Wind power forecast, toward spatio-temporal modeling

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Content

Wind power and spatio-temporal modeling: a small tour
State of the art in wind power forecasting
The SafeWind Project
Spatio-temporal modeling of wind power: what for?

Exploratory analysis of forecast errors: Propagation?
Case study
Propagation and empirical correlation structure
Propagation and meteorological conditions
Propagation and planar wave model

Forecasting, the benefit of Spatio-temporal models (On going work)
Alerting for large variation of wind power production
Forecasting wind power production
**Content**

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Why do we forecast wind power for?

Power forecast (few hours up to days in advance) and associated uncertainty.

1. Transmision system operator
   - Network security
   - Scheduling/unit commitment \((D - 3 \rightarrow 1)\)
   - Primary and secondary reserves allocation \((D - 1)\)
   - Maintenance plannification \((D - 4)\)
   - Exchange plannification

2. Producer’s point of view
   - Maintenance Plannification
   - Participation to the electricity market.
The “PC Model”.

In theory, wind power production is related to wind speed through the **Power Curve**:

The PC model uses this power curve to transform meteorological forecast into power.
The “PC Model”.

In theory, wind power production is related to wind speed through the Power Curve:

![Power Curve Diagram](image)

Difficulty: the power curve is not perfect, neither is the wind forecast
The “PC Model”.

In theory, wind power production is related to wind speed through the **Power Curve**:

![Power Curve](image)

Also, even the measurement can be of bad quality: can you identify in the Figure: cut-off, downregulation, curtailment, maintenance, anemometer breakdown?
The wind power forecast

\[ \hat{P}_{t+h|t} = f_h(P_t, \ldots, P_{t-l}, NWP_{t+h|t}, \text{Meas}_t) \]
The wind power forecast

\[ \hat{P}_{t+h|t} = f_h(P_t, \ldots, P_{t-l}, NWP_{t+h|t}, \text{Meas}_t) \]

Numerical weather prediction \( NWP_{t+h|t} \) of wind (speed and direction), as well as other weather parameters...

- If grid point are not located by the wind farm \( \Rightarrow \) nearest point, interpolation of met field ...
- The choice of the model \( \Rightarrow \) Mesoscale ? global model? combination of many different models ?
- Problem of meteorological updates, granularity of horizons \( \Rightarrow \) interpolation.

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The wind power forecast

\[ \hat{P}_{t+h|t} = f_h(P_t, \ldots, P_{t-l}, NWP_{t+h|t}, Meas_t) \]

Numerical weather prediction $NWP_{t+h|t}$ of wind (speed and direction), as well as other weather parameters...

- If grid point are not located by the wind farm $\Rightarrow$ nearest point, interpolation of met field ...
- The choice of the model $\Rightarrow$ Mesoscale ? global model? combination of many different models ?
- Problem of meteorological updates, granularity of horizons $\Rightarrow$ interpolation.

Other measures $Meas_t$:

- Meteorological synoptic stations, “upwind”
- Other measurement, for example from other wind farms.
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Path toward The SafeWind project (1/3)

Public final workshop the 31\textsuperscript{th} of August (send me an email for more info robin.girard@mines-paristech.fr).
Path toward The SafeWind project (1/3)

HIGHLIGHT PROJECTS:

ANEMOS: FP5, 2002-2006

ANEMOS.plus: FP6, 2008-2011

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Path toward The SafeWind project (1/3)

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The SafeWind project (2/3)

The SafeWind Consortium

The SafeWind project (2/3)

The SafeWind Consortium

The SafeWind project (2/3)

The SafeWind Consortium

2008-2012

9 countries, 22 partners
End-users
Industry
Research
Universities
Meteorologists

Budget: 5.6 Mio €
Duration: 4 years
Resources: 512 PMs
The SafeWind project: S& T Objectives (3/3)

Improve wind predictability with focus on extremes:

- at various **temporal scales**:
  - Very short-term (order of 5 min)
  - Short term (hours to days)
  - Longer term (beyond few days ahead)

- at various **spatial scales**:
  - **local scale**: Extreme gusts or shears.
  - **regional scale**: Extreme events (like thunderstorms) can cause the loss of significant amounts of wind energy with potential impact on the grid management.
  - **continental (European) scale**: Extreme weather situations (like fronts) can propagate causing impacts in different member states.
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Forecasting, the benefit of Spatio-temporal models (On going work)
Wind power forecast and meteorological models

- Power measurement every 10-15 minutes
- Met measurement frequency: 1 to 3 hours
Wind power forecast and meteorological models

- Power measurement every 10-15 minutes
- Met measurement frequency: 1 to 3 hours
- Most operational met models have 6 hourly updates, 3 hourly is possible, research about “rapid update”.

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Wind power forecast and meteorological models

- Power measurement every 10-15 minutes
- Met measurement frequency: 1 to 3 hours
- Most operational met models have 6 hourly updates, 3 hourly is possible, research about “rapid update”.
- Below: M1 to M3: with NWP and Measurement as input. M4 and M5 only NWP as input.

![Graph showing normalized mean absolute error of wind power forecast over look-ahead time]
Spatio-temporal patterns in errors

- Forecast errors propagating in Denmark
- Is there something significant that can be said about this propagation?
- Modeling this can be useful for
  - Network design (Power flow constraint), Reserve sizing, ...
  - Analysis of future market with nodal prices, optimal portfolio configuration
  - Improving forecast for up to 6 hours ahead.
Network of sensors

- More than 5000 turbines installed across Denmark
- Temporal resolution of $10 - 15$ min \(\rightarrow\) How to assimilate those data?
- A meteorological system might pass through Denmark in 1 hour.
- Alerting?
Netwok of sensors

- More than 500 wind farms installed across France
- Temporal resolution of 10 – 15 min → How to assimilate those data?
- A meteorological system might pass through France in few hours to a day.
- Alerting?
Content

Wind power and spatio-temporal modeling: a small tour

Exploratory analysis of forecast errors: Propagation ?
  Case study
  Propagation and empirical correlation structure
  Propagation and meteorological conditions
  Propagation and planar wave model

Forecasting, the benefit of Spatio-temporal models (On going work)
Case study and objectives

- **Case Study:**
  - Transformation stations assimilated as wind farms
  - Wind farms 23 and 25 are more specifically studied.
  - Red X is the grid point with met data
  - Errors $\epsilon_{t+h|t}^p$ are given

Joint work with D. Allard, to be published in Wind Energy Journal
Case study and objectives

Case Study:
- Transformation stations assimilated as wind farms
- Wind farms 23 and 25 are more specifically studied.
- Red X is the grid point with met data
- Errors $e_{t+h|t}^p$ are given

Objectives:
- Describe errors through their spatio-temporal characteristics.
- Prepare further modeling, conditionally to meteorological situation.

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Forecasting, the benefit of Spatio-temporal models (On going work)
Characterization of the dependence structure at two distant wind farms

- \((\epsilon_{t+15}^{25}, \epsilon_{t+h}^{23})\) is not bi-gaussian.
- It has a strong negative mode (density represented below, red point is the mean).
Characterization of the dependence structure at two distant wind farms

- $(\epsilon_{t+15|t}^{25}, \epsilon_{t+h|t}^{23})$ is not bi-gaussian.
- It has a strong negative mode
- $y = f(x) = E[\epsilon_{t+h|t}^{23} | \epsilon_{t+15|t}^{25} = x]$ is almost monotone, not linear.

\begin{align*}
  y &= E[\epsilon_{t+15|t}^{23} | \epsilon_{t+15|t}^{25} = x] \\
  y &= E[\epsilon_{t+60|t}^{23} | \epsilon_{t+15|t}^{25} = x] \\
  y &= E[\epsilon_{t+90|t}^{23} | \epsilon_{t+15|t}^{25} = x] \\
  y &= E[\epsilon_{t+180|t}^{23} | \epsilon_{t+15|t}^{25} = x]
\end{align*}
Characterization of the dependence structure at two distant wind farms

- \( (\epsilon_{t+15|t}, \epsilon_{t+h|t}) \) is not bi-gaussian.
- It has a strong negative mode
- \( y = f(x) = E[\epsilon_{t+h|t} | \epsilon_{t+15|t} = x] \) is almost monotone, not linear.
- The local maximum (along look ahead times) \( \Rightarrow \) propagations.

![Exploratory analysis of forecast errors: Propagation?](image-url)

Characterization of the dependence structure at two distant wind farms
Characterization of the dependence structure at two distant wind farms

- \((\epsilon_{t+15}^{25}, \epsilon_{t+h}^{23})\) is not bi-gaussian.
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- \(y = f(x) = E[\epsilon_{t+h}^{23} | \epsilon_{t+15}^{25} = x]\) is almost monotone, not linear.
- The local maximum (along look ahead times) \(\rightarrow\) propagations.

- Here WF 25 is said to be “upwind” to WF 23 denoted \(WF\ 23 \prec WF\ 25\).
Propagation time, Along the whole test case

- Propagation time $T(p_1, p_2)$ can be defined for any pair of WF $(p_1, p_2)$ (here represented from WF 49 (with negative value when $p < WF 49$))
Propagation time, Along the whole test case

- Propagation time $T(p_1, p_2)$ can be defined for any pair of WF $(p_1, p_2)$
- The strength of the “propagated” errors decreases with distance
Propagation speed (scalar)

- Propagation speed

\[ v(p_1, p_2) = \frac{d(p_1, p_2)}{T(p_1, p_2)} \text{ if } p_1 \prec p_2, \]  

(1)

Global spatial average for all pairs "directed" with angle \( \theta \):

\[ V(\theta) = \frac{\sum_{i,j} v(p_i, p_j) \chi(p_i, p_j)}{\sum_{i,j} \chi(p_i, p_j)}, \]  

(2)

where \( \chi(p_i, p_j) = 1 \text{ if } p_i \prec p_j, \angle(p_i, p_j) \in (\theta - \delta \theta, \theta + \delta \theta) \), and \( \chi(p_i, p_j) = 0 \text{ otherwise}. \)

Signed spatial average \( V_s(\theta) \):

\[ \chi(p_i, p_j) = \begin{cases} 
1 & \text{if } p_i \prec p_j \text{ and } \angle(p_i, p_j) \in (\theta - \delta \theta, \theta + \delta \theta) \\
-1 & \text{if } p_i \prec p_j \text{ and } \angle(p_i, p_j) + \pi \in (\theta - \delta \theta, \theta + \delta \theta) \\
0 & \text{otherwise} \end{cases} \]  

(3)
Propagation speed (scalar)

- Propagation speed

\[ v(p_1, p_2) = \frac{d(p_1, p_2)}{T(p_1, p_2)} \text{ if } p_1 \prec p_2, \quad (1) \]

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- Global spatial average for all pairs “directed” with angle \( \theta \):
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- Signed spatial average \( V^s(\theta) \):
  \[ \chi(p_i, p_j) = \begin{cases} 
  1 & \text{if } p_i \prec p_j \text{ and } \\
  -1 & \text{if } p_i \prec p_j \text{ and } \\
  0 & \text{otherwise}
  \end{cases} \text{ if } \angle(p_i, p_j) + \pi \in (\theta - \delta\theta, \theta + \delta\theta) \]  
  (3)
Propagating speed (scalar)

- Velocity and direction of propagation of maximum correlation, from all wind farms.
- Left: $V(\theta)$ and $V^s(\theta)$ as a function of $\theta$.
- Right: maximum correlation $\rho_{max}(p_1, p_2)$ with a color scale as a function of the vector $p_1 - p_2$, the corresponding propagation time $T(p_1, p_2)$ is represented on the same graph in minutes with level set contour lines.

![Graph showing velocity and direction of propagation](image1)

![Graph showing maximum correlation](image2)
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Forecasting, the benefit of Spatio-temporal models (On going work)
Propagation conditionnallly to wind (direction and speed)

Global average propagation speed (vector):

$$
\vec{V} = \frac{1}{\pi} \int_{-\pi/2}^{\pi/2} V^s(\theta) \vec{u}_\theta \, d\theta
$$

(4)

where $\vec{u}_\theta$ is the unit vector in direction $\theta$. 

![Graph showing propagation direction and speed](image-url)
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Alternative definition of propagation

- Planar wave model:

\[
\epsilon_{t+h|t}^p = f_t(p - \vec{v}_t(h - 15)) + \eta_{t+h|t}^p
\]  
(5)

- \(\vec{v}_t\) the propagation speed vector
- \(\eta_{t+h|t}^p\) a centered noise
- \(f_t(\cdot)\) “shape” function

- For a fixed speed vector \(\vec{v}_t\), \(f_t(\cdot)\) defined by:

\[
\min_{f_t \in F} \sum_{h=1}^{H} \sum_{p \in P} \left( \epsilon_{t+h|t}^p - f_t(p - \vec{v}_t(h - 15)) \right)^2
\]  
(6)

- “best speed vector” that maximizes the fit’s quality:

\[
R^2(\vec{v}_t) = 1 - \frac{\sum_{h=1}^{H} \sum_{p \in P} \left[ \epsilon_{t+h|t}^p - \hat{f}_t(p - \vec{v}_t(h - 15)) \right]^2}{\sum_{h,p} \left( \epsilon_{t+h|t}^p - \bar{\epsilon}_{t+.|t} \right)^2}, \quad (7)
\]
**Propagation speeds**

Planar wave modeling with only east-west propagation considered.

**Figure:** Average propagation speeds for 4 different maximum look ahead times: $H = 90$ minutes, dashed-dotted lines; $H = 120$ minutes, dotted lines; $H = 150$ minutes, dashed lines; $H = 180$ minutes, solid lines. Propagation speed maximizes the fit in the East-West propagation model given by Equation 5.
Content

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Exploratory analysis of forecast errors: Propagation?

Forecasting, the benefit of Spatio-temporal models (On going work)
  Alerting for large variation of wind power production
  Forecasting wind power production
“Ramp” of wind power production: Definition

Filtering

n ~ temporal scale

Thresholding

Detected Ramp support
“Ramp” of wind power production: Definition

Filtering

\[ n \sim \text{temporal scale} \]

Thresholding

- intensity
- timing \( t \)
- support
Other possible definitions

- Use a smoother filter (for example gaussian filtering).
  - More robust,
  - Less easy to understand.
- Take the difference between min and max in a window of a given size
  - Easier to understand
  - Lack of robustness
Temporal uncertainty

Example of forecasts

![Graph showing observations and control forecast]

- Power [% of Nominal Power]
- Observations
- Control forecast
- 39 members

Toward Spatio-temporal uncertainty?
Temporal uncertainty

Example of forecasts

Power [% of Nominal Power]

0 10 20 30 40 50 60 70 80 90 100

0 3 6 9 13 17 21 25 29 33 37 41 45 53 57 61 65 69

70% 61% 39% 40% 30% 20%

observations control forecast

39 members 15 members

Toward Spatio-temporal uncertainty?
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Reference model:

\[
\log \left( \frac{p}{1 - p} \right) = \alpha + \beta \hat{f}
\]

\( p \): probability of ramp

\( \hat{f} \): filtered forecast production

Spatio-temporal model:

\[
\log \left( \frac{p}{1 - p} \right) = \alpha + \beta \hat{f} + \sum_i \gamma_i \hat{q}_i(l - vi)
\]

\( \hat{q}_i(l - vi) \): forecast quantile of filtered forecast production with temporal lag \( i \) at longitude \( l - vi \).
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Obtained results (1h ahead)

Further work:

- Adaptive estimation of propagation speed (with meteorological parameters).
Content

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Forecasting wind power production
Case study

We considered 2 case studies with power measurements $p_t^x$

- In Denmark 41 locations, almost 6 years
- In Ireland 7 locations almost 2 years
Case study

We considered 2 case studies with power measurements $p_t^x$

- In Denmark 41 locations, almost 6 years
- In Ireland 7 locations almost 2 years

3 different models (for a given horizon $h$):

- **Model 1**, $\hat{p}_{t+h}^x = c + \sum_{l=0}^{10} a_l p_{t-l}^x$
- **Model 2**, $\hat{p}_{t+h}^x = c + \sum_y \sum_{l=0}^{10} a_{l,y} p_{t-l}^y$
- **Model 3** $\hat{p}_{t+h}^x = c + \sum_y \sum_{l=0}^{10} a_{l,y} (WD) p_{t-l}^y$

Algorithm for fitting:

- Model 1 and 2 are fitted with least square.
- Model 2 when the number of sites is large is fitted by a penalized weighted least square (lasso).
- Model 3 is fitted with a weighted least square (exponential weights function of $WD$)
Obtained results in Ireland: Case study

[Map of Ireland with markers indicating power plants or measurement points]
Obtained results in Ireland

Figure: Left: Obtained improvement with Model 2 over Model 1. Right: Obtained improvement on Model 3 over Model 1.
Obtained results in Denmark

Figure: Left: Obtained improvement with Model 2 over Model 1. Right: Considered region with transformation stations. Color is a function of latitude (red is east and blue is west)
Further Work

- Denmark case conditionally to wind direction
- Whole Danmark case with a propagation modeling, conditionally to meteorological information (i.e. WS, WD measurement).
- Local conditionning.

**Figure:** Left: around 5000 Turbines in Denmark. Right: around 400 transformation stations in Denmark)
Thanks for your attention! Questions?