Probabilistic Forecasting of Wind Power Generation

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Introductory Lecture - 28/10/14

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Why forecast wind power?

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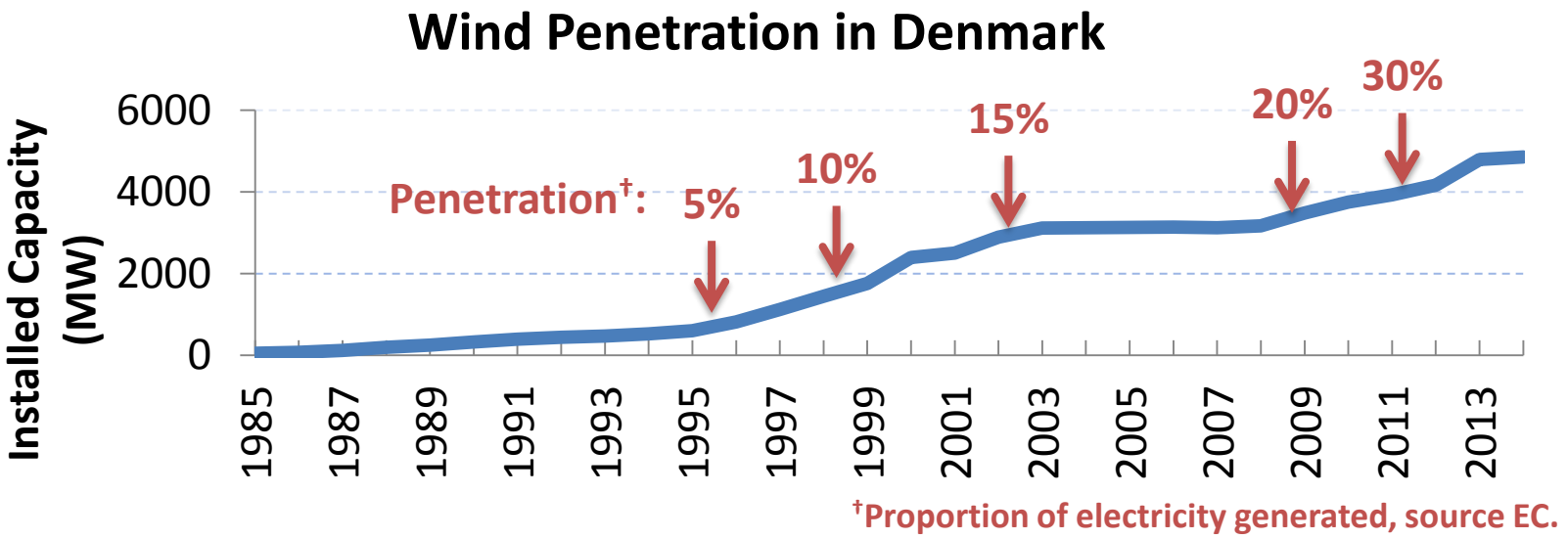
- Wind is variable, but electricity grids and markets were designed for controllable power generation:
  - "Conventional" power plants have high availability and behave predictably.
  - Load forecasts are very accurate.
  - Therefore **penalties** exist for deviating from declared power production.

- Some specifics:
  - Define reserve requirements, unit commitment, economic dispatch, operating combined wind-storage, designing trading strategies…

- More significant for high penetration!

Why forecast wind power?

The Danish Experience



Penetration	Danish Experience
>5%	Basic forecasts are important
>10%	Reliable probabilistic forecasts are needed
>15%	Energy system integration
>20%	Demand side management
>25%	New methods for operating reserves are needed

Source: EERA Workshop Presentation 8/5/14, Henrik Madsen.

Who uses wind power forecasts?

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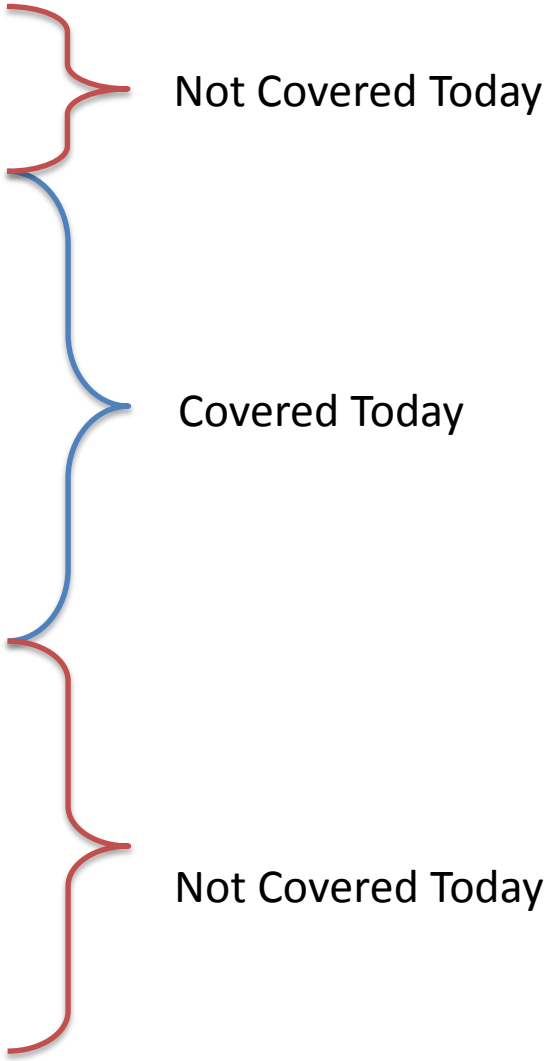
- Transmission Companies
  - *RTE, NationalGrid, Tannet, 50Hertz, Red Electrica de España, Energynet.dk, CaISO, AEMO…*
- Utilities
  - *DONG Energy, Vattenfall, Acciona, Iberdrola, E.On, NUON, RWE, EnBW…*
- Everyone else trading on markets with large wind penetration!

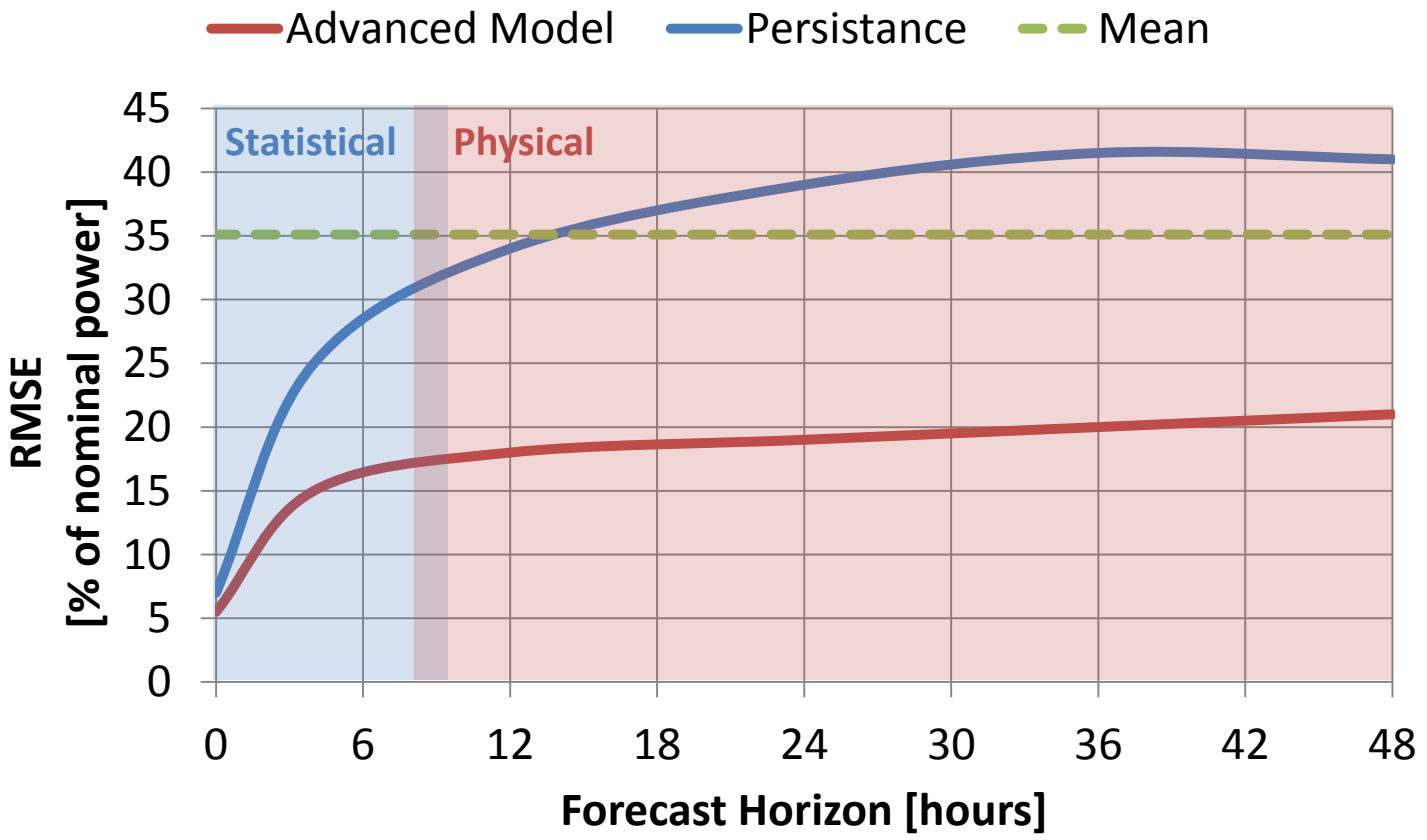
Time Scales

- Seconds (extremely-short-term)
  - Turbine/Farm Control
- Minutes (very-short-term)
  - Balancing and Transmission
- Hours (short-term)
  - Scheduling conventional plant
- Days
  - Day-ahead scheduling, large CHP operation
- Weeks
  - Maintenance
- Years
  - Investment/financing, cash flow etc.



Time Scales & Methodologies

Types of Model



Popular Error Metric – Root Mean Squared Error:
(This is also a common cost function!)

$$\mathrm{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T} e_t^2}$$

Forecasting Methodologies

Types of Model

Statistical	Physical
Auto-regression - (AR, ARMA, ARIMA,…) Neural Networks Nonlinear Regression Learning Algorithms …and many more…	**Weather** Meso-scale Models Numerical Weather Prediction **Power Curve Model** Statistical model of wind-to-power conversion process

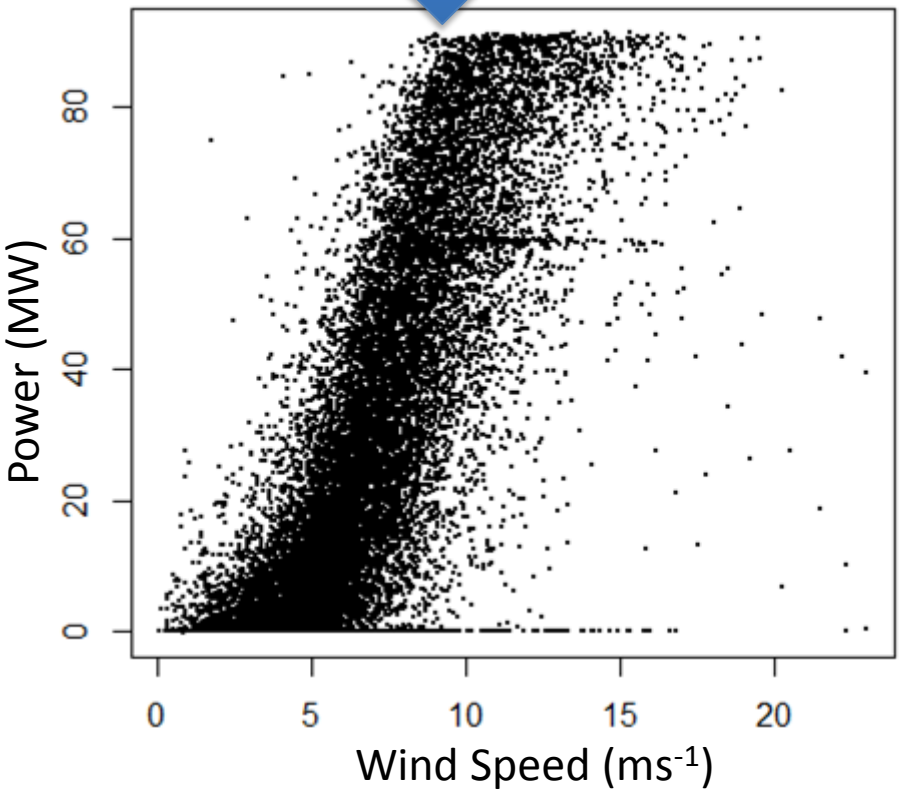
Inputs:
Recent Measurements SCADA Farm/Regional Aggregated Power Met. Measurements*

*Req. Power Curve

Inputs:
Meteorological Forecast NWP Outputs Met. Measurements + Meso-scale model

Forecasting Methodologies

Types of Model



Physical

Weather
Meso-scale Models
Numerical Weather Prediction

Power Curve Model
Statistical model of wind-to-power conversion process

Inputs:

Meteorological Forecast
NWP Outputs
Met. Measurements + Meso-scale model

Forecasting Methodologies

Types of Model

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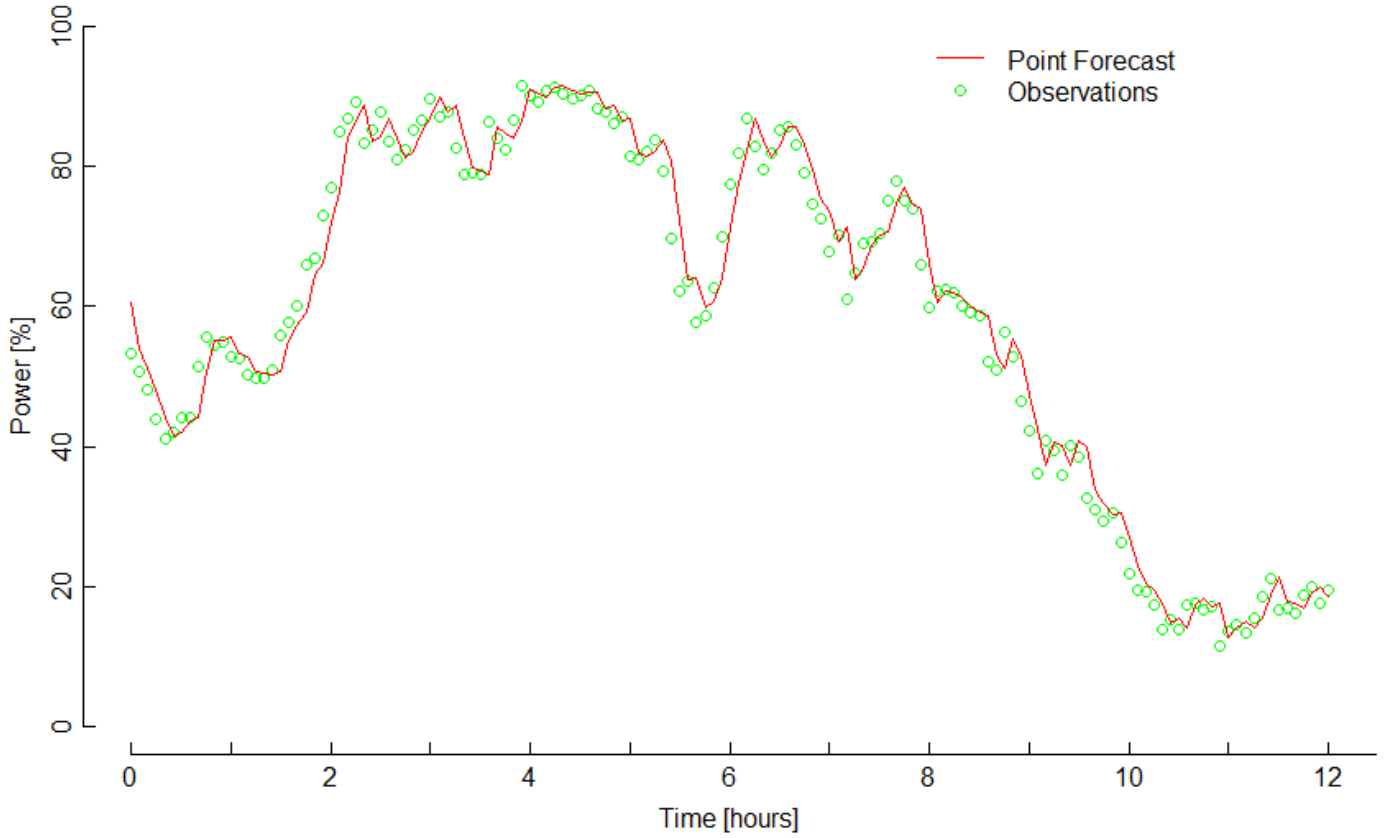
Statistical	Physical
Auto-regression - (AR, ARMA, ARIMA,…) Neural Networks Nonlinear Regression Learning Algorithms …and many more…	**Weather:** Meso-scale Models Numerical Weather Prediction **Power Curve Model:** Statistical model of wind-to-power conversion process
Commercial products employ many techniques and draw on as much input information as possible!	
Examples:	*WPPT, MORE-CARE, Sipreolico, WPMS, LocalPred, Prediktor, Previento, TrueWind,…*
Service Providers:	3Tier, TrueWind, Windlogics, Precisionwind, Eurowind, DNV-GL (GarradHassan), UK MetOffice, Kjeller Vindtekknik, met.no, metro group,…

Point/Deterministic Forecast

- ‘Best guess’ of generation at some point in the future:



Why Probabilistic Forecasting?

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- The value of a forecast is in its application to decision a making problem.
  - Complex cost/loss functions (nonsymmetrical!)
  - The optimal point forecast for one application my not be optimal for another.
  - There is value in quantifying **uncertainty** and **risk**.
- Examples of probabilistic forecasts:
  - Quantiles, intervals, predictive distributions, trajectories/scenarios, risk indices.

Why Probabilistic Forecasting?

Example: APX/TanneT

- Bids are made at noon for each hour of the next day:

$$\text{Revenue} = P_s \times \text{Actual} - \begin{cases} P_D \times (\text{Acutal} - \text{Bid}) & \text{Over produce} \\ P_U \times (\text{Bid} - \text{Actual}) & \text{Under produce} \end{cases}$$

€€€

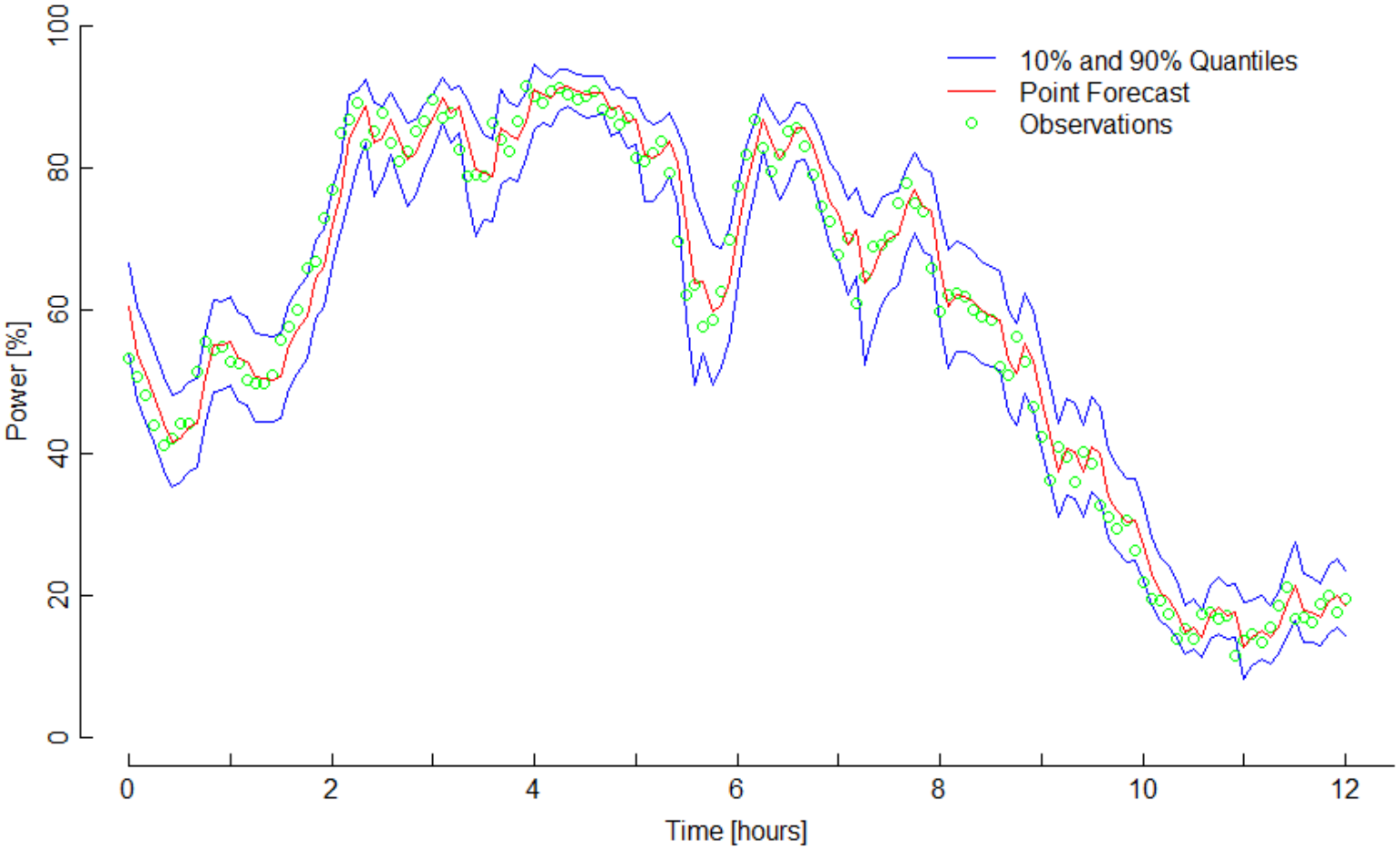
Spot Price

Power Produced

Price of Up/Down Regulation

P_U is typically much greater than P_D ⇒ Revenue will be maximised if we reduce exposure to up-regulation at the risk of more down-regulation ⇒ Bid on some quantile.

Quantiles and Intervals



Predictive Distribution

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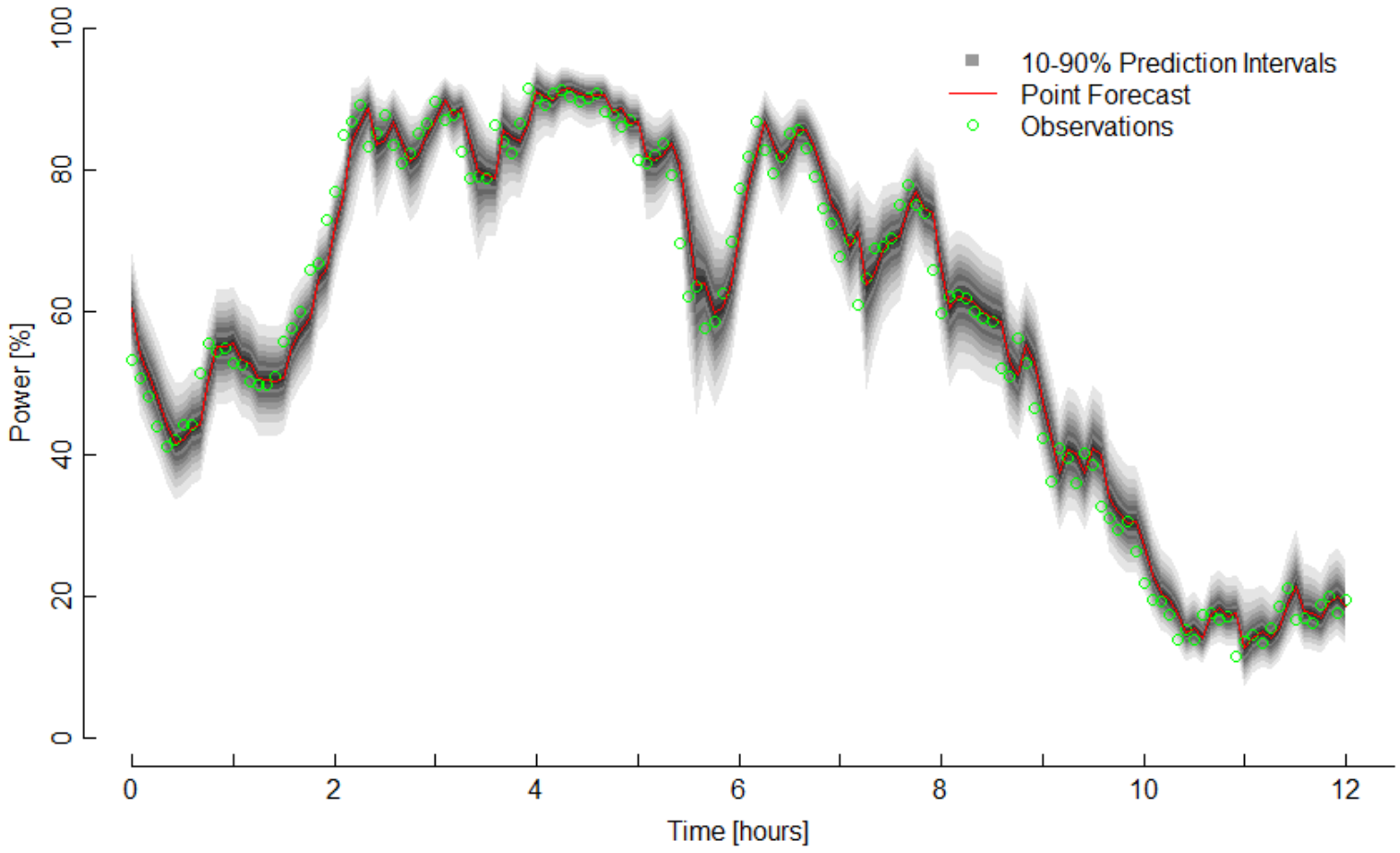
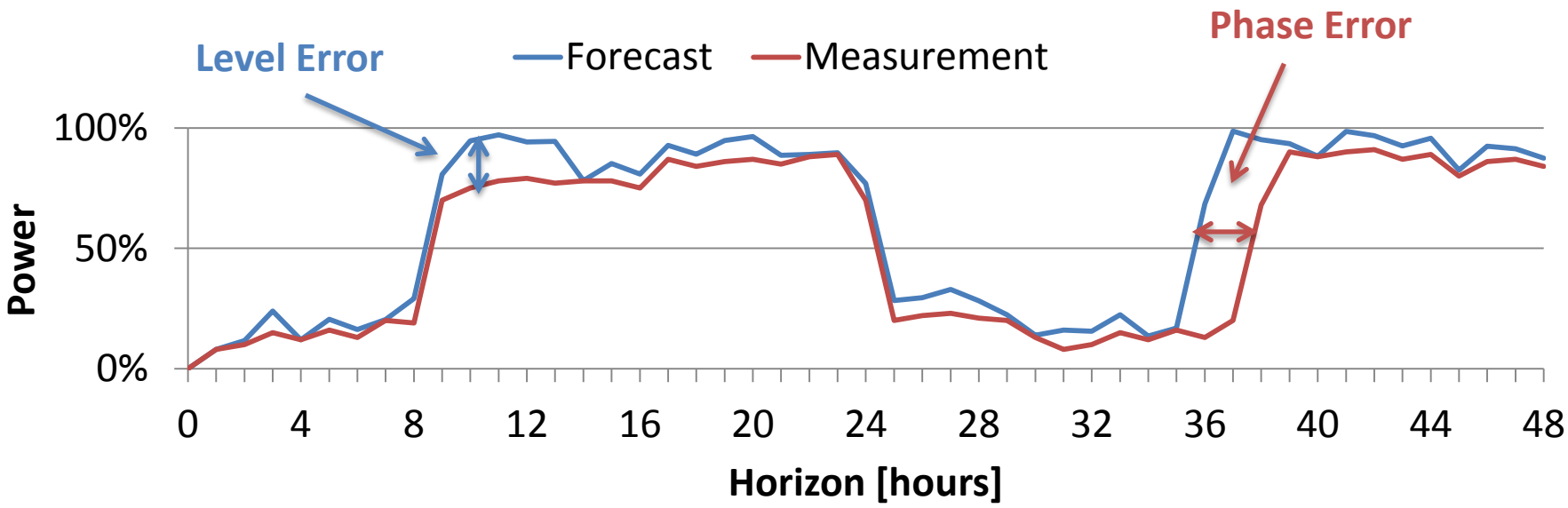
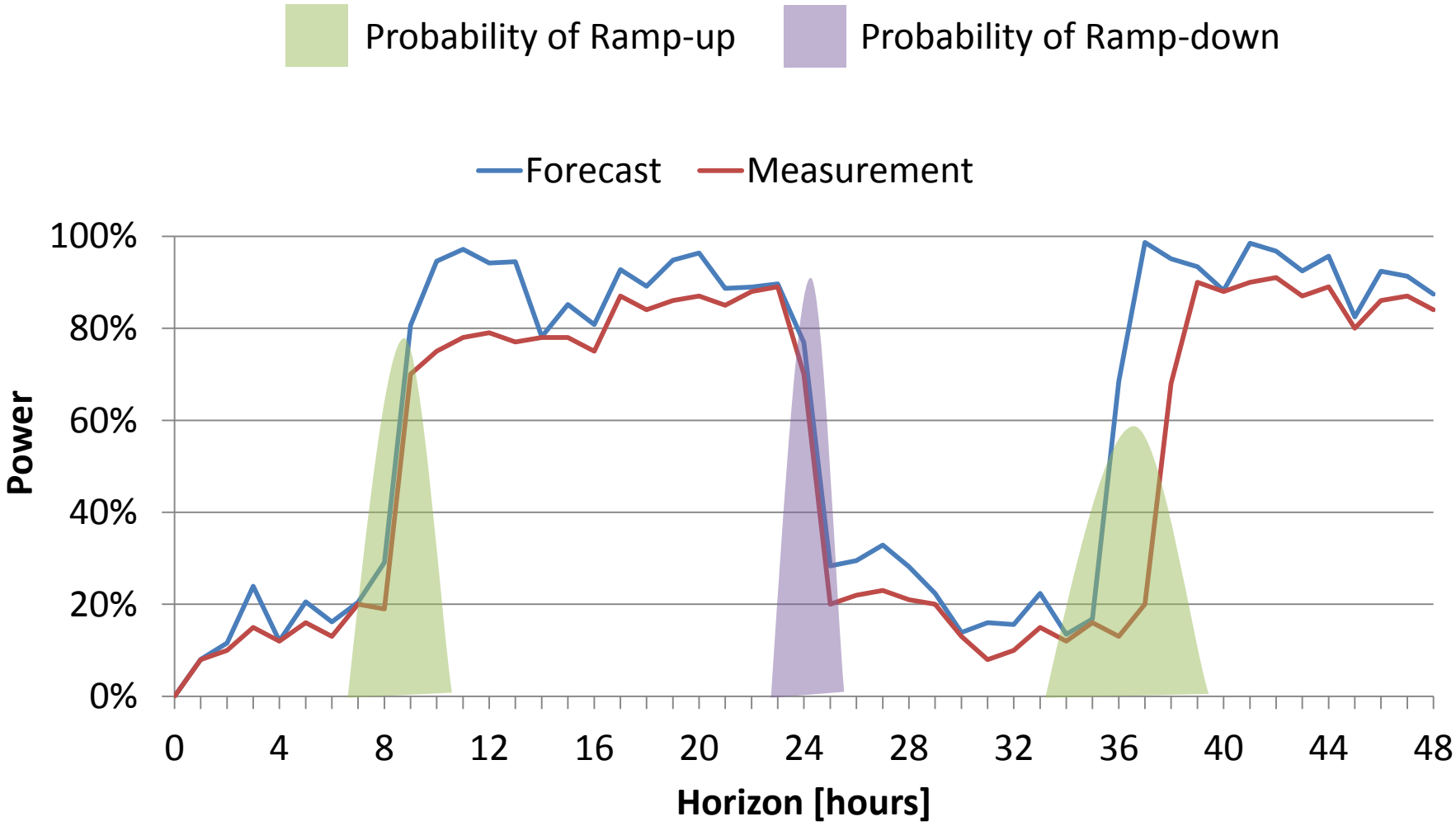


Chance of Ramp Event

- There are two error categories from NWP:
  - Level Error (incorrect intensity)
  - Phase Error (incorrect timing)
- Phase errors are more common and have larger impact on power systems.



Chance of Ramp Event



Summary so far:

- Lots of players require forecasts:
  - TSOs, Utilities, energy traders,…
- Quantifying uncertainty is extremely important!
- Many different types of forecast:
  - For specific applications
  - To suit the expertise of decision-makers
- Where is research now?

Current Research

Spatio-temporal Approaches

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VIDEO: Hydra Wind Dataset
http://youtu.be/WvY85U_0Ins

[Hydra dataset of potential wind across NL, source: www.knmi.nl/samenw/hydra]

Current Research

Spatio-temporal Approaches

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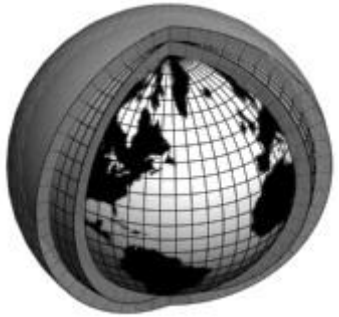
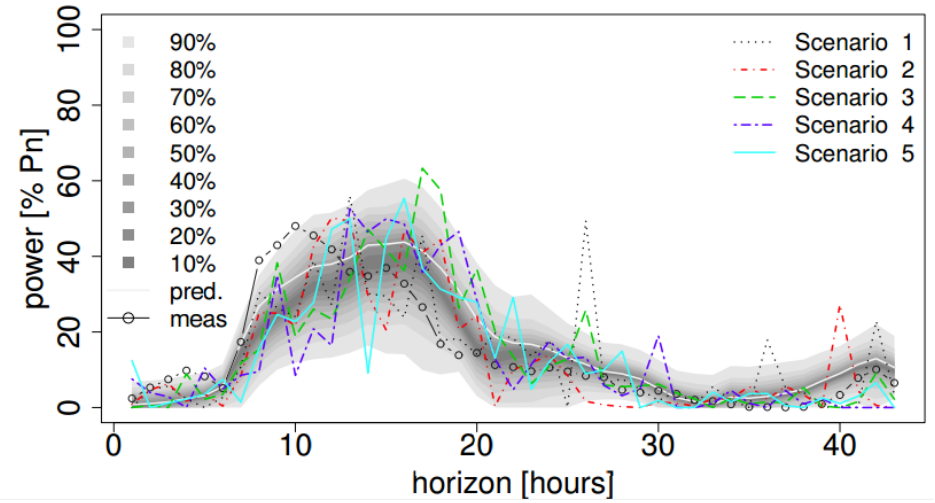
- NWP are already very sophisticated spatial models…
  - leave that to the meteorologists!
  - NWP output calibration and power curve modelling are still very active areas.

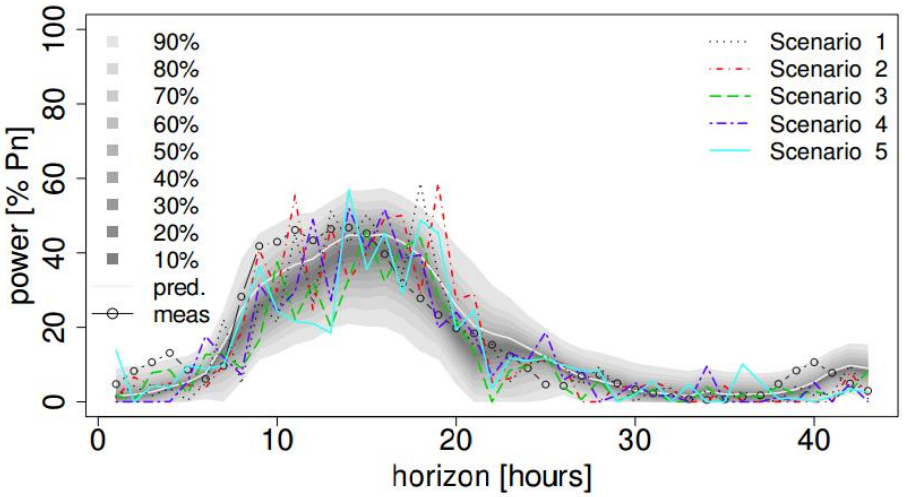


- Spatio-temporal statistics can improve short-term wind power forecasts significantly:
  - Vector regression, multivariate learning,…

Current Research

Scenarios





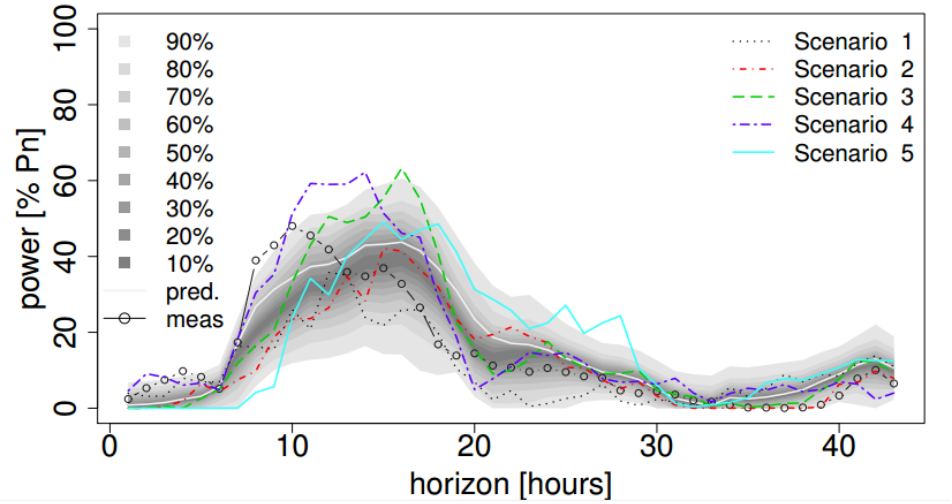
Naïve Approach

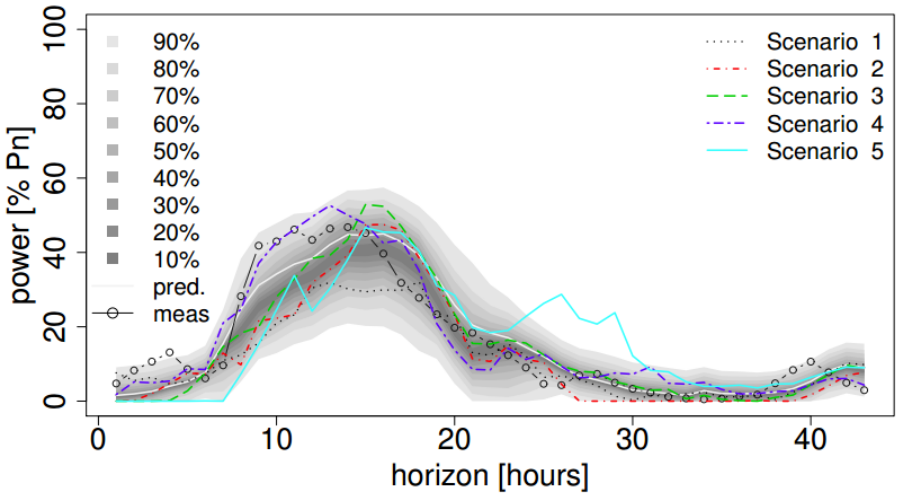
Spatial and temporal dependencies ignored.

Source: J. Tastu, P. Pinson, H. Madsen (2014). Space-time trajectories of wind power generation: Parameterized precision matrices under a Gaussian copula approach. *Lecture Notes in Statistics: Modeling and Stochastic Learning for Forecasting in High Dimension*, in press.

Current Research

Scenarios





Considered Approach

Spatial and temporal dependence captured.

Source: J. Tastu, P. Pinson, H. Madsen (2014). Space-time trajectories of wind power generation: Parameterized precision matrices under a Gaussian copula approach. *Lecture Notes in Statistics: Modeling and Stochastic Learning for Forecasting in High Dimension*, in press.

Current Research

Radar@Sea

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VIDEO: Radar@Sea
www.youtube.com/watch?v=YShQDCdVykM

Current Research

Offshore Maintenance

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