Conditional Probabilistic Wind Power Forecasting in Transmission Grids – Making use of Spatial Correlation

WIPFOR'13, Paris

Raik Becker, Christoph Weber ■ 06.06.2013

Wind power development and forecasting

- Installed wind power capacity increased significantly in Germany over the last years (2000: 6,057 MW; 2012: 30,747 MW) and will increase further
- Even relatively small forecast errors lead to large unexpected power changes

Consequences

- Critical systems states occur more often
- Redispatch of conventional power plants becomes necessary
- Curtailments of wind farms occur more often
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Motivation

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Estimation of the forecast uncertainty

Probabilistic wind power forecasts

- Provide full information about the forecast error
- Make comparisons to deterministic models

Simulation of the forecast uncertainty

Copula models

- Capture the full relationship between forecast error distributions at different grid nodes
- Allow to assess the range of future system states
- Help to prepare remedial measures in advance in order to maintain system security

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Agenda

Methodology

Data

Results

Summary

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Required properties of probabilistic wind power forecasts for TSOs

Temporal resolution

- Depends on the TSO, but at least hourly
- Look-ahead time of the wind power forecast should be considered

Spatial resolution

- Grid node level
  - Captures spatio-temporal interdependences that are inherent in weather/wind forecasts
  - Optimal for operational issues

Conditional properties

- Use of explanatory variables in order to sharpen the forecast interval

Information content

- Ideally the entire probability distribution function (pdf)

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Definition of the forecast error

For a certain forecast start time t and look-ahead time k the *wind power forecast error* is defined as

$$E_{t+k,i} = \hat{P}_{t+k,i} - P_{t+k,i},$$

where $P_{t+k,i}$ is the measured and $\hat{P}_{t+k,i}$ the forecasted wind power feed-in at the grid node i with $\hat{P}_{t+k,i} \in [0,1]$.

Thus, $\hat{P}_{t+k,i} = 0 \rightarrow E_{k,i} \in [-1,0]$ and $\hat{P}_{t+k,i} = 1 \rightarrow E_{k,i} \in [0,1]$.

Approch	Remarks	Applied to
Spline quantile regression	Quantiles may cross	Single wind farm (Nielsen, H. A., Madsen, H., Nielsen, T. S., 2006)
Fuzzy inference model (Pinson, 2006)	Allows only for one specific power curve	Single wind farm (Pinson and Kariniotakis, 2010), Single wind farm (Pinson, Juban and Kariniotakis, 2006)
Conditional kernel density estimation (CKDE)	Provides complete pdf	Single wind farms (Juban, Siebert, and Kariniotakis, 2007), Single wind farms (Bessa et al., 2012), Single wind farms (Jeon and Taylor, 2012)

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- So far, applications focus on single wind farms
- Complete (c)pdf is only provided by (C)KDE

Estimation of the forecast error's cpdf

Nadaraya-Watson estimator:

$$\hat{f}_{E_{k,i}}(\epsilon|\hat{P}=\hat{p}) = \frac{\sum_{j=1}^{J} K^{\star}_{e_{k,i},h_{e_{k,i}}}(e_{k,i,j}) \cdot K^{\star}_{\hat{p},h_{\hat{p}_{k,i}}}(\hat{p}_{k,i,j})}{\sum_{j=1}^{J} K^{\star}_{\hat{p}_{k,i},h_{\hat{p}_{k,i}}}(\hat{p}_{k,i,j})},$$

where $K^{\star}$ is a beta kernel according to (Chen, 1999). The selection of the smoothing parameters $h_{e_{k,i}}$ and $h_{\hat{p}_{k,i}}$ is based upon least squares cross-validation (Härdle, 2004).

Advantage:

- No dangerous assumptions about the distribution necessary
- Easy to apply

Data transformation

1. Compute conditional cumulative distribution function (ccdf):
   $\hat{F}_{E_{k,i}}(e|\hat{P} = \hat{p}) = \int_{-\infty}^{e} \hat{f}_{E_{k,i}}(u|\hat{P} = \hat{p})du$,
2. Run through a large historic set of $e_{t+k,i}$ and $\hat{p}_{t+k,i}$ with the length T,
3. Compute the respective estimates of the ccdf: $\hat{F}^{T}_{E_{k,i}}$ and
4. Transform the outcome into Gaussian distributed random variables using the inverse standard normal distribution Φ^{-1}: $\mathbf{x}_{k,i} = \Phi^{-1}(\hat{F}^{T}_{E_{k,i}})$.

Estimation of a Gaussian copula

$$C_k(F^{T}_{E_{k,i}}, \ldots, F^{T}_{E_{k,I}}; \rho) = \Phi_{\rho}(\mathbf{x}_{k,1}, \ldots, \mathbf{x}_{k,I})$$

Estimation

- *Input:* $\hat{p}_{k,i}$, $p_{k,i}$
- *Estimation/transformation:* $\hat{f}_{E_{k,i}}(\epsilon|\hat{P}=\hat{p}) \Longrightarrow \hat{F}_{E_{k,i}}(e|\hat{P}=\hat{p}) \Longrightarrow \hat{F}^T_{E_{k,i}} \Longrightarrow \mathbf{x}_{k,i} \Longrightarrow C_k$
- *Ouput:* C_k (copula)

Simulation

- *Input:* C_k, $\hat{p}_{t+k,i}$
- *Simulation/Transformation:*
  $C_k \Longrightarrow \hat{F}^T_{E_{k,i}} \Longrightarrow \hat{F}_{E_{k,i}}(e|\hat{P}=\hat{p}_{t+k,i}) \Longrightarrow \hat{E}_{k,i} = (\hat{F}_{E_{k,i}}(e|\hat{P}=\hat{p}_{t+k,i}))^{-1}$
- *Ouput:* $\hat{E}_{k,i}$ (simulation of the forecast error)

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Wind farms and transmission grid

- 5773 wind farms in Germany, which account for more than 27 GW of the installed capacity
- Wind farms are assigned to German transmission grid nodes based on distances

Wind power measurements

- W2P model (Input: measured wind speed of about 240 weather stations, turbine power curves)

Wind power forecasts

- State-of-the-art forecasting methods (Input: wind speed and direction from a numeric weather model (COSMO-EU), turbine power curves, power measurements)

Time frame

- 1/2010-12/2010: training of the point forecast model
- 1/2011-7/2012: estimation of the conditional forecast error distribution

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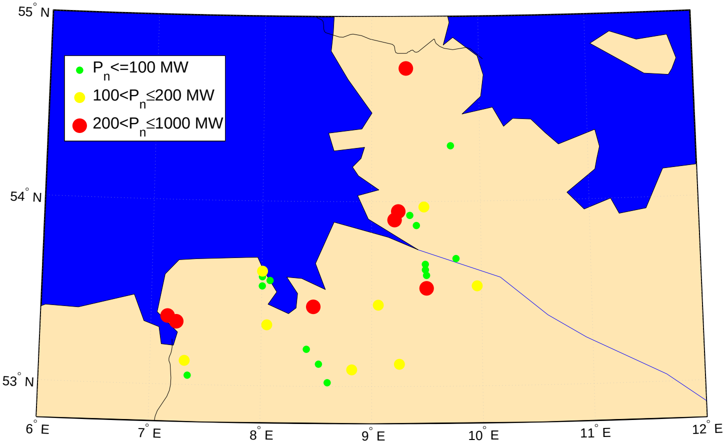
Case study


P_n<=100 MW
100<P_n≤200 MW
200<P_n≤1000 MW
55° N
54° N
53° N
6° E
7° E
8° E
9° E
10° E
11° E
12° E

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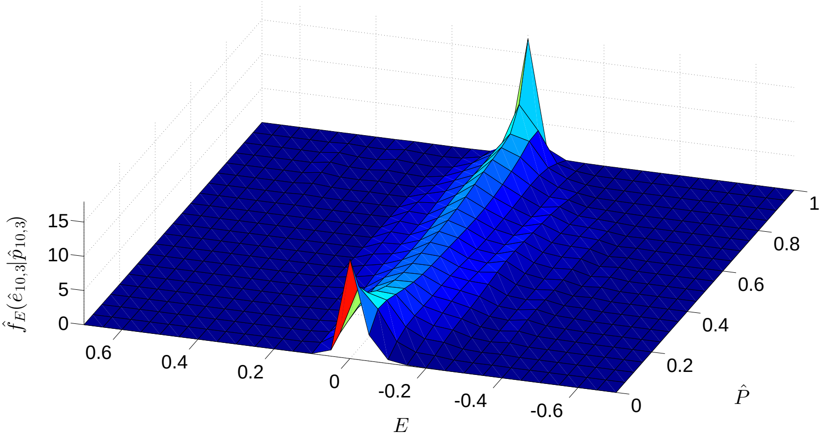
Conditional pdf of the forecast error



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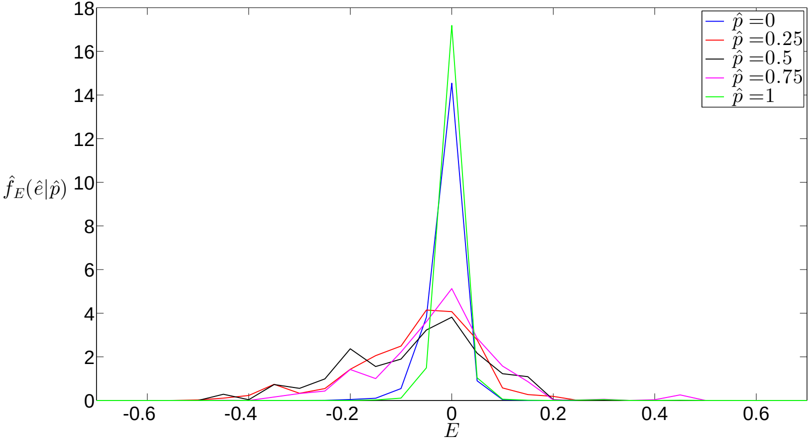
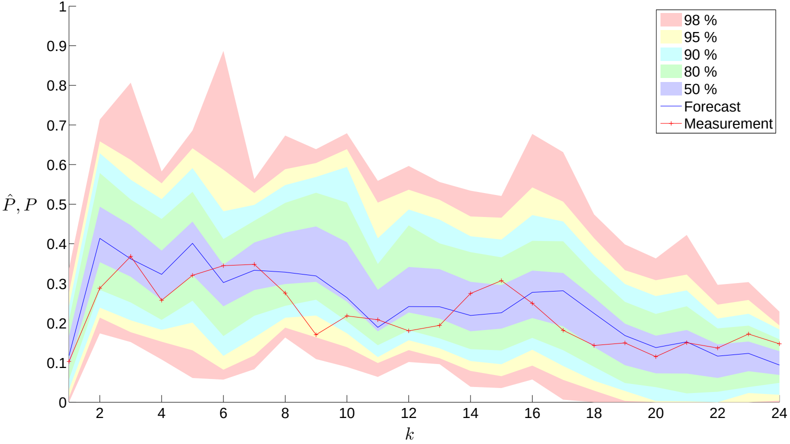
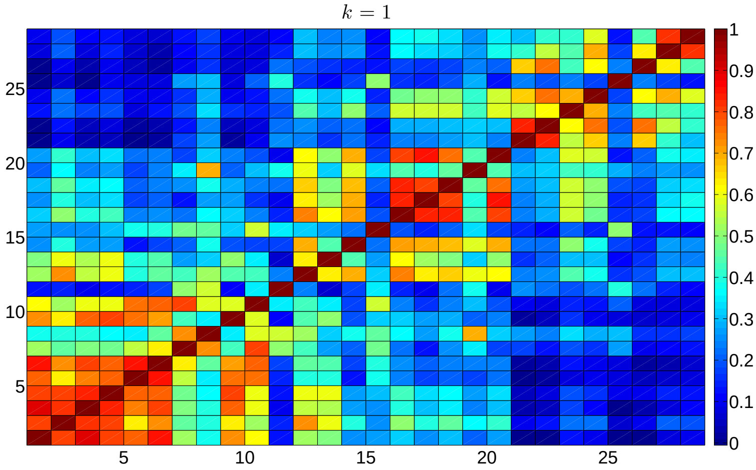


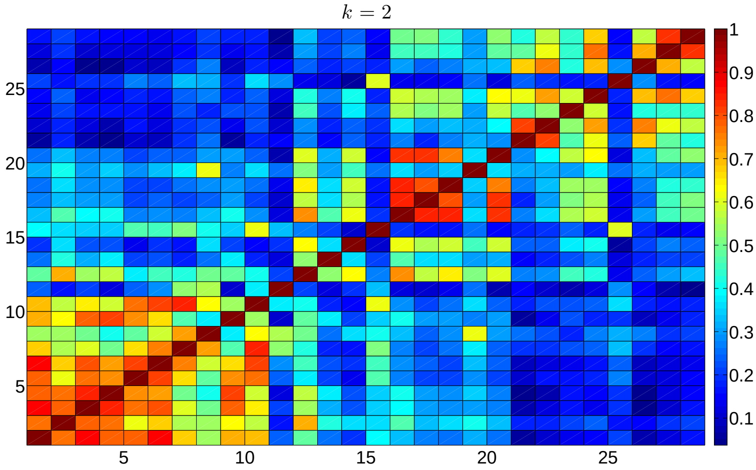
Probabilistic wind power forecast



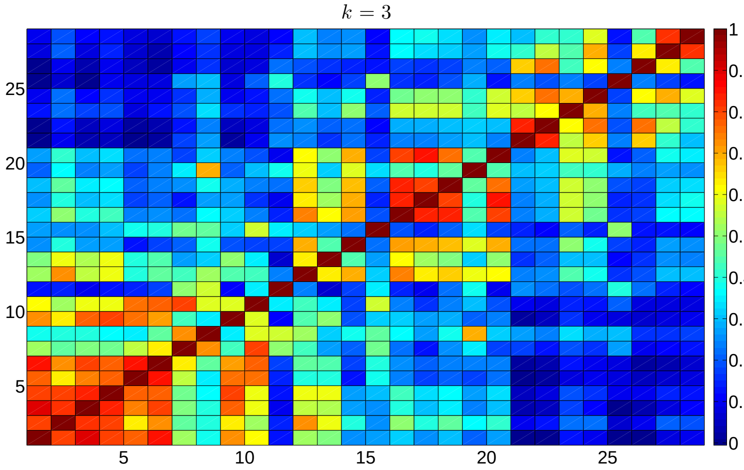
Correlation matrix



Correlation matrix



Correlation matrix



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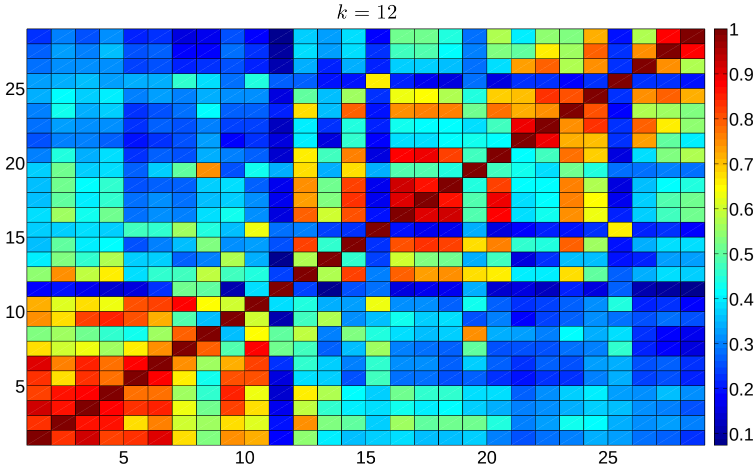

Correlation matrix

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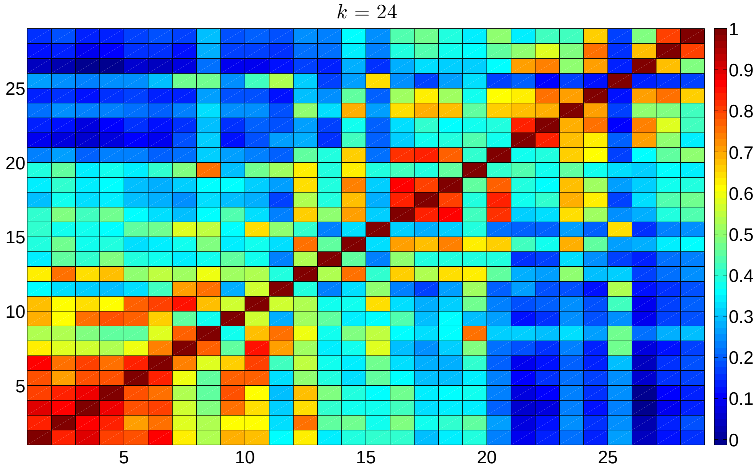
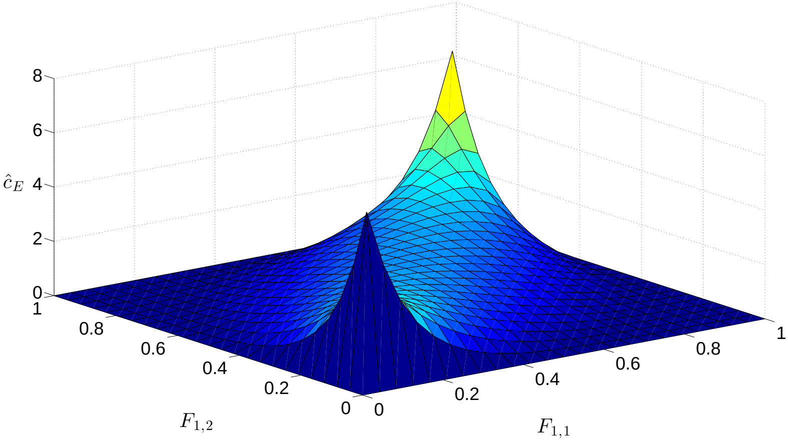


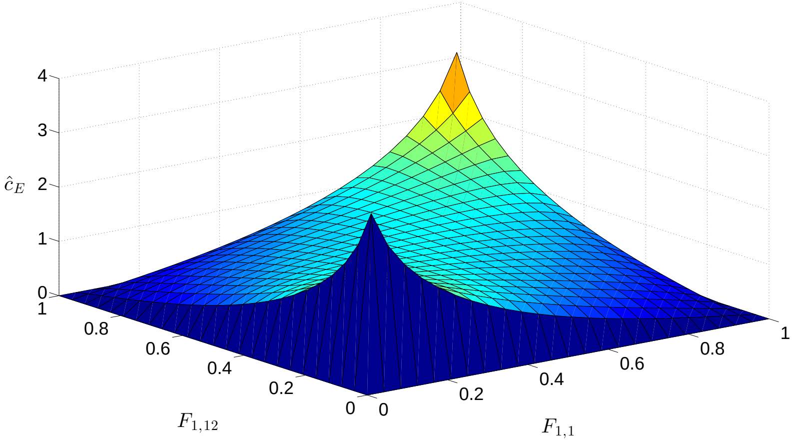
Copula density

Distance: 3.34 km



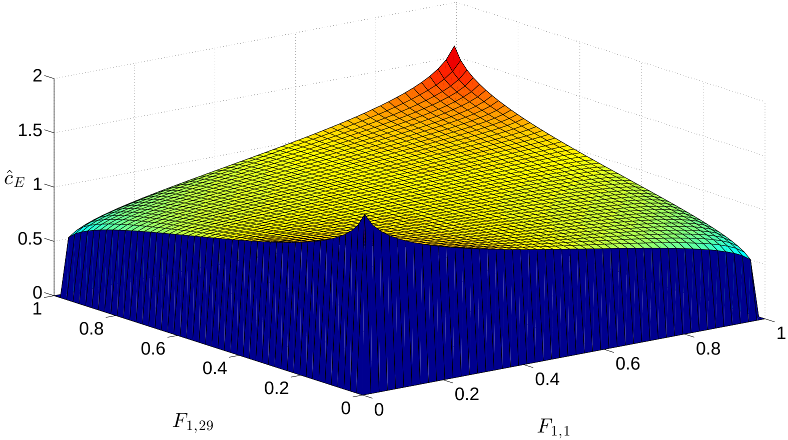
Copula density

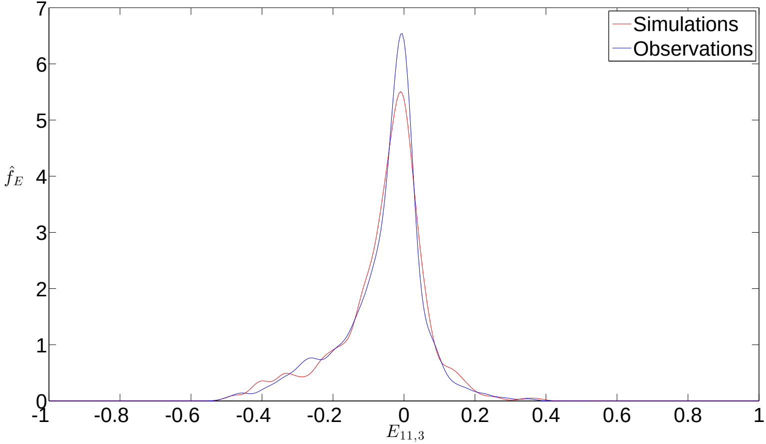
Distance: 62.12 km



Copula density

Distance: 158.03 km




Simulations
Observations
$\hat{f}_E$
$E_{11,3}$
0
1
2
3
4
5
6
7
-1
-0.8
-0.6
-0.4
-0.2
0
0.2
0.4
0.6
0.8
1

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Probabilistic wind power forecasting

- CKDE is able to provide useful additional information for the TSO
- Conditional approach narrows the forecast interval
- Historic wind power measurements and forecasts are necessary to estimate the cpdf

Forecast error simulation

- Copulas are able to capture the dependence structure between forecast errors at grid nodes
- Only point forecasts are required for the simulation

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Thank you for your attention

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Umbrella Project