Probabilistic forecasting and its importance for energy systems

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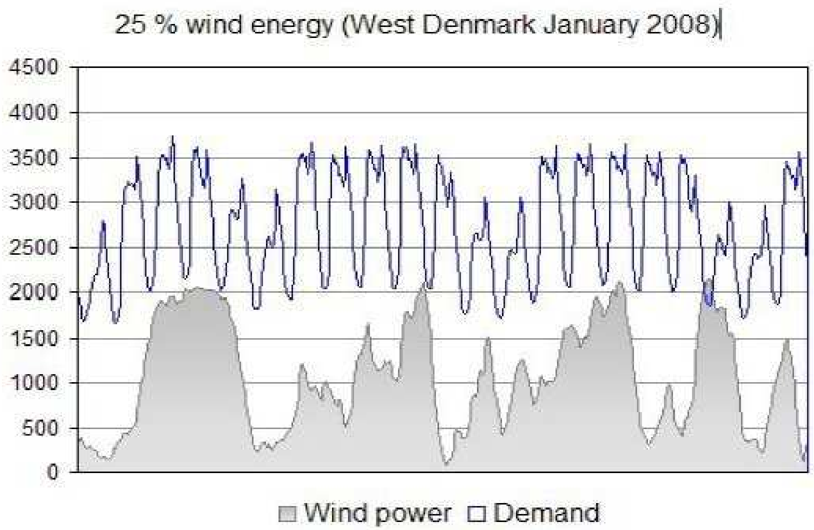
Outline

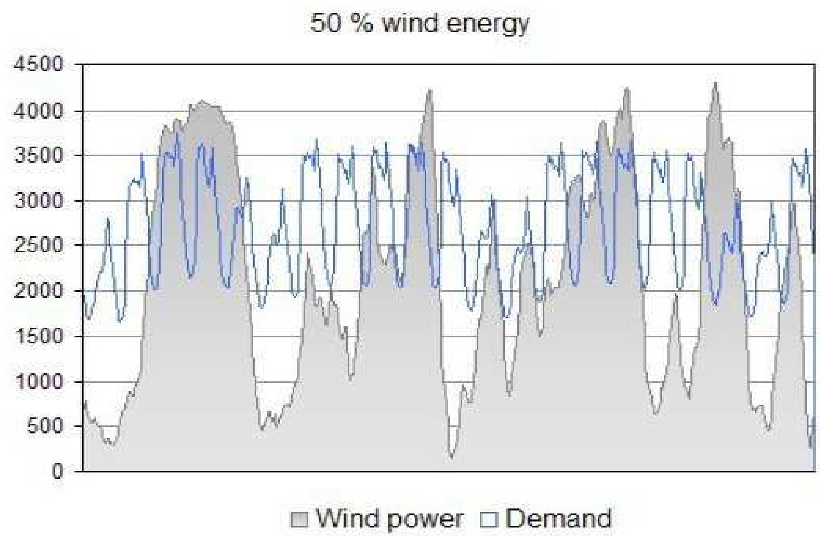
I shall focus on wind power - and briefly mention solar power:

- Status in Denmark
- Energy-System OS
- Forecasting and optimization/control
- Wind power point forecasting
- Use of several providers of MET forecasts
- Probabilistic forecasting
- Scenario forecasting
- Space-time scenario forecasting
- Use of stochastic differential equations
- Examples on the use of probabilistic forecasts
- Solar power forecasting

Wind Power Statistics for Denmark



In 2008 wind power did cover the entire demand of electricity in 200 hours (West DK)

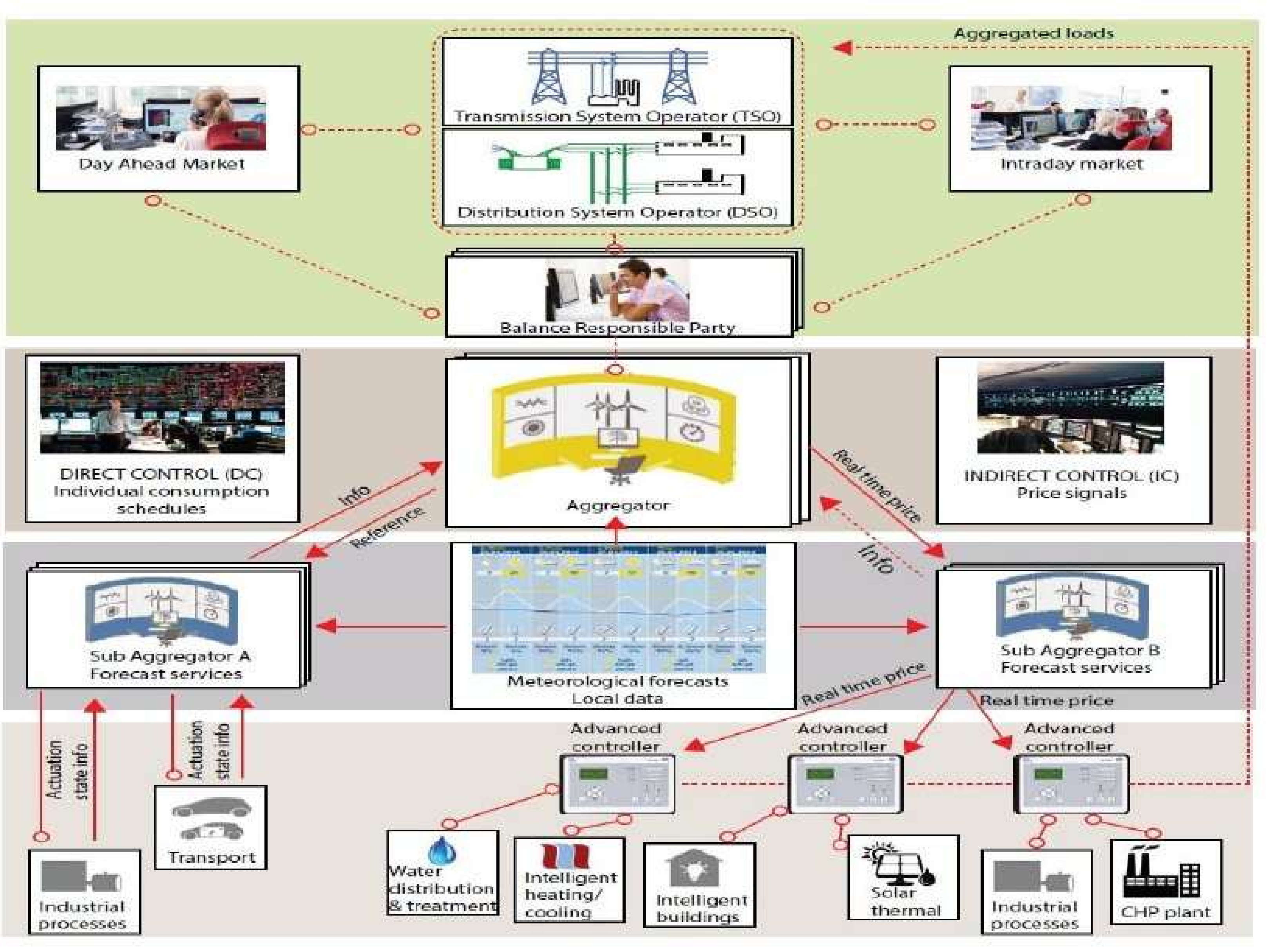


In 2015 more than 42 pct of electricity load was covered by wind power.

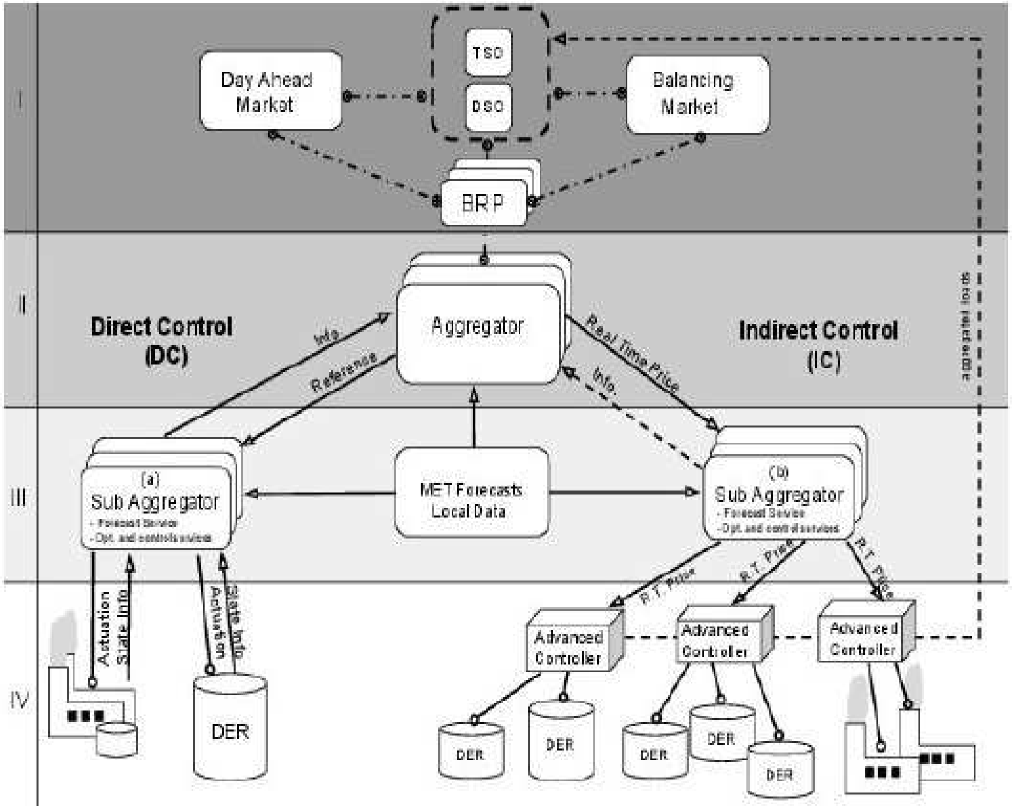
For several days in 2015 the wind power production was more than 120 pct of the power load.

July 10th, 2015 more than 140 pct of the power load was covered by wind power

Smart-Energy OS



Stochastic Control and Optimization



In New Wiley Book: Control of Electric Loads in Future Electric Energy Systems, 2015

Day Ahead:

Stoch. Programming based on eg. Scenarios

Cost: Related to the market (one or two levels)

Direct Control:

Actuator: **Power**

Two-way communication

Models for DERs are needed

Constraints for the DERs (calls for state est.)

Contracts are complicated

Indirect Control:

Actuator: **Price**

Cost: E-MPC at **low (DER) level**, One-way communication

Models for DERs are not needed

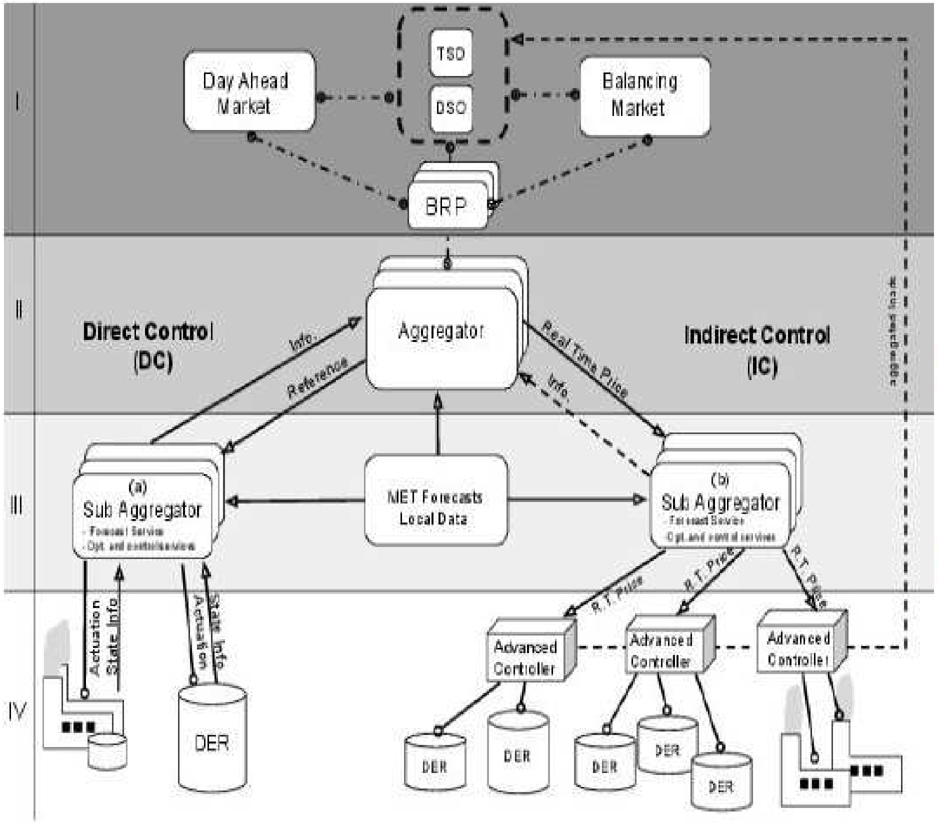
Simple 'contracts'

Direct vs Indirect Control

Level	Direct Control (DC)	Indirect Control (IC)
III	$\min_{x,u} \sum_{k=0}^{N} \sum_{j=1}^{J} \phi_j(x_{j,k}, u_{j,k})$	$\min_{\hat{z},p} \sum_{k=0}^{N} \phi(\hat{z}_k, p_k)$ s.t. $\hat{z}_{k+1} = f(p_k)$
IV	$\downarrow_{u_1} \cdots \downarrow_{u_J} \quad \uparrow_{x_1} \cdots \uparrow_{x_J}$ s.t. $x_{j,k+1} = f_j(x_{j,k}, u_{j,k}) \quad \forall j \in J$	$\min_u \sum_{k=0}^{N} \phi_j(p_k, u_k) \quad \forall j \in J$ s.t. $x_{k+1} = f_j(x_k, u_k)$

Table 1: Comparison between direct (DC) and indirect (IC) control methods. (DC) In direct control the optimization is globally solved at level III. Consequently the optimal control signals u_j are sent to all the J DER units at level IV. (IC) In indirect control the optimization at level III computes the optimal prices p which are sent to the J-units at level IV. Hence the J DERs optimize their own energy consumption taking into account p as the actual price of energy.

Forecast Requirements



Day Ahead:

- Forecasts of loads
- Forecast of Grid Capacity (using eg. DLR)
- Forecasts of production (eg. Wind and Solar)

Direct Control: .

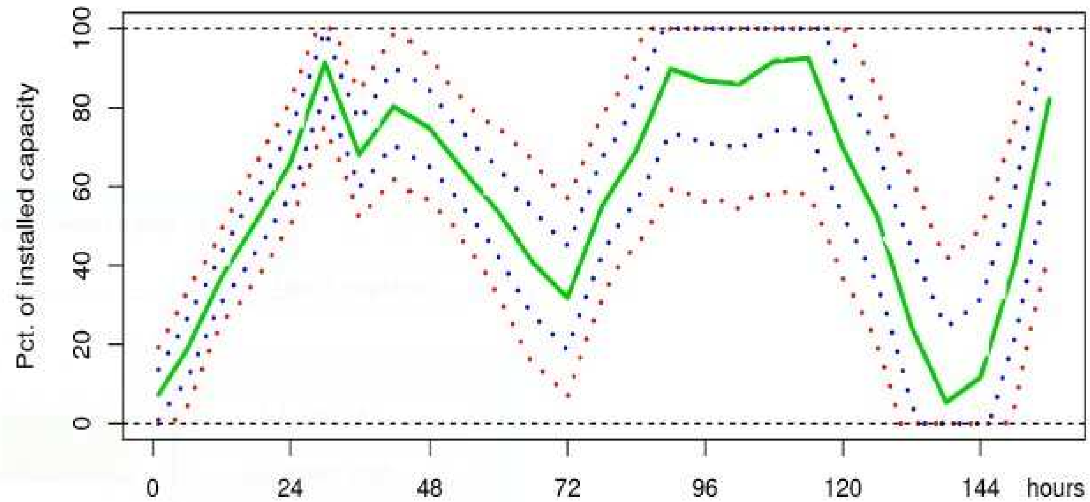
- Forecasts of states of DERs
- Forecasts of load

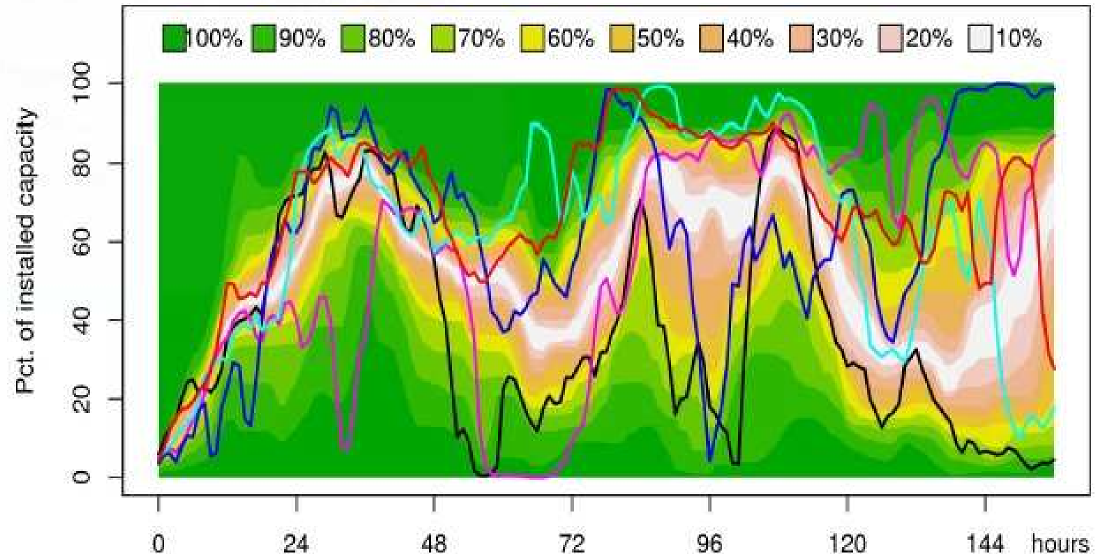
Indirect Control:

- Forecasts of prices
- Forecasts of load

Type of Forecasts

- Point forecasts
- Conditional mean and covariances
- Conditional quantiles (Prob. forecasts)
- Conditional scenarios
- Conditional densities
- Stochastic differential equations





Wind Power Forecasting - History

Our methods for probabilistic wind power forecasting have been implemented in the **Anemos Wind Power Prediction System**, **Australian Wind Energy Forecasting Systems (AWEFS)**, **WPPT**, ...

- The methods have been continuously developed since 1993 - in collaboration with
  - Energinet.dk,
  - Dong Energy,
  - Vattenfall,
  - Risø – DTU Wind,
  - The ANEMOS projects partners/consortium (since 2002),
  - Overspeed GmbH (Anemos: www.overspeed.de/gb/produkte/windpower.html)
  - ENFOR (WPPT: www.enfor.dk)
- Used operationally for predicting wind power in Denmark since 1996.
- Now used by all major players in Denmark (Energinet.dk, DONG, Vattenfall, ..)
- Anemos/WPPT is now used eg in Europe, Australia, and North America.
- Often used as forecast engine embedded in other systems.

Uncertainty and adaptivity

The ramdom part of errors in MET forecasts will end up in errors in wind power forecasts, but some time-varying systematic errors in MET forecasts and other factors call for adaptive methods

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 should 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.

The power curve model

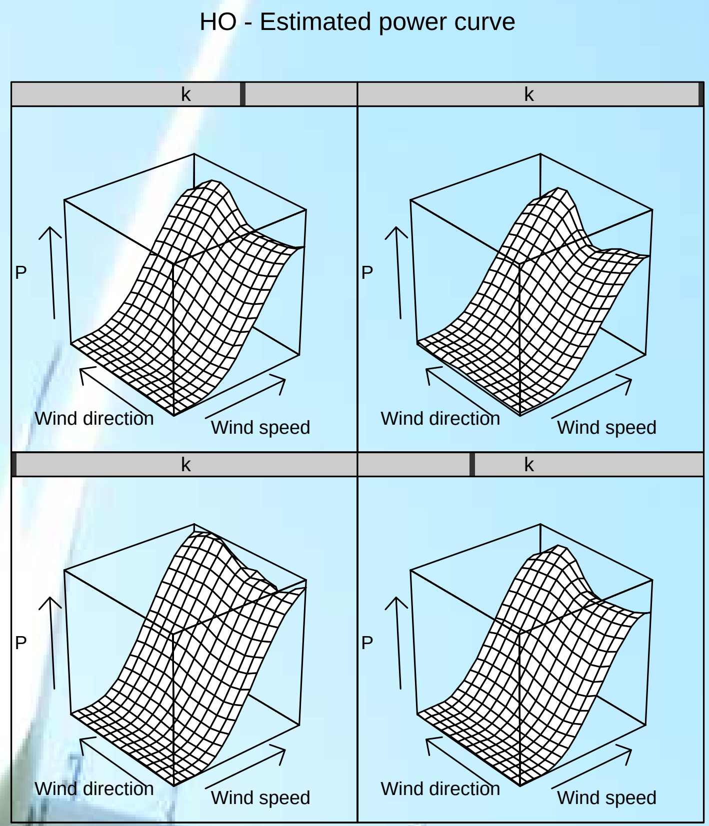
The wind turbine "power curve" model, $p^{tur} = f(w^{tur})$ is extended to a wind farm model, $p^{wf} = f(w^{wf}, \theta^{wf})$, by introducing wind direction dependency. By introducing a representative area wind speed and direction it can be further extended to cover all turbines in an entire region,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

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.



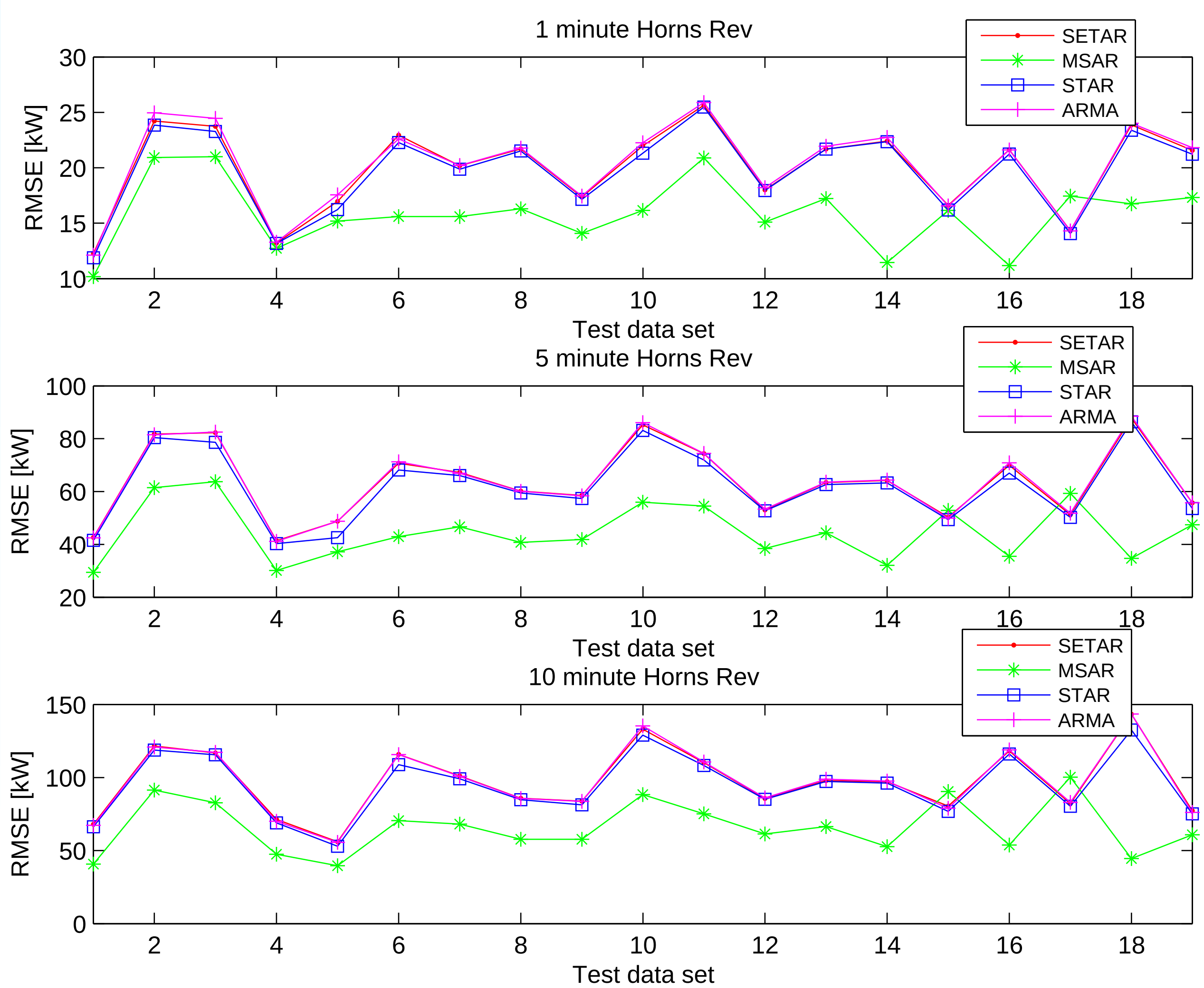
Plots of the estimated power curve for the Hollandsbjerg wind farm.

Regime-switching models

- The evaluation set is divided in 19 different periods of different lengths and characteristics

- MSAR models generally outperform the others

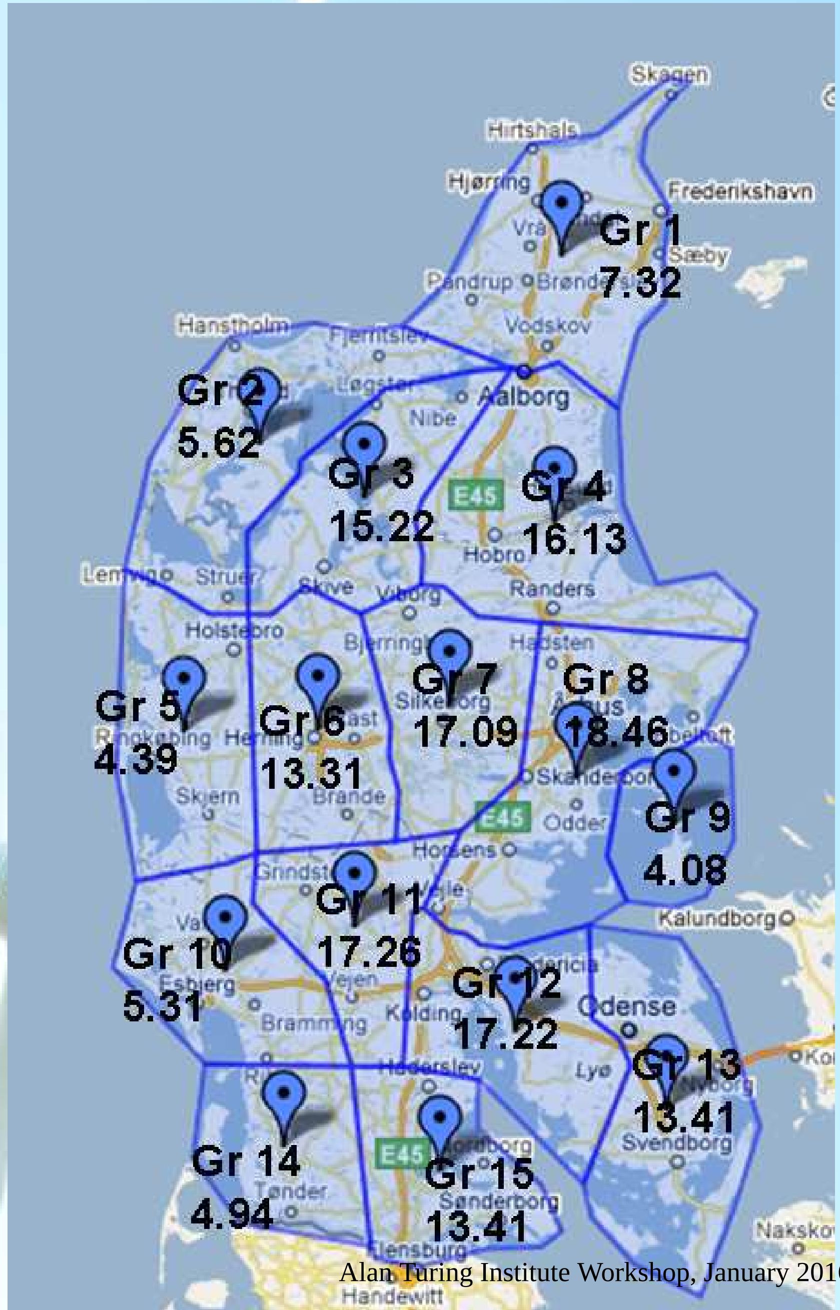
- In the RADAR@sea project the regime shift is linked to convective rain events – which now are detected by a weather radar.



Spatio-temporal forecasting

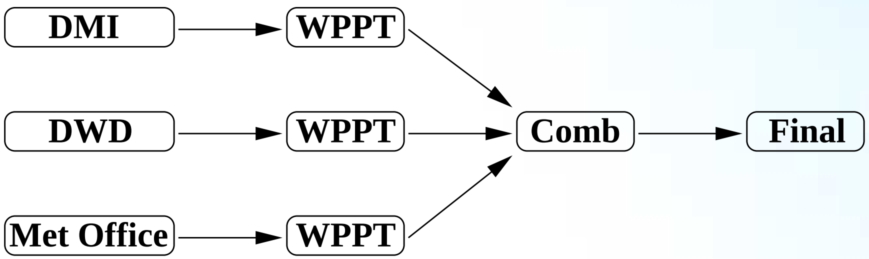
Predictive improvement (measured in RMSE) of forecasts errors by adding the spatio-temperal module in WPPT.

- 23 months
- 15 onshore groups
- Focus here on 1-hour forecast only
- Larger improvements for eastern part of the region
- Needed for reliable ramp forecasting.

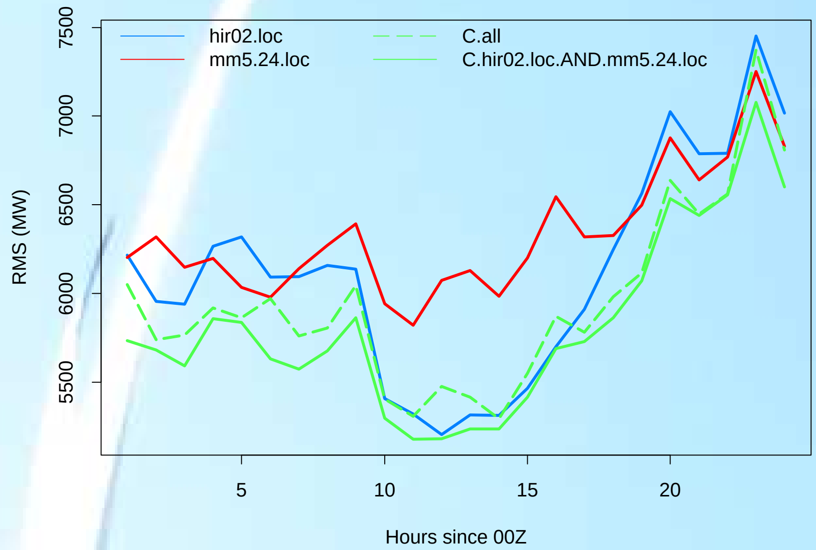


Combined forecasting

- 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

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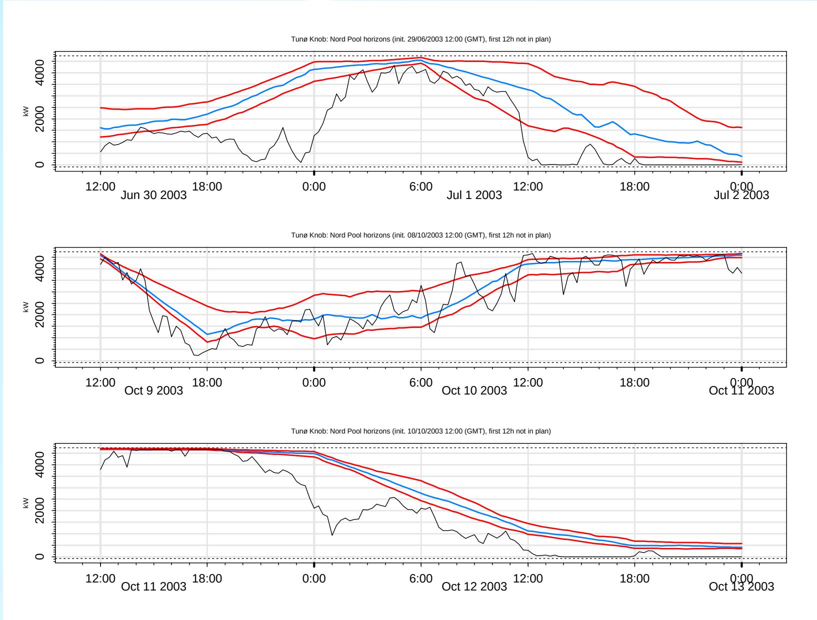
Uncertainty estimation

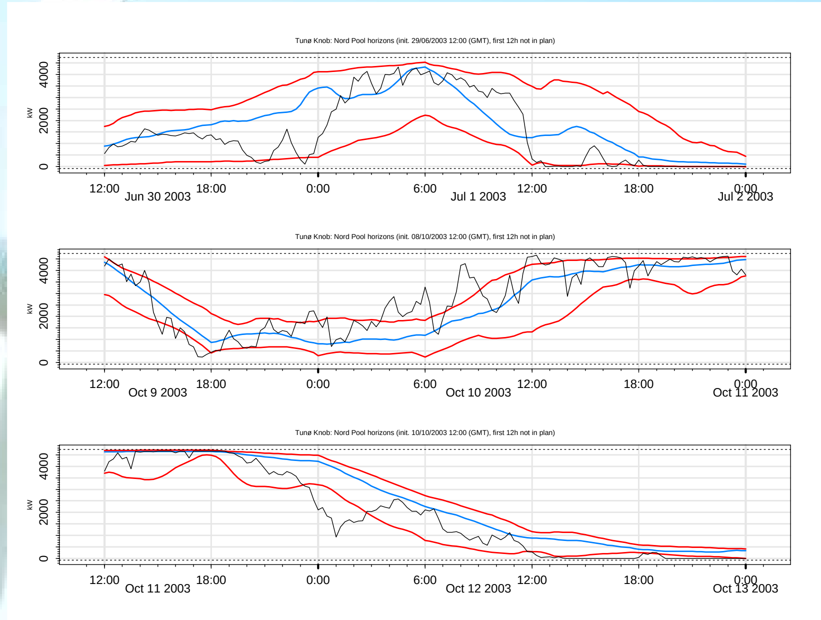
In many applications it is crucial that a prediction tool delivers reliable estimates (probabilistc forecasts) of the expected uncertainty of the wind power prediction.

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

- 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.





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.

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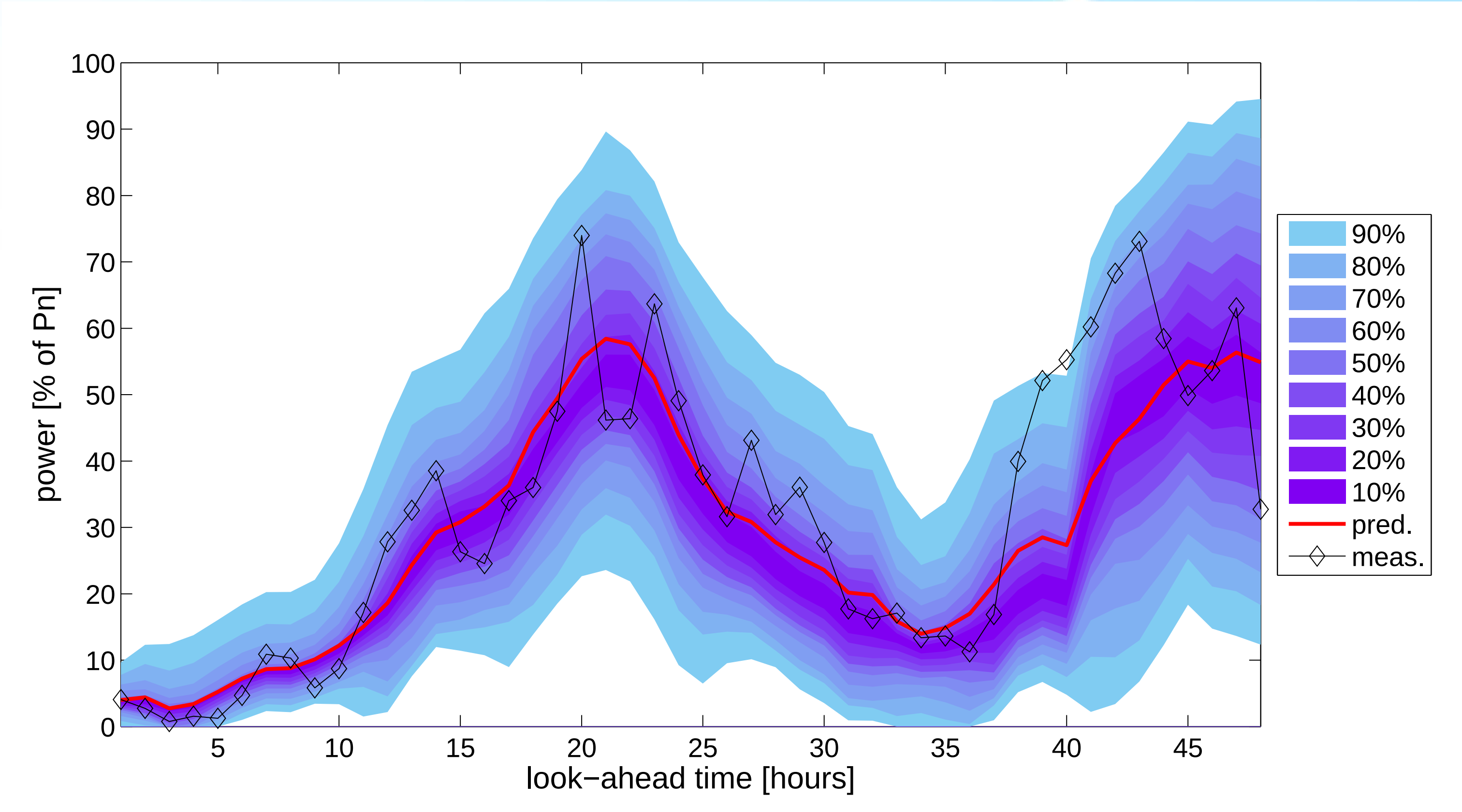
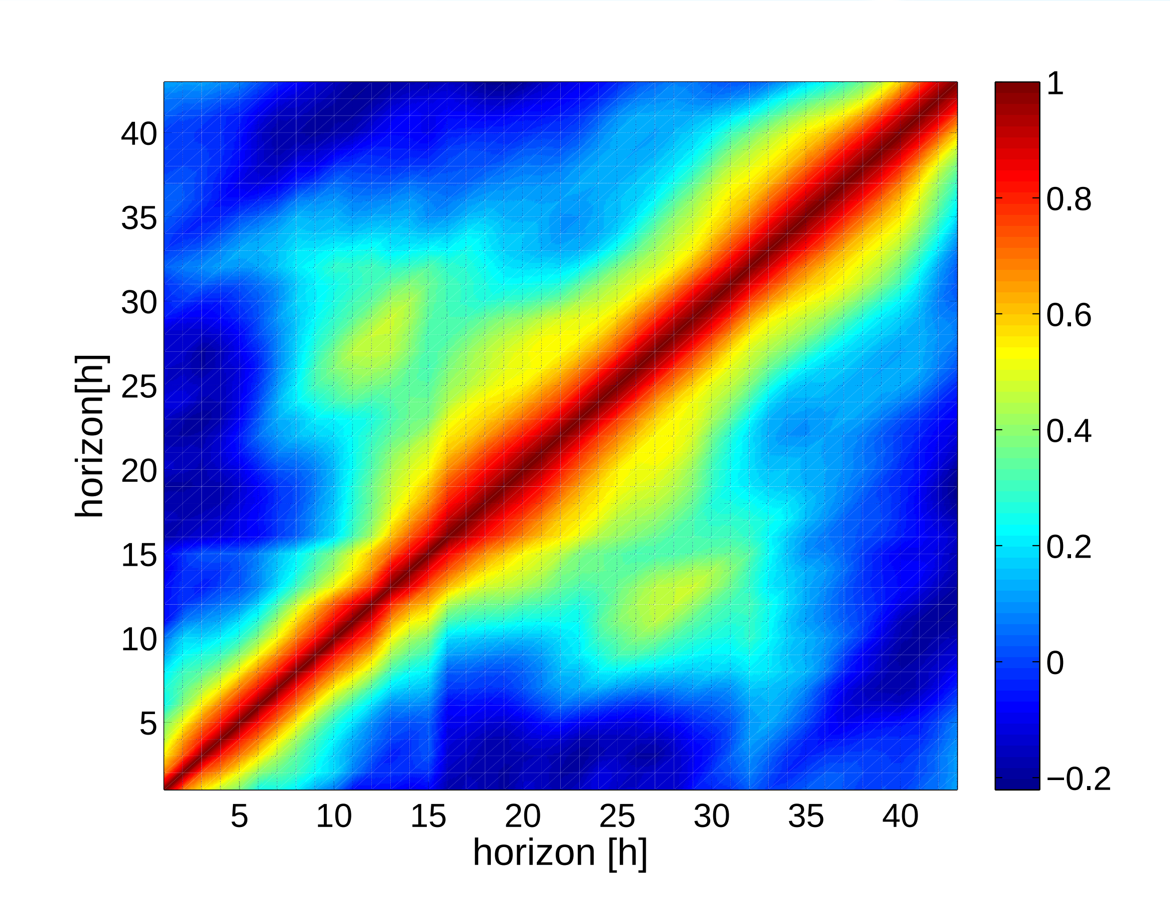
Example: Probabilistic forecasts



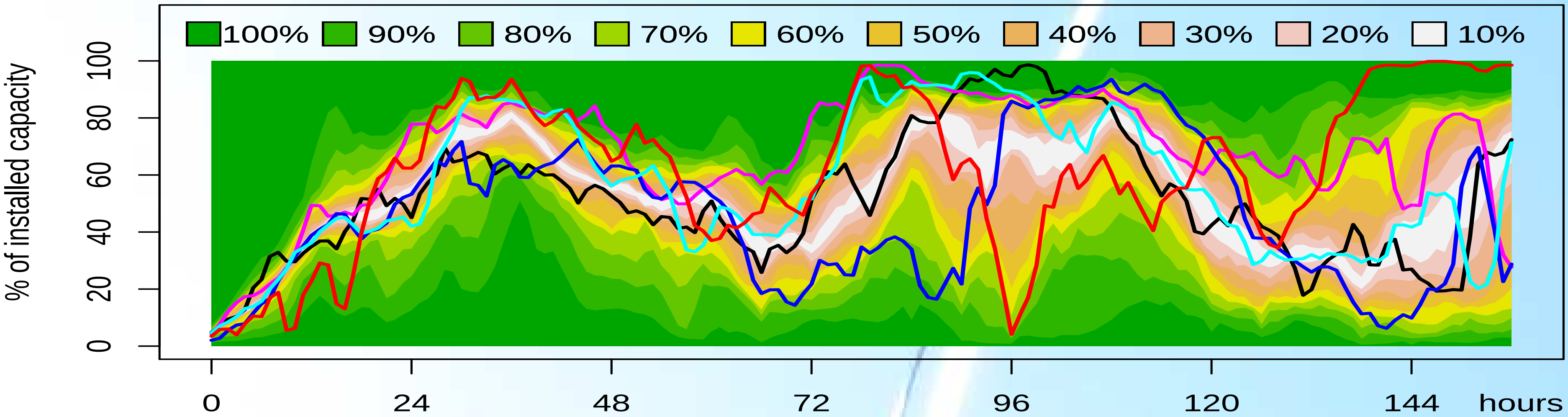
- Notice how the confidence intervals varies ...
- But the correlation in forecasts errors is not described so far.

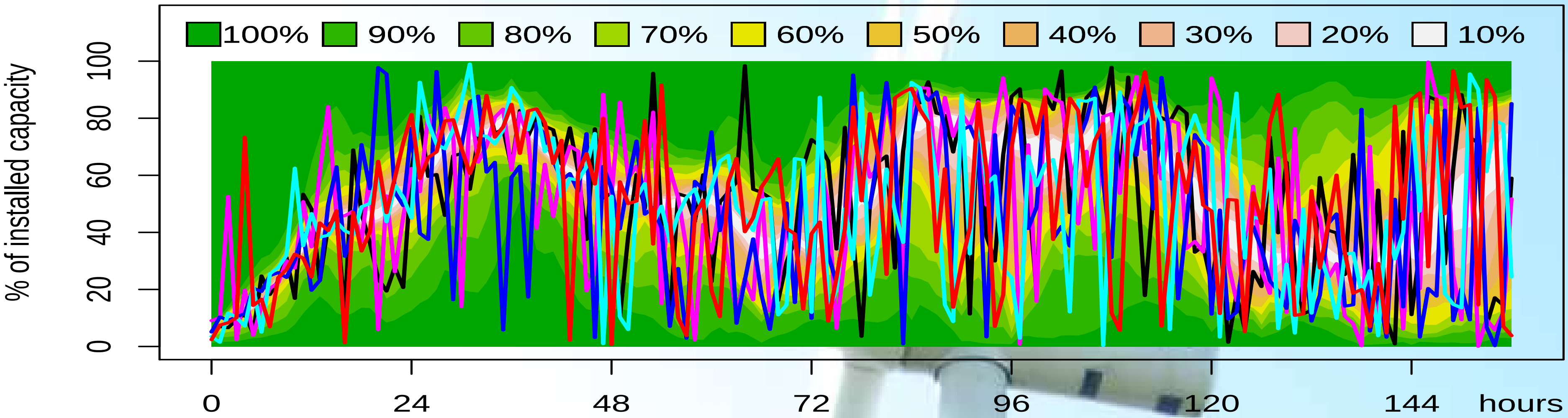
Correlation structure of forecast errors

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



Correct (top) and naive (bottom) scenarios





Use of SDEs - Simple example

The state equation describes the future wind power production

$$dx_t = -\theta(\boldsymbol{u_t}) \cdot (x_t - \hat{p}_{t|0})dt + \\ 2\sqrt{\theta(\boldsymbol{u_t})\alpha(\boldsymbol{u_t})\hat{p}_{t|0}(1-\hat{p}_{t|0})x_t \cdot (1-x_t)}dw_t,$$

with $\alpha(\boldsymbol{u_t}) \in (0,1)$, and the observation equation

$$y_h = x_{t_h|0} + e_h,$$

where $h \in \{1, 2, ..., 48\}$, $t_h = k$, $e_h \sim N(0, s^2)$, $x_0 =$ *“observed power at t=0”*, and

- $\hat{p}_{t|0}$ point forecast by **WPPT** (Wind Power Prediction Tool)
- $\boldsymbol{u_t}$ input vector (here t and $\hat{p}_{t|0}$)

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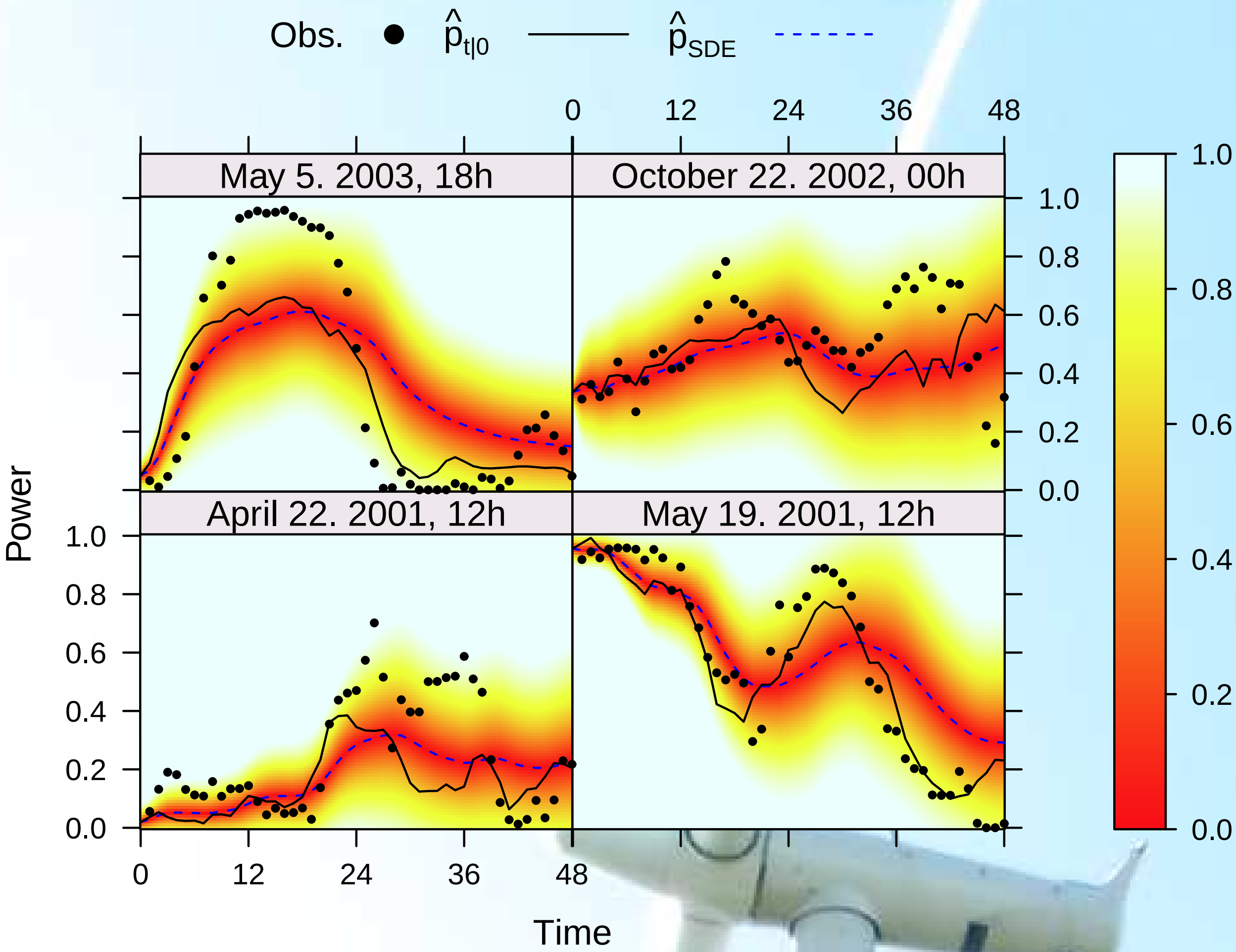
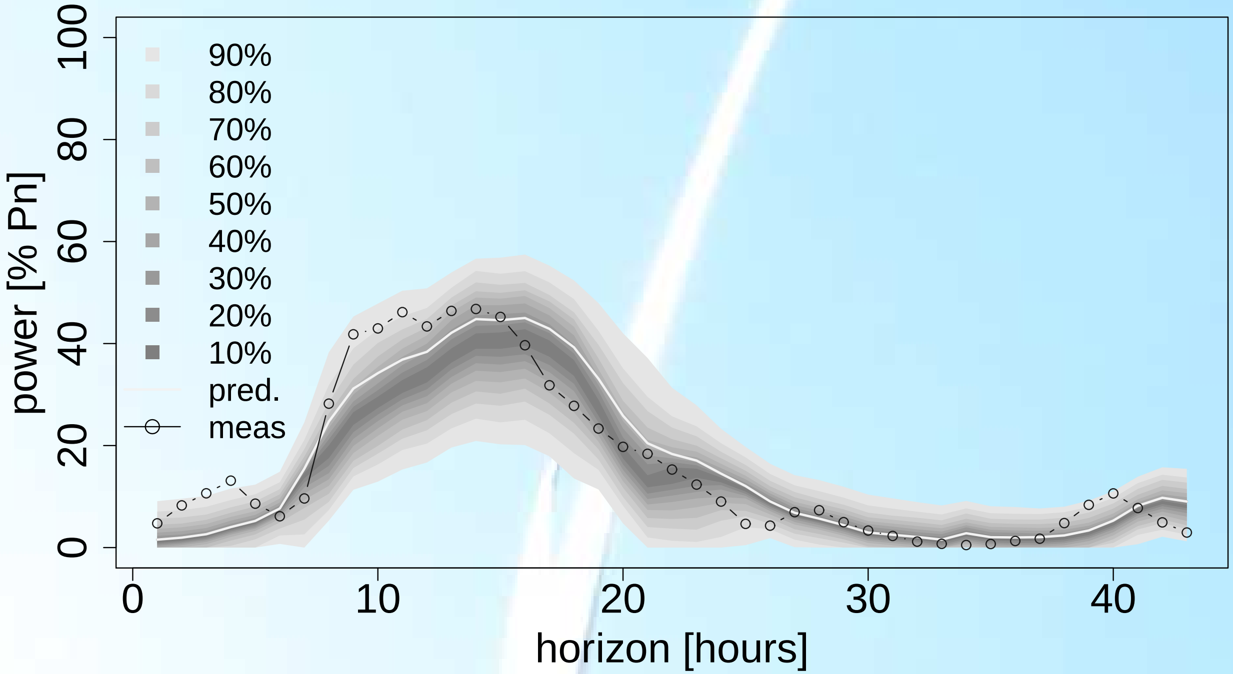
Examples of using SDEs



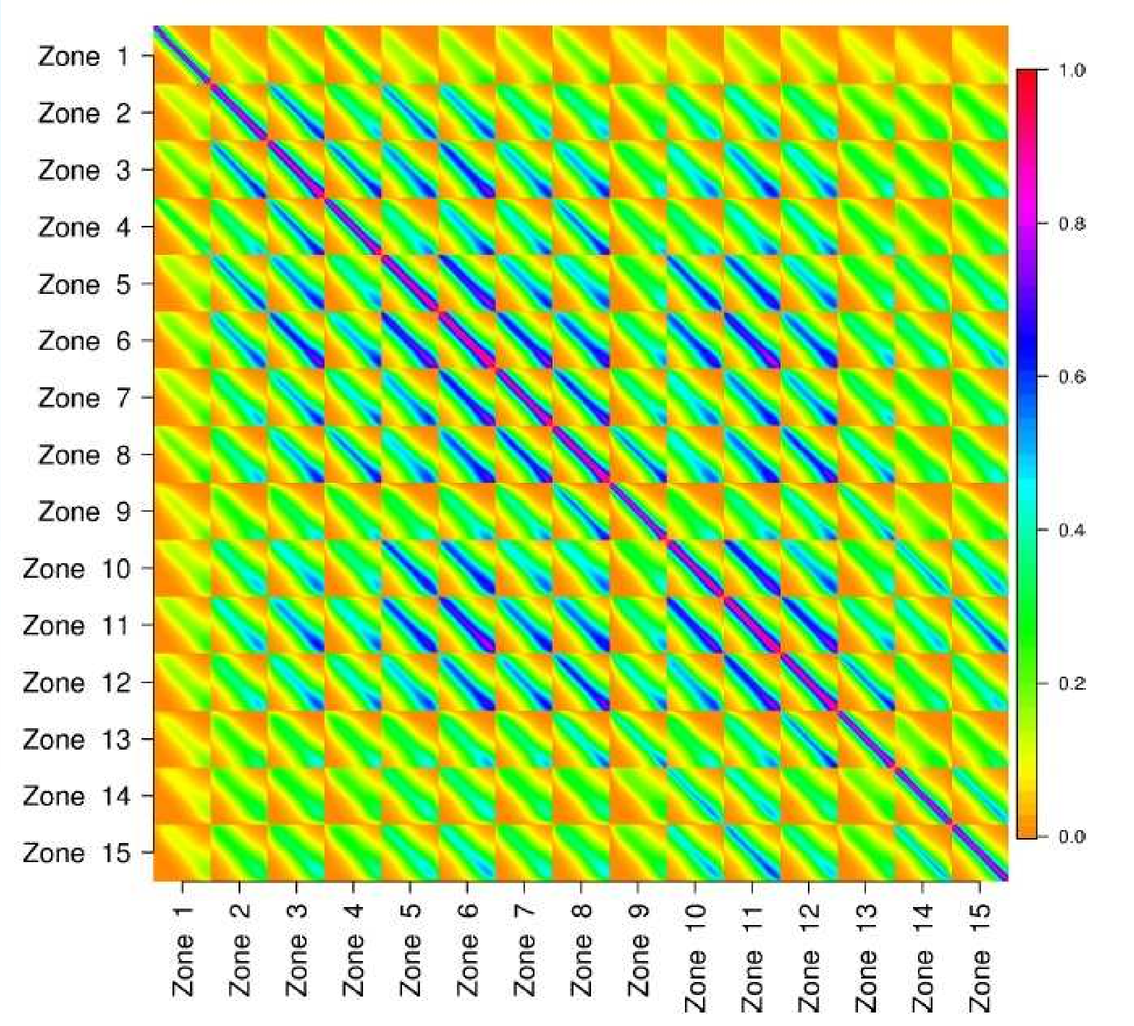
Use of SDEs provides a possibility for a joint description of both non-symmetrical conditional densities as well as the interdependence of the forecasts.

Motivation - Space-Time Dependencies

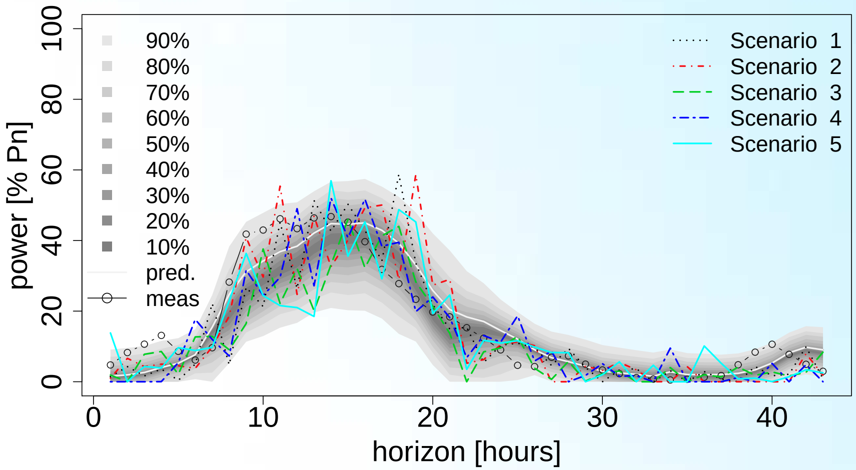


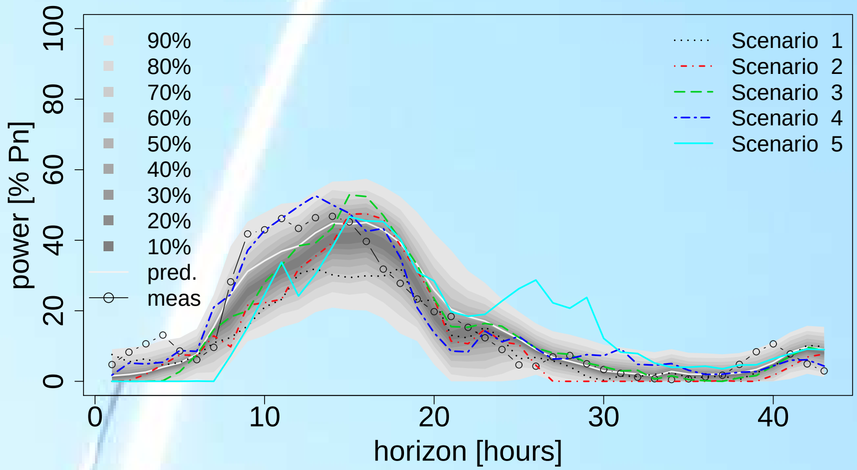
This is not enough...

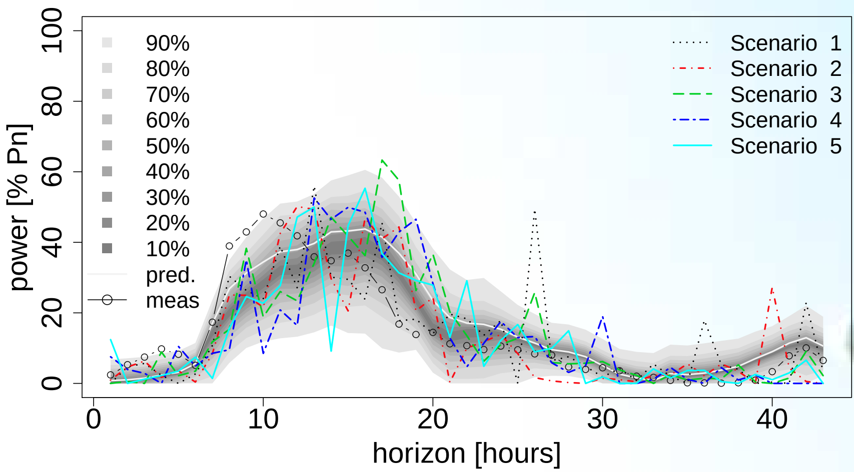
Space-Time Correlations

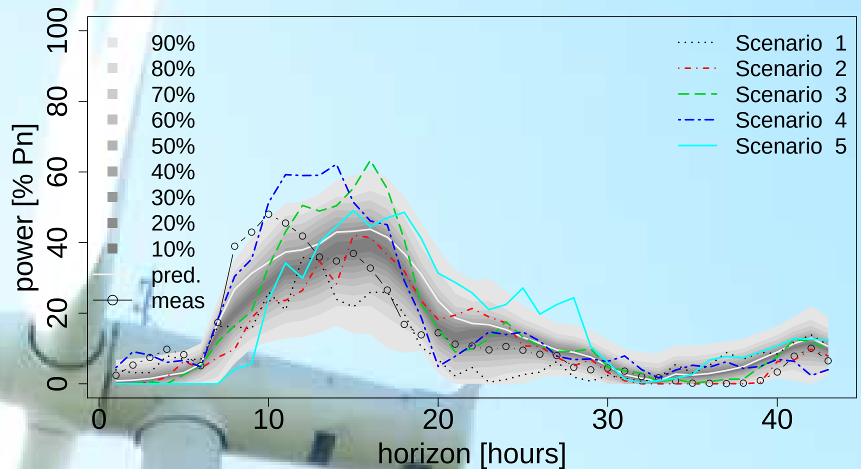


Space-time trajectories









no space-time correlation **appropriate space-time correlation**

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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.

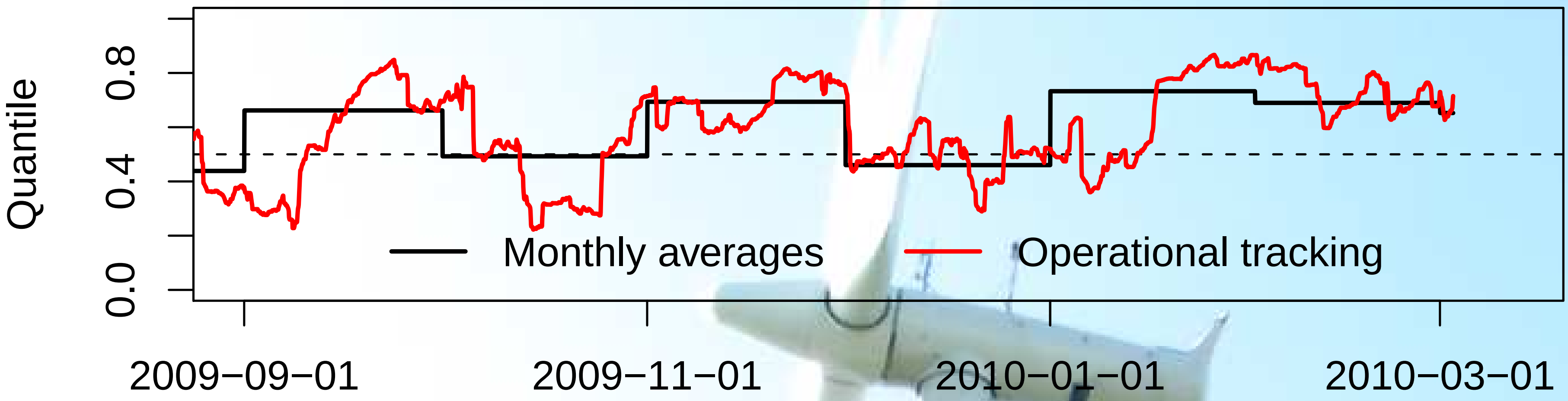
- The bid maximising the expected revenue is the following **quantile**

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

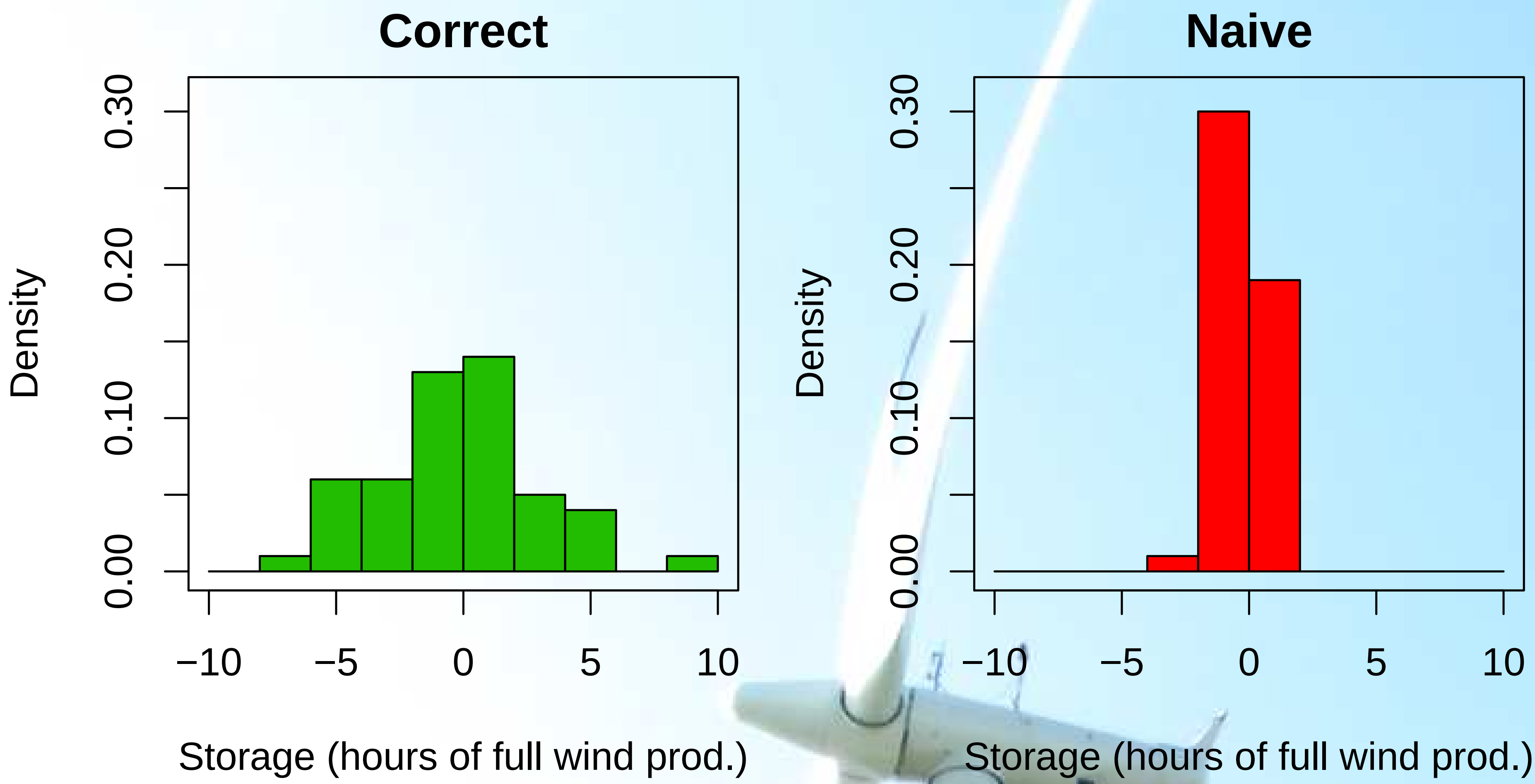
  in the conditional distribution of the future wind power production.

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:**



Sizing of Energy Storage



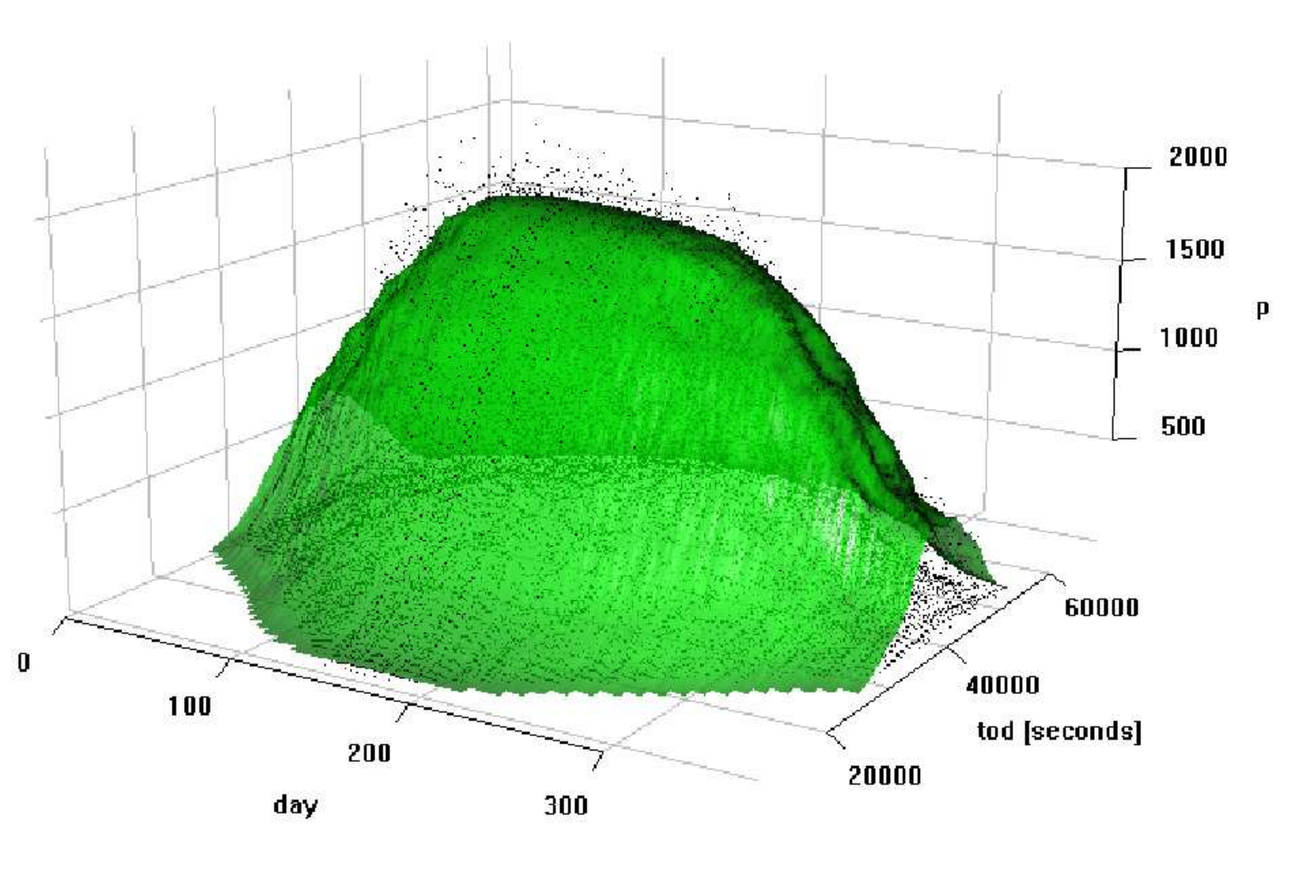
(Illustrative example based on 50 day ahead scenarios. Used for calculating the risk for a storage to be too small)

Solar Power Forecasting

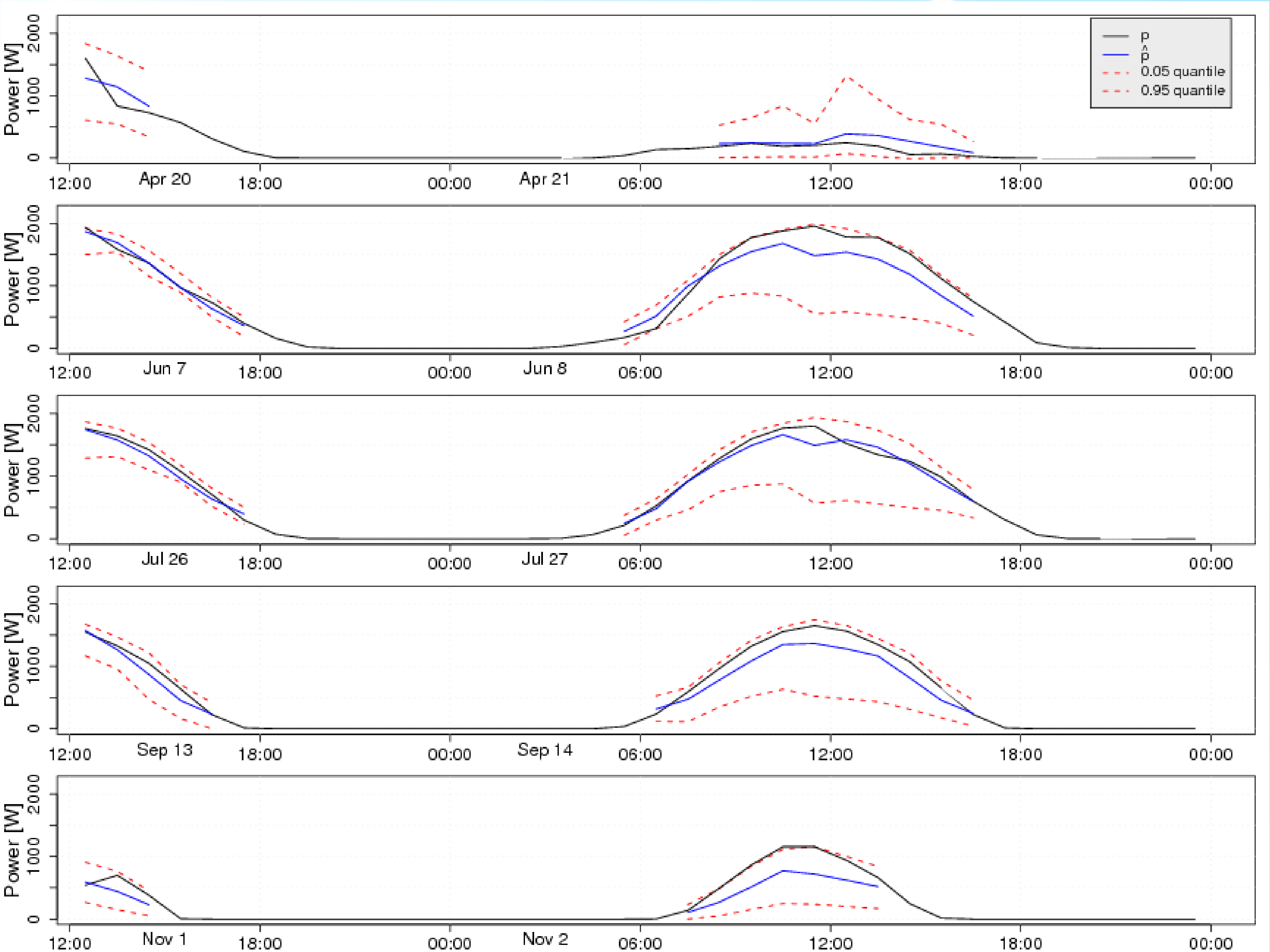
- Same principles as for wind power ....
- Developed for grid connected PV-systems mainly installed on rooftops
- Average of output from 21 PV systems in small village (Brædstrup) in DK

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

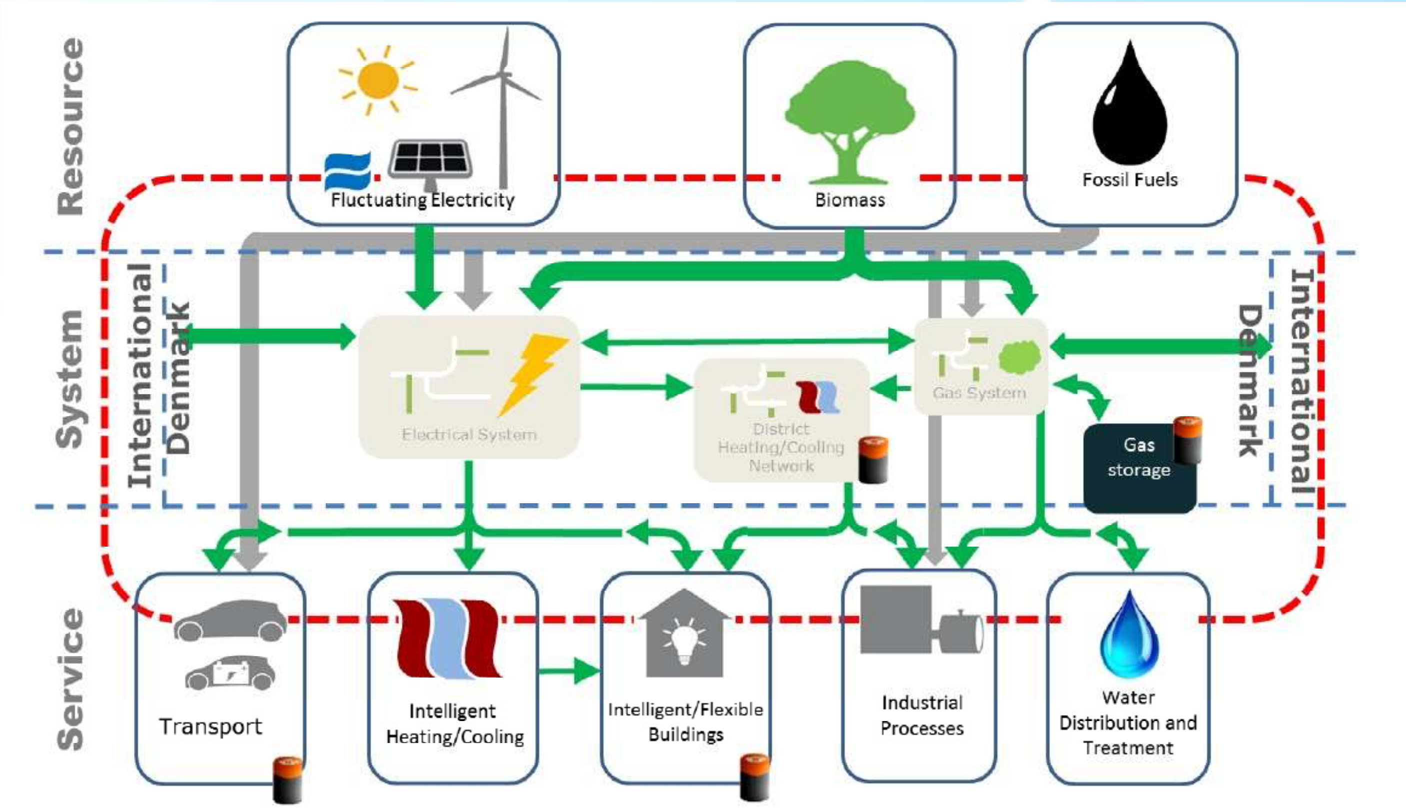


Software Modules for Wind Power Forecasting

- Point prediction module
- Probabilistic (quantile) forecasting module
- Scenario generation module
- Spatio-temporal forecasting module
- Space-time scenario generation module
- Even-based prediction module (eg. cut-off prob.)
- Ramp prediction module

Same modules are available for solar Power Forecasting

Energy Systems



Wind Power Forecasting - Lessons Learned

- 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 a given 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 of installed power 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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