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...)
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- **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 $u_k \sim U[0, 1]$

- **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
  \[
  \hat{y}_{t+k|t} = y_t, \quad \forall k,
  \]
  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: \textit{m}-point averaging approach

- There might be a gain in considering more than the last observation only...
- At time $t$, the \textbf{m-point averaging} forecast, for all lead times $t + k$, $k = 1, \ldots, 48$, is based on an \textit{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 $i$\textsuperscript{th} latest measurement available

\textbf{Right:}
- Example of a \textbf{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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- Still, **we may be able to do something better**
  - based on more *dynamic approaches*
  - *extracting more information* within available data
Use the self-assessment quiz to check your understanding!