The state of the art in short term prediction of wind power - from an offshore perspective

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The State of the Art in Short-term Prediction of Wind Power - From an Offshore Perspective

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Abstract

Nowadays, the installed wind capacity in Europe has reached 30 GW while end-users, such as transmission system operators, use already operational tools to predict the wind production up to 48 hours ahead especially in countries with high wind development. Prediction tools are recognized as helpful for a secure and economic management of a power system. Especially, in a liberalized electricity market, they enhance the position of wind energy compared to easily dispatchable generation.
The paper presents the state of the art wind power forecasting techniques, their performance, as well as their value for the operational management or trading of wind power. Emphasis is given to the current developments of wind power prediction models to meet offshore specificities. Finally the main research projects in the area are presented.

Keywords: Wind power, short-term forecasting, offshore.

1 Introduction

The capacity to manage efficiently wind integration into a power system depends primarily on the predictability rather than the variability of wind generation. Wind power forecasting is currently recognized as a cost efficient solution able to provide adequate information on the production of wind parks in the next hours up to the next days. Increasing the value of wind generation through the improvement of prediction systems' performance is one of the priorities in wind energy research needs for the coming years [1]. Such forecasts can be used for:

- Optimisation of the management of a power system by functions such as economic dispatch, unit commitment, dynamic security assessment, reserves allocation, power exchanges with neighbour systems, hydro storage planning etc. The prediction horizon depends on the size of the system and the type of conventional units. For interconnected systems or for large isolated systems with "slow" units (i.e. steam turbines) it is typically 48 to 72 hours. For small autonomous systems including only fast units, such as diesel gensets or gas turbines, the horizon can be in the order of 3-6 hours. Only few on-line applications of this type currently exist, mainly in island systems. A project that has developed tools for isolated systems is the European project MORE-CARE [2].
- Optimal trading of wind production in an electricity market. Participants in the market (energy service providers, energy traders, independent power producers etc.) must provide their generation schedule for the considered horizon while deviations from this schedule impose penalties. Short-term wind forecasts permit to minimise these penalties. The time-scale of interest is defined by the market rules but horizons lie usually within 48 hours ahead.
- Additionally, longer time scales would be interesting for the maintenance planning of large power plant components, wind turbines or transmission lines. However, the accuracy of weather predictions decreases strongly looking at 5-7 days in advance. Such systems are only just now starting to appear [3, 4]. Nevertheless, as Still [5] reports, also shorter horizons can be considered for maintenance, when "it is important that the crew can safely return from the offshore turbines in the evening".

This paper aims at giving an overview of the available forecasting techniques and of their level of performance. It also presents the actual research efforts for the adaptation of existing forecasting methodologies to offshore as well as the studies that are carried out to better understand offshore specificities.

2 Description of the wind power forecasting techniques

2.1 Definitions

The wind power forecast made at time origin t for a look ahead time $t+k$ is the average power $\hat{p}_{t+k/t}$ the wind farm is expected to produce during the considered period if it would operate under an equivalent constant wind. Forecasts are made for a horizon T indicating the total length of the forecast period (usually 48 hours ahead) in the future. The time resolution of the forecasts is denoted by the time-step k. The length of the time step (number of minutes) is related to the length of the horizon. Usually for horizon in the order of 24-48 hours the time step is hourly. Intra-time-step (i.e. intra-hourly) variations of power and their impact are not considered. This convention comes also from the fact that Numerical Weather Predictions (NWPs) of wind speed that are often used as input, are given as constant values for the step ahead considered (i.e. next hour). Note that for very short horizons (<4-6 hours), pure time-series models relying only on on-line production data are able to give forecasts with a time resolution of 10-15 minutes.

In practice, and following the above conventions, the value for the measured power p_t is derived from averaging higher resolution measurements (i.e. each 1 min or 10 min etc.), which can be instantaneous power values or energy ones depending on the acquisition system.

The prediction error is defined as:

$$e_{t+k/t} \;\equiv\; p_{t+k} - \hat{p}_{t+k/t}. \tag{1}$$

Often it is convenient to introduce the normalized prediction error:

$$\epsilon_{t+k/t} \;\equiv\; \frac{1}{P_n}\big(p_{t+k} - \hat{p}_{t+k/t}\big), \tag{2}$$

where P_n is the installed capacity of the wind farm. The normalization enables comparisons of prediction errors related to wind farms of different installed capacity. It is noted that Equation (1) gives the formal definition of error in time-series analysis theory where a positive error means under-prediction of power while a negative one means over-prediction. This is contrary to the intuitive feeling one would have for the error.

2.2 Reference models

It is worthwhile to use operationally an advanced tool for wind forecasting only if this is able to outperform naïve techniques resulting from simple considerations without special modelling effort. Such simple techniques are used as reference to evaluate advanced ones. The most commonly used reference predictor is Persistence, which states that the future wind generation will be the same as the last measured power value, i.e.

$$\hat{p}^{P}_{t+k/t} = p_t. \tag{3}$$

According to the above definition the error for zero time step ahead is zero. Despite its apparent simplicity, this model might be hard to beat for the first look-ahead times (up to 4-6 hours). This is due to the scale of changes in the atmosphere, which are relatively slow, in the order of days (this is true for the case of Europe). It takes about one or three days for a low-pressure system to cross the continent. Since the pressure systems are the driving force for the wind, the rest of the atmosphere has time scales of that order. High-pressure systems can be even more stationary, but they are not associated with high winds and so not really interesting for wind power prediction.

A generalization of Persistence model consist in using the average of the last n measured values:

$$\hat{p}^{MA,n}_{t+k/t} = \frac{1}{n}\sum_{i=0}^{n-1} p_{t-i}. \tag{4}$$

Such models are often referred to as moving average predictors. Asymptotically (as n goes to infinity), they tend to the global average

$$\hat{p}^{0}(t+k|t) = \overline{p_t}. \tag{5}$$

where $\overline{p_t}$ is the average of all the available observations of wind power at time t.

This last one, which is the climatologicaly mean, can also be seen as a reference model, but since it is not dynamic, its performance may be very poor for the first prediction horizons. However, for further look-ahead times, its skill is far better than the one of Persistence. The performance of Persistence and the mean as prediction models has been analytically studied in [6], where it is shown that for longer horizons, the climatology model is twice as good as Persistence. Consequently, Nielsen et al. proposed to merge the two models in order to get the best of their performance over the whole range of prediction horizons. The merging yields a new reference model:

$$\hat{p}^{NR}_{t+k/t} \;=\; a_k p_t + (1-a_k)\overline{p_t}, \tag{6}$$

where a_k is defined as the correlation coefficient between p_t and p_{t+k}.

The drawback of this new reference model is that the a_k have to be estimated based on some assumptions. Though, this is in disagreement with the definition given for a reference model, and this is probably why this model is not really used in practice as a reference by the wind power forecasting community.

2.3 The mainstream approaches

As mainstream are characterised the wind power forecasting approaches that involve Numerical Weather Predictions (NWP) and eventually measurements as input. These are the only approaches capable of providing acceptable accuracy for the next 24-48 hours. Alternatively, models receiving only measurements as input (wind power, speed etc) can be built. However, the performance of such models can be acceptable only up to 3-6 hours ahead. For longer horizons the inclusion of NWP data is necessary. The inclusion of measurements as input to the mainstream approaches, together with NWPs, contributes to their good performance in the first slot of the prediction horizon (0-6 hours). Models involving only NWPs do not outperform Persistence in these first hours.

Two different schools exist w.r.t. short-term prediction: the physical and the statistical ones. In some systems, a combined approach of both is used, as indeed both approaches can be needed for successful forecasts.

2.3.1 The physical approach

In short, the physical models try to use physical considerations as much as possible to reach the best possible estimate of the local wind speed before using Model Output Statistics (MOS) to reduce the remaining error. The basic input to a physical model is:

- **dynamic information**: Numerical Weather Predictions for the next hours given by a meteorological service; rarely on-line measurements are used for adapting the MOS part,

- **static information**: description of the wind farm installation (number of turbines, power curve, etc.); description of the terrain including orography, roughness, layout of the wind turbines, and obstacles.

The basic operating chain of a physical model is composed by the steps shown in Figure 1:

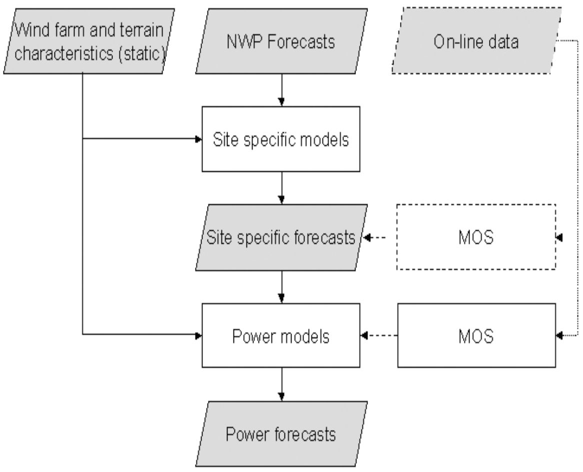

FIGURE 1: *The basic steps of the prediction systems based on the physical approach. MOS may be used after the site-specific modelling step or after the curve model, the latter being more common.*

Site-specific modelling - Downscaling

The NWP system (meteorological service) usually provides wind speed forecasts for a grid of surrounding points around the wind farm. According to the type of NWP system, these forecasts are given with a spatial resolution of a few kilometres, usually 10-15 km. The aim of the first step of "site specific modelling" or "downscaling" is to interpolate these wind speed forecasts (and other variables such as direction) to the level of the wind farm. As a first step, it is necessary to decide which is the best-performing NWP level (often the wind speed at 10 m a.g.l. or at one of the lowest model or pressure levels).

Whether the word "downscaling" comes from the earliest approach, where the geostrophic wind high up in the atmosphere was used and then downscaled to the turbine hub height, or whether it is used because in some newer approaches the coarser resolution of the NWP is scaled down to the turbines surroundings using a meso- or micro-scale model with much higher resolution, is not clear.

The physical approach uses a meso- or micro-scale model for the downscaling. This can be done in two ways: either the model is run every time the NWP model is run, using the NWP model for boundary conditions and initialisation, or the meso-scale model can be run for various cases in a look-up table approach. The same is true for micro-scale models. The difference between the two is mainly the maximum and minimum domain size and resolution attainable. Note that the use of a meso-scale model is not needed if the NWP prediction is already good enough on its own. In some cases, however, the NWP resolution is too coarse to resolve local flow patterns, and additional physical considerations of the wind flow can be helpful.

For running the downscaling models it is necessary to have a detailed description of the terrain surrounding the wind farm. Usually the information required is the layout of the wind farm, the roughness, the obstacles and the orography. Collecting this information is one of the main difficulties in the implementation of physical models.

Landberg [7] has shown that a simple NWP plus physical downscaling approach is effectively linear, thereby being very easily amenable to MOS improvements - even to the point of overriding the initial physical considerations.

Some more sophisticated flow modelling tools (CFD, MM5, etc.) are starting to be used for the prediction of wind flow over wind farm sites [8, 9]. While further validation work and more computer power is required before such models are used at an operational level, it is considered that such models have the potential to significantly improve the modelling of the flow at wind farm sites, particularly in complex terrain.

Finally, in some cases the NWPs are directly provided by the meteorological service at the level of the wind farm as interpolated values (Figure 2). However, if interpolation is based on simple mathematical relations, not taking into account the non-linearities introduced by the terrain, significant errors may be introduced. In that case it is preferable to use grid predictions instead.

Power curve modelling

The downscaling yields a wind speed and direction for the turbine hub height. This wind is then converted to power with a power curve. The use of the manufacturers power curve is the easiest approach, although newer research from a number of groups has shown it advantageous to estimate the power curve from the forecasted wind speed and direction (or maybe nacelle or mast wind measures) and measured power [10]. Typically the transformation of wind speed to power is achieved via a wind farm power matrix, using multiple direction and wind speed bins to represent the power output of the wind farm. It should be stressed that the method of producing this power matrix is crucial if this stage is not to introduce further uncertainty into the forecasts.

Depending on forecast horizon and availability, measured power data can be used as additional input. In most cases, actual data is beneficial for improving on the resid-

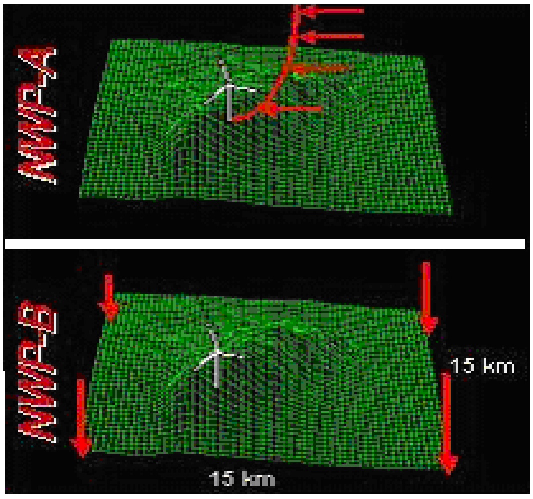

FIGURE 2: *NWPs can be delivered by a meteorological service as interpolated values at the level of the wind farm (upper figure) or as a grid of points surrounding the farm (lower figure).*

ual errors in a MOS approach. If online data is available, then a self-calibrating recursive model is highly advantageous. Often only offline data is available, with which the model can be calibrated in hindsight. MOS is a statistical technique. However the global model is still called physical since the main skill comes from physical considerations.

2.3.2 The statistical approach

The alternative main approach for wind power forecasting is based on purely statistical modelling. Then, the site specific and power curve modelling steps presented in Figure 1 are replaced by a unique step that directly converts input variables (NWPs, online data) to power. If NWPs are provided for a grid of points around the wind farm (NWP-B in Figure 2), then the whole procedure can be considered as "statistical downscaling".

Statistical models in their pure form try to find the relationships between a wealth of explanatory variables including NWPs, and online measured data (mainly power, but also wind speed or direction if available), usually employing recursive techniques. Often, black-box models like Artificial Neural Networks (ANN) are used. Some approaches exploit knowledge on wind power properties to define the model structure (grey-box models). Some models can be expressed analytically; some (like ANNs) cannot. The statistical models can also be used to provide wind speed forecasts. However, this intermediate step is often neglected and a unique model is developed that directly provides power.

In the following, a simplified example is given on how a statistical model can be formulated. The model uses NWPs and measured production (if available on-line), to forecast future power production. The general form of the model is:

$$\begin{aligned}\hat{p}_{t+k/t} &= f\big(\mathbf{p}_t, \hat{u}_{t+k/t_{NWP}} \\ &\qquad \hat{\theta}_{t+k/t_{NWP}}, \hat{\mathbf{x}}_{t+k/t_{NWP}}\big) \qquad (7)\end{aligned}$$

where:

- $\hat{p}_{t+k/t}$ is the power forecast for time $t+k$ made at time t,
- $\mathbf{p}_t$ are the past production measures at time t. Additionnaly, measured values of wind speed, direction, etc. can be added,
- $\hat{u}_{t+k/t_{NWP}}$ is the NWP wind speed forecast for time $t+k$ made at time t_{NWP},
- $\hat{\theta}_{t+k/t_{NWP}}$ is the NWP wind direction forecast for time $t+k$ made at time t_{NWP},
- $\hat{\mathbf{x}}_{t+k/t_{NWP}}$ stands for the other available NWP variables forecast at time t_{NWP} for time $t+k$,

The function $f(.)$ can be for example a neural or fuzzy-neural networks, a NARX (non-linear autoregressive with exogenous variables) function, etc. Multi-step ahead forecasts can be generated either by developing a specific model for each horizon or by using the model in an iterative way. I.e., in order to produce a forecast for $t+2$, the forecast $\hat{p}_{t+1/t}$ for $t+1$ is fed back as input to the model in place of the observed power.

2.3.3 The combined approach

Lately several approaches have been developed based on the combination of various models. The ultimate objective is to benefit from the advantages of each model and obtain a globally optimal performance for the examined horizon. The types of combinations can be:

- combination of physical and statistical approaches (e.g. Zephyr [11]),
- combination of models for the short-term (0-6 hours) and for the medium term (0-48 hours) (e.g. MORE-CARE),
- combination of alternative statistical models (e.g. Sipreolico [12]).

The combination can be made by using as criterion the horizon, after it has been identified offline which model is best for what horizon (e.g. MORE-CARE), or by a selection process based on the recent performance of each individual model (e.g. Sipreolico).

3 Typical performance of wind power prediction models

The verification of a wind power prediction model is not trivial, since depending on the cost function involved different conclusions can be drawn. The usual error descriptors are the Root Mean Square Error (RMSE), the Mean

Absolute Error (MAE), the Mean Error (commonly referred as bias), histograms of the frequency distribution of the error, the correlation function and the R or R2 values. Mostly, the standard error figures are given as a percentage of the installed capacity, since this is what the utilities are most interested in (installed capacity is easy to measure). Then the above introduced error measures are referred to as NRMSE and NMAE, standing for Normalized RMSE and MAE. Sometimes these measures are given as percentage of the mean production or in absolute numbers. A standardised protocol for the evaluation of wind power prediction models has recently been proposed by [13].

The added value of an advanced model w.r.t. a reference simple model is measured as an improvement on the value of the error criterion. If Persistence is used as reference, the "improvement" with respect to Persistence is defined as follows

$$Imp_{EC}^{k} = \frac{EC_{pers}^{k} - EC_{model}^{k}}{EC_{pers}^{k}} \quad (100\,\%), \qquad (8)$$

where k is the lead time and EC the considered evaluation criterion (i.e. NMAE or NRMSE).

Figure 3 depicts the typical NMAE and NRMSE performance obtained by a statistical prediction model (a fuzzy-neural network based model - F-NN) and by Persistence for the case of an offshore wind farm in Denmark. The improvement obtained by this model is shown in Figure 4 for both error measures.

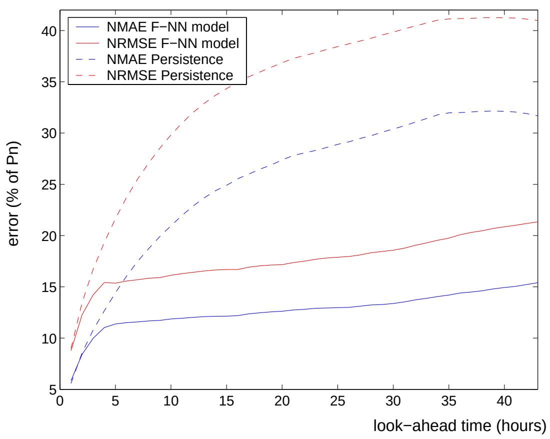

FIGURE 3: *Comparison of Persistence and Fuzzy-NN model performance, using both NMAE and NRMSE (normalization by the wind farm nominal power).*

One can see that the advanced model outperforms Persistence even for short prediction horizons (ca. 3-6 hours). Normally, statistical models using measurements are input are able to do so. In general, this is not the case for physical models. Since they only rely on NWPs (they do not use measurements except for MOS), they do not manage to catch the persistent behaviour of the wind and perform worse for the first say 3-6 hours.

However, for further look-ahead times, Persistence is much easier to beat. For forecasting horizons beyond ca.

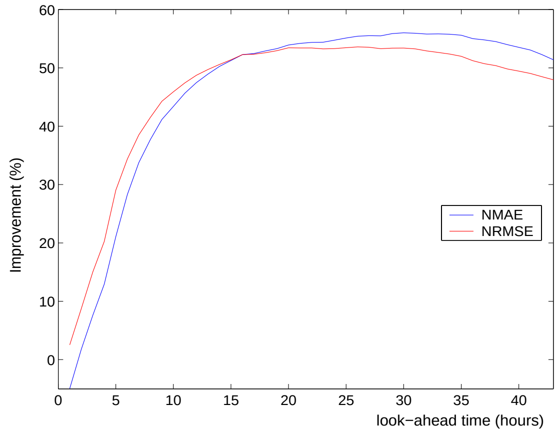

FIGURE 4: *Improvement over Persistence obtained by an advanced model for both NMAE and NRMSE criteria.*

15 hours, even forecasting with the climatologicaly mean is better. This is not surprising, since it can be shown theoretically [6] that the mean square error of forecasts based on the mean value is half the error of a completely de-correlated time-series with the same statistical properties (read: Persistence for very long horizons). Therefore, all the state-of-the-art prediction models should be able to propose a high improvement w.r.t. Persistence for those horizons (up to 40-65%, depending on the wind farm and meteorological conditions).

If we had to give an idea of the general performance of the models currently in use, we would say that:

- Typical model results for single wind farm forecasting are RMSEs around 4-8% of the installed capacity for the first time step rising up to 15-25% for 48 hours ahead.

- Typical results for regional/national forecasting are in the order of 8-10% of the installed capacity for 24 hours ahead. It is noted that although the evaluation for single wind farm forecasting is straightforward, this is not the case for regional forecasting especially if upscaling is applied. This is because, by definition, in the upscaling case, measurements of the total power, with a time-resolution (usually 1 hour) that would permit comparisons, are not available. In some cases a global evaluation result is reported in the literature but this may refer to quantities such as the total monthly energy produced by the wind farms.

Note that the performance of a wind power prediction tool may greatly vary depending on the site [14]. Predicting wind power for wind farms located in a flat or complex terrain situation is different than for wind farms located nearshorenear shore or offshore. Offshore conditions affect the wind vertical profile, which may not be logarithmic as this is the usual assumption. Moreover, the available meteorological forecasts are of great influence on the prediction skills. Most of the errors on wind power forecasting stem from the NWP model. There are two types of error: level errors and phase errors. Consider a passing storm front: a level error misjudges the severity of the storm, while a phase error misplaces the onset and peak of the storm in time. While the level error is easy to get hold of using standard time-series error measures, the phase error is harder to quantify, although it has a determining impact on the traditional error scores.

Landberg and Watson [15] pointed out that the use of the mean error may lead to misinterpretation as both high and low absolute errors may give a low mean error. Kariniotakis [16] emphasises the importance of evaluating the performance of a model against a variety of criteria, and particularly of using both RMSE and MAE of forecasts. The MAE values are in general lower than that RMSE ones. This is because MAE weights all errors equally while RMSE weights more large errors but also because the models parameters are estimated based on a quadratic error minimisation. In some cases a positive RMSE may even correspond to a negative MAE improvement over Persistence for the first time steps. The same has also been found by Giebel [17], where optimising a MOS function's parameters lead to different results depending on whether the MAE was the cost function or the RMSE.

Nielsen and Ravn [18] rigorously show that the optimal prognosis parameter depends on the error criterion. They identify three different criteria: "The prognosis value of the wind power production should be close to the average of the realised values. The sum of deviations between the prognosis value and realised values should be small. The prognosis should result in a low cost of the consequences of prognosis errors." The first and second criterion are important for the electrical balance in the grid, the last one is important to optimize the cost integration of wind energy in the market.

Among the most critical situations to forecast are sudden and pronounced changes, like a storm front passing the utility's area. To develop a measure for the quality of these forecasts is very difficult, and the best way to get a feeling for the quality of the forecasts is visual inspection of the data. Other uses of short-term prediction, related to storms, are the possibility of scheduling maintenance after or during a storm, as has happened in Denmark during the Dec 1999 hurricane. The same applies for maintenance on offshore wind farms, where the sea might be too rough to safely access the turbines. Nowadays, the use of wind power forecasts for trading wind production in an electricity market leads to the consideration of criteria able to assess in a wider way the uncertainty of a prediction model. I.e., given that underestimation of the expected production has a different financial impact than an overestimation, the frequency of positive and negative errors, as well as the cumulative energy deficit or surplus, become of particular importance.

4 The value of forecasting

Even though it easy to argue for a forecasting model on the overall level, there are not many analyses that have looked in detail into the benefits of forecasting for a utility or an independent wind power producer. This lack of analyses partly stems from the fact that a lot of input data and a proper operation simulation model are needed to be able to draw valid conclusions. To estimate the benefit of forecasting in a model of the NordPool electricity markets, the WILMAR[1] project is developing the market model and a model for the simulation of wind power predictions.

Some first studies have appeared recently on the participation of wind energy in power markets, But, since the market rules differ from one European country to another, it is not easy to draw general conclusions.

Morthorst [19] studied how large amounts of wind power may be dealt within the NordPool electricity markets for the case of the western Denmark area. He noticed that in general the cost of down-regulation was higher than the cost for up-regulation, and also that the quantity of participating wind power has no real influence on the spot price in the exchange market.

Holttinen et al. [20] simulated the participation of Danish energy producers in the NordPool electricity market with or without the use of an advanced wind power forecasting tool (WPPT in this case, which is described in Section 5). A similar study was carried out by Usaola et al. [21], where they consider the specific case of the Spanish electricity market and of the participation of wind energy producers using Sipreolico (see also Section 5) for predicting the expected wind power generation. The benefits of using a wind power prediction tool are quantified. Moreover, they show the interest of aggregating the output of several wind farms when trading, in order to diminish the level of forecasting error and thus the imbalance costs.

The potential value of forecasting to wind power generators in the UK was illustrated by Bathurst and Strbac [22] shortly after the introduction of the New Electricity Trading Arrangements (NETA) in March 2001. Under NETA, the imbalance charges (charges for over- or under-delivery) are determined by market conditions and can lead to severe penalties for generators who cannot make accurate production forecasts. Indeed, in the first week of NETA's operation, imbalance charges were such that wind generation had net negative value: -0.41 p/kWh (≃ -0.6 c/kWh) using a standard forecasting method. In a follow-up paper by the authors [23], they analyse the participation of independent wind energy producers in the NETA and propose a methodology for determining the optimum contract level, considering the uncertainty of wind energy forecasts and the fact that the costs of Spill and TopUp energy may not be the same.

Mylne [24] used a multi-element contingency table technique to estimate the value of Persistence and NWP forecasting for a single 1.65 MW turbine under the UK NETA trading system at a look-ahead of between 7.5 and 13 hours. The value of the NWP forecast over Persistence was found to range from a few pence to as much as £7 per hour. Assuming a 30% capacity factor, this corresponds to a forecast value ranging from around 0.03 to 0.3 c/kWh.

Milligan et al. [25] used the Elfin model to assess the financial benefits of good forecasting for a utility, taking into account the load time-series, a wind time-series, the

[1] www.wilmar.risoe.dk

distribution of power plants for different utilities, and the forced outage probabilities of the normal plant mix. Even though his method of simulating the forecast error was not very close to reality, some general conclusions could be drawn. When varying the simulated forecast error for three different utilities, zero forecast error always came out advantageously. The relative merit of over- and under-predicting varied between the two analysed utilities: while under-predicting was cheaper for one utility, the opposite held true for the other. The cost penalty in dependency of the forecast error was very much dependent on the structure of the plant mix and the power exchange contracts. Generally speaking, a utility with a relatively large percentage of slow-start units is expected to benefit more from accuracy gains.

Kariniotakis and Miranda [26] propose a methodology to assess the benefits from the use of advanced wind power and load forecasting techniques for the scheduling of a medium or large size autonomous power system. The case study of the Greek island of Crete is examined. The impact of forecasting accuracy on the various power system management functions is analysed [27].

5 Prediction tools currently available

It appears that there is a wealth of wind power prediction models currently available, either as commercial products or in the general case as results of research efforts. However, only few models are actually in operation. The description below emphasises on the operational models. Already in 1990, Landberg [28] developed a short-term prediction model based on physical reasoning similar to the methodology developed for the European Wind Atlas [29]. The idea is to use the wind speed and direction from a NWP, then transform this wind to the local site, use the power curve and finally correct this with the park efficiency. Note that the statistical improvement module MOS can either set in before the transformation to the local wind, or before the transformation to power, or at the end of the model chain trying to change the power. A combination of all these is also possible. He found that for the MOS to converge, about 4 months worth of data were needed (which might not be available when setting up the model for a new customer). Landberg used the Danish or Risø version for all the parts in the model: the HIRLAM model of the DMI as NWP input, the WAsP model from Risø to convert the wind to the local conditions and the Risø PARK model to account for the lower output in a wind park due to wake effects.

Two general possibilities for the transformation of the HIRLAM wind to the local conditions exist: the wind could be from one of the higher levels in the atmosphere, and hence be treated as a geostrophic wind, or the wind could be the NWPs offering for the wind in 10m a.g.l. Usually this wind will not be very accurately tailored to the local conditions, but will be a rather general wind over an average roughness representative for the area modelled at the grid point. In the NWP, even orography on a scale smaller than the spatial resolution of the model is frequently parameterised as roughness. This point is less important now, with the advances in computing power since the inception of the model and the subsequently increased horizontal resolution. If the wind from the upper level is used, the procedure is as follows: from the geostrophic wind and the local roughness, the friction velocity u_* is calculated using the geostrophic drag law. This is then used in the logarithmic height profile, again together with the local roughness. If the wind is already the 10m-wind, then the logarithmic profile can be used directly.

The site assessment regarding roughness is done as input for WAsP. There, either a roughness rose or a roughness map is needed. From this, WAsP determines an average roughness at hub height. This is the roughness used in the geostrophic drag law or the logarithmic profile. Only one WAsP correction matrix is used, which could be too little for a larger wind farm [30]. In their original work, Landberg and Watson [7] determined the ideal HIRLAM level to be modelling level 27, since this gave the best results. However, the DMI changed the operational HIRLAM model in June 1998, and Joensen et al. [31] found that after the change the 10 m wind was much better than the winds from the higher levels. So in the last versions of the Risoe model, the 10 m wind is used. After the change, passing storm systems were also better predicted, only missing the level once and not missing the onset at all [32]. The model has also been tested at ESB (Electricity Supply Board, Ireland) [33] and in Iowa [34]. There, for predictions of the Nested Grid Model of the US National Weather Service, the use of MOS was essential. This was partly because the resolution of the Nested Grid Model was ca. 170 km, and no local WAsP analysis of the site was available. Prediktor is also used in the generic SCADA (Supervisory Control And Data Acquisition) system CleverFarm for maintenance scheduling [35].

A rather similar approach to Prediktor was developed at the University of Oldenburg [36]. They named it Previento [37]. They use the Deutschlandmodell or nowadays the Lokalmodell (LM) of the German Weather Service (DWD) as the NWP model. Previento is now distributed by energy & meteo systems and provides EnBW, the 3rd largest energy company in Germany, with wind predictions.

The Wind Power Prediction Tool (WPPT) has been developed by the Institute for Informatics and Mathematical modelling (IMM) of the Technical University of Denmark. WPPT is running operationally in the western part of Denmark since 1994 and in the eastern part since 1999. Initially, they used adaptive recursive least squares estimation with exponential forgetting in a multi-step set-up to predict from 0.5 up to 36 hours ahead. However, due to the lack of quality in the results for the higher prediction horizons, the forecasts were only used operationally up to 12 hours ahead. In a later version, HIRLAM forecasts were added [38], which allowed the range of useful forecasts to be extended to 39 hours ahead. This version is successfully operated by Elsam and other Danish utilities [39].

WPPT includes an upscaling module for predicting the total wind power production in a larger region based on a combination of on-line measurements of power production from selected wind farms, power measurements for all wind turbines in the area and numerical weather predictions of wind speed and wind direction. If necessary, the total region is broken into a number of sub-areas. Details of that method are given in [40].

The WPPT implies statistical modelling and namely conditional parametric models. These models outperform traditional parametric models. They are non-linear models formulated as linear ones in which the parameters are replaced by smooth, but otherwise unknown, functions of one or more explanatory variables. These functions are called coefficient-functions. For on-line applications it is advantageous to allow the function estimates to be modified as data become available. Furthermore, because the system may change slowly over time, observations should be down-weighted as they become older. For this reason a time-adaptive and recursive estimation method is applied.

The time-adaptivity of the model parameters is an important property wind power prediction models should have to face changes in the environment of the application such as changes in the surroundings or even the number of wind farms in the considered area, changes in the NWP model, etc. This is caused by effects such as aging of the wind turbines, changes in the surrounding vegetation and maybe most importantly due to changes in the NWP models used by the weather service as well as changes in the population of wind turbines in the wind farm or area.

IMM and Risoe have recently started a collaboration under the Zephyr name[11].

ARMINES and RAL have developed work on short-term wind power forecasting since 1993. Initially, short-term models for the next 6-10 hours were developed based on time-series analysis to predict the output of wind farms in the frame of the LEMNOS project (JOU2-CT92-0053). The developed models were integrated in the Energy Management System (EMS) software developed by AMBER S.A and installed for on line operation in the island of Lemnos.

ARMINES has tested various approaches for wind power forecasting based on ARMA, neural networks of various types (backpropagation, RHONN etc), fuzzy neural networks, wavelet networks etc. From this benchmarking procedure, models based on fuzzy neural networks were found to outperform the other approaches [41, 42].

In the frame of the project CARE (JOR-CT96-0119), more advanced short-term models were developed for the wind farms installed in Crete. In the project MORE-CARE (ERK5-CT1999-00019), ARMINES developed models for the power output of wind parks for the next 48/72 hours based on both on-line production data and NWPs. The developed forecasting system can generically accept as input different types of meteorological forecasts (e.g. Hirlam, Skiron etc.). The ARMINES Wind Power Prediction System (AWPPS) integrates:

- short-term models based on the statistical time-series approach able to predict wind power for horizons up to 10 hours ahead with time steps in the order of 10-15 min.
- longer-term models based on adaptive fuzzy neural networks able to predict the output of a wind farm up to 72 hours ahead. These models receive as input on-line SCADA data and NWPs [43].
- combined forecasts: such forecasts are produced from intelligent weighting of short-term and long-term forecasts for an optimal performance over the whole forecast horizon.

The core prediction module of AWPPS is integrated in the MORE-CARE EMS software and installed for on-line operation in the power systems of Crete and Madeira. In the island of Crete, wind penetration reaches high levels since 80 MW of wind power are installed for a demand varying between 170-450 MW. Due to the fact that it is an autonomous power system, the use of wind power forecasting is crucial for an economic and secure wind integration. Currently, the MORE-CARE system is installed and operated by PPC in Crete and provides wind power forecasts for all the wind farms for a horizon of 48 hours ahead. NWPs provided by the SKIRON system, operated by IASA, as well as measurements provided on-line by the SCADA system of the island are used as input. A stand alone application of the wind forecasting module is configured for on-line operation in Ireland [44]. An evaluation of this application is presented in [45].

The core prediction module of AWPPS is also integrated in (in the frame of Dispower project) and provided through the e-terra system of AREVA T&D.

ISET (Institut für Solare Energieversorgungstechnik) has operatively worked with short-term forecasting, using the DWD model and neural networks since 2000. It came out of the German federal monitoring program WMEP (Wissenschaftliches Mess- und EvaluierungsProgramm), where the growth of wind energy in Germany was to be monitored in detail. Their first customer was E.On, who initially lacked an overview of the current wind power production and therefore wanted a tool for nowcasting [46]. Then, their model was called Advanced Wind Power Prediction Tool AWPT.

Ernst and Rohrig [47] reported in Norrköping on the latest developments of ISET's Wind Power Management System WPMS. They now predict for 95% of all wind power in Germany. In some areas of German TSOs E.On Netz and Vattenfall Europe Transmission, wind power has exceeded 100% coverage at times. One additional problem in Germany is that the TSOs even lack the knowledge of the currently fed-in wind power. In the case of E.On Netz, the ca. 5 GW installed capacity are upscaled from 16 representative wind farms totalling 425 MW. Their input model is the Lokalmodell of the DWD, which they then feed into an ANN. To improve on the LM, they transform the predicted wind to the location of wind farms using the numerical meso-scale atmospheric model KLIMM (KLImaModell Mainz). The LM is run twice daily with a horizontal resolution of 7 km, forecasting up to 48 hours ahead. The ANN can also be seen as an area power curve.

eWind is an US-American model by TrueWind, Inc [48]. Instead of using a once-and-for-all parameterisation for the local effects, like the Risø approach does with

WAsP, they run the ForeWind numerical weather model as a meso-scale model using boundary conditions from a regional weather model. This way, more physical processes are captured, and the prediction can be tailored better to the local site. In the initial configuration of the eWind system, they used the MASS (Mesoscale Atmospheric Simulation System) model. Nowadays, additional mesoscale models are used: ForeWind, MM5, WRF, COAMPS, workstation-ETA and OMEGA. To iron out the last systematic errors they use adaptive statistics, either a traditional multiple screening linear regression model, or a Bayesian neural network. Their forecast horizon is 48 hours. They published a 50% improvement in RMSE over Persistence in the 12-36 hour range for 5 wind towers in Pennsylvania [49]. Recently, they proposed a new technique based on a rapid update cycle that will be able to assimilate a large volume of meteorological and remotely-sensed input data [50].

The strong wind energy growth in Spain led Red Eléctrica de España (the Spanish TSO) to have the Sipreólico tool developed by the University Carlos III of Madrid [12]. The tool is based on Spanish HIRLAM forecasts, taking into account hourly SCADA data from 80% of all Spanish wind turbines. These inputs are then used in adaptive non-parametric statistical models, together with different power curve models. There are 9 different models, depending on the availability of data: one that works along the lines of the models for very short-term prediction, not using NWP input at all. Three more, increasingly include higher terms of the forecasted wind speed, while further three are also taking the forecasted wind direction into account. The last two are combinations of the other ones, plus a non-parametric prediction of the diurnal cycle.

These 9 models are recursively estimated with both a Recursive Least Squares (RLS) algorithm or a Kalman Filter (this leads to 18 models). For the RLS algorithm, a novel approach is used to determine an adaptive forgetting factor based on the link between the influence of a new observation, using Cook's distance as a measure, and the probability that the parameters have changed. The results of these 18 models are then used in a forecast combination, where the error term is based on exponentially weighted mean squared prediction error with a forgetting factor corresponding to a 24-h memory. The main problem of the Spanish case is the Spanish HIRLAM model in conjunction with the complex terrain. The resolution of HIRLAM is not high enough to resolve the flow in many inland areas.

LocalPred and RegioPred are a family of tools developed by a research team initially in CIEMAT and now with CENER. It involves adaptive optimisation of the NWP input, time-series modelling, meso-scale modelling with MM5, and power curve modelling. They showed for a case of rather complex terrain near Zaragoza (Spain), that the resolution of HIRLAM was not good enough to resolve the local wind patterns [51]. The two models in Spain are running on a 0.5°x0.5° and 0.2°x0.2° resolution, which made a novel downscaling procedure necessary, based on principal component analysis and taking further variables into account, predominantly the pressure field. The use of WPPT as a statistical post-processor for the physical reasoning was deemed very useful [52].

Additionally, some of the traditional power companies have shown interest in the field, like Siemens, ABB or Areva. This could start the trend to treating short-term prediction models as a commodity to be integrated in EMSs or wind farm control and SCADA systems. Information and communication technology is expected to play a major role for integrating wind power prediction tools in the market infrastructure.

A more complete overview on the state of the art of wind power forecasting is available at the ANEMOS website [53]. This report mentions and describes other models that are not dealt with here.

6 Current research for the adaptation of models to the offshore conditions

Future major developments of wind power capacities are more likely to take place offshore. Higher and more regular wind speeds [54], as well as the possibility to install numerous and powerful (multi-megawatt) wind turbines, are the main advantages of going offshore to produce electricity. Wind speeds in the power production classes in the offshore environment are more persistent than those onshore. Calms are less frequent and less persistent [55]. In addition, offshore wind energy could be sufficient to feed the local demand in countries like the United Kingdom or Denmark [56]. For instance the Horns Rev wind farm of 160 MW in Denmark (in operation since December 2002) consists a first technical achievement of that kind of large-scale offshore projects. This specific wind farm is alone able to supply up to 2% of the whole electricity consumption of Denmark [57]. Several other examples of very ambitious offshore projects are under study or development in some of the European countries.

All state-of-the-art prediction models were originally designed for the onshore. For the case of offshore, special modelling considerations have to be made for adapting physical models. This fact has already been recognized for the problem of resource assessment [58]. Due to the spread of the wind turbines over a large area, wake effects and influence of the coast have to be studied [59]. Large offshore wind farm clusters may be modelled with the standard wind farm models, but they tend to underestimate the wind recovery distances [60]. There is still room for improvement of those models.

The adaptation of physical prediction models is not straightforward since, as for resource assessment, a real understanding of the offshore wind speed profiles — and wind characteristics in general, is needed. In the northern part of Europe, offshore wind monitoring for more than 10 years has permitted to gain more insight on the offshore wind characteristics [61]. Studies concerning offshore wind modelling are ongoing [62, 63] and will serve for the adaptation of physical forecasting models [64, 65].

The effect of the variable roughness of the sea surface has been studied by Lange et al. [62] for the resource assessment problem, and it was found that a constant-roughness model was sufficient. It is not clear if that can be extended to the case of short-term prediction.

The statistical alternatives, and more precisely the artificial intelligence based methods, do not need a very precise knowledge of offshore conditions for designing suitable prediction models. Indeed, these methods can be trained to give an estimation of the wind farm power output for given meteorological conditions, allowing one to avoid all the intermediate physical modelling steps. Recently, the Fuzzy-Neural Network based approach has been adapted and evaluated for an offshore wind farm in Denmark [66]. The results are encouraging and first model configurations based on a virtual clustering of large offshore wind farms are developed.

7 The ANEMOS project

The ANEMOS project aims to substantially improve methods for short-term wind power forecasting. It responds to the needs of different end-users through the development of approaches for single wind farm, for regional or national forecasting, and for different time scales ranging from a few hours to a few days ahead. Emphasis is given to challenging situations such as complex terrain, extreme weather conditions, as well as to offshore prediction for which no specific tools currently exist. New methods are being developed to estimate on-line the level of uncertainty of the predictions, as well as the expected risk based on ensemble weather forecasts. A benchmarking process has been set up in which up to ten prediction systems are compared to physical and statistical models developed in the project on test cases covering various conditions. This comparison will permit an analysis of wind predictability as a function of the site characteristics, the type of weather predicted etc.

For the offshore, new methodologies are developed to cope with spatio-temporal characteristics of large offshore parks taking into account the impact of high-resolution meteorological forecasts, the contribution of information from satellite-radar images, etc. Indeed, the understanding of such characteristics is required to be efficient in critical situations, for instance in modelling gradients resulting from coming fronts crossing the wind park or switch off behaviour of turbines due to high wind speeds. The high installed capacities in offshore projects imply that this behaviour must be accurately modelled.

The project partners are developing the ANEMOS prediction platform that integrates the various advanced models developed by the partners. Early 2005, the software will be installed in six countries for on-line operation at onshore and offshore wind farms by the end-users participating in the project. The benefits from wind prediction will be evaluated at national, regional, and single wind farm level.

8 Conclusions

Short-term forecasting has come a long way since the first attempts at it. First models appeared in the early 90s, but more players came into the field since that period leading to a wealth of models available today throughout the world. These models are either developed with a research status or for commercial purposes. Although they follow different approach, they can be classified into two categories: *(i)* the physical one, for which the terrain characteristics are considered for downscaling the forecast wind speed at the level of the wind farm, and the wind farm power curve used consequently to determine the power output; and *(ii)* the statistical one, for which purely mathematical models are designed and trained for computing the power output from various input data (that may be NWPs and/or online onsite/offsite measures).

The accuracy of the state-of-the-art prediction models is a central concern nowadays. Such analysis of the models performance is done in the frame of the ANEMOS project in order to inform end-users on the level of prediction error they can expect depending on the site characteristics, the considered forecasting approach, the employed NWPs, etc. [14]

Wind power prediction software is not "plug-and-play" since it is always site-dependent. In order to run with acceptable accuracy when installed to a new site, it is always necessary to devote considerable effort for tuning the models (in an off-line mode) on the characteristics of the local wind profile or on describing the environment of the wind farms. It is here where the experience of the installing institutions makes the largest difference. Due to the differences in the existing applications (flat, complex terrain, offshore) it is difficult to compare prediction systems based on available results. An evaluation of prediction systems needs however to take into account their robustness under operational conditions and other factors.

Despite the appearance of multiple similar approaches today, further research is developed in several areas to further improve the accuracy of the models but also to assess the uncertainty of the predictions [67, 68, 69, 70]. Combination of approaches is identified as a promising area. The feedback from existing on-line applications continues to lead to further improvements of the state-of-the-art prediction systems.

Now that major wind power developments are expected to take place offshore, there is a need to adapt the current wind power forecasting approaches. It will also be necessary to develop new forecasting methodologies, especially dedicated to the offshore case. These new methodologies will account for the specificities of offshore wind characteristics, as well as for the large size and clustered nature of such offshore wind farms.

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