Probabilistic Forecasting of Wind and Solar Power Generation

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Outline

shall focus on Wind - and briefly mention Solar:

- Wind power point forecasting
- Use of several providers of MET forecasts
- Uncertainty and confidence intervals
- Scenario forecasting
- Space-time scenario forecasting
- Examples on the use of probabilistic forecasts
- Optimal bidding for a wind farm owner
- Solar power forecasting
- Lessons learned in Denmark

Vind Power Forecasting - History

ur methods for probabilistic wind power forecasting have been implemented several rediction tools like the **Anemos Wind Power Prediction System**, **Australian Wind nergy Forecasting Systems (AWEFS)** and **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.

or Denmark: Wind power covers **on average more than 42 pct** of the system load (2015).

Prediction of wind power

n 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 nsure safe and economic operation of the power system.

ccurate wind power predictions are needed with different prediction horizons in order to nsure

- (**up to 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.

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

or some grids/in some situations the focus is on methods for **ramp forecasting**, in some ther cases the focus in on reliable probabilistic forecasting.

Jncertainty and adaptivity

rrors in MET forecasts will end up in errors in wind power forecasts, but other factors lead
› a need for adaptation which however leads to some uncertainties.

he total system consisting of wind farms measured online, wind turbines not measured
nline 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.

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

/e started (some 20 years ago) assuming Gaussianity; but this is a very serious (wrong)
ssumption !

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

The power curve model

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

he power curve model is defined as:

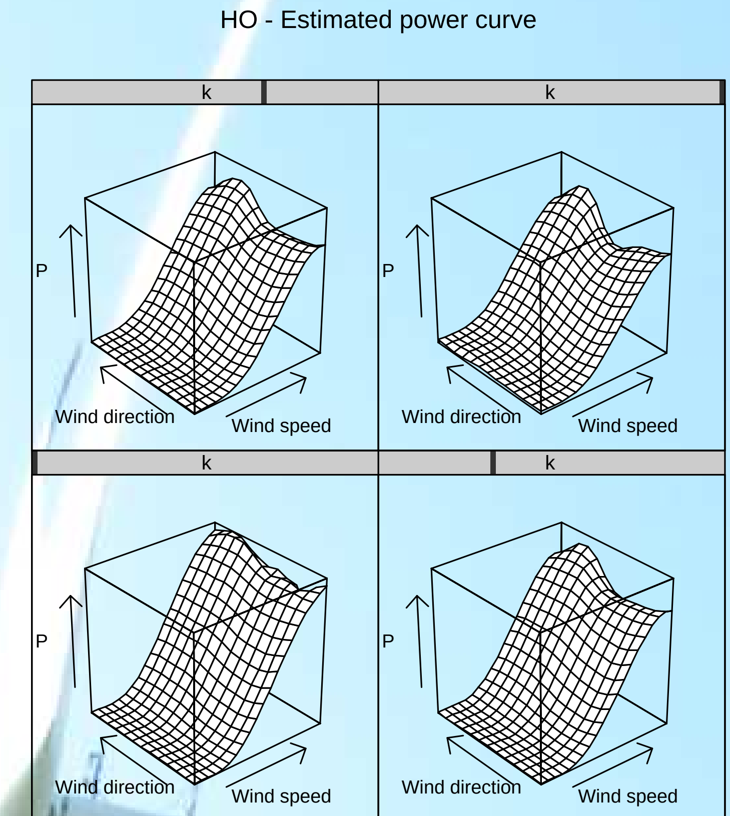
$$\hat{p}_{t+k|t} = f(\ \bar{w}_{t+k|t},\ \bar{\theta}_{t+k|t},\ k\ )$$

here

$_{t+k|t}$ is forecasted wind speed, and

$_{t+k|t}$ is forecasted wind direction.

he characteristics of the NWP change with e prediction horizon.

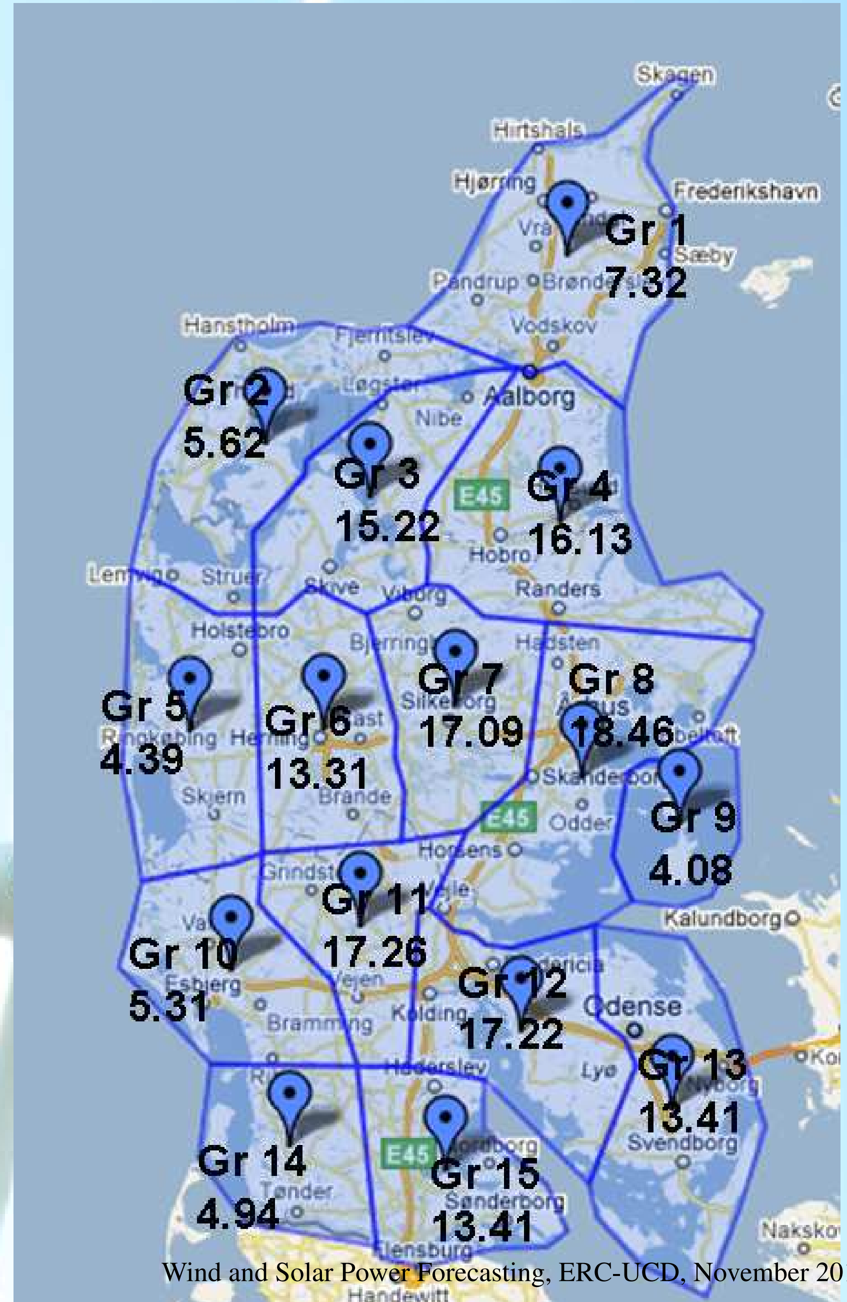


Plots of the estimated power curve for the Hollandsbjerg wind farm.

patio-temporal forecasting

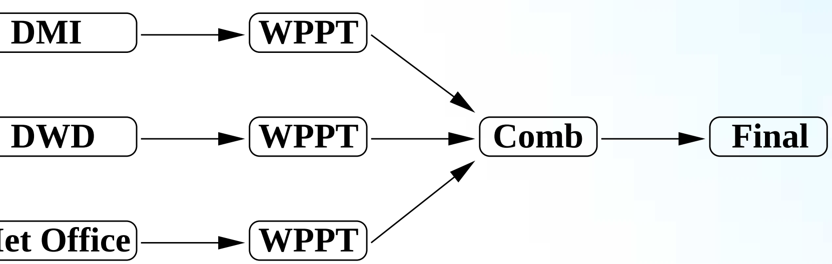
redictive improvement (measured in MSE) of forecasts errors by adding the patio-temperal module in WPPT.

- 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

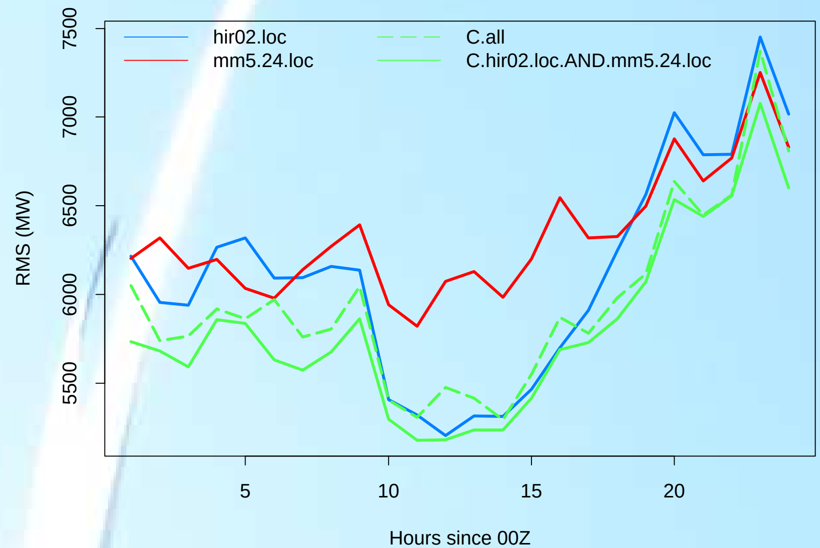


Combined forecasting

- 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.



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

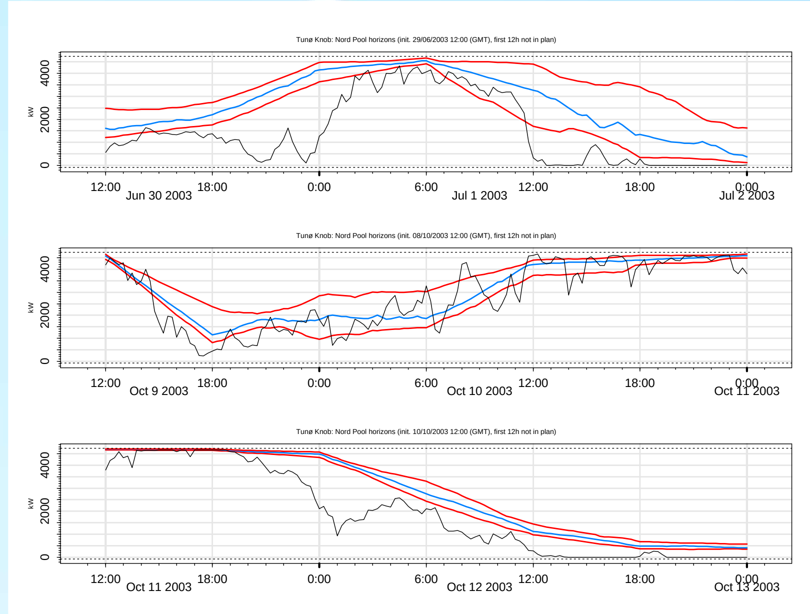
Jncertainty estimation

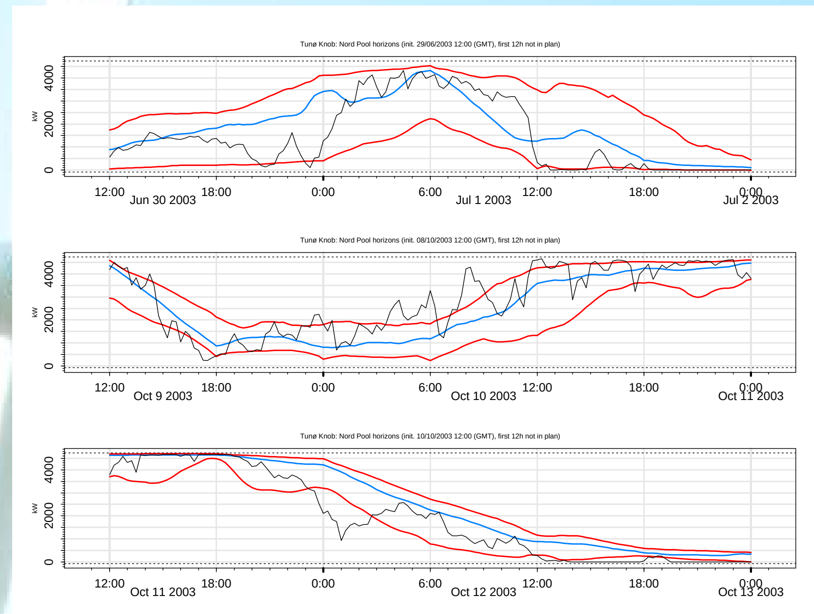
ı many applications it is crucial that a pre-ction tool delivers reliable estimates (prob-bilistc forecasts) of the expected uncertainty f the wind power prediction.

Ve consider the following methods for esti-nating the uncertainty of the forecasted wind ower production:

- Ensemble based - but corrected - quantiles.
- Quantile regression.
- Stochastic differential equations.

he plots show raw (top) and corrected (bot-om) uncertainty intervales based on ECMEF nsembles for Tunø Knob (offshore park), 9/6, 8/10, 10/10 (2003). Shown are the 5%, 50%, 75%, quantiles.





Quantile regression

A (additive) model for each quantile:

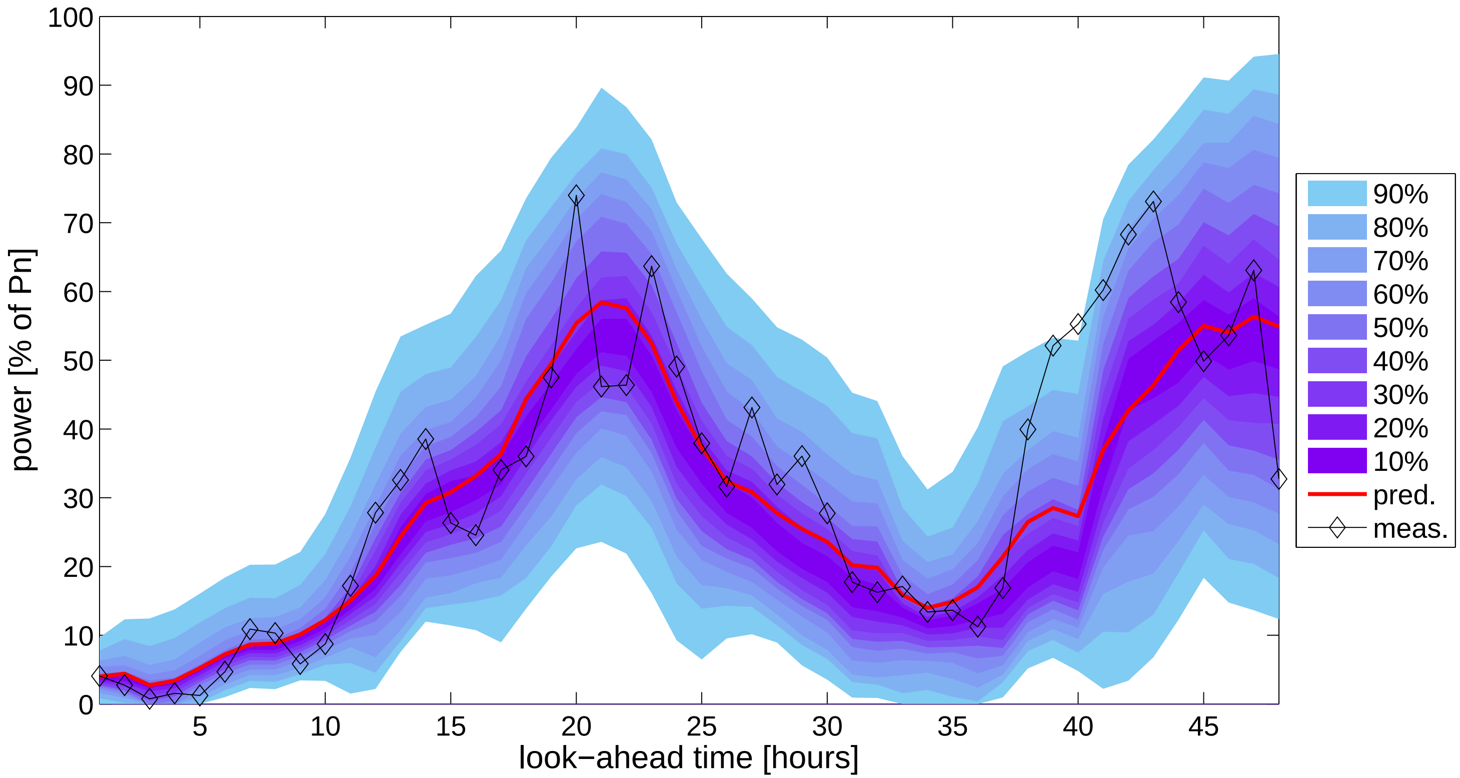
$$Q(\tau) = \alpha(\tau) + f_1(x_1;\tau) + f_2(x_2;\tau) + \ldots + f_p(x_p;\tau)$$

$Q(\tau)$	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.

Example: Probabilistic forecasts



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

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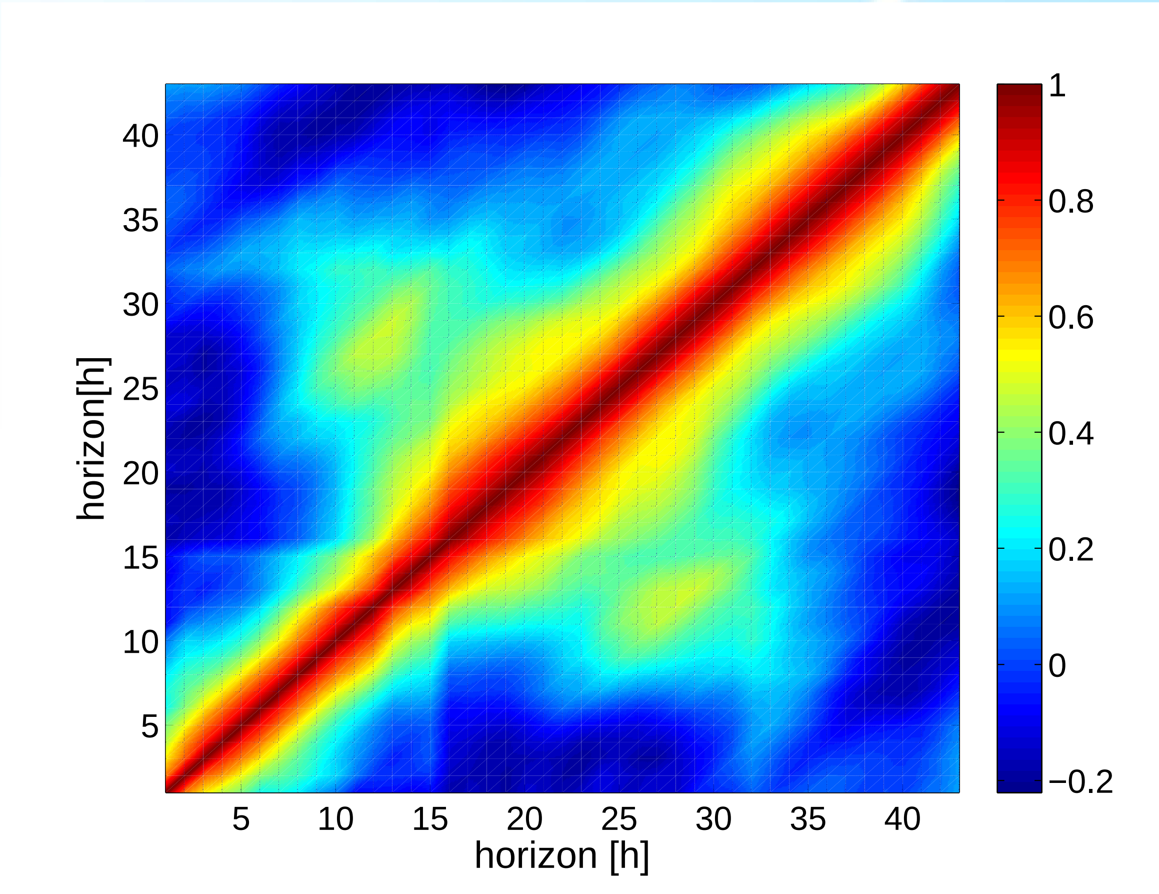
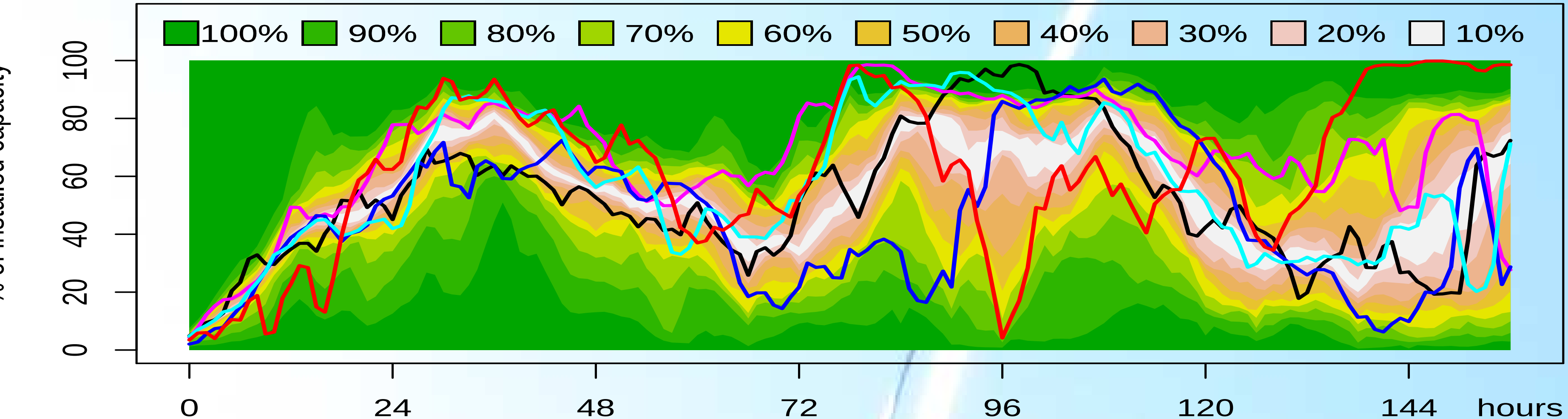
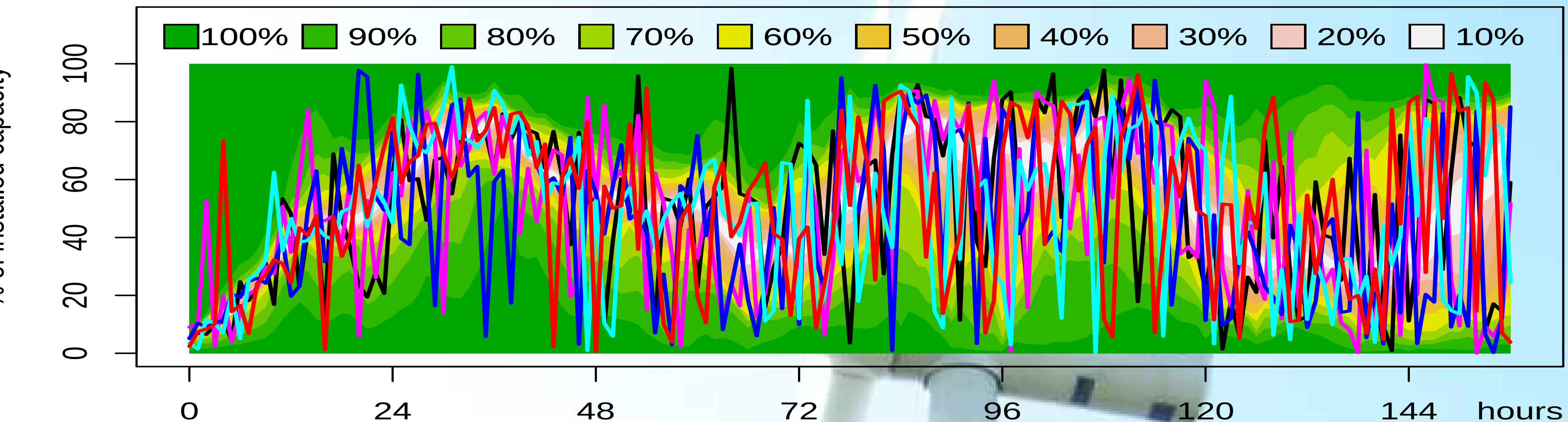
Correlation structure of forecast errors

- 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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Jse of Stoch. Diff. Equations

he state equation describes the future wind power production

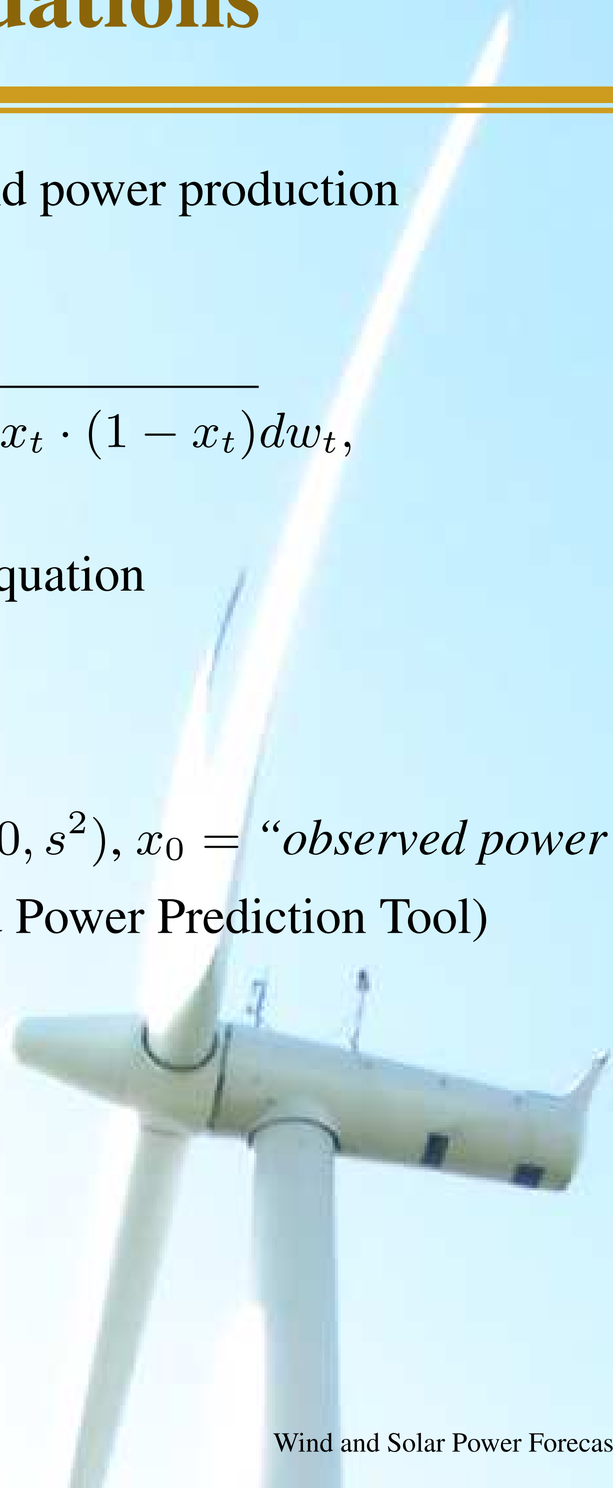
$$dx_t = -\theta(\boldsymbol{u_t}) \cdot (x_t - \hat{p}_{t|0})dt + 2\sqrt{\theta(\boldsymbol{u_t})\alpha(\boldsymbol{u_t})\hat{p}_{t|0}(1-\hat{p}_{t|0})x_t \cdot (1-x_t)}dw_t,$$

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

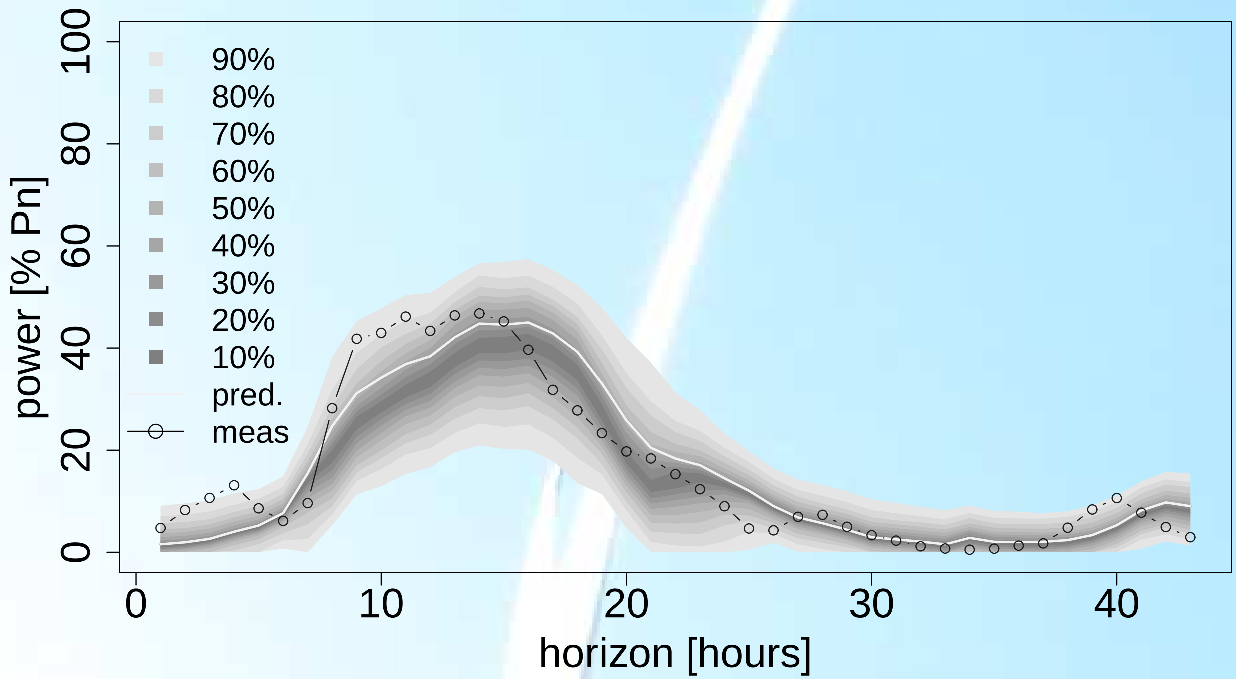
$$y_h = x_{t_h|0} + e_h,$$

here $h \in \{1, 2, ..., 48\}$, $t_h = k$, $e_h \sim N(0, s^2)$, $x_0 =$ *"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 $\hat{p}_{t|0}$)



Motivation - Space-Time Dependencies



This is not enough...

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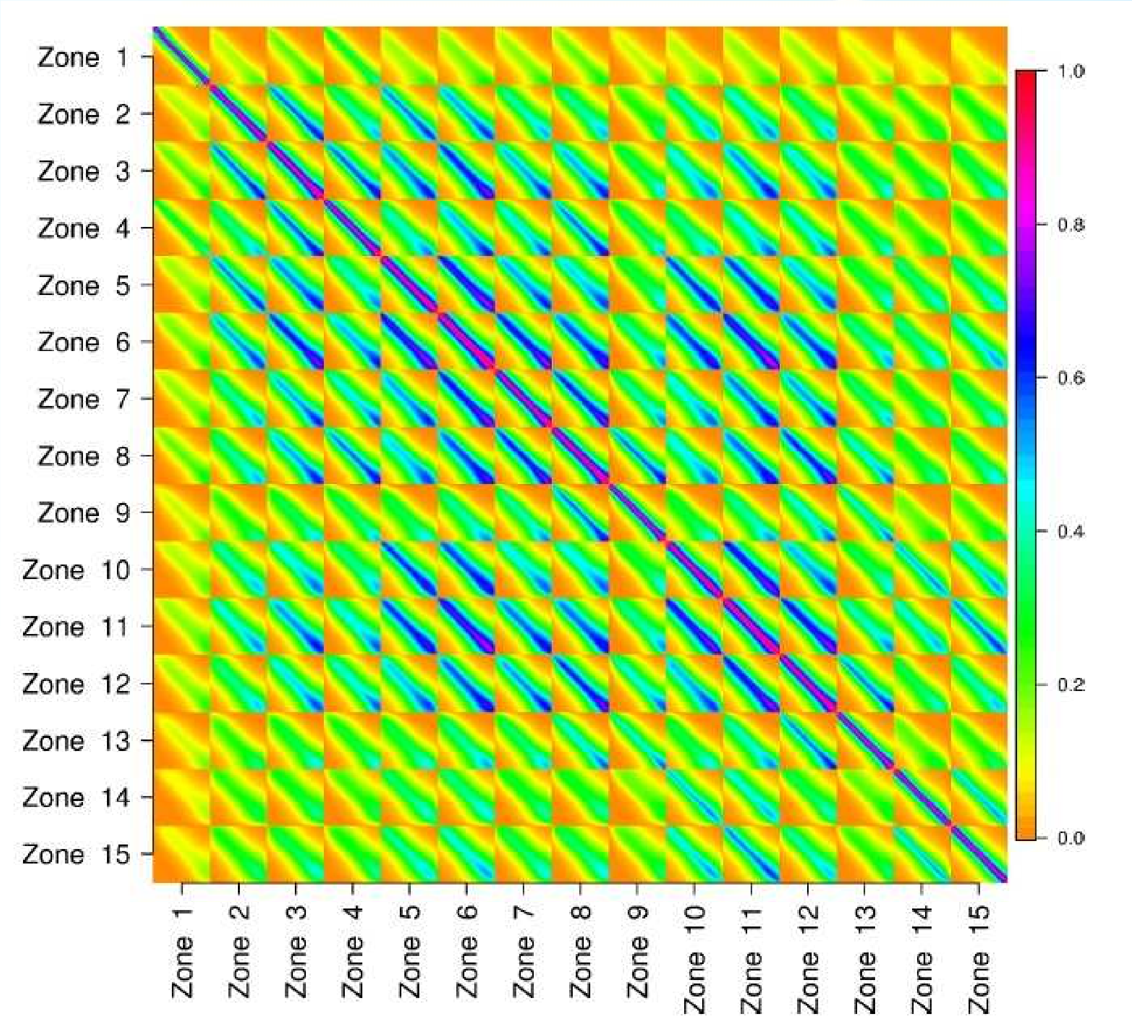
Space-Time Correlations



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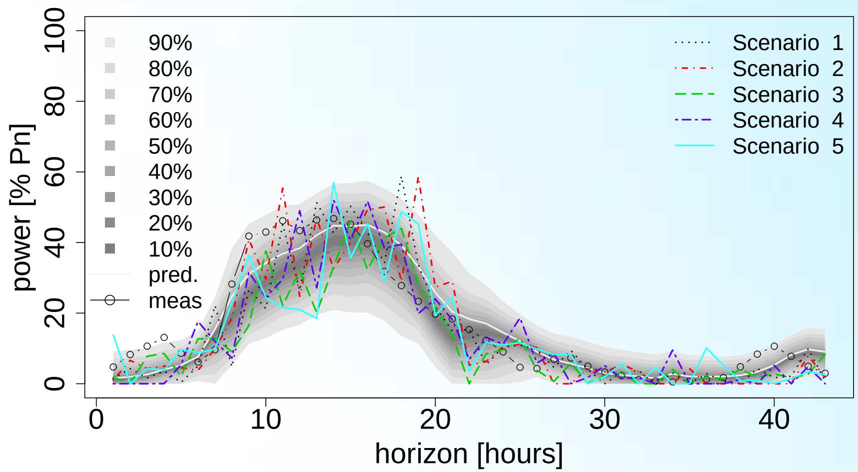
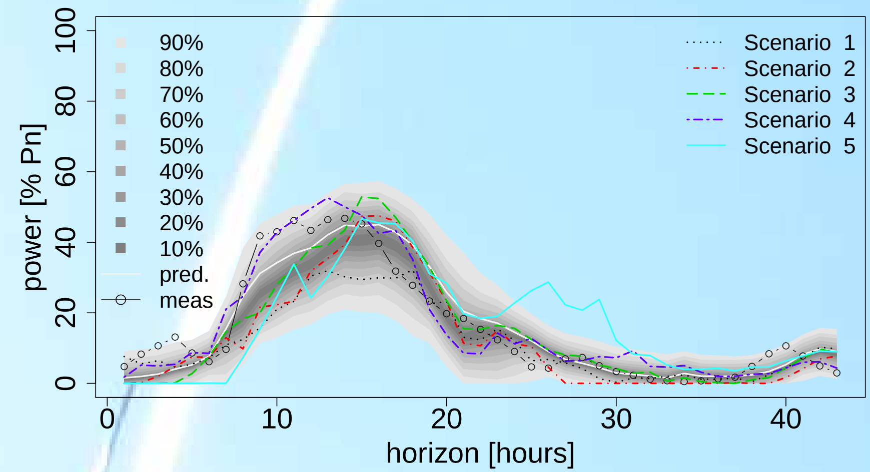
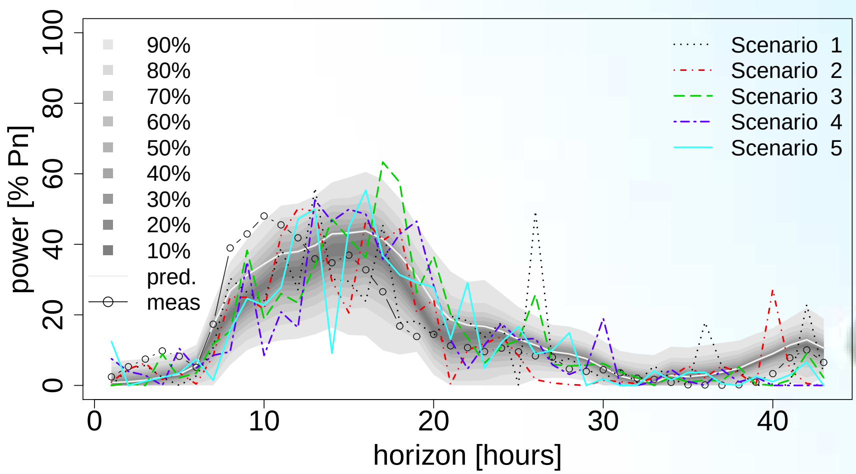
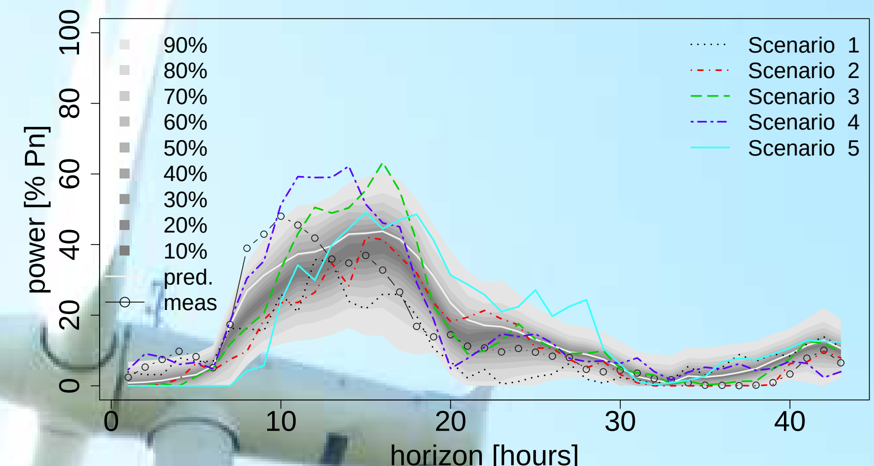
Space-time trajectories









no space-time correlation

appropriate space-time correlation

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.

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.

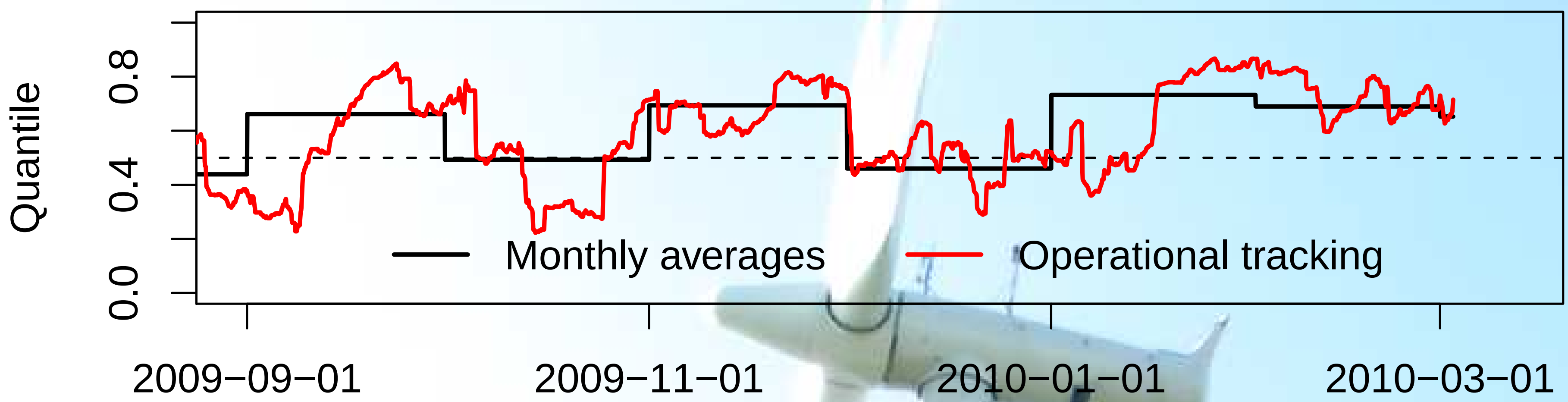
- The bid maximising the expected revenue is the following **quantile**

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

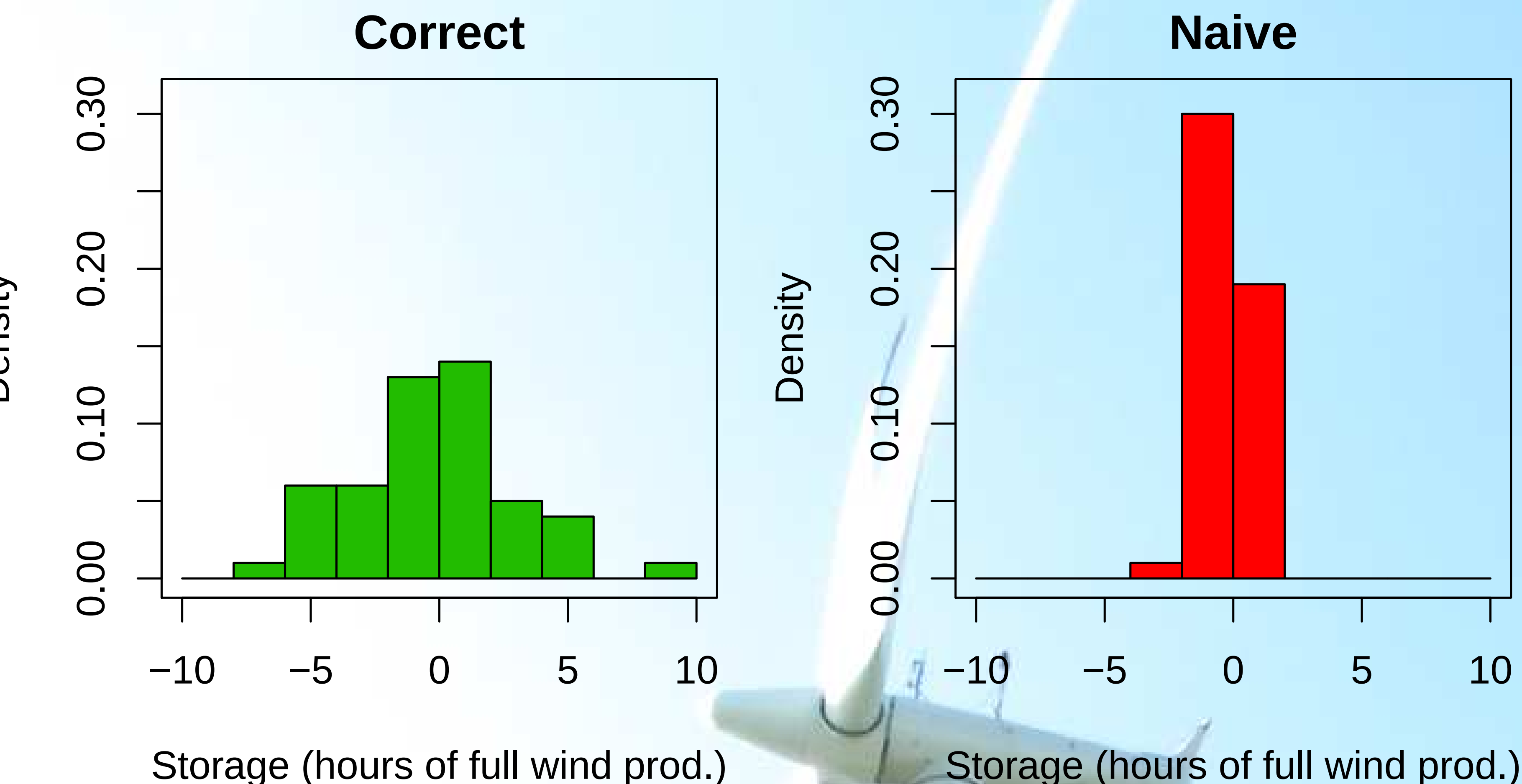
  in the conditional distribution of the future wind power production.

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



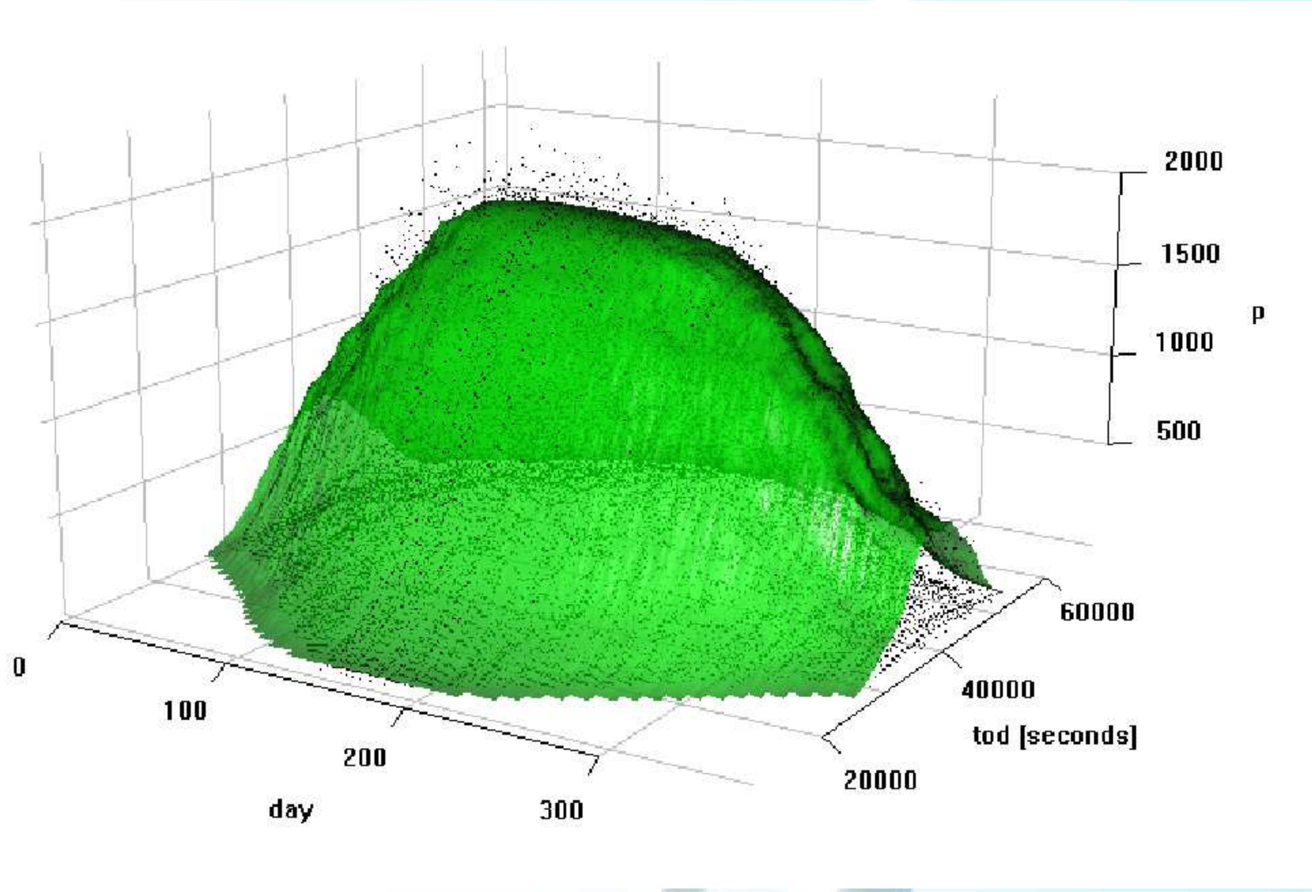
llustrative example based on 50 day ahead scenarios. Used for calculating the risk for a storage to be too nall)

Solar Power Forecasting

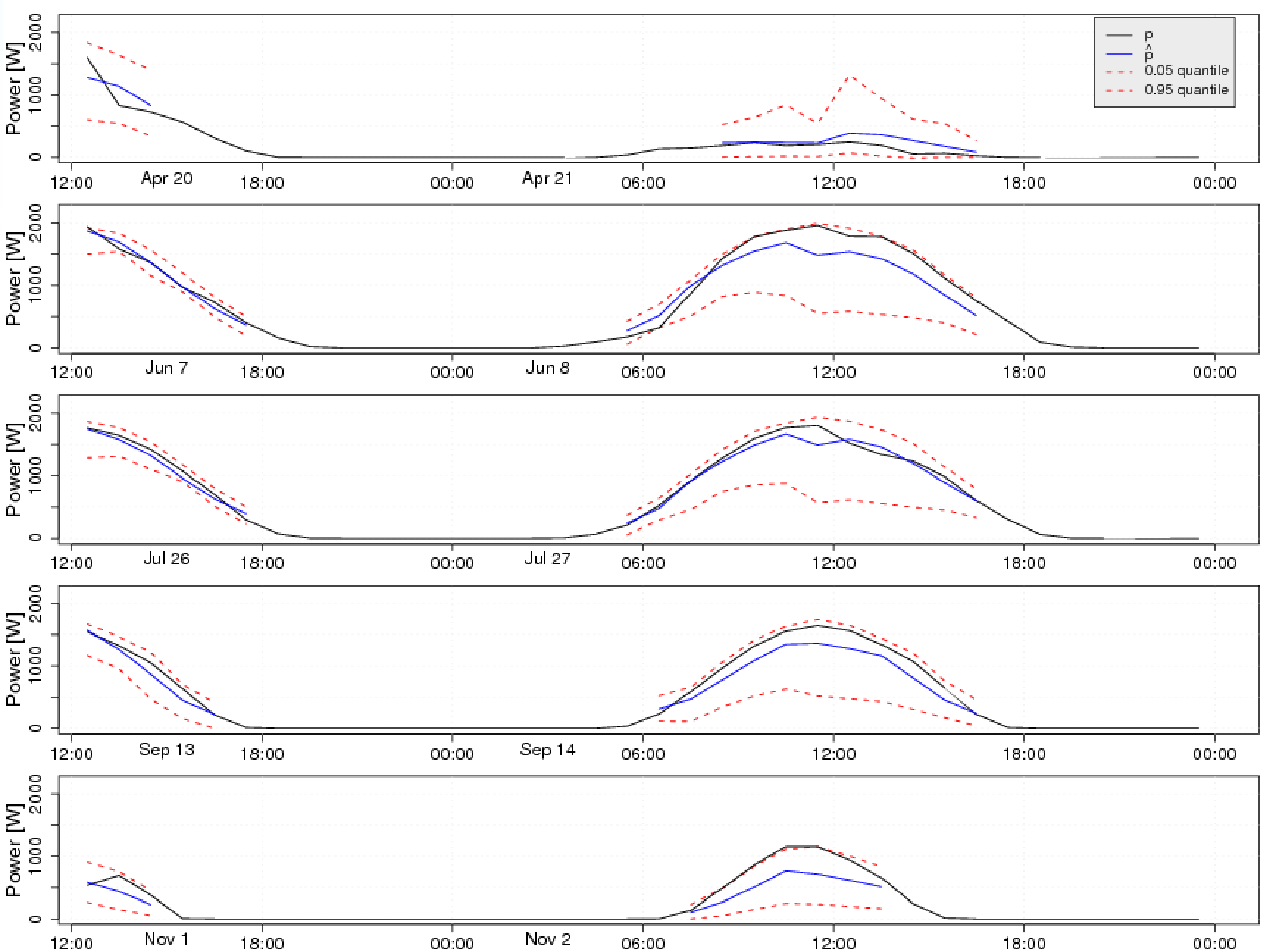
- Same principles as for wind power ....
- Developed for grid connected PV-systems mainly installed on rooftops
- Average of output from 21 PV systems in small village (Brædstrup) in DK

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



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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, icing,...)
- Ramp prediction module

ame modules are available for solar Power Forecasting

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VG-Integration: Lessons Learned in Denmark

- (> 5 pct wind): Tools for Wind/Solar Power forecasting are important
- (> 10 pct wind): Tools for reliable probabilistic forecasting are needed
- (> 15 pct wind): Consider Energy Systems Integration (not Power only)
- (> 20 pct wind): Consider Methods for Demand Side Management
- (> 25 pct wind): New methods for finding the optimal spinning reserve are needed (based on prob. forecasting of wind/solar power production)
- Joint forecasts of wind, solar, load and prices are essential
- Limited need - or no need - for classical storage solutions
- Huge need for virtual storage solutions
- Intelligent interaction between power, gas, DH and biomass very important
- ICT and use of data, adaptivity, intelligence, and stochastic modelling is very important

he largest national strategic research project: **Centre for IT-Intelligent Energy Systems in ities - CITIES** have been launched 1. January 2014. International expertice from NREL JS), UCD/ERC (Ireland), AIT (Austria) becomes important.

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**.

Some Forecasting Tools from DTU

- Forecasting and optimisation tools enabling the integration of a large share of renewables:
    - Electricity load forecasts: LoadFor
    - Wind power production: WPPT
    - Solar power production: SolarFor
    - Gas load: Gasfor
    - Heat load: PRESS
    - Optimal operation of CHP systems: PRESS
    - Price forecasts: PriceFor
    - Lately: Wave power forecasts

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