Advantages of using probabilistic forecasts of wind power production

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Outline

- Wind power forecasting
- Use of several providers of MET forecasts
- Uncertainty and confidence intervals
- Scenario forecasting
- Value of wind power forecasts
- Electricity price 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 - History

Our methods for probabilistic wind power forecasting have been implemented in the **Anemos Wind Power Prediction System/WPPT**

- The methods have been continuously developed since 1993 - in collaboration with
  - Energinet.dk,
  - Dong Energy,
  - Vattenfall,
  - The ANEMOS projects partners/consortium (since 2002)
  - ENFOR (Denmark)
- The methods have been used operationally for predicting wind power in Denmark since 1996.
- Anemos/WPPT is now used all over Europe, Australia, and North America.

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

Sources for uncertainty and adaptivity

Errors in MET forecasts will end up in errors in wind power forecasts, but other factors lead to a need for adaptation which however leads to some uncertainties.
The total system consisting of wind farms measured online, wind turbines not measured online and meteorological forecasts will inevitably change over time as:

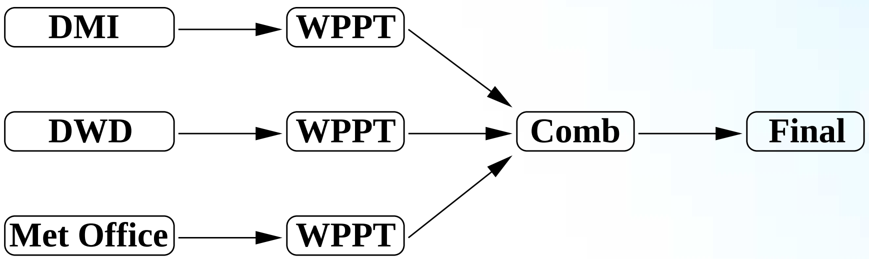
- the population of wind turbines changes,
- changes in unmodelled or insufficiently modelled characteristics (important examples: roughness and dirty blades),
- changes in the NWP models.

A wind power prediction system must be able to handle these time-variations in model and system. An adequate forecasting system may use **adaptive and recursive model estimation** to handle these issues.

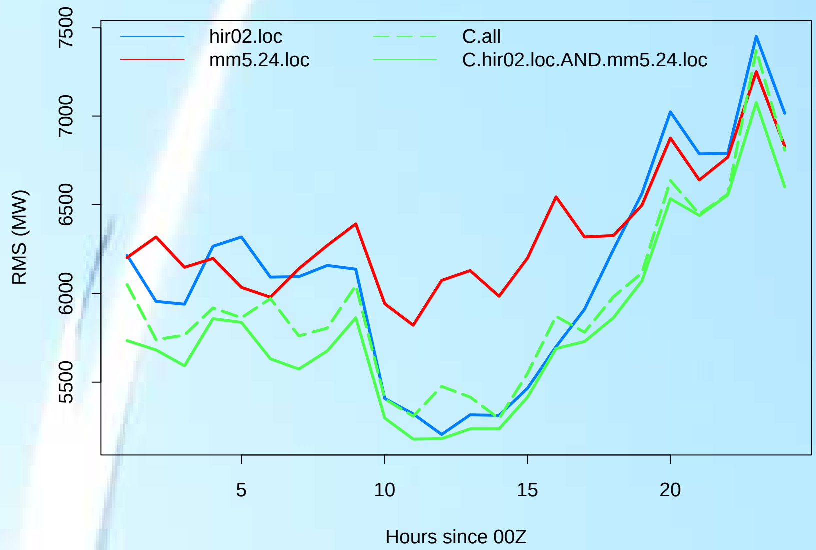
Following the initial installation the software tool will automatically calibrate the models to the actual situation.

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.



Typically an improvement on 10-15 pct in accuracy of the point prediction is seen by including more than one MET provider. Two or more MET providers imply information about uncertainty

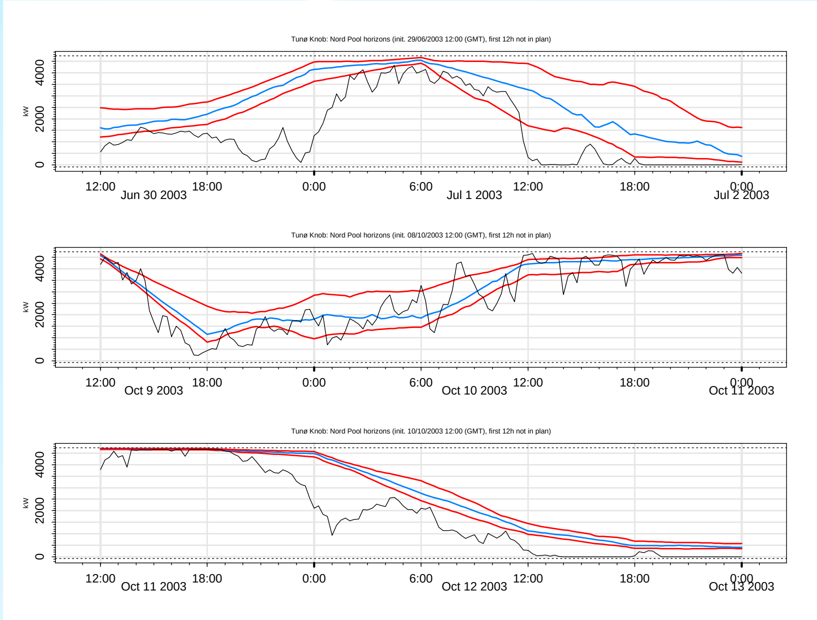
Uncertainty estimation

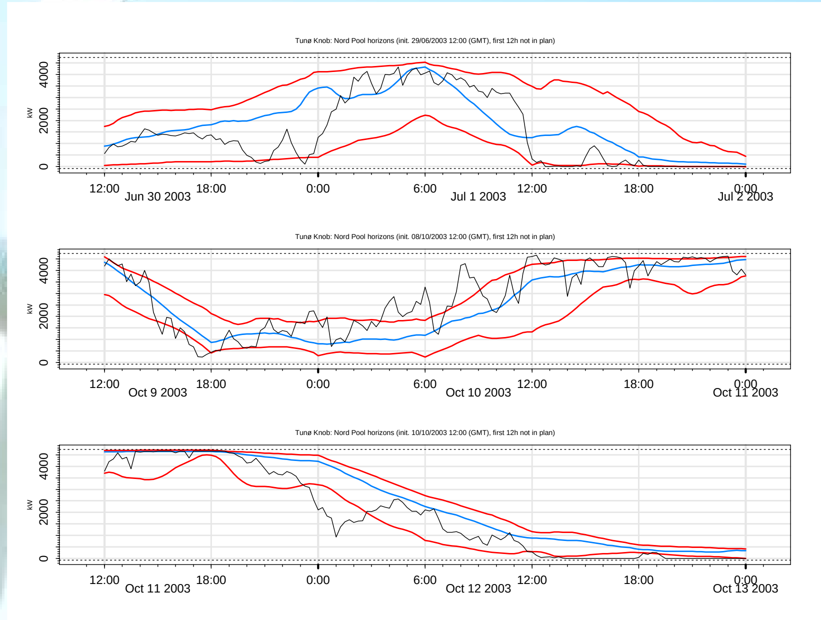
In many applications it is crucial that a prediction tool delivers reliable estimates (probabilistc forecasts) of the expected uncertainty of the wind power prediction.

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

- Adaptive estimation of variances
- Resampling techniques.
- Ensemble based - but corrected - quantiles.
- Quantile regression.
- Stochastic differential equations.

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.





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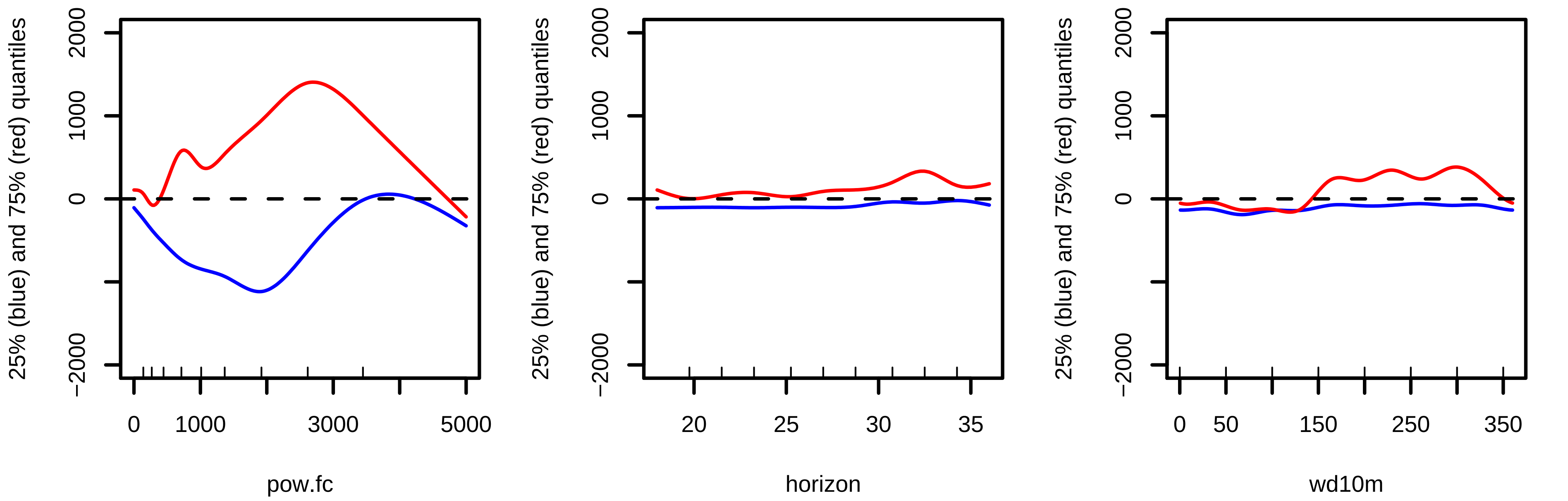
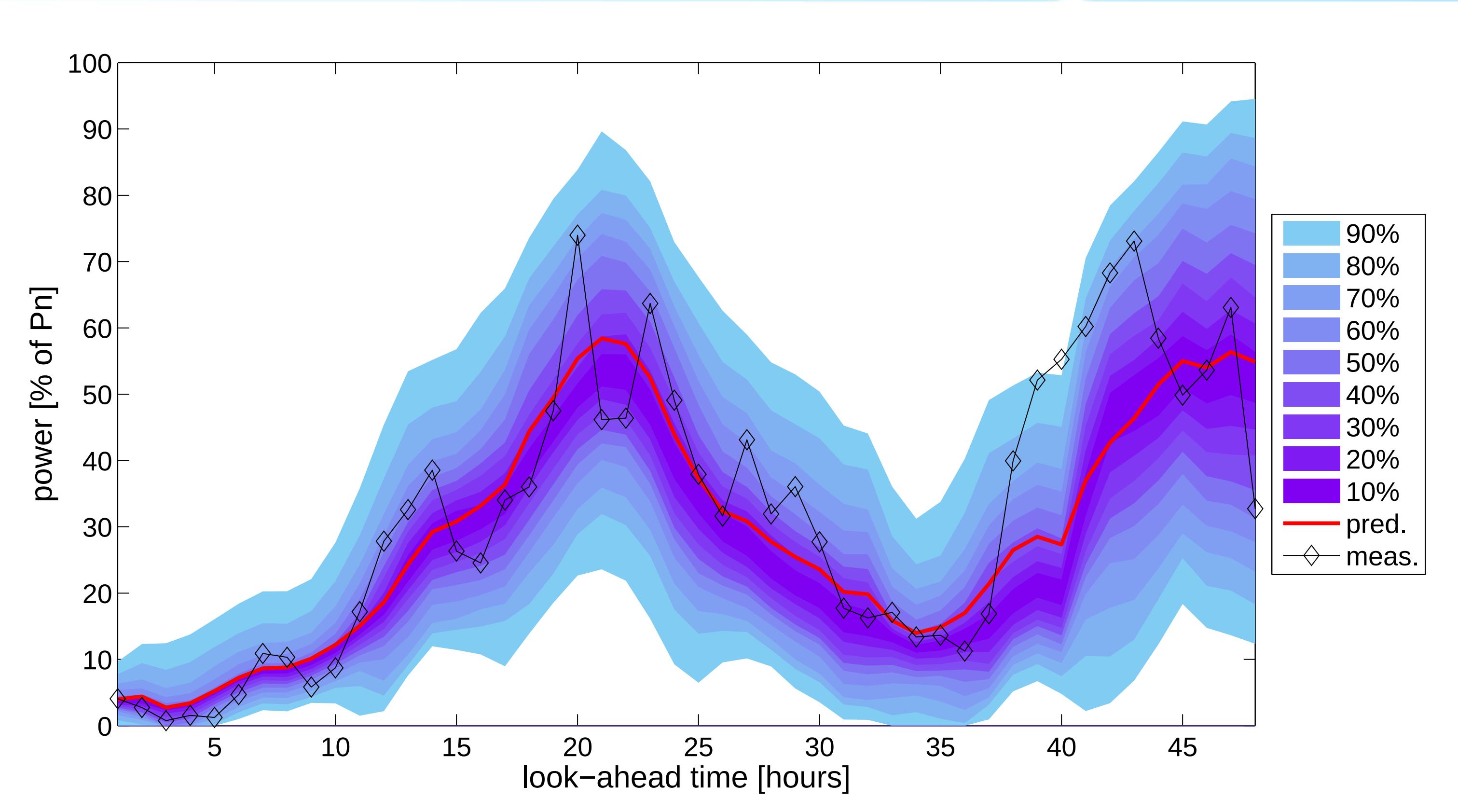
Quantile regression - An example

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.

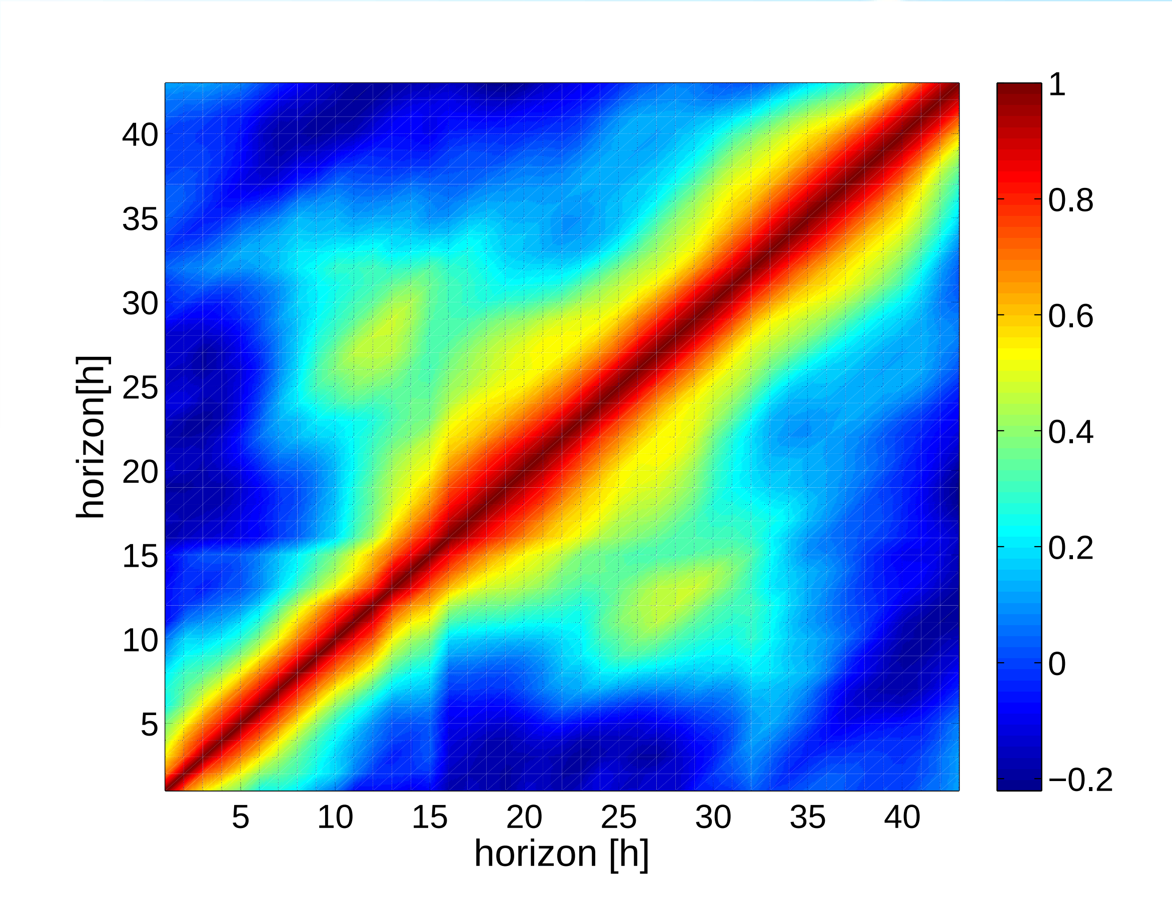
Example: Probabilistic forecasts



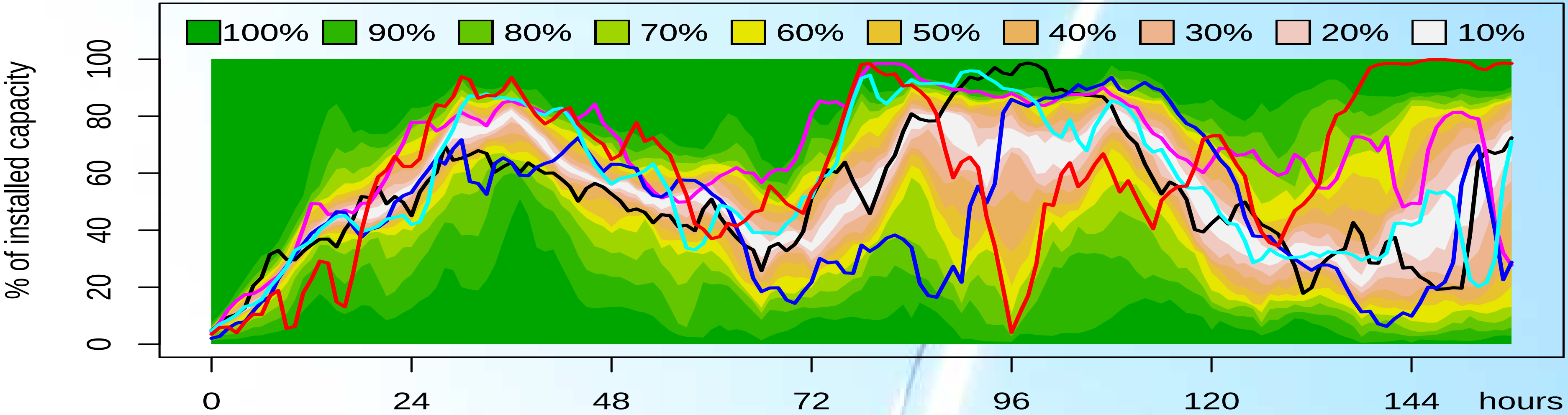
- Notice how the confidence intervals varies ...
- But the correlation in forecasts errors is not described so far.

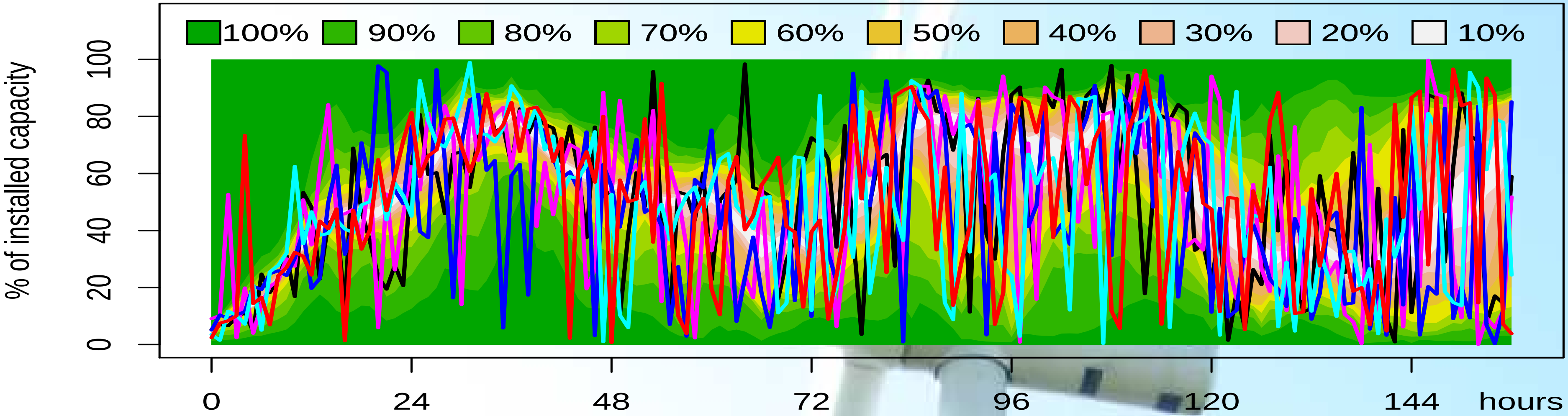
Correlation structure of forecast errors

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

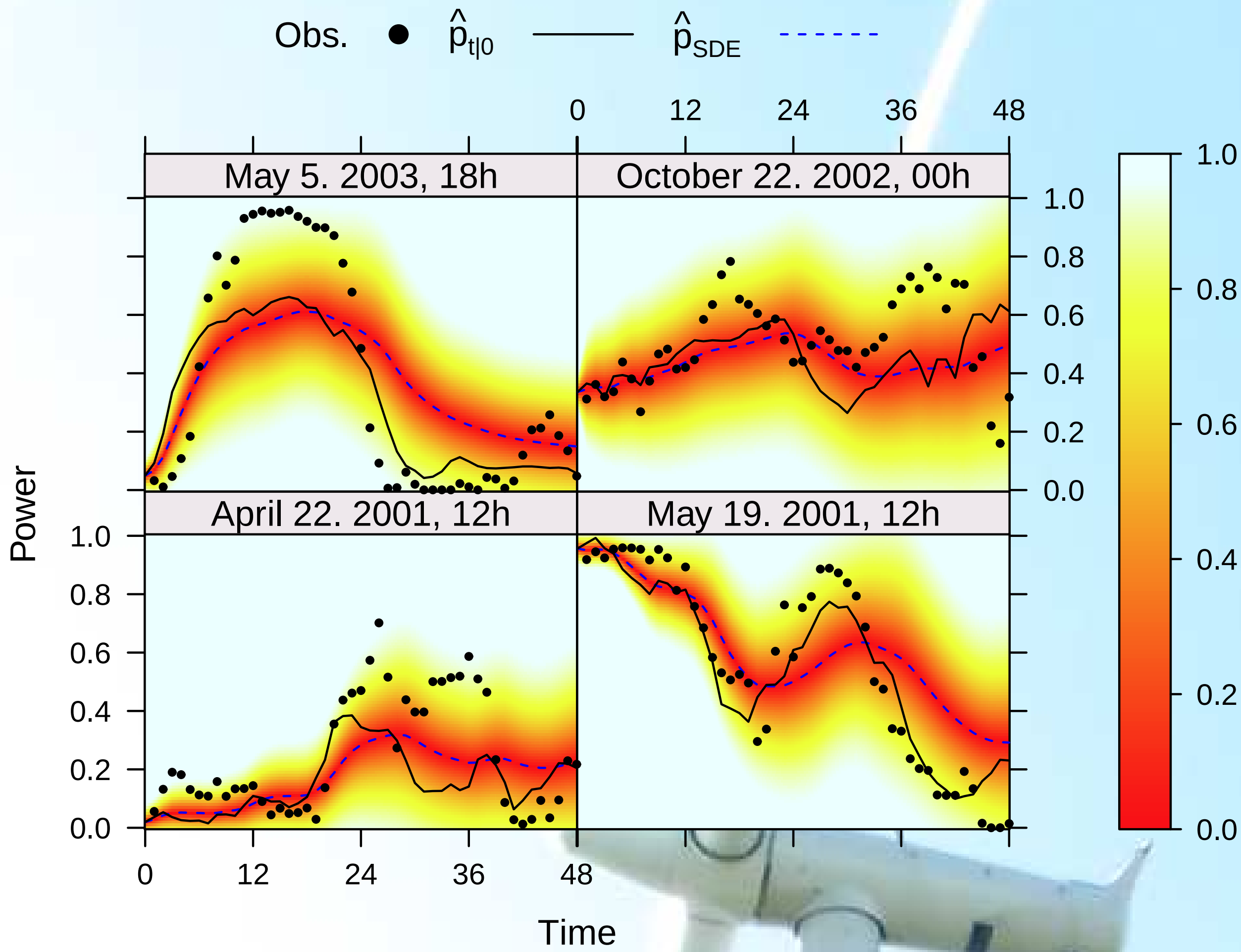


Correct (top) and naive (bottom) scenarios



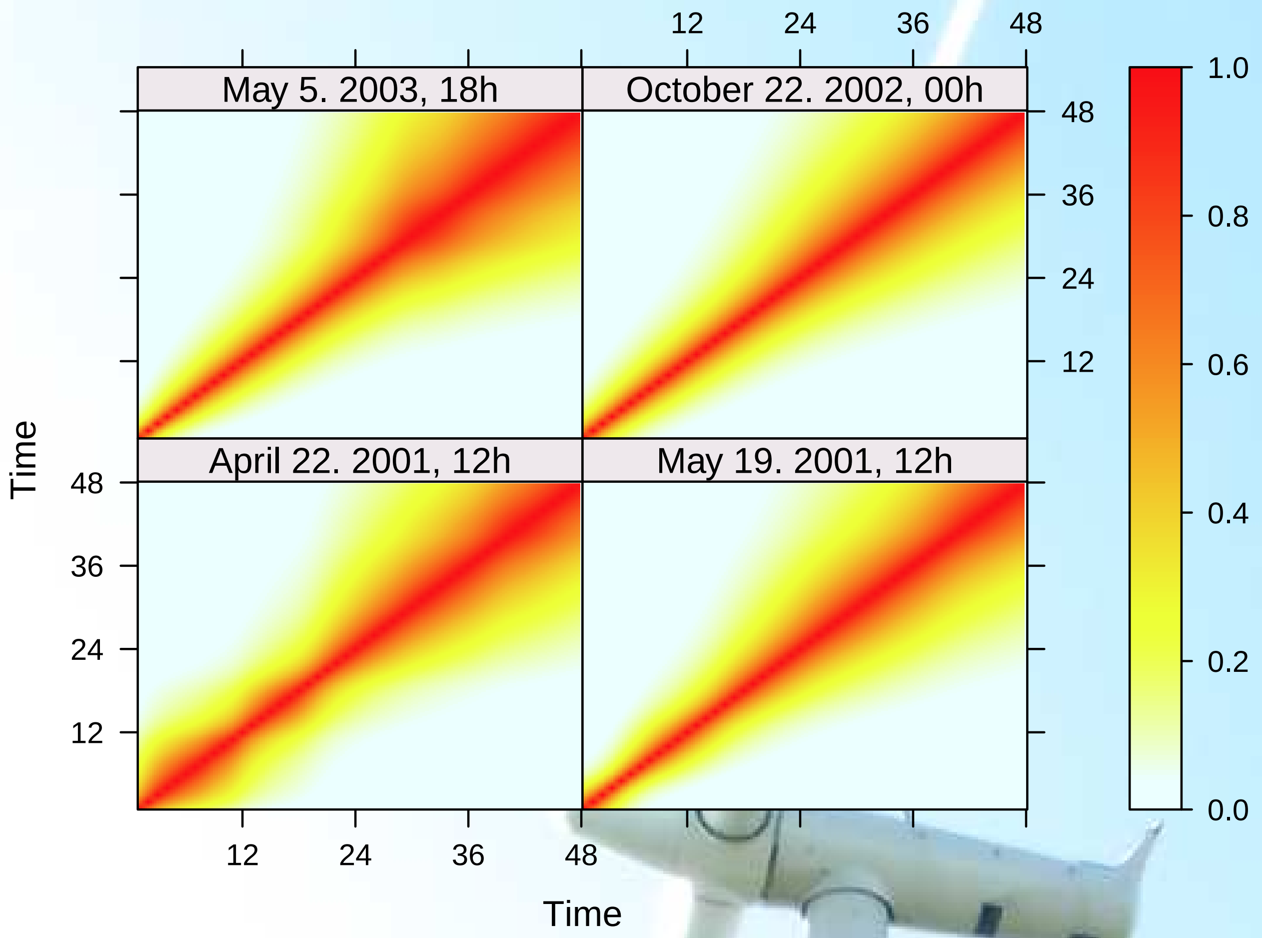


Examples of using SDEs



Use of SDEs provides a possibility for a joint description of both non-symmetrical conditional densities as well as the interdependence of the forecasts.

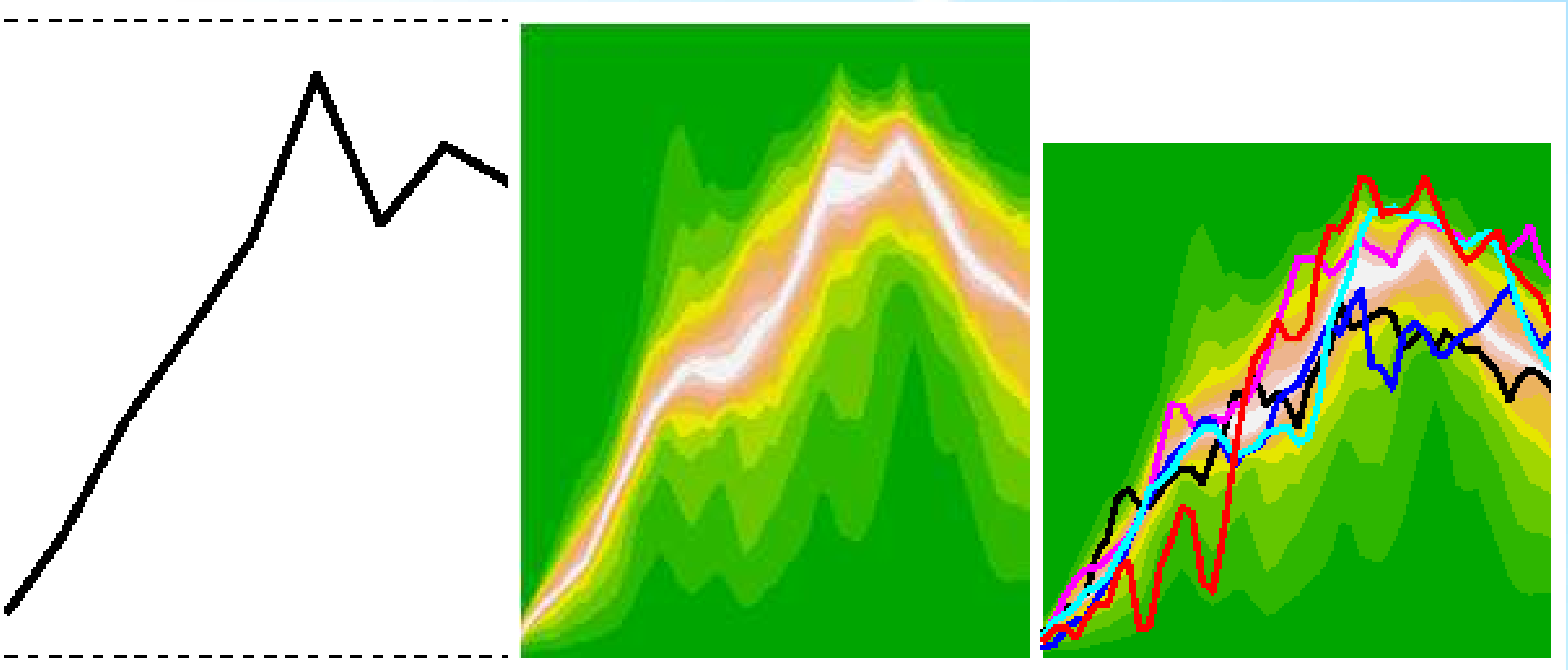
SDE approach – Correlation structures



Use of SDEs provides a possibility to model eg. time varying and wind power dependent correlation structures.

Type of forecasts required

- **Point forecasts (normal forecasts)**; a single value for each time point in the future. Sometimes with simple error bands.
- **Probabilistic or quantile forecasts**; the full conditional distribution for each time point in the future.
- **Scenarios**; probabilistic correct scenarios of the future wind power production.



Value of knowing the uncertainties

- 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.**

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.

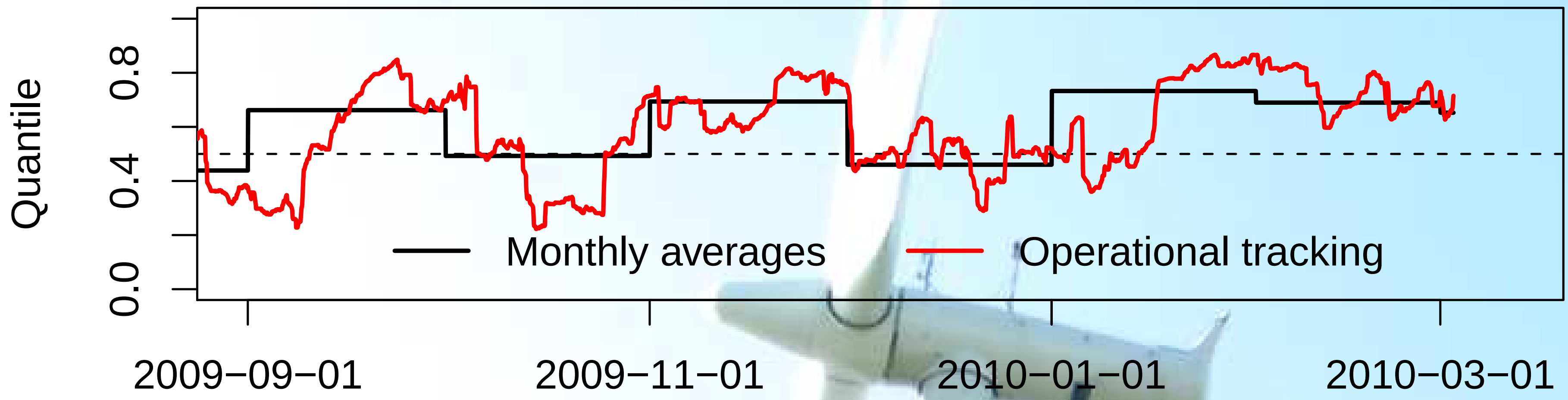
- The bid maximising the expected revenue is the following **quantile**

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

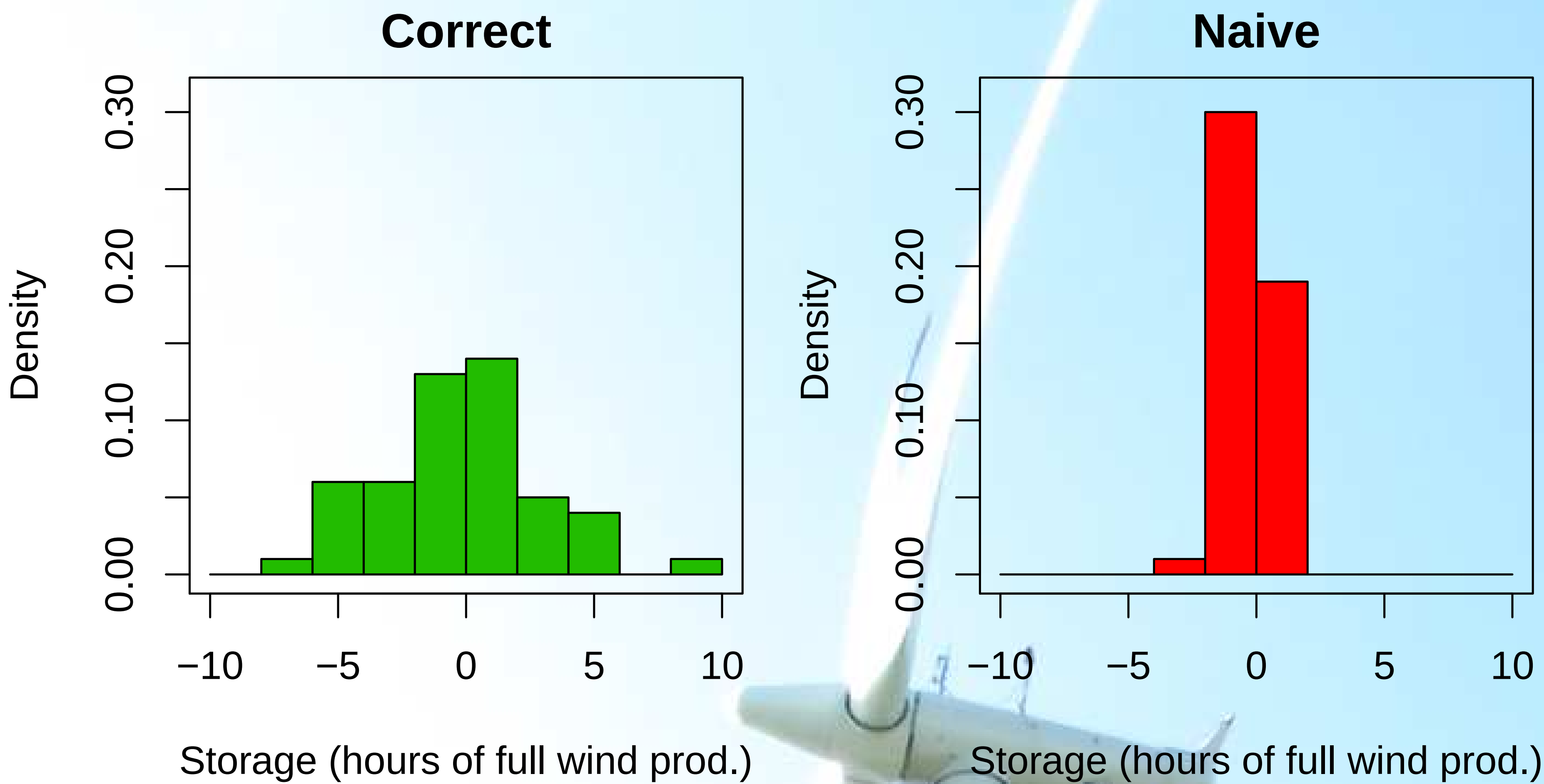
  in the conditional distribution of the future wind power production.

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:**



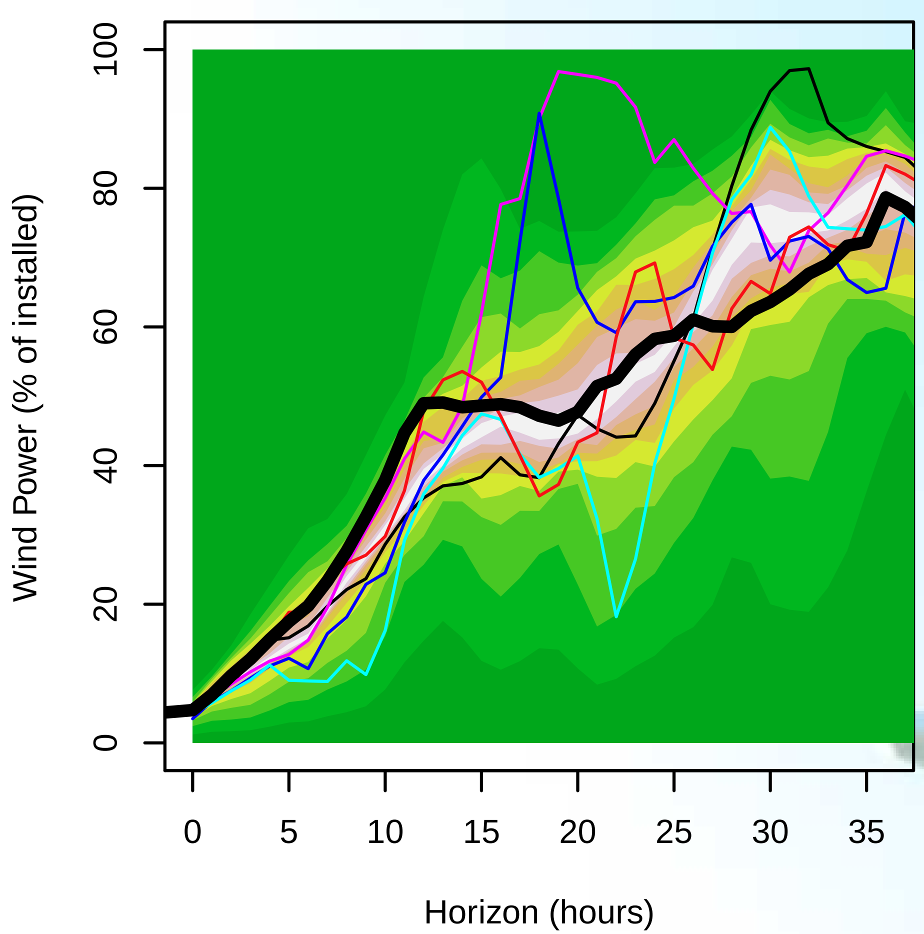
Balancing wind by varying other production

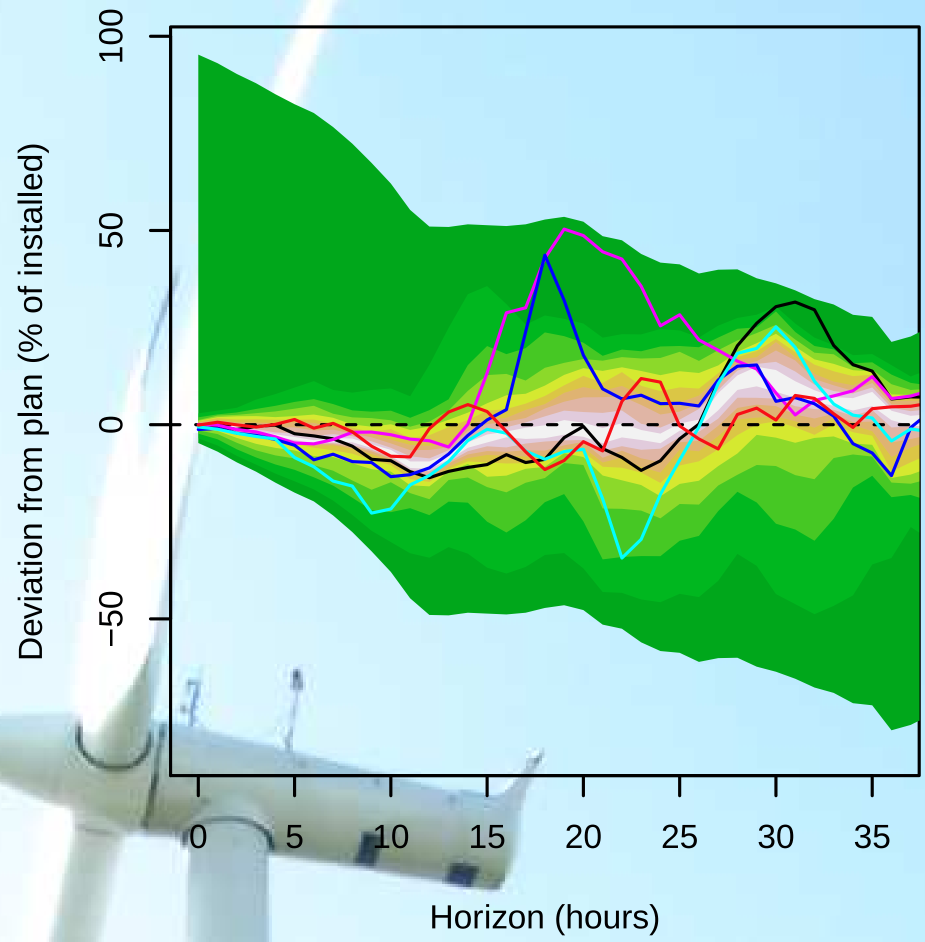


(Illustrative example based on 50 day ahead scenarios as in the situation considered before)

Imbalance scenarios

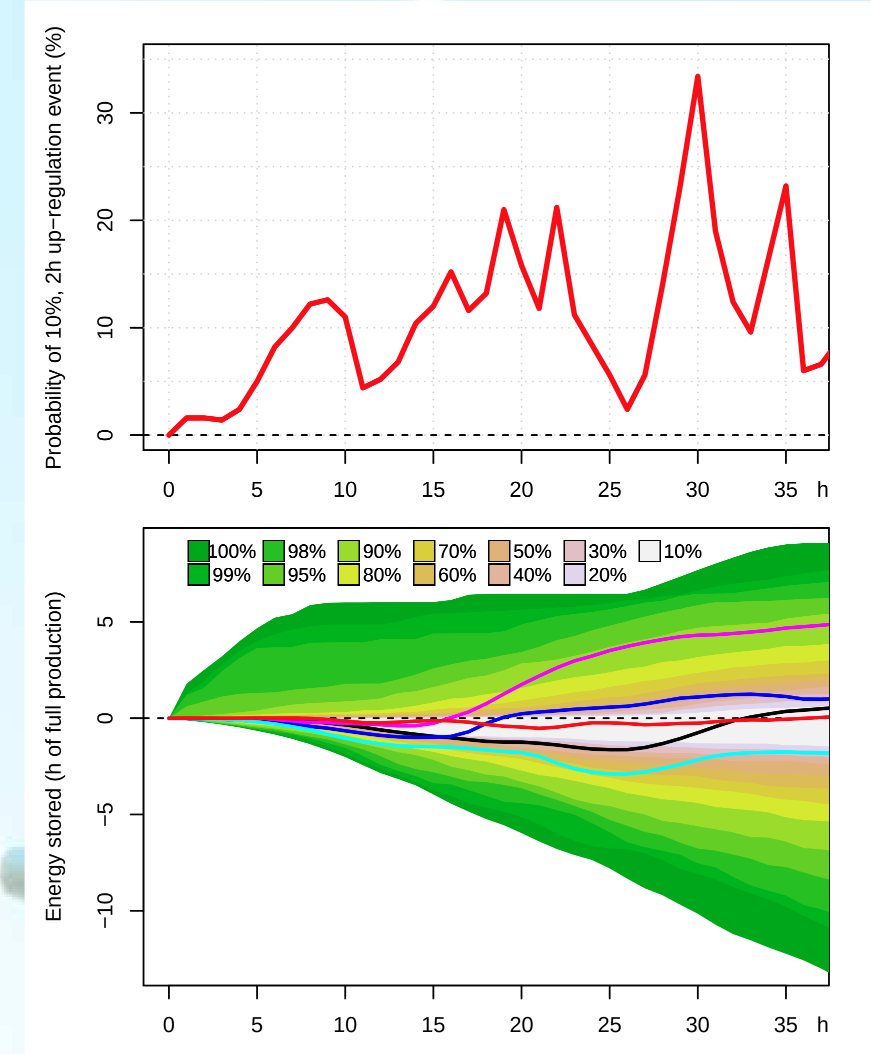
First 36 hours with the current plan overlayed in bold. Deviations from the plan; negative values correspond to up-regulation and positive to down-regulation.



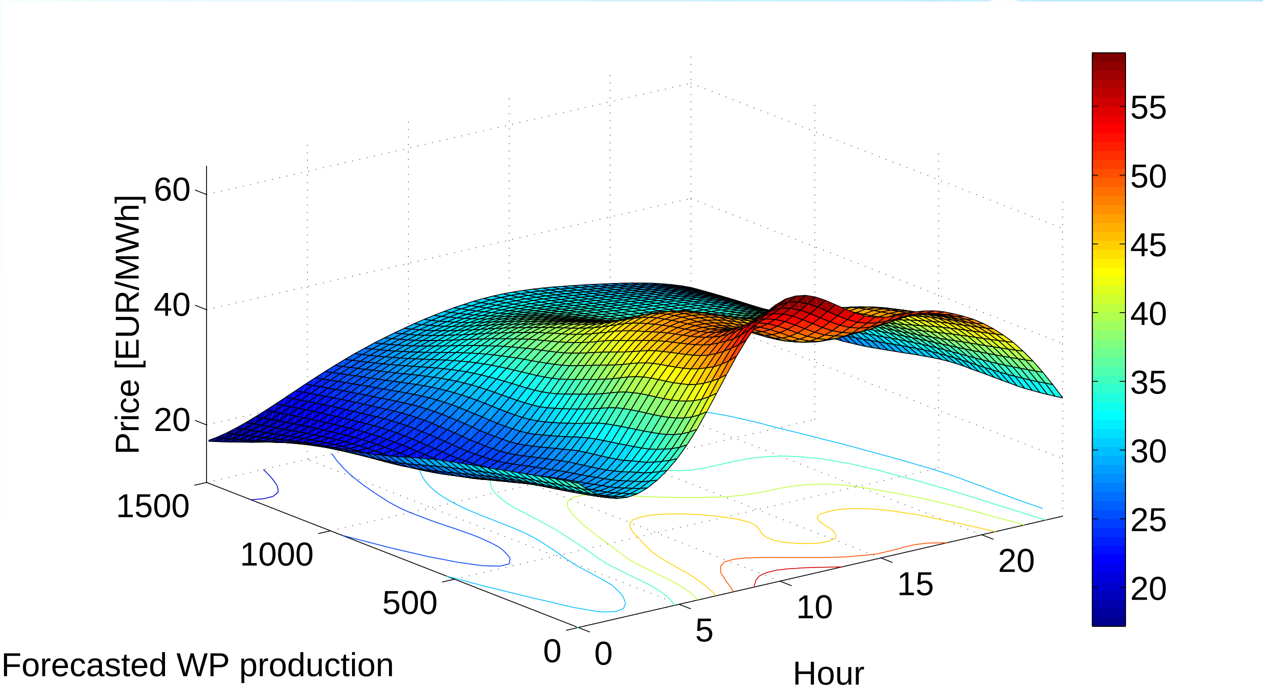


Use of imbalance scenarios - Examples

- Imbalance ramp forecasting; probabilities of imbalance ramp events
- Calculation of required storage as a function of horison (possibly obtained by varying hydro power production). Also show is the probability that this storage will be sufficient.



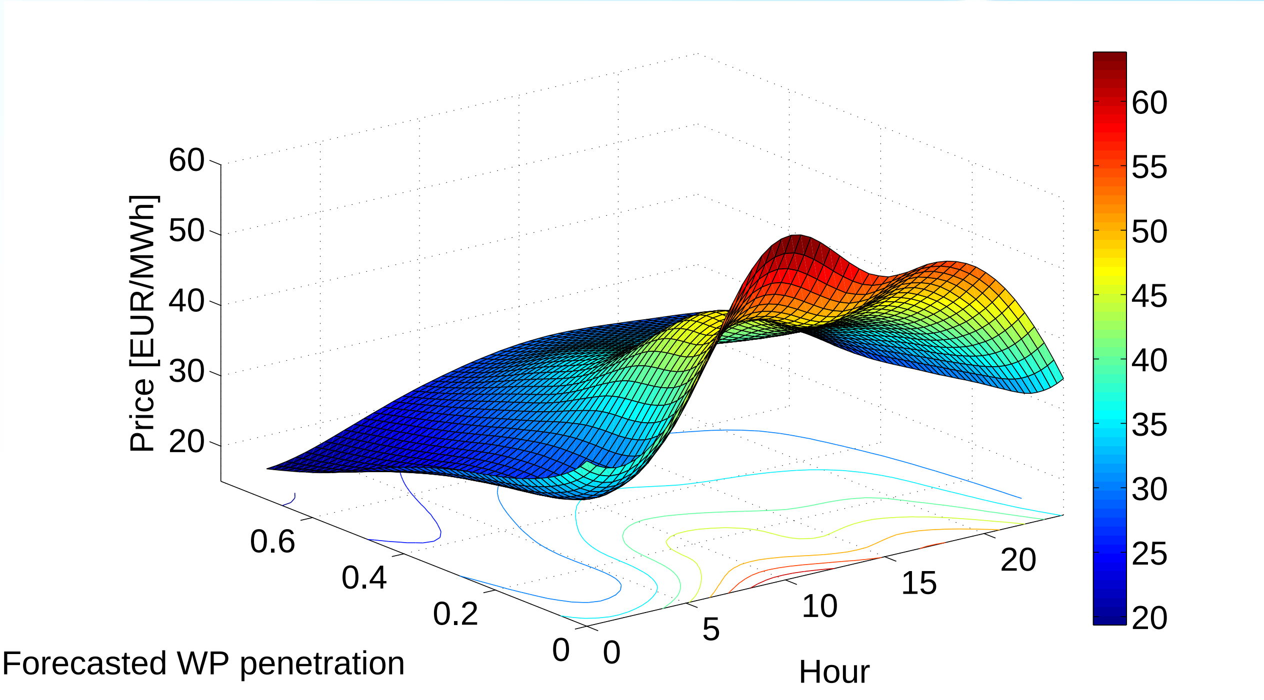
Forecasting the electricity prices



- Lower price for higher predicted production/penetration
- Daily peaks flatten out with higher predicted production/penetration
- Prices vary through out the year in accordance with water level in reservoirs

Using forecasted penetration of wind power

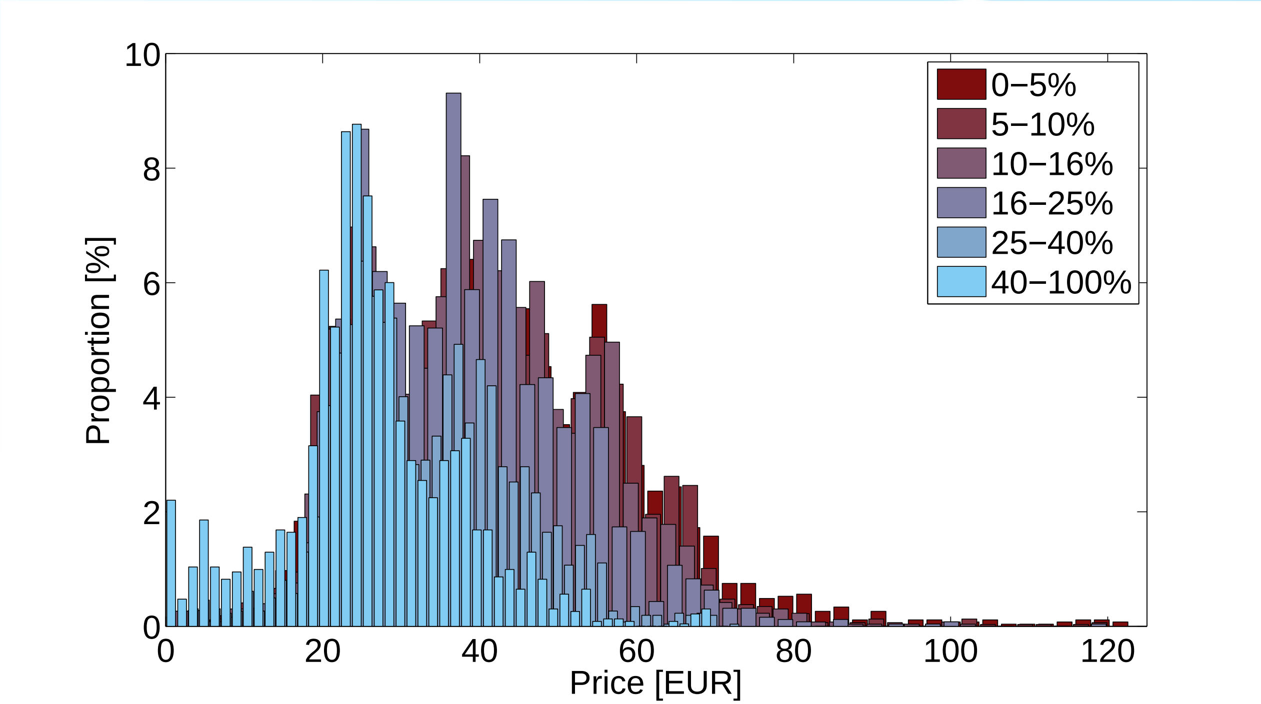
A better model for price forecasting is obtained ...



... by using forecasted penetration instead of forecasted production. In conclusion: The forecasted penetration (forecasted wind power / forecasted load) is an important explanatory variable.

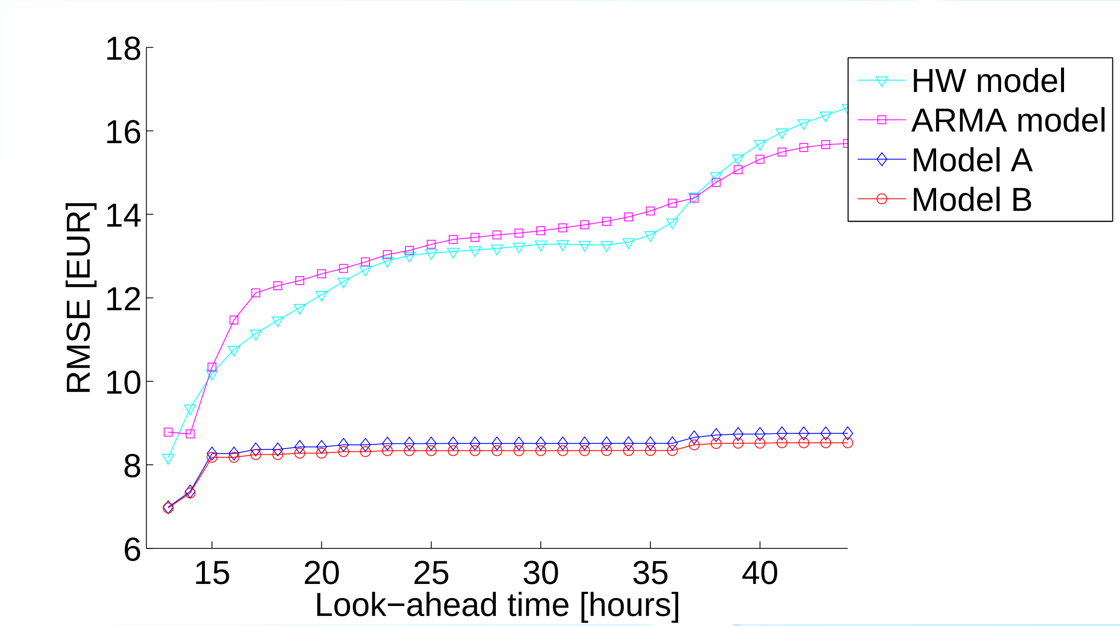
Effect of wind power forecasts

Forecasted Wind power penetration also affects the distribution of prices



	0-5%	5-10%	10-16%	16-25%	25-40%	40-100%
Mean	42.9807	41.1261	40.2579	38.0966	33.2420	26.0200
Std. Dev.	16.9512	15.3161	14.1772	13.0830	11.3455	11.2317

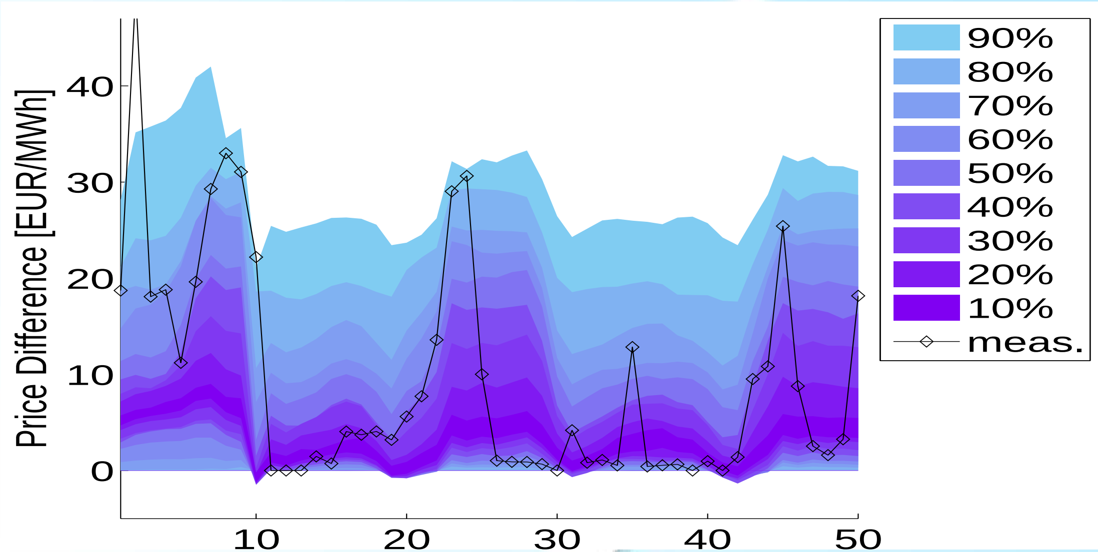
Price forecasting performance



- As illustrated we observe a large improvement by the use of conditional parametric models as compared to classical time series models.
- The correlation between the predicted and observed price is about 88 pct.

Prices related to up/down regulation

- Consider the **up regulation** as an example.
- Here Quantile Regression is used to obtain quantiles for the prices related to up regulation (given the event ’up regulation’).



- Higher prices for up regulation is more likely during day time. (Similar plot exists for down regulation)

Conclusions

- 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).
- Reliable probabilistic forecasts are important to gain the **full economical value**.
- Use **more than a single MET provider** for delivering the input to the prediction tool – this improves the accuracy of wind power forecasts with 10-15 pct.
- Estimates of the **correlation in forecasts errors** important.
- Forecasts of '**cross dependencies**' between load, prices, wind and solar power are important.
- **Probabilistic forecasts are very important for asymmetric cost functions**.
- Probabilistic forecasts can provide **answers** for questions like
  - What is the probability that this storage is large enough for the next 5 hours?
  - What is the probability of an increase in wind power production of more that 50 pct over the next two hours?
  - What is the probability of a down-regulation due to wind power on more than x GW within the next 4 hours.

The same conclusions hold for our tools for **eg. solar power forecasting**.

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