variability of the wind itself but on the size of the wind farm, the number of wind turbines and their geographic dispersion. Indeed, it has been shown by several authors that for offshore wind farms, the small geographic dispersion of the wind turbines results in an increased power variability in the minute scale, compared to widely dispersed onshore wind turbines [8].

The enhanced variability in those time scales shows itself in rapid changes in wind power generation (ramp events). These unexpected events are mainly caused by extreme changes in wind speed and/or direction in a very short period of time, and are frequently associated with the passage of weather fronts. Despite being critical for the management of the grid, the dynamic allocation of reserves and the stability of the system [9,10], it is an individual process of the end-user to define critical ramps and thereby ramp events. A recent publication on the history of wind power ramp forecasting [11] gives an overview of the definitions used in ramp event detection, the meteorological conditions associated to those events and the current forecasting techniques. For most wind power forecasting applications however, the definition of what is critical for an end-user is very individual and dependent on the application as well as the available reserves. For example, a system operator on an island grid or badly interconnected grid will have to have all reserves available within the control zone in order to prevent that a critical ramp could cause security issues. A trader may also be very interested in ramp forecasts, as just one event with a large error may cause 95% of the imbalance costs in a month.

Ramp events are often classified into ramp-up and ramp-down events, according to the direction of the power gradient. The example time series in Figure 2 illustrates a number of steep ramps in both

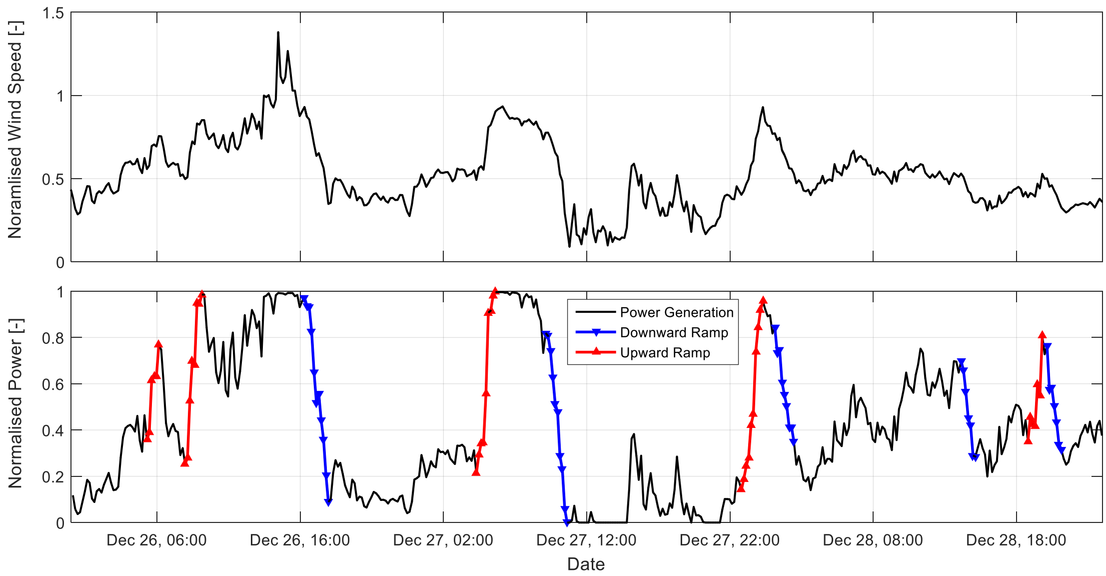

Figure 2. Example time series of wind speed and generated power of a single wind turbine with wind ramps marked for a time window of 60 min and a change of power of 40%. The time series is based on 10-minute averages [12].

directions. While ramp-up events always can be handled in the very short-term with curtailments, ramp-down events can become extremely critical due to the sudden missing generation. This enhances the importance of generating accurate minute-scale forecasts of wind power.

The forecast horizon and the parameters that are needed to be forecast however, depend on the application of the forecast. Three applications have been identified where minute-scale forecasts of wind speed or power are needed.

1. **Wind farm control**: Wind turbine and wind plant controllers need the information to optimize e.g. the power output of the turbines.
2. **Physical balancing**: They are required by the Transmission System Operator (TSO) in order to optimally operate reserves for the continuous balance of the power system and grid constraint management.
3. **Economic balancing**: Trading and balancing of wind power in the intra-day or rolling power markets require minute-scale updates of the forecasts with real power output in order to reduce imbalance costs and increase incomes.

The next step in the evolution will be storage system planning and optimization in the real-time markets, where the bulk of the energy production will come from renewable energy sources. However, this paper focuses on the applications listed above. In the following each application is discussed in more detail.

2.1. Wind turbine and wind farm control

Preview information of the wind field is helpful for the control of wind turbines and wind plants. Wind turbines are highly dynamic systems that are excited by stochastic influences from the wind and most of the wind turbine control is designed to deal with variations in this disturbance. However, traditional feedback controllers are only able to react to impacts of wind changes on the turbine dynamics after these impacts have already occurred. Lidar-assisted control algorithms, which can exploit preview information of the wind, are promising to provide improved operation over conventional control algorithms, with the ultimate aim of increasing the energy yield while keeping the structural loads low. Regarding the required preview time, the following classification is useful:

1. around 1 s: Feedforward control is used to compensate wind changes to reduce structural loads. For e.g. the blade pitch, the rotor-effective wind speed is needed only a short time before the wind reaches the rotor to overcome the pitch actuator dynamics.
2. around 5 s: For Model Predictive Control, the control inputs are optimized to get a chosen compromise of load reduction, energy production, and actuator wear [13]. Here, a short time horizon of wind characteristics such as wind speed, direction, and shears is used, typical 5-10 s.
3. around 1-10 min: For yaw control, a wind direction estimation is used to align the wind turbine with the mean wind direction. For this, a preview in the minute scale is helpful.

Active wind farm control is a promising technology to increase the energy production of wind farms [14]. However, flow models are still an important research topic, and the validation of flow models and control strategies are still ongoing. Wind preview for flow control is mainly used for induction control and wake steering for higher energy capture and management of fatigue loading. Regarding the required preview time, following classification is useful:

1. around 10 sec to 1 min for induction control: Usually the blade pitch angle is used to reduce the power and thus the thrust to weaken wake effects on downstream turbines, which increase the overall production. At partial load this is done by adjusting the "fine pitch" settings which is usually based on a filtered wind speed estimate. Wind preview might help to better adjust the power balancing.
2. around 1-10 min for wake steering: The yaw misalignment is used to deflect wakes away from downstream turbines and thus similar preview times compared to the conventional yaw control is useful. A preview of the wind direction might help to better adjust the yaw misalignments in a wind farm.

2.2. Power grid balancing, frequency control and power quality in reserve market

The focus in this section is on grid balancing, frequency control and power quality embedded in reserve market while the energy market and ancillary services are discussed in the following Section 2.3. The balancing term can be employed in a much broader sense in the context of balancing longer time scales. However in these time scales of mainly energy and reserve market, where balancing actions are scheduled before the real time, there are several other means of observations with lower resolutions available. [15–17]. However, these are not in the time scales of minute-scale forecasting that is the focus of this section. It should be noted that there are differences in terminology in different countries for same and slightly different balancing actions. In this section, the EU terminology is adapted for the rest of the discussions.

To guarantee the stability of the grid, supply and demand always have to be balanced in spite of the fluctuating power sources. Power quality is achieved if the grid frequency stays within a certain range of a rated value. An imbalance between supply and demand impacts voltage stability and grid frequency, hence there is a need for power balancing [15,18–20].

The volatility of wind resources creates volatility in the supply and as a result, balancing control actions are needed. One can distinguish between different time scales in this phase of controls embedded in the reserve market, which are known as primary, secondary, and tertiary control. The autonomous response of the system to supply/demand imbalances is automatically addressed with primary controls, which is in the scale of microseconds, milliseconds to seconds. In the secondary controls, there are automatic actions and manual actions in scales of seconds to minutes. In the tertiary controls, both manual and automatic controls are in action from minutes to quarter of an hour to half an hour scale. All of these actions of balancing are carried out in order to ensure power system quality. Any forecast data that is available in scale of microseconds to minutes can be automatically employed in the state estimator of the controller [15,18–20]. The state estimator corrects with observational data, the state of the system.

From the market point of view, primary and/or secondary controls do not involve auction mechanisms. The participation to primary and secondary control can be traded by auction. This results in the availability of reserve for primary and/or secondary control. The market period can be day to year. The reserve market addressed in the context of primary and/or secondary controls consists of generators that can allocate themselves to be available as reserves for primary and/or secondary control. This availability is for a predefined time period for automatic control. This is achieved without any bidding as a result of commercial agreements or participation based on the context of the country. If there is utilization of reserve service, an utilization price is employed based on [21].

Wind power and other renewable energy create low levels of rotational inertia since these energy conversion systems do not normally act on rotational inertia which has impacts on the power grid frequency. Moreover asynchronous machines and Double Fed Induction Generator (DFIG) are disconnected by inverter from rotating mass of inertia. Suppliers have started to make changes to create synthetic inertia that can emulate inertia synthetically [22]. Synthetic inertia is about acting to AC frequency, possibly after the loss of a big power plant which makes the grid under-supplied and will result with the AC frequency beginning to fall. This makes the accurate short term forecasting even more important since all of these emulations are dependent on accurate estimation of wind speeds. Hence automatic control for primary and/or secondary controls will certainly benefit from more accurate forecasting on the short time scales of minutes in control applications.

2.3. Energy and ancillary services markets

Electricity markets need to be balanced in order to match the supply and demand of energy. This physical balancing of the transmission grid is carried out by the transmission system operators (TSO) or by an independent system operator (ISO). Given the increased integration of power generation from variable sources of energy like wind and solar, the physical balancing has become more complicated. Therefore, electricity markets with such intermittent and variable sources have to become more flexible and introduce either rolling markets (e.g. in the UK and Australia) or introduce shorter intra-day auctions, additional to the day-ahead auction, which have become very popular in Europe. Among the intra-day market platforms, one can distinguish between discrete auctions or continuous intra-day markets. In intra-day auction markets like in Italy, Spain or Portugal, intra-day bids are restricted to a few established auctions. By contrast, in continuous intra-day markets, counter parties match the bids using a trading platform that operates continuously. Those continuous intra-day balancing markets operate in Europe with different lead times ranging from 5 to over 100 minutes and most of the countries work with trading blocks of 15 minutes. Table 1 includes the lead times and smallest trading blocks for several countries in Europe and for Turkey. Hence, the importance of the use of updated available minute-scale forecast of wind power has arrived to stay.

Table 1. Lead times and smallest trading blocks for different countries. Sources: Epex [23], Nordpool [24], EXIST [25], and BSP South Pool [26].

Country	Lead time (minutes)	Trading blocks (minutes)	Market
Austria and Germany	5	15	EPEX Spot
Bulgaria, Denmark, Estonia, Finland, Lithuania, Norway and Sweden	60	15	NordPool
Belgium, France and the Netherlands	5	60	EPEX Spot
Slovenia	60	15	BSP Southpool
Switzerland	30	15	EPEX Spot
Turkey	90	60	EXIST

In light of this, the forecast process can be split into three components: (1) production of a smooth day-ahead forecast tuned for economic adjustment via the intra-day market, (2) targeting intra-day forecasts for the predictable part of the day-ahead forecast errors and (3) application of forecasts on minute-scale to manage the wind after gate closure of the intra-day. The two first components correspond to current practices in long-term and short-term processes with some enhancements. The third component is a process running on minute-scale with 1 or 2 hour look ahead [e.g. 27]. A more detailed description of the electricity markets and their time lines can be found in [28].

Minute-scale forecasts are also necessary when applying to provide ancillary services, secondary or tertiary reserve or balancing capacity for the pool of large utilities. For instance, a recent pilot project in Germany allows wind power generators to participate in the reserve market by down-regulating their production. The possible or available power produced by the wind farms needs to be calculated in one-minute intervals. Furthermore, the standard deviation of the percentage error of the possible or available wind farm power, during the pilot phase, should be less than 5% [29].

3. Minute-scale forecasting techniques

3.1. State of the art forecasting of wind power - where are the gaps?

State of the art wind power forecasting methodologies utilize wind speeds from weather forecasts and on-site real-time measurements to compute wind power.

Figure 3 shows qualitatively the forecast error levels of day-ahead, hours-ahead and minutes-ahead compared to a persistence error, where the persistence forecast is the most recent available measurement. It can be seen that the margin of possible improvements by minutes-ahead forecasts in the first 30 min of the forecast is rather small in comparison to persistence. This is so in average weather conditions and when measured over longer time. However, when weather conditions are changeable and more extreme with strongly ramping wind speeds, only a combined use of forecast and measured wind speed can predict ahead with a reasonable accuracy.

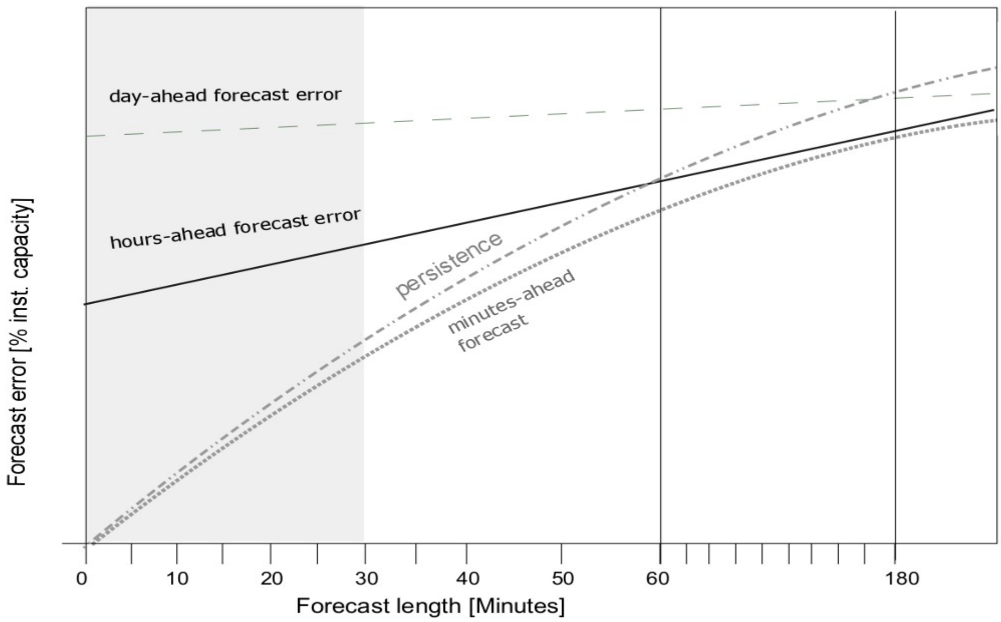

Figure 3. Error decomposition in a minute-ahead forecasting environment inclusive persistence.

Current average error growth of up to 2% of the installed capacity of a short-term forecast of 15 minute time resolution is rather steep (see Figure 3). It is therefore fair to say that the improvement over persistence, which is the objective in the very short time ranges of minutes and hours, is therefore rather modest. This is often used as a reason for system operators not to base decisions on forecasts today, but rather use persistence, even during ramping, where the persistence forecast is a poor approximation. If the previous 15-minute forecast already appears to be off track, then the control room cannot justify to trust in the forecast. Also, the similarity between the average error of a short-term forecast and persistence over the next 15 minutes strongly indicates whether the short-term forecast has good quality or less good quality.

Forecast providers are continuously looking for enhancements, which can improve the hour-ahead and minute-scale forecast in the less good quality periods, because these result in the most significant power system benefits. Use of wind speed measurements in addition to wind power measurements is therefore a key to improve forecasts in periods, where the wind speed is in the flat ranges of the power curve ($< 5\,\mathrm{m/s}$ or $>12\,\mathrm{m/s}$). Without wind speed measurements, the minute-scale forecast is in fact unable to correct the weather forecast for phase errors in periods, where the generation is zero or at full capacity.

A steady increase in wind speed from 15 m/s to above the high speed shutdown point at 25 m/s can also be improved by using wind speed measurements in the short-term algorithms. At the high-speed shutdown points (> 25 m/s), the wind speed forecast uncertainty is at least 2 m/s even in high predictability events. The timing of the shutdown is therefore uncertain, even a few minutes before it happens. Wind speed measurements from the wind farms reduce this uncertainty significantly. The timing of the high speed shutdown is important for grid security, because there are potentially many Megawatts instantly ramping down. In combination with forecasting on the minute-scale, such wind speed measurements can help to bridge the gap between the actual generation and both short-term and long-term forecast.

For wind speeds below the cut-in level there are similar considerations. Mostly, a cut-in wind speed occurs at a low aggregated wind power generation. Nevertheless, a large and strong low pressure centre may have near zero wind speeds from different directions. Both, the changes in wind direction and wind speed are better identified by wind speed measurements than wind power measurements. Thus, information about wind speeds below cut-in can be crucial for the forecast accuracy near a low pressure system centre at high aggregated wind power generation. During periods of moderate and high generation, wind speed measurements can be used to calculate current turbine availability or validate the delivered availability value. To conclude, measurements of low, medium and high wind speeds all add value to forecasting, while those measurement signals in the steep range of the power curve are least important.

From a technical perspective of the instrumentation, one of the most reported gaps for forecasting hours-ahead and minutes-ahead is the quality of the measurement signals. While wind farm developers have to use qualified instrumentation and standardized methodologies in order to obtain a bankable level of siting accuracy in the first phase of a wind project, the planning and commissioning phase, the use of meteorological measurements is mostly not or badly defined, documented nor standardized in the following operational phase. Although the measurements are important in many ways, e.g. situational awareness in extreme events, scheduling and dispatch of generation on power system level, the balancing of large forecast errors, maintenance of instrumentation, there are no standards for the quality of the signals in real-time environments today. For example, if a measurement stops working correctly and sends constant values, a persistence forecast will benefit in a verification, while the forecast is penalized for providing a more realistic view of the situation. Dependent on the amount of such periods with constant values, this can easily lead to an overestimation of the performance of a persistence forecast in comparison to minutes-ahead forecasts and thereby prevent use and application of minutes-ahead forecasts.

Due to such missing standards and industry guidelines, the main gaps for the use of and collection of meteorological measurements and thereby advances in minute-scale forecasting can be summarized as:

- lack of requirements in the grid codes
- lack of strategy for handling of missing or constant signals from measurements in real-time
- lack of quality of measurements in real-time

3.2. Using remote sensing data for forecasting

Remote sensing techniques are a new technology development in wind energy applications, which has its roots in the desire to find alternative measurements for expensive and at times difficult installation and erection of met masts. Especially with increasing hub heights, met mast heights have grown to a size, where the erection requires planning permission and cranes of significant size. Hence, it has become so expensive that previously never considered alternatives from the remote sensing area have become price competitive. An additional compelling justification is that the cost of lidar instruments have fallen significantly over the same time, driven in tandem by competition and the telecommunications boom, which has resulted in affordable optical fiber components becoming available.

The main driver of recent developments has been the competitiveness in price, the ease of installation and the increasing heights of wind turbines and size of the projects, where it is often no longer sufficient to measure at only one site. Nevertheless, the disadvantage of not directly measuring the target value is still present, as remote sensing devices only measure the wind speed in direction of the emitted beam. With increasing experience and technical advances in technology, the remote sensing devices have however become a real alternative. This has also been reflected in the IEC 61400-12-1 2017 standard [30], where remote sensing devices have been incorporated as possible devices to carry out wind measurements for wind energy applications. A new application for remote sensing devices is forecasting. Especially scanning devices such as scanning lidars and radars offer the possibility to carry out minute-scale forecasts by delivering high resolution temporal and spacial previews of the upstream wind field of a wind turbine or wind farm. Therefore, the next two sub chapters give an overview of using those devices for forecasting purposes and finally lessons learned with remote sensing instruments in real-time forecasting projects are summarized.

3.2.1. Scanning lidar-based forecasts

Wind lidars can measure the line of sight (LOS) wind speed at distances from a few centimeters to several kilometers [31]. The first commercial wind lidar systems targeted at wind energy applications appeared in the early 2000's [32]. Because of their costs and ease of installation, lidars have become accepted as an alternative to the traditional mast-based wind sensors for site assessment and power performance testing, as evidenced by their inclusion in international standards [30]. Additionally, because they can measure upwind of operating turbines, wind lidars are used for feed-forward control of wind turbines [33]. For this application nacelle-based lidar systems are used to measure the wind speed several hundred meters upwind, thus forecasting the rotor effective wind speed seconds before it hits the rotor just in time to pitch the rotor blades and reduce loads. A new application for scanning lidars is wind power forecasting for power grid balancing. Commercial lidar manufacturers increased the range of their systems and pulsed compact scanning wind lidars may now measure up to 10 km away, enabling measurements across an entire site from one location [see e.g., 34,35]. The basic idea is to use the spacial and temporal high resolution wind field information measured several kilometers upwind of a wind turbine or wind farm to forecast the power output ahead in time.

The forecast process (Figure 4) is the same for both applications- control and power grid balancing. First the raw lidar data is filtered for outliers and the horizontal wind speed and direction is reconstructed from the measured LOS wind speeds. Depending on the number of synchronized lidar measurements, different assumptions need to be made in order to resolve both horizontal wind speed and direction. For instance, a velocity-azimuth display (VAD) retrieval technique is used to resolve both wind speed and direction when only one lidar measurement is available [36]. Then the wind speed in the distance is propagated towards the wind turbine by means of a propagation model. The simplest model is based on Taylor's hypothesis which claims that turbulent eddies are transported with the mean flow and do not change their properties. With this assumption the time can be calculated that the wind speed measured in a certain distance needs to reach the turbine or wind farm. Thus the farthest measured distance determines the forecast horizon. The forecasted wind speed

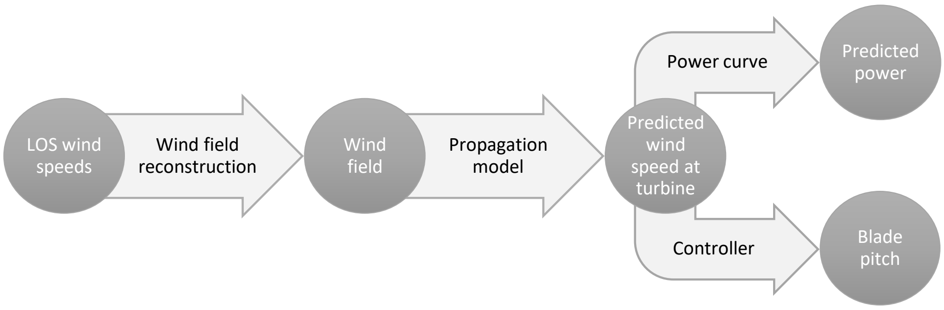

Figure 4. Forecast process using lidar data.

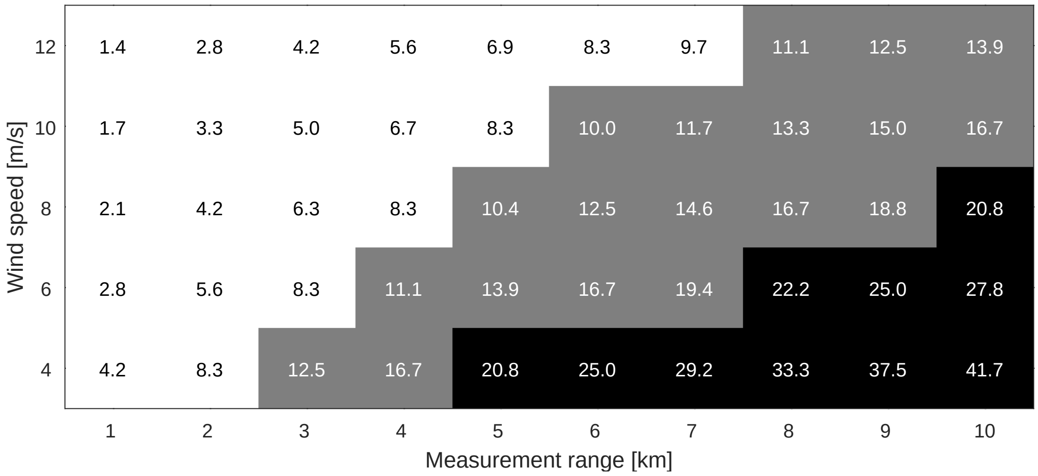

Figure 5. Forecast- horizon based on Taylor for different wind speeds and measurement ranges; horizon given in minutes; white: <10 min, grey: 10-20 min, black: >20 min [37].

at the turbine or farm location is then used either to forecast the power output by means of a power curve or as an input to the wind turbine controller.

As mentioned, the forecast horizon is determined by the measurement distance of the lidar and the magnitude of the wind speed (Figure 5). For wind speeds above rated wind speed, the maximum forecast horizon with a state-of-the-art long-range scanning lidar that ideally measures up to 10 km is around 15 min. The maximum horizon increases to around 40 minutes for a wind speed of 4 m/s that corresponds to cut-in wind speed.

The advantage of scanning lidars is that they offer the possibility to directly measure the wind speed upstream of a turbine. All the long-range scanning lidars are pulsed devices, which means that the wind speed information is gathered simultaneously at different measurement distances. Thus the wind flow can be tracked over the span of the measurement and local changes in the wind speed are captured. Modern lidars have compact dimensions of around one cubic meter which allows for flexible measurement campaigns and the installation for instance on the nacelle of a wind turbine or other alleviated points such as an offshore substation. Then the scanning of the area on e.g. a horizontal arc leads to the desired horizontal wind speed information after reconstruction without having to take into account shear effects.

Recent investigations have shown that lidar-based forecasting models were able to predict near-coastal winds better than the benchmarks persistence and ARIMA for a forecasting horizon of 5 min [38]. Another relevant study is Simon et al. (2018) [39] which explores space-time correlations of upwind lidar observations measured on a flat horizontal plane, as well as implements a 1-60 minute ahead forecast method utilizing the lidar inflow scans which significantly outperforms the persistence method.

However, there are some drawbacks when using lidar data for forecasting. One of the major barriers to overcome is the availability of the measurements. The lidar measurement principle is based on the interaction of laser pulses with particles suspended in the air. The wavelength of the backscattered light is shifted relative to the speed of the aerosols according to the Doppler principle [40]. This means that the measurement depends on the existence of these aerosols and if the concentration in the air is too high or too low, the device records a noisy signal. It also means that the measurement range fluctuates due to environmental conditions such as fog or rain showers [37]. And as the measurement range determines the forecast horizon, realtime forecasts are not possible if the lidar is blind. As physics cannot be changed, and the measurement principle is what it is, as a consequence a fallback solution needs to be implemented in case the lidar does not provide measurements. Data from other sensors such as radar or drone measurements could be one solution. Using statistical models (see Section 3.3.1) or the coupling of the measurements with NWP models (cf. Section 3.3.2) could be another solution. Also more investigations have to be carried out to determine the optimum conditions for good range measurements of lidars.

Another drawback of lidars so far have been the high costs and the inaccuracies of signals in complex terrain. According to the white paper of the Deutsche Windguard [41] and [42], especially "in complex terrain sites, influence of the relatively large scanning volume of today's LiDAR and SODAR must be carefully considered in terms of its influence on the measurement accuracy...". This has been a general observation and an ongoing research topic [see e.g., 43–48].

Another obstacle when working with lidars is that currently there is no standard or Recommended Practices for the use of scanning lidar for wind speed forecasting. More research is needed to find out what the ideal measurement setup looks like, in particular how many lidars are needed and where to place those devices within a wind farm. Also the optimal measurement strategy is not clear. To that end different use cases have to be investigated to find out what the best campaign setup and measurement strategy is. Such use cases should include on- and offshore wind farms of different scales. Recommended practices then need to be consolidated so that the widespread use of lidar for forecasting becomes possible on a commercial level.

3.2.2. Radar-based forecasts

Radars are remote sensing systems which can determine the position, angle or motion of objects and are being used in multiple applications including traffic control, ocean surveillance, weather monitoring, flight control systems and antimissile systems. Similar to wind lidars, Doppler radars can be used for wind power forecasting as they are able to determine the velocity of the objects. The working principle is the same as for lidars, but rather than sending light waves, they emit radio waves. Thus, in an environment where meteorological particles with high humidity such as water droplets or ice crystals are present, radars are able to measure the wind speed by determining the motion of the hit particles.

The maximum range that radars can measure is given by the wavelength of the signal emitted, but in this paper we only focus on radars which work on wavelengths that are of interest for minute-scale forecasting of wind power. Thus, we limit our review to radars working between the C-Band and the Ka-band radars, or with a wavelength of 3.2 cm to 8.6 mm.

Doppler-radars working in the Ka-band (35 GHz) are optimal candidates for wind power forecasting (Figure 6). The short wavelength employed allows for high temporal and spatial resolution of the measured wind fields. As lidars, Doppler radars measure the LOS wind speed. Thus, measuring with one Doppler radar over a defined Plan Position Indicator (PPI) trajectory, the horizontal wind speed can be determined by applying a VAD retrieval technique. To derive the two horizontal wind speed components, two synchronized Doppler radars are needed [49]. The number of publications on the use of Doppler radars for wind energy applications has grown in the last years. Hirth et al.

Figure 6. A Doppler radar unit deployed on the shore of the Westermost Rough wind farm [51,54].

coupled wind farm operational data with wind fields measured by two synchronized Doppler radars (dual-Doppler radar) to further investigate wind farm wake effects [50]. Dual-Doppler measurements of the wake behind an offshore wind farm were also reported by Nygaard et al. [51]. The performance of wind turbines was also validated with dual-Doppler measurements in [52].

First evidence of the promising application of Doppler radar systems for forecasting purposes was documented by Hirth et al. [53]. An extreme wind ramp event observed by the Texas Tech University Ka-band radars at a wind farm in Oklahoma was presented. The authors merged dual-Doppler wind fields with operational data from 32 wind turbines to document the observed transient wind event and its effect on the wind turbines' performance. They also coupled data from a meteorological tower to analyze the weather conditions that originated the transient event.

Recently, it was shown that Doppler radar wind field observations can be employed to derive minute-scale density forecasts of wind power. In [54] the authors proposed a methodology that uses dual-Doppler radar observations of wind speed and direction in front of a wind turbine to forecast the power generated in a probabilistic framework. In a case study, they predicted the power generated by seven turbines in the North Sea with a temporal resolution of one minute and with a lead time of five minutes. They showed that the radar-based forecasting model is able to outperform the persistence and climatology benchmarks in terms of overall forecasting skill and generate reliable density forecasts in the case of optimized trajectories.

One of the main advantages of Doppler radars is the extended range they can measure (over 30 km). Additionally, the optimal trade-off between the temporal (one minute) and spatial (50 m) resolution of dual-Doppler radar measurements, compared to that of typical wind measurements from met-masts or satellites, makes them promising candidates for minute-scale forecasting of wind power. As with lidars, the same wind power forecasting process can be implemented to derive a wind power forecast. Besides, the fact that they can perform volumetric measurements (wind field measurements at multiple heights), allows to infer further information such as horizontal and vertical wind shear.

However, as with lidars, one of the main obstacles to the adoption of radar as a forecasting tool is the availability of the measurements. The radar measurement principle is mainly based on the backscatter signal of particles in the air containing high humidity such as water droplets or ice crystals. Therefore, the quality of the measurements relies on the concentration of these particles in the air [49]. Besides, the relatively large dimensions of Doppler radars complicate their installation and reduces the range of possibilities for placing them, especially in offshore environments. The advantage of Doppler radar with respect to lidars is the maximum range that they can measure. However, compared to lidars, the wider beam width of radar results in larger beam spread at large ranges.

Although we have mainly focused on the use of Doppler radars for forecasting applications, weather radars have been also identified as promising candidates for very short-term power forecasting of offshore wind power. Modern weather radars working in the C and X-band measure the intensity of precipitation. They are, consequently, able to anticipate precipitation fields associated with severe wind speed and power fluctuations. The capabilities of anticipating strong wind power fluctuations in offshore wind farms using local weather radars was introduced in [55]. There, the authors were able to monitor the arrival of precipitation events in the vicinity of an offshore wind farm, which highly correlate with strong power fluctuations. The authors also identified shortcomings of the use of weather radars for wind power forecasting, which included: interception of radar waves (cluttering), beam attenuation due to intense precipitation, anomalous propagation of the radar waves during specific atmospheric conditions, underestimation of precipitation reflectivity (beam filling) during convective events, and overshooting at long ranges due to the curvature of the Earth.

3.2.3. Lessons learned with remote sensing instruments in real-time forecasting projects

Several research projects have been conducted with the goal of integrating remote sensing measurement into real-time forecasting projects. For this purpose not only scanning devices were deployed, but also profiling, ground-based devices. In the largest and longest measurement campaigns targeted towards real-time forecasting of wind energy in recent years were two projects funded by the United States Department of Energy, the wind forecasting improvement project (WFIP I and II) [56] there were used 12 wind profiling radars, 13 sodars and three lidars amongst other meteorological sensors. The lidars as well as sodars are basic equipment used in meteorological data assimilation today and have been quality checked following meteorological standards through the Meteorological Assimilation Data Ingest System (MADIS) [57]. This was a necessary step in order to improve the simulation into the real-time model forecast systems [58]. In the second project, "Distributed Resource Energy Analysis and Management System (DREAMS) Development for Real-time Grid", a number of sodars, lidars were used to enhance the Hawaiian system operator's EMS (Energy Management System) tools for situational awareness in critical events [59]. Here, the instruments were for the first time part of the operational management system at a system operator in real-time.

From the above described studies and experimental measuring campaigns as well as real-time testing it can be concluded that the remote sensing instruments need to be serviced well and maintained similarly to any other real-time instrument operating under changing conditions throughout the yearly cycles. If this is not done, echoes, interfering noise sources, laser beam disturbances deteriorate the instruments and make the further processing of the data impossible and the quality of the data deteriorates significantly over time. It is also commonly understood that it requires skilled personnel to install and maintain such instrumentation, if it should run continuously and reliably.

The following lists their findings and recommended technical requirements to ensure high quality data in long-term real-time operation:

- Lightning protection and recovery strategy after lightning should be ensured.
- Instruments must be serviced and maintained by skilled staff.
- Version control must be maintained for signal processing.
- Measurements must be raw or technical requirements must include maintenance and software updates.
- Profiling measurements should be taken at a height appropriate for the wind farm, either at one height or preferable at both hub height and around 30 m.

- Wind characteristics data must be measured on wind turbine level.
- Remote sensing devices in complex terrain require special consideration.

From these findings and studied projects and measurement campaigns, it can be concluded that in active weather conditions, i.e. at the flat range of the power curve as well as under strong precipitation events, it must be expected that met mast anemometers are more reliable than sodar or lidar devices. From a forecasting and operational monitoring perspective, it has been found that the conditions outside of the instrument's range are some of the most critical conditions for grid operation, such as storms with precipitation or high winds. Sodars are more prone to data delivery failures than lidar, but to this date it is still also an issue for lidar devices that measurement information is not accessible in critical conditions, where it is most needed.

3.3. Adaptation of models with different types of measurements

When there is sparse, inaccurate, irregularly distributed data in space and time which is generally the case in atmospheric science, models can be used to infer the evolving state of the system. However, to infer the evolving state of the system being modeled, data needs to be employed or assimilated by a model. This model can employ physical single point or multiple point time series data that calibrates itself based on measurements or spatially distributed time dependent or independent physical model that assimilates which will be discussed in the next sections.

3.3.1. Statistical time series models

Statistical approaches to forecasting problems mainly rely on deducing patterns from past observational data and extrapolating these relationships to predict future values over a desired time step. With wind energy applications in mind, in this section we consider the task of forecasting a one dimensional time series signal such as a wind speed measurement, or a SCADA source such as wind turbine or wind farm active power signal. The chosen forecast horizon should relate to the time resolution of available input data, and at minimum be one sample (time step) ahead to avoid errors introduced by interpolation. Statistical forecasting methods used on the minute scale are largely identical to techniques employed for longer horizons. The main differences being the temporal resolution of the data and the variability of the physical process being predicted (see Section 2).

Data acquisition systems are ordinarily capable of sampling and saving data at high frequency, although historically this data has not always been used nor recorded. For the purposes of minute-scale forecasting, 10-minute or hourly averaged data sets are not sufficient for capturing signal characteristics needed to construct and validate a well performing statistical model. For this reason we recommend that all data generators ensure that they have access to and are logging their high frequency data. The lower bound of the recorded sampling rate should be at minimum twice the highest frequency in the analog signal you wish to capture, in order to avoid aliasing in the discrete signal transformation (Nyquist sampling theorem). In practice, 1 Hz (1 sample per second) is proposed as a compromise between functionality and transmission/storage considerations.

Time series data contrasts to cross-sectional data in that it is naturally ordered in time. Samples which are closer together will normally express a higher correlation than those further apart. This temporal link should be explored through inspection of the autocorrelation and partial autocorrelation function of the time series before beginning any attempts to build a model.

There are often a number of characteristic sub-components embedded in the time series which can be obtained through decomposition techniques in order to normalize samples across time. Examples include differencing an integrated series, removing an overall trend (usually by either mean subtraction or model fitting to obtain the residuals), accounting for cyclic fluctuations, and adjusting for seasonal variations.

A common assumption made by statistical forecasting methods is that of stationarity. Stationary processes comprise of data where the mean, variance, and autocorrelation structure do not change over time. By implementing the techniques described above, it is possible to transform a non-stationary time series into a stationary one which can be used with traditional forecasting methods.

Benchmarking in any forecasting exercise is crucial. Commonly for forecasting at these short timescales the persistence and climatology models are employed; these simple methods assume that the forecast for the target variable is the most recent available measurement or summary statistics of historical measurements, respectively. Statistical methods for wind speed and power forecasting are typically based on time-series models such as autoregressive [60] (AR) and autoregressive moving average (ARMA) [61,62] models as well as other soft computing techniques such as neural networks [63].

Purely AR models are formulated as a weighted combination of past observations (lags) where the coefficients are normally estimated via ordinary least squares regression. The order of the AR model, or maximum lag, is crucial and can be chosen most simply by inspection of the auto-correlation and partial auto-correlation functions of the signal. Cross-validation or an information criterion provide an alternative method for defining the model order. Domain knowledge of the local meteorological conditions can also be used to extend these simple models. For example, in certain regions the wind/power time series may exhibit strong diurnal trends which would necessitate the inclusion of time-of-day into the model.

Beyond time series models, machine learning techniques also are widely employed. These techniques can be more flexible than classic time series models in terms of easily allowing for more explanatory variables and are typically more naturally able to capture non-linear relationships. It should be noted that this comes at the expense of additional model tuning to optimize algorithm specific hyper-parameters and possible overfitting of the data unless careful cross-validation procedures are followed. Examples include artificial neural networks [63], hybrid multi-models with blending [64] together with feature selection [65], and penalized regression [66].

Artificial neural networks, particularly recurrent neural networks (RNN), have been widely applied for sequence prediction including time-series data. Long short-term memory (LSTM) networks are explicitly designed to capture data patterns of arbitrary lags, and assimilate long-term temporal dependencies [67]. This has led to numerous applications in energy forecasting which outperform traditional time-series modelling approaches. Wu et al. [68] demonstrates such a probabilistic 4-hour ahead wind power forecast model employing a LSTM network architecture.

Statistical forecasting models can also be made dependent on the current behaviour of the target time-series or on exogenous variable(s). These are termed regime-switching models and can be based on unobserved regimes [69,70] or by observed regimes like atmospheric conditions [71,72]. It follows that these regimes can be derived from lidar/radar measurements [73]. The benefit of regime switching is that the statistical models can react faster to changing conditions, as opposed to having a fixed coefficient models or by tracking slower changes in behaviour via for instance an online update of the coefficient estimates.

Concurrent information from spatially distributed wind farm or met mast measurements also provide a route for improvements in forecast skill [74,74]. Multivariate forecasts which encode information on the spatio-temporal dependency of neighbouring sites can be tackled via a vector autoregressive models (VAR) at these time horizons. With an increasing number of sites, making sparse estimates of the coefficient matrices becomes more important, as does estimating them via efficient numerical procedures [75–77].

These discussed statistical methods have been widely proven to increase forecast skill over persistence at time-horizons generally at a minimum of 10 minutes ahead. Further research is required to evaluate the suitability of statistical methods below this time horizon and at what time range forward facing lidar/radar based systems or hybrid statistical and radar/lidar systems are a more suitable choice.

3.3.2. Statistical data assimilation based on physical models

Data assimilation performs an essential role in the forecasts of wind power systems. While the concept is very inclusive, meaning inherently assimilation of any data with any model, in this section, the term is used in more exclusive sense without addressing statistical time series models, which is a special case of data assimilation where usually non-physical models are taken into consideration. This was discussed in the previous section. The concept is inherent from the fact that neither the model nor the observations are perfect. As a result to have an accurate state of the system, the numerical model without guidance of how accurate the current state is, is not sufficient and guidance from observations is required. This is even more so for weather forecast systems, where the system itself is very sensitive to initial conditions and boundary conditions. Data assimilation was employed first in engineering however it is more than an engineering tool today.

In summary, data assimilation is the technique to adopt multiple measurements and observations of different types into a 3-dimensional model space. In meteorology it is used to generate an initial state of the atmosphere from observations that is required as input field, together with boundary conditions to any numerical weather prediction (NWP) model.

In renewable energy production, data assimilation and state estimation also has an important role, in a classical way, but also with possibility of assimilation on control zone level or even park level. System operators and Wind farm operators require advanced knowledge of ramp-up and ramp-down events [78–80]. In a ramp/extreme event forecast you want to analyze and use outliers in order to get the risk of a critical ramp/event to occur, while some data assimilation algorithms can dismiss outliers. The increased frequency of assimilation can address this challenge. The frequency of assimilation is important for ramp prediction, while the challenge comes from the model size and assimilation method chosen for the task, however simplified models with higher frequency can be adapted for the applications discussed here.

The work on data assimilation and state estimation spans many disciplines and several decades, where various approaches of data assimilation to adapt numerical weather model states to measurements [81,82] have been developed. The initial development of data assimilation has started as an objective analysis [e.g., 83,84], which was also referred as successive correction methods.

This work was followed by optimum interpolation (OI) [e.g. 81,85]. In the sequential data assimilation techniques (OI), the model solution is recursively updated during a forward integration with weights on observations and model output according to their corresponding uncertainties. These uncertainties are static and based on predefined model output statistics and hence lack the dynamical and non-linear behaviour of the weather and model system. OI methods have lead to development of variational methods in data assimilation, where constraints were introduced in variational data assimilation methods. These methods are namely 1DVAR, 2DVAR, 3DVAR [e.g. 86,87] and 4DVAR [88,89, e.g.,] where D stands for Dimension. Variational approaches can be also formulated in the context of a Bayesian problem.

In parallel the Kalman filter was introduced which is an observer feedback control system. The main difference between 4DVar and Kalman filters are the way that they address the mode and mean when the distributions are non-normal. There are several existing methods used in state estimation and data assimilation and most of them are based on the Kalman filtering theory introduced by Kalman and Bucy [90]. The pure form of the Kalman filter has been widely employed for the state estimation of the linear Gaussian systems [91], however it is linear and is not preferred for non-Gaussian and nonlinear systems [91,92]. For transition of Kalman filtering to the nonlinear and non-Gaussian systems, techniques such as extended Kalman filter (EKF), ensemble Kalman filter (EnKF), unscented Kalman filter (UKF) and particle filter (PF) algorithms are developed [91,92] and are employed to wide range of problems from low to high dimensional systems. The EKF method is implemented by linearisation of the non-linearities via using a Jacobian matrix. The EnKF uses Monte Carlo methods that helps to estimate the error covariances of the background error, gets an approximation to the Kalman-Bucy filter and produces an ensemble of initial conditions that can be utilized in an ensemble forecasting system. The EnKF embeds the non-linearities into the original linear KF solution and it uses an extra covariance inflation to consider the nonlinearities [93,94]. Later, adjustment solutions [e.g., 95] and also sequential solutions of the filter have been developed [e.g., 96].

Some of the limitation of the Kalman filter technique in meteorological context is however not a limitation in wind power context, because there the area of observational distribution is rather small, even if the area spans over an entire country. Most of the data used in meteorology are sparse in time, but widespread over the entire globe. Nevertheless, if the traditional KF should be applied for a data assimilation task in a wind power context, where the true state of the atmosphere is the target, this would imply that the models would have to generate forecasts in a small area, which is undesired, or it would require unrealistically many computing resources and observational input of meteorological variables. As described by Anderson and Anderson [95] and Houtekamer and Mitchell [96], the standard KF propagates the error covariance from one assimilation step to the next, which is computationally expensive. In the EnKF, this procedure is approximated by using an ensemble of short-range forecasts, where the forecast error covariance is directly computed from the ensemble when they are needed for the data assimilation. Meng and Zhang [97] found that it was beneficial to use a multi-scheme ensemble approach rather than a single-scheme approach, because it does not require such a large ensemble size to cover the uncertainties. They built an ensemble based on a Penn-State University WRF model kernel and different parameterisation schemes. Möhrlen et al. [98] developed what they called an "inverted" Kalman Filter approach where they make use of the ensemble Kalman filter technique and translate this into a wind power context. This approach does not only solve the problem of distribution of observations in space, but also in time. By taking the weather situation into account, the well-known timing problem (phase errors) and temporal influence of measurements can be solved mathematically with the help of a forecast covariance matrix. The additional feature of making use of situations with anti-correlating weather conditions adds to the physical correctness of the approach, as it identifies, where the borders, or in meteorological context, fronts are in space and time.

This feature is an important factor, especially, if large wind farms are located in a relatively small area, where sharp fronts pass over the area and where there is risk for cut-off or situations of rapid decrease of power production over short times. Such situations are for example reported regularly at offshore wind farms in the North Sea, Baltic Sea, the United Kingdom, Ireland, Alberta, Canada and Oregon, USA at the foothills of the Rocky Mountains.

Möhrlen et al. [98] set up an inverted Ensemble Kalman Filter approach (iEnKF) that is designed for short-term wind and solar energy forecasting, upscaling and data assimilation. They report that this type of iEnKF approach has been tested in a number of areas around the world and its capabilities demonstrated with large amount of measurements, typical for a TSO area with larger amounts of wind and solar power on the grid. The algorithm allows for any kind of measurements that is in any kind of relation to the target parameter, e.g. wind power, solar power to be used and mixed into the matrices. Hence, it is the first physically consistent methodology, where meteorological ensemble forecasts provide the framework for the distribution of observational influence and where it is possible to back-scale aggregated total production measures of an area physically consistent for the statistical training of wind power forecasts (see Figure 7). In that sense the iEnKF provides an indirect feedback mechanism to the NWP input for the generation of power curves.

This is a milestone in variable energy generation forecasting and is of great value for the large-scale integration and requirements of reliable handling of these power sources for transmission system operators, and also for traders and wind farm operators in the electricity markets with fast growing wind capacity and liberalised market rules, especially because it can be applied on all time scales, from minutes to hours ahead, as it has an inherent dependency of the measurement influence on the forecasts built into it. The computationally expensive part of this point assimilation technique is done on the typical 6-hourly meteorological cycle, while the Kalman Filter can run on minute basis handling thousands of measurements within a few seconds due to the simple linear algebra that the covariance matrix computations are based on.

The unscented Kalman filter (UKF) employs the calculation of an approximate mean and covariance as a linear combination of a number of propagated points (called as sigma points). The PF and its variants also use the Monte Carlo simulation with sampling method based approximation of the posterior density of the state vector rather than doing any explicit functions so it simulates non-linearity and non-Gaussianity. Even though PF is a competent tool for the estimation of the nonlinear and non-Gaussian systems [99], it can be computationally demanding because of size that increases accuracy however this can be addressed adaptively with careful selection of ensembles introduced by Uzunoğlu [100].

The computational complexity in the above summarized methods can be addressed in the subspace of ensembles that was one of the focuses of the Maximum Likelihood Ensemble Filter (MLEF) that employs ensembles in the pre-conditioner. This approach differs from the EnKF and PF by working on state space rather than sample space and it optimizes a nonlinear cost function through maximum likelihood practice which reduces the computational time and addresses the stochasticity and the discontinuity while it utilizes the sampling in low dimensional space and employs the Hessian information. This method has been applied to many disciplines such as power systems as well as to the wind energy industry [19,101]. In the workshop, the successful application of this method to second scales were presented.

3.3.3. Use of different types of measurements to identify extreme events

Extreme events in a meteorological sense are events that deviate from the mean and exceed beyond specific threshold values. In the power system, extreme events can occur under meteorological average conditions as well and not be considered extreme, when meteorological threshold values, such as wind speed, are exceeded. The differences are mainly due to the constraints in the power lines and the supply and demand relationship. Only in areas where wind turbines shut down due to high wind speeds - so called high-speed shutdowns can such wind speeds challenge both life and the ability to safely control the grid.

The way to deal with extreme events in both meteorology and the power industry is by applying uncertainty forecasts that provide an objective measure of the possible extreme. Deterministic forecasts cannot serve such situations, as they are tuned for best average conditions, i.e. in the setup, statistical training and model output statistics, outliers and extremes are filtered out. While statistical approaches can be used in many life science applications, in power system applications, it is crucial to employ an approach that provides a valid uncertainty of the forecast inclusive extremes in every hour of the forecast. Such extreme forecasts must be established based on probabilities computed from a probabilistic prediction system that can take the spatial and temporal scales into consideration in order to capture the temporal evolution and spatial scale of e.g. low pressure systems that contain wind speeds leading to large scale shut-down of wind farms.

This can for example be provided by such a physical approach based on a NWP ensemble that ideally contains all extreme values inherent in the approach without the requirement of statistical training such as the multi-scheme method. Alternative solutions may exist from statistical approaches by employing an extreme event analysis to a statistical ensemble [see e.g., 102]. However, statistical approaches are always limited to past climatology and require large amounts of data. The requirement for such forecasts is that they must be able to provide probabilities of extreme events, where each forecast or “forecast member” provides a valid and consistent scenario of the event. The probabilities need to be suitable solutions for a decision process. They can be computed for very critical and less critical events, depending on the end-users’ requirements.

If the target is to achieve a feedback mechanism for all kinds of data that are in any kind of relation to wind or solar power data, which by default is not reversible, the solution requires a unified methodology to measure the value of an observation and its impact on the total system. This is a

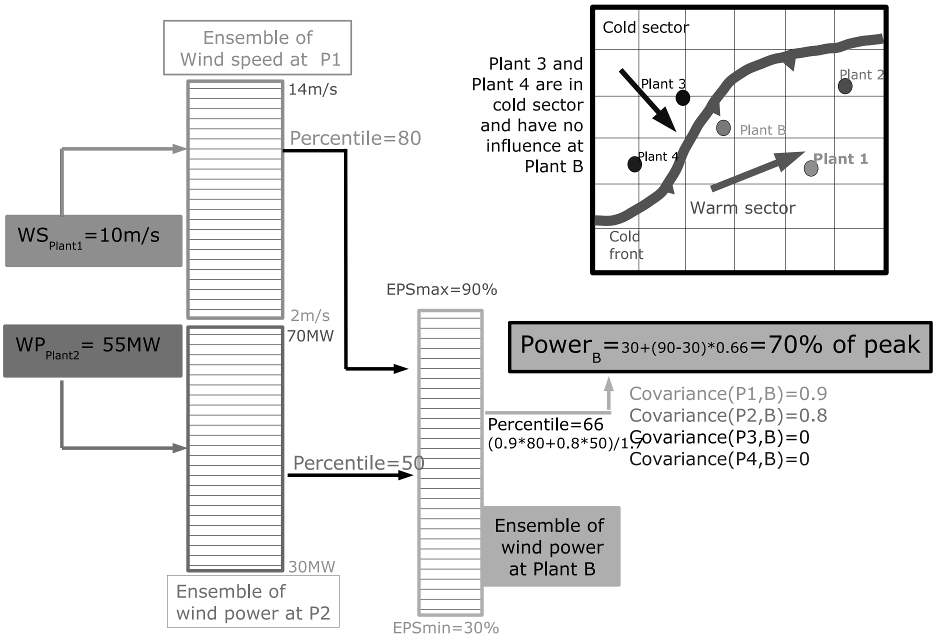

Figure 7. Functionality of the inverted Ensemble Kalman Filter when using different kind of measurements.

well known problem in meteorology, which has been extensively researched, because more and more sophisticated observational instrumentation is developed and deployed that require transformations of observations into the numerical weather prediction systems [97,103–106].

Modern Doppler radar measurements for example require retrieval transformation algorithms, where wind fields are computed with continuity equations and the thermodynamic properties through physical constraints, once the wind field is known. Snyder and Zhang [105] and Zhang et al. [106] discovered that the ensemble Kalman filter is a practical approach for the generation of state estimates with convective-scale data assimilation from such Doppler radar measurements. Applying an EnKF approach [27] with input from a multi-scheme ensemble is able to use an inherent intelligence, if the input ensemble data contains a combination of historical calibration, actual and historic weather and a transformation method for the use of different types of measurements. Generating percentiles from such an ensemble method enables the construction of a uniform covariance matrix and in fact ensures that measurements are handled consistently without the need of any physical considerations of their compatibility or irreversibility inside the iEnKF itself. The example in Figure 7 shows the functionality of an inverted Kalman Filter approach for the assimilation of point measurements in (wind and solar) power space with a multi-scheme ensemble approach. This MSEPS (multi-scheme ensemble prediction system) has 75 ensemble members with various different parameterisation schemes for the advection and the fast physical processes such as condensation and vertical diffusion. The principles of this MSEPS are described in detail in [98]. The spread in the MSEPS is physically based, because all members in the ensemble are essentially equally valid descriptions of the physical properties in the atmosphere and full-scale NWP models. The iEnKF method in combination with ensemble forecasts follows in principle these developments in data assimilation methodologies and hence provides a compatible and extendible solution with the combination of meteorological and wind and solar power observations and also presents major improvements and reliability enhancement in the short-term forecasting and data assimilation of wind and solar power.

4. Challenges for the Implementation of Minute-Scale Forecasting in Large Energy Systems

There are several use cases for predictions shorter than 1 to 2 hours. In Australia, the system runs on a 5-min schedule [107] and requires renewable energy and load forecasts on those time scales. In Germany, renewable energy plants can be pre-qualified to participate in the reserve market, and need to predict their possible power with less than 5% accuracy in the pilot phase and less than 3.3% in the implementation phase. This is calculated in one-minute intervals. In Denmark, with hourly wind penetrations of over 140%, the grid is run proactively in hourly steps, predicting the imbalance and reacting accordingly on the basis of spatio-temporal forecasts [108]. So the use cases for minute scale forecasts are there, and the best forecasts require upstream information in real time.

In a large energy system with moderate penetration from wind sources, a system operator can choose to outsource balancing of wind. This is the approach chosen widely in central Europe. A major reason behind the liberalized strategy in Europe is a wish to make the market more competitive and indeed it happened faster than anybody expected in both Denmark (2009) and Germany (2012) [109] with the result of lower spot market prices in the NordPool market and the German-Austrian part of EPEX.

The difference between a TSO and a power trader's prioritized optimization lies in the target horizon. The trader is looking up to several weeks ahead, while the TSO's optimisation horizon is over one year. In particular once the commercial path is taken, then the TSO lacks information about the generation and must rely on the information from the trading companies. In Germany, the TSOs have today little control of the renewable energy generation and relies on out-sourced solutions for critical system information to a degree, which has not been considered acceptable for many years from a system security perspective.

Although Germany has the highest capacity of wind and solar generation in Europe, it is apparent that the system lacks information for optimization. This is seen in frequent down regulation of wind farms in day-time and recovery during the middle of the night, often many hours after the wind has dropped again. This process has become highly inefficient in recent years, because there are no requirements for wind farms to provide real-time data to the system operator.

German experience shows that wind energy loses efficiency and value unless there are obligations for wind farms to provide data required by various forecasting and system operation processes.

Based on this experience, it is crucial to define standards regarding setup and maintenance of instrumentation, collection and provision of data, as well as required quality of data. Beside the standards, in transparent markets the grid codes should also contain a clear definition about the rights on the use and the obligation to provide the data. Without such regulations, the required quality is hard to achieve in order to improve forecasts. Corrupt and wrongly calibrated instrumentation can do more damage to a forecast than not having data. This is one of the greatest challenges at present and the reason for slow progress on minute-scale forecasting. Especially in large systems such as Germany with many thousands of individual wind turbines and small wind farms, this is a difficult challenge to overcome. Nevertheless, the need to make appropriate changes to the grid codes is the same for all markets.

5. Conclusions

Minute-scale forecasting of wind power is a discipline that is becoming crucial to accomplish in globally transitioning power systems with increasing amounts of variable generating power sources from Renewables. The participants of the collaborative IEA Wind Task 32 and 36 workshop established a framework for forecasting at the minute scale and discussed new techniques that will push the limits of state-of-the-art forecasting methods to a new level.

Three applications were identified that can benefit from minute-scale forecasting and their respective forecasting horizons. Wind turbine and wind farm controllers need wind speed forecasts to optimize the turbine and farm operation. The task of balancing the power grid and optimizing energy markets relies heavily on precise wind power forecasts as well. To carry out forecasts that range

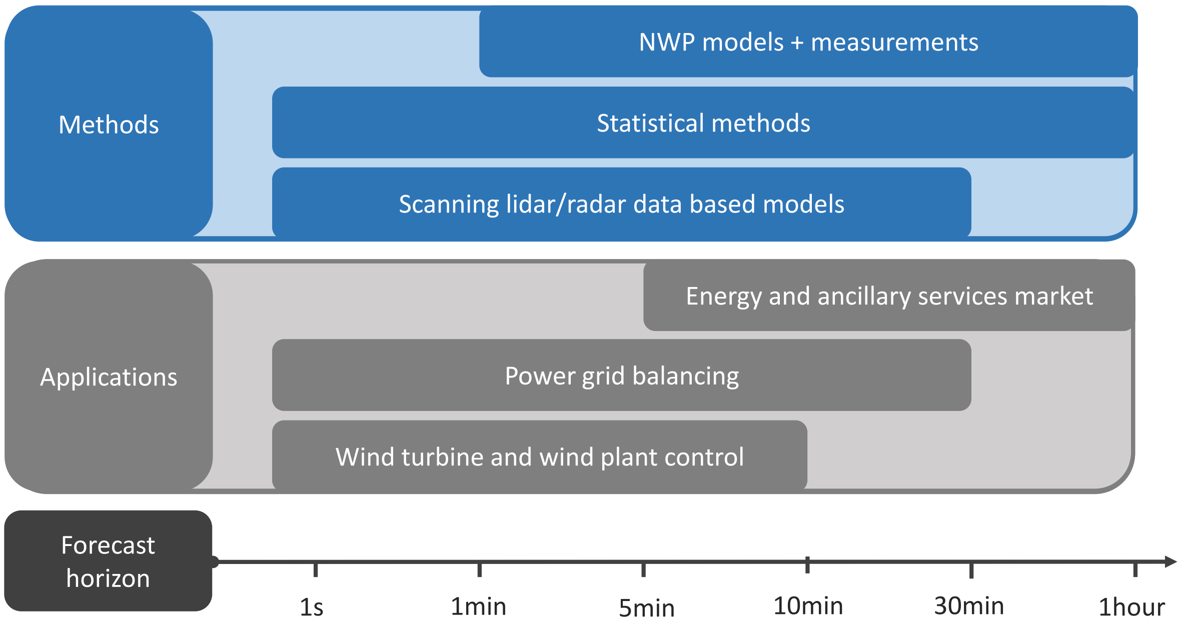

Figure 8. Overview of forecast horizons of different wind energy applications and forecast methods in the second and minute scale.

from 1 second to 60 minutes, forecasters have the choice between different methods (Figure 8). In our discussions at the workshop and this review we differentiate between using preview data from remote sensing devices, statistical approaches that deduce patterns from observational data to predict future values and finally methods that are based on data assimilation into physical models. These assimilated data can originate both from remote sensing devices or other existing observational data sources from meteorological masts or wind turbine data.

By investigating more deeply the respective methods it became clear that they all have advantages, but also barriers that need to be overcome in order to achieve reliable forecasts on a commercial level. The following list provides an overview of focus areas for the near future to advance further with minute-scale forecasting:

- **Research Requirements.** At this point, many methods are still under development. There are a lot of open questions to solve and the optimal forecasting techniques for the different applications has not been found yet. It is also not sufficiently demonstrated that all methods add value. So more research needs to be carried out and both measurement experts and meteorological modelers need to collaborate closely to find solutions.
- **Data Requirements.** All forecasting methods rely on data. This might sound obvious, but what is needed is high resolution, high quality data delivered in real-time to forecast systems. Wind turbine or wind farm operators often only log 10-minute averages of their operational data. However, to train and validate models, high frequency data is necessary.
- **Requirement for standards.** End users have more confidence in data when the collection and use of the data is supported by recommended practices and standards. Community-driven recommended practices are available for some applications of wind lidar but not in the context of forecasting.
- **Expert Training.** As with any emerging technology, there are a limited number of experts that know how to carry out a remote sensing measurement campaign, feed data into neural networks or know how to assimilate data into a NWP model. This forms a barrier to the widespread commercialization of minutes-scale forecasting. IEA Wind Tasks form an ideal platform for the

international exchange and dissemination of knowledge order to establish more widespread training in this topic.

Supplementary Materials: IEA Wind Task 32 is operated by the Chair of Wind Energy at the Institute of Aircraft design at the faculty of Aerospace Engineering at the University of Stuttgart. More details about IEA Wind Task 32, including minutes from the workshops and other documents, can be found at www.ieawindtask32.org. IEA Wind Task 36 Forecasting is operated by Gregor Giebel of DTU Wind Energy at Risø, Denmark. See www.ieawindforecasting.dk for more information. General information about IEA Wind can be found at www.ieawind.org. IEA Wind TCP functions within a framework created by the International Energy Agency. Views, findings, and publications of the IEA Wind TCP do not necessarily represent the views or policies of the IEA Secretariat or of all its individual member countries. IEA Wind TCP is part of IEA's Technology Collaboration Programme (TCP).

Author Contributions: Ines Würth was a co-organizer of the workshop, led the paper and wrote the abstract, introduction, Section 3.2.1, conclusion, some section introductions, and edited all sections. Laura Valldecabres Sanmartin was a co-organizer of the workshop and contributed to the introduction of Section 2, to Section 3.2.1, and 3.2 and led Section 2.3 and 3.2.2. Elliot Simon was a co-organizer of the workshop, led Section 3.3.1, and contributed text in Sections: 2, 3.2.1, and 3.2. David Schlipf led Section 2.1. Bahri Uzunoğlu led Section 2.2 and wrote Section 3.3.2 and 3.3.3 together with Corinna Mörlen who also led Section 3.1 and 3.2.3 and contributed to Section 3.2, 3.3.1, 2.3 and 4. Gregor Giebel contributed to Section 3.1. Ciaran Gilbert contributed to Section 3.3.1. Anton Kaifel and all other co-authors participated in the paper review and revision process.

Funding: This publication was supported by the Open Access Publishing Fund of the University of Stuttgart and has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie Grant No. 642108.

Acknowledgments: We would like to thank DTU Wind Energy (Risø campus) for graciously hosting the workshop, and all of the workshop participants who contributed their ideas and knowledge.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Giebel, G.; Brownsword, R.; Kariniotakis, G.; Denhard, M.; Draxl, C. The State-Of-The-Art in Short-Term Prediction of Wind Power. Technical report, Technical University of Denmark (DTU), Roskilde, Denmark, 2011. doi:10.11581/DTU:00000017.
2. Fraile, D.; Mbistrova, A. Wind in power 2017: Annual combined onshore and offshore wind energy statistics. Technical report, WindEurope, 2018.
3. Fraile, D.; Komusanac, I. Wind energy in Europe: Outlook to 2022. Technical report, WindEurope, 2018.
4. Larsén, X.; Larsen, S.; Lundtang Petersen, E. Full-Scale Spectrum of Boundary-Layer Winds. *Boundary-Layer Meteorology* **2016**, *159*, 349–371. doi:10.1007/s10546-016-0129-x.
5. Apt, J. The spectrum of power from wind turbines. *Journal of Power Sources* **2007**, *169*, 369–374. doi:10.1016/j.jpowsour.2007.02.077.
6. Vincent, C.L.; Trombe, P.J. 8 - Forecasting intrahourly variability of wind generation. In *Renewable Energy Forecasting*; Kariniotakis, G., Ed.; Woodhead Publishing Series in Energy, Woodhead Publishing, 2017; pp. 219 – 233. doi:https://doi.org/10.1016/B978-0-08-100504-0.00008-1.
7. Sørensen, P.; Cutululis, N.A.; Vigueras-Rodríguez, A.; Madsen, H.; Pinson, P.; Jensen, L.E.; Hjerrild, J.; Donovan, M. Modelling of power fluctuations from large offshore wind farms. *Wind Energy*, *11*, 29–43. doi:10.1002/we.246.
8. Akhmatov, V.; Abildgaard, H.; Pedersen, J.; Eriksen, P. Integration of Offshore Wind Power into the Western Danish Power System. *Proc. Copenhagen Offshore Wind 2005* **2005**.
9. van Kooten, G.C. Wind power: the economic impact of intermittency. *Letters in Spatial and Resource Sciences* **2010**, *3*, 1–17. doi:10.1007/s12076-009-0031-y.
10. Ela, E.; Kirby, B. ERCOT Event on February 26, 2008: Lessons Learned. Technical report, National Renewable Energy Laboratory, 2008. doi:10.2172/1218412.
11. Gallego-Castillo, C.; Cuerva-Tejero, A.; Lopez-Garcia, O. A review on the recent history of wind power ramp forecasting. *Renewable and Sustainable Energy Reviews* **2015**, *52*, 1148 – 1157. doi:10.1016/j.rser.2015.07.154.
12. Würth, I.; Ellinghaus, S.; Wigger, M.; Niemeier, M.J.; Clifton, A.; Cheng, P.W. Forecasting wind ramps: can long-range lidar increase accuracy?; IOP: Hamburg, Germany, 2018.

13. Schlipf, D.; Schlipf, D.J.; Kühn, M. Nonlinear Model Predictive Control of Wind Turbines Using LIDAR. *Wind Energy* **2013**, *16*, 1107–1129.
14. Bossanyi, E. Combining induction control and wake steering for wind farm energy and fatigue loads optimisation. *J. Phys.: Conf. Ser.* **2018**, *1037*. doi:10.1088/1742-6596/1037/3/032011.
15. Momoh, J.A. *Smart grid: fundamentals of design and analysis*; Vol. 63, John Wiley & Sons, 2012.
16. Menin, M.; Uzunoglu, B. Parametric Sensitivity Study for Wind Power Trading through Stochastic Reserve and Energy Market Optimization. 2015 Seventh Annual IEEE Green Technologies Conference, 2015, pp. 82–87. doi:10.1109/GREENTECH.2015.37.
17. Uzunoglu, B.; Bayazit, D. A generic resampling particle filter joint parameter estimation for electricity prices with jump diffusion. 2013 10th International Conference on the European Energy Market (EEM), 2013, pp. 1–7. doi:10.1109/EEM.2013.6607409.
18. Uzunoglu, B.; AkifÜlker, M.; Bayazit, D. Particle filter joint state and parameter estimation of dynamic power systems. 2016 57th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON), 2016, pp. 1–7. doi:10.1109/RTUCON.2016.7763152.
19. Uzunoğlu, B.; Ülker, M.A. Maximum Likelihood Ensemble Filter State Estimation for Power Systems. *IEEE Transactions on Instrumentation and Measurement* **2018**, *67*, 2097–2106. doi:10.1109/TIM.2018.2814066.
20. Ülker, M.A.; Uzunoğlu, B. Simplex optimization for particle filter joint state and parameter estimation of dynamic power systems. IEEE EUROCON 2017 -17th International Conference on Smart Technologies, 2017, pp. 399–404. doi:10.1109/EUROCON.2017.8011142.
21. Eriksson, R.; Modig, N.; Elkington, K. Synthetic inertia versus fast frequency response: a definition. *IET Renewable Power Generation* **2018**, *12*, 507–514. doi:10.1049/iet-rpg.2017.0370.
22. Díaz-González, F.; Haub, M.; Sumper, A.; Gomis-Bellmuntac, O. Participation of wind power plants in system frequency control: Review of grid code requirements and control methods. *Renewable and Sustainable Energy Reviews* **2014**, *43*, 551–564. doi:10.1016/j.rser.2014.03.040.
23. EPEX Spot SE. *Intraday Continous: Intraday Lead Times*, (accessed December 10, 2018).
24. NordPool. *Intraday Trading*, (accessed December 10, 2018).
25. Energy Exchange Istanbul (EXIST). *Intra-day Market*, (accessed December 10, 2018). https://www.epias.com.tr/en/intra-day-market/phases.
26. BSP South Pool. *Intraday Continous Market*, (accessed December 10, 2018). https://www.bsp-southpool.com/intraday-continuous-market.html.
27. Möhren, C., J.J. A new algorithm for Upscaling and Short-term forecasting of wind power using Ensemble forecasts; Energynautics GmbH: Bremen, Germany, 2009.
28. Mazzi, N.; Pinson, P. 10 - Wind power in electricity markets and the value of forecasting. In *Renewable Energy Forecasting*; Kariniotakis, G., Ed.; Woodhead Publishing Series in Energy, Woodhead Publishing, 2017; pp. 259 – 278. doi:https://doi.org/10.1016/B978-0-08-100504-0.00010-X.
29. 50Hertz.; Amprion.; Tennet.; TransnetBW. Leitfaden zur Präqualikation von Windenergieanlagen zur Erbringung von Minutenreserveleistung im Rahmen einer Pilotphase / Guidelines for Prequalification of Wind Turbines to provide Minute Reserves during a Pilot Phase. Technical report, German Transmission System Operators: Germany, German Transmission System Operators: Germany, 2016.
30. IEC. Wind energy generation systems - Part 12-1: Power performance measurements of electricity producing wind turbines. Standard, International Electrotechnical Commission, Geneva, CH, 2017.
31. Clifton, A.; Clive, P.; Gottschall, J.; Schlipf, D.; Simley, E.; Simmons, L.; Stein, D.; Trabucchi, D.; Vasiljevic, N.; Würth, I. IEA Wind Task 32: Wind Lidar - Identifying and mitigating barriers to the adoption of wind lidar. *Remote Sensing* **2018**, *10*, 413–433. doi:10.3390/rs10030406.
32. Emeis, S.; Harris, M.; Banta, R.M. Boundary-layer anemometry by optical remote sensing for wind energy applications. *Meteorologische Zeitschrift* **2007**, *16*, 337–347. doi:10.1127/0941-2948/2007/0225.
33. Simley, E.; Pao, L.Y.; Frehlich, R.; Jonkman, B.; Kelley, N. Analysis of light detection and ranging wind speed measurements for wind turbine control. *Wind Energy* **2014**, *17*, 413–433. doi:10.1002/we.1584.
34. Clifton, A.; Boquet, M.; Burin Des Roziers, E.; Westerhellweg, A.; Hofsass, M.; Klaas, T.; Vogstad, K.; Clive, P.; Harris, M.; Wylie, S.; Osler, E.; Banta, B.; Choukulkar, A.; Lundquist, J.; Aitken, M. Remote Sensing of Complex Flows by Doppler Wind Lidar: Issues and Preliminary Recommendations. Technical Report TP-5000-64634, National Renewable Energy Laboratory, 2015.

35. Vasiljević, N.; L. M. Palma, J.M.; Angelou, N.; Carlos Matos, J.; Menke, R.; Lea, G.; Mann, J.; Courtney, M.; Frölen Ribeiro, L.; M. G. C. Gomes, V.M. Perdigão 2015: methodology for atmospheric multi-Doppler lidar experiments. *Atmospheric Measurement Techniques* **2017**, *10*, 3463–3483. doi:10.5194/amt-10-3463-2017.
36. Courtney, M.; Simon, E. *Deploying scanning lidars at coastal sites*; DTU Wind Energy: Denmark, 2016.
37. Würth, I.; Brenner, A.; Wigger, M.; Cheng, P.W. How far do we see? Analysis of the measurement range of long-range lidar data for wind power forecasting. German Wind Energy Conference DEWEK, 2017.
38. Valldecabres, L.; Peña, A.; Courtney, M.; von Bremen, L.; Kühn, M. Very short-term forecast of near-coastal flow using scanning lidars. *Wind Energy Science* **2018**, *3*, 313–327. doi:10.5194/wes-3-313-2018.
39. Simon, E.; Courtney, M.; Vasiljevic, N. Minute-Scale Wind Speed Forecasting Using Scanning Lidar Inflow Measurements. *Wind Energy Science Discussions* **2018**. doi:10.5194/wes-2018-71.
40. Kokhanovsky, A. *Aerosol Optics: Light Absorption and Scattering by Particles in the Atmosphere*; Springer-Verlag Berlin Heidelberg, 2008.
41. Performance Verification of Galion. Technical Report Report 13001, Deutsche Windguard, 2013.
42. Bradley, S. Wind speed errors for LIDARs and SODARs in complex terrain; , 2008.
43. Bradley, S., Y.P.P.B.; Oldroyd, A. Corrections for wind-speed errors from sodar and lidar in complex terrain. *Boundary-Layer Meteorology* **2012a**, *143*, 37–48.
44. Bradley, S., S.v.H.; Mikkelsen, T. A bistatic sodar for precision wind profiling in complex terrain. *Journal of Atmospheric and Oceanic Technology* **2012b**, *29(8)*, 1052–1061.
45. Emeis, S., H.M.B. Boundary-layer anemometry by optical remote sensing for Wind energy applications. *R.M. Meteorologische Zeitschrift* **2007**, *16(4)*, 337–347.
46. Kindler, D., O.A.M.A.F.D. An eight month test campaign of the Qinetiq ZephIR system: Preliminary results. *Meteorol. Zeitschrift* **2007**, *16(5)*, 479–489.
47. Yang, Q., B.L.P.M.F.J.N.R. Evaluation of WRF-Predicted Near-Hub-Height Winds and Ramp Events over a Pacific Northwest Site with Complex Terrain. *J. of Appl. Meteo. and Climatology* **2013**, *52*, 1753–1763. doi:10.1175/JAMC-D-12-0267.1.
48. Clifton, A.; M.Boquet.; Burin, E.; Hofsäß, M.; Klaas, T.; Vogstad, K.; Clive, P.; Harris, M.; Wylie, S.; E.Osler.; Banta, R.; Choukulkar, A.; Lundquist, J.; Aitken., M. Remote Sensing of Complex Flows by Doppler Wind Lidar: Issues and Preliminary Recommendations. Technical report, National Renewable Energy Laboratory, 15013 Denver West Parkway, Golden, CO 80401, 2015.
49. Hirth, B.D.; Schroeder, J.L.; Gunter, W.S.; Guynes, J.G. Measuring a Utility-Scale Turbine Wake Using the TTUKa Mobile Research Radars. *Journal of Atmospheric and Oceanic Technology* **2012**, *29*, 765–771. doi:10.1175/JTECH-D-12-00039.1.
50. Hirth, B.D.; Schroeder, J.L.; Gunter, W.S.; Guynes, J.G. Coupling Doppler radar-derived wind maps with operational turbine data to document wind farm complex flows. *Wind Energy*, *18*, 529–540. doi:10.1002/we.1701.
51. Nygaard, N.G.; Newcombe, A.C. Wake behind an offshore wind farm observed with dual-Doppler radars. *Journal of Physics: Conference Series* **2018**, *1037*, 072008. doi:10.1088/1742-6596/1037/7/072008.
52. Marathe, N.; Swift, A.; Hirth, B.; Walker, R.; Schroeder, J. Characterizing power performance and wake of a wind turbine under yaw and blade pitch. *Wind Energy*, *19*, 963–978. doi:10.1002/we.1875.
53. Hirth, B.D.; Schroeder, J.L.; Irons, Z.; Walter, K. Dual-Doppler measurements of a wind ramp event at an Oklahoma wind plant. *Wind Energy* **2016**, *19*, 953–962. doi:10.1002/we.1867.
54. Valldecabres, L.; Nygaard, N.G.; Vera-Tudela, L.; von Bremen, L.; Kühn, M. On the Use of Dual-Doppler Radar Measurements for Very Short-Term Wind Power Forecasts. *Remote Sensing* **2018**, *10*. doi:10.3390/rs10111701.
55. Trombe, P.J.; Pinson, P.; Vincent, C.; Bøvith, T.; Cutululis, N.A.; Draxl, C.; Giebel, G.; N.Hahmann, A.; E.Jensen, N.; Jensen, B.P.; Le, N.F.; Madsen, H.; Pedersen, L.B.; Sommer, A. Weather radars – the new eyes for offshore wind farms? *Wind Energy*, *17*, 1767–1787. doi:10.1002/we.1659.
56. Marquis, M., W.J.F.C.F.J. Wind Forecasting Improvement Project (WFIP) final report. Technical report, National Oceanographic and Atmospheric Administration (NOAA), Boulder, CO, USA, 2014.
57. *Meteorological Assimilation Data Ingest System (MADIS)*, (accessed December 10, 2018).
58. Wilczak, J., C.F.J.F.J.C.L.B.J.O.I.D.L.S.M.A.J.M.J.Z.J.R.C.S.B.R.C.L.K.B.J.M.K.C.E.N.; Marquis, M. The Wind Forecast Improvement Project (WFIP): A Public–Private Partnership Addressing Wind Energy Forecast Needs. *Bull. Amer. Meteor. Soc.* **2015**, *96*, 1699–1718.

59. Nakafuji, D. Distributed Resource Energy Analysis & Management System (DREAMS) Development for Real-time Grid Operations. Technical Report DOE-EE0006331-FTR1, Hawaiian Electric Company to U.S. Department of Energy, 2016.
60. Pinson, P. Very-short-term probabilistic forecasting of wind power with generalized logit–normal distributions. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, *61*, 555–576. doi:10.1111/j.1467-9876.2011.01026.x.
61. Torres, J.; García, A.; Blas, M.D.; Francisco, A.D. Forecast of hourly average wind speed with ARMA models in Navarre (Spain). *Solar Energy* **2005**, *79*, 65 – 77. doi:https://doi.org/10.1016/j.solener.2004.09.013.
62. Erdem, E.; Shi, J. ARMA based approaches for forecasting the tuple of wind speed and direction. *Applied Energy* **2011**, *88*, 1405 – 1414. doi:https://doi.org/10.1016/j.apenergy.2010.10.031.
63. Li, G.; Shi, J. On comparing three artificial neural networks for wind speed forecasting. *Applied Energy* **2010**, *87*, 2313 – 2320. doi:https://doi.org/10.1016/j.apenergy.2009.12.013.
64. Feng, C.; Cui, M.; Hodge, B.M.; Zhang, J. A data-driven multi-model methodology with deep feature selection for short-term wind forecasting. *Applied Energy* **2017**, *190*, 1245 – 1257. doi:https://doi.org/10.1016/j.apenergy.2017.01.043.
65. Niu, T.; Wang, J.; Zhang, K.; Du, P. Multi-step-ahead wind speed forecasting based on optimal feature selection and a modified bat algorithm with the cognition strategy. *Renewable Energy* **2018**, *118*, 213–229. doi:10.1016/j.renene.2017.10.075.
66. Pinson, P. Introducing distributed learning approaches in wind power forecasting. 2016 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS), 2016, pp. 1–6. doi:10.1109/PMAPS.2016.7764224.
67. Hochreiter, S.; Schmidhuber, J. Long Short-Term Memory. *Neural Computation* **1997**, *9*, 1735–1780. doi:10.1162/neco.1997.9.8.1735.
68. Wu, W.; Chen, K.; Qiao, Y.; Lu, Z. Probabilistic short-term wind power forecasting based on deep neural networks. 2016 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS), 2016, pp. 1–8. doi:10.1109/PMAPS.2016.7764155.
69. Ailliot, P.; Monbet, V. Markov-switching autoregressive models for wind time series. *Environmental Modelling & Software* **2012**, *30*, 92 – 101. doi:https://doi.org/10.1016/j.envsoft.2011.10.011.
70. Pinson, P.; Madsen, H. Adaptive modelling and forecasting of offshore wind power fluctuations with Markov-switching autoregressive models. *Journal of Forecasting*, *31*, 281–313. doi:10.1002/for.1194.
71. Browell, J.; Drew, D.R.; Philippopoulos, K. Improved very short-term spatio-temporal wind forecasting using atmospheric regimes. *Wind Energy*, *0*. doi:10.1002/we.2207.
72. Browell, J.; Gilbert, C. Cluster-based regime-switching AR for the EEM 2017 Wind Power Forecasting Competition. 2017 14th International Conference on the European Energy Market (EEM), 2017, pp. 1–6. doi:10.1109/EEM.2017.7982034.
73. Trombe, P.; Pinson, P.; Madsen, H. Automatic Classification of Offshore Wind Regimes With Weather Radar Observations. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* **2014**, *7*, 116–125. doi:10.1109/JSTARS.2013.2252604.
74. Hering, A.S.; Genton, M.G. Powering Up With Space-Time Wind Forecasting. *Journal of the American Statistical Association* **2010**, *105*, 92–104. doi:10.1198/jasa.2009.ap08117.
75. Dowell, J.; Pinson, P. Very-Short-Term Probabilistic Wind Power Forecasts by Sparse Vector Autoregression. *IEEE Transactions on Smart Grid* **2016**, *7*, 763–770. doi:10.1109/TSG.2015.2424078.
76. Messner, J.W.; Pinson, P. Online adaptive lasso estimation in vector autoregressive models for high dimensional wind power forecasting. *International Journal of Forecasting* **2018**. doi:https://doi.org/10.1016/j.ijforecast.2018.02.001.
77. Cavalcante, L.; Bessa, R.J.; Reis, M.; Browell, J. LASSO vector autoregression structures for very short-term wind power forecasting. *Wind Energy*, *20*, 657–675. doi:10.1002/we.2029.
78. Yıldırım, N.; Uzunoğlu, B., Data Mining via Association Rules for Power Ramps Detected by Clustering or Optimization. In *Transactions on Computational Science XXVIII: Special Issue on Cyberworlds and Cybersecurity*; Springer Berlin Heidelberg: Berlin, Heidelberg, 2016; pp. 163–176. doi:10.1007/978-3-662-53090-0_9.
79. Yildirim, N.; Uzunoglu, B. Spatial Clustering for Temporal Power Ramp Balance and Wind Power Estimation. 2015 Seventh Annual IEEE Green Technologies Conference, 2015, pp. 214–220. doi:10.1109/GREENTECH.2015.39.

80. Yildirim, N.; Uzunoglu, B. Association Rules for Clustering Algorithms for Data Mining of Temporal Power Ramp Balance. 2015 International Conference on Cyberworlds (CW), 2015, pp. 224–228. doi:10.1109/CW.2015.72.
81. Dey, C. Evolution of objective analysis methods of NMC's Medium-Range Model. *Wea. Forecasting* **1989**, *4*, 391–400.
82. Ide, K., C.P.G.M.L.A. Unified Notation for Data Assimilation: Perational, Sequentialm Variational. *J. Met. Soc. Japan, Special Issue on Data Assimilation in Meteorology and Oceanography: Theory and practice* **1997**, *75*, 181–189.
83. CRESSMAN, G.P. AN OPERATIONAL OBJECTIVE ANALYSIS SYSTEM. *Monthly Weather Review* **1959**, *87*, 367–374, [https://doi.org/10.1175/1520-0493(1959)087<0367:AOOAS>2.0.CO;2]. doi:10.1175/1520-0493(1959)087<0367:AOOAS>2.0.CO;2.
84. Gandin, L., Objective Analysis of meteorological fields; Gidromet, English translation Jerusalem: Israel program for scientific translation, 1965.
85. Kanamitsu, M. Description of the NMC Global Data Assimilation and Forecast System. *Wea. Forecasting* **1989**, *4*, 335—-342.
86. Courtier, P., E.A.W.H.J.P.D.V.M.H.A.H.F.R.; Fisher, M. The ECMWF implementation of three-dimensional variational assimilation (3D-Var). Part 1: formulation. *Quart. J. Roy. Meteor. Soc.* **1998**, *124*, 1783–1807.
87. Wu, W.-S., R.J.P.; Parrish, D.F. Three dimensional variational analysis with spatially inhomogeneous covariance. *Mon. Wea. Rev* **2002**, *130*, 2905–2916.
88. Courtier, P. Thepaut, J.H.A. A strategy for operational implementation of 4D-Var, using an incremental approach. *Quart. J. Roy. Meteor. Soc.* **1994**, *120*, 1367–1387.
89. Zupanski, D. A General Weak Constraint Applicable to Operational 4DVAR Data Assimilation Systems. *Mon. Wea. Rev.* **1997**, *125*, 2274—-2292.
90. Kalmann, R.; Bucy, R.S. New Results in Linear Filtering and Prediction Theory. *ASME. J. Basic Eng.* **1961**, *83*, 95–108. doi:10.1115/1.3658902.
91. Jazwinski, A. *Stochastic Processes and Filtering Theory*; Mathematics in Science and Engineering, Elsevier Science, 1970.
92. Ristic, B.; Arulampalm, S.; Gordon, N. *Beyond the Kalman filter: particle filters for tracking applications*; The Artech House radar library, Artech House, Incorporated, 2004.
93. Evensen, G. Sequential data assimilation with a nonlinear quasi-geostrophic model using Monte Carlo methods to forecast error statistics. *J. Geophys. Res.* **1994**, *99*, 10143—-10162.
94. Todling, R., S.C.; Sivakumaran, N. Suboptimal Schemes for Retrospective Data Assimilation Based on the Fixed-Lag Kalman Smoother. *Mon. Wea. Rev.* **1998**, *126*, 2274–2286.
95. Anderson, J. An ensemble adjustment Kalman Filter. *Mon. Wea. Rev.* **2001**, *129*, 2884–2903.
96. Houtekamer, P.; Mitchell, H. A Sequential Ensemble Kalman Filter for Atmospheric Data Assimilation. *Mon. Wea. Rev.* **2001**, *129*, 123—137.
97. Meng, Z.; Zhang, F. Tests of an Ensemble Kalman Filter for Mesoscale and Regional-Scale Data Assimilation. Part III: Comparison with 3DVAR in a Real-Data Case Study. *Mon. Wea. Rev.* **2002**, *136*, 522—-540.
98. Möhrlen, C. Uncertainty in wind energy forecasting. PhD thesis, National University of Ireland, Cork, Ireland, 2004.
99. Xiong, X.; Navon, I.; Uzunoglu, B. A Note on the Particle Filter with Posterior Gaussian Resampling. *Tellus A* **2007**, *58*.
100. Uzunoglu, B.; Fletcher, S.J.; Zupanski, M.; Navon, I.M. Adaptive ensemble reduction and inflation. *Quarterly Journal of the Royal Meteorological Society* **2007**, *133*, 1281–1294. doi:10.1002/qj.96.
101. Zupanski, M. Maximum Likelihood Ensemble Filter: Theoretical Aspects. *Monthly Weather Review* **2005**, *133*, 1710–1726, [https://doi.org/10.1175/MWR2946.1]. doi:10.1175/MWR2946.1.
102. Bessa, R.J.; Möhrlen, C.; Fundel, V.; Siefert, M.; Browell, J.; Haglund El Gaidi, S.; Hodge, B.M.; Cali, U.; Kariniotakis, G. Towards Improved Understanding of the Applicability of Uncertainty Forecasts in the Electric Power Industry. *Energies* **2017**, *10*. doi:10.3390/en10091402.
103. Houtekamer, P.L., H.M.G.P.M.B.M.C.L.S.; Hansen, B. Atmospheric Data Assimilation with an Ensemble Kalman Filter: Results with Real Observations. *Mon. Wea. Rev* **2005**, *133*, 604—-620.
104. Hamill, T.; Snyder, C. Using Improved Background-Error Covariances from an Ensemble Kalman Filter for Adaptive Observations. *Mon. Wea. Rev.* **2002**, *130*, 1552—-1572.

105. Snyder, C.; Zhang, F. Assimilation of simulated Doppler radar observations with an ensemble Kalman filter. *Monthly Weather Review* **2003**, *131*, 1663–1677.
106. Zhang, F., C.S.; Sun, J. Impacts of initial estimate and observation availability on convective-scale data assimilation with an ensemble Kalman filter. *Monthly Weather Review* **2004**, *132*, 1238–1253.
107. DISPATCH. Technical report, Australiaen Electricity Market Operator (AEMO), Level 22, 530 Collins Street Melbourne VIC 3000, Australia, 2018.
108. Borup, L. IEA Wind Task 36 Forecasting webinar: How to run 40% RE in the Danish system. https://www.youtube.com/watch?v=IGhUasWctUM, last accessed 3. 12. 2018, 2018.
109. Germany, B. *EEG in Zahlen 2016*, 2016.