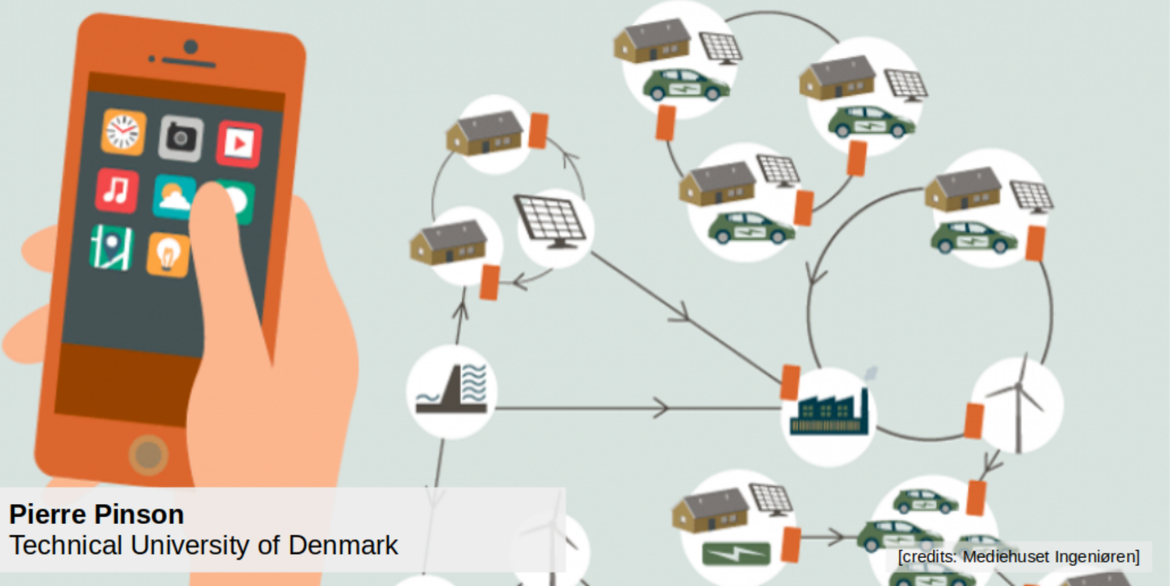
Module 9 – Renewable Energy Forecasting: First Steps

9.1 Generalities and benchmark approaches



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Basis for the lecture(s)

Wind Energy

Wave Energy (same ideas can be used)

... *Also for* **Solar Energy**, *the same concepts can be applied!*

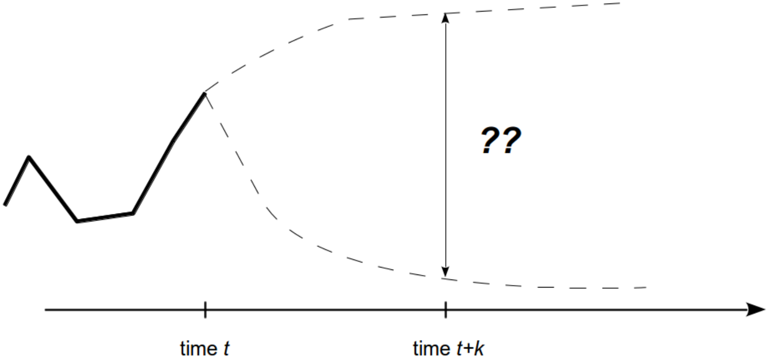
Test case: the Klim wind farm

- The wind farm:
  - *full name*: Klim Fjordholme
  - *onshore/offshore*: onshore
  - *year of commissioning*: 1996
  - *nominal capacity* (P_n): 21 MW
  - *number of turbines in farm*: 35
  - *average annual electricity generation*: 49 GWh
  - *data available*: 1999-2003 (for some researchers)
  - *temporal resolution*: 5 mins, and hourly averages
  - *weather forecasts*: wind speed and direction, temperature
- A link to the online description:
  Vattenfall's Klim wind farm
- The wind farm was rerecommissioned a few years ago

Remember that we normalize power generation - in practice, $y_t \in [0, 1], \ \forall t$

General considerations

- Forecasting is about the future! Lead times within 0-48 hours, in line with market-based operations
- When being at time t and aiming to generate a forecast for time $t+k$, **only knowledge available at time t can be used...**
  - observations up to time t: power generation, meteorological measurements, etc.
  - weather forecasts for the period of interest



- Since forecasts **will always have a part of error**, just accept, and *try to minimize it*

No need to make it difficult...

What is the easiest way to predict wind power generation?

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What is the easiest way to predict wind power generation?

- Data-free approaches:
  - *making random guesses* (it could actually work...)
  - *making* **educated** *guesses* (works fine in certain places and seasons, e.g., summer in Crete, all-year-round in Egypt)

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What is the easiest way to predict wind power generation?

- Data-free approaches:
  - *making random guesses* (it could actually work...)
  - *making* **educated** *guesses* (works fine in certain places and seasons, e.g., summer in Crete, all-year-round in Egypt)

- Data-based approaches:
  - *persistence*
  - *climatology*
  - *simple statistical models, etc.*

The random guess approach

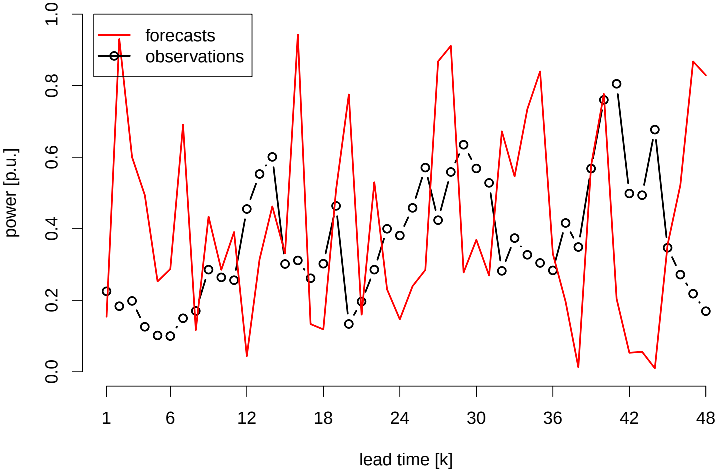
- At time t, we make a **random guess** for all lead times $t+k$, $k = 1, \ldots, 48$

- This translates to

$$\hat{y}_{t+k|t} = u_k, \ \forall k,$$

where $u_k \sim \mathcal{U}[0,1]$

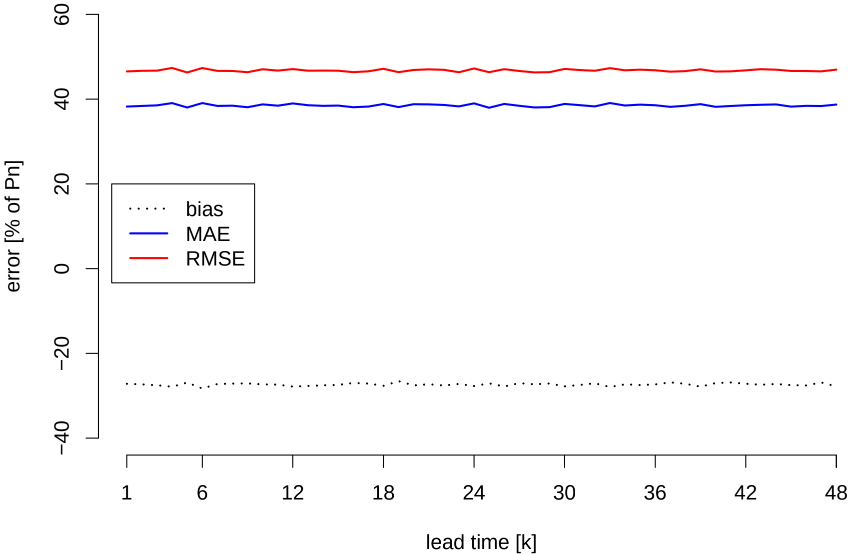
- *Right:*
Example of **random guess forecast** for Klim, issued on 28 April 2002, 00:00UTC



- Let us apply that forecast strategy for a whole sample year (2002), and analyse its performance...

Evaluation of the random guess approach

- The quality of the forecasts is summarized in terms of **bias**, **MAE** and **RMSE**



How does that look like?

The persistence approach

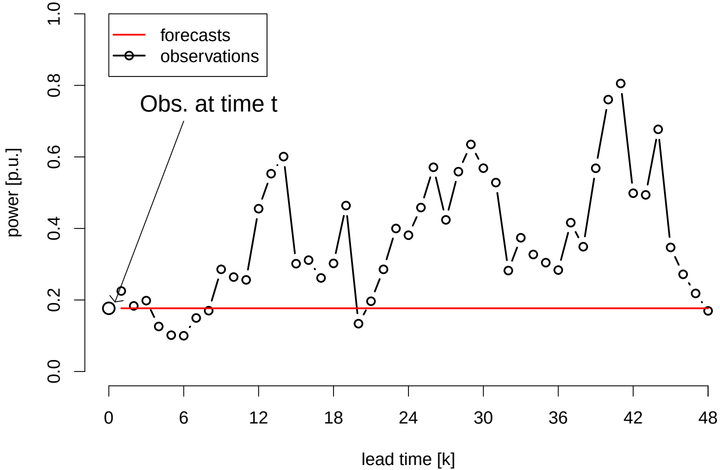
- At time t, the **persistence** forecast (*"what you see is what you get"*) for all lead times $t+k$, $k=1,\ldots,48$ is based on the idea that *your best guess is your latest piece of information*...

- This translates to

$$\hat{y}_{t+k|t} = y_t, \ \forall k,$$

  where y_t is the latest measurement available

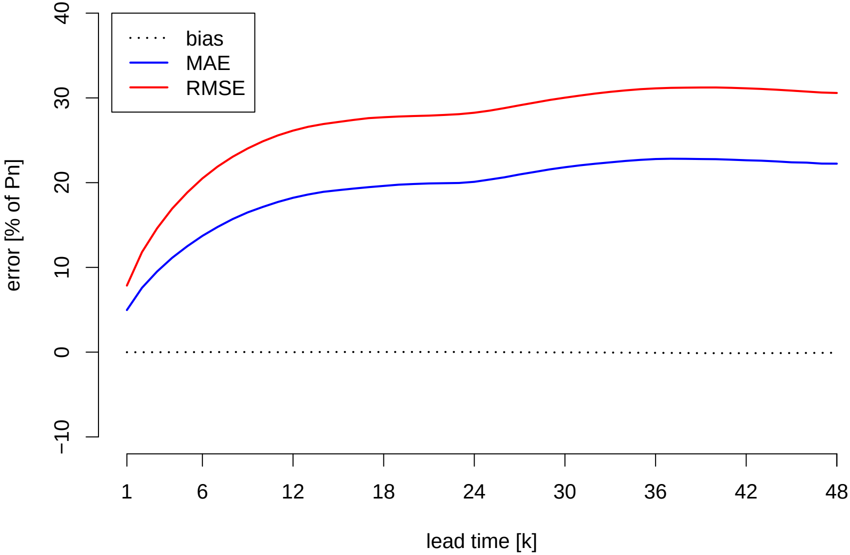
- *Right:*
  Example of a **persistence** forecast for Klim, issued on 28 April 2002, 00:00UTC



- Let us similarly apply that strategy for a whole sample year (2002), and analyse its performance...

Evaluation of the persistence approach

- Similar scores: **bias**, **MAE** and **RMSE**



- Such score values can be explained by the “inertia” in wind power dynamics

A generalization: m-point averaging approach

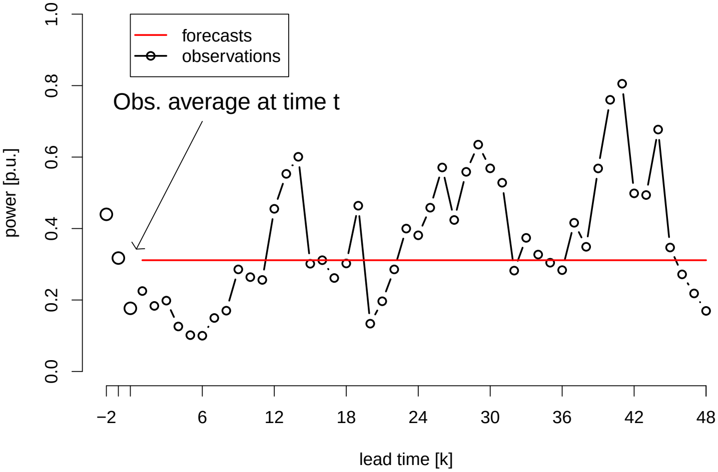
- There might be a gain in considering more than the last observation only...
- At time t, the m-**point averaging** forecast, for all lead times $t+k$, $k = 1, \ldots, 48$, is based on an *average of recent information*

- This translates to

$$\hat{y}_{t+k|t} = \sum_{i=1}^{m} y_{t-i}, \quad \forall k,$$

  where y_{t-i} is the i^{th} latest measurement available

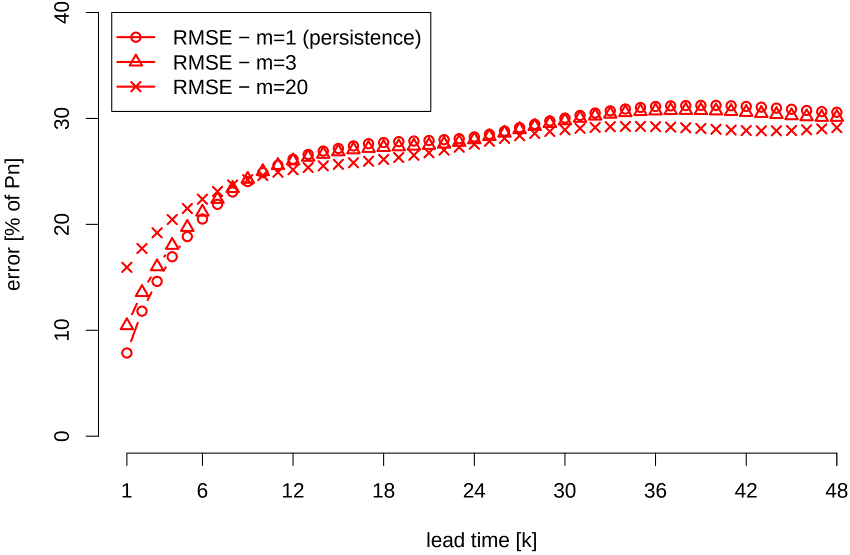
- *Right:*
  Example of a m-**point averaging** (with $m = 3$) forecast for Klim, issued on 28 April 2002, 00:00UTC



- Let us similarly apply that strategy for a whole sample year (2002), and analyse its performance...

Evaluation of the *m*-point averaging approach

- Focus on **RMSE** only



- There is a compromise to be made between short-term and longer-term forecast quality

The limiting case: Climatology

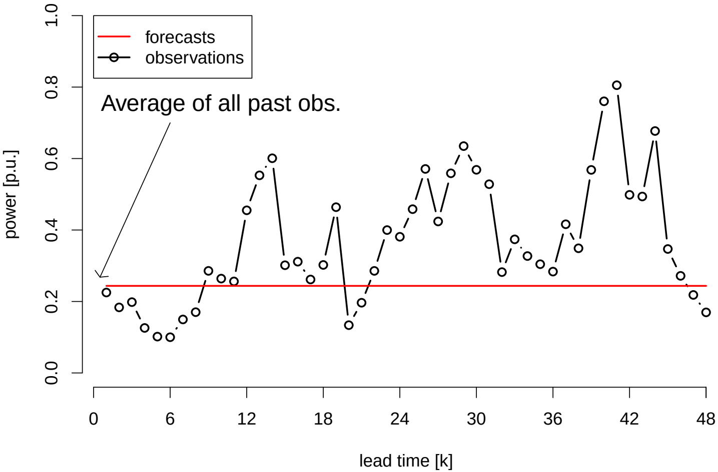
- Climatology is for the case where $m \to \infty$
- At time t, the **climatology** forecast, for all lead times $t+k$, $k = 1, \ldots, 48$, is based on an *average of all information ever available* (= wind farm capacity factor)

- This translates to

$$\hat{y}_{t+k|t} = \sum_{i=1}^{\infty} y_{t-i}, \quad \forall k,$$

  where y_{t-i} is the i^{th} latest measurement available

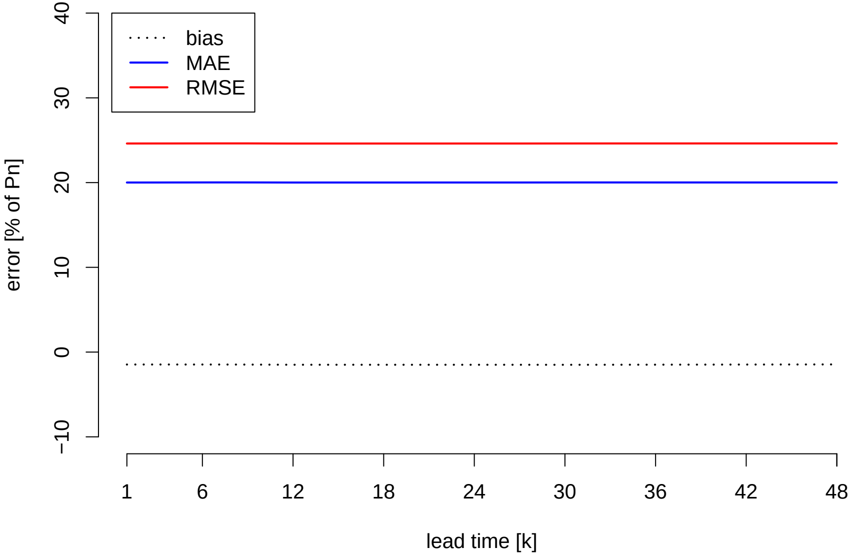
- *Right:*
  Example of a **climatology** forecast for Klim, issued on 28 April 2002, 00:00UTC



- Let us similarly apply that strategy for a whole sample year (2002), and analyse its performance...

Evaluation of the climatology forecast approach

- Similar scores: **bias**, **MAE** and **RMSE**



- So, it is like random guessing, but somewhat better!

A few conclusions at this stage

- Even though these forecasting strategies do not look very smart...
- **They are difficult to beat!**
- Especially:
  - *Persistence* is difficult to outperform for lead times between *0 and 6 hours* ahead
  - *Climatology* is difficult to outperform for the furthest lead times (say, *after 24 hours* ahead)

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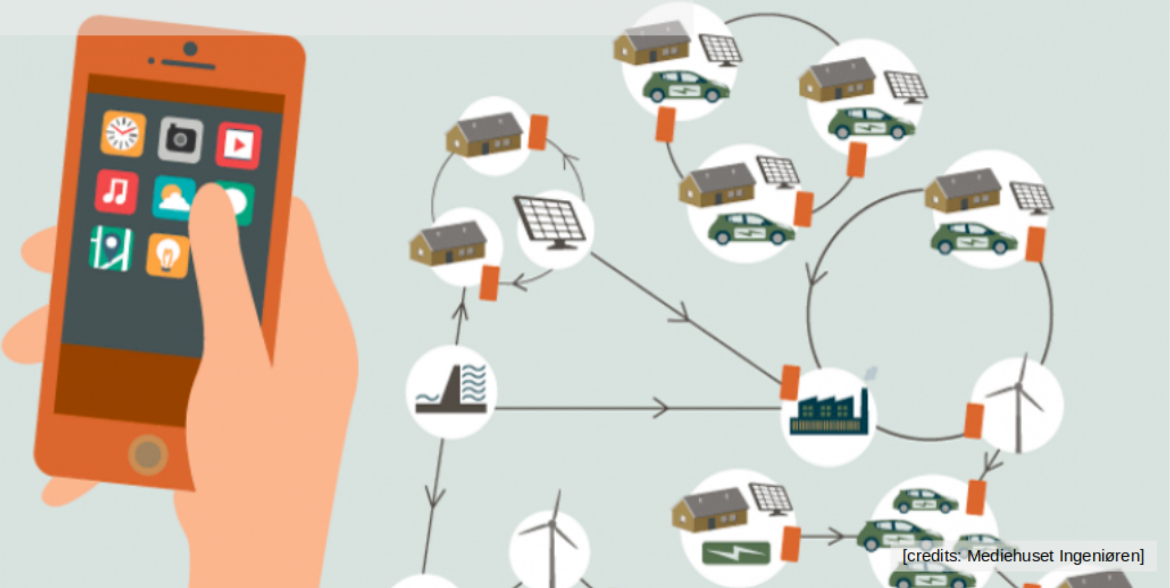
- Even though these forecasting strategies do not look very smart...
- **They are difficult to beat!**
- Especially:
  - *Persistence* is difficult to outperform for lead times between *0 and 6 hours* ahead
  - *Climatology* is difficult to outperform for the furthest lead times (say, *after 24 hours* ahead)
- Still, **we may be able to do something better**
  - based on more *dynamic approaches*
  - *extracting more information* within available data

Use the self-assessment quizz to check your understanding!



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