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The State-of-the-Art in Short-Term Prediction of Wind Power From a Danish Perspective

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Abstract:
This presentation is based on a longer report trying to summarise more than 100 papers written in the field over the last decades. Many regions have nowadays such high penetrations of wind energy (the host region Western Denmark has in the order of 25%) that without good short-term prediction tools, an economic and secure integration of wind power with maximal ecological benefits of the wind power could not be realised. A historical perspective will lead to an account of the current crop of models, including to a high degree the experiences made in Denmark with operative use of the tools since 1994.
Three horizons are interesting for utilities: a short horizon determined by the ramping and start-up times of conventional power plants for the scheduling (4-8 hours ahead), a longer horizon dealing with the trading on the different electricity exchanges (in the case of NordPool, 13-37 hours ahead), and a long horizon where the models could be used for maintenance planning (all the way to weeks ahead). For the first case, one could get away with using a time-series analysis model coupled to climatology, but for even medium horizons, the accuracy of the model is getting much better by using numerical weather prediction, typically from the local meteorological institute.
The most prominent source of error is the numerical weather prediction model used, and in that it is phase errors (timing errors) that have a decisive impact on the traditional error scores, and on the financial bottom line. Current work is trying to estimate the uncertainty of the forecasts.
The longer report has been prepared in the framework of work for the EU Commission, especially a Marie-Curie-Fellowship and the ANEMOS project.

1. INTRODUCTION

This paper is a shortened version of a larger report produced 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,

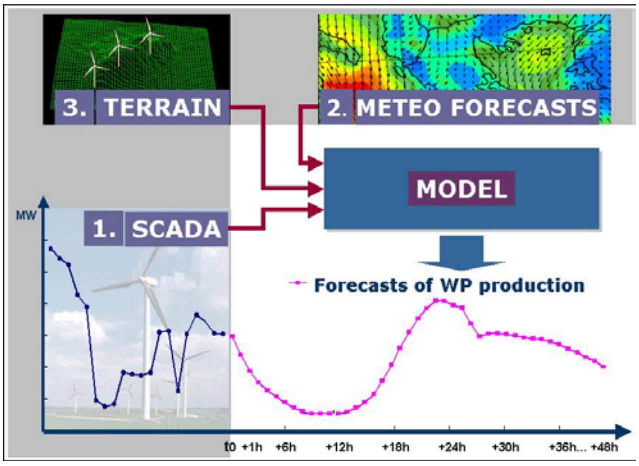

Figure 1: The various forecasting approaches can be classified according to the type of input (SCADA indicates data available on-line). All models involving Meteo Forecasts have a horizon determined by the NWP model, typically 48 hours.

(1):	Short-term statistical approaches using only SCADA as input (horizons: <6 hours).
(2):	Physical or statistical approaches. Good performance for >3 hours.
(2)+(3):	Physical approach. Good performance for >3 hours.
(1)+(2):	Statistical approach.
(1)+ (2)+(3):	Combined approach.

and such systems are only just now starting to appear [2,3,4]. As Still [5] 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.

The even shorter horizon for turbine control in the seconds range is not topic of this paper.

2. THE TYPICAL MODEL CHAIN

A gentle introduction to short-term predictions can also be found in [6]. In general, the models can be classified as either involving a Numerical Weather Prediction model (NWP) or not. Whether the inclusion of a NWP model 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. 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

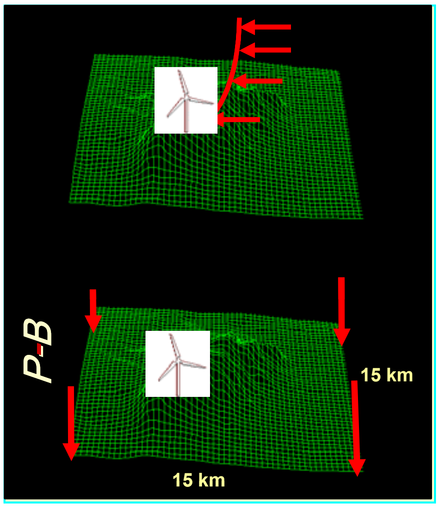

Figure 2: Two different approaches for downscaling. NWP-A represents physical considerations, NWP-B a statistical approach or the use of a meso- or microscale model.

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 is the so-called **downscaling** procedure.

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. 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 Model Output Statistics 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.

- 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 hundreds 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

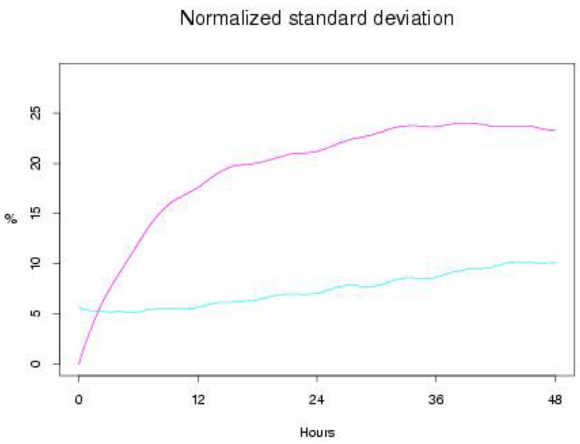

Figure 3: Error (Standard Deviation in % of installed capacity) for Zephyr/WPPT (blue) and the naïve predictor (red) as a function of prediction horizon. The results shown are for the configuration used by Eltra (system operator in the Western part of Denmark) based on data from June 2002 to May 2003 [7].

single farm.

A so explicit model formulation is typical for physical models. Statistical models instead often employ 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 to 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.

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.

3. 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); 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 and NWP is shown in Figure 3.

A number of features are noteworthy. 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.

Persistence beats a purely NWP-based model easily for short prediction horizons (ca 3-6 hours, even less in this example). The model shown here uses both NWP and measured data. 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 behaviour shown in the graph is quite common across all kinds of short-term forecasting models and not specific to Zephyr, although details can vary, 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 10-15% of the installed capacity. Complex terrain and NWPs of a low resolution, as in the example, penalise performance. In the case of regional/national forecasting, the model performance benefits from a smoothing effect of the errors and is usually in the order of 10% or even lower.

4. EVALUATION OF FORECASTING MODELS

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 storm front passing through: 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 [8] 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 [9] 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 improvement of one model over another as measured by MAE is lower than that by RMSE as the RMSE is weights large errors. In some cases a positive RMS may even correspond to a negative MAE improvement for certain time steps. The same has also been found by Giebel [10], 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 [11] 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 for the lowest cost integration of wind energy in the market.

These error measures work well when used for the same farm and the same time series. Farms with differently variable time series are not that easy to compare. For this reason the skill score was developed, which takes the different variability of the time series into account. In this way, different results can be compared against each other, without having to worry about the properties of the different time series.

Among the most important forecasts are the forecasts of 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, however, and the best way to get a feeling for the quality of the forecasts is visual inspection of the data set [*eg* 12]. 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 hurricane in Dec 1999. 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 a free electricity market emerges the consideration of criteria able to assess in a more wide 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.

5. DEMANDS ON FORECASTING MODELS

Schwartz and Brower [13] interviewed schedulers, research planners, dispatcher and energy planners at seven US utilities and asked for their needs in a wind energy forecast. Among the most needed was a day-ahead forecast, to be given in the morning for the unit commitment schedule and energy trading for the following day. Hourly forecasts, expressed in likely MW and with error bars, were another wish. However, one important result was that if good tools were available, operators in utilities with enough penetration would use these tools. This is also our experience with operators from Danish utilities.

The Irish TSO gave the following list of demands [14]:

- *"Forecasts should be available for individual wind farms and groups of wind farms.*
- *Forecasts should be wind power output, in MW, rather than wind speed,*
- *hourly forecasts extending out to a forecast horizon of at least 48 hours,*
- *an accurate forecast with an associated confidence level (dispatchers would tend to be more conservative when dealing with larger forecast uncertainties),*
- *a reliable forecast of likely changes in wind power production and*
- *a better understanding of the meteorological conditions which would lead to the forecasts being poor.*
- *Use of historical data to improve accuracy of forecast over time - the method for doing this needs to be built into the program."*

In Norway [15], a questionnaire sent to Norwegian wind energy producers and visits to a few of the larger energy companies revealed the following five points:

- "*The forecasts should be available early in the morning (before 08:00) in order to give time for consideration of the forecast before trading at noon.*
- *Wind power production should be predicted hourly, uncertainty intervals should also be given.*
- *Forecasts up to +36 h length are desirable.*
- *Updated forecasts in the afternoon based on production data.*
- *Forecasts several days ahead are useful for planning of maintenance.*"

6. 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. Partly this lack of analyses stems from the fact that a lot of data input and a proper time step 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 project is developing the market model and a model for the simulation of wind power predictions.

Milligan *et al* [16] used the Elfin model to assess the financial benefits of good forecasting, taking into account the load time series, a wind time series, the 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 underpredicting varied between the two utilities analysed in detail: while underpredicting was cheaper for one utility, the opposite held true for the other. The cost penalty in dependency of the forecast error was dependent very much 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.

Hutting and Cleijne [17] analysed the proposed structure of the Dutch electricity exchange, and found that 1500 MW of offshore wind power could achieve an average price of 3.5 €c/kWh, when coupled with back-up conventional plant. This assumes that "*75% of the output can be predicted well enough for the market*". Perfect prediction would raise the price to 4 €c/kWh. However, building 6000 MW of wind power would decrease the price to 2.9 €c/kWh. Reducing the specific power of the rotor from 500 to 300 W/m^2 would decrease the overall power output, but increase the capacity factor, thereby increasing the predictability and therefore enhancing the value by an extra 0.05 €c/kWh. This would actually improve the price performance ratio by about 10%, just by installing larger blades on the turbines. Spreading out the wind farms along the coast would increase the reliability of the generation and therefore lead to another 0.15 €c/kWh.

Nielsen *et al* [18] assessed the value for Danish wind power on the NordPool electricity exchange to be 2.4 €c/kWh in a year with normal precipitation (the NordPool system is dominated by Norwegian and Swedish hydropower). This would be reduced by 0.13-0.27 €c/kWh due to insufficient predictions. The same result is expressed as the penalty due to bad prediction of wind power being 12% of the average price obtained on NordPool by Sørensen and Meibom [19].

Kariniotakis and Miranda [20] 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.

According to the calculations in [21] the accuracy of the prognostic tools should be improved to more than 90% to reduce the costs for regulating power to an acceptable level.

Gilman *et al* [22] state that TrueWind's forecasting saved Southern California Edison $ 2 million in imbalance cost for December 2000 alone, compared to a system based on pure climatology.

Mylne [23] 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.

The potential value of forecasting to wind power generators in the UK was illustrated by Bathurst and Strbac [24] 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.

Ensslin [25] talks about the value of a forecasting tool in the framework of an "*Internet-based information system for integration of Renewable Energy Sources and Distributed Generation in Europe*".

7. MODELS IN USE AT UTILITIES

A number of models are currently used by large-scale utilities or TSOs. These include Zephyr/WPPT in Denmark, the Wind Power Management System in Germany, and Sipreólico in Spain. More-Care is also used operatively, but only in the smaller island grids of Madeira and Crete. Additionally, Zephyr/Prediktor has been the first model employing NWP forecasts to be used operatively in Eastern Denmark.

Already in 1990, Landberg [26 (with Troen), 27] developed a short-term prediction model based on physical reasoning similar to the methodology developed for the European Wind Atlas [28]. The idea is to use the wind speed and direction from a NWP, then transform this wind to the local site, then to use the power curve and finally to modify this with the park efficiency. The statistical improvement module MOS is also part of the package. 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 wake effects. The wind speeds from HIRLAM were in the beginning from level 27 [8], but after the DMI changed the operational HIRLAM model in June 1998, Joensen *et al* [29] found that after the change the 10 m wind was much better. After the change, passing storm systems were also better predicted, only missing the level once and not missing the onset at all [30]. 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 [31].
The model was in use operatively in eastern Denmark between 1993 and 1999. It also has been used at ESB (Electricity Supply Board, Ireland) [32] and in Iowa [33]. There, for predictions of the Nested Grid Model of the US National Weather Service, the use of MOS was essential. Prediktor is also used in the generic SCADA system *CleverFarm* for maintenance scheduling [34].

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 has been 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 [35], 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 [36].
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 [37].
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 NWP model will be subject to changes over time. This is caused by effects such as aging of the wind turbines and changes in the surrounding vegetation 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 [38]. 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.

In the project MORE-CARE (ERK5-CT1999-00019), ARMINES developed a wind power prediction system (AWPPS) for the power output of multiple wind parks for the next 48/72 hours using both on-line SCADA and NWPs (*ie* Hirlam, Skiron etc.). The AWPPS 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 numerical weather predictions.
- **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 prediction system is installed for on-line operation in the power systems of Crete and Madeira and operated by PPC and EEM respectively. A stand alone application of the wind forecasting module is configured for on-line operation in Ireland [7]. The AWWPS is integrated in an industrial SCADA system as well as in the More-CARE Energy Management System Platform.

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) [39], 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 [40]. Then, their model was called Advanced Wind Power Prediction Tool AWPT.
Ernst and Rohrig [41] 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 now 50 representative wind farms with 1/3 of the total installed capacity [42]. Their input model is the Lokalmodell of the DWD, which they then feed into an ANN. The LM is run twice daily with a horizontal resolution of 7 km,

forecasting up to 48 hours ahead. The ANN also provides for an area power curve. The WPMS runs at E.On since 2001, at RWE since June 2003, and the version for Vattenfall Europe is in the works (as of 09/2003). A version for two hours horizon has been developed for National Windpower in the UK. For the E.On total area, they claim RMSE values of 2,5% for 1h horizon (persistence would be 3,3%), 5,2% (7,3% for p.) at 3h, 6% (9% for p.) at 4h, and reach the error of a purely NWP based prognosis (7,5%) at 7h horizon.

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 [43]. The tool is based on Spanish HIRLAM forecasts, taking into account hourly SCADA data from 80% of all Spanish wind turbines [44]. 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 does not use 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 and a Kalman Filter. 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).

8. 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 that can reach 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 strategy 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. This contrasts nicely to the first EWEC in Madrid in 1990, where just 2 papers were presented (one by Troen and Landberg [26] of Risø, the other one by Fellows and Hill [45] of Uni Strathclyde / Rutherford Appleton Lab).

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.

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