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"Development of a Next Generation Wind Resource Forecasting System for the Large-Scale Integration of Onshore and Offshore Wind Farms"

The State-Of-The-Art in Short-Term Prediction of Wind Power

A Literature Overview

Version 1.1

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Abstract: Based on an appropriate questionnaire (WP1.1) and some other works already in progress, this report details the state-of-the-art in short term prediction of wind power, mostly summarising nearly all existing literature on the topic.

Contents

NOTE:

- *Updates of this Report will be made available in the future at the project web site (http://anemos.cma.fr).*
- *The next update (Version 2.0) will follow the release of the 2003 EWEC Conference Proceedings.*

1. Introduction

This report will give an overview over past and present attempts to predict wind power for single turbines or for whole regions, for a few minutes or a few days ahead. It has been 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. The literature search involved has been extensive, and it is hoped that this report can serve as a reference for all further work.

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 the following 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 [2,60,108]. 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 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 (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) cannot. The statistical

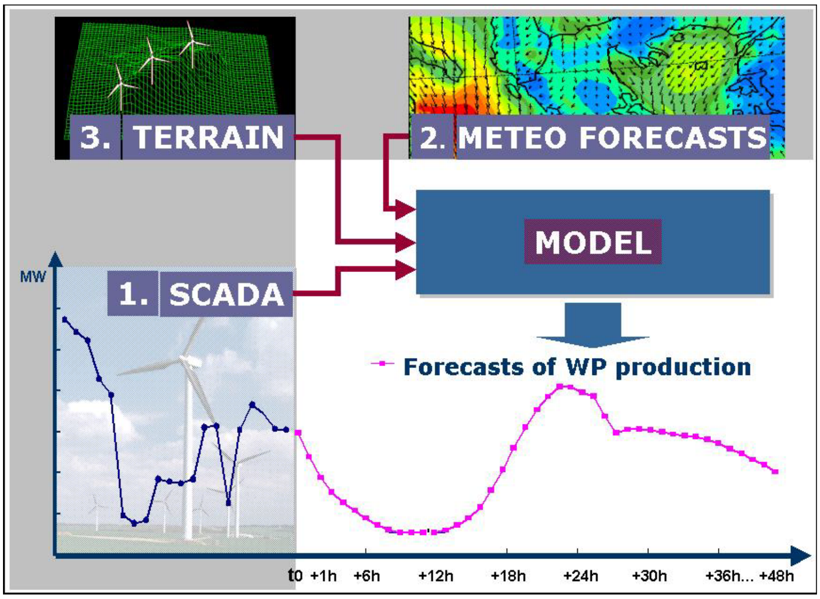

Figure 1: The various forecasting approaches can be classified according to the type of input (SCADA indicates data available on-line). All models involving Meteo Forecasts have a horizon determined by the NWP model, typically 48 hours.

(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.

models can be used at any stage of the modelling, and often they 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.

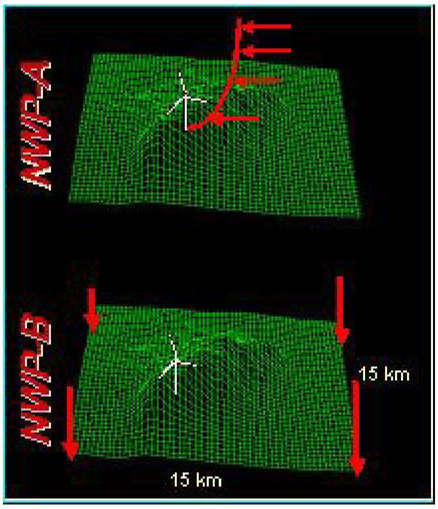

Figure 2: Two different approaches for downscaling. NWP-A represents physical considerations, NWP-B a statistical approach or the use of a meso- or microscale model.

- 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 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.

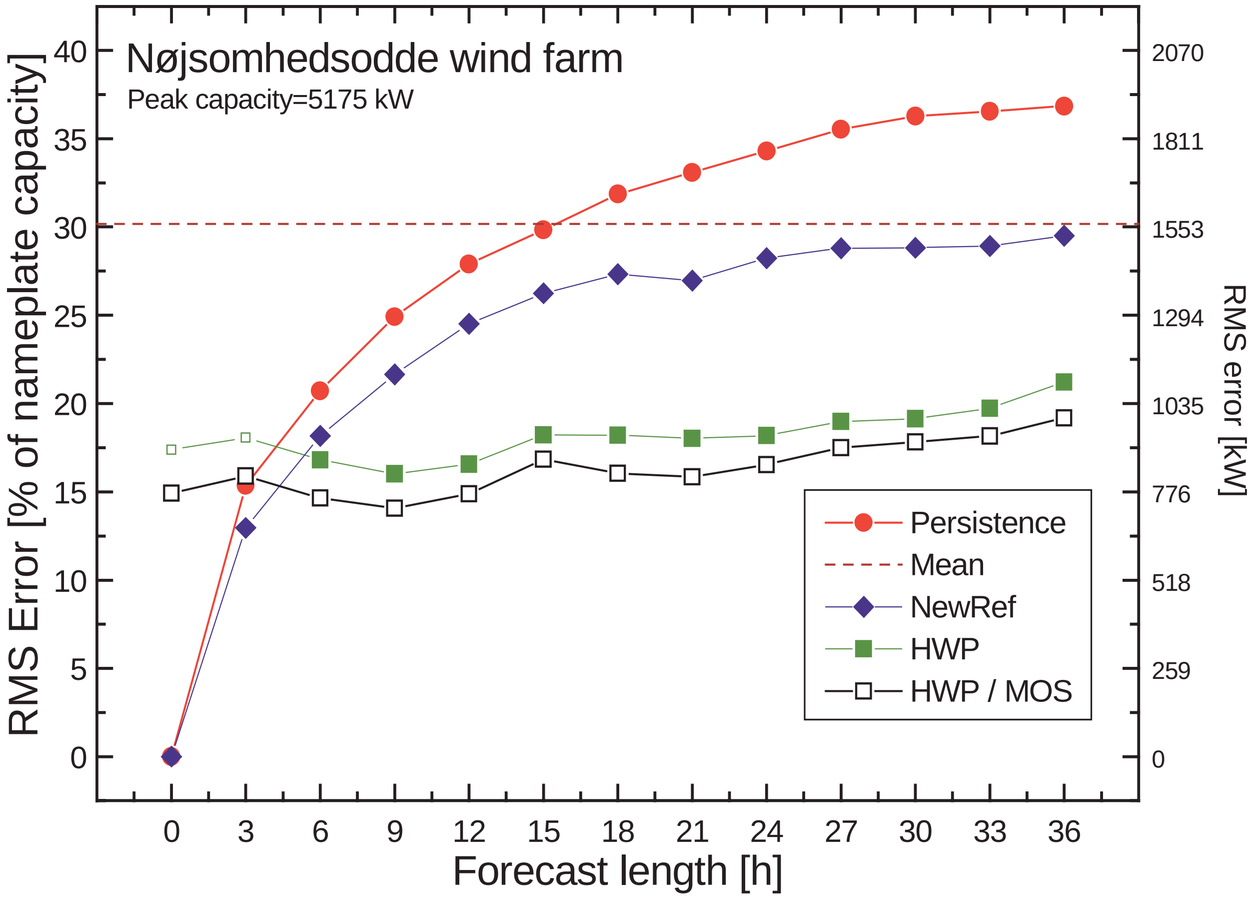

Figure 3: Root Mean Square (RMS) error for different forecast lengths and different prediction methods. The wind farm is the old Nøjsomheds Odde farm (before repowering) with an installed capacity of 5175 kW. NewRef refers to the New Reference Model. HWP/MOS refers to the HWP approach (HIRLAM/WAsP/Park, nowadays called Prediktor) coupled with a MOS model (Model Output Statistics).

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); 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.

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. 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 [27] 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 quality of the New Reference Model is reached after 5 hours. 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. Literature overview

2.1 Time series models for up to a few hours

For rather short horizons, the relevant time scales are given by:

- the mechanics of the wind turbine: typically the generator, gearbox, yaw mechanism and most of all, the (blade) pitch regulation. The time scales involved are in the order of the short-term turbulence, *ie* seconds. The purpose is the active control of the wind turbines.

- the type of the power system where the wind turbines are integrated. As mentioned in the introduction in small or medium isolated systems the relevant time scale is given by the type of conventional units (“fast” or “slow”) and the functions for which the forecasts are required (*ie* for economic dispatch horizons can be 10 minutes to 1 hour while for units scheduling a few hours head).

The typical approach is to use time series analysis techniques or neural networks.

2.1.1 Direct time series models

Bossanyi [6] used a Kalman Filter with the last 6 values as input and got up to 10% improvement in the RMS error over persistence for 1-min averaged data for the prediction of the next time step. This improvement decreased for longer averages, and disappeared completely for 1-hourly averages.

A similar approach is used in Wilhelmshaven [7] for the estimation of the wind with the aim of flicker reduction. Vihriälä [8] uses a Kalman filter for the control of a variable speed wind turbine.

Dambrosio and Fortunato [9] used a one-step-ahead adaptive control by means of a recursive least squares algorithm for the electrical part of the turbine. They show a fast and reliable response to a step in the wind.

Nogaret *et al* [10] reported that for the control system of a medium size island system, persistent forecasting is best with an average of the last 2 or 3 values, *ie* 20-30 minutes.

Tantareanu [11] found that ARMA models can perform up to 30% better than persistence for 3-10 steps ahead in 4-sec averages of 2.5Hz-sampled data.

Dutton *et al* [12] used a linear autoregressive model and an adaptive fuzzy logic based model for the cases of Crete and Shetland. They found minor improvements over persistence for a forecasting horizon of 2 hours, but up to 20% in RMS error improvement for 8 hours horizon. However, for longer horizons, the 95% confidence band contained most of the likely wind speed values, and therefore a meteorological-based approach was deemed more promising on this time scale.

In the same team, Kariniotakis *et al* [13,14] were testing various methods of forecasting for the Greek island of Crete. These included adaptive linear models, adaptive fuzzy logic models and wavelet based models. Adaptive fuzzy logic based models were installed for on-line operation in the frame of the Joule II project CARE (JOR3-CT96-0119).

Fukuda *et al* [15] worked on an AutoRegressive model for blade angle optimisation. Using data mining, they found that the use of additional variables was helpful only in December, but not in June.

Hunt and Nason [16] used an analysis of principal components of wavelets derived from wind speed time series for a measure-correlate-predict technique. The use of the words “short-term prediction” is not the same as the one used in our context.

2.1.2 Modelling wind speed versus wind power

Comparison of direct wind power prediction against wind speed forecasts with subsequent conversion to wind power [17,18] using autoregressive models showed use of wind speed predictions as explanatory variable is important for prediction horizon up to 8-12 hrs. For longer prediction horizons, use of separate wind speed forecasts offers no advantage over direct wind power prediction.

Madsen [19] and Nielsen [20] found that two-stage modelling (conversion of wind speed predictions to wind power, in which correlation structure in power measurements is disregarded) are generally inferior to models that take the power correlation into account.

Wind farm forecasting using any of the above methods is likely to benefit from forms of statistical post-processing such as the MOS system. Any use of meteorological models must involve a two-stage process, but if forecast winds are converted to power before insertion into the MOS system then it should be possible to optimise the training of the system for power prediction.

Giebel [21] shows that, when using NWP models, it is best to use MOS acting on the downscaled wind speed rather than on the final power output.

2.1.3 Neural networks

Another possibility to use just the input from online measurements is to use artificial neural networks. Most groups in the field have used them, but despite their scientific merits in improvements over plain persistence, they did not catch on. The improvements attainable were usually deemed not enough to warrant the extra effort in training the neural networks.

Beyer *et al* [22] found improvements in RMS error for next-step forecasting of either 1-min or 10-min averages to be in the range of 10% over persistence. This improvement was achieved with a rather simple topology, while more complex neural network structures did not improve the results further. A limitation was found in extreme events that were not contained in the data set used to train the neural network.

Tande and Landberg [23] examined 10s forecasts for the 1s average output of a wind turbine and found that the neural networks did perform only marginally better than persistence.

Alexiadis *et al* [24] used the differences of wind speeds from their moving averages (differenced pattern method) and found this technique to be superior to the wind speed normally used as input. They achieved improvements of up to 13% over persistence, while for the same time series the standard neural network approach yielded only 9.5% improvement.

Bechrakis and Sparis [25] used neural networks to utilise information from the upwind direction. Their paper does not give any numbers on the increase over persistence, since their aim is to predict the resource rather than to do short-term prediction.

Sfetsos [26] applied ARIMA and feed-forward neural net methods to wind speed time-series data from the UK and Greece, comparing the results of using either 10-minute or hourly averaged data to make a forecast one hour ahead. For both data sets, neither forecasting method showed a significant improvement compared to persistence using hourly-averaged data, but both showed substantial (10-20%) improvement using 10-minute averages. The result is attributed to the inability of hourly averages to represent structure in the time series on the high-frequency side of the 'spectral gap', lying at a period of typically around 1 hour.

2.1.4 An explanation of the time series model improvements

A general note on time series models (neural network or otherwise): Some of the improvement of the time series approach over persistence can be explained with a term taking the time series (running) mean into account. We tried a few years ago to introduce this as the New Reference Model [27] (see the blue line marked NewRef in fig. 3). In essence, it predicts the power p(t) using the power p(t-n) (n being n timesteps back) and the mean μ of the time series. Of course, disregarding μ and having n=1, this would be the persistence model itself. However, the new reference is written as

$$p(t)=a(n)*p(t-n) + (1-a(n))*\mu.$$

a(n) is the autocorrelation of the time series n steps back. This simple model can achieve the typically 10% RMS error improvements found by many other authors using more or less advanced time series analysis techniques.

2.2 Numerical Weather Prediction-based models

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[a]. 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.

2.2.1 Models no longer or never in action

Probably the earliest model was developed by McCarthy [28] for the Central California Wind Resource Area. It was run in the summers of 1985-87 on a HP 41CX programmable calculator, using meteorological observations and local upper air observations. The program was built around a climatological study of the site and had a forecast horizon of 24 hours. It forecast daily average wind speeds with better skill than either persistence or climatology alone.

Vitec AB from Sweden is working on a model based on meteorological forecasts from the Swedish Meteorological and Hydrological Institute SMHI. So far (2000), nothing is published [29].

Martin *et al* [30] started to develop a prediction tool for the rather special case of Tarifa/Spain. Due to the unique situation of the wind farms at the Strait of Gibraltar, they could predict the power output from pressure differences between the measurements at Jerez and Malaga airports (west and east of Gibraltar), with the additional use of the Spanish HIRLAM. However, since the utilities felt at that time that 48 hours of forecasts would not be useful enough, the project was stopped half-way through [31].

Papke *et al* [32] used a data assimilation technique together with three models to get a forecast of about 1 hour for the wind fed into the Schleswag grid in the German land of Schleswig-Holstein. These three models were a statistical model, analysing the trend of the last three hours, a translatorical model which moved a measured weather situation over the utility's area, and a meteorological model based on very simple pressure difference calculations. No accuracy was given. The translatorical model developed into the Pelwin system [33]. On a time scale of one hour, the weather fronts coming over the North Sea to Schleswig-Holstein are predicted to predict high negative gradients due to the shutdown of wind turbines.

Another translatorical model was proposed by Alexiadis *et al* [24,34], which uses a cleaning of local influence much like the methodology used in the European Wind Atlas. The Spatial

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[a] A quite prominent example was during the Euro'96 football championships, when in England after the semifinal England-Germany a sudden increase of about 1 GW demand could be logged within some 20 min. Germany had won in the penalties, and everyone needed a tea to calm down, most of which were brewed with an electrical kettle.

Correlation Predictor avoids the drawback of the usual constant delay method and shows improvements over the latter of up to 30% and more.

Not directly related to wind energy, Jacobs [35] uses a Kalman Filter to forecast road surface temperatures in the Netherlands based on the 2m temperatures of the HIRLAM model of the Royal Dutch Meteorological Institute (KNMI).

2.2.2 Research models

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. A good overview over the parameters and models influencing the result of a meteorological short-term forecasting system has been given by Mönnich [38]. 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 [39] 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 [40]. 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 [41].

A new approach is described by Jørgensen *et al* [42]: 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 a study with the Danish HIRLAM model for one site in Ireland [43] she points out the reasons why NWP models are delivering inadequate accuracy of surface wind speeds. Amongst other things, these were: so far, no customers made it necessary to increase the accuracy of surface winds, since for the existing ones the accuracy was good enough. The topography resolution is not good enough to account *eg* for tunnel effects in valleys. Accurate predictions require high resolution and large covered area, however running both is numerically too expensive - only few NWP models are able to distinguish between land and sea and can adjust the resolution accordingly. In order to improve on the state of things, she calculated the power directly in the NWP model. This has the advantage that "*major physical properties like direction dependent roughness, actual density, and stratification of the atmospheric boundary layer can be used in the calculations.*"

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 (MAE, RMSE, correlation etc) 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. As one possible remedy, she proposes to use free-standing turbine data as input for the NWP, thereby increasing the observational meteorological network.

In a follow-up paper [44], she shows the difference between the usual one-hour average wind speed and the instantaneous wind speeds. She concludes that is important to calculate the power within the model itself, to make use of its significantly shorter time step. (The difference comes of course because the energy in the wind is proportional to the cube of the wind speed, and does not depend linearly on it.)

For the same set-up, Jørgensen *et al* [45] 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. On the weather dependence of the errors, he writes: "*The more steady the flow is and the longer the controlling low pressure is towards the north, the better the quality of the forecast.*" He also notes on the (usually in NWP models just one value per grid box) roughness: "*Most turbines are positioned such that the local roughness is lower than the average roughness in the corresponding NWP model grid box. This is at least true for the prevailing wind direction [...]. Thus, a NWP model will in average have a negative wind bias where turbines are installed unless direction dependent roughness is used.* "

Barstad [46] used a library of pre-calculated meso-scale model results to downscale the wind from the large-scale weather situation to the actual site in Nord-Trøndelag county, Norway. The classification of the overall weather was derived from NCEP/NCAR Reanalysis data [47]. For the 32 cases found, MM5 was run to transform the large-scale flow to the wind at the actual (very complex) site. This approach was used together with Reanalysis to determine the resource in the vicinity, and was also used in conjunction with the HIRLAM system of the Norwegian Meteorological Institute to yield short-term forecasts. Berge [48] presented the whole system in Norrköping. A larger report [49] additionally compares the performance of MM5 with results from the CFD model 3DWind. HIRLAM was run on a horizontal resolution of 10 km, MM5 on 1 km and 3DWind with a resolution varying from 30 m to 500 m. To compare these models, a statistical model has been developed. Bremnes [50] reported during the Norrköping workshop on the use of “ensemble” forecasts, to yield the uncertainty of a forecast. His approach was to transform the forecasts according to the error distribution, standardise the centred forecast errors using the variance estimate, and retransform the wind speed. The larger report shows that the predicted frequencies actually are fairly accurate (*ie*, the 95% fractile, defined as a 95% probability that the power production will be below this value, was reached ca. 95% of the time). The best selection of explanatory variables based on HIRLAM10 was to use the wind speed at 10 m a.g.l., the wind direction, the wind speed increase and the time of day/horizon. One result of the comparison of the physical models was that despite the fact that the finer models did present more details of the forecasts, they always were fed with the initial and boundary conditions from the coarser HIRLAM model, and therefore were bound to have the same temporal development as the larger model. Also, the improvements in the details being brought by the mesoscale model and the CFD model did not show up in the error scores for a horizon of more than 20 hours. As a side note, the model speed-ups from MM5 and WAsP were compared, showing that in the highly complex terrain of Norway, MM5 (on 1 km resolution) tended to underpredict the speed-up effects by around 20%.

Enomoto *et al* [51] used the LOCALS model (Local Circulation Assessment and Prediction System) to forecast the power production of the TAPPI wind farm in Aomori Prefecture, Japan. Despite using the model with a 500-m grid, the result is still an RMSE of 15% of the installed capacity. Their results indicate that the significant differences in turbulence intensity between the turbines are not modelled correctly.

GEO mbh and GKSS [52] are currently developing the non-hydrostatic meso-scale model GEOFFREY (GESIMA-based Optimisation of Forecasts For Renewable Energy Yield). The model is going to be driven by the medium-range forecast of a private weather forecaster.

2.2.3 Models currently in use

Already in 1990, Landberg [53] developed a short-term prediction model based on physical reasoning similar to the methodology developed for the European Wind Atlas [54]. 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. 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.[b] Only one WAsP correction matrix is used, which could be too little for a larger wind farm [55]. In his original work, Landberg and Watson [56] 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* [57] 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 [58]. The model has also been used at ESB (Electricity Supply Board, Ireland) [59] and in Iowa [103]. 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 [60].

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

[b] In Previento, the geostrophic profile is used in conjunction with the roughness used by the NWP, not the mesoscale roughness.

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 [61], 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 [62].

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 [63].

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 [64]. 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 [14,65,66].

In the frame of the project CARE (JOR-CT96-0119) [67], more advanced short-term models were developed for the wind farms installed in Crete. In the ongoing 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 Numerical Weather Predictions (meteorological forecasts). 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 numerical weather predictions [68].
- **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 [69]. A stand alone application of the wind forecasting module is configured for on-line operation in Ireland [70]. An evaluation of this application is presented in [71]. 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 [70].

80 MW of wind power are installed on the island of Crete where the demand varies between 170-450 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 [72] 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) [73], 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 [74]. Then, their model was called Advanced Wind Power Prediction Tool AWPT.

Ernst and Rohrig [75] 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. The ANN also provides for an area power curve.

EWind is an US-American model by TrueWind, Inc [76]. 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 [78]. 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 [77].

EWind and Prediktor are currently being used in California [78]. 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.

That report also names a few papers I had never seen before, such as works by Wendell [79], Gilhousen [80], Carter and Gilhousen [81], Wegley [82] and Notis [83] (all works quoted as found in [78]).

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 [84]. The tool is based on Spanish HIRLAM forecasts, taking into account hourly SCADA data from 80% of all Spanish wind turbines [85]. 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 work along the lines of the models in section 2.1, 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).

2.2.4 The Norrköping workshop

A good overview over some of the activity going on in the field was provided at the recent (Sept. 2002) IEA Joint Action Symposium in Norrköping (Sweden). Some of the papers have already been cited in the relevant paragraphs below or above.

Garrad Hassan [86] now has a forecasting model, based on NWP forecasts from the British MetOffice. It uses "*multi-input linear regression techniques*" to convert from NWP to local wind speeds. For T+24h, they reach 35-60% improvement over persistence.

3Tier Environmental Forecast Group [87] works with a nested NWP and statistical techniques for the very short term in the Pacific Northwestern US. They show performance figures in line with most other groups in the field.

Tammelin [88] reported for the Finnish case that the Finnish Meteorological Institute is working on wind power forecasts, using their version of the HIRLAM model plus a number of smaller scale models to scale the wind speed down to the surface. An additional problem appearing in Finland is the difference in power curve due to low temperatures and icing.

Magnusson [89] spoke about wind forecasts for wind engineering purposes, protecting bridges and airports. Since the Swedish Meteorology and Hydrology Institute's HIRLAM model is not running in sufficient resolution for direct coupling into a CFD model (44 or 22 km), they use DYNAD as an intermediate tool. The CFD modelling is done on a scale of 25 m and yields turbulence levels as the main result.

Schwartz and Milligan [90] tried different ARMA models (AutoRegressive Moving Average) for forecasts up to 6 hours for two wind farms in Minnesota and Iowa. Their main conclusion was that model performance was highly dependent on the training period - one should always try to have a parameter set-up procedure using data from a very recent period.

ECN [91] has developed a forecasting system similar to Prediktor.

Holttinen [92] presented a different perspective to short-term forecasting. Since all current models have the error rising with the forecasting horizon, she looks at the benefits of adjusting the market rules to be more wind power friendly. In particular, the current NordPool agreement does trade on 1200 hours for the next full day ahead. This means that the most important forecasting has to be done for the 13-37 h prediction horizon at 1100 hours. The penalty for wrong predictions are fairly steep in this set-up, since either the producer has to sell the electricity on the spot market (if there is demand at all), or has to pay an up-regulation fee to the market. This could be avoided with more flexible market mechanisms, eg looking only 6 hours or even only 1 hour ahead. Using the current forecasting tools for Denmark (WPPT), she calculates a 15% higher value of wind power for a 6-12-h market, and a 30% higher income for a 1-h market, compared to the current 13-37-h market. She also makes the point that wind power could yield higher income in Denmark, if there would be a cable connecting the western part with the east. In this set-up, the wind power forecasting errors would be reduced by 9 % due to the larger catchment area.

2.3 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 [56] 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 [93] 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 weights large errors. In some cases a positive RMSE may even correspond to a negative MAE improvement for certain time steps. The same has also been found by Giebel [21], where optimising a MOS function's parameters lead to different results depending on whether the MAE was the cost function or the RMSE.

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* 94]. 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.

Costello *et al* [70] show an interesting approach: "*In order to focus on particular situations, a dynamic approach was developed to examine correlations in detail. The aim is to estimate the probability of situations where Hirlam fails to predict local conditions for a certain period of time (i.e. due to local weather situations). For this purpose, cross-correlation was estimated using a sliding window of 100 hours. Then, the distribution of the obtained values was estimated as shown in Figure 4. The range of the values is between {–0.4 to 0.92}. This indicates that one should expect short periods at which, Hirlam forecasts will not be reliable. The frequency of these periods is however limited since the distributions are centered around the 0.8 correlation value.*"

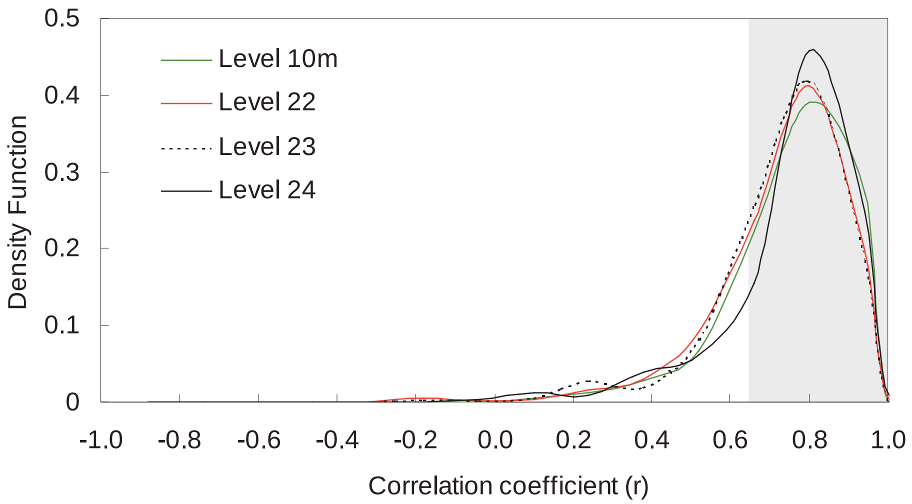

Figure 4: Distribution of correlation coefficient r(100) between Hirlam wind speed forecasts and measured wind park power. Source: [70]

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.

2.4 Uncertainty of wind power predictions

Spot predictions of the wind production for the next 48 hours at a single wind farm or at a regional/national level are a primary requirement for end-users. However, for an optimal management of the wind power production it is necessary to also provide end-users with appropriate tools for on-line assessment of the associated prediction risk. Confidence intervals are a response to that need since they provide an estimation of the error linked to power predictions.

While the estimation of confidence intervals for various types of mathematical models is an established field, only few papers specific to the short-term wind power prediction problem are published.

While statistical models already have an estimate of the uncertainty explicitely integrated in the method, physical models need some additional processing to yield an uncertainty result as well.

Typical confidence interval methods, developed for models like neural networks, are based on the assumption that the prediction errors follow a Gaussian distribution. This however is often not the case for wind power prediction where error distributions may exhibit some skewness, while the confidence intervals are not symmetric around the spot prediction due to the form of the wind farm power curve. On the other hand, the level of predicted wind speed introduces some nonlinearity to the estimation of the intervals; *eg* at the cut-out speed, the lower power interval may suddenly switch to zero.

Pinson and Kariniotakis [95] propose a methodology for the estimation of confidence intervals based on the resampling approach. This method is applicable to both physical and statistical wind power forecasting models. The authors also present an approach for assessing on-line the uncertainty of the predictions by appropriate prediction risk indices based on the weather stability.

The limits introduced by the wind farm power curve (min, max power) are taken into account by the method proposed by Luig *et al* [96] and Bofinger *et al* [97]. This method is models errors using a ß-distribution, the parameters of which have to be estimated by a post-processing algorithm. This approach is applicable to models that use a well-defined wind park power curve.

Lange and Waldl [99,98] classified wind speed errors as a function of look ahead time. The errors in wind speed of the older DWD Deutschlandmodell are fairly independent of the forecasted wind speed, except for significantly lower errors for the 0 and 1 m/s bins [99].Another result was that the error only for some wind farms depended on the *Grosswetterlage*, as classified by the DWD. Due to the non-linearity of the power curve, wind speed forecasting errors are amplified in the high-slope region between the cut-in wind speed of the turbine and the plateau at rated wind speed, where errors are dampened. Landberg *et al* [107] reported the same behaviour. Nielsen [100] also shows the WPPT error for western Denmark to have its peak at a forecast of half the installed capacity. This method is only applicable to models that provide intermediate forecasts of wind speed at the level of the wind park.

These are results for single wind farms. Since the correlation between forecast errors is rather weak with distance, the forecasts for a region are much more accurate than the forecast for single wind farms (as Focken points out [101, 102]). This error reduction scales with the size of the region in question. This means that only a certain number of wind farms is needed to predict the power production in a region well enough. For regions, the error autocorrelation is also stronger on a time scale of days than for single wind farms.

2.5 Ensemble forecasts

The increase in available computer power led to some thinking on how to use the increase properly. Instead of just upping the resolution more and more, the processing cycles might be better used in reducing the other errors. This can be done using ensembles of forecasts, either as a multi-model ensemble, using many different NWP models of at least different parameterisations within the same model, or by varying the input data and calculating an ensemble of different input values. The use of this is to be able to point out the uncertainty inherent in the forecasts. For example, if a slight variation in the initial state of the model (which still is consistent with the measured data) leads to a larger variation a few days ahead, where *eg* a low pressure system takes one of two distinct tracks, then the situation is different from one where all low pressure tracks more or less run over the same area. A number of groups in the field are currently investigating the benefits of ensemble forecasts.

Giebel *et al* [103] and Waldl and Giebel [104,105] investigated the relative merits of the Danish HIRLAM model, the Deutschlandmodell of the DWD and a combination of both for a wind farm in Germany. There, the RMSE of the Deutschlandmodell was slightly better than the one of the Danish model, while a simple arithmetic mean of both models yields an even lower RMSE.

Moehrlen *et al* [106] use a multi-model ensemble of different parameterisation schemes within HIRLAM. They make the point that, seeing that the observational network has a spacing of 30-40 km, it might be a better use of resources to run the NWP model not in the highest possible resolution (in the study 1.4 km), but use the computer instead for calculating ensembles. A doubling of resolution means a factor 8 in running time (since one has to double the number of points in all four dimensions). The same effort could therefore be used to generate 8 ensemble members. The effects of lower resolution would not be so bad, since effects well below the spacing of the observational grid are mainly invented by the model anyway, and could be taken care of by using direction dependent roughnesses instead.

Their group is also the leader of an EU-funded project called Honeymoon. One part of the project is to reduce the large-scale phase errors using ensemble prediction.

Landberg *et al* [107] used a poor man's ensemble to estimate the error of the forecast for one wind farm. A poor man's ensemble is formed using the overlapping runs of the forecasting model from different starting times for a given point in time. In his case, HIRLAM comes every 6 hours with a model horizon of 48 hours, leading to an ensemble size of up to 8 members for the same time. The assumption is that when the forecasts change from one NWP run to the next, then the weather is hard to forecast and the error is large. However, no conclusive proof for this intuitive assumption could be found.

In Denmark, the Zephyr collaboration has now a PSO-funded (ORDRE-101295 / FU 2101) three-year project [108] on the use of different kinds of ensembles for utility grade forecasting. Amongst others, the NCEP/NCAR and ECMWF ensembles are used, multi-model ensembles (with input from both DMI and DWD) are compared, and some methods for a good visual presentation of the uncertainty are researched.

While Bremnes [50] talks of ensemble forecasting, his method of probabilistic forecasts is not comparable to the other ensembles in this section, since they are not based on different runs of NWP models.

Roulston *et al* [109] evaluated the value of ECMWF forecasts for the power markets. Using a rather simple market model, they found that the best way to use the ensemble was what they called climatology conditioned on EPS (the ECMWF Ensemble Prediction System). The algorithm was to find 10 days in a reference set of historical forecasts for which the wind speed forecast at the site was closest to the current forecast. This set was then used to sample the probability distribution of the forecast. This was done for the 10^{th}, 50^{th} and 90^{th} percentile of the ensemble forecasts.

2.6 The value of forecasting

Even though the case for forecasting is an easy one, 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.

Milligan *et al* [110] 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- respectively 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 [111] 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* [112] assessed the value for Danish wind power on the NordPool electricity exchange to be 2.4 €c/kWh in a year with normal precipitation. 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 [113].

Kariniotakis and Miranda [114] 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 [115] 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* [116] 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 [117] 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 [118] 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 [119] 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*”.

While not directly connected to wind power forecasts, Klein and Pielke [120,121] looked at lawsuits brought against weather forecaster in the US. Generally speaking, the results are only valid for the US. The public forecasters there are usually immune under the law, which especially applies to exercise of a discretionary duty. This is strictly true for the federal government, while state legislation usually provides similar arrangements. However, "*the government's failure to follow a mandatory statute, regulation, or policy could expose it to liability*". The situation is different for private forecasters. Only two cases were filed for weather related forecasts so far, both of which were ruled in favour of the defendant. In the case Brandt vs. The Weather Channel, the judges (amongst other things) argued that "*because prediction of weather is precisely that — a prediction — a weather forecaster should not be subject to liability for an erroneous forecast. Predicting possible future events whose outcome is uncertain is not an exact science for which a broadcaster should be held liable.*" From other fields (think securities), more court cases are available. In these cases, the main allegation was fraud, which is reasonable enough (and thrown out of court relatively easily if it is a false allegation). The authors conclude with three pieces of advice to limit the exposure of professional forecasters to lawsuits: "*The best defense against liability is, first, for a company and its employees to make their forecasts in good faith using reasonable care. Second, companies should engage in a rigorous evaluation of their forecasts products. This would provide evidence of the skill of their forecast products generally, which may be useful should a liability issue arise, but could also help to scale their customers' expectations about the accuracies and uncertainties of the products and services that they are purchasing. Third, the company 's services agreement should clearly warn customers that forecasting is not a precise science. While these measures will help to avoid lawsuits in the first place, lawsuits may still be filed. Consequently, liability insurance makes sense.*"

2.7 Demands on forecasting models

Schwartz and Brower [122] 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 [70]:

- *"Forecasts should be available for individual windfarms 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 [49], 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 considertion 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 ueful for planning of maintenance.*"

3. The ANEMOS project

The ANEMOS project ("Development of a Next Generation Wind Resource Forecasting System for the Large-Scale Integration of Onshore and Offshore Wind Farms") is a 4 years R&D project that started in October 2002. It is funded by the European Commission under the 5th Framework Programme (ENK5-CT-2002-00665). A number of 22 partners participate from 7 countries including research institutes, universities, industrial companies, utilities, TSOs, and agencies.

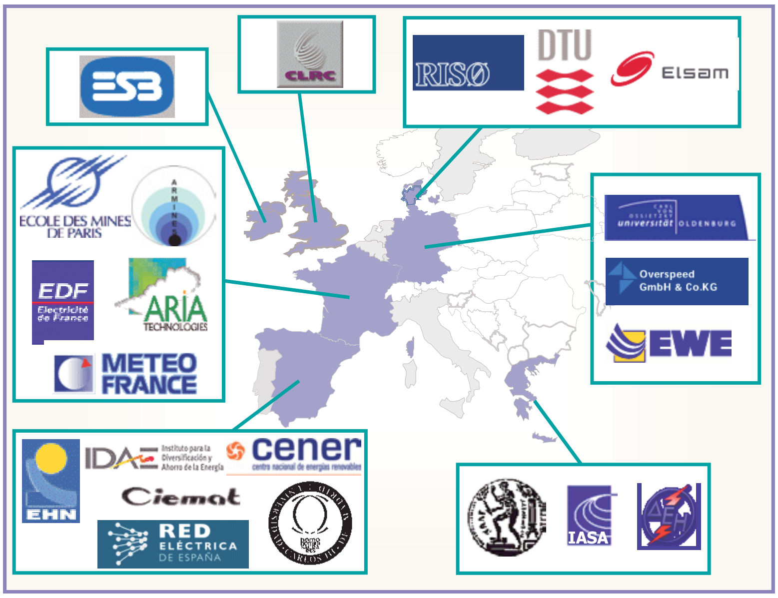

Figure 5: The consortium of the Anemos project (from http://anemos.cma.fr/).

The aim of the project is to develop advanced forecasting models that will substantially outperform current methods. Emphasis is given to situations like complex terrain, extreme weather conditions, as well as to offshore prediction for which no specific tools currently exist. The prediction models are implemented in a software platform and installed for online operation at onshore and offshore wind farms by the end-users participating in the project. The project demonstrates the economic and technical benefits from accurate wind prediction at different levels: national, regional or at single wind farm level and for time horizons ranging from minutes up to several days ahead.

Initially, the prediction requirements are defined in collaboration with end-users. Research on physical models gives emphasis to techniques for use in complex terrain and the development of prediction tools based on CFD techniques, advanced model output statistics or high-resolution meteorological information. Statistical models are developed for downscaling, power curve representation, upscaling for prediction at regional or national level, etc. A benchmarking process is set-up to evaluate the performance of the developed models and to compare them with existing ones using a number of case studies. The synergy between statistical and physical approaches is examined, together with the performance of purely meteorological forecasts.

Appropriate physical and statistical prediction models are also developed for offshore wind farms taking into account advances in marine meteorology (interaction between wind and waves, coastal effects). The benefits from the use of satellite radar images for modelling local weather patterns are investigated.

A next generation forecasting software, ANEMOS, is developed to integrate the various models. The tool is enhanced by advanced ICT functionality and can operate both in stand alone, or remote mode, or can be interfaced with standard EMS/DMS systems. The software will be installed for on-line operation at a number of onshore and offshore wind farms. Finally, the benefits from wind prediction will be evaluated during on-line operation, while guidelines will be produced for the optimal use of wind forecasting systems.

This report has actually been prepared as a Deliverable (D1.1) in the project. Additionally, a questionnaire was circulated to project partners, requesting details of their current wind forecasting models. The information to be supplied in the questionnaire included a short description of the model and its operational status and details of on-line data and numerical weather prediction requirements, prediction time resolution and horizon, and methods of downscaling, statistical post-processing (MOS), and upscaling.

Details of the questionnaire responses are summarized in the Annex of D1.1 Deliverable.

The institutes and corresponding models for which questionnaire responses were received are as follows:

Institute	Model name
Risø	Prediktor
ARMINES/RAL	More Care
Uni Oldenburg	Previento
IASA/AMWFG	SKIRON and RAMS
CENER	LocalPred-RegioPred
Uni Carlos III	SIPREOLICO
IMM/DTU	WPPT
ARMINES	AWPPS

An overview of operational models is given in the following table.

PREDICTION MODEL	DEVELOPER	METHOD	OPERATIONAL STATUS	OPERATIONAL SINCE
Prediktor	Risø	Physical	Spain, Denmark, Ireland, Germany, (US)	1994
WPPT	IMM; University of Copenhagen	Statistical	≈1GW, Denmark (E & W)	1994
Zephyr, Combination of WPPT and Prediktor	Risø and IMM	Physical, Statistical	-	-
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	-

4. 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% instananeous 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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6. Glossary

a.g.l.	Above ground level
ANN:	Artificial Neural Network
ARMINES:	Joint Research Unit with Ecole des Mines de Paris.
CLRC:	Council for the Central Laboratory of the Research Councils, UK
DMI:	Danish Meteorological Institute
DMS:	Distribution Management System.
DTU:	Technical University of Denmark
DWD:	Deutscher Wetterdienst (German Weather Service)
ECMWF:	European Centre for Medium Range Weather Forecasts, Reading, UK
EMS:	Energy Management System
EPS:	(The ECMWF) Ensemble Prediction System
ESP:	Energy Service Provider
HIRLAM:	High Resolution Limited Area Model, a NWP model developed by the met. Institutes of Denmark, France, Norway, Finland, Spain, and Ireland
Horizon:	The look-ahead time, sometimes used for the maximum a NWP can deliver
IMM:	Informatics and Mathematical Modelling at DTU, Lyngby, Denmark
IPP:	Independent Power Producer
LM:	Lokalmodell (the current NWP model of the DWD)
MAE:	Mean Absolute Error

MM5:	Mesoscale Model 5, a popular mesoscale code developed at Pennsylvania State University and NCAR
MOS:	Model Output Statistics, a means to remove residual error
NCEP/NCAR:	National Center for Environmental Protection / National Center for Atmospheric Research, Golden, Colorado, US
NWP:	Numerical Weather Prediction, usually run by meteorological institutes
Persistence:	Simple prediction method assuming that the wind production in the future will be the same as now.
Prediktor:	Short-term prediction system developed by Risø National Laboratory, Denmark
Previento:	Short-term prediction system developed by University of Oldenburg, Germany
PSO:	Power System Operator. In Denmark PSO stands for Public Service Obligation, a statute under which some money is collected from the electricity bills and used towards strengthening the network (including research)
RAL:	Rutherford Appleton Laboratory, Didcot, UK. Part of CLRC.
RLS:	Recursive Least Squares
RMSE:	Root Mean Square Error
SCADA:	Supervisory Control and Data Acquisition
Sipreólico:	Short-term prediction system developed by University Carlos III, Madrid, Spain
TSO:	Transmission System Operator
WPPT:	Wind Power Prediction Tool, the forecasting system developed at IMM (DTU)
Zephyr:	The new short-term prediction tool merging WPPT and Prediktor

7. References

1 See http://anemos.cma.fr/

2 Moreno, P., L. Benito, R. Borén and M. Cabré: *Short-Term Wind Forecast. Results of First Year Planning Maintenance at a Wind Farm.* Poster presented on the European Wind Energy Conference and Exhibition, Madrid (ES), 16-20 June, 2003

3 Still, D., B. Grainger: *Demanding Seas – The UK's First Offshore Wind Farm*. Proceedings of the European Wind Energy Conference, Copenhagen, Denmark, 2-6 June 2001, pp. 169-171, ISBN 3-936338-09-4. *Note: This statement was done during the talk.*

4 Landberg, L., G. Giebel, H.Aa. Nielsen, T.S. Nielsen, H. Madsen: *Short-term Prediction – An Overview*. Wind Energy **6**(3), pp. 273-280, June 2003. DOI 10.1002/we.96

5 Landberg, L.: *A Mathematical Look at a Physical Power Prediction Model.* Wind Energy **1**, pp. 23-28 (1998). DOI: 10.1002/(SICI)1099-1824(199809)1:1<23::AID-WE9>3.0.CO;2-9

6 Bossanyi, E.A.: *Short-Term Wind Prediction Using Kalman Filters*. Wind Engineering **9**(1), pp. 1-8 (1985)

7 Informationen aus dem Forschungsschwerpunkt Energieversorgung mit dezentralen Kleinkraftwerken in leistungsbegrenzten Versorgungsnetzen. Fachhochschule Wilhelmshaven, Fachbereich Elektrotechnik, Oktober 1999

8 Vihriälä, H., P. Ridanpää, R. Perälä, and L. Söderlund: *Control of a variable speed wind turbine with feedforward of aerodynamic torque*. Proceedings of the European Wind Energy Conference, Nice, France, 1-5 March 1999, pp. 881-884**,** ISBN 1 902916 00 X

9 Dambrosio, L, and D. Fortunato: *One-step-ahead control of a wind-driven, synchronous generator system*. Energy **24**, pp. 9-20 (1999), doi:10.1016/S0360-5442(98)00067-X

10 Nogaret, E., G. Stavrakakis, J.C. Bonin, G. Kariniotakis, B. Papadias, G. Contaxis, M. Papadopoulos, N. Hatziargyriou, S. Papathanassiou, J. Garopoulos, E. Karagounis, J. Halliday, G. Dutton, J. Pedas-Lopes, A. Androutsos, and P. Pligoropoulos: *Development and Implementation of an Advanced Control System for Medium Size Wind-Diesel Systems*. Proceedings of the EWEC '94 in Thessaloniki, 10.-14. Okt, pp. 599-604

11 Tantareanu, C.: *Wind Prediction in Short Term: A first step for a better wind turbine control*. Nordvestjysk Folkecenter for Vedvarende Energi, October 1992, ISBN 87-7778-005-1

12 Dutton, A.G., G. Kariniotakis, J.A. Halliday, and E. Nogaret: *Load and Wind Power Forecasting Methods for the Optimal Management of Isolated Power Systems with High Wind Penetration*. Wind Engineering **23**(2), pp. 69-87 (1999)

13 Kariniotakis, G., E. Nogaret, and G. Stavrakis: *Advanced Short-Term Forecasting of Wind Power Production*. Proceedings of the European Wind Energy Conference held in Dublin, Ireland, October 1997, pp. 751-754, ISBN 0 9533922 0 1

14 Kariniotakis, G.N., E. Nogaret, A.G. Dutton, J.A. Halliday, and A. Androutsos: *Evaluation of Advanced Wind Power and Load Forecasting Meghods for the Optimal Management of Isolated Power Systems*. Proceedings of the European Wind Energy Conference, Nice, France, 1-5 March 1999, pp. 1082-1085, ISBN 1 902916 00 X

15 Fukuda, H., S. Tamaki, M. Nakamura, H. Nagai, F. Shijo, S. Asato, K. Onaga: *The Development of a Wind Velocity Prediction Method Based on a Data-Mining Type Auto-Regressive Model*. Proceedings of the European Wind Energy Conference, Copenhagen, Denmark, 2-6 June 2001, pp. 741-744, ISBN 3-936338-09-4

16 Hunt, K., and G.P. Nason: *Wind speed modelling and short-term prediction using wavelets.* Wind Engineering **25** (1), pp. 55-61 (2001)

17 Jensen, U.S., E. Pelgrum and H. Madsen: *The Development of a Forecasting Model for the Prediction of Wind Power Production to be Used in Central Dispatch Centres.* Proceedings of the EWEC '94 in Thessaloniki, 10.-14. Okt, pp. 353-356

18 ELSAM, Final Report on EU JOULE II Project JOU-CT92-0083, 1996

19 H. Madsen (ed.): *Wind Power Prediction Tool in Control Dispatch Centres.* ELSAM, Skaerbaek, Denmark (1995), ISBN 87-87090-25-2

20 Nielsen, T.S., and H. Madsen: *Using Meteorological Forecasts in On-line Predictions of Wind Power*. ELSAM, Skaerbaek, Denmark (1996)

21 Giebel, G.: *On the Benefits of Distributed Generation of Wind Energy in Europe.* PhD thesis from the Carl von Ossietzky Universität. Fortschr.-Ber. VDI Reihe 6 Nr. 444. Düsseldorf, VDI Verlag 2001. ISBN 3-18-344406-2

22 Beyer, H.G., T. Degner, J. Hausmann, M. Hoffmann, and P. Ruján: *Short Term Prediction of Wind Speed and Power Output of a Wind Turbine with Neural Networks.* Proceedings of the EWEC '94 in Thessaloniki, 10.-14. Okt, pp. 349-352

23 Tande, J.O., and L. Landberg: *A 10 sec. Forecast of Wind Turbine Output with Neural Networks*. Proceedings of the 1993 ECWEC in Travemünde, 8.-12. March 1993, pp. 774-777, ISBN 0-9521452-0-0

24 Alexiadis, M.C., P.S. Dokopoulos, H.S. Sahsamanoglou, and I.M. Manousaridis: *Short-Term Forecasting of Wind Speed and Related Electrical Power*. Solar Energy **63**, pp. 61-68 (1998), doi:10.1016/S0038-092X(98)00032-2

25 Bechrakis, D.A. and P.D. Sparis: *Wind Speed Prediction Using Artificial Neural Networks*. Wind Engineering **22**(6), pp. 287-295 (1998)

26 Sfetsos, A.: *A novel approach for the forecasting of mean hourly wind speed time series*. Renewable Energy **27** , pp. 163-174 (2001)

27 Nielsen, T.S., A. Joensen, H. Madsen, L. Landberg and G. Giebel*: A New Reference for Predicting Wind Power*. Wind Energy **1**, pp. 29-34 (1998). DOI: 10.1002/(SICI)1099-1824(199809)1:1<29::AID-WE10>3.0.CO;2-B

28 Ed McCarthy: *Wind Speed Forecasting in the Central California Wind Resource Area.* Paper presented in the EPRI-DOE-NREL Wind Energy Forecasting Meeting March 23, 1998, Burlingame, CA

29 Törnevik, H.: private communication, 21.12.1999

30 Martin, F., R. Zubiaur, P. Moreno, S. Rodriguez, M. Cabre, M. Casanova, A. Hormigo, and M. Alonso: *Operational Tool for Short Term Prediction Model of Energy Production in Wind Power Plants at Tarifa (Spain)*. Proceedings of the 1993 ECWEC in Travemünde, 8.-12. March 1993, pp. 802-803, ISBN 0-9521452-0-0

31 Martí Perez, I.: private communication, 8.3.2000

32 Papke, U., A. Petersen, and V. Köhne: *Evaluation and Short-Time-Forecast of WEC-Power within the power grid of SCHLESWAG AG*. Proceedings of the 1993 ECWEC in Travemünde, 8.-12. March 1993, pp. 770-773, ISBN 0-9521452-0-0

33 Papke, U., and V. Köhne: *Pelwin -- ein Windleistungsprognosesystem zur Unterstützung des EVU-Lastverteilers*. In 2. Deutsche Windenergie-Konferenz 1994, Tagungsband Teil 1 (DEWEK '94), Wilhelmshaven, Deutschland, 1994. Deutsches Windenergie Institut GmbH (DEWI).

34 Alexiadis, M.C., P.S. Dokopoulos, H.S. Sahsamanoglou: *Wind Speed and Power Forecasting Based on Spatial Correlation Models.* IEEE Trans. Energy, **14**(3) (1999), 836-842.

35 Jacobs, A.: *KALCORR: a Kalman-correction model for real-time road surface temperature forecasting*. KNMI technical report TR-198, DeBilt, 1997, ISBN 90-369-2119-8

36 Beyer, H.G., D. Heinemann, H. Mellinghoff, K. Mönnich, and H.-P. Waldl: *Forecast of Regional Power Output of Wind Turbines*. Proceedings of the European Wind Energy Conference, Nice, France, 1-5 March 1999, pp. 1070-1073, ISBN 1 902916 00 X

37 Focken, U., M. Lange, H.-P. Waldl: *Previento – A Wind Power Prediction System With an Innovative Upscaling Algorithm*. Proceedings of the European Wind Energy Conference, Copenhagen, Denmark, 2-6 June 2001, pp. 826-829, ISBN 3-936338-09-4

38 Mönnich, K.: *Vorhersage der Leistungsabgabe netzeinspeisender Windkraftanlagen zur Unterstützung der Kraftwerkseinsatzplanung*. PhD-thesis, Carl von Ossietzky Universität Oldenburg, 2000.

39 Martí Perez, I.: *Wind Forecasting Activities*. Proceedings of the First IEA Joint Action Symposium on Wind Forecasting Techniques, Norrköping, Sweden, December 2002, pp. 11-20. Published by FOI - Swedish Defence Research Agency.

40 Martí Perez, I., T.S. Nielsen, H. Madsen, J. Navarro, A. Roldán, D. Cabezón, C.G. Barquero: *Prediction Models in Complex Terrain*. Proceedings of the European Wind Energy Conference, Copenhagen, Denmark, 2-6 June 2001, pp. 875-878, ISBN 3-936338-09-4

41 Martí Perez, I., T.S. Nielsen, H. Madsen, A. Roldán, S. Pérez: *Improving Prediction Models in Complex Terrain*. Poster P_GWP185 on the Global Windpower Conference and Exhibition, Paris, France, 2-5 April 2002, 4 p. on the Proceedings CDROM

42 Jørgensen, J., C. Moehrlen, B. Ó Gallaghóir, K. Sattler and E. McKeogh: *HIRPOM: Description of an operational numerical wind power prediction model for large scale integration of on- and offshore wind power in Denmark.* Poster on the Global Windpower Conference and Exhibition, Paris, France, 2-5 April 2002, 5 p. on the Proceedings CDROM

43 Moehrlen, C.: *On the Benefits of and Approaches to Wind Energy Forecasting*. Invited Speaker at the Irish Wind Energy Association Annual Conference "Towards 500MW", (2001).

44 Moehrlen, C., J. Jørgensen, K. Sattler, E. McKeogh: *On the accuracy of land cover data in NWP forecasts for high resolution wind energy prediction.* Proceedings of the European Wind Energy Conference, Copenhagen, Denmark, 2-6 June 2001, pp. 854-857, ISBN 3-936338-09-4

45 Jørgensen, J., C. Moehrlen, E. McKeogh: *A New Generation Operational On- and Offshore Numerical Prediction System*. Talk (?) on the World Wind Energy Conference in Berlin, Germany, June 2002

46 Barstad, I.: *Down-Scaling of Wind in a Dynamic Framework*. Proceedings of the European Wind Energy Conference, Copenhagen, Denmark, 2-6 June 2001, pp. 713-716, ISBN 3-936338-09-4

47 Kalney, E. *et al*: *The NCEP/NCAR 40-year reanalysis project*. Bulletin of the American Meteorological Society **77**, (1996), pp. 437–471; See also *http://wesley.wwb.noaa.gov/reanalysis.html*

48 Berge, E.: *Experiences with wind forecasting techniques in Norway*. Proceedings of the First IEA Joint Action Symposium on Wind Forecasting Techniques, Norrköping, Sweden, December 2002, pp. 59-64. Published by FOI - Swedish Defence Research Agency.

49 Berge, E., F. Nyhammer, L. Tallhaug, F. Villanger, J.b. Bremnes, M.Ø. Køltzow, J. Smits, A. Knauer: *Forecasting wind and wind energy production in Norwegian wind farms. Final report of the NFR project: 138848/212 "Korttidsprognoser for energiprokuksjon fra vindkraft"*. Kjeller Vindteknikk Report number KVT/EB/2003/005, Kjeller (NO), 2003

50 Bremnes, J.B.: *Probablilistic wind power forecasts by means of a statistical model*. Proceedings of the First IEA Joint Action Symposium on Wind Forecasting Techniques, Norrköping, Sweden, December 2002, pp. 103-114. Published by FOI - Swedish Defence Research Agency.

51 Enemoto, S., N. Inomata, T. Yamada, H. Chiba, R. Tanikawa, T. Oota, H. Fukuda: *Prediction of Power Output from Wind Farm Using Local Meteorological Analysis*. Proceedings of the European Wind Energy Conference, Copenhagen, Denmark, 2-6 June 2001, pp. 749-752, ISBN 3-936338-09-4

52 GEO mbh and GKSS: *Optimierung von Windprognosen zur präzisen Vorausberechnung von Windstromerträgen als Handlungsgrundlage im dezentralen Energiemanagement (Optimisation of wind power forecasts for the precise calculation of wind power yields as a decision basis in the decentralised energy management)*. Projekt funded by the Deutsche Bundesstiftung Umwelt. 02/2003-01/2005

53 Landberg, L.: *Short-term Prediction of Local Wind Conditions*. PhD-Thesis, Risø-R-702(EN), Risø National Laboratory, Roskilde, Denmark 1994, ISBN 87-550-1916-1

54 Troen, I., and E.L. Petersen: *European Wind Atlas*. Published for the EU Commission DGXII by Risø National Laboratory, Denmark (1998), ISBN 87-550-1482-8

55 Landberg, L.: *Short-term Prediction of the Power Production from Wind Farms.* J. Wind Eng. Ind. Aerodyn. **80**, pp. 207-220 (1999)

56 Landberg, L., and S.J. Watson: *Short-term Prediction of Local Wind Conditions*. Boundary-Layer Meteorology **70**, p. 171 (1994)

57 Joensen, A., G. Giebel, L. Landberg, H. Madsen, and H. Aa. Nielsen: *Model Output Statistics Applied to Wind Power Prediction*. Proceedings of the European Wind Energy Conference, Nice, France, 1-5 March 1999, pp. 1177-1180, ISBN 1 902916 00 X

58 Landberg, L.: *Short-term Prediction of Local Wind Conditions.* J. Wind Eng. Ind. Aerodyn. **89**, pp. 235-245 (2001)

59 Watson, R., L. Landberg, R. Costello, D. McCoy, P. O'Donnell: *Evaluation of the Prediktor Wind Power Forecasting System in Ireland*. Proceedings of the European Wind Energy Conference, Copenhagen, Denmark, 2-6 June 2001, pp. 703-706, ISBN 3-936338-09-4

60 Giebel, G., L. Landberg, C. Bjerge, M.H. Donovan, A. Juhl, K. Gram-Hansen, H.-P. Waldl, T. Pahlke, J. Giebhardt, M. Rebbeck, R. Ruffle, O. Brady: *CleverFarm - First results from an*

intelligent wind farm. Paper presented at the European Wind Energy Conference and Exhibition, Madrid, Spain, 16-19 June 2003.

61 Nielsen, T.S., and H. Madsen: *Statistical Methods for Predicting Wind Power*. Proceedings of the European Wind Energy Conference held in Dublin, Ireland, October 1997, pp. 755-758, ISBN 0 9533922 0 1

62 Nielsen, T.S., H. Madsen, and J. Tøfting: *Experiences with Statistical Methods for Wind Power Prediction*. Proceedings of the European Wind Energy Conference, Nice, France, 1-5 March 1999, pp. 1066-1069, ISBN 1 902916 00 X

63 Nielsen, T.S., L. Landberg, G. Giebel: *Prediction of Regional Wind Power.* Poster P_GWP148 on the Global Windpower Conference, Paris, France, 2-5 April, 2002.

64 Giebel, G., L. Landberg, T.S. Nielsen, H. Madsen: *The Zephyr Project – The Next Generation Prediction System*. Poster P_GWP145 on the Global Windpower Conference and Exhibition, Paris, France, 2-5 April 2002

65 Kariniotakis G., G.S. Stavrakakis, E.F. Nogaret: *Wind power forecasting using advanced neural network models.* IEEE Transactions on Energy Conversion, Vol. 11, No. 4, December 1996, pp. 762-767. (96 SM 552-0 EC), *Presented at the 1996 IEEE/PES Summer Meeting, July 28-Aug. 1, 1996, Denver, Colorado.*

66 Kariniotakis, G.N.: *Contribution au développement d'un système de contrôle avancé pour les systèmes éolien-diesel autonomes.* Thèse de doctorat européen, Ecole des Mines de Paris, Spécialité énergétique, Décembre 1996.

67 Wind Engineering, CARE Special Issue, Vol **23**(2), 1999

68 Kariniotakis, G.N., D. Mayer: *An Advanced On-Line Wind Resource Prediction System for the Optimal Management of Wind Parks*. Paper presented on the 3rd MED POWER conference 2002, Athens (GR), November 4-6, 2002

69 Kariniotakis, G.N., D. Mayer, J.A. Halliday, A.G. Dutton, A.D. Irving, R.A. Brownsword, P.S. Dokopoulos, M.C. Alexiadis: *Load, Wind and Hydro Power Forecasting Functions of the More-Care EMS System*. Paper presented on the 3rd MED POWER conference 2002, Athens (GR), November 4-6, 2002

70 Costello, R., D. McCoy, P. O'Donnell, A.G. Dutton, G.N. Kariniotakis: *Potential Benefits of Wind Forecasting and the Application of More-Care in Ireland*. Paper presented on the 3rd MED POWER conference 2002, Athens (GR), November 4-6, 2002

71 Kariniotakis, G., P. Pinson: *Evaluation of the More-Care Wind Power Prediction Platform. Performance of the Fuzzy Logic Based Models*. Paper presented at the European Wind Energy Conference and Exhibition, Madrid, Spain, 16-19 June 2003.

72 Hatziargyriou, G.C., M. Matos, J.A. Pecas Lopes, G. Kariniotakis, D. Mayer, J. Halliday, G. Dutton, P. Dokopoulos, A. Bakirtzis, J. Stefanakis, A. Gigantidou, P. O'Donnell, D. McCoy, M.J. Fernandes, J.M.S. Cotrim, A.P. Figueira: *"MORE CARE" Advice for Secure Operation of Isolated Power Systems with Increased Renewable Energy Penetration & Storage.* Proceedings

of the European Wind Energy Conference, Copenhagen, Denmark, 2-6 June 2001, pp. 1142-1145, ISBN 3-936338-09-4

73 Durstewitz, M. C. Ensslin, B. Hahn, M. Hoppe-Kilpper: *Annual Evaluation of the Scientific Measurement and Evaluation Programme (WMEP)*. Kassel, 2001

74 Ernst, B., K. Rohrig, H. Regber, Dr. P. Schorn: *Managing 3000 MW Wind Power in a Transmission System Operation Center*. Proceedings of the European Wind Energy Conference, Copenhagen, Denmark, 2-6 June 2001, pp. 890-893, ISBN 3-936338-09-4

75 Ernst, B., K. Rohrig: *Online-Monitoring and Prediction of Wind Power in German Transmission System Operation Centres*. Proceedings of the First IEA Joint Action Symposium on Wind Forecasting Techniques, Norrköping, Sweden, December 2002, pp. 125-145. Published by FOI - Swedish Defence Research Agency.

76 Bailey, B., M. C. Brower, and J. Zack: *Short-Term Wind Forecasting*. Proceedings of the European Wind Energy Conference, Nice, France, 1-5 March 1999, pp. 1062-1065, ISBN 1 902916 00 X; see also *http://www.truewind.com/*.

77 Zack, J.W., M.C. Brower, B.H. Bailey: *Validating of the Forewind Model in Wind Forecasting Applications*. Talk on the EUWEC Special Topic Conference Wind Power for the 21st Century, Kassel, Germany, 25-27 Sept 2000

78 *California Wind Energy Forecasting System Development and Testing, Phase 1: Initial Testing*. EPRI Final report 1007338, Jan 2003.

79 Wendell, L.L., H.L. Wegley, M.G. Verholek: *Report from a Working Group Meeting on Wind Forecasts for WECS Operations.* PNL-2513, Batelle-Pacific Northwest Laboratory, Richland, WA 99352, 1978

80 Gilhousen, D.B.: *Development and Testing of Model Output Statistics for Wind Forecasts at Wind Turbine Generator Sites.* DOE/RL/10046-1. NWS/NOAA, Silver Spring, MD 20910, 1979, 25pp.

81 Carter, G.M., D.B. Gilhousen: *The Potential Impact of Automated Wind Guidance on Wind Energy Conversion Operations.* 1980, 13pp.

82 Wegley, H.L.: *The Development and Evaluation of Wind Forecasts for Wind Energy Applications.* Battelle-Pacific Northwest Laboratory, Contract DE-AC06-76ALO, 1980

83 Notis: *Learning to Forecast Wind at Remote Sites for Wind Energy Applications.* 1983

84 González Morales, G.: *Sipreólico. Wind power prediction experience*. Talk slides accompanied by the paper: Sánchez, I., J. Usaola, O. Ravelo, C. Velasco, J. Domínguez, M.G. Lobo, G. González, F. Soto, B. Díaz-Guerra, M. Alonso: *Sipreólico - A wind power prediction system based on flexible combination of dynamic models. Application to the Spanish power system.* Proceedings of the First IEA Joint Action Symposium on Wind Forecasting Techniques, Norrköping, Sweden, December 2002, pp.197-214. Published by FOI - Swedish Defence Research Agency.

85 Sánchez, I., J. Usaola, O. Ravelo, C. Velasco, J. Domínguez, M.G. Lobo, G. González, F. Soto: *SIPREÓLICO - A Wind Power Prediction System Based on Flexible Combination of Dynamic Models. Application to the Spanish Power System.* Poster on the World Wind Energy Conference in Berlin, Germany, June 2002

86 Gow, G.: *Short Term Wind Forecasting in the UK*. Proceedings of the First IEA Joint Action Symposium on Wind Forecasting Techniques, Norrköping, Sweden, December 2002, pp. 3-10. Published by FOI - Swedish Defence Research Agency.

87 Westrick, K.: *Wind Energy Forecasting in the Pacific Northwestern U.S.*. Proceedings of the First IEA Joint Action Symposium on Wind Forecasting Techniques, Norrköping, Sweden, December 2002, pp. 65-74. Published by FOI - Swedish Defence Research Agency.

88 Tammelin, B.: *Wind Power Forecasting*. Proceedings of the First IEA Joint Action Symposium on Wind Forecasting Techniques, Norrköping, Sweden, December 2002, pp. 75-81. Published by FOI - Swedish Defence Research Agency.

89 Magnusson, M.: *CFD as tool for wind forecasts*. Proceedings of the First IEA Joint Action Symposium on Wind Forecasting Techniques, Norrköping, Sweden, December 2002, pp. 83-91. Published by FOI - Swedish Defence Research Agency.

90 Schwartz, M., M. Milligan: *Statistical Wind Forecasting at the U.S. National Renewable Energy Laboratory*. Proceedings of the First IEA Joint Action Symposium on Wind Forecasting Techniques, Norrköping, Sweden, December 2002, pp. 115-124B. Published by FOI - Swedish Defence Research Agency.

91 Brand, A.J., J.K. Kok: *Wind power by a quarter of the hour*. Proceedings of the First IEA Joint Action Symposium on Wind Forecasting Techniques, Norrköping, Sweden, December 2002, pp. 163-169. Published by FOI - Swedish Defence Research Agency.

92 Holttinen, H., T.S. Nielsen, G. Giebel: *Wind energy in the liberalised market - forecast errors in a day-ahead market compared to a more flexible market mechanism*. Proceedings of the First IEA Joint Action Symposium on Wind Forecasting Techniques, Norrköping, Sweden, December 2002, pp. 171-181. Published by FOI - Swedish Defence Research Agency.

93 Kariniotakis, G.: Position Paper on JOULE Project JOR3-CT96-0119, (1997)

94 Landberg, L.: *Short-term prediction of local wind conditions*. Wind Engineering into the 21st Century, Proceedings of the Tenth International Conference on Wind Engineering, Copenhagen/Denmark, 21-24 June 1999, Larsen, Larose & Livesey (eds), Balkema, Rotterdam, ISBN 90 5809 059 0, pp. 1997-2003

95 Pinson, P., G. Kariniotakis: *On-line Assessment of Prediction Risk for Wind Power Production Forecasts*. Proceedings of the European Wind Energy Conference and Exhibition, Madrid, Spain, 16-19 June 2003.

96 Luig, A., S. Bofinger, H.G. Beyer: *Analysis of confidence intervals for the prediction of regional wind power output*. Proceedings of the European Wind Energy Conference, Copenhagen, Denmark, 2-6 June 2001, pp. 725-728, ISBN 3-936338-09-4

97 Bofinger, S., A. Luig, H.G. Beyer: *Qualification of Wind Power Forecasts*. Poster P_GWP093 on the Global Windpower Conference and Exhibition, Paris, France, 2-5 April 2002

98 Lange, M., D. Heinemann: *Accuracy of short term wind power predictions depending on meteorological conditions*. Poster P_GWP091 on the Global Windpower Conference and Exhibition, Paris, France, 2-5 April 2002

99 Lange, M., H.-P. Waldl: *Assessing the Uncertainty of Wind Power Predictions with Regard to Specific Weather Situations*. Proceedings of the European Wind Energy Conference, Copenhagen, Denmark, 2-6 June 2001, pp. 695-698, ISBN 3-936338-09-4. *(Note: the paper is misprinted in the proceedings, better follow the link provided to their university homepage.)*

100 Nielsen, H.Aa.: *Analyse og simulering af prædiktionsfejl for vindenergiproduktion ved indmelding til NordPool*. Report, IMM, DTU, 20. February 2002

101 Focken, U., M. Lange, H.-P. Waldl: *Reduction of Wind Power Production Error by Spatial Smoothing Effects.* Proceedings of the European Wind Energy Conference, Copenhagen, Denmark, 2-6 June 2001, pp. 822-825, ISBN 3-936338-09-4

102 Focken, U., M. Lange, K. Mönnich, H.-P. Waldl, H.G. Beyer, A. Luig: *Short-term prediction of the aggregated power output of wind farms – a statistical analysis of the reduction of the prediction error by spatial smoothing effects.* J. Wind Eng. Ind. Aerodyn. **90**(3), pp. 139-249 (March 2002), DOI 10.1016/S0167-6105(01)00222-7

103 Giebel, G., L. Landberg, K. Mönnich, H.-P. Waldl: *Relative Performance of different Numerical Weather Prediction Models for Short Term Prediction of Wind Energy*. Proceedings of the European Wind Energy Conference, Nice, France, 1-5 March 1999, pp. 1078-1081, ISBN 1 902916 00 X

104 Waldl, H.-P., and G. Giebel: *The Quality of a 48-Hours Wind Power Forecast Using the German and Danish Weather Prediction Model.* Wind Power for the 21st Century, EUWEC Special Topic Conference, Kassel (DE), 25-27 Sept 2000

105 Waldl, H.-P., and G. Giebel: *Einfluss des dänischen und des deutschen Wettervorhersage-modells auf die Qualität einer 48-Stunden-Windleistungsprognose*. 5. Deutsche Windenergie-konferenz DEWEK 2000, Wilhelmshaven (DE), 7-8 Jun 2000, pp. 145-148

106 Moehrlen, C., J. Jørgensen, K. Sattler, E. McKeogh: *Power Predictions in Complex Terrain With an Operational Numerical Weather Prediction Model in Ireland Including Ensemble Forecasting*. Poster on the World Wind Energy Conference in Berlin, Germany, June 2002

107 Landberg, L., G. Giebel, L. Myllerup, J. Badger, T.S. Nielsen, H. Madsen: *Poor man's ensemble forecasting for error estimation.* AWEA, Portland/Oregon (US), 2-5 June 2002

108 Giebel, G., L. Landberg, J. Badger, K. Sattler, H. Feddersen, T.S. Nielsen, H.Aa. Nielsen, H. Madsen: *Using Ensemble Forecasting for Wind Power*. Paper presented on the European Wind Energy Conference and Exhibition, Madrid (ES), 16-20 June, 2003

109 Roulston, M.S., D.T. Kaplan, J. Hardenberg, L.A. Smith: *Value of the ECMWF Ensemble Prediction System for Forecasting Wind Energy Production*. Proceedings of the European Wind Energy Conference, Copenhagen, Denmark, 2-6 June 2001, pp. 699-702, ISBN 3-936338-09-4

110 Milligan, M.R., A.H. Miller, and F. Chapman: *Estimating the Economic Value of Wind Forecasting to Utilities*. Presented at Windpower '95, Washington, D.C., March 27-30, 1995. NREL/TP-441-7803. Get it from *OSTI.gov*.

111 Hutting, H.K., and J.W. Cleijne: *The Price of Large Scale Offshore Wind Energy in a Free Electricity Market*. Proceedings of the European Wind Energy Conference, Nice, France, 1-5 March 1999, pp. 399-401, ISBN 1 902916 00 X

112 Nielsen, L.H., P.E. Morthorst, K. Skytte, P.H. Jensen, P. Jørgensen, P.B. Eriksen, A.G. Sørensen, F. Nissen, B. Godske, H. Ravn, C. Søndergreen, K. Stærkind, and J. Havsager: *Wind Power and a Liberalised North European Electricity Exchange*. Proceedings of the European Wind Energy Conference, Nice, France, 1-5 March 1999, pp. 379-382, ISBN 1 902916 00 X

113 Sørensen, B. and P. Meibom: *Can Wind Power be Sold in a Deregulated Electricity Market?* Proceedings of the European Wind Energy Conference, Nice, France, 1-5 March 1999, pp. 375-378, ISBN 1 902916 00 X

114 Kariniotakis G., M. Matos, V. Miranda: *Assessment of the benefits from advanced load & wind power forecasting in autonomous power systems*. Proceedings of the European Wind Energy Conference, Nice, France, 1-5 March 1999, pp. 391-394, ISBN 1 902916 00 X.

115 Nogaret, E., G.S. Stavrakakis, G.N. Kariniotakis: *An advanced control system for the optimal operation and management of medium size power systems with a large penetration from renewable power sources.* Renewable Energy, Vol **12**(2), pp. 137-149, 1997

116 Gilman, B., M. Cheng, J. Isaac, J. Zack, B. Bailey, M. Brower: *The Value of Wind Forecasting to Southern California Edison.* Paper 021 on the Conference Proceedings CD-ROM of the AWEA Windpower 2001 conference in Washington, USA, 3-7 June 2001

117 Mylne, K.R.: *Maximising the Commercial Value of Wind Energy through Forecasting*. Report ETSU W/11/00555/REP on behalf of UK Department of Trade & Industry

118 Bathurst, G., and G. Strbac: *The Value of Intermittent Renewable Sources in the First Week of NETA*, Tyndall Briefing Note No. 2, 3 April 2001

119 Ensslin, C.: *Wind Power Integration into Energy Trading Systems and Power Plant Scheduling Schemes*. Proceedings of the European Wind Energy Conference, Copenhagen, Denmark, 2-6 June 2001, pp. 321-324, ISBN 3-936338-09-4

120 Klein, R., and R.A. Pielke Jr.: *Bad Weather? Then Sue the Weatherman! Part I: Legal Liability for Public Sector Forecasts.* Bulletin of the American Meteorological Society, Vol **83**(12), pp. 1791–1799, Dec 2002

121 Klein, R., and R.A. Pielke Jr.: *Bad Weather? Then Sue the Weatherman! Part II: Legal Liability for Private Sector Forecasts.* Bulletin of the American Meteorological Society, Vol **83**(12), pp. 1801–1807, Dec 2002

122 Schwartz, M.N, and B.H. Bailey: *Wind Forecasting Objectives for Utility Schedulers and Energy Traders*. Presented at Windpower '98, Bakersfield, CA, April 27-May 1, 1998. NREL/CP-500-24680. Available from *OSTI.gov* .