Basics of Renewable Energy Forecasting

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Learning objectives

Through this lecture and additional study material, it is aimed for the students to be able to:

1. Describe the **different types of renewable energy forecasts**, in plain words and in a more mathematical manner
2. Explain why using such or such forecasts for **different type of decision-making problems**
3. Discuss the origins and characteristics of **forecast uncertainty**

Basis for the lecture(s)

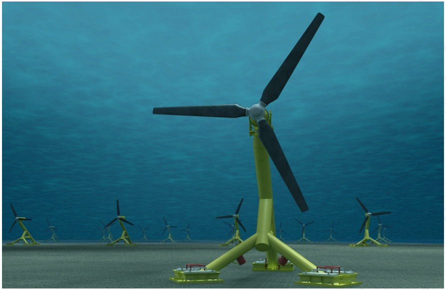
Wind Energy

Wave Energy (could be)

... *Also nothing on* **Solar Energy** *today, though all concepts are similar.*

And for another time...!

These actually are tidal energy converters



Do you know what these are?

Outline

1. **Forecast: why and in what form?**
   - forecasting in electricity markets
   - the case of renewable energy forecasts
   - forecasts as input to decision-making problems
   - benefits from considering uncertainty
2. **Uncertainty origins and basic characteristics**
   - origins of uncertainty: weather forecasts, power curves, etc.
   - basic characteristics
3. **From deterministic to probabilistic forecasts**
   - what a deterministic forecast really is...
   - illustration of forecast types: point, quantile, intervals, densities, trajectories

1. **Forecast: why and in what form?**

Why forecasting?

- Forecasting is a *natural first step* to decision-making
- Believing we know what will happen
  - helps making decisions
  - but mainly, makes us more confident about it!
- Key application areas include:
  - weather and climate
  - economics and finance
  - logistics
  - insurance, etc.

"But to be fair, there's a fifty percent chance of just about anything."

What to forecast?

- Different actors may have different needs...
  - market participant, **supply side** (e.g., conventional generator, wind farm operator)
  - market participant, **demand side** (e.g., retailer)
  - participants in neighboring markets
  - **market operator**
  - **system operator**

  - but also, *you and I*

What to forecast?

- Different actors may have different needs...
  - market participant, **supply side** (e.g., conventional generator, wind farm operator)
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  - participants in neighboring markets
  - **market operator**
  - **system operator**
  - but also, *you and I*
- One may want forecasts for:
  - the *electric load*
  - *day-ahead prices*
  - potential *imbalance sign*
  - *regulation prices/penalties*
  - potential *congestion on interconnectors*
  - etc.
  - *Generation from renewable energy sources!!!*
- **Nearly all these quantities are driven by weather and climate!**

Renewable energy forecasts in decision-making

- Forecast information is widely used as input to several decision-making problems:
  - definition of **reserve** requirements (i.e., backup capacity for the system operator)
  - **unit commitment** and **economic dispatch** (i.e., least costs usage of all available units)
  - coordination of renewables with **storage**
  - design of optimal **trading** strategies
  - electricity **market-clearing**
  - optimal **maintenance planning** (especially for offshore wind farms)

- Inputs to these methods are:
  - deterministic forecasts
  - probabilistic forecasts as **quantiles, intervals, and predictive distributions**
  - probabilistic forecasts in the form of **trajectories** (/scenarios)
  - **risk indices** (broad audience applications)

- For nearly all of these problems, optimal decisions can only be obtained if fully considering forecast uncertainty...

A recommended book

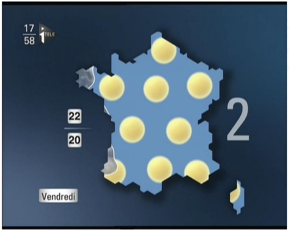
S. Makridakis, R. Hogarth, A. Gaba

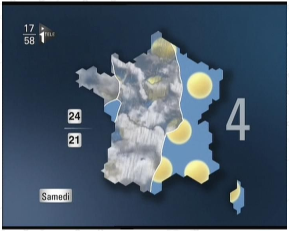
Dance with Chance:
Making Luck Work for You

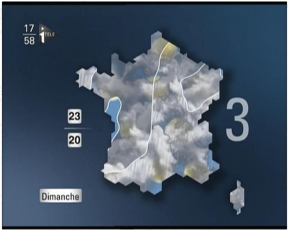
The problem with forecast uncertainty estimation

- The French National meteorological office (Meteo-France) has been communicating *"confidence indices"* (indices de confiance) along with their forecasts for quite a while...

- Example set of forecasts: (from "1 = low confidence" to "5 = high confidence")







- *Do you get something out of it?*

Now... the "big mouth" paradox

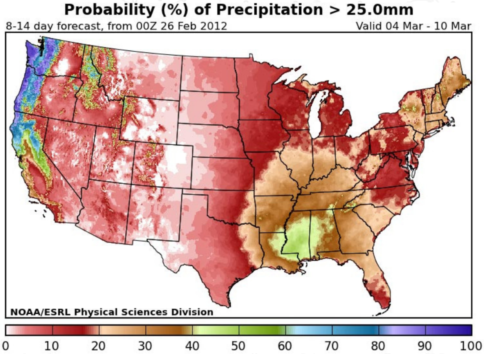
- It might always be difficult to trust someone providing you with forecasts
- Even more so if these are probabilistic...

- Let us consider a simple american setup (focus on **New Orleans**), with two rival forecasters:

- The two competing forecasters tell you that:

  - **Forecaster A:**
    It will rain next Monday, and the precipitation amount will be of 22mm

  - **Forecaster B:**
    There is a probability of 38% that precipitation is more than 25mm next week



- Who would you hire?

[Extra reading: S Joslyn, L Nadav-Greenberg, RM Nichols (2009) Probability of precipitation: Assessment and enhancement of end-user understanding. *Bulletin of the American Meteoreological Society* **90**: 185–193 (pdf)
UR Karmarkar, ZL Tormala (2010). Believe me - I have no idea what I'm talking about: The effects of source certainty on consumer involvement and persuasion. *Journal of Consumer Research* **36**(6): 1033–1049 (pdf)]

Example use of forecasts: market participation

- **Dutch electricity market** over the year 2002:
  - day-ahead market APX
  - regulation mechanism managed by TenneT, the TSO for the Netherlands

- Participation of a **15 MW wind farm**, without any storage device and without any control on the power production

- **Point** and **probabilistic** predictions (full predictive distributions) generated with state-of-the-art statistical methods

- **Revenue-maximization** strategies
  - based on point predictions only (persistence or advanced method)
  - derived from probabilistic predictions and a model of the participant's sensitivity to regulation costs

Trading results

	Pers.	Adv. point pred.	Prob. pred.	Perfect pred.
Contracted energy (GWh)	44.37	45.49	62.37	46.41
Surplus (GWh)	18.12	9.87	4.89	0
Shortage (GWh)	16.08	8.95	20.85	0
Down-regulation costs (10^3 €)	195.72	119.99	42.61	0
Up-regulation costs (10^3 €)	79.59	52.01	61.46	0
Total revenue (10^3 €)	1041.38	1145.69	1212.61	1317.69
Av. down-reg. unit cost (€/MWh)	10.80	12.15	8.71	0
Av. up-reg. unit cost (€/MWh)	4.95	5.81	2.95	0
Av. reg. unit cost (€/MWh)	8.05	9.13	4.04	0
Av. energy price (€/MWh)	**22.44**	**24.68**	**26.13**	**28.37**
Part of imbalance (% prod. energy)	**73.69**	**40.55**	**55.46**	**0**
Performance ratio (%)	**79.1**	**86.99**	**92.1**	**100**

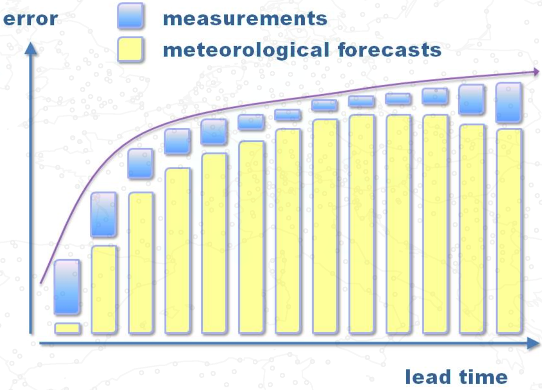
[Source: P Pinson, C Chevallier, G Kariniotakis. Trading wind generation from short-term probabilistic forecasts of wind power. *IEEE Trans. on Power Systems* **22**(3): 1148-1156 (pdf)]

2. **Uncertainty origins and basics**

Contribution to forecast uncertainty/error

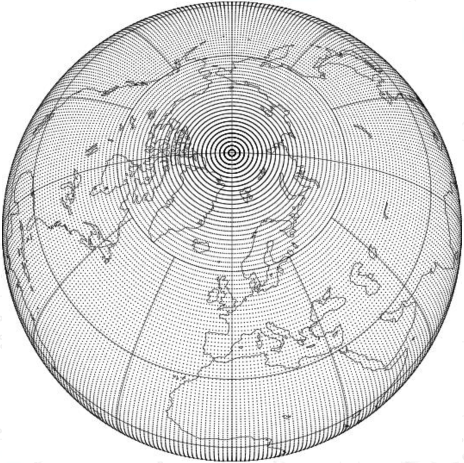
- To generate renewable energy forecasts in electricity markets, necessary inputs include:
  - recent power generation measurements
  - weather forecasts for the coming period
  - possibly extra info (off-site measurements, radar images, etc.)

- Their importance varies as a function of the lead time of interest...
  - *short-term* (0-6 hours): you definitely need measurements
  - *early medium-range* (6-96 hours): weather forecasts are a must have!



Numerical Weather Prediction

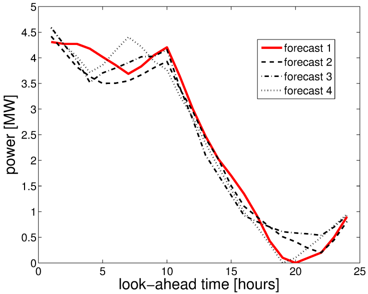
- Future values of meteorological variables (wind, temperature, etc.) on a grid
- Temporal/spatial resolution, domain, forecast update and forecast length vary depending upon the NWP system
- Large number of alernative system today (global, mesoscale, etc.) providing free or commercially available output.

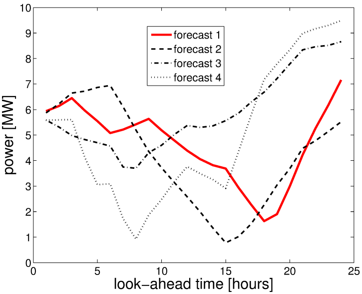


- **Origins of uncertainty in NWPs**: initial state, model/physics, numerical aspects (filtering)

Predictability of meteorological variables

- A large part of the prediction error directly comes from prediction of weather variables
- This uncertainty in the meteorological forecast is then amplified or dampened by the power curve (model)

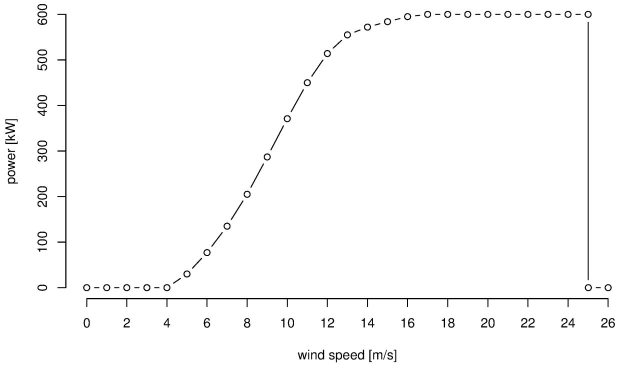




Typical representation of what could be more and less easily predictable situations...

The manufacturer power curve

- Power curve of the Vestas V44 turbine (600 kW)

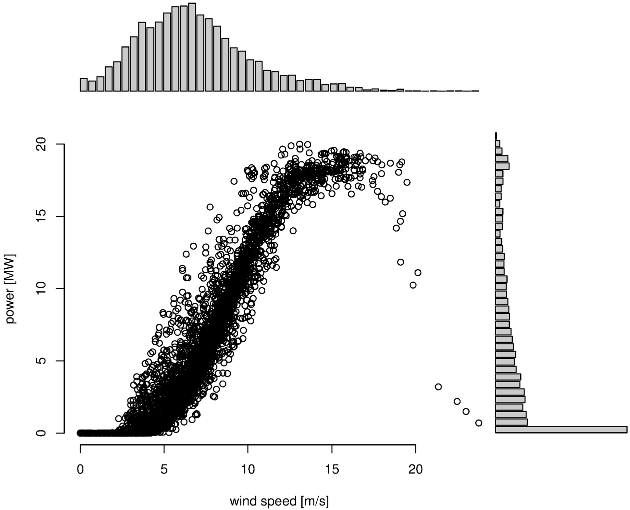


- **Klim wind farm** (North of Jutland, Denmark): 35 V44 turbines
- **Nominal capacity**: 21 MW
- Straightforward scaling of the power curve from 600kW to 21MW!

The *actual* power curve looks different!

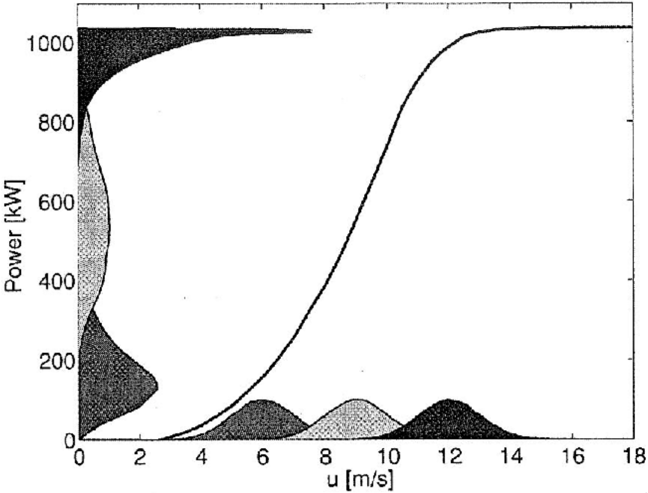
Origins of uncertainty in the conversion process:

- actual meteorological conditions seen by turbines,
- aggregation of individual curves,
- non-ideal power curves,
- etc.



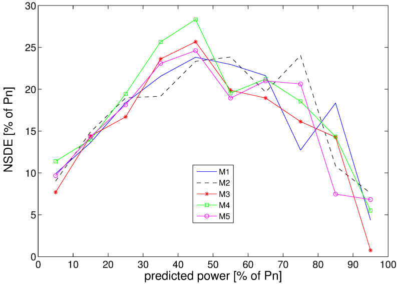
Shaping forecast uncertainty

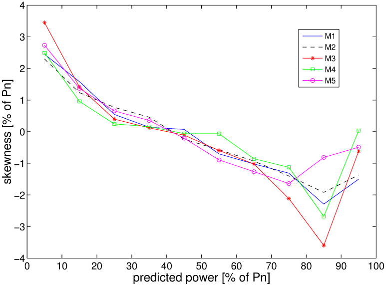
courtesy of Matthias Lange



Resulting characteristics of error distributions

The power curve of a wind farm shapes the distributions of prediction errors



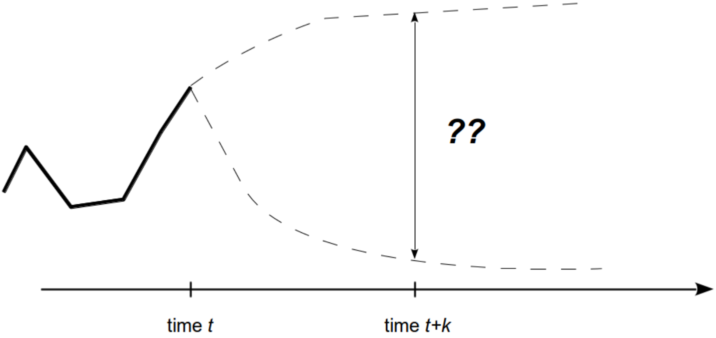


the above example involves 5 different approaches to point prediction, for the same site, over the same period and with the same inputs...

3. **From deterministic to probabilistic forecasts**

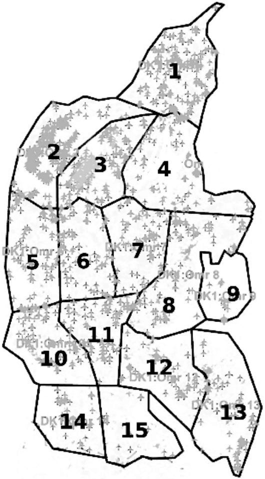
Forecast setup: Forecasting is about the future!

- The practical setup:
  - we are at time t (e.g., at 11am, placing offers in the market)
  - and interested in what will happen at time $t + k$ (any market time unit of tomorrow, e.g., 12-13)
  - **k is referred to as the lead time**
  - Y_{t+k}: the random variable "power generation at time $t + k$"



- A forecast is an estimate for time $t + k$, conditional to information up to time t...
- **This motivates the notation** $\hat{\cdot}_{t+k|t}$

For illustration: the Western Denmark dataset



Agg. zone	Orig. zones	% of capacity
1	1, 2, 3	31
2	5, 6, 7	18
3	4, 8, 9	17
4	10, 11, 14, 15	23
5	12, 13	10

Figure: The Western Denmark dataset: original locations for which measurements are available, 15 control zones defined by Energinet, as well as the 5 aggregated zones, for a nominal capacity of around 2.5 GW.

Point forecast: definition

A point forecast informs of the conditional expectation of power generation

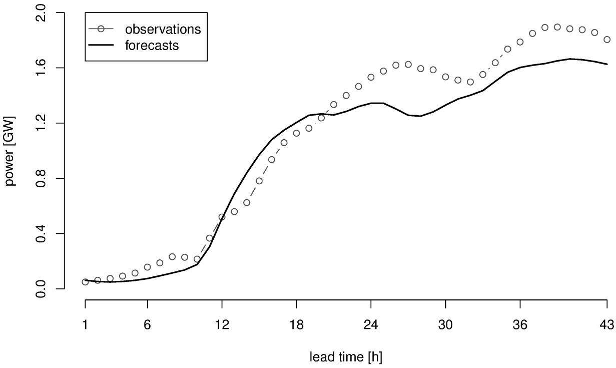
Mathematically:

$$\hat{y}_{t+k|t} = \mathbb{E}[Y_{t+k}|\Omega, M, \hat{\theta}]$$

given

- the information set Ω
- a model M
- its estimated parameters $\hat{\theta}$

at time t



(Ω, M, $\hat{\theta}$ omitted in other definitions)

Point forecasting

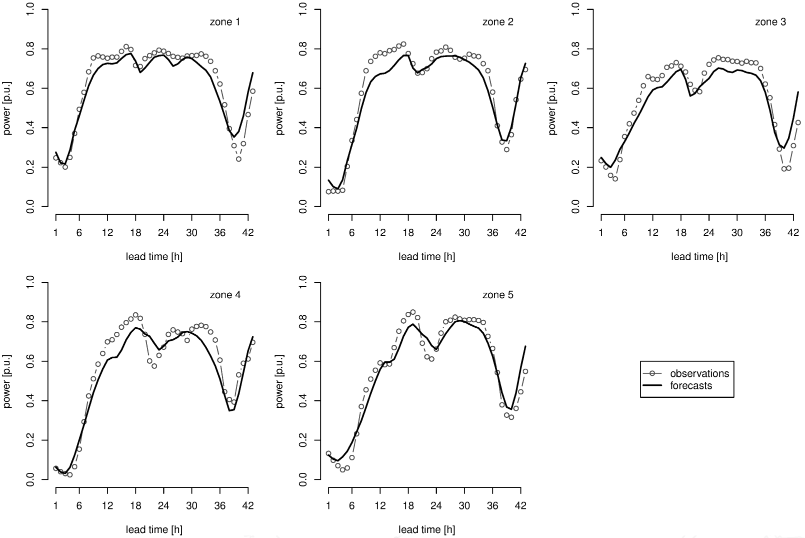


Figure: Example episode with point forecasts for the 5 aggregated zones of Western Denmark, as issued on 16 March 2007 at 06 UTC, along with corresponding power measurements, obtained a posteriori.

Quantile forecast: definition

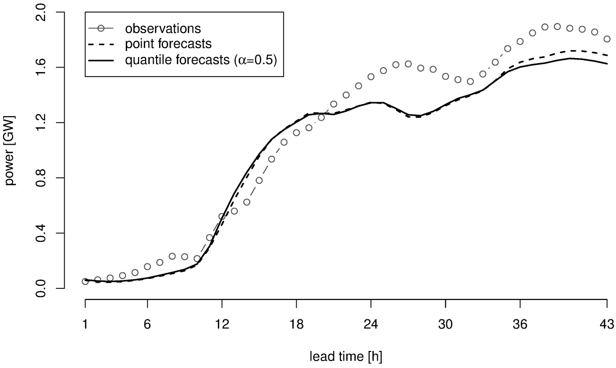
A quantile forecast is to be seen as a probabilistic threshold for power generation

Mathematically:

$$\hat{q}^{(\alpha)}_{t+k|t} = \hat{F}^{-1}_{t+k|t}(\alpha)$$

with

- α: the nominal level (ex: 0.5 for 50%)
- $\hat{F}$: (predicted) cumulative distribution function for Y_{t+k}



Prediction interval: definition

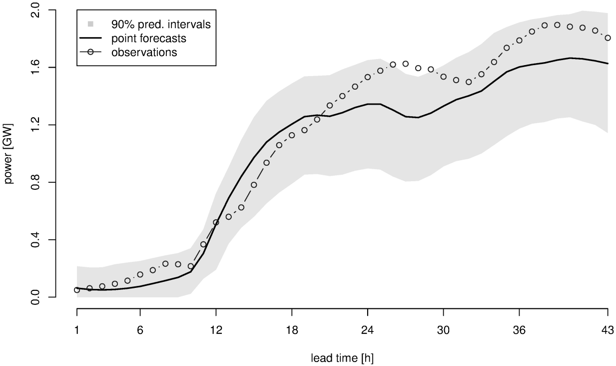
A prediction interval is an interval within which power generation may lie, with a certain probability

Mathematically:

$$\hat{I}^{(\beta)}_{t+k|t} = \left[\hat{q}^{(\underline{\alpha})}_{t+k|t},\ \hat{q}^{(\overline{\alpha})}_{t+k|t}\right]$$

with

- β: nominal coverage rate (ex: 0.9 for 90%)
- $\hat{q}^{(\underline{\alpha})}_{t+k|t}$, $\hat{q}^{(\overline{\alpha})}_{t+k|t}$: interval bounds
- $\underline{\alpha}$, $\overline{\alpha}$: nominal levels of quantile forecasts



Predictive densities: definition

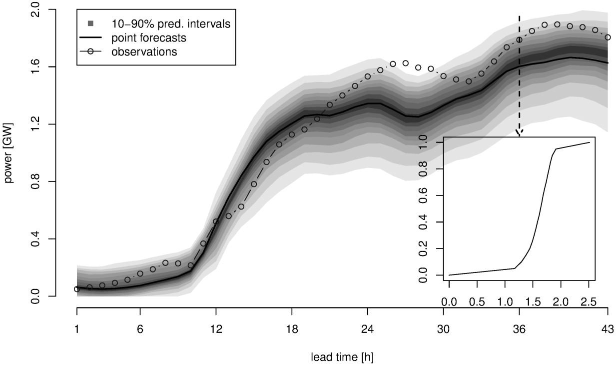
A predictive density fully describes the probabilistic distribution of power generation for every lead time

Mathematically:

$$Y_{t+k} \sim \hat{F}_{t+k|t}$$

with

- $\hat{F}_{t+k|t}$: cumulative distribution function for Y_{t+k} (predicted given information available at time t)



Predictive densities

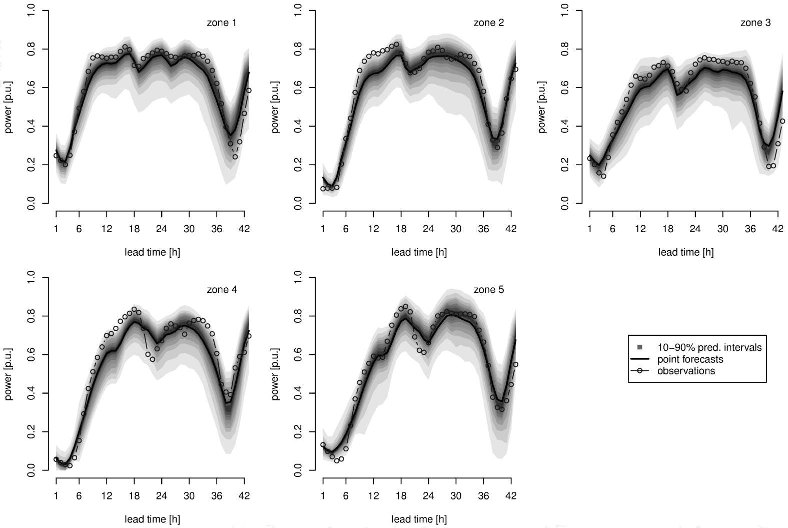
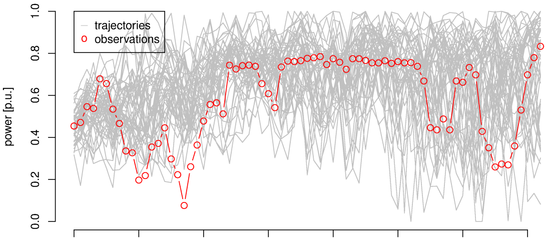


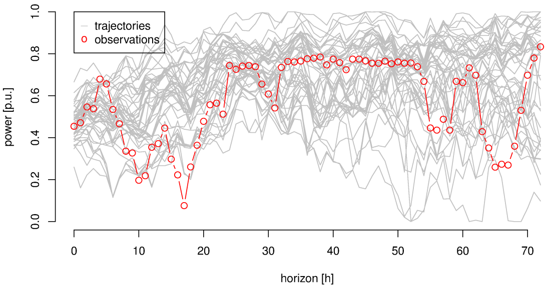
Figure: Example episode with probabilistic forecasts for the 5 aggregated zones of Western Denmark, as issued on 16 March 2007 at 06UTC. They take the form of so-called river-of-blood fan charts, represented by a set of central prediction intervals with increasing nominal coverage rates (from 10% to 90%).

The conditional importance of correlation

- almost no temporal correlation



- appropriate temporal correlation



Trajectories (/scenarios): definition

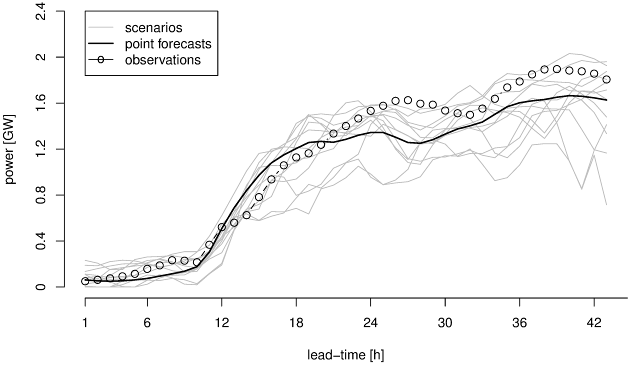
Trajectories are equally-likely samples of multivariate predictive densities for power generation (in time and/or space)

Mathematically:

$$z_t^{(j)} \sim \hat{F}_t$$

with

- $\hat{F}$: multivariate predictive cdf for $\mathbf{Y}_t$
- $z_t^{(j)}$: the j^{th} trajectory



Space-time trajectories (/scenarios)

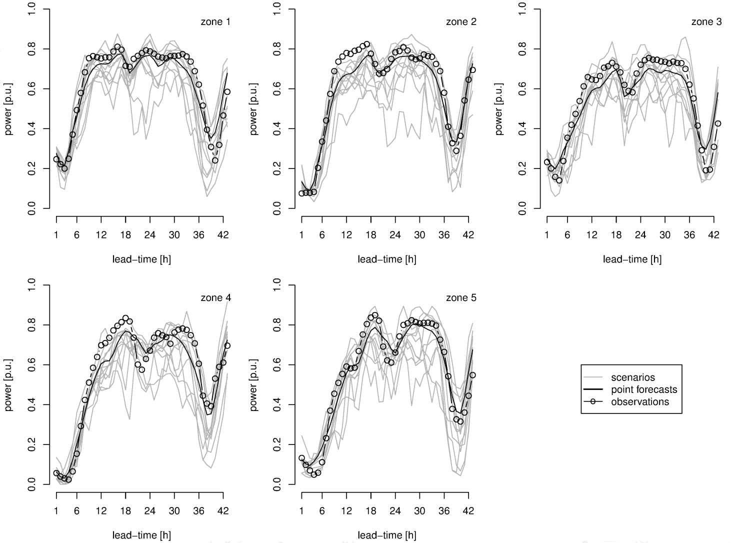


Figure: Spatio-temporal scenarios of wind power generation for the 5 aggregated zones of Western Denmark, issued on the 16 March 2007 at 06 UTC.

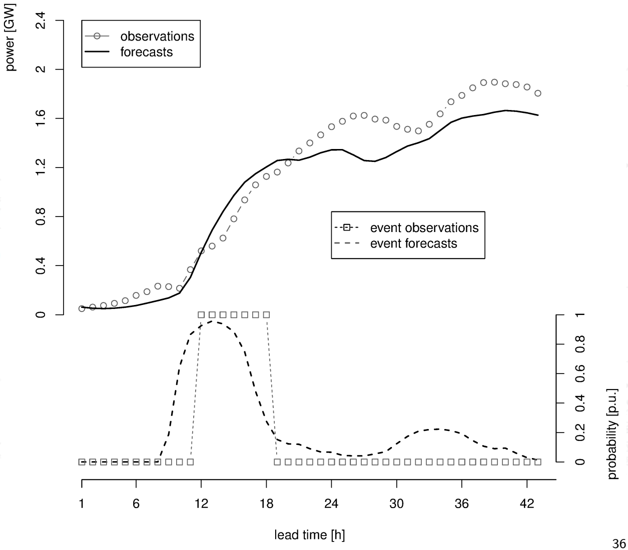
Bonus track: event-based forecasts!

Some decision-makers only want forecasts for user defined events

Examples are:

- ramp forecasts
- high-variability forecasts
- etc.

On the right: **probability of ramp forecasts (more than 500 MW swing in 6 hours)!**



Final remarks

- **Uncertainty is a key feature** of all renewable energy forecasts
- Lots of **different types of forecasts** inform of uncertainty, depending upon:
  - what they are to be used for
  - the expertise/feeling of the decision-maker
  - computing power available
- Approaches to characterizing, modelling and forecasting uncertainty in the following lectures...
- Before to generate forecasts, one should know how to verify(/evaluate) them!

Thanks for your attention! - Contact: ppin@dtu.dk - web: www.pierrepinson.com