Best Practice in short-term Forecasting. A users Guide

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Abstract

Short-term forecasting of wind power for about 48 hours in advance is an established technique by now. Any utility getting over a few percent wind power penetration is buying a system or a service on the market. However, once the system is installed and running day-to-day in the control room or on the trading floor, what is the best way to use the predictions? Which pitfalls are there to be aware of, and how can one maximise the value of the short-term forecasts? For this purpose, a workshop was organised in Delft in October 2006. The aim of the paper is to present the results of this study and analyse how practices are influenced by the initial choice of the prediction approach or prediction system, the level of penetration, the intended use of the forecasts, the acceptance operators may have for wind energy, the power system management tools or functions where the forecasts are used, and many more

1. Introduction

Short-term forecasting of wind power for about 48 hours in advance is an established technique by now. Any utility getting over a few percent wind power penetration is buying a system or a service on the market. However, once the system is installed and running day-to-day in the control room or on the trading floor, what is the best way to use the predictions? Which pitfalls are there to be aware of, and how can one maximise the value of the short-term forecasts?

Up to 15 years of experience with different forecasting systems have been built up in some utilities in Denmark and Germany, but also the Spanish, Dutch, Irish, Northern Irish, Greek, and some US and Australian ones have used forecasting now. However, the tips and tricks and general experiences from the control room have not been circulated to a wider audience yet.

For this purpose, a workshop was organised in Delft in October 2006. The aim of the paper is to present the results of that workshop and analyse how practices are influenced by the initial choice of the prediction approach or prediction system, the level of penetration, the intended use of the forecasts, the acceptance operators may have for wind energy, the power system management tools or functions where the forecasts are used, and many more.

Out of the experience of the forecasters comes a more basic guide for new users how to choose the right model for their application. This is in part based on the report on the State-of-the-Art in Short-term Prediction written for the Anemos project [2], but also on the technical issues different from case to case. The proper way to assess prediction performance is also addressed in the report.

Usually predictions are not used in an automated way as can be the case for load forecasts. Given the uncertainty they involve, users need to develop expertise on the optimal decisions to make as a function of the current or expected power system state or market conditions. Therefore, there is a need emerging to fully integrate predictions and information on their uncertainty in management functions (i.e. unit commitment, economic dispatch, reserves estimation etc.). The accumulated expertise on using predictions should not be neglected in this process.

2. Short-term prediction – an overview

Requirements for prediction models cover mainly five timescales:

- Ultra short-term: **Seconds** range. Such predictions are useful for controling wind turbines when some form of active control is available.
- Very short-term: **minutes** range (1-10 minutes ahead up to one hour) for functions such as dispatching, load following etc.
- Short-term: **hours** range (0 up to 6-8 hours). Such predictions are useful for pre-dispatch, scheduling in small size power sustems etc.

- Medium term: **days** range (0 hours up to 7 days ahead). Such predictions are useful for functions such as pre-dispatch, unit commitment, trading in electricity markets and even maintenance planning.
- Long-term: **weeks** range. This range includes applications that can range from 1-2 weeks for maintenance planning up to months for hydro-storage planning. Some end-users require predictions even up to 2 years.

Not many applications are found for time scales other than the short and medium term ones. For ultra short-term usually persistence is used, but the most promising approach is to directly measure the wind field upstream of the turbine with remote sensing, eg with a Lidar. For very long term usually regression models based on climatology and analysis of historical measurements can be used.

Short-term prediction of wind power for grid scheduling purposes was established in its current form including Numerical Weather Prediction ca 1990 by Lars Landberg of Risø National Laboratory. His model, now called Prediktor (www.Prediktor.dk) was used operatively by some Danish TSOs from 1993, while the other Danish TSO started to use the Wind Power Prediction Tool WPPT developed at the Technical University of Denmark in 1994. Denmark was the first country to get significant wind power development, therefore it is not surprising that short-term prediction started there first. Early operational wind forecasting applications appeared within Energy Management Systems developed for the management of isolated power systems with wind farms such as the Lemnos (1994) and Care (1996) projects. Some German TSOs (Transmission System Operators) started to use short-term prediction ca 2000, using a model developed by ISET. At this stage, the market for short-term prediction systems was quite small, but as more and more wind turbines were installed in the leading countries, these started to have sizeable penetration as well, and started to use short-term prediction systems, usually supplied by a national company or university. Now, short-term prediction is in use by many TSOs around the world, and being installed in a few more.

Additionally, some electricity markets require the wind farm owners to get their own wind power forecasts to be able to sell to the market. This set-up obviously leads to large competition for customers of short-term forecasting services, and to many short-term prediction providers.

In the beginning, short-term prediction was used mostly for power plant scheduling and security of supply. In the process of unbundling of the electricity supply, especially in Europe, markets were instantiated, and wind power was traded alongside other power on those markets. Therefore, the money was aligned on the lead times dictated by the markets. In many markets, the most important time scale is next day, traded at noon, or +13 to +37 hours lead time.

Currently there is a wealth of models (>50) either at research or at commercial level. Of the commercial models, two modes of operation have to be distinguished: the models can be installed at the premises of the client and run operationally by the client, or the model can be run by a service provider taking over the task of dealing with the NWP and just reporting the final result to the customer, often as email or web pages / services.

3. Reliability of prediction tools.

The provision of very short-term predictions can be quite critical in terms of operational application since if some error appears in the process the short time frame does not permit human intervention. For this, it is needed to have adequate IT infrastructure and redundant servers to meet high reliability requirements. Delivery of medium-term forecasts may be critical also for the functions where they are destined such as market participation. Enhanced IT infrastructure is also needed to meet reliability of the service.

Errors in the process can be due to:

- <u>Failure of SCADA system</u> or communication system with the wind farm. In that case it is necessary to have functionalities to detect such errors and to have alternative models available that do not use on-line SCADA data as input. It is noted that the problem is amplified if one uses multiple data sources. For this reason, the classic principle of parsimony in prediction models acts favourably to anticipate such situations.
- <u>Failure of NWPs delivery</u>. The simple remedy is to use predictions delivered in a previous cycle of the NWP model if the NWP horizon is sufficiently long to permit that. For critical applications it is obvious that the provision of NWPs by alternative providers can solve the problem.
- <u>Failure of wind power prediction models</u>: The reason for this can be a not robust enough implementation that makes that the model gives unacceptable or not at all output. In that case it is worth to have alternative models and also base-line robust models available as alternatives. For critical applications, it is necessary before launching a model operationally to test it extensively at a pre-production mode.
- Other sources of problems may be security problems, database problems, bugs in the software, problematic graphical user interfaces etc.

It is obvious that for critical applications it is important to have reliable and well tested prediction systems. A good practice is to ask for an exhaustive reference list and collect information from the clients of the provider.

4. Accuracy of prediction models.

The accuracy of short-term prediction has improved on the whole during the last years. For wind farms in not too complex terrain, a Normalised Mean Absolute Error NMAE of around 8% for the day-ahead forecast is attainable, while for wind farms in complex terrain, a NMAE of up to 20% and even above is not uncommon. The Anemos project did for the first time show results from several state-of-the-art short-term prediction models run for identical test cases. In order to compare the results reasonably, Madsen et al. [5] defined the most common error measures. Some aggregated results are shown in Figure 1, where the average NMAE of 12 models is shown for the six test cases according to their Ruggedness IndeX RIX, which essentially is an objective measure of the complexity of the terrain.

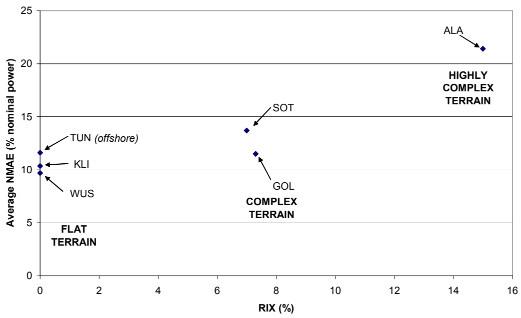

Figure 1: *Average NMAE for 12 hours forecast horizon vs RIX at each test case. Qualitative comparison.*

In a typical short-term prediction model, the largest source of error is the NWP input. Within the weather forecast, the largest error possibilities are due to the (limited) horizontal and vertical resolution of the model, the number of weather observations used (especially upstream) and the quality of the data assimilation, plus the actual model physics as well. The limited horizontal resolution is especially important in complex terrain, which is why wind farms in mountains and to some extent, near-shore conditions, show typically higher errors than wind farms in easy terrain.

On the side of the actual short-term prediction model, typical error sources are the power curve modelling and the taking into account of the stability of the atmosphere.

The error can be one of two forms: a level error, where the wind power production does not reach or exceeds the amount which had been forecasted, and a phase error, where eg. the onset of a storm is predicted correctly in shape, but at the wrong time. Of course, both errors rarely occur completely separate, but the error of a particular forecast is a composite of both.

The following are typical, recommended ways to reduce the above mentioned error sources:

- **Use several NWPs.** It has been shown that the use of two (or more) NWP feeds not only increases the resilience of the application, but also improves the accuracy of the forecast. The more different the NWP models, the better. This goes not only for the model physics of the actual model doing the forecast, but also for the global model which drives it. For example, many European models are driven by the global model from ECMWF. The largest improvement is achieved by mixing one of those with NWP output of a model using a different global model as input, eg the one from Deutscher Wetterdienst, which runs its own global model.
- **Use several forecasting models.** The above said is also true for a mix of short-term prediction models, especially mixing a physical model to a statistical model.
- **Aggregate your forecasts.** Due to smoothing effects, the prediction for several wind farms is always more accurate than the predictions for a single wind farm. This is due to two effects: the errors in the predictions are only partly correlated, and due to the only partly correlated production of the wind farms themselves, which leads to a less variable production, which is easier to predict.
- **Use shorter horizons for the trading.** If your application is trading, then try to use shorter markets for the trading, as the accuracy of the forecast is better. Especially going down from the typical day-ahead forecasts to a look-ahead time of only a few hours increases the accuracy quite substantially.

Another point worth mentioning is the dependence of the accuracy on the trading strategy. Predictions produced for participation in an electricity market do not necessarily represent the optimal expected value of wind generation. This is because they can be biased because of the perception the energy trader might have for the risk related to the participation to the market (i.e. deviations from the contract). For this reason, a particular energy trader might want to always bid low, to be sure to have enough wind power available. For this reason, it is preferable for TSOs, when the aim is power system operation, to avoid using forecasts that come from market participants (i.e. wind energy producers). The safest practice is that the TSO makes its own forecasts for each wind farm or for the total wind generation in its area to guarantee optimal accuracy.

5. Uncertainty estimation

The majority of operational prediction tools were initially designed to provide deterministic forecasts, in the form of a unique value for each hour of the prediction horizon. As wind penetration increases, end-users require complementary information on the uncertainty of such forecasts. Uncertainty estimation is for wind power forecasting is a relatively new field developed in the last 6 years. At early stages some simple approaches were assuming Gaussian distributions for prediction errors, which is erroneous. Lately more elaborate methods have been developed that are appropriate for the particularities of the wind power application. Operational modules for on-line uncertainty estimations are integrated in tools like Anemos for providing prediction intervals with predefined levels of confidence. The state of the art moves to fully probabilistic models that are able to predict directly the predictive probability density functions for each time step ahead of the prediction horizon.

It is necessary to consider that uncertainty estimation is provided by mathematical models and they should be subject to extensive validation as such in similarity to power prediction models. Often this is neglected since uncertainty estimates are considered as a simple result of statistical treatment of prediction errors. More precisely, if a model is designed to provide prediction intervals of 80 %, this means that operationally ~80% of times the measured value should lie within the these intervals and not 70 % or 90 %. It is thus important to know what is the theoretical approach behind the on-line uncertainty estimation tool and how this approach has been evaluated.

In practice, a question that arises is what is the best level of confidence to consider i.e. for taking decisions or for visualization purposes. Unless the decision making tool suggests a specific level of confidence, then it seems that a good compromise is to take intervals of 80-85%. Lower than this would give too many measurements falling outside. Higher than 85 %, would result to too wide intervals with no practical value for decision-making.

Among the challenges of uncertainty estimation one can consider the problem of regional forecasting. In applications with several wind farms one cannot add prediction intervals of individual wind farms to have intervals for the sum of wind farms. The quantiles of the prediction have to be calculated specifically for the new aggregate.

It is noted that when ensemble predictions are provided as forecasting product, it is necessary to have appropriate methods to calibrate and convert ensemble power predictions to predictive distributions that can be then used to produce prediction intervals or other quantities expressing uncertainty.

In addition to conventional approaches for uncertainty estimation, new complementary tools are proposed today for predicting the level of uncertainty in the form of prediction risk indices. Such indices may indicate what is the expected predictability for the future period considered based on ensemble forecasting. Prediction indices are well documented in several publications of Anemos project and are actually under demonstration for evaluating the benefits from their use [6].

Even in the case uncertainty can be provided it can be rarely considered as input in an automatic way in decision-making tools. This is because such tools are often based on deterministic approaches in which uncertainty of wind power predictions is considered in a simplistic way. Development and demonstration of operational tools based on a stochastic paradigm is one of the R&D priorities in projects such as Wilmar or Anemos.plus.

6. Views of end-users

The following are views of end users presented on the workshop 'Best practice in the use of short-term forecasts of wind power' in Delft in 2006. The presentations are (as pdf) available from powwow.risoe.dk/BestPracticeWorkshop.htm.

6.1 TSO of an Island System

Manolis Thalassinakis, PPC Greece (Crete): Public Power Corporation PPC is (among other duties) the system operator for the island of Crete. Between 1965 and 2005, demand increased from 22 to 560 MW peak, i.e. 8% a year. Due to the small extension of the island, wind power gradients occur in most parts of the island at the same time. This leads to >50% of total installed capacity gradients over 20 minutes in 8% of the year – therefore spinning reserve has to be at minimum 50% of the forecasted wind power. Wind power penetration swings between 10 and 17% on monthly basis.
Security of supply, power quality and economic operation of the system are (often) conflicting demands on the TSO. In order to achieve a workable compromise, 20-min forecasts for spinning reserve allocation are used. Additionally, for network and unit maintenance planning 5-day forecasts are used.

6.2 TSOs of interconnected systems

Gerardo Gonzalez Morales, REE (ES): Spain is now the country with the second largest installed base of wind power. Unlike Denmark, where the penetration is still much higher, Spain is not very well connected to the neighbours, which means that imbalances have to be caught mainly within their own network. Red Eléctrica de España (REE) uses the Sipreólico tool developed by University Carlos III de Madrid. From the system operators point of view, the general experiences with wind power are: no influence on primary (20-sec) and secondary (2-min) control, but on tertiary. In Spain, all wind farm owners have to provide their own prediction – but the sum of those predictions is usually worse than Sipreólico. The differences can easily be over 600 MW, so the question for the TSO is, what to believe? Recently, with the large number of installations, the maximum wind power gradient in the grid reached 1 GW/hr – therefore, REE starts to use 15-min updates of the forecasts.

Doireann Barry, EirGrid (IE): The Republic of Ireland plus Northern Ireland have one of the best wind resources world-wide, and soon also large quantities of wind power: On the 6 GW grid, the currently installed

and the new applications add up to 4.5 GW. At the same time, Ireland is only very weakly connected with the rest of the world, and even internally has bottlenecks between the Republic of Ireland and Northern Ireland, and between the wind-rich north-west and the population centres on the eastern coast. In November 2007, both part-grids will operate under the same market. Frequency is a problem for Eirgrid, the Irish TSO: the maximum gradient for the installed wind power was 39% on 2 hrs. In order to deal with this, they develop a unique management technique, the so-called Wind Following Capability. This is a 'reserve' type service that ensures that adequate ramping capability is dispatched to cover for potential increases and decreases in wind output over varying time scales.
Eirgrid currently uses forecasts for 4 regions, but will eventually cover the whole grid. The forecasts are used for generation and interconnector schedule.

6.3 Wind energy traders

Clemens Krauß, EnBW Trading (DE): At the trading arm of a German TSO, they use three different prediction systems, all of which got better during the last two years. They conclude from this development that competition improves forecasts. Frequent intraday updates of predictions make it possible to use intraday trading, in order to exploit the smaller forecast error on the shorter horizons. They also benefited from meteorological training for the operators, and from a meteorological hotline for special cases. They also perform an explicit consideration of changing uncertainty for dispatch. One main recommendation was to **balance load and wind together**, as the load error is larger than the wind error (at least for current penetration levels), and both errors are uncorrelated.

Frank Hochmuth, NUON (NL): The Dutch utility NUON is balance responsible, but it has own generation and own customer, ie load. The best is to balance the two together, as at least some of the time, the forecast errors are in opposite directions. The price on the Amsterdam Power Exchange APX drops with increasing wind speed (2005) due to the amount of wind power being traded on the APX. As power plant efficiency goes down for part-load, the value of grey power decreases with more wind on the system.
Very little power storage (e.g. hydro) available in NL – this would help in making wind power more valuable. Increased day-ahead forecast accuracy helps reducing imbalance cost and leads to a better use of grey power assets. On their wish list was an increased opportunity to trade in form of an intraday APX, and to do own import or export.

7. Best practice

Some major results of the workshop were:
- Competition improves accuracy.
- The value of accurate wind power predictions is appreciated.
- The market for wind power prediction models is mature, with many service providers.

The Best Practice in the use of short-term forecasting of wind power can be summarised as:

- Get a model
- Get another model (NWP and / or short-term forecasting model)
- Balance all errors together, not just wind
- Use the uncertainty / pdf
- Use intraday trading
- Use longer forecasts for maintenance planning
- Meteorological training for the operators
- Meteorological hotline for special cases

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