A tool for predicting the wind power production of off-shore wind plants

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Abstract

The paper describes the main concepts behind the tool called WPPT (Wind Power Prediction Tool) for on-line prediction of the wind power production for the next few days. WPPT can be used for predicting the wind power for single wind farms, a group of on-shore or off-shore wind farms, and for larger regions like the Western part of Denmark.

Some general aspects of setting up models for the variation of wind power production with the purpose of forecasting wind power based on meteorological forecasts are discussed. This forms the basis for a description of the most important models used in WPPT. For off-shore wind farms the dynamical characteristics of a typical large wind power production can change rather dramatically within few minutes. It is argued that it is very important that any prediction system also supplies information about the uncertainty of the prediction.

1 Introduction

Large off-shore wind farms may contribute seriously to the stability or instability of power systems. The passage of a thunderstorm or a low pressure front may change the dynamical characteristics of the local wind regime considerably within few minutes, and, hence it is very important to be able to reliably predict the wind power also on a rather short time scale.

The Wind Power Prediction Tool (WPPT) [11, 13, 12] can be configured in many ways. The system can be set up so the focus is on a single large off-shore wind farm, or on a combination of some off-shore and on-shore wind farms. WPPT (Wind Power Prediction Tool) is a system for forecasting the wind power for up to, say 48 hours ahead depending on the horizon of the MET forecasts, with a resolution of typically 30 minutes.

The computer system run at a number of locations. The system uses on-line meteorological forecasts together with on-line measurements in order to continuously update the underlying models. WPPT is one of the products for wind power prediction covered by the collaboration between Risø National Laboratory and Informatics & Mathematical Modelling. This collaboration also covers the Prediktor system [11].

Section 2 briefly describes the computer system. In Section 3 the preconditions and some desirable properties of such a computer system are described, these set the basis for the methods used which are outlined in the subsequent sections. Section 4 and 5 describe details about the models used today in WPPT, and examples of configurations of WPPT showing its flexibility is shown in Section 6. An example of providing information about the uncertainty in predictions for an off-shore wind farm is given in Section 7. Finally, in Section 8 we conclude on the paper.

2 Overview of the Computer System

The computer system works on-line. By on-line we understand that the system continuously receive the most recent information and updates the underlying models for generating the forecasts periodically (typically every 30 minutes). The system have been coded in C/C++/Java and runs under Linux, Unix and Windows.

WPPT is a system for forecasting the wind power production in relatively large geographical regions and for individual wind farms. The forecasts for the individual wind farms are upscaled with the purpose of generating regional forecasts, cf. Section 4 and 5.

The wind turbines may be grouped into a region according to geographical similarities or legislation governing the connection. In Denmark wind turbines have been grouped in prioritized production and non-prioritized production.

In Fig. 1 an overview of the information flow of the forecasting system is depicted. Note that measured values of the dependent variable (e.g. wind power production) is used as input to the forecasting system. The output of WPPT also includes information regarding the uncertainty of the forecasts. This is very important for off-shore wind farms where the uncertainty is known to vary from time to time.

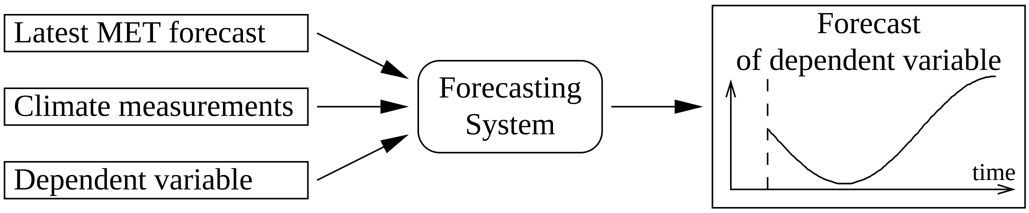

Figure 1: Overview of the information flow of the WPPT forecasting system. The dashed line on the plot of the forecast indicates the time at which the forecast is generated. The climate measurements are optional.

3 System Considerations

The main information which is supplied to the computer system is indicated in Fig. 1. Furthermore, information from the physical system, such as the fraction of wind turbines actually running i.e. not being out for maintenance or other reasons, and time/calendar information is supplied to the computer system.

Except for the meteorological forecasts, typically the information can be sampled with the frequency required for the purpose of being able to update the forecasts with the desired frequency. However, the meteorological forecasts are not updated very frequently, nor is the resolution very high [14] and interpolation is used to circumvent this.

Since the physical system considered is non-stationary it is a precondition for the computer system to be able to adapt to changes in the physical system. A typical example is changes in the roughness; e.g. due to the annual variation or new obstacles near the wind turbines. Also changes in the NWP models, the population of wind turbine, and dirty blades call for the system to be able automatically to adapt to changes. The computer system should detect this and adapt to the new situation without human intervention.

In the paper [10] simulations and theoretical consideration have be used to prove that the following general considerations has to be taking into account when constructing a system for wind power prediction:

- As input variable to a prediction model the *MET forecasts* of the wind speed and the wind direction must be used. In fact for linear models it is shown in [10] that it is generally better to use estimates based on the forecasts of the explanatory variables rather than on the actual explanatory variables

- The principle of tracking changes over time is that old information is disregarded as new information become available. Since long periods without high winds often occur it is crucial that the procedure for tracking the relationship between the meteorological forecast and the wind power production only disregards old information near wind speeds actually occurring. Hence a dedicated adaptive scheme for parameter estimation must be used. In WPPT a non-parametric model for the power curve is used, which allow for a strait forward approach to only disregard old information for wind speeds actually occurring – see [9, 14].

- The procedure outlined assumes that the dependent variable is available on-line. For wind power production the values are available on-line for certain reference wind farms while data for smaller farms and individual turbines typically is available only trough the total wind power production of sub-areas, which typically is available with a considerable time-delay (say a month). Hence the upscaling to regional forecasts is important.

4 Models in WPPT

The WPPT modelling system described in the following calculates predictions of the available wind power from wind turbines in a region. For a larger region this is done by separating the region into a number of sub-areas. Wind power predictions are then calculated for each sub-area and hereafter summarized to get a prediction for the total region.

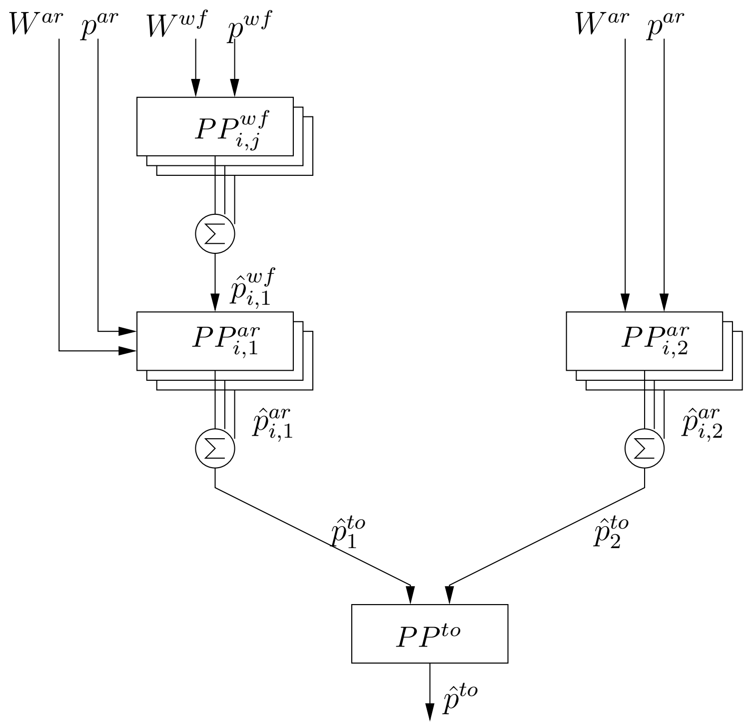

Figure 2: Overview of a model structure in WPPT. Two different predictions are calculated for the wind power production in a region: In the left model branch the wind farm models, $PP^{wf}_{i,j}$, are used to calculate power predictions for the reference wind farms in sub-area i. The predictions for the reference wind farms in sub-area i are summarized to $\hat{p}^{wf}_{i,1}$, which hereafter is upscaled by the upscaling model $PP^{ar}_{i,1}$ to a power prediction, $\hat{p}^{ar}_{i,1}$, for all wind turbines in the sub-area. The predictions for the sub-areas are then summarized to get the power prediction of the left model branch for the total region, $\hat{p}^{to}_1$. In the right model branch power predictions of the power production in sub-area i, $\hat{p}^{ar}_{i,2}$, are calculated directly by the area model $PP^{ar}_{i,2}$. The predictions for the sub-areas are then summarized to get the power prediction of the right model branch for the total region, $\hat{p}^{to}_2$. The final power prediction for the region, $\hat{p}^{to}$, is calculated by model $\hat{p}^{to}$ as a weighted average of the predictions from the two model branches.

The predictions are calculated using on-line production data from a number of wind farms in the area (reference wind farms), off-line production data for the remaining wind turbines in the area and numerical weather predictions of wind speed and wind direction covering the area. The predictions covers a horizon corresponding to the prediction horizon of the numerical weather predictions hours – typical from 0 to approximately 48 hours ahead in time. The time resolution of the predictions can be chosen freely but a reasonable choice for the longer prediction horizons is to use the same time resolution as the numerical weather predictions.

All possible models in WPPT is most easily illustrated by a two branch as in Figure 2.

- In the left model branch predictions of wind power are calculated for a number of reference wind farm using on-line measurements of power production as well as numerical weather predictions as input. The predictions from the reference wind farms in a sub-area are summarized and hereafter upscaled to get the prediction of power production of all wind turbines in the sub-area. This model branch takes advantage of the auto-correlation which is present in the power production for prediction horizons less than approximately 12 hours.

- The right model branch predicts the power production in a sub-area explicitly by using a model linking off-line measurements of total power production in the sub-area to the numerical weather predictions. This model branch takes advantage of the smooth properties of the total production as well as the fact that the numerical weather models perform well in predicting the weather patterns but less well in predicting the local weather at a particular wind farm.

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 model two branches.

5 Prediction models

Conditional parametric models are used to describe the relationship between observed power production in wind farms or areas and meteorological forecasts of wind speed and wind direction (the power curve). These relationships are difficult to parameterize explicitly, but can, as it is shown in [11], readily be captured by conditional parametric models. The dynamic relationship between observed production and predicted production from the (static) power curve models are described using a set of linear k-step predictions models, which are estimated recursively and adaptively as described in [2] and [9], whereas the model structure in the k-step models is identified in [4] and [5].

5.1 The wind farm model ($PP^{wf}_{i,j}$)

The wind farm model uses wind direction dependent power curves in the transformation of forecasted wind speed and wind direction to power. The prediction model for the jth wind farm in the ith sub-area is given as

$$\begin{aligned}\hat{p}^{pc}_{i,j}(t+k|t) &= f(w^{wf}_{i,j}(t+k), \theta^{wf}_{i,j}(t+k), k) \\ \hat{p}^{wf}_{i,j}(t+k|t) &= a_1 p^{wf}_{i,j}(t) + a_2 p^{wf}_{i,j}(t-1) + b\hat{p}^{pc}_{i,j}(t+k|t) +\end{aligned}$$

$$\sum_{i=1}^{3}[c_i^c \cos\frac{2i\pi h^{24}(t+k)}{24} + c_i^s \sin\frac{2i\pi h^{24}(t+k)}{24}] + m \quad (1)$$

where $\hat{p}_{i,j}^{wf}(t+k|t)$ is the predicted power for time $t+k$ calculated at time t, and $\hat{p}_{i,j}^{pc}(t+k|t)$ is the power predicted by the direction dependent power curve. $w_{i,j}^{wf}(t+k)$ and $\theta_{i,j}^{wf}(t+k)$ are local forecasts of wind speed and wind direction, respectively, and $a_{\cdot}$, b, $c_{\cdot}$, and m are time-varying model parameters to be estimated. The function h^{24} simply transforms the running time onto the time of day.

The wind farm model takes advantage of the auto-correlation which is present in the power production for prediction horizons less than approximately 12 hours.

The choice of model order and input variables for each prediction horizon is described in [4].

In [11] the performance of the proposed model is evaluated for six different wind farms - five in Denmark and one from the Zaragoza region in Spain (La Muela). The wind farm at La Muela is investigated further in [6] and [7], where the performance of the wind farm model is evaluated for various wind forecasts.

5.2 The upscaling model ($PP_{i,1}^{ar}$)

The predicted power production in sub-area i is calculated by multiplying the summarized power predictions for the wind farms in the sub-area by a upscaling function, which depends on area forecasts of wind speed and wind direction. The model is given as

$$\begin{aligned}\hat{p}_{i,1}^{ar}(t+k|t) &= \\ & b(w_i^{ar}(t+k), \theta_i^{ar}(t+k), k) \sum_j \hat{p}_{i,j}^{wf}(t+k) \quad (2)\end{aligned}$$

where $w_i^{ar}(t+k)$ and $\theta_i^{ar}(t+k)$ are area forecasts of wind speed and wind direction, respectively, and b is a smooth time-varying function to be estimated.

5.3 The area model ($PP_{i,2}^{ar}$)

The area model transforms area forecasts of wind speed and wind direction to power in a way similar to the wind farm power curve model by explicitly linking weather forecasts for the area to off-line observations of the power production in the area. For sub-area i the model is given as

$$\hat{p}_{i,2}^{ar}(t+k|t) = f(w_i^{ar}(t+k), \theta_i^{ar}(t+k), k). \quad (3)$$

where f is a smooth time-varying function to be estimated.

This model takes advantage of the smooth properties of summarized power productions and the fact that the numerical weather models perform well in predicting the weather patterns but less well in predicting the local weather at a particular wind farm.

5.4 The total model (PP^{to})

The prediction of the total power production in the region is calculated as a combined forecast using the total predictions from the two model branches in Figure 2. The prediction is calculated as a prediction horizon dependent weighted average of the power predictions for the two model branches using Root Mean Square (RMS) as weighting criterion. The model is given as

$$\hat{p}^{to}(t+k|t) = b_1(k)\hat{p}_1^{ar}(t+k|t) + b_2(k)\hat{p}_2^{ar}(t+k|t) \tag{4}$$

where $\hat{p}_1^{ar}(t+k)$ and $\hat{p}_1^{ar}(t+k)$ are the power predictions for model branch 1 and 2, respectively, and b_1 and b_2 are smooth time-varying functions to be estimated.

The predictions from the two model branches are closely correlated especially for the longer prediction horizons. Thus a regularized estimation procedure must be used to ensure stable estimates of the b_1 and b_2 functions. Here Ridge Regression [1] has been used.

6 Some possible configurations of WPPT

WPPT is very flexible, since the system can be used for a single wind farm, for a collection of wind farms, for small and large regions. It is able to simultaneously to provide a forecast for single wind farms and large regions. This section describes a couple of possibilities for the configuration of WPPT.

Depending on the configuration WPPT requires input from the following sources:

- On-line measurements of wind power production from some wind farms (update interval, say, between 5 min. and 1 hr.).
- Aggregated high resolution energy off-line readings from nearly all wind turbines in the groups/regions defined (updated with a delay of upto, say, 1 month).
- Forecasts of wind speed and wind direction covering wind farms and sub-areas (horizon 0–48 hours, say, updated 1-4 times a day)
- Local climate measurements (optional - mostly used for error detection).

6.1 Example 1. Only off-line data

This configuration, which is shown in Figure 3, is used by a large TSO. The following characterizes the setup:

- No online data enter the models.
- A large number of wind farms and stand-alone wind turbines.
- Frequent changes in the population of wind turbines as old turbines are decommissioned and replaced by new and larger machines.
- Off-line wind power production data with a resolution of 15 min. are available for more than 99% of the wind turbines in the area. The data is released with a delay of 3-5 weeks.

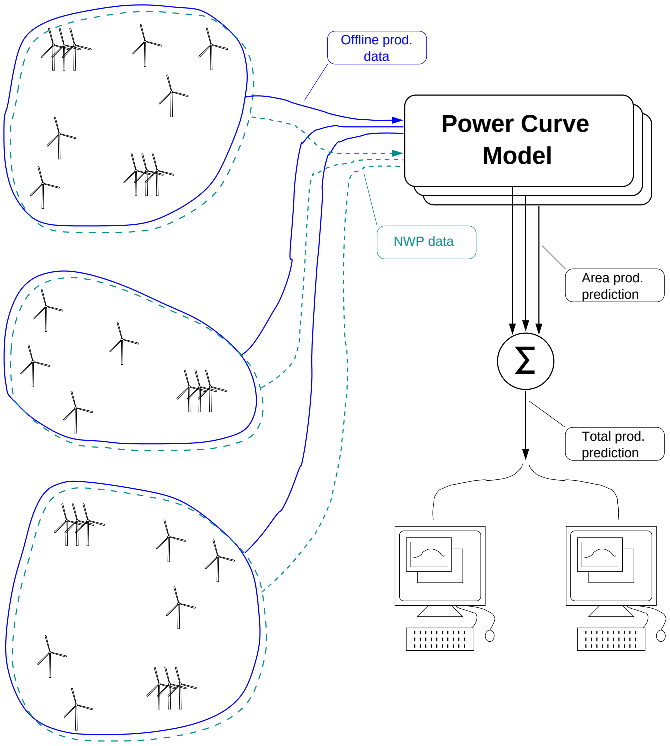

Figure 3: Configuration Example No. 1. Only off-line production data and NWP data are used.

6.2 Example 2. Both on-line and off-line data

Again this configuration is used by a large TSO. The setup, which is shown in Figure 4, has the following characteristics:

- A large number of wind farms and stand-alone wind turbines.
- Frequent changes in the wind turbine population.
- Off-line production data with a resolution of 15 min. are available for more than 99% of the wind turbines in the area.
- On-line data for a number of wind farms are available (about 30 pct.). The number of on-line wind farms increases quite frequently.

In this example the TSO wants forecasts for both a collections of wind turbines and for sub-regions. This information is used for instance for transmission purposes. Also a prediction of the total production in the area is supplied.

6.3 Performance example

This case study corresponds to the first configuration example, i.e. no on-line data is used.

The period is from June 2002 to May 2003 (both month included). The power data is available (off-line - up to one month delay) every 15 minutes. The NWP data is gridded values

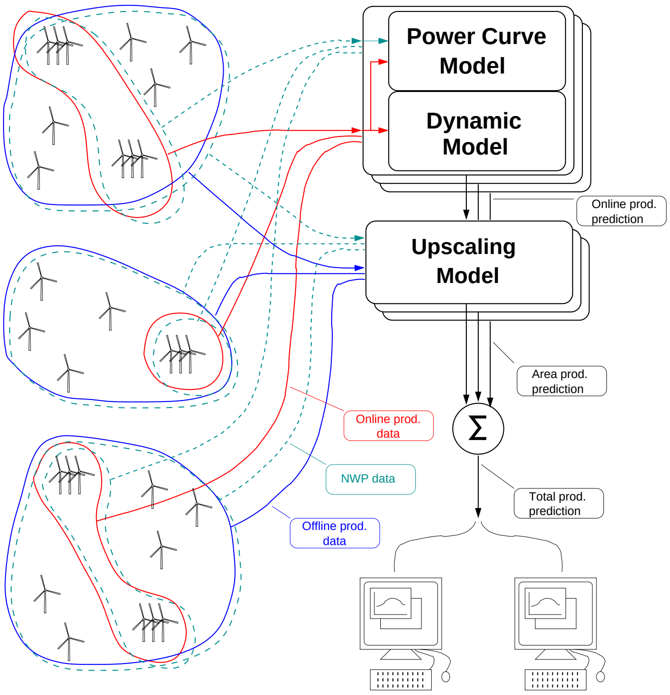

Figure 4: Configuration Example No. 2.

of 10 m wind speed and direction covering the Eltra area and updated four times a day. The prediction range is from 0 to 48 hours with a one hour resolution. The area wind speed and direction is calculated as the geographical mean of the gridded NWP values.

In Figure 5 the performance of WPPT is compared to the performance of the naive predictor. The performance measure used is the normalized Root Mean Squared Error (NRMSE), see [3], which is defined as

$$NRMSE(k) = \sqrt{\frac{\sum_{t=1}^{N}(\epsilon(t+k|t))^2}{N-p}}. \tag{5}$$

where $\epsilon(t+k|t)$ is the *normalized prediction error*

$$\epsilon(t+k|t) \;=\; \frac{1}{p_{inst}}(p(t+k) - \hat{p}(t+k|t)), \tag{6}$$

and where p_{inst} is the installed capacity. Both systematic and random errors contribute to the $NRMSE$ criterion.

It is seen that the performance of WPPT in general is much better than the performance of the naive predictor. However, for very small horizons the performance of the naive prediction is the best. This is due to the fact that this example relates to configuration Example 1, where no on-line data is used (as opposed to the naive predictor where on-line data is used). If the configuration changes to Example 2, i.e. including on-line data, the values for WPPT will improve, and for all horizons the value will be better than for the naive prediction.

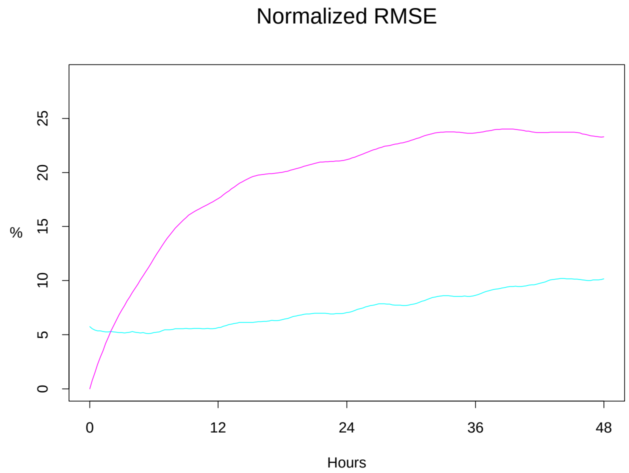

Figure 5: Performance comparison of WPPT (lower curve) and the naive predictor.

7 Confidence intervals for the predictions

Today a lot of tools and methods for predicting wind power exist; but only a few tools consider the problem of reliably estimating the uncertainty of the wind power prediction.

The developers behind WPPT have recently developed a method using MET ensembles typically from either ECMWF or NCEP as the input to a model which uses the information embedded in the ensembles to obtain reliable estimates of the quantiles of the future values of the wind energy. An example from the small off-shore wind farm Tunø near the East coast of Jutland is shown in Figure 6. The method is further described in [8].

It is clearly seen in the figure that occasionally the prediction is rather accurate, whereas for other periods the prediction is encumbered with a large uncertainty. This is due to a varying predictability of the weather situation.

8 Conclusion

The preconditions and methods for short term forecasts of wind power are outlined in the paper. It is argued that the uncertainty of the meteorological forecasts should affect the models being used.

A tool, called WPPT, for wind power predictions is briefly described. WPPT can easily be configured to use a mixture of off-line and on-line data. Furthermore, WPPT can be used to provide simultaneous forecasts for wind farms, and smaller and larger regions.

Two examples of actually used configurations of WPPT are described. For the most simple setup of WPPT the performance of system is exemplified.

Finally, it is argued that it is important that wind power predictions are supplied with some information regarding how reliable the prediction is. An example of reliable wind power forecasts for an off-shore wind farm is shown.

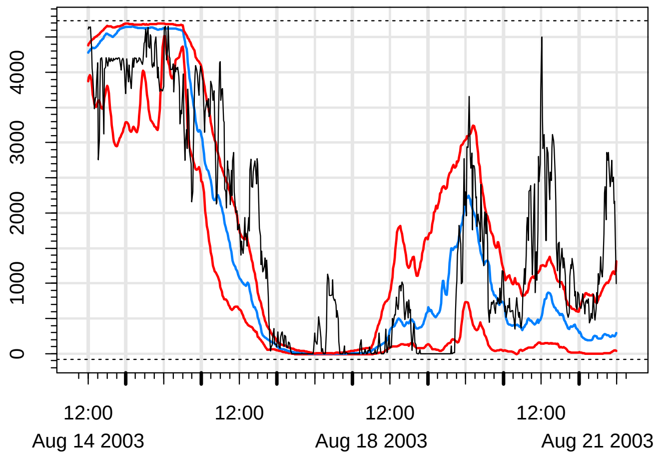

Figure 6: Ensemble based predictions with reliable confidence intervals for an off-shore wind farm. The smooth curve in the middle is the median of the forecasts, and the confidence interval shown is defined by the 25% and 75% quantile.

9 Acknowledgments

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