State-of-the-Art on Methods and Software Tools for Short-Term Prediction of Wind Energy Production

G. Giebel*, L. Landberg,
Risoe National Laboratory
Denmark

G. Kariniotakis,
Ecole des Mines de Paris
France.

R. Brownsword
Rutherford Appleton Laboratory,
UK

* Gregor.Giebel@risoe.dk, Phone +45 4677 5095, Fax –5970, Risø National Laboratory, DK-4000 Roskilde, Denmark

Abstract:

The installed wind energy capacity in Europe today is 20 GW, while the projections for 2010 according to the Kyoto protocol and the EC directives is up to 40-60 GW. The large-scale integration of wind energy emerges the use of advanced operational tools for short-term forecasting of the wind production in the next hours up to the next 2-7 days. End-users (independent power producers, electric companies, transmission system operators, etc) recognize the contribution of wind prediction for a secure and economic operation of the power system. Especially, in a liberalized electricity market, prediction tools enhance the position of wind energy compared to other forms of dispatchable generation.

The paper presents in detail the state-of the-art on the methods, the software tools and the relevant R&D projects for wind power forecasting. The paper finally presents experience by end-users that run operationally such prediction systems today as stand-alone applications or interfaced to EMS/DMS systems.

The paper reviews the related literature on wind power prediction. Emphasis is given on operational tools such as WPPT, Prediktor, Zephyr, Previento, SIPREÓLICO, LocalPred, More-Care etc. The various models or tools are classified using criteria like:

- The type of implemented approach i.e. timeseries (neural networks, ARMA etc) or physical.
- The specific spatial scale focused by the models (regional, wind park scale, micro-scale).
- The on-line performance of the prediction tools and their coupling to Energy Management Systems.

1   INTRODUCTION

This paper will give an overview over past and present attempts to predict wind power for single turbines or for whole regions, mostly for a few days ahead. This paper is a subset of a much larger effort for the ANEMOS project [1], which brings together many groups from Europe involved in the field, with up to 15 years of experience in short-term forecasting.

One of the largest problems of wind power, as compared to conventionally generated electricity, is its dependence on the volatility of the wind. This behaviour happens on all time scales, but two of them are most relevant: One is for the turbine control itself (from milliseconds to seconds), and the other one is important for the integration of wind power in the electrical grid, and therefore determined by the time constants in the grid (from minutes to weeks).

One can distinguish two types of applications:

Optimisation of the scheduling of the conventional power plants by functions such as economic dispatch etc. The prediction horizons can vary between 3-10 hours depending on the size of the system and the type of conventional units included (*ie* for systems including only fast conventional units, such as diesel gensets or gas turbines, the horizon can be below 3 hours). Only few on-line applications of this type are met today in island or isolated systems and the approach remains marginal.

Optimisation of the value of the produced electricity in the market. Such predictions are required by different types of end-users (utilities, TSOs, ESPs, IPPs, energy traders etc.) and for different functions such as unit commitment, economic dispatch, dynamic security assessment, participation in the electricity market, etc. The ANEMOS project mainly is concerned with the time scale given by the electricity markets, from 0-48 hours.

Additionally, even 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, and such systems are only just now starting to appear [2,21]. As Still [3] reported, 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.

1.1   The typical model chain

A gentle introduction to short-term predictions can also be found in [4]. In general, the models can be classified as either involving a Numerical Weather Prediction model (NWP) or not. Whether the inclusion of NWPs is worth the effort and expense of getting hold of it, depends on the horizon one is trying to predict. Typically, prediction models using NWP forecasts outperform time series approaches after ca 3-6 hours look-ahead time (see also section 1.2). Therefore, all models employed by utilities use this approach.

Two different schools of thought exist w.r.t. short-term prediction: the physical and the statistical approach. In some models a combination of both is used, as indeed both approaches can be needed for successful forecasts. In short, the physical models try to use physical considerations as long as possible to reach to the best possible estimate of the local wind

speed before using Model Output Statistics (MOS) to reduce the remaining error. Statistical models in their pure form try to find the relationships between a wealth of explanatory variables including NWP results, and online measured power data, usually employing recursive techniques. Often, black-box models like advanced Recursive Least Squares or Artificial Neural Networks (ANN) are used. The more successful statistical models actually employ grey-box models, where some knowledge of the wind power properties is used to tune the models to the specific domain. Some of the statistical models can be expressed analytically, some (like ANNs) can not. The statistical models can be used at any stage of the modelling, and more often than not combine various steps into one.

If the model is formulated rather explicitly, as is typical for the physical approach, then the stages are downscaling, conversion to power, and upscaling:

The wind speed and direction from the relevant NWP level is scaled to the hub height of the turbine. This involves a few steps, first finding 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).

The NWP model results can be for the geographical point of the wind farm or for a grid of surrounding points. In the first case the models could be characterised as "advanced power curve models", in the second case as a "statistical downscaling" model.

The next step is the so-called **downscaling** procedure. Whether the word 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 microscale model with much higher resolution, is not clear.

The physical approach uses a meso- or microscale 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 mesoscale model can be run for various cases in a look-up table approach. The same is true for microscale 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.

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 and measured power.

Some statistical models leave this step out and do a direct prediction of the power production, but all physical and some statistical models have this intermediate step explicitly or at least implicitly.

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 residual errors in a MOS approach. If online data is available, then a self-calibrating recursive model is highly advantageous. This is part of the statistical approach. It can have the form of an explicit statistical model employed with advanced auto-regressive statistical methods, or as an ANN type black-box. However, often only offline data is available, with which the model can be calibrated in hindsight.

If only one wind farm is to be predicted, then the model chain stops here (maybe adding the power for the different turbines of a wind farm while taking the wake losses into account). Since usually, utilities want a prediction for the total area they service, the **upscaling** from the single results to the area total is the last step. If all wind farms in an area would be predicted, this would involve a simple summation. However, since practical reasons forbid the prediction for thousands of wind farms, some representative farms are chosen to serve as input data for an upscaling algorithm. Helpful in this respect is that the error of distributed farms is reduced compared to the error of a single farm.

Not all short-term prediction models involve all steps. Actually, leaving out a few steps can be an advantage in some cases. So is *eg* Prediktor independent of online data, and can bring results for a new farm from day 1, while the advanced statistical models need older data to learn the proper parameterisations. However, this is bought with a reduced accuracy for rather short horizons. Alternatively, models not using NWP data have a quite good accuracy for the first few hours, but are generally useless for longer prediction horizons (except in very special cases of thermally driven winds with a very high pattern of daily recurrence). Landberg [5] has shown that a simple NWP + physical downscaling approach is effectively linear, thereby being very easily amenable to MOS improvements – even to the point of overriding the initial physical considerations.

The opposite is a direct transformation of the input variables to wind power. This is done by the use of grey- or black-box statistical models that are able combine input such as NWPs of speed, direction, temperature etc. of various model levels together with on-line measurements such as wind power, speed, direction etc. With these models, even a direct estimation of regional wind power from the input parameters in a single step is possible. Whether it is better for a statistical model to leave out the wind speed step depends on a number of things, like the availability of data or the representativity of the wind speed and power for the area of the wind farm or region being forecasted.

The optimal model is a combination of both, using physical considerations as far as necessary to capture the air flow in the region surrounding the turbines, and using advanced statistical modelling to make use of every bit of information given by the physical models.

1.2 Typical results

The verification of these models is not trivial, since it depends on the cost function involved. The usual error descriptors are the Root Mean Square Error (RMSE), the Mean Absolute Error (MAE), the Mean Error (ME), histograms of the frequency distribution of the error, the correlation function and the R or R^2 values. Mostly, the standard error figures are given as percent of the installed capacity, since this is what the utilities are most interested in (installed capacity is easy to measure);
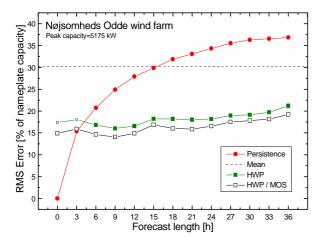
Figure 1: Root Mean Square (RMS) error for different forecast lengths and different prediction methods. The wind farm is the old Nøjsomheds Odde farm (before repowering) with an installed capacity of 5175 kW. HWP/MOS refers to the HWP approach (HIRLAM/WAsP/Park, nowadays called Prediktor) coupled with a MOS model (Model Output Statistics).

sometimes they are given as percent of the mean production or in absolute numbers. The typical behaviour of the error function for models using time series approaches or NWP is shown here for the case of Prediktor applied to an older Danish wind farm in the mid-nineties, using RMSE as the error measure.

Persistence (also called the naïve predictor) is the model most frequently used to compare the performance of a forecasting model against. It is one of the simplest prediction models, only second to predicting the mean value for all times, a.k.a. a climatology prediction. In this model, the forecast for all times ahead is set to the value it has now. Hence, by definition the error for zero time steps ahead is zero. For short prediction horizons (*eg*, a few minutes or hours), this model is the benchmark all other prediction models have to beat. This is because the time scales in the atmosphere are in the order of days (at least in Europe, where the penetration of wind power is highest). It takes in the order of 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 more stationary, but these are typically not associated with high winds, and therefore not so important in this respect. To predict much better than persistence for short horizons using the same input, that is, online measurements of the predictand, is only possible with some effort.

One can see that persistence beats the NWP-based model easily for short prediction horizons (ca 3-6 hours). However, for forecasting horizons beyond ca 15 hours, even forecasting with the climatological mean (the dashed line) is better. This is not surprising, since it can be shown theoretically that the mean square error of forecasting by mean value is half the one of the mean square error of a completely decorrelated time series with the same statistical properties (read: persistence for very long horizons).

After about 4 hours the quality of the "raw" NWP model output (marked HWP, full squares) is better than persistence

even without any postprocessing. The relatively small slope of the line is a sign of the poor quality of the assessment of the current state of the atmosphere by the NWP. However, calculating forward from this point onwards introduces hardly any more errors. This means that the data collection and the assessment of the current state of the atmosphere for the NWP is a weak point, while the mathematical models are quite good. The first two points in the HWP line are fairly theoretical; due to the data acquisition and calculating time of HIRLAM (~4 hours) these cannot be used for practical applications and could be regarded as hindcasting. The improvement attained through use of a simple linear MOS (the line marked HWP/MOS, open squares) is quite pronounced.

One line of results is missing in this graph (for reasons of sharper distinction between time-series analysis methods and NWP methods): a result for current statistical methods using both NWP and online data as input. That line would of course be a horizon-dependent weighting of the persistence and the HWP/MOS approach, being lower for all horizons than all the other lines. However, for short horizons, it cannot do (significantly) better than persistence, while for long horizons the accuracy is limited by the NWP model. Therefore, the line would rise close to the persistence results, and continue staying close to the HWP/MOS line.

The behaviour shown in the graph is quite common across all kinds of short-term forecasting models and not specific to Prediktor, although details can vary slightly, such as the values of the RMSE error or the slope of the error quality with the horizon. Typical model results nowadays are RMSEs around 10% of the installed capacity. The improvement over the graph shown here is mostly due to improvements in NWP models. Model specific items are to be found in the next chapter.

2 SHORT-TERM PREDICTION MODELS FOR UTILITY USE

For the electrical utility, wind power only has a real influence on day-to-day operations when its output surpasses the prediction uncertainty of the load. Contrary to wind, however, load forecasting has much higher accuracy, since the load patterns are not so variable and change from day to day and from week to week according to (mostly) deterministic parameters like temperature and TV program. Therefore, the electrical load can be predicted with about 1.5% accuracy for a 24-h forecast, and with ca 5% accuracy for one week. This is fundamentally different from wind power forecasts.

For the utility, there are two time scales involved: the scheduling of power plants, and the market. The typical time scales for start-up of conventional power plants are between 20 min. for gas turbines and 8 hours (or perhaps more) for large coal or oil plant. This is different from maintenance scheduling, which needs much longer time scales (weeks or months). This is a resource optimisation problem, which needs good forecasts. However, for strongly interconnected networks, it lost its relevance in favour of buying electricity on the market. The assumption here is that there is a sufficiently sized market embedding the utility, with high resources and a fast response time. Therefore, in this situation the technical constraints can be circumvented with money.

2.1 Research models

A rather similar approach to Prediktor was developed at the University of Oldenburg [6]. They named it Previento [7]. They use the Deutschlandmodell or nowadays the Lokalmodell (LM) of the German Weather Service (DWD) as the NWP model. A good overview over the parameters and models influencing the result of a meteorological short-term forecasting system has been given by Mönnich [8]. He found that the most important of the various submodels being used is the model for the atmospheric stability. The submodels for orography and roughness were not always able to improve the results. The use of MOS was deemed very useful. However, since the NWP model changed frequently, the use of a recursive technique was recommended. A large influence was found regarding the power curve. The theoretical power curve given by the manufacturer and the power curve found from data could be rather different. Actually, even the power curve estimated from data from different years could show strong differences. The latter might be due to a complete overhaul of the turbine. The largest influence on the error was deemed to come from the NWP model itself.

LocalPred and RegioPred [9] are a family of tools developed by Martí Perez (formerly CIEMAT, now CENER). It involves adaptive optimisation of the NWP input, time series modelling, mesoscale modelling with MM5, and power curve modelling. He could show 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 [10]. 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 [11].

A new approach is described by Jørgensen *et al* [12]: they integrate the power prediction module within the NWP itself. They call it HIRPOM (HIRlam POwer prediction Model). Moehrlen has looked at the resolution needed for successful application of NWP forecasting. In different runs with horizontal model resolutions of 30 km, 15 km, 5 km and 1.4 km for two months in January 2001, the most common statistical accuracy measures did improve only slightly with higher resolution. However, peak wind speeds were closer to the measured values for the high-resolution forecasts. For the higher resolution forecasts, the best model layers were ones closer to the ground than in the coarser models. For the errors, she points out that phase errors (the timing of the frontal system) has a much larger influence on the error scores (and eventual payments) than level errors. For the same set-up, Jørgensen *et al* [13] make a number of interesting points on the coupling of a NWP model to wind power forecasts. Examining 25 especially bad forecasted days from 15 months for the Danish TSO Eltra, he found that in all cases the error came from the NWP model and not from the WPPT upscaling. Here too he found that using higher resolution in HIRLAM, the scores do not improve substantially, indicating that level errors are smaller and gradients sharper in the higher resolution. This leads to higher error measures for phase errors.

2.2 Models currently in use

An overview of the models currently in operation is given in Table 1.

Already in 1990, Landberg [14] developed a short-term prediction model based on physical reasoning similar to the methodology developed for the European Wind Atlas [15]. It is the perfect example for the model chain in the introduction. 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. 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). If the wind from one of the upper NWP levels 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 [16]. In his original work, Landberg and Watson [17] 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* [18] found that after the change the 10 m wind was much better than the winds from the higher levels. So in the last iterations of the Risø 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 [19]. The model has also been used at ESB (Electricity Supply Board, Ireland) [20] and in Iowa. 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 system *CleverFarm* for maintenance scheduling [21].

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 [22], which allowed the range of useful forecasts to be extended to 39 hours ahead. A data-cleaning module was developed, as was a rudimentary upscaling model. This version has successfully operated at Elsam and other Danish utilities [23].

WPPT is a modelling system 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. The predictions for the total region are then calculated using a two-branch approach:

In the first model branch predictions of wind power are calculated for a number of wind farm using on-line measurements of power production as well as numerical weather predictions as input. The prediction of the total power production in the area is calculated by up-scaling the sum of the predictions for the individual wind farms.

The second model branch predicts the area power production explicitly by using a model linking off-line measurements of area power production to the numerical weather predictions [24].

For both model branches the power prediction for the total region is calculated as a sum of the predictions for the sub-areas. The final prediction of the wind power production for the total region is then calculated as a weighted average of the predictions from the two model branches.

A central part of this system is statistical models for short-term predictions of the wind power production in wind farms or areas. Recent research has demonstrated that conditional parametric models show a significant improvement of the prediction performance compared to more traditional parametric models. The conditional parametric is a non-linear model formulated as a linear model 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 estimation is an important property in this application of the method as the total system consisting of wind farm or area, surroundings and numerical weather prediction (NWP) model will be subject to changes over time. 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.

The WPPT and Prediktor lines have recently been combined and extended to become Zephyr [25]. This new model is about to be installed in Western Denmark, with installation in all other major Danish utilities coming before the end of 2003.

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 EMS software developed by AMBER S.A and installed for on line operation in the island of Lemnos. Various approaches have been tested 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 [26,27].

In the frame of the project CARE (JOR-CT96-0119) [28], 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 a wind park for the next 48/72 hours based on both on-line SCADA and NWPs. The developed forecasting system can generically accept as input different types of meteorological forecasts (*ie* Hirlam, Skiron etc.).

The wind forecasting system of ARMINES integrates:

- **short-term models** based on the statistical time-series approach able to predict efficiently wind power for horizons up to 10 hours ahead.
- **longer-term models** based on 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

Table 1: An overview of existing short-term prediction models.

PREDICTION MODEL	DEVELOPER	METHOD	OPERATIONAL STATUS	OPERATIONAL SINCE
Prediktor	Risø	Physical	Spain, Denmark, Ireland, Germany, (US)	1993
WPPT	IMM; University of Copenhagen	Statistical	~1GW, Denmark (E & W)	1994
Zephyr, Combination of WPPT and Prediktor	Risø and IMM	Physical, Statistical	Denmark	2003
Previento	University of Oldenburg, Germany	Physical	-	-
AWPPS (More-Care)	Armines/Ecole des Mines de Paris	Statistical, Fuzzy-ANN	Ireland, Crete, Madeira	1998, 2002
RAL (More-Care)	RAL	Statistical	Ireland	-
SIPREÓLICO	University Carlos III, Madrid Red Eléctrica de España	Statistical	~ 4 GW, Spain	2002
LocalPred-RegioPred	CENER	Physical	La Muela, Soria, Alaiz	2001
HIRPOM	University College Cork, Ireland Danish Meteorological Institute	Physical	Under development	-
AWPT	ISET	Statistical, ANN	~ 10 GW, Germany	-

numerical weather predictions [29].

- **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 developed prediction system is integrated in the MORE-CARE EMS software and is installed for on-line operation in the power systems of Crete and Madeira [30]. A stand alone application of the wind forecasting module is configured for on-line operation in Ireland [31]. An evaluation of this application is presented in [32]. The average reported error is in the order of 10% of the installed power.

For Ireland, they show that using a power curve derived from HIRLAM wind and measured power can improve the forecast RMSE by nearly 20% in comparison to using the manufacturers power curve [31].

80 MW of wind power are installed on the island of Crete where the demand varies between 170-500 MW throughout the year. Wind penetration reaches high levels. Furthermore, the fact that the network is an autonomous one, makes the use of wind power forecasting necessary for an economic and secure integration of wind farms in the grid. Currently, the MORE-CARE system [33] 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. These forecasts are based on numerical weather predictions provided by the SKIRON system, which is operated by IASA. On-line data are provided by the SCADA system of the island.

In Portugal, the MORE-CARE system is operated by EEM and provides forecasts for the production of the wind farms at the island of Madeira. The prediction modules provide forecasts for the short-term up to 8 hours ahead using on-line SCADA data as input. Moreover, MORE-CARE provides predictions for the run-of the river hydro installations of the island.

The ISET (Institut für Solare Energieversorgungstechnik) has since 2000 operatively worked with short-term forecasting, using the DWD model and neural networks. It came out of the German federal monitoring program WMEP (Wissenschaftliches Mess- und EvaluierungsProgramm) [34], 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 good tool for nowcasting [35]. Then, their model was called Advanced Wind Power Prediction Tool AWPT.

Ernst and Rohrig [36] 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 mesoscale atmospheric model KLIMM (KLImaModell Mainz). The LM is run twice daily

with a horizontal resolution of 7 km, forecasting up to 48 hours ahead.

EWind is an US-American model by TrueWind, Inc [37]. 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 [39]. 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 [38].

EWind and Prediktor are currently being used in California [39]. Both are delivering forecasts for two large wind farm areas, 900 turbines worth 90 MW in Altamont Pass and 111 turbines worth 66.6 MW at San Gorgognio Pass. The first results for an initial 28-day period are published in this report. TrueWind reaches a MAE of 10.8% of the installed capacity for same day forecasting, and 11.7% for next day. Prediktor (using the ETA model run by NOAA of the US) achieved a MAE of 2.4 m/s for the 48-hour horizon, but was not yet fully optimised for this application.

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 [40]. The tool is based on Spanish HIRLAM forecasts, taking into account hourly SCADA data from 80% of all Spanish wind turbines [41]. 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 time series analysis model, not using NWP input at all. Three more include increasingly 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. 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 R^2 for all of Spain is more than 0.6 for a 36-h horizon. The main problem of the Spanish case is the Spanish HIRLAM model in conjunction with the complex terrain. The resolution of HIRLAM is not enough to resolve the flow in many inland areas. The model itself works very well when driven by measured wind speeds instead of predicted ones (with R^2 over 0.9 for the whole horizon).

3   CONCLUDING REMARKS

Short-term forecasting has come a long way since the first attempts at it. Often, running the grid would not be possible without it, in situations with more than 100% instantaneous power from wind in the grid. The current crop of models, typically combining physical and statistical reasoning, are fairly good, although the accuracy is limited by the employed NWP model.

Short-term prediction consists of many steps. For a forecasting horizon of more than 6 hours ahead, it starts with a NWP model. Further steps are the downscaling of the NWP model results to the site, the conversion of the local wind speed to power, and the upscaling from the single wind farms power to a whole region. On all these fronts, improvements have happened since the first models. Typical numbers in accuracy are an RMSE of about 10-15% of the installed wind power capacity for a 36 hour horizon.

The main error in a short-term forecasting model stems from the NWP model. One current *Ansatz* to overcome this error source, and to give an estimate of the uncertainty of one particular forecast, is to use ensembles of models, either by using multiple NWP models or by using different initial conditions within those. Research work carried out in Anemos project aims to evaluate the performance of alternative NWP forecasts, including high-resolution ones, on a number of specific wind farms.

Noteworthy is the current explosion in working models. During the early nineties, Prediktor and WPPT were nearly alone on the market. In the second half of the nineties, the commercialisation of wind power forecasting began, by Risø and IMM/DTU, but also by dedicated companies like TrueWind. More players were coming into the field, such as Armines/Ecoles des Mines de Paris and RAL with the MoreCare project, Oldenburg with the Previento model, the ISET cornering the German market, and others. But since just before 2000 there were suddenly a whole lot more models coming from Europe and beyond. Spain developed an interest, and started to use the Sipreolico model, while for the moment relegating LocalPred/RegioPred to research status. France is looking at forecasting options now. Ireland has started in the last years, adapting existing models and developing new ones in Cork University. ECN has scored their first contract in the Netherlands. In the recent European Wind Energy Conference in Madrid (June 2003), more than 30 papers were presented, including a number of new models.

Additionally, some of the traditional power companies have shown interest in the field, like Siemens, ABB or Alstom. This could start the trend to treating short-term prediction models as a commodity to be integrated in energy management systems 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.

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 institute 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. 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.

The aim of the present report is to contribute to the current research on wind power forecasting though a thorough review of the work developed in the area in the last decades. Wind power forecasting is a multidisciplinary area requiring skills from meteorology, applied mathematics, artificial intelligence, energetic, software engineering, information technology and others. It appears as an emerging technology today, with leaders from the European Union Institutes. This has been the result of an early recognition by the EU, as well as the pioneer countries in wind energy, of the necessity to anticipate efficient solutions for an economic and secure large-scale integration of wind power. The expectations from short-term wind power forecasting today are high since it is recognised as the means to allow wind power to compete on equal footing with the more traditional energy sources in a competitive electricity marketplace.

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