Short-term Wind Power Forecasting Using Advanced Statistical Methods

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Abstract

This paper describes some of the statistical methods considered in the ANEMOS project for short-term forecasting of wind power. The total procedure typically involves various steps, and all these steps are described in the paper. These steps include downscaling from reference MET forecasts to the actual wind farm, wind farm power curve models, dynamical models for prediction of wind power or wind speed, estimating the uncertainty of the wind power forecast, and finally, methods for upscaling are considered. The upscaling part considers how a total regional production can be estimated using a small number of reference wind farms.

Keywords: Forecasting, power curve, wind farm power curve, upscaling, uncertainty estimation, probabilistic forecasts, adaptation.

1 Introduction

Wind energy is the fastest growing technology in the range of alternative power generation sources. However, in order to be able to absorb a large fraction of wind power in the electrical systems reliable short-term (say 36 hours) predictions of the future wind power generation are needed. Furthermore it is clear that reliable uncertainty information is needed for optimising the decision making process resulting from the use of predictions.

This paper briefly reports some of the statistical state of the art models and methods for wind power forecasting which have been developed and used in the ANEMOS project. In this project a large number of next generation tools for facilitating short-term wind power predictions have been developed, tested and implemented. The system complexity and the fast fluctuations of wind speed call for a statistical approach, and hence the development and use of statistical approaches have been one of the highest priorities during the ANEMOS project. The ANEMOS project also considers physical approaches to wind power forecasting and an overview of the advances made within this topic is given in Giebel et al. (2006).

An overview of a state of art wind power prediction system is outlined in Section 2. Numerical Weather Prediction (NWP) is a primary input to the statistical models, and methods for improving the NWP predictions are mentioned in Section 3 followed by methods for statistical downscaling in Section 4. The wind farm power curve constitutes an important part of many prediction systems as described in Section 5. Models for predicting the wind power in wind farms and the related uncertainty are dealt with in Sections 6 and 7, respectively. Finally, methods for upscaling are considered in Section 8.

2 Overview and system considerations

In Figure 1 an overview of the information flow of a typical ANEMOS 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 the forecasting system also includes information regarding the uncertainty of the forecasts. 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

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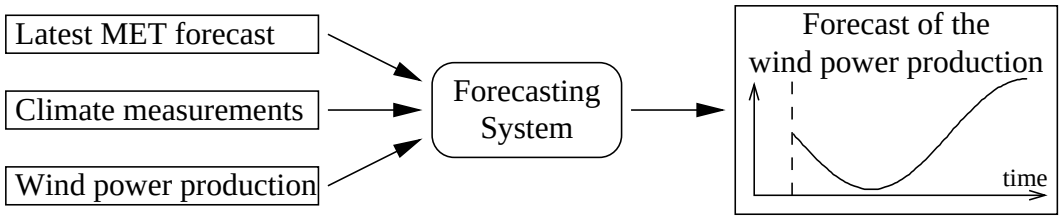

Figure 1: Overview of the information flow in an advanced forecasting system. The dashed line on the plot of the forecast indicates the time at which the forecast is generated.

the system.

The ANEMOS system for wind power forecasts 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 typically generates forecasts on a broad scale ranging from a wind farm, a region of interest, and the total considered area. The forecasts for the individual wind farms are upscaled with the purpose of generating regional forecasts, or forecasts for the entire region.

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

In the following we shall briefly describe some of the models and methods developed and used in the ANEMOS project. An excellent overview of models for wind power predictions is found in Giebel et al. (2003).

3 Improving NWPs

Numerical Weather Predictions (NWP) is a primary input to models for short-term forecasting of wind power. It is, however, well-known that NWP models usually exhibit systematic errors in the forecast of certain meteorological parameters especially near the surface.

In general it is an open question as to whether the use of higher resolution limited area models improves the forecast skill, and should that be the case, it is still uncertain whether such improvements compensate the usage of increasing computational resources required for such calculations.

In order to reduce these disadvantages, a variety of approaches using statistical methods have been used to post-process NWPs. Most of them are derived from Model Output Statistics (MOS) or classical linear regression models. One of the most successful approaches to this problem is the use of Kalman filters, which is an optimal method for estimating the states of a linear dynamical system.

The Kalman filter is linked to linear systems. However, during the ANEMOS project a new way of encapsulation of non-linear dynamics in the Kalman filter algorithm was developed and applied to improve NWP data and particular wind speed – see Louka et al. (2005) for further details.

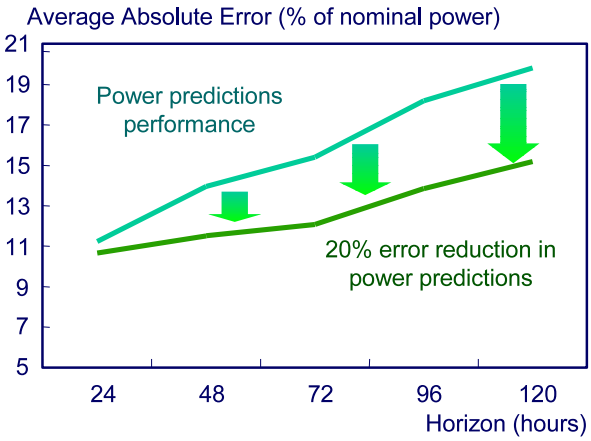

Figure 2: Improvement on average absolute error by using the Kalman filtering

Kalman filtering has been applied to SKIRON NWPs using observations obtained at the Roka wind farm in Crete for the whole year of 2003. Wind farm power predictions are provided using the ARMINES AWPPS model. Compared to the case of using raw SKIRON NWPs, the Kalman filtering processing of the NWPs lead to a reduction in the order of 20 % of the forecast error. The largest improvement is seen for large horizons, as seen in Figure 2.

4 Statistical downscaling

The MET forecasts are available directly only for grid points in the vicinity of the wind farm, and hence methods for estimating the wind speed at the wind farm are needed. A simple approach is spatial interpolation from the wind speed forecasts from the surrounding

grid points.

Analysis during the ANEMOS project have shown that statistical methods for downscaling (MOS) using not only the wind speed in grid points, but also the pressure gradients, gives improved wind power predictions. The statistical methodology for the downscaling is based on principal components analysis with multiple regression. Principal components analysis is done in order to transform the selected set of variables (which are strongly correlated) into a new set of variables not correlated, reducing the number of variables.

It is found that the statistical procedure for downscaling reduces forecast errors significantly, especially in complex terrain, as shown in Figure 3 for the Alaiz test case. A performance comparison for two different methods is shown in Figure 4:

MOS Here an intermediate step to from the main principal components to wind speed is made using linear regression. The forecasts of power production are then obtained using a fuzzy logic approach as described in Section 5.

MOSP Here the forecasted power production is obtained by using the main principal components directly as input to a fuzzy logic model thereby removing the dependency on measured wind speed.

From the analysis it is seen that the MOSP downscaling model without the intermediate step to wind speed clearly outperforms the MOS downscaling model.

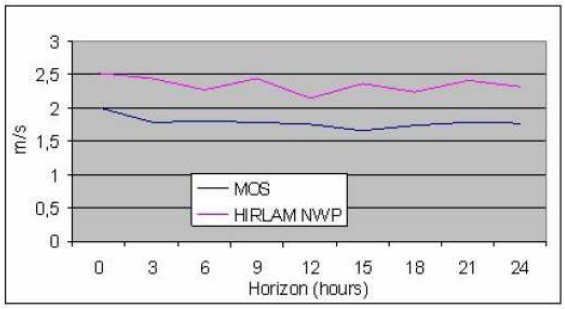

Figure 3: Statistical downscaling reduces forecast errors. The plot shows RMSE for forecasted wind speed at the Alaiz wind farm (ES) before downscaling (HIRLAM NWP) and after downscaling (MOS) for the 0.2^o HIRLAM model.

5 Wind Farm Power Curve

In order to model the wind farm power, the conventional wind turbine "power curve" model, $p^{tur} = f(w^{tur})$ is typically extended to a wind farm model, $p^{wf} = f(w^{wf}, \theta^{wf})$, by introducing wind direction dependency. By introducing a representative area wind speed and direction it can be further extended to cover all turbines in an entire region, $p^{ar} = f(\bar{w}^{ar}, \bar{\theta}^{ar})$.

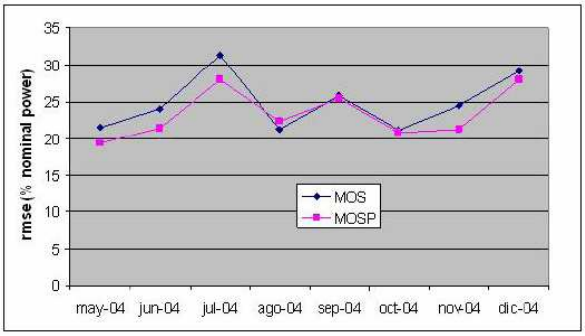

Figure 4: Two methods for downscaling with (MOS) and without (MOSP) intermediate step to wind speed. The plot shows normalised RMSE for forecasted power production at the Alaiz wind farm (ES).

Such a two dimensional wind farm power curve model is illustrated in Figure 5. This is estimated for the Alaiz (ES) wind farm using a fuzzy logic approach.

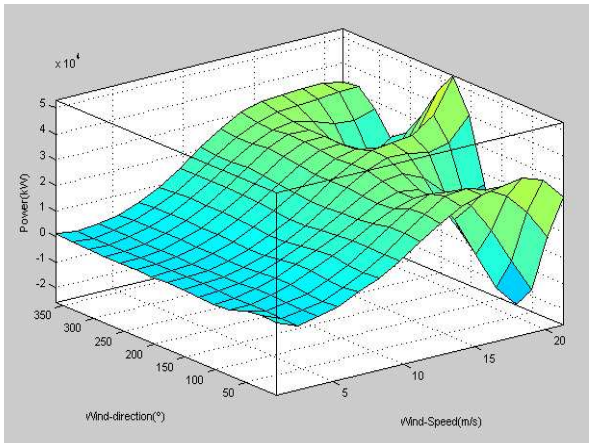

Figure 5: A two-dimensional power curve model

The characteristics of the NWP change with the prediction horizon. Hence, in WPPT also the prediction horizon is included, and the power curve model is:

$$\hat{p}_{t+k|t} = f(\ \bar{w}_{t+k|t},\ \bar{\theta}_{t+k|t},\ k\ )$$

where
$\bar{w}_{t+k|t}$ is forecasted wind speed, and
$\bar{\theta}_{t+k|t}$ is forecasted wind direction. where *k* is the prediction horizon – see Figure 6.

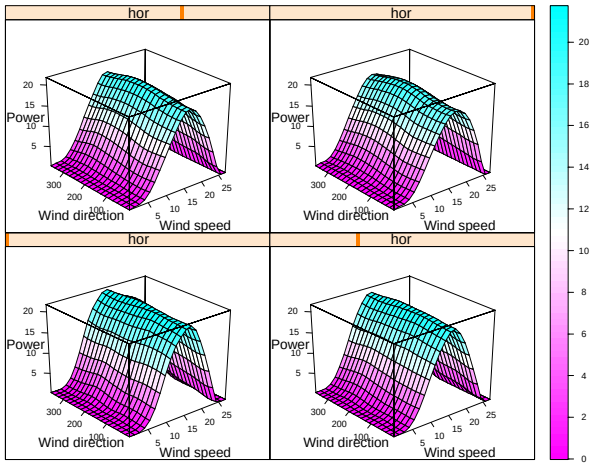

Figure 6: Plots of the estimated power curve for the Klim (DK) wind farm (k = 0, 12, 24 and 36 hours).

6 Wind farm prediction models

Statistical models such as ARMA, ARX and Box-Jenkins methods have been used historically for short-term wind forecasting up to few hours ahead – see for instance Nielsen and Madsen (1996) and Landberg et al. (2003). It has been mentioned in Pinson (2006) that the parameters of the models should depend on the season due to the fact that the optimal model substantially varies between summer and winter. This calls for models which allow for adaptively estimated parameters.

A dynamical prediction model for power production in wind farms and regions used in WPPT is given as

$$\begin{aligned}\hat{p}t+k|t &= a_1 p_t + a_2 p_{t-1} + \hat{p}^{pc}_{t+k|t} + \\ &\sum_{i=1}^{3}[c_i^c \cos\frac{2i\pi h^{24}_{t+k}}{24} + c_i^s \sin\frac{2i\pi h^{24}_{t+k}}{24}] + m\end{aligned}$$

where p_t is observed power production, $k \in [1;48]$ (hours) is prediction horizon, $\hat{p}^{pc}_{t+k|t}$ is power curve prediction and h^{24}_{t+k} is time of day. Model features include

- multi-step prediction model to handle non-linearities and unmodeled effects,
- the number of terms in the model depends on the prediction horizon,
- non-stationarity are handled by adaptive estimation of the model parameters,
- the deviation between observed and forecasted diurnal variation is model by a Fourier expansion.

During the ANEMOS project the fuzzy logic based approach developed by (Kariniotakis and Pinson (2003)) has been widely applied. The fuzzy inference systems are using 'if-then' rules which are trained using a period of recorded production data. A simulated annealing algorithm controls the learning process and cross-validation is used to optimise the learning process. An important advantage of using this expert system is the flexibility of the models that one can build. Output from NWP models are used as input variables. A final version of the forecasting method developed by Kariniotakis has led to AWPPS (the ARMINES Wind Power Prediction System).

Sanchez (Sanchez (2006)) has proposed a statistical approach that consists in a dynamic combination of several prediction models ranging from reference models to conditional non-parametric models similar to the one used in WPPT. The method introduces a competition between the models, and depending on their recent performance, a combination procedure yield a weighted average of the best models' estimates. This prediction system is called Sipreolico and is used by a Spanish utility.

In the initial phase of the ANEMOS project a protocol for standardising the performance evaluation of short-term wind power prediction models has been suggested (Madsen et al. (2006)). It is recommended that a minimum set of error measures includes the normalised root mean squared errors and the normalised bias, where the normalisation is with respect to the installed capacity in the wind farm.

Furthermore a number of reference prediction models is described, and it is argued that the use of persistence as a reference model leads to misleading and over-optimistic conclusions about the performance.

7 Prediction Intervals

During the ANEMOS project a considerable attention has been put on developing methods for estimating the uncertainty of wind power forecasts. For the classical methods in time series analysis the variance of the prediction error depends only on the horizon (see Box and Jenkins (1976)). However, in the case of wind power it is well known that the prediction error depends on the predicted power as illustrated in Figure 7. As shown in Lange and Heinemann (2003) and Lange (2003) the error of the wind power forecast is linked to the prevailing weather situation and can be modelled by propagating the wind speed uncertainty through the non-linear power curve.

Tools for on-line estimation of the prediction uncertainty are expected to play a major role in trading of wind power in a liberalised market since they can prevent or reduce penalties in situations of poor prediction accuracy.

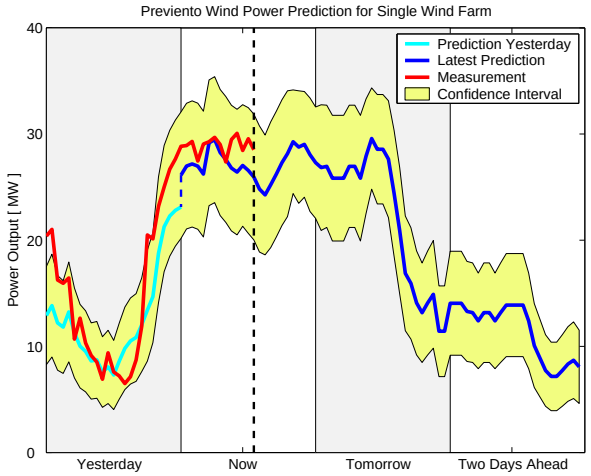

Figure 7: The prediction uncertainty provides a confidence interval adapted to the individual forecast situation.

Using data from a 15 MW wind farm in the Dutch electricity market, and prices and measurements from the entire year 2002, Pinson (2006) has demonstrated by using an advanced tool for wind power forecasts, the costs on the regulation market are diminished by nearly 38 % compared to the use of the persistence forecasts. Furthermore he showed that having reliable values of the uncertainty of the forecasts, a further decrease of up to 39 % is observed for the regulation costs.

During the ANEMOS project two important methods for reliably estimating the uncertainty of wind power forecasts have been considered. The first one is based on MET ensembles, which can be provided by meteorological centres (eg. ECMWF, NCEP, etc.). It has been demonstrated that the raw MET ensembles do not provide a picture of the true uncertainty, and hence statistical methods for mapping the MET ensembles into reliable quantiles have been developed (Nielsen et al. (2004)). Another approach described in Pinson and Kariniotakis (2003) and Pinson and Kariniotakis (2004) based on MET ensembles is using a risk index approach. Two episodes with a 4 member ensemble forecasts of wind speed is shown in Figure 8. A method based on quantile regression is described in Nielsen et al. (2006).

An important approach for estimating the uncertainty is based on a fuzzy inference model, which permits to produce conditional error distributions given the forecast conditions. Predictive distributions of the future wind power generation corresponding to a mixture of conditions is then obtained by combining the probability distributions using either a linear opinion pool or the adapted resampling approach (Pinson (2006)). An example illustrating the probabilistic forecasting approach

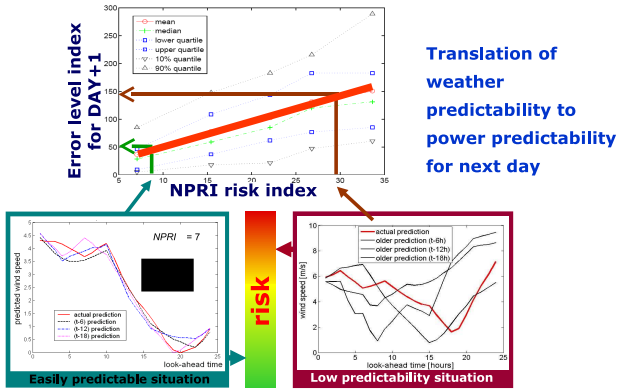

Figure 8: Risk index based uncertainties. Bottom-left: the alternative predictions are very similar and we hare quite confident on what will happen. Bottom-right: the alternative predictions significantly differ – this lower the confidence on the future weather predictability. Each situation is represented by a value of the risk index.

is shown in Figure 9.

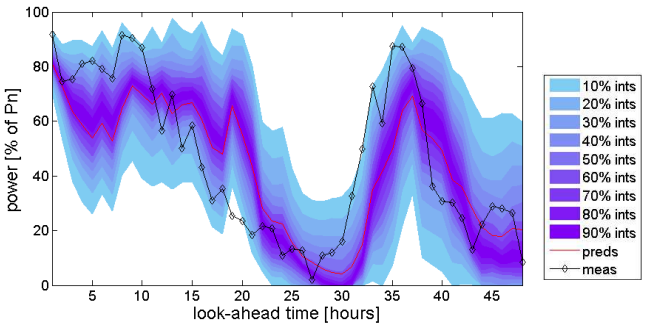

Figure 9: Probabilistic forecasting

8 upscaling Models

8.1 Reference Wind Farms

Within the ANEMOS project two case studies of regional forecasting were studied to evaluate the performance of advanced upscaling models and the methodology of reference wind farms selection.

For the upscaling it has been shown in Siebert and Kariniotakis (2006) that in the optimal upscaling procedure only a limited number of reference wind farms shall be used.

In an investigation using data from the Jutland area in Denmark, where in total 23 reference farms where available, they showed that the optimal number of reference wind farms is 3 to 5. The low value of the optimal

number of reference wind farms can be explained by the fact that increasing the number of reference farms increases the amount of available information, but also the amount of noise the model has to filter. It is important to select the best combination of reference wind farms, and it has been shown that best combination appear to be those that offer the best coverage of the region in terms of meteorological data. An example of a reasonable set of reference farms is shown in Figure 10.

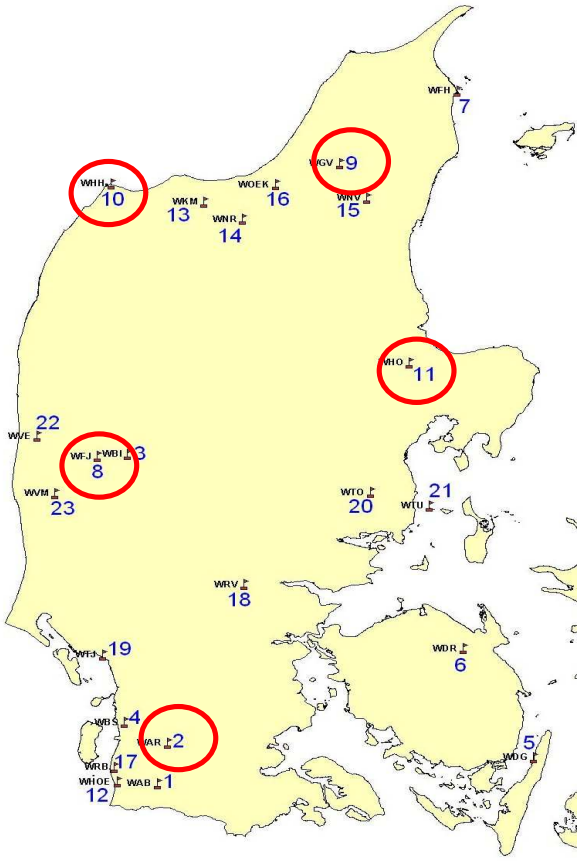

Figure 10: A set of reference wind farms for upscaling

For the case of Ireland ESB National Grid provided data for 11 wind farms. The wind farms are mainly located in the north-western quarter of Ireland.

The results show that, due to the smoothing effect, forecast accuracy is higher for regional forecasting than for individual wind farm forecasting. The average error for 24 hours ahead for the 2.2 GW capacity in Jutland is 6.2 %. For Ireland, due to the lower spatial smoothing, the error for 24 hours ahead is 11.6 %.

8.2 Models for upscaling

The dynamic upscaling model used in WPPT for a region is:

$$\hat{p}^{reg}_{t+k|t} = f(\bar{w}^{ar}_{t+k|t}, \bar{\theta}^{ar}_{t+k|t}, k)\hat{p}^{loc}_{t+k|t}$$

where $\hat{p}^{loc}_{t+k|t}$ is a local (dynamic) power prediction within the region, $\bar{w}^{ar}_{t+k|t}$ is forecasted regional wind speed, and $\bar{\theta}^{ar}_{t+k|t}$ is forecasted regional wind direction. The characteristics of the NWP and $\hat{p}^{loc}$ change with the prediction horizon. Hence the dependency of prediction horizon *k* in the model.

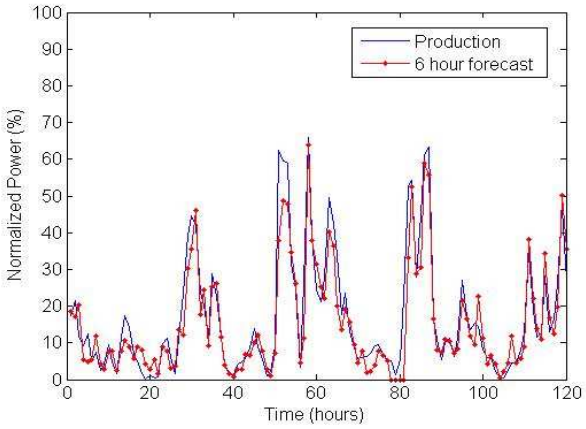

Figure 11: The observed production and the corresponding 6 hour forecast

In Lange (2003) the effect of spatial smoothing has been investigated, and it is shown that spatial smoothing gives a 22-50 % error reduction for a fairly small area.

An upscaling method based on linear regression has been developed by the University of Oldenburg. The coloured squares on Figure 12 indicate how large a fraction of the total the local wind farm represents, while the circles denote the weight of each reference wind farm. The RMS of the upscaled wind forecasts is compared with the average of the reference wind farm in Figure 13.

A method for upscaling of regional wind generation by a dynamic fuzzy neural network based approach is described in Pinson et al. (2003).

9 Automatic tuning of models

9.1 Adaptivity

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

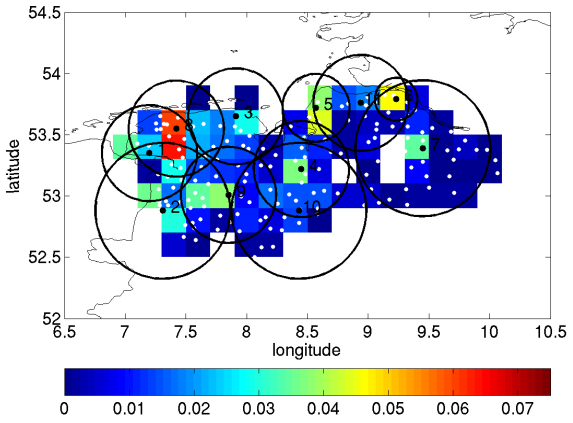

Figure 12: Upscaling in North-West Germany

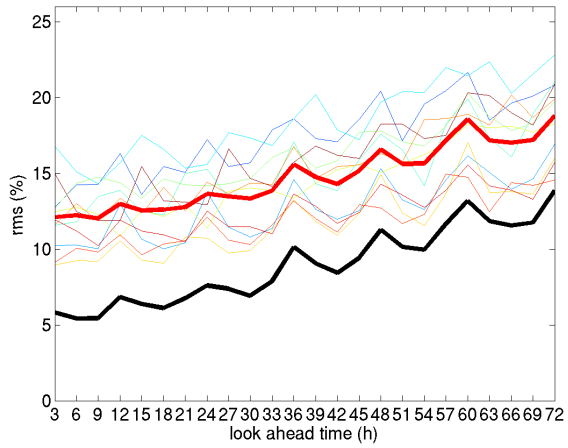

Figure 13: Performance of upscaling in North-West Germany

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 dirtiness of the 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.

A simple procedure for tracking changes over time is to disregard old information as new information becomes 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 Nielsen et al. (2000, 2002).

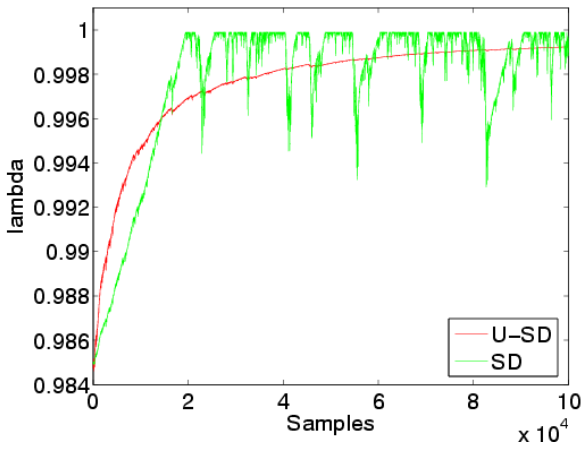

Figure 14: Variation of the forgetting factor

Typically the forgetting of old information is obtained by using a forgetting factor which is multiplied on the available information, ie. a forgetting factor equal one means that all the old information is kept in the model. During the ANEMOS project various methods for optimally calculating the forgetting factor has been developed. Examples showing the variations of the forgetting factor is shown in Figure 14. The curves show the resulting values of the forgetting factor using two different methods for calculating the time varying forgetting factor. In both cases the problem of initialising a dynamic model is considered. For a given value of the forgetting factor λ, the effective number of observations, N_{eff} is given as

$$N_{eff} = \frac{1}{1-\lambda}$$

The SD marked curve in Figure 14 corresponds to a method where a bounded value ($\lambda \leq 1$) for the forgetting factor is used. It it seen that occasionally the forgetting factor drops to a value which actually implies that nearly all historical information is lost.

During the ANEMOS project an alternative method is developed (Christiansen et al. (2006)) which allow for an unbounded optimisation in finding the optimal value of λ. This method is represented by the smooth curve, and it is seen that a more reasonable variation of the forgetting is obtained.

9.2 Bandwidth

During the ANEMOS project non-parametric and conditional parametric methods are used widely to describe non-linear relations like the wind farm power curve. If linear parametric model contains some coefficients

which are unknown functions of some explanatory variables one possibility is to use a conditional parametric model, which 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. When using local regression to estimate the coefficient functions in a conditional parametric model a number of distinct points are selected as fit points for the local models, and the data points in the neighbourhood of the fit point is used to fit the local model. The size of the neighbourhood entering into the estimation of the local model is determined by *the bandwidth* associated with the fit point. During the ANEMOS project a method for finding the optimal bandwidth has been developed.

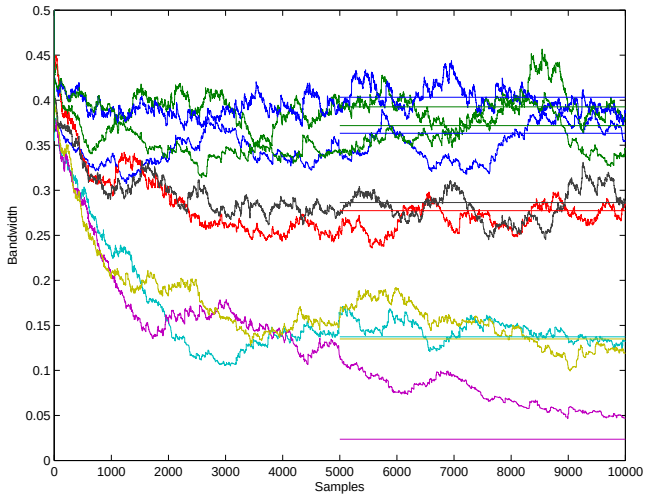

Figure 15: A Gaussian weight function is used to optimise the bandwidth at nine fitting points. Both steepest descent traces and fix bandwidth optimised on the last half of the data are shown.

In Figure 15 a Gaussian weight function is used to optimise the bandwidth at nine fitting points. By this approach an optimal smooth estimate of for instance the wind farm power curve can be estimated.

On top of the nine traces of the bandwidth as optimised by steepest descent are corresponding lines showing the optimal fixed bandwidth measured over the last 5,000 samples. It is seen that the steepest descent does find the optimal value relatively fast when the initial value is not too far from the optimal value. The only trace that didn't converge within this timespan is the purple. That particular line is still converging after 10,000 samples so it should have been started at a more appropriate level if fast convergence was of interest, alternatively a larger step size could have been chosen. Here the main focus was to show that it does converge towards the optimal value.

10 Acknowledgements

The work described here is financially supported by EU contract No. ENK5-CT-2002-00665, which is hereby greatly acknowledged.

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