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Review Article

Short-term Prediction—An Overview

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This article gives an overview of the different methods used today for predicting the power output from wind farms on the 1–2 day time horizon. It describes the general set-up of such prediction systems and also gives examples of their performance. Copyright © 2003 John Wiley & Sons, Ltd.

Introduction

The amount of wind energy-produced electricity which is fed into the electrical grid grows by around 30%–40% every year. Wind energy is still in its infancy, so despite this impressive growth rate, not many utilities have until now had problems with this—at times—highly variable producer of electricity. This situation is slowly changing, since many countries and especially certain areas within these countries now have penetration levels of 10% or more (e.g. Denmark). It is therefore necessary to have some kind of system which predicts the power production over the next 1–2 days in order to control the dispatch of the conventionally fired plant, to increase its value in the markets operating on a 48 h time scale, and to take full advantage of the produced wind energy. This article will give a general introduction to the systems currently in use. It will start by giving a description of all the basic building blocks required to construct such a system.

General Overview of Systems

There are now quite a few methods which address the problem of predicting the power output from wind farms, but they can all in general terms be described in the same way. This is illustrated in Figure 1. As can be seen from this figure, most prediction systems consist of some or all of the following ingredients: Numerical Weather Prediction (NWP) model output, input of observations, a model, and output. In the following, each of these building blocks will be described.

Numerical Weather Prediction Models

To be able to receive NWP model output on a frequent and regular basis, it is necessary to use the meteorological service's operational model, since a lot of effort is put into making sure that these models always run.

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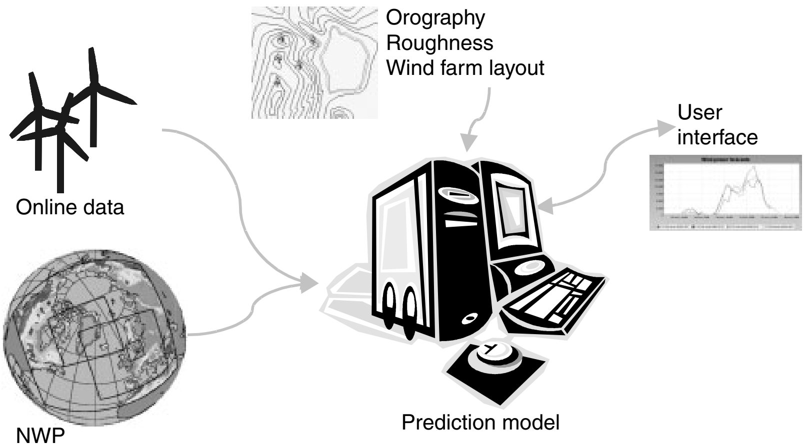

Figure 1. A general illustration of the building blocks used in prediction systems for wind farm output

An operational NWP model is characterized by the fact that it covers large areas, typically several 1000s of km, and has grid sizes in the range of 5–25 km. Since the equations employed are very sophisticated and the number of grid points is very large, supercomputers are required to run these models.

Typically an NWP model is run every 6 or 12 h and generates forecasts out to 48 h. From the time the last initialization data (i.e. weather data from much of the globe) are received until the predictions are available, normally 2–4 h of computing is required.

A wind farm prediction system obtains the data either via a dedicated e-mail service or through ftp. Examples of NWP models are the Danish Meteorological Institute's (DMI) version of HIRLAM (High Resolution Limited Area Model) (Figure 2) and the US National Weather Service's Eta models.

Model Input

Figure 1 also indicates that there is a basic set of inputs that prediction models will require. These include—for physical models—the layout of the wind farm, to take into account the directional dependence of wake effects, and the power curve of the turbines in the wind farm, to establish a relation between the wind speed at the site and the power produced. Finally, measurements of the production of the wind farm or individual turbines are needed, either on-line for models based on autoregression or off-line for models needing the information for update of some of the model parameters. Micro- and mesoscale models will also require information about the terrain: the orography (terrain height variations) and roughness (land-use).

State of the Art of Models

One of the earliest models was developed for the Central California Wind Resource Area[1]. It was run in the summers of 1985–87 on a programmable calculator, using meteorological observations and local upper air observations. Since then many new models have appeared, and in the following a brief description of the models in use today will be given (see Table I for an overview).

Prediktor (www.prediktor.dk) was developed in 1990 and is a mainly physical model.[2] It takes input from NWP models and uses WAsP and PARK[11] to take the local conditions into account. It then employs MOS (Model Output Statistics) to correct for biases and scaling errors. Input to the MOS module is historical wind farm data. Prediktor is an on-line, web-based system.

Systems similar to Prediktor include Previento[6,12] and EWind. In Ewind the tailoring to local conditions is based on a mesoscale model (ForeWind). EWind and Prediktor are currently being used in California.[13] Both

Figure 2. The scope of the different nested DMI HIRLAM versions. Source: DMI

Table I. Overview of the different types of prediction systems. Column 1 gives the name of the prediction system, column 2 states whether or not input from a Numerical Weather Prediction model is used, column 3 whether simple Model Output Statistics is used, column 4 whether more advanced MOS (such as advanced mathematical modelling) is used, column 5 whether input from a microscale model (e.g. WAsP) is used, column 6 whether input from a mesoscale model is used, column 7 whether observations are used and, finally, in column 8 the typical prediction horizon is given. A full circle indicates that the feature is used fully and an open circle that the feature is used partially

	NWP	MOS	MOS+	Micro	Meso	Obs	Time (h)	Ref.
Persistence		○				•	48	
Prediktor	•	•		•		○	48	2
WPPT	•		•			•	48	3
Zephyr	•		•	○		•	48	4
E Wind	•	•			•	○	48	5
Previento	•	•		•		○	48	6
HIRPOM	•	•				○	48	7
MORE-CARE	•		•			•	36	8
LocalPred/RegioPred	•	•			○		48	9
WPMS	•		•			•	48	10

are delivering forecasts for two large wind farm areas, totalling 1011 turbines rated at 157 MW. The systems developed by Brand and Kok[14] and Gow[15] are also forecasting systems similar to Prediktor.

A system combining NWP, MM5 (a mesoscale model) and a CFD (Computational Fluid Dynamics) model is being developed by Berge.[16]

WPPT (Wind Power Prediction Tool) uses NWP forecasts and models both the power curve and the extrapolation from a small number of wind farms to the wind power production of a region.[3] All versions of WPPT are self-calibrating systems, automatically adapting to e.g. changes in the NWP model and annual variations. WPPT Version 4 uses a carefully designed method which allows adaption to changes without introducing erratic behaviour in the case of e.g. high winds following a long period with low winds.[18,19]

WPPT-like systems include MORE-CARE,[8] which also has the ability to forecast river run-off, and the Sipreólico tool.[20] LocalPred and RegioPred[21] (also I. Martí *et al.*, poster presented at the Global Windpower Conference and Exhibition, Paris, 2002) involve adaptive optimization of the NWP input, time series modelling, mesoscale modelling with MM5, and power curve modelling. WPMS (Wind Power Management System)[22] now predicts for 95% of all wind power in Germany. Input is the forecast from an NWP model and fed into an ANN (Artificial Neural Network). Westrick[10] works with a nested NWP and statistical techniques for the very short term in the Pacific Northwestern USA.

As a new development, Prediktor and WPPT have been combined into a new model, Zephyr,[4,17] consisting of two strings, one based on on-line data using an autoregressive model and one based on off-line data using a statistical estimated power curve model, which in combination give the optimal forecast at all prediction horizons.

A new approach, HIRPOM (HIRLAM Power Prediction Model), is described by J. Jørgensen *et al.*, (poster presented at the Global Windpower Conference and Exhibition, Paris, 2002). Here the power prediction module is integrated within the NWP model itself.

Outputs

Outputs from prediction systems are normally the energy production of the wind farm or group of wind farms in hourly or three-hourly steps from 0 to 48 h ahead. Most often an estimate of the error of each prediction is also given, either as the estimated standard deviation or as confidence intervals. An example can be seen in Figure 3.

Predictions of the expected power production of a wind farm or several wind farms can e.g. be given in the form of HTML pages via the Internet, a custom GUI or a Java client/server set-up.

Another very useful type of output is a plot that displays e.g. the four latest predictions. This *ensemble* prediction might give an idea of how certain the forecast is. An example of such a plot is shown in Figure 4.

Performance

There are a number of ways that the performance of a prediction system can be evaluated. Utilities traditionally evaluate models by comparing them with the performance of what they have prior to the implementation of the new prediction system. Since most utilities do not yet have a prediction system, this is normally persistence (the production observed now is the one which is forecast for each of the following hours up to e.g. 48 h) and/or climatology (the average production taken over the past years of the time of day at this time of year).

Model performance is also traditionally measured using usual statistical measures: mean error, standard deviation of the error, absolute mean error. See Figure 5 for an example.

To compare the performance of the prediction system directly with either persistence or climatology, a number called the *skill score*, SS_x, is often used. This is given by the formula

$$SS_x = \frac{MAE_x - MAE_{model}}{MAE_x} = 1 - \frac{MAE_{model}}{MAE_x} \tag{1}$$

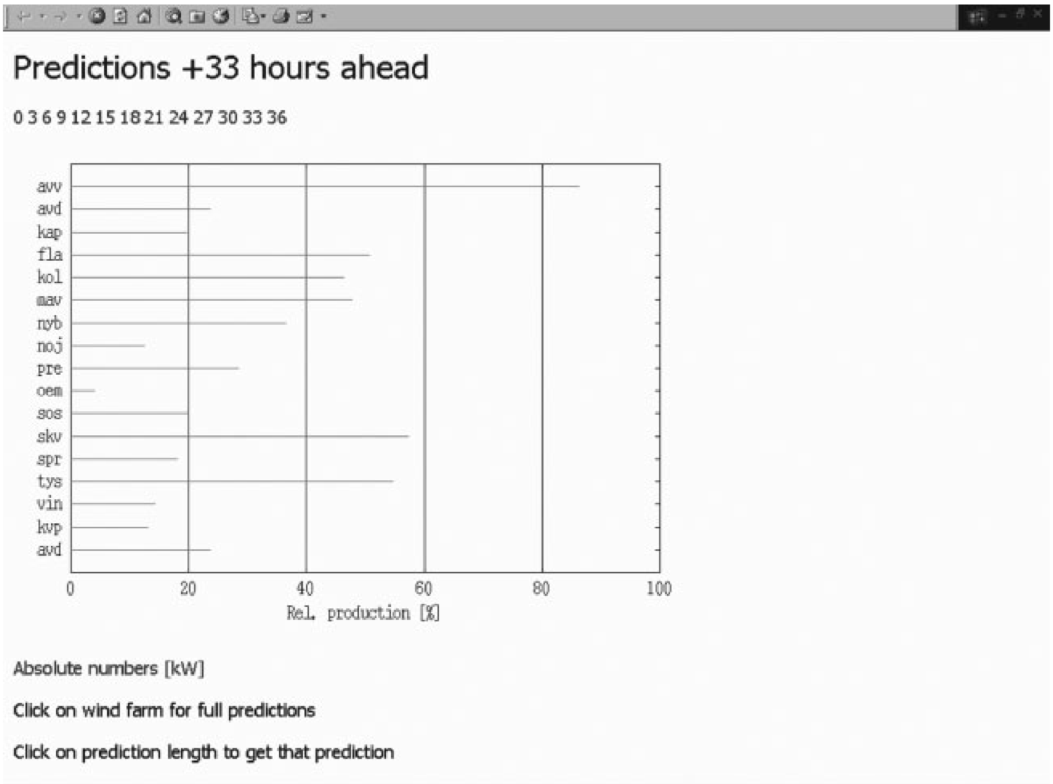

Figure 3. Example of output from a prediction system. Shown here is the HTML page produced by Prediktor for the 33 h prediction of a wind farm in the Elkraft area. Source: Risø

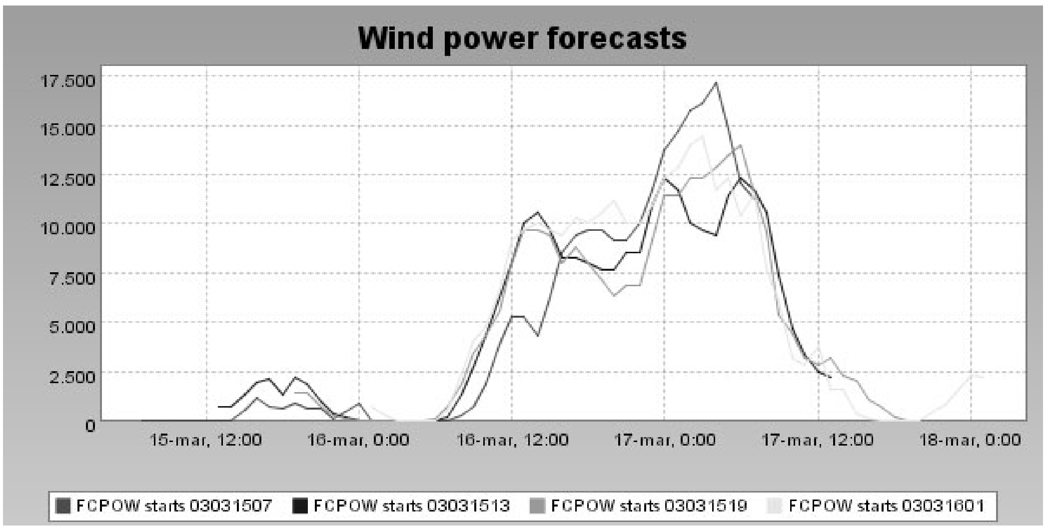

Figure 4. Example of output from a prediction system. Shown here is the ensemble plot produced by Prediktor for a wind farm. Source: Risø

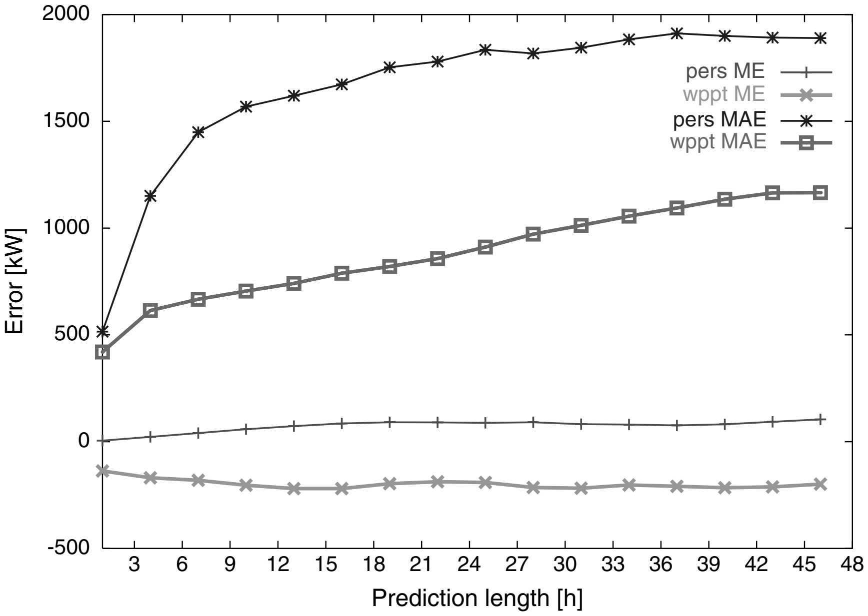

Figure 5. The performance of WPPT (Version 2, 1997) and persistence for a Danish wind farm. ME is the mean error and MAE is the mean absolute error. The relatively large mean error is due to the fact that part of the period used in the estimation was a low-wind summer period. Source IMM

where MAE_x is the mean absolute error of either the persistence model or climatology and MAE_{model} is the mean absolute error of the model under investigation. The definition of the skill score used here is the one traditionally used in meteorology; other definitions exist, e.g. where MAE is replaced by MS (Mean Squared Error).

The skill score ranges from 0 (when the model does not perform any better than persistence/climatology) to 1 (when the model is much better than persistence/climatology). Negative values of the skill score are of course also possible, indicating that climatology/persistence outperforms the model.

With the introduction of the electricity market it has become possible to assign monetary values to the performance, e.g. how large a cost the model has avoided by correctly predicting a storm or a low-wind period. A growing number of publications are appearing on this subject, e.g. References 23–26.

Finally, to get a good subjective idea of the performance of the model, one can plot the actual performance of the model together with the observed production for e.g. all extreme events (storms) in a year (see Figure 6). This approach should be used only in qualitative ways.

Challenges

There are a number of directions we see the research taking.

- Improving on existing models (e.g. better statistical algorithms, more sophisticated adaptive algorithms).
- Improving and tuning the NWP model to predict the hub-height wind. Today the main goal of NWP models is not to predict the near-surface wind; more often, accurate predictions of pressure and temperature are required.
- Obtaining a better understanding of the uncertainties, including on-line estimations of these. This can greatly enhance the economic value of the predictions.
- Extending the forecasts further into the future by e.g. going to 5 day forecasts, thus making the predictions useful in the more long-term planning, e.g. for maintenance.

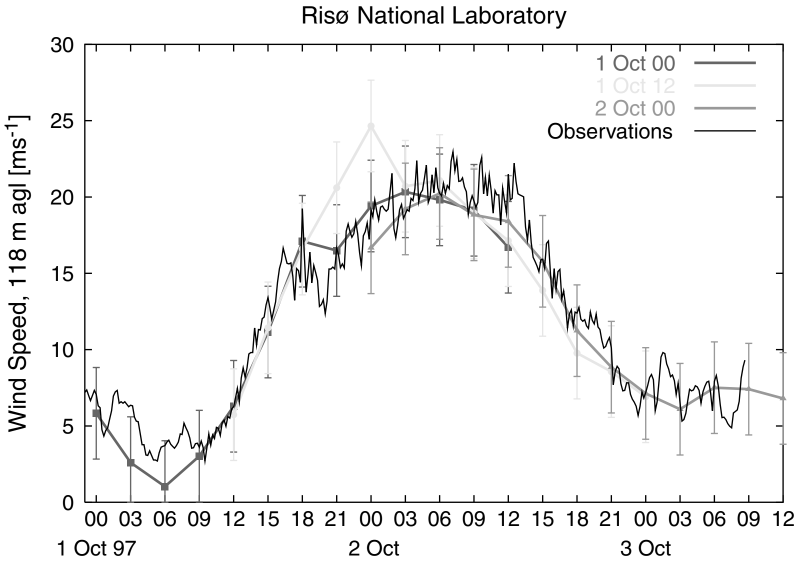

Figure 6. A storm lasting 2·5 days predicted by Prediktor. The black line is the observed wind speed at the 118 m tall Risø mast. The grey lines are the twice-daily predictions of Prediktor

- Putting more physical content into the models by developing and tailoring the micro- and mesoscale models to short-term predictions. This can be used both to make more accurate forecasts and also as 'inspiration' for the design of the statistical models.
- Using ensemble forecasting (e.g. combining forecasts from different NWP models). This will increase the overall accuracy and most likely also give better estimates of the error (www.risoe.dk/zephyr).

Summary

This article has given an overview of the types of prediction systems currently available. It was demonstrated that all systems can be seen as being put together from a few basic building blocks. An overview of these blocks was given and performance measures were discussed.

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