Forecasting Wind and Solar Power Production

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Outline

- Some ongoing projects ...
- Wind Power Forecasting in Denmark
- Methods used for predicting the wind power
- Configuration example for a large system
- Spatio-temporal forecasting
- Use of several providers of MET forecasts
- Uncertainty and confidence intervals
- Scenario forecasting
- Value of wind power forecasts
- Solar power forecasting

Some projects ....

- FlexPower (PSO)
- iPower (SPIR)
- Ensymora (DSF) (wind, solar, heat load, power load, price, natural gas load)
- Optimal Spining Reserve (Nordic)
- SafeWind (FP7)
- AnemosPlus (FP7)
- NORSEWind (FP7)
- Radar at Sea (PSO)
- Mesoscale (PSO)
- Integrated Wind Planning Tool (PSO)
- Vind i Øresund (Intereg IV)
- Solar and Electric Heating in Energy Systems (DSF)

Wind Power Forecasting in Denmark

WPPT (Wind Power Prediction Tool) is one of the wind power forecasting solutions available with the longest historie of operational use.

- WPPT has been continuously developed since 1993 – initially at DTU (Technical University of Denmark and since 2006 by ENFOR – in close co-operation with:
  - Energinet.dk,
  - Dong Energy,
  - Vattenfall,
  - The ANEMOS projects and consortium (since 2002)
  - DTU (since 2006).
- WPPT has been used operationally for predicting wind power in Denmark since 1996.
- WPPT (partly as a part of ’The Anemos Wind Power Prediction System’) is now used in Europe, Australia, and North America.

Now in Denmark (DK1): Wind power covers on average about 26 pct of the system load.

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Prediction of wind power

In areas with high penetration of wind power such as the Western part of Denmark and the Northern part of Germany and Spain, reliable wind power predictions are needed in order to ensure safe and economic operation of the power system.

Accurate wind power predictions are needed with different prediction horizons in order to ensure

- (a few hours) efficient and safe use of regulation power (spinning reserve) and the transmission system,
- (12 to 36 hours) efficient trading on the Nordic power exchange, NordPool,
- (days) optimal operation of eg. large CHP plants.

Predictions of wind power are needed both for the total supply area as well as on a regional scale and for single wind farms.

Today also reliable methods for **ramp forecasting** is provided by most of the tools.

Modelling approach – the inputs

Depending on the configuration the forecasting system can take advantage of input from the following sources:

- Online measurements of wind power prod. (updated every 5min. – 1hr).
- Online measurements of the available production capacity.
- Online “measurements” of downregulated production.
- Aggregated high resolution energy readings from all wind turbines in the groups defined above (updated with a delay of 3-5 weeks).
- MET forecasts of wind speed and wind direction covering wind farms and sub-areas (horizon 0–48(120)hrs updated 2–4 times a day).
- Forecasted availability of the wind turbines.
- Other measurements/predictions (local wind speed, stability, etc. can be used).

System characteristics

The total system consisting of wind farms measured online, wind turbines not measured online and meteorological forecasts will inevitably change over time as:

- the population of wind turbines changes,
- changes in unmodelled or insufficiently modelled characteristics (important examples: roughness and dirty blades),
- changes in the NWP models.

A wind power prediction system must be able to handle these time-variations in model and system. WPPT employes **adaptive and recursive model estimation** to handle this issue.

Following the initial installation WPPT will automatically calibrate the models to the actual situation.

The power curve model

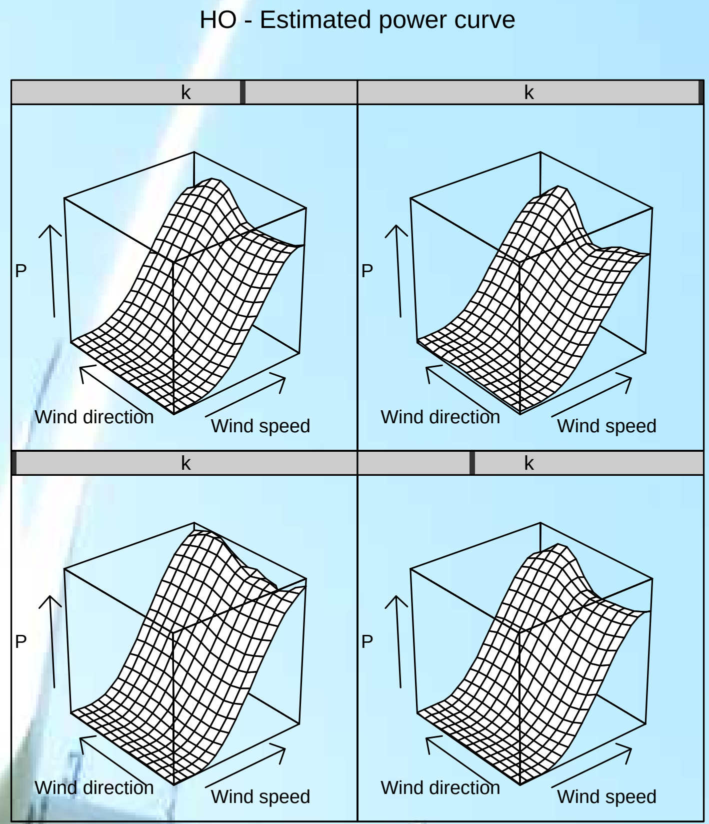
The wind turbine "power curve" model, $p^{tur} = f(w^{tur})$ is extended to a wind farm model, $p^{wf} = f(w^{wf}, \theta^{wf})$, by introducing wind direction dependency. By introducing a representative area wind speed and direction it can be further extended to cover all turbines in an entire region,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

The power curve model is defined as:

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

where
$\bar{w}_{t+k|t}$ is forecasted wind speed, and
$\bar{\theta}_{t+k|t}$ is forecasted wind direction.

The characteristics of the NWP change with the prediction horizon. Hence the dependency of prediction horizon k in the model.



Plots of the estimated power curve for the Hollandsbjerg wind farm (k = 0, 12, 24 and 36 hours).

The dynamical prediction model

The power curve models are used as input for an adaptively estimated **dynamical model**, which (as a **simple example**) leads to the following k-stop ahead forecasts:

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

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 unmodelled 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 described using Fourier expansions.

A model for upscaling

The dynamic upscaling model for a region is defined as:

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

where

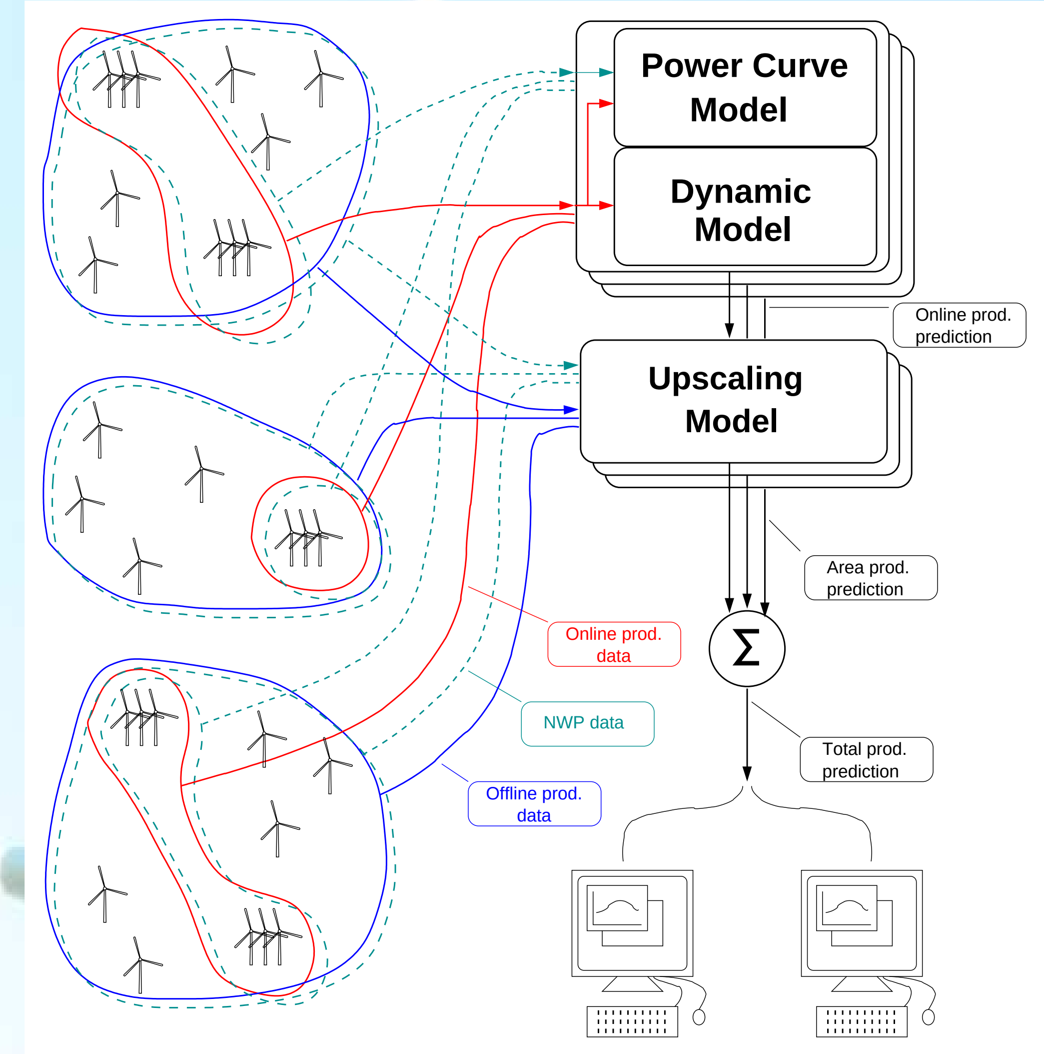
$\hat{p}^{loc}_{t+k|t}$ is a local (dynamic) power prediction within the region,
$\bar{w}^{ar}_{t+k|t}$ is forecasted regional wind speed, and
$\bar{\theta}^{ar}_{t+k|t}$ is forecasted regional wind direction.

The characteristics of the NWP and $\hat{p}^{loc}$ change with the prediction horizon. Hence the dependendency of prediction horizon k in the model.

Configuration Example

This configuration of WPPT is used by a large TSO. Characteristics for the installation:

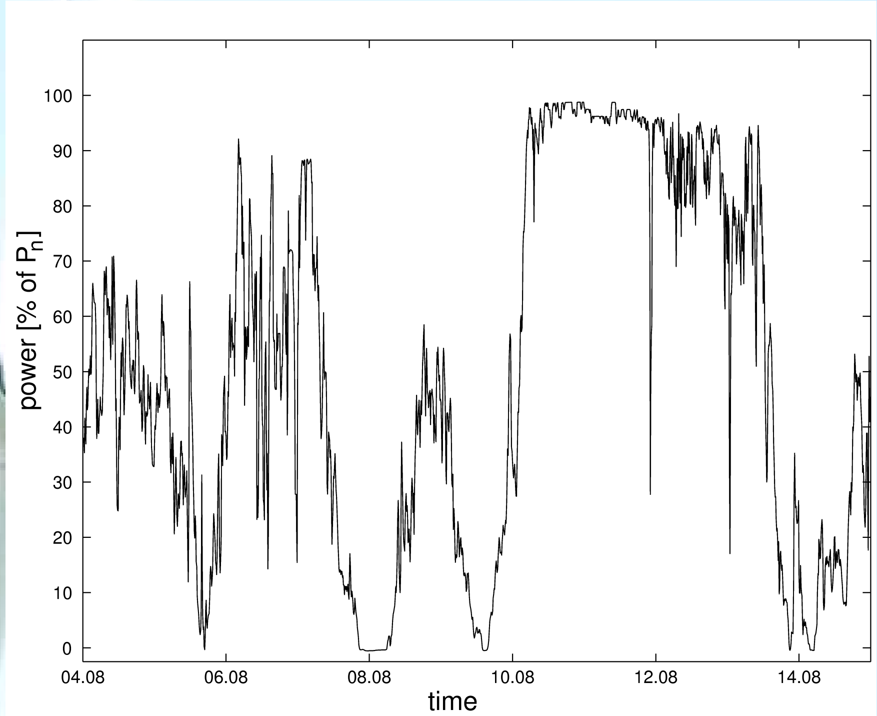
- A large number of wind farms and stand-alone wind turbines.
- Frequent changes in the wind turbine population.
- Offline production data with a resolution of 15 min. is available for more than 99% of the wind turbines in the area.
- Online data for a large number of wind farms are available. The number of online wind farms increases quite frequently.



Fluctuations of offshore wind power

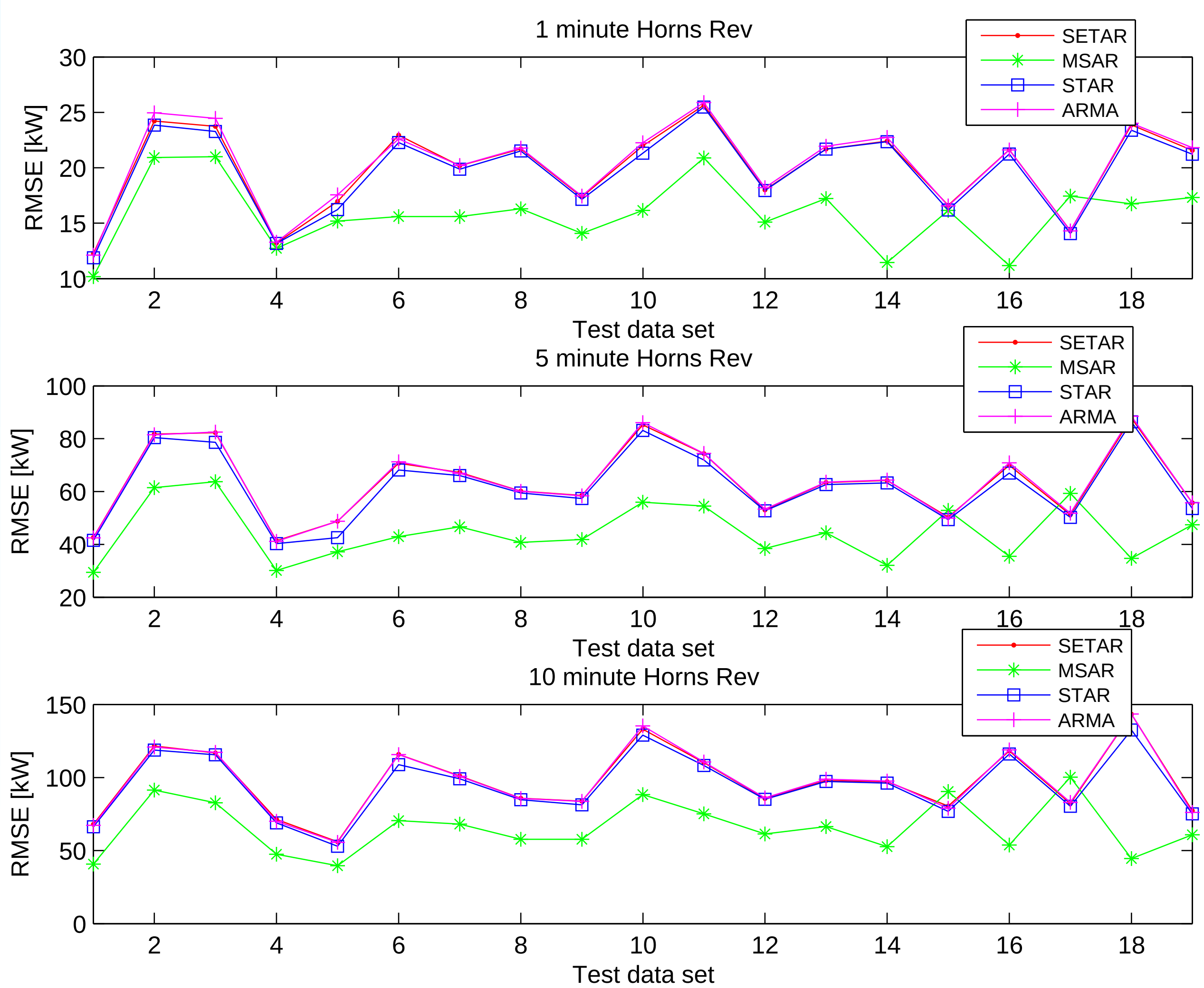
- Fluctuations at large offshore wind farms have a significant impact on the control and management strategies of their power output
- Focus is given to the minute scale. Thus, the effects related to the turbulent nature of the wind are smoothed out
- When looking at time-series of power production at Horns Rev (160MW/209MW) and Nysted (165 MW), one observes successive periods with fluctuations of larger and smaller magnitude

- We aim at building models
  - based on historical wind power measures only...
  - ... but able to reproduce this observed behavior
  - this calls for **regime-switching models**



Results - Horns Rev

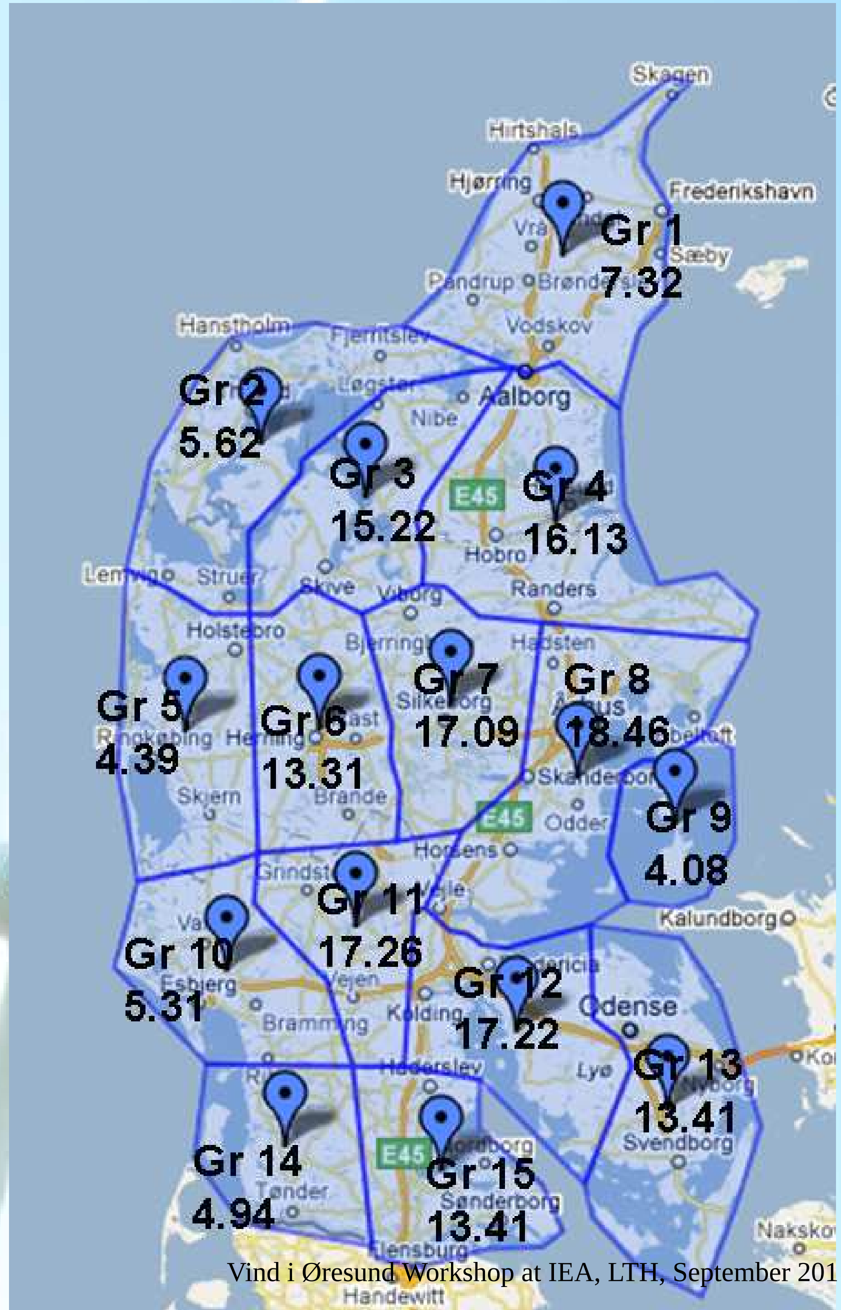
- The evaluation set is divided in 19 different periods of different lengths and characteristics
- MSAR models generally outperform the others
- In the RADAR@sea project the regime shift is linked to convective rain events – which are detected by a weather radar.



Spatio-temporal forecasting

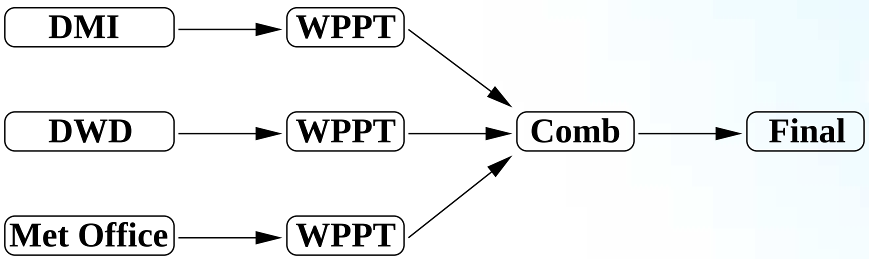
Predictive improvement (measured in RMSE) of forecasts errors by adding the spatio-temperal module in WPPT.

- 23 months (2006-2007)
- 15 onshore groups
- Focus here on 1-hour forecast only
- Larger improvements for eastern part of the region
- Needed for reliable ramp forecasting.
- The EU project NORSEWinD will extend the region

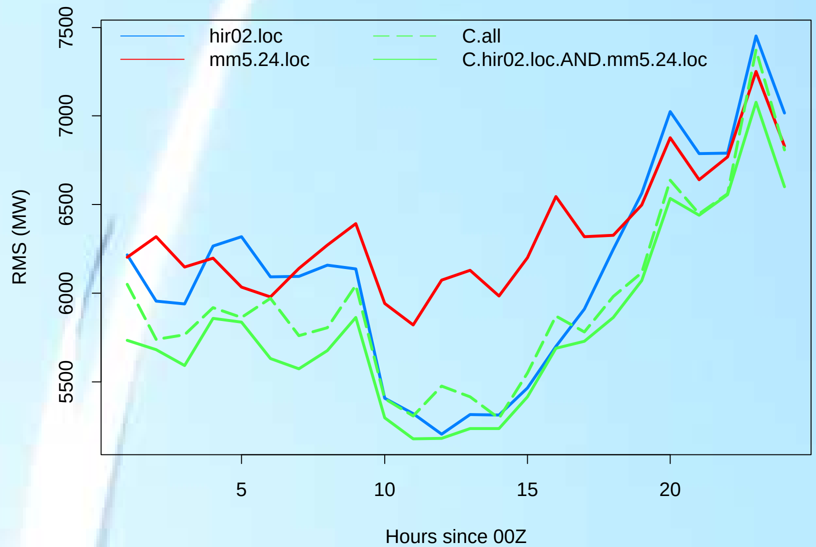


Combined forecasting

- A number of power forecasts are weighted together to form a new improved power forecast.
- These could come from parallel configurations of WPPT using NWP inputs from **different MET providers** or they could come from other power prediction providers.
- In addition to the improved performance also the robustness of the system is increased.



The example show results achieved for the Tunø Knob wind farms using combinations of up to 3 power forecasts.



If too many highly correlated forecasts are combined the performance may decrease compared to using fewer and less correlated forecasts. Typically an improvement on 10-15 pct is seen by including more than one MET provider.

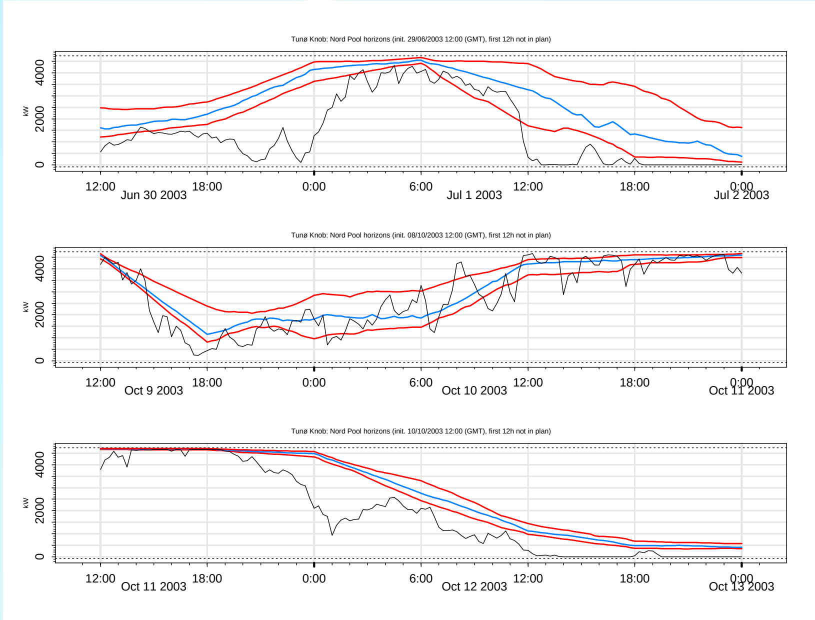
Uncertainty estimation

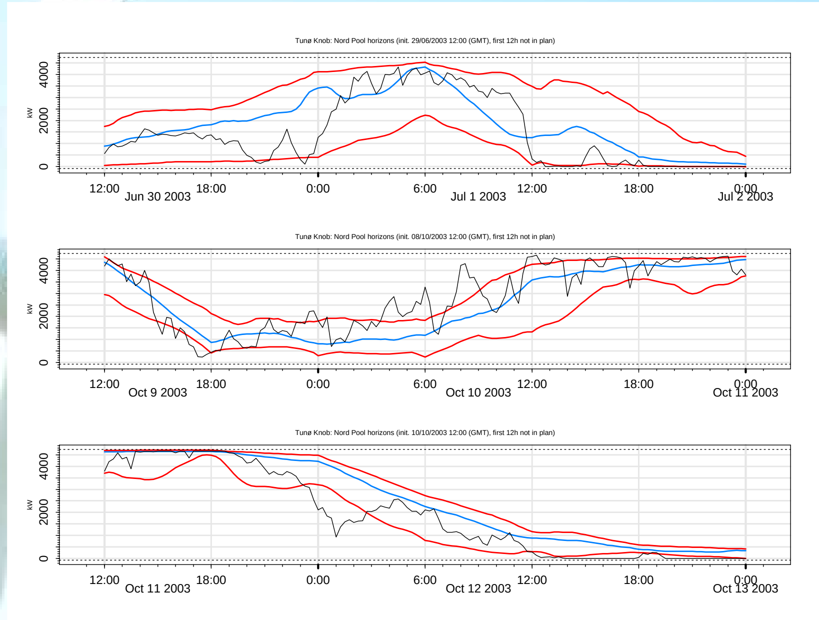
In many applications it is crucial that a prediction tool delivers reliable estimates (probabilistc forecasts) of the expected uncertainty of the wind power prediction.

We consider the following methods for estimating the uncertainty of the forecasted wind power production:

- Resampling techniques.
- Ensemble based - but corrected - quantiles.
- Quantile regression.
- Stochastic differential eqs.

The plots show raw (top) and corrected (bottom) uncertainty intervales based on ECMEF ensembles for Tunø Knob (offshore park), 29/6, 8/10, 10/10 (2003). Shown are the 25%, 50%, 75%, quantiles.





Quantile regression

A (additive) model for each quantile:

$$Q(\tau) = \alpha(\tau) + f_1(x_1; \tau) + f_2(x_2; \tau) + \ldots + f_p(x_p; \tau)$$

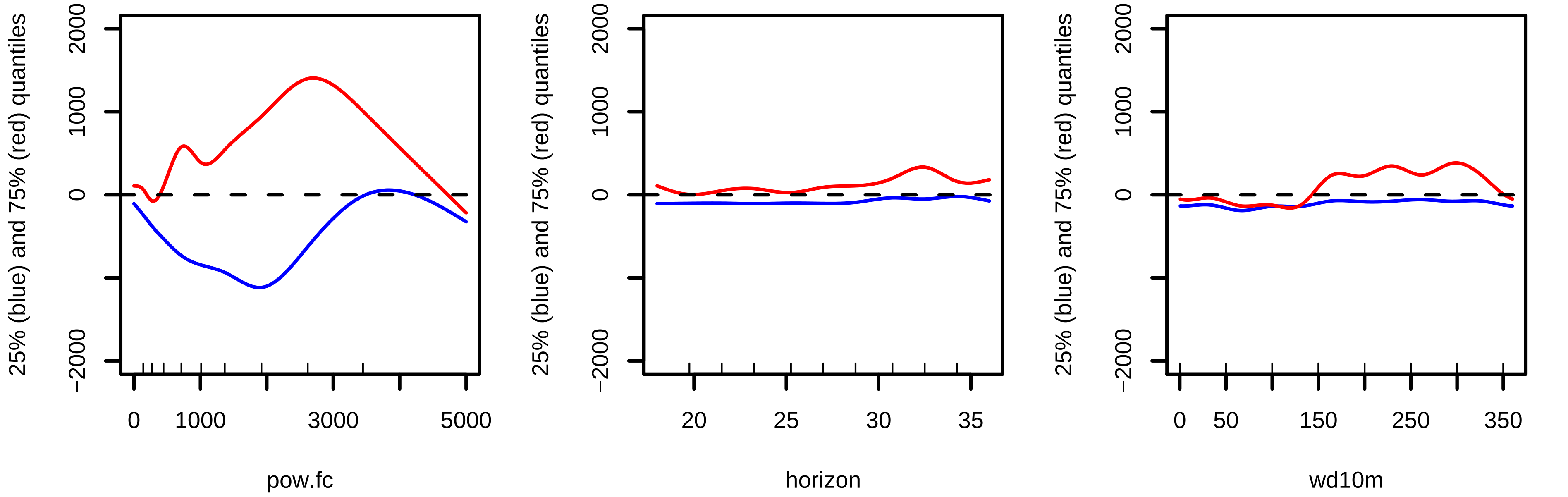
$Q(\tau)$	Quantile of **forecast error** from an **existing system**.
x_j	Variables which influence the quantiles, e.g. the wind direction.
$\alpha(\tau)$	Intercept to be estimated from data.
$f_j(\cdot; \tau)$	Functions to be estimated from data.

Notes on quantile regression:

- Parameter estimates found by minimizing a dedicated function of the prediction errors.
- The variation of the uncertainty is (partly) explained by the independent variables.

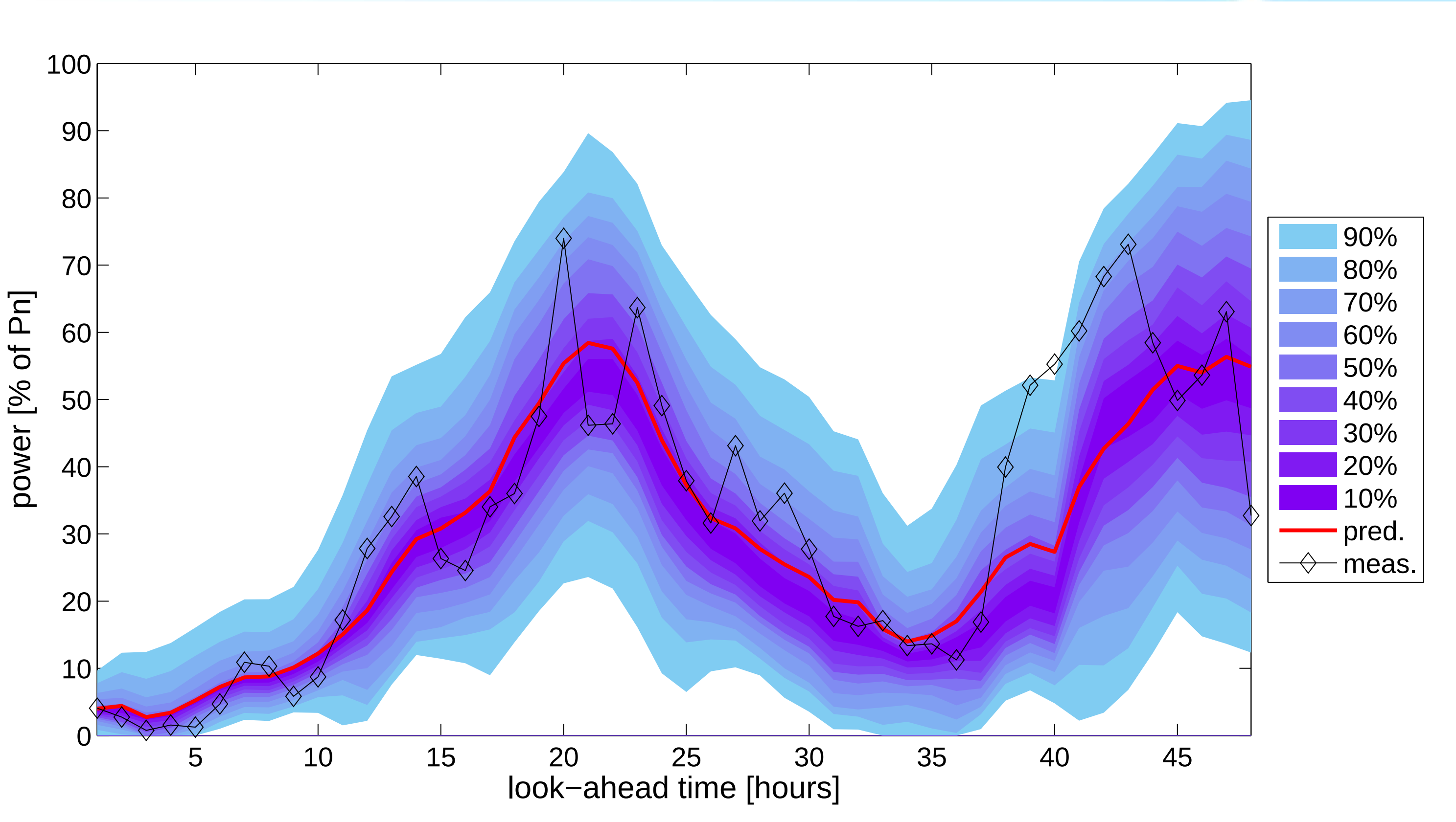
Quantile regression - An example

Effect of variables (- the functions are approximated by Spline basis functions):



- Forecasted power has a large influence.
- The effect of horizon is of less importance.
- Some increased uncertainty for Westerly winds.

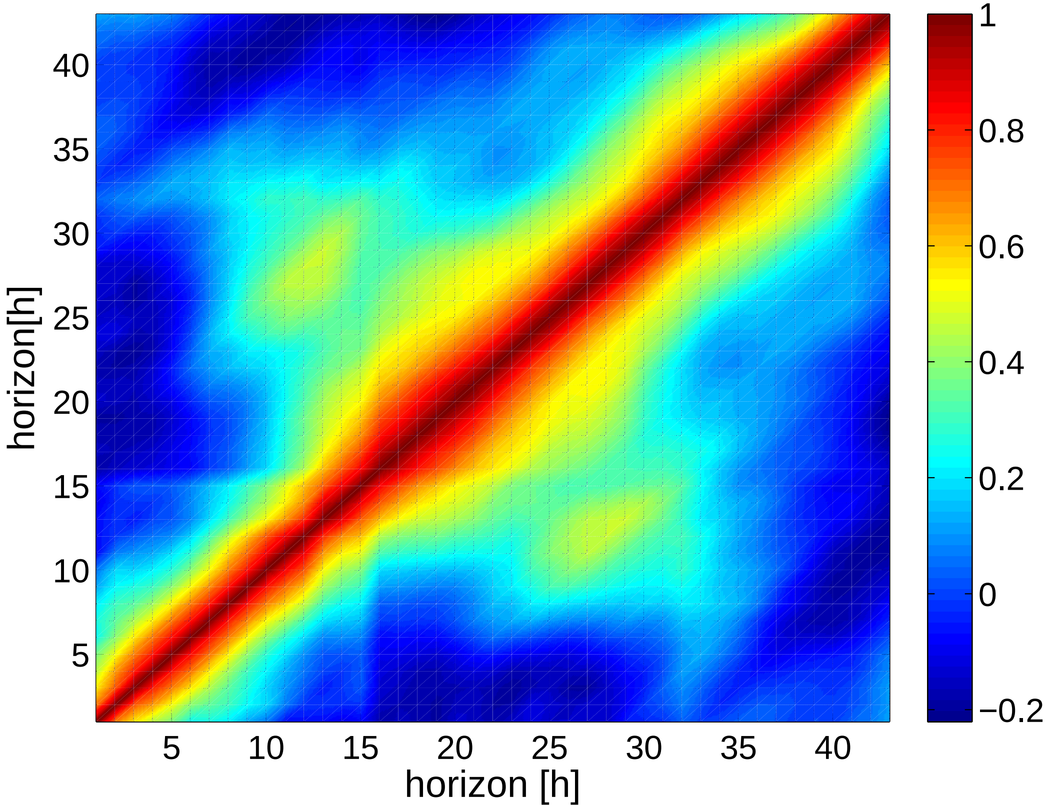
Example: Probabilistic forecasts



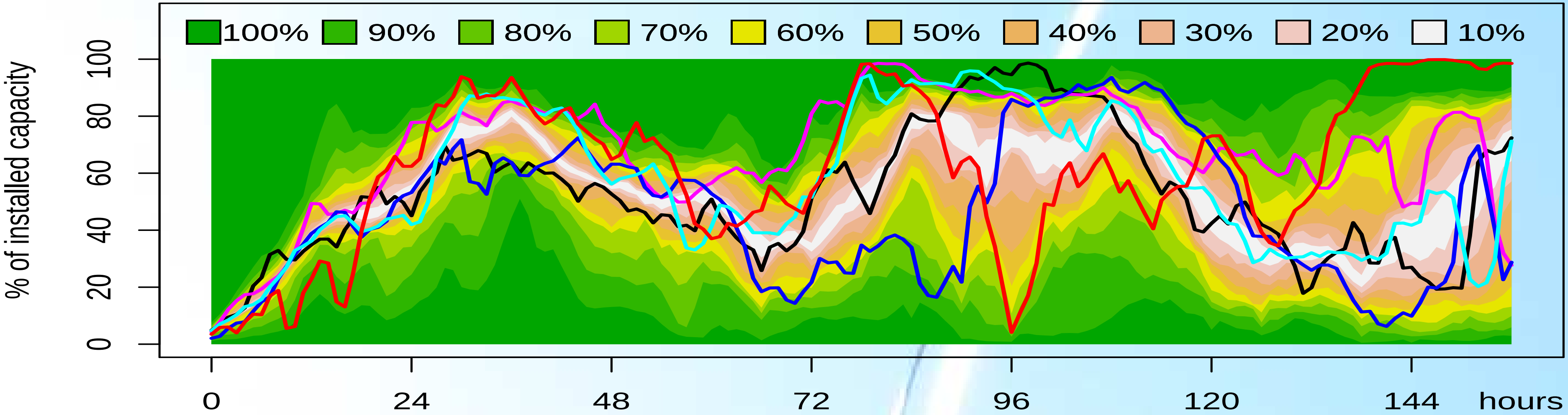
- Notice how the confidence intervals varies ...
- But the correlation in forecasts errors is not described so far.

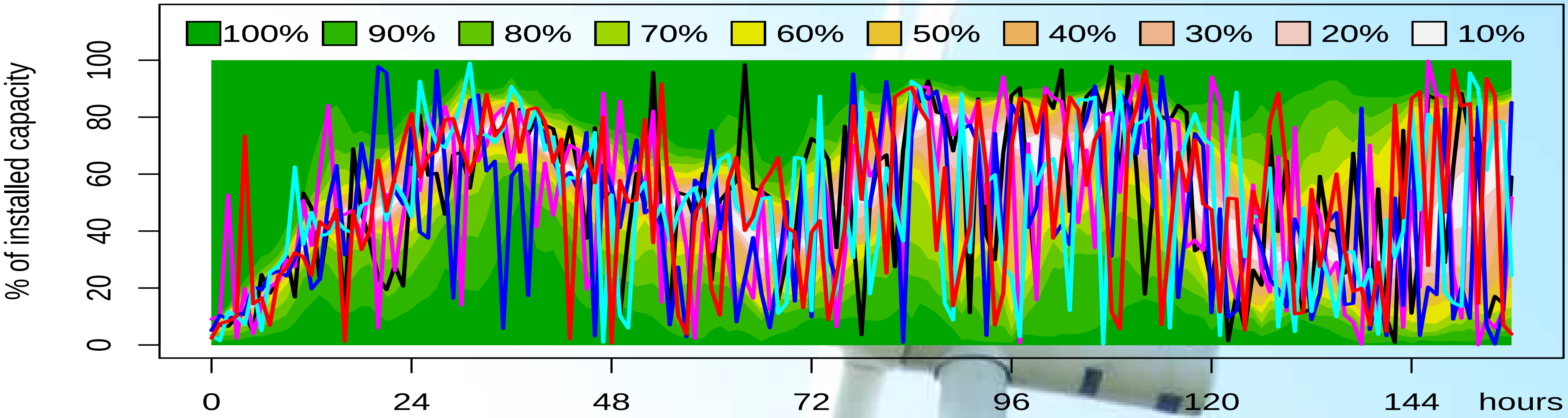
Correlation structure of forecast errors

- It is important to model the **interdependence structure** of the prediction errors.
- An example of interdependence covariance matrix:



Correct (top) and naive (bottom) scenarios





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Types of forecasts required

- Basic operation: Point forecasts
- Operation which takes into account asymmetrical penalties on deviations from the bid: Quantile forecasts
- Stochastic optimisation taking into account start/stop costs, heat storage, and/or 'implicit' storage by allowing the hydro power production to be changed with wind power production: Scenarios respecting correctly calibrated quantiles and auto correlation.

Wind power – asymmetrical penalties

- The revenue from trading a specific hour on NordPool can be expressed as

$$P_S \times \text{Bid} + \begin{cases} P_D \times (\text{Actual} - \text{Bid}) & \text{if} \quad \text{Actual} > \text{Bid} \\ P_U \times (\text{Actual} - \text{Bid}) & \text{if} \quad \text{Actual} < \text{Bid} \end{cases}$$

  P_S is the spot price and P_D/P_U is the down/up reg. price.

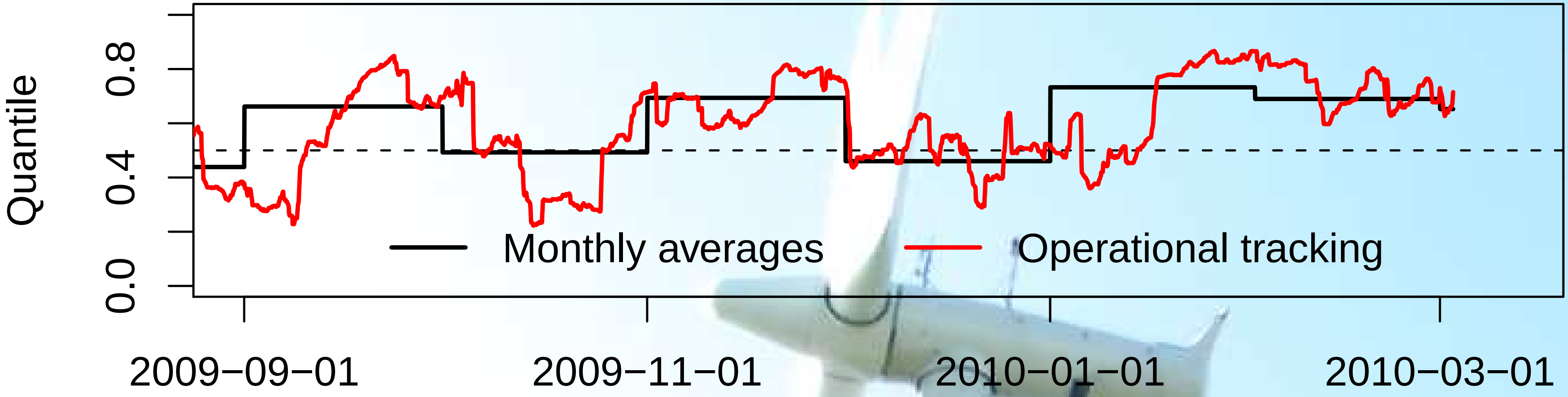
- The bid maximising the expected revenue is the following **quantile**

$$\frac{E[P_S] - E[P_D]}{E[P_U] - E[P_D]}$$

  in the conditional distribution of the future wind power production.

Wind power – asymmetrical penalties

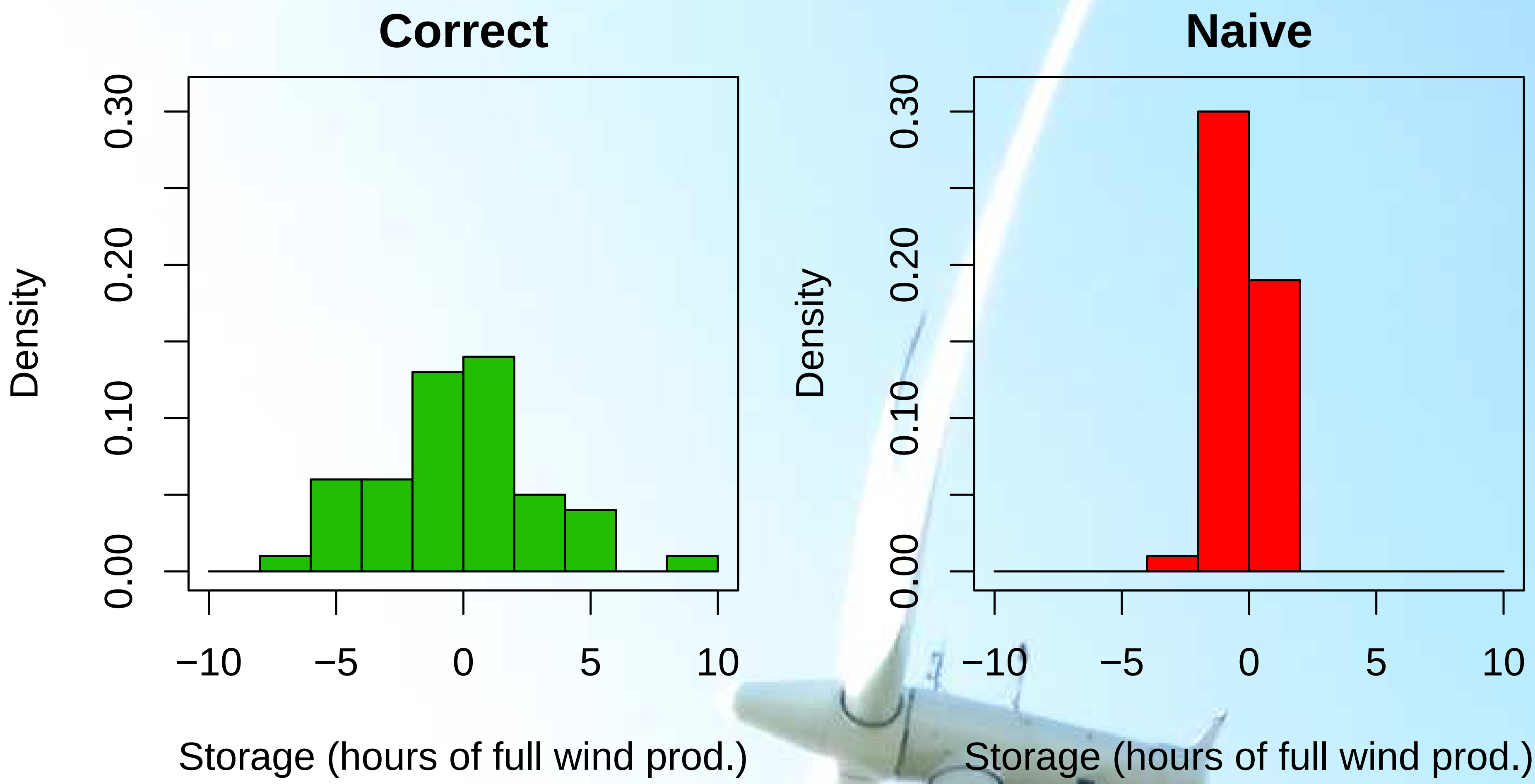
- It is difficult to know the regulation prices at the day ahead level – research into forecasting is ongoing.
- The expression for the quantile is concerned with expected values of the prices – just getting these somewhat right will increase the revenue.
- A simple tracking of C_D and C_U is a starting point.
- **The bids maximizing the revenue during the period September 2009 to March 2010:**



Value of wind power forecasts

- Case study: A 15 MW wind farm in the Dutch electricity market, prices and measurements from the entire year 2002.
- From a phd thesis by Pierre Pinson (2006).
- The costs are due to the imbalance penalties on the regulation market.
- Value of an advanced method for point forecasting: **The regulation costs are diminished by nearly 38 pct.** compared to the costs of using the persistance forecasts.
- Added value of reliable uncertainties: **A further decrease of regulation costs – up to 39 pct.**

Balancing wind by varying other production



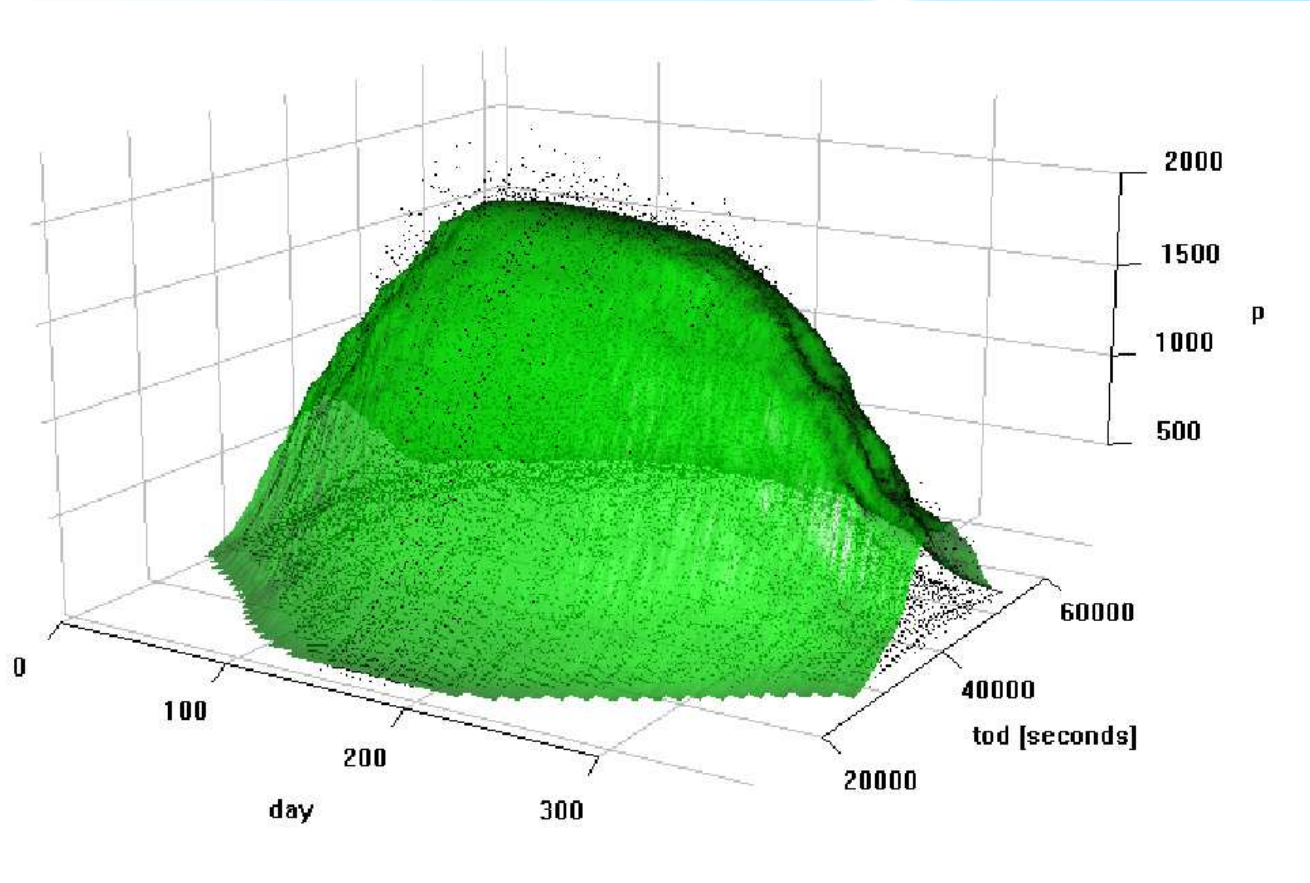
(Illustrative example based on 50 day ahead scenarios as in the situation considered before)

Solar Power Forecasting

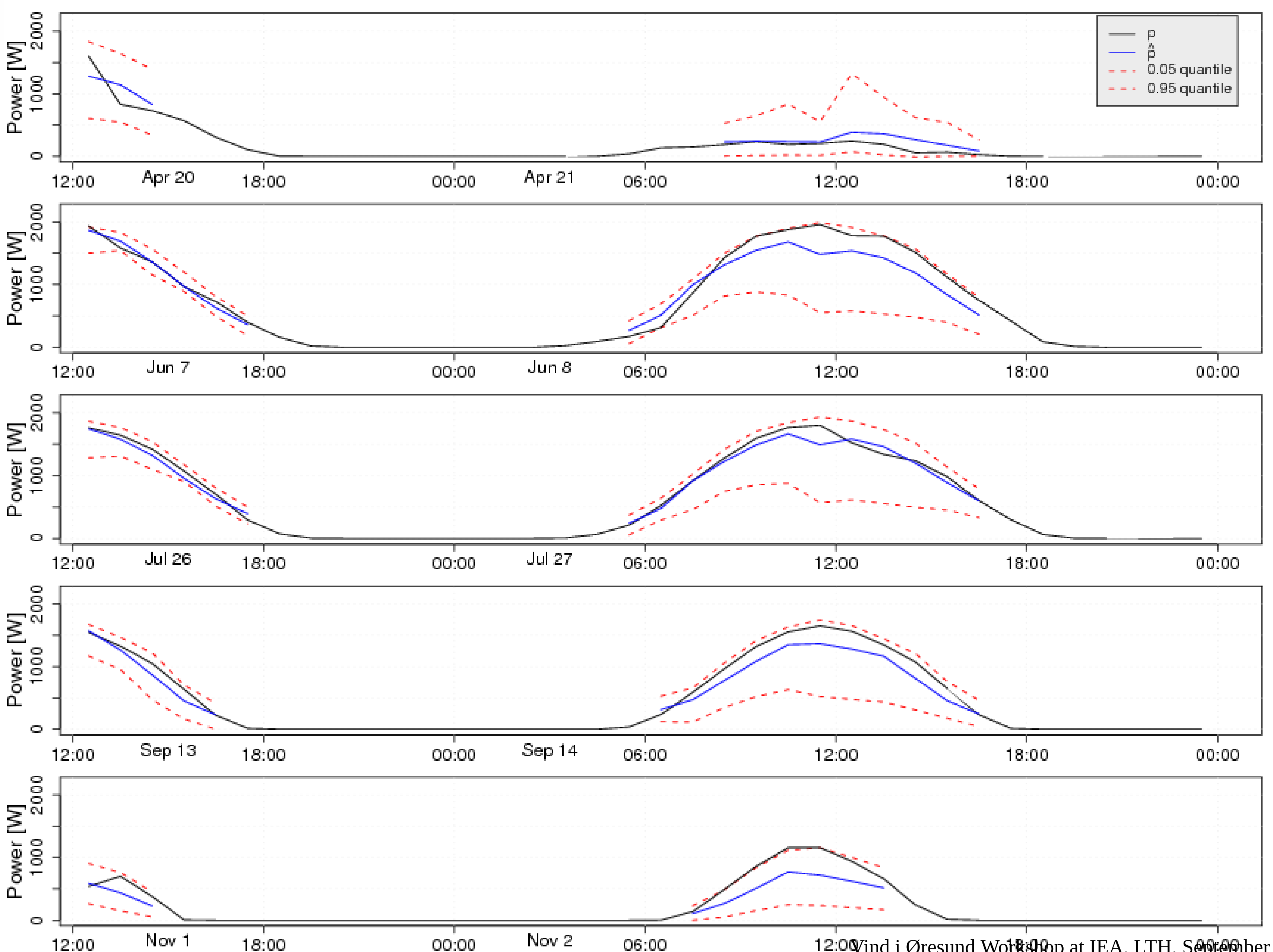
- Same principles as for wind power ....
- Developed for grid connected PV-systems mainly installed on rooftops
- Average of output from 21 PV systems in small village (Brædstrup) in DK

Method

- Based on readings from the systems and weather forecasts
- Two-step method
- Step One: Transformation to atmospheric transmittance τ with statistical clear sky model (see below). Step Two: A dynamic model (see paper).

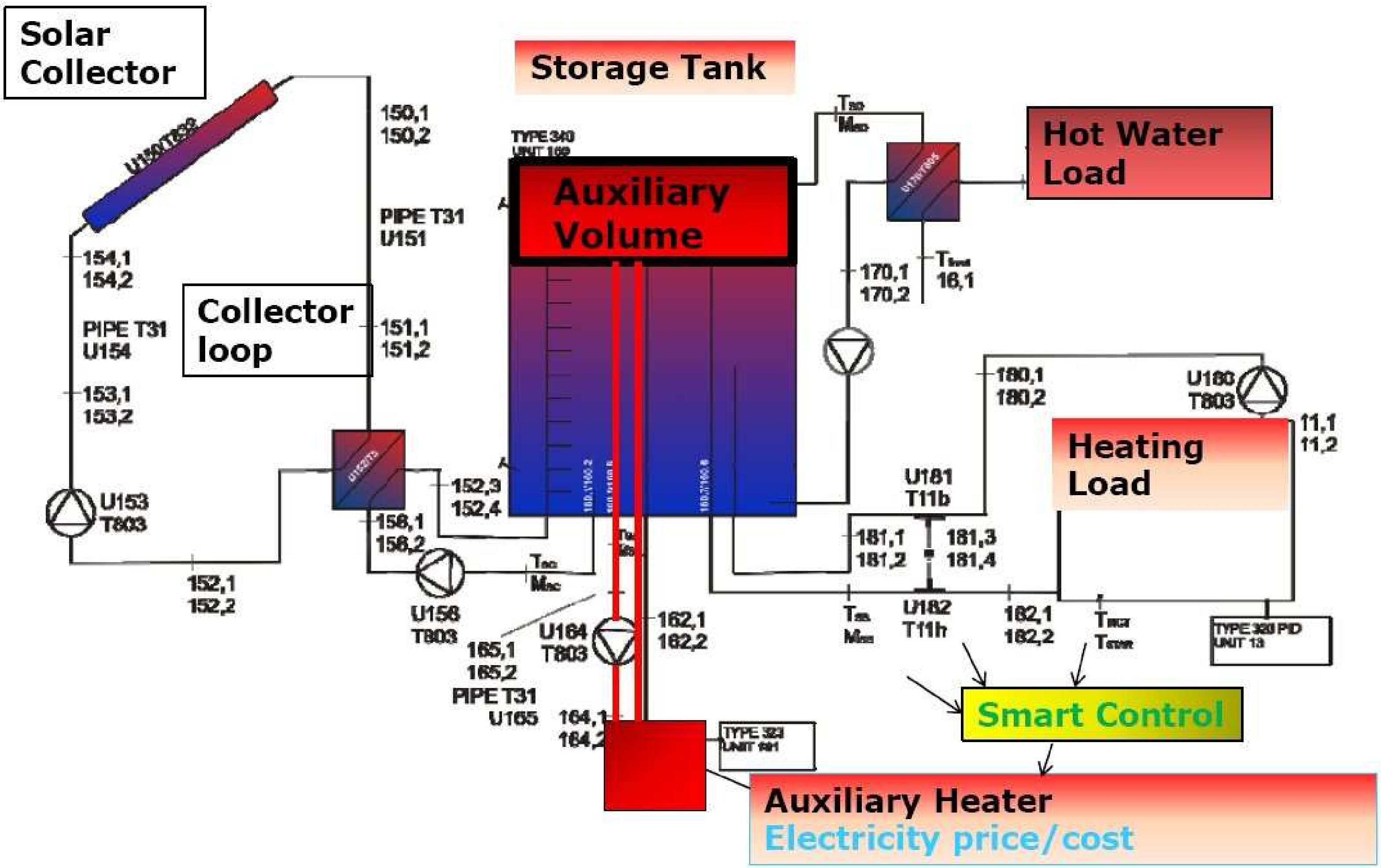


Example of hourly forecasts



Solar Power and Electric Heating (House)

The Solar Combisystem (heating and hotwater)



Conclusions

Some conclusions from more that 15 years of wind power forecasting:

- The forecasting models must be adaptive (in order to taken changes of dust on blades, changes roughness, etc. into account).
- Reliable estimates of the forecast accuracy is very important (check the reliability by eg. reliability diagrams).
- Use more than a single MET provider for delivering the input to the wind power prediction tool – this improves the accuracy with 10-15 pct.
- It is advantegous if the same tool can be used for forecasting for a single wind farm, a collection of wind farms, a state/region, and the entire country.
- Use statistical methods for phase correcting the phase errors – this improves the accuracy with up to 20 pct.
- Estimates of the correlation in forecasts errors important.
- Forecasts of ’cross dependencies’ between load, wind and solar power might be of importance. Will be tested on Bornholm in cooperation with CET at DTU Elektro.

Almost the same conclusions hold for **solar power forecasting**.

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