Predicting the Wind


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Models and Methods of Wind Forecasting for Utility Operations Planning

ELECTRICITY GENERATED FROM WIND POWER WILL PLAY AN IMPORTANT ROLE in the future energy supply in many countries. This implies the need to integrate this power into the existing electricity supply system, which was mainly designed for large units of fossil fuel and nuclear power stations. Wind power has different characteristics and therefore this integration leads to some important challenges from the point of view of the electricity system.

The availability of the power supply generated from wind energy varies fundamentally from that generated conventionally from fossil fuels. The most important difference is that wind power generation depends on the availability of the wind; i.e., it is weather dependent. In the electricity system, supply and demand must be equal at all times. Thus, in an electricity system with an important share of wind power, new methods of balancing supply and demand are needed.

Wind power forecasting plays a key role in tackling this challenge. It is the prerequisite for the integration of a large share of wind power in an electricity system, as it links the weather-dependent production with the scheduled production of conventional power plants and the forecast of the electricity demand, with the latter being predictable with reasonable accuracy.

The wind power forecast accuracy is directly connected to the need for balancing energy and hence to the cost of wind power integration. Consequently, a large amount of research has been directed toward the development of good and reliable wind power forecasts in recent years and many different forecasting systems with different approaches have been developed. In countries with a substantial share of wind power in the electricity system like Denmark, Germany or Spain, wind power forecasting systems are already an essential part of grid and system control. Figure 1 provides an illustration of a wind power management system operating in Germany. Similar developments are underway in North America as well.

North American Example: Xcel Energy

Xcel Energy is a major utility operator in the central and north-central areas of the United States. Commercial wind power development within the Xcel Energy service areas is currently growing to a point where wind generation will no longer be a negligible fraction of the regional electric energy supply.

Xcel system operators will require accurate wind estimates, both in the operations scheduling and real-time operations time frames, to deal with a variety of issues around meeting energy demands of customers. With financial support from the Xcel Energy Renewable Development Fund in Minnesota, Xcel and WindLogics have been leading a major project to define, design, build, and demonstrate a complete wind power forecasting system for use by Xcel system operators. Key objectives are to optimize the way wind forecast information is integrated into the control room environment and evaluate the impact of the wind forecast on control room operations. Figure 2 provides an illustration of the system under development for Xcel Energy.

The project approach consists of three critical pieces blended into a cohesive effort. First, a wind plant output forecasting system has been designed and implemented to deal with all wind plants on the Northern States Power (NSP) portion of the Xcel system and deliver results in a way that aligns with the way that the control room operator views the system. The second piece is to use the forecasting results in both operations planning and real-time operations time frames to reduce the cost of ancillary services required to integrate the wind plants into the power

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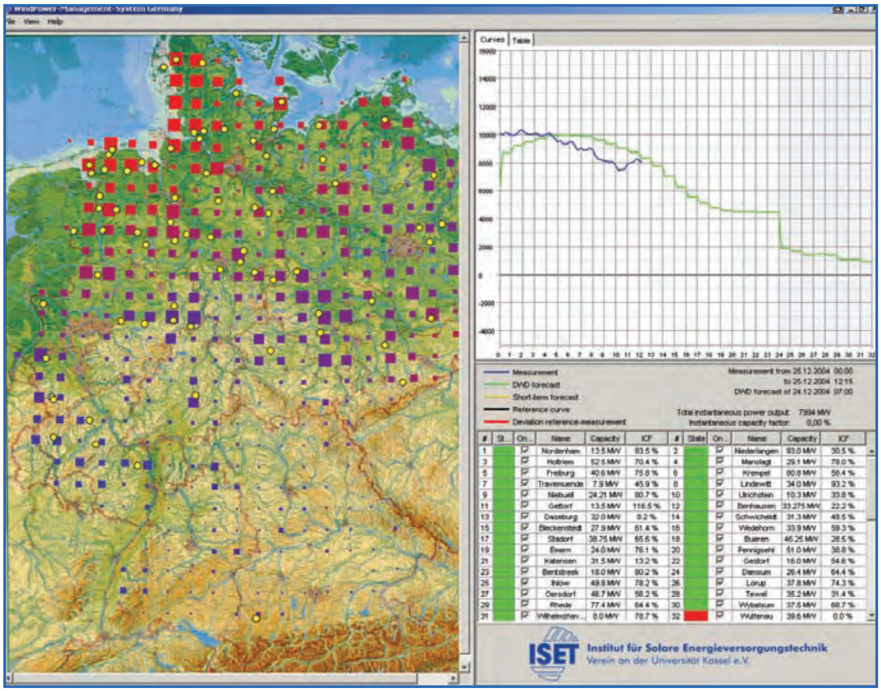

figure 1. Screenshot of ISET wind power management system (WPMS).

system operation. The third aspect is to assess the tools currently used to schedule, commit generation, and operate the system in real time, and then identify prospective approaches, algorithms, and operating procedures that can lead to more optimal reserve scheduling and operation in the face of increasing wind generation.

As will be discussed below, several challenges exist in the application of weather models to the prediction of wind facility output, such as the impact of local scale terrain and land use, how best to utilize outputs from multiple prediction models, and how to incorporate site-specific information such as directionally dependant array loss. A combination of technologies must be used to address these challenges, thereby reducing the forecast errors and the uncertainty in the forecast.

As the amount of wind energy production grows in proportion to the electric load and other resources in the generation portfolio, errors in wind generation forecasting can become very significant to operations, and accurate wind power forecasts will become increasingly important. The growth of wind across all three of Xcel Energy's operating systems is requiring a greater scrutiny and investigation into operational concerns, future resource timing and capabilities, and improvement in Xcel's predictive and forecasting tools to continuous provide reliable, lowest cost energy to customers.

It is also important to note that the issues related to wind integration can vary from one system to another. For example, the wind integration impacts on Xcel's Colorado system, where a large percentage of the generation is from gas, are somewhat different than those on Xcel's NSP system, where coal generation is on the margin. While gas units are generally more flexible in following load changes, uncertainty in the schedule of wind energy may impact the purchase and storage of gas for system operations. Unit commitment planning, gas purchasing, and unforced outage contingencies all require various lead times for cost and operational optimization. While wind energy brings economic and environmental benefits to the system, it also introduces some challenges, and wind forecasting is clearly one of the most direct and valuable ways to reduce the uncertainty of the wind energy production schedule for the power system.

Applications of Wind Power Forecasting

The most important application for wind power forecasting is to reduce the need for balancing energy and reserve power, which are needed to integrate wind power into the balancing of supply and demand in the electricity supply system; i.e., to optimize the power plant scheduling. This leads to lower integration costs for wind power, lower emissions from the power plants used for balancing, and subsequently to a higher value of wind power.

A second application is to provide forecasts of wind power feed-in for grid operation and grid security evaluation, as wind farms are often connected to remote areas of the transmission grid. To forecast congestion as well as losses due to high physical flows, the grid operator needs to know the current and future wind power feed-in at each grid connection point.

The objectives of a wind power forecast therefore depend on the application:

- ✔ For optimized power plant scheduling and power balancing, an accurate forecast of the wind power generation for the whole control area is needed. The relevant time horizon depends on the technical and regulatory framework; e.g., the types of conventional power plants in the system and the trading gate closure times.
- ✔ For determining the reserve power that has to be held ready to provide balancing energy, a prediction of the accuracy of the forecast is needed. As the largest forecast errors determine the need for reserve power, these have to be minimized.
- ✔ For grid operation and congestion management, the current and forecast wind power generation in each grid area or grid connection point are needed. This requires a forecast for small regions or even single wind farms.

Steps in a Forecasting System

In producing a wind power forecast, different steps can be distinguished:

- ✔ numerical weather prediction
- ✔ wind power output forecast
- ✔ regional upscaling.

As the first step, a weather prediction including the forecast of the wind speed and possibly some other meteorological parameters is needed for the wind power forecast. This is provided by numerical weather prediction (NWP) models.

The NWP data are used as input to the next step, the wind farm power output forecasting. This takes into account the local meteorological influences on the wind speed and direction, the power conversion characteristics of the turbine, wind farm shading, and other effects that influence the overall power output. Different approaches and combinations of approaches have been developed and are in use. For forecasts with a shorter time horizon, online measured wind speeds and/or wind farm power output are used as additional input to the forecasting.

If the forecast is needed for a larger region with very many wind farms or wind turbines, forecasts are compiled only for some representative wind farms and the results from these are scaled up to regional forecasts as a third step. This minimizes the effort involved in making the forecasts and reduces the amount of data needed from NWP models as input. The accuracy of the forecasts does not decrease much, since wind farms close to each other show a similar behavior.

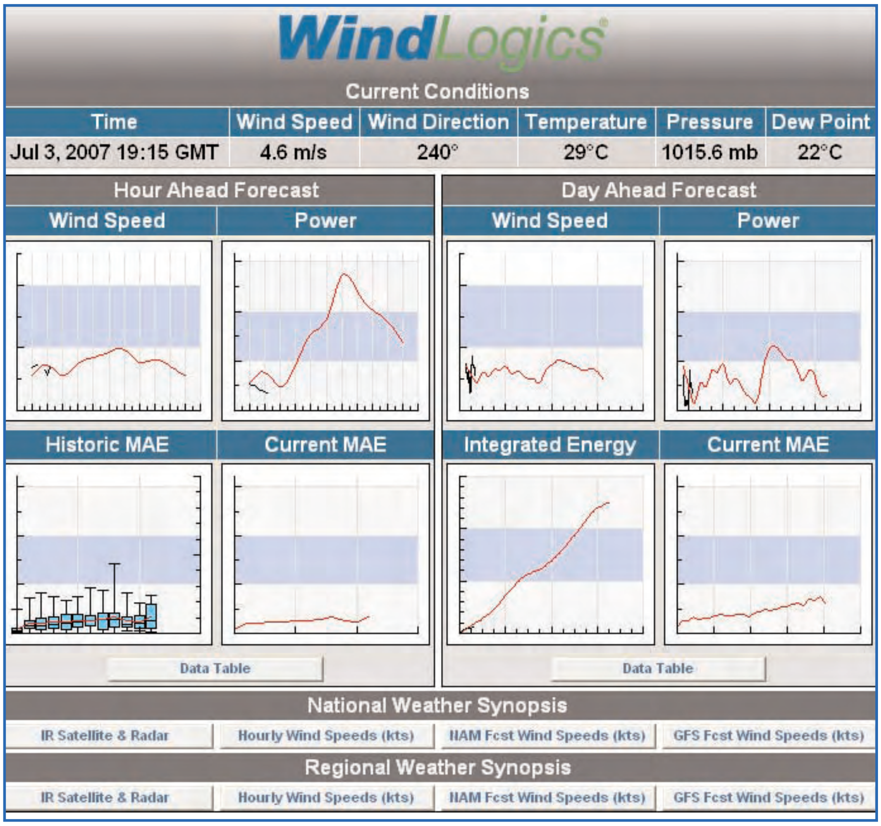

figure 2. Xcel energy wind power forecasting system screenshot.

Numerical Weather Prediction

Weather forecasts from NWP models are the most essential input needed for almost all wind power forecast models. Usually a model chain of hierarchical levels with different NWP models and increasing resolution is used.

The model chain starts with meteorological observations and measurements all over the globe, carried out by meteorologists, weather stations, satellites, etc. All available data are used as input to compute a global NWP model, which models the atmosphere of the planet. The NWP model calculates the future state of the atmosphere from the physical laws

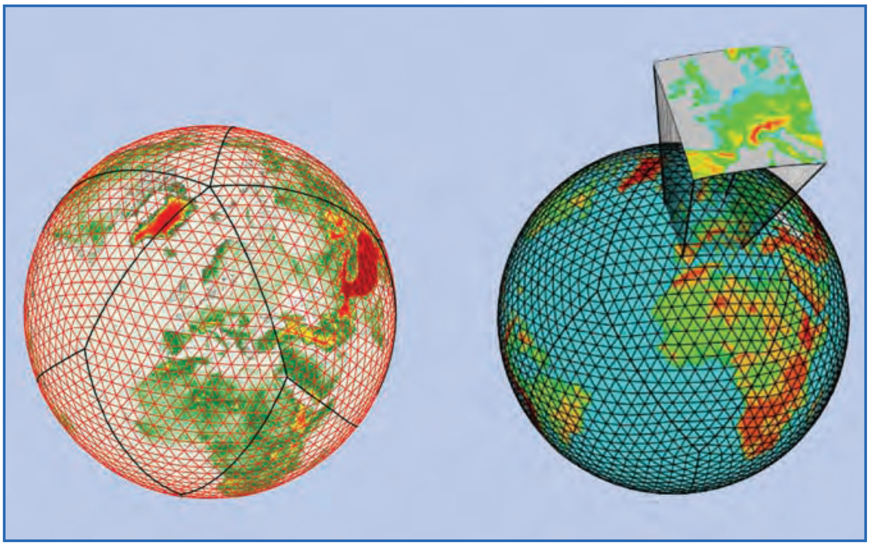

figure 3. Horizontal grid of a global numerical weather prediction model and enlarged area covered by a local area model (figures taken from the German Weather Service).

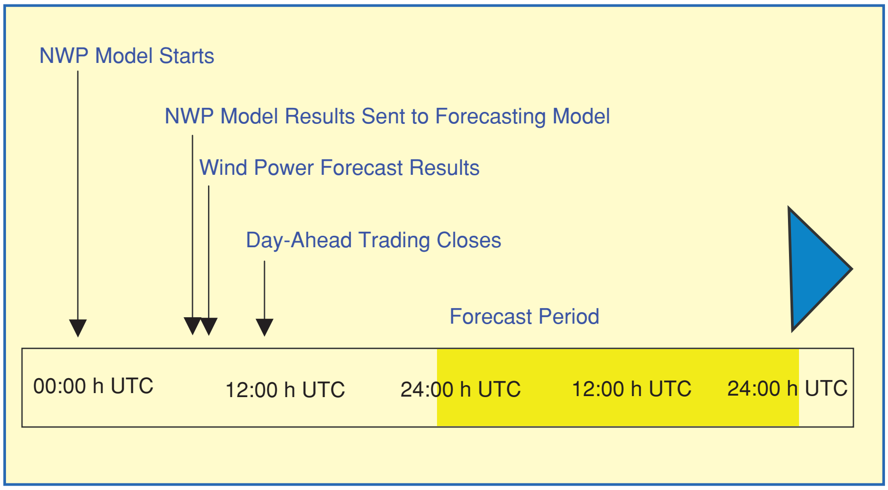

figure 4. Typical time schedule for wind power forecasting used for day-ahead trading.

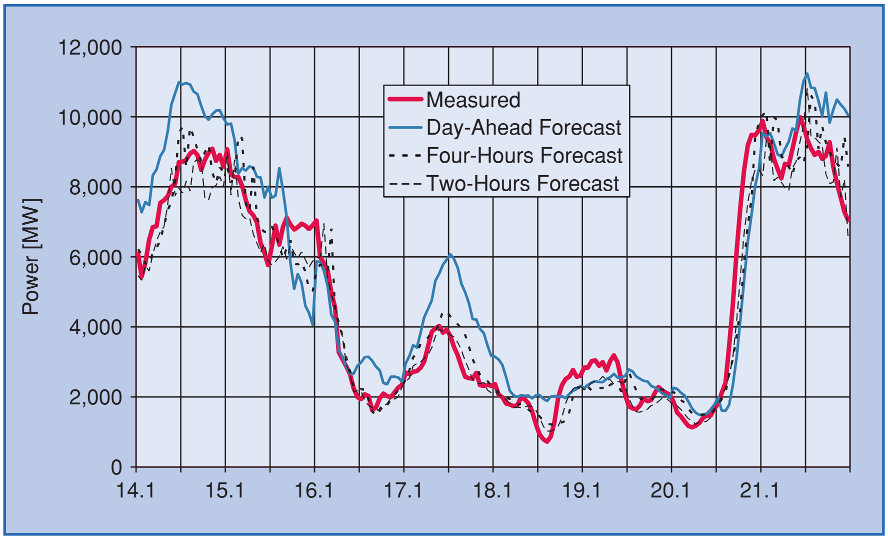

figure 5. Example time series of online measurement and forecasts of wind power generation in Germany; forecasts with different forecast horizons are shown.

governing the weather. Since these calculations are very computationally expensive, the resolution of a global model has to be rather coarse (see Figure 3, left). Global models are in operation at only about 15 national weather services.

To provide more accurate weather forecasts, local area models (LAMs) are used, which cover only a small part of the Earth, but can be run with a much higher resolution (see Figure 3, right). These models use as input the forecasts of the global model and calculate a weather forecast taking into account the local characteristics of the terrain.

One example of a LAM is the LME model of the German Weather Service (DWD). It covers central Europe with 105,625 grid cells (325 by 325). This leads to a horizontal resolution (cells size) of about 7 × 7 km. The forecast horizon of the operational model is 48 hours and the resolution is one hour. Model runs are started twice daily at 00 UTC and 12 UTC.

Different Approaches for the Power Output Forecast

The aim of a wind power forecast is to link the wind prediction of the NWP model to the power output of the turbine. Three fundamentally different approaches can be distinguished:

- ✔ the *physical approach* aims to describe the physical process of converting wind to power and models all of the steps involved
- ✔ the *statistical approach* aims at describing the connection between predicted wind and power output directly by statistical analysis of time series from data in the past
- ✔ finally the *learning approach* uses artificial intelligence (AI) methods to learn the relation between predicted wind and power output from time series of the past.

In practical applications the methods are sometimes combined or mixed. Methods using a physical approach almost always use data from the past to tune their models or use model output statistics (MOSs) for a correction of the result. On the other hand, approaches using statistical or AI methods often use knowledge of the physical processes, like the shape of the power curve, in designing their models.

The physical approach contains a chain of models of the different physical processes involved:

- ✔ wind conditions at the site and hub height of the turbines
- ✔ wind farm shading effects
- ✔ turbine power curve
- ✔ model output statistics.

Statistical approaches analyze the connection between weather forecasts and power production from time series of the past and describe this connection in a way that enables it to be used for the future.

Like statistical models, AI methods also describe the connection between input data (the predictions of the NWP model) and output data (wind farm power output). But instead of an explicit statistical analysis, they use algorithms that are able to implicitly describe nonlinear and highly complex relations between these data. For both the statistical and

AI approach, long and high-quality time series of weather predictions and power output of the past are of essential importance. Each of these approaches is used in practical applications.

Forecast Horizon

The forecast horizon is the time period between the time at which the forecast is available and the forecast point in time. Different forecasts are used for different purposes and their forecast horizons depend on the requirements of the user, stemming from technical and regulatory conditions and on the feasibility of forecasting.

For current wind power forecasting, deterministic forecasts are used up to a forecast horizon of three to five days. Two primary forecast horizons have to be distinguished: The day-ahead forecast and the very-short-term forecast. The day-ahead forecast is mainly used for day-ahead power trading. The forecast horizon therefore depends on the organization of the trading; e.g., the gate closure time and the trading days.

An example for a gate closure time of 1200 hours for the next day is shown in Figure 4. The NWP model starts running at midnight with the observations from the day before. It finishes calculation around 0700 hrs in the morning and sends the information to the wind power forecasting system. This usually has a very short calculation time and the results are available a few minutes later. They are analyzed and used for trading the power for the next day until at 1200 hrs the trading ends.

This means that the calculation of the forecast starts 48 hours ahead, counted from the start of the NWP model. If there is no trading on weekends and public holidays, lead time for the calculation for the "day-ahead" trading actually can be 96 hours or longer.

Very-short-term wind power forecasting is mainly used for intraday trading and activation of reserves. Its main characteristic is that it utilizes online data from measurements of actual power output and/or wind speed. For very short forecast horizons, this leads to a very important increase in forecast accuracy (see Figure 5). Usually NWP model data and online measurement data are combined for the short-term forecast, giving more weight to the NWP data for longer forecast horizons and more weight to online data for shorter horizons.

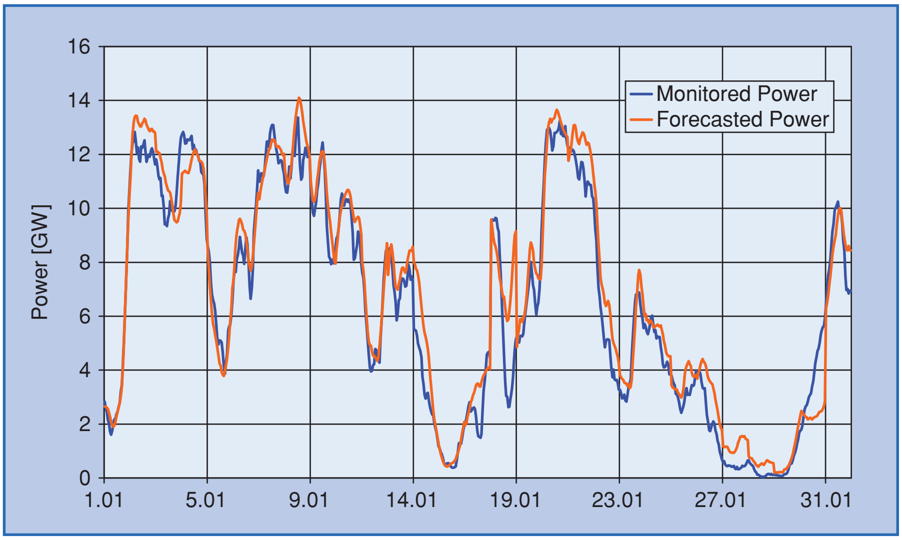

figure 6. Example time series of monitored and forecast power output for Germany.

Forecast Accuracy

The accuracy of a wind power forecast is of course the most important criterion for its quality and value. Figure 6 shows an example time series of the day-ahead forecast for Germany together with its monitored values for one month.

Since the forecast accuracy changes with time, a long time period has to be considered to evaluate the quality of a forecasting system.

The forecast error can be displayed in as a frequency distribution. Figure 7 shows an example using forecast data from a day-ahead forecast performed with ISET's wind power management system (WPMS) using NWP data from the German weather service.

"Learning Curve" of the Forecasting Accuracy

Since the WPMS forecasting system was first implemented in 2001, it has been improved constantly. The result is a continuous

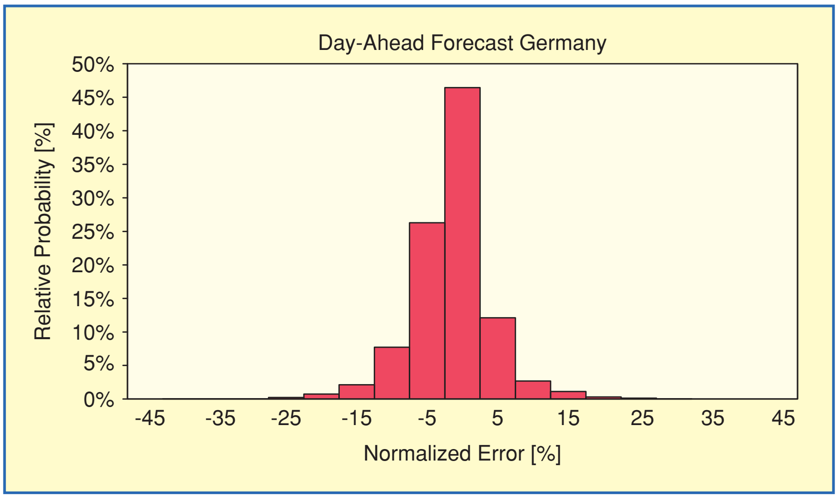

figure 7. Frequency distribution of the difference between forecast and monitored power output.

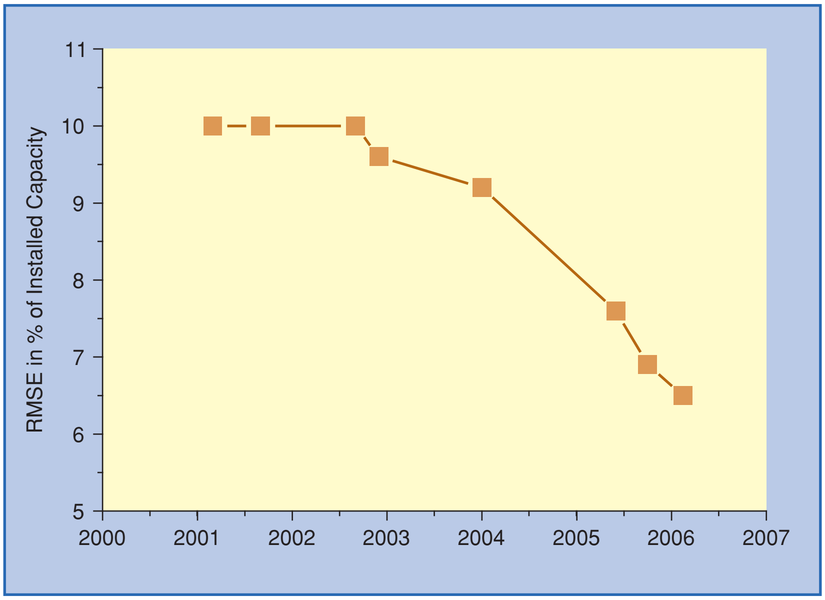

figure 8. Development of the forecasting error of the operational day-ahead forecast for a control zone; shown is the root mean square error of the forecast time series compared to that of the online monitoring.

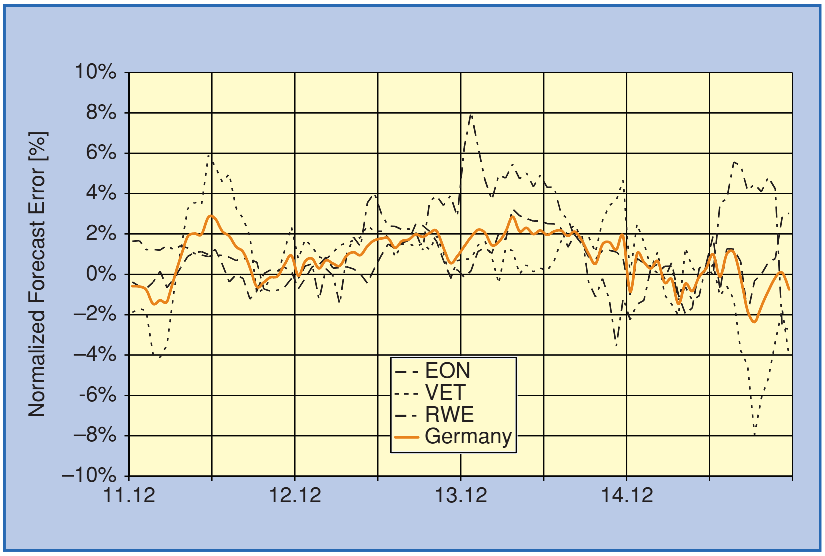

figure 9. Example time series of relative forecast error for the individual control zones of E.on, VET, and RWE, and for the whole of Germany.

reduction of the forecast error, resulting in a "learning curve" of decreasing forecast error over time, as can be seen in Figure 8, which shows the development of the forecasting error for the example of the E.on control area. The accuracy of the operational wind power forecast has improved from approximately 10% root mean square error (RMSE) at the first implementation in 2001 to an RMSE of about 6.5% in 2005.

Effect of Spatial Spread

If many wind farms are forecast together, the forecast error decreases and the aggregation of large regions with several gigawatts of installed capacity will lead to a decrease in the relative forecast error, since there will be cases where the forecast errors of different regions will partly cancel each other out. An example of this is shown in Figure 9. It shows the forecast error for the three German control areas with large wind power capacity (those of E.on, VE-T, and RWE) together with the error of the aggregated forecast for an example time series of four days. It can be seen that the forecast error for the aggregated wind power always stays below 2.5%, while the error for single control areas reaches up to 8% of the installed capacity.

Examples of Current Research

Multimodel Approach for Wind Power Output Forecast

To improve the forecast accuracy, other types of AI models were investigated in a comparative study. In detail, these were:

- ✔ artificial neural networks (ANNs) as reference
- ✔ mixture-of-experts (ME)
- ✔ nearest-neighbor search (NNS) combined with particle swarm optimization (PSO)
- ✔ support vector machines (SVMs).

Additionally we built an ensemble including all models. A comparative study between the different forecasting methods has been performed using power output measurements of ten wind farms in the E.on control area and corresponding NWP prediction data for these points from the German weather service. Figure 10 shows the comparison of the mean RMSE for the ten wind farms. It can be seen that the SVM yields the best results in this case. Also, a simple ensemble approach has been tested by averaging the outputs of the models studied. As can be seen in Figure 10, even this simple ensemble improves the forecast accuracy compared to the results of the single ensemble members.

Multimodel Approach for Numerical Weather Forecast Models

Up to now the usual practice of calculating wind power involved using only a single NWP model, with the risk of high and costly errors in prediction. Particularly in the case of extreme events, individual models can go wrong. In such cases improvements in

> Whenever possible, aggregating wind power over a large area should be performed as it leads to significant reduction of forecast errors as well as short-term fluctuations.

forecast accuracy bring decisive economic advantages in the face of high energy costs. Deviations in prediction do not occur simultaneously in all NWP models. Depending on the weather conditions, each has its own strengths and weaknesses.

A study to investigate the influence of merging different NWP models on the accuracy of the wind power forecast has been performed by ISET. Three different NWP models have been used for a day-ahead wind power forecast for Germany. All three models have been used as input to the WPMS based on the ANN method. A simple combination of the three models has been tested by averaging their forecasts. It can be seen that even this simple approach improves the forecast accuracy very significantly compared to the results of the single models. The resulting RMSE for the combined model for Germany is 4.7%, while the values for the individual forecasts are between 5.8% and 6.1%.

Following the idea of combination, the next step is to find an optimal combination of weather models with regard to different weather situations. Energy & Meteo Systems has developed a special procedure to automatically classify weather conditions. Consequently, the behavior of the models can be analyzed in typical weather conditions and an optimal weighting can be achieved in order to use the specific strengths of various weather models.

This project on forecast combination is jointly carried out by Energy & Meteo Systems, the German weather service DWD, and RWE TSO, one of the German transmission system operators. The project is supported by the German Ministry for the Environment. Data of NWP models from ten European weather services are used to calculate forecasts of the anticipated power production of wind farms. In order to be used in the combination, the physical wind power prediction system Previento is individually optimized for each NWP model and the characteristic behavior of the different forecasts is carefully analyzed. Based on these high-quality single forecasts, combinations are formed.

To find optimal combinations for specific weather situations, a classification scheme based on meteorological experience and automatic weather classification is used. With this advanced combination tool, the best weight for each meteorological model according to the prevailing weather situation can be determined. Choosing a combination of the best performing weather models for the specific situation leads to a significantly improved wind power prediction.

The results show that the combined wind power forecast significantly outperforms the best forecast based on a single weather model, as well as a simple fixed combination (Figure 11). In particular, in dynamic weather situations the combined forecast reduces large and costly forecast errors; i.e., it can be shown that the combination has most benefits for extreme situations (Figure 12).

The weather-dependent combination of numerical weather models has been implemented as a software tool and is running operationally at the RWE TSO.

Multischeme Ensemble Approach for Wind Power Predictions

Instead of using existing NWP models, Weather & Wind Energy Prognosis (WEPROG), based in Germany and Denmark, goes one step further and runs their own multischeme

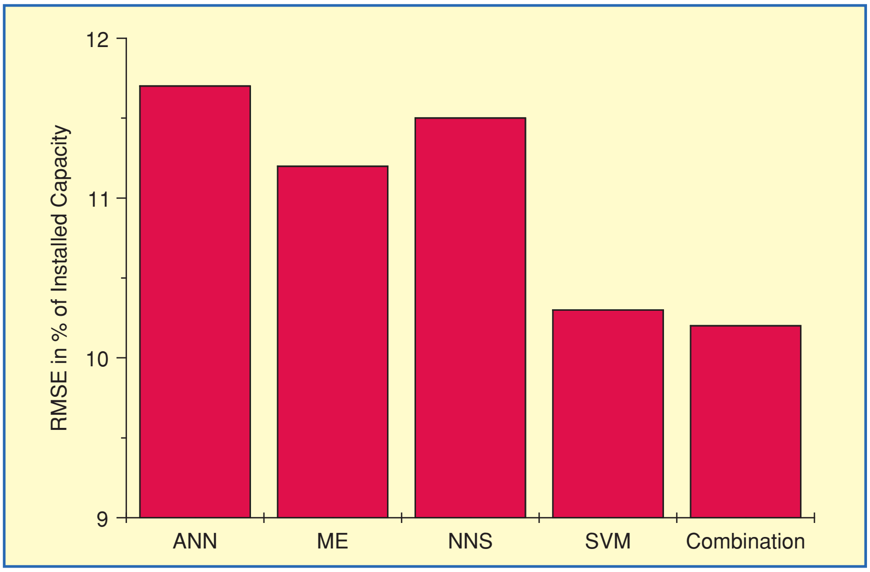

figure 10. Comparison of the mean RMSE of a wind power forecast for a group of single wind farms obtained with different AI methods and with a combination of all methods.

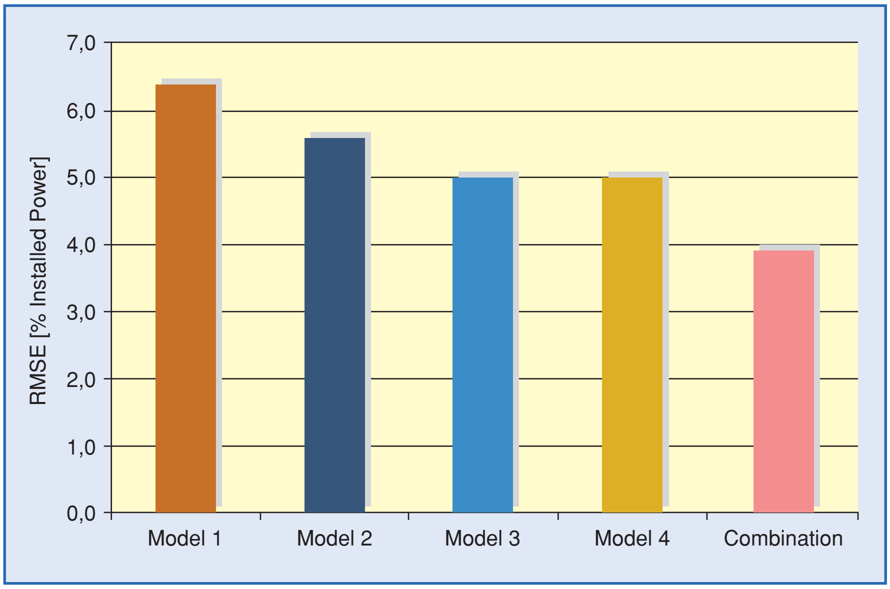

figure 11. Results from the weather-dependent combination of different NWP models by energy and meteo systems for the aggregated wind power production in Germany. The combination clearly outperforms predicitons based on one single model.

ensemble prediction system (MSEPS) as an integrated weather and wind power forecasting system.

The purpose of this system is to generate a best guess and especially probabilities of the evolution of the local weather.

The MSEPS contains 75 ensemble members, which are individual forecasts referred to as "members." They are formed with a multischeme approach. This means that each forecast member comprises a different set of equations for certain physical or dynamical processes (called the "parameterization schemes").

The ensemble approach is targeted to generate the uncertainty of the weather forecast. The differences in the equations lead to different methods of solving these equations and thereby generates different end results. Because all the equations used in the different forecast "ensemble members" are describing the same processes, but vary in their assumptions to make them solvable, they in fact describe the changing physical uncertainty of the weather forecast. Figure 13 shows an example on how the observed wind power changes within the uncertainty band over the forecast length.

As mentioned above, it is important to have knowledge of uncertainties of this forecast. A confidence interval of the forecast gives a quantitative measure of the possible deviation of the actual wind power from the forecast, depending on the meteorological input data for each time stamp. Beside the best guess of the actual wind power, the multischeme approach creates this uncertainty of the forecasts like the multimodel does. However, the disadvantage of the multimodel, the lack of knowledge about the exact differences of the models, does not apply to the multischeme approach.

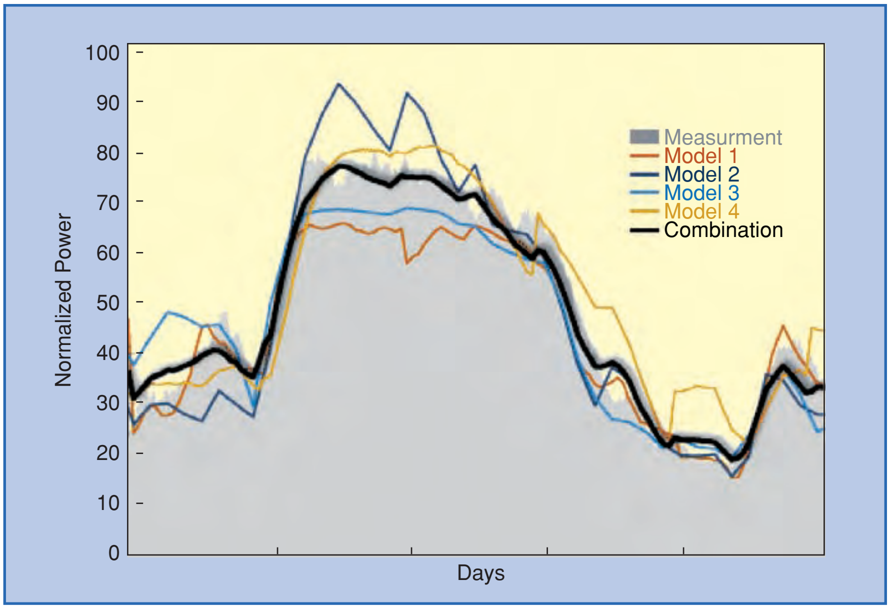

figure 12. Selecting the optimal combination of numerical weather models (same as Figure 11) for individual weather situations reduces the danger of large forecast errors in extreme events such as storm fronts.

The Use of Ensemble Data for Different Wind Power Prediction Methods

A recent study investigated the impact on the forecasting error of converting from meteorological parameters to wind power by using different data sets from the MSEPS ensemble. Six different methods were applied at different locations to convert wind and other weather parameters into wind power output.

The results of approximately one year of data showed forecast improvements relative to the most simple algorithm of 9% to 24%, dependent on the location and size of the forecasted area.

Hence, the forecast quality could be improved significantly

Wind forecasting is clearly one of the most direct and valuable ways to reduce the uncertainty of the wind energy production schedule for the power system.

for all investigated methods, from a relatively simple power curve conversion method to a more complex method, when making use of the additional information from the ensemble.

Another recent study by ISET developed a new wind power prediction model based on an artificial neural network (ANN) approach, where various combinations of ANNs with input from WEPROG's MSEPS ensemble prediction system were generated.

The statistical results at two selected wind farms showed that the improvement for the day-ahead forecasts by intelligently combining the ensemble data was approx. 10%. To conclude, combining the individual wind power forecasts derived from a physically consistent ensemble prediction system (multi-scheme approach) such as WEPROG's MSEPS does not only result in significant improvements compared to single forecasts, but has also the advantage of being a more cost efficient alternative to

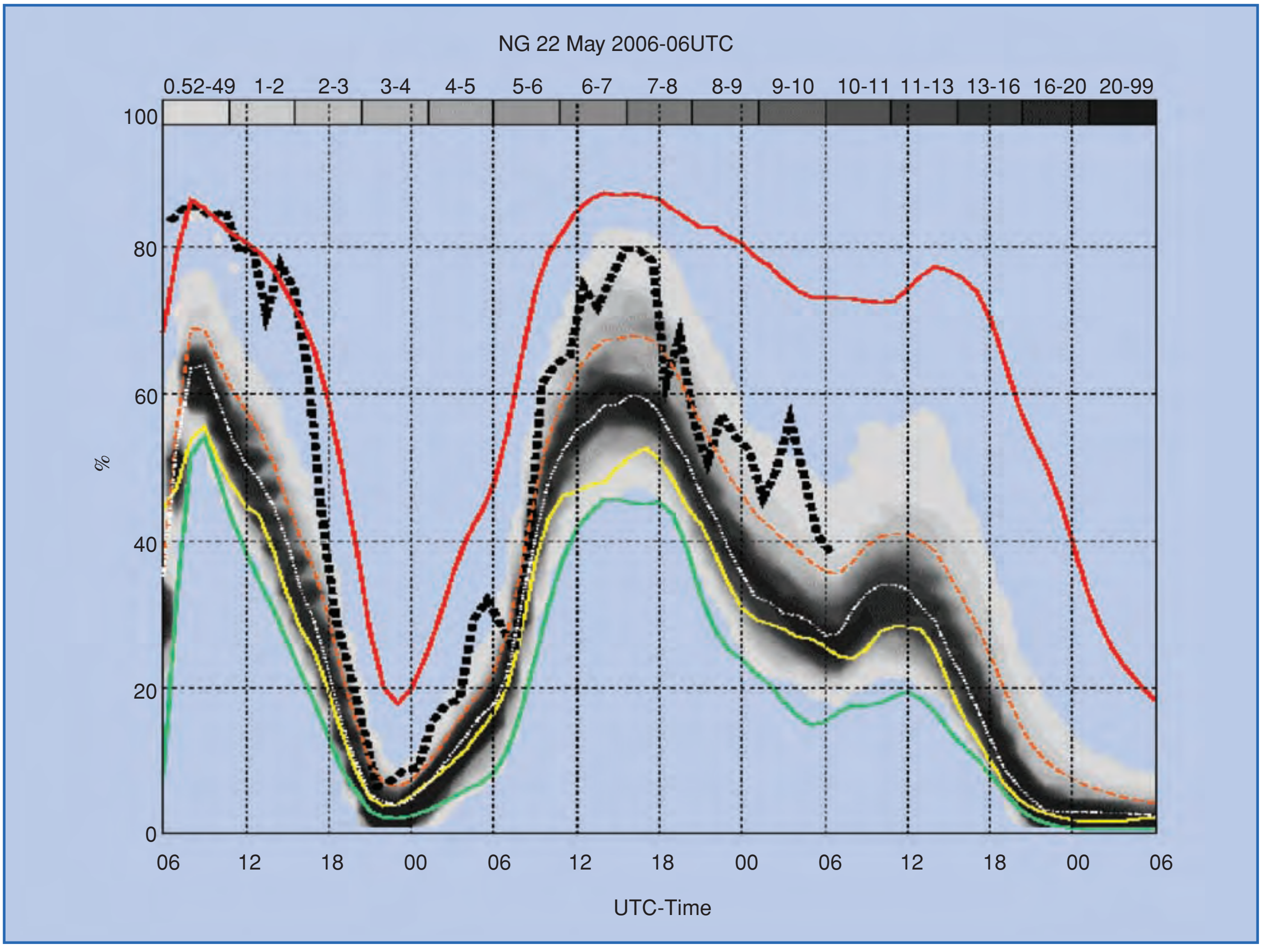

figure 13. Example of a 72-hour wind power forecast with changing uncertainty from WEPROG's MSEPS ensemble system for the national grid in Ireland (52 wind farms with 645-MW installed capacity). The black dashed line is the observation, the red line is the EPS maximum, and the green line is the EPS minimum. The orange line is the EPS mean, and the yellow and white dashed lines are best guesses with different emphasis on the end result; the gray shading indicates the probability distribution of the ensemble members: low uncertainty is dark and high uncertainty is indicated by light gray or no color.

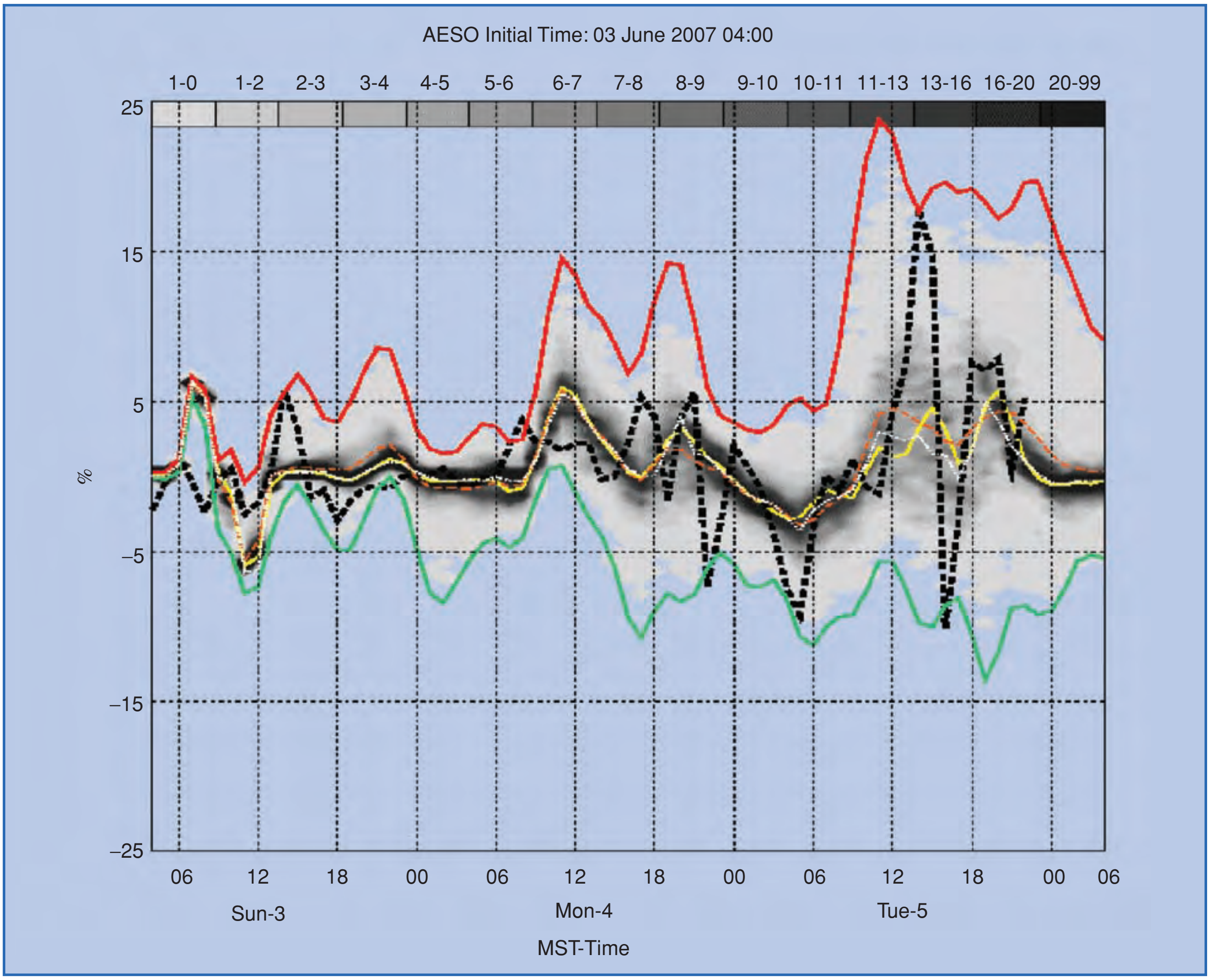

figure 14. Example of a ramp rate forecast for the pilot study of the Alberta transmission system operator.

the use of combination of forecasts from different NWP providers (multimodel approach).

Additional Applications from the Ensemble Information

Apart from improvements relative to single forecasts, the ensemble approach gives the opportunity to predict the reserve requirements from the uncertainty of the weather development and also the weather extremes that cause steep ramp rates of wind power. A wind power pilot forecasting study initiated by the Alberta Electric System Operator (AESO) compares three different forecasting methods on the single best forecast but also uncertainty estimates and ramp rate predictions in a one-year evaluation period. An example of such a ramp rate forecast over 72 hours is shown in Figure 14.

Future Challenges

As wind power capacity quickly grows, forecast accuracy becomes increasingly important. This is especially true for large offshore wind farms, where an accurate forecast is crucial due to the high concentration of capacity in a small area. Encouragingly, in recent years the forecast accuracy has improved constantly, and it can be expected that this increase can be maintained into the future. Anticipated improvements for the future include the following:

- ✔ The development of operational ensemble model systems using the data from several numerical weather prediction models will clearly improve the forecast accuracy. Also, an improved method for model combination will be developed.
- ✔ Improvements in the NWP models and more frequent updates of the weather predictions will improve the input data for wind power forecasting.
- ✔ Further improvements in the forecasting methods and improved methods for the combination of different forecasting methods can be expected to further reduce forecasting errors.
- ✔ Especially for short-term wind power forecasting, additional use of online wind measurement data has the potential for improved forecasts.

Forecast accuracy is only one of the challenges for wind power forecasting systems of the future. Additionally, the scope of systems will have to be extended to meet future challenges:

- ✔ Wind power forecast in the offshore environment has the potential to become more reliable than on land, if specific offshore forecast models are developed. The meteorological situation in the near-shore marine atmospheric boundary layer differs from that over land. The atmospheric stability and the distance to the shore have an especially important influence over the sea.
- ✔ Improved forecasts for short time horizons will be needed for grid safety and intraday trading.
- ✔ Prediction of the probability distribution of the forecasting error and reduction of events with large errors give the opportunity to reduce the reserve capacity for balancing wind power forecast errors.
- ✔ Forecasts in high spatial resolution for each grid node of the high-voltage grid will be needed for high wind power penetration, in order to tackle the problem of congestion management.

Conclusions

Due to increasing wind power penetration, the need for and usage of wind power prediction systems have increased during the last 10 or 15 years. At the same time, much research has been done in this field, which has led to a significant increase in the prediction accuracy recently. With many ongoing research programs in the field of NWP, as well as in the power output prediction models (transforming wind speed into electrical power output), one can expect further improvements in the future.

For the time being, three measures are taken as best practices to reduce prediction errors:

Combination: Combinations of different models can be done with power output forecast models as well as with NWP models (multimodel and multischeme approaches). Reductions in RMSE of up to 20% were shown with intelligent combinations.

Forecast horizon: As expected, a shorter forecast horizon leads to lower prediction errors. However, the organization of the electricity market as well as the conventional generation pool have a large influence on the needed forecast horizon.

Spatial spread: The forecast error depends on the number of wind turbines and wind farms and their geographical spread. In Germany, typical forecast errors for representative wind farm forecasts are 10–15% RMSE of installed power, while the error for the control areas calculated from these representative wind farms is typically 6–7%, and that for the whole of Germany only 5–6%. Whenever possible, aggregating wind power over a large area should be performed as it leads to significant reduction of forecast errors as well as short-term fluctuations.

For Further Reading

Parts of this paper have been taken with kind permission of the publisher from the book chapter B. Lange et al., "Wind Power Forecasting," in *Renewable Electricity and the Grid,* G. Boyle, Ed. Serling, VA: Easthscan, London, 2007, pp. 95–120.

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