UNIVERSITÄT DUISBURG ESSEN

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USING TIME-ADAPTIVE PROBABILISTIC FORECASTS FOR GRID MANAGEMENT – CHALLENGES AND OPPORTUNITIES

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Umbrella Project

MOTIVATION

Why TSOs need probabilistic wind power forecasts?

- Installed wind power capacity increased significantly in Germany over the last years (2000: 6,057 MW; 2011: 28,600 MW) and will increase further
- Consequences:
  - Critical systems states occur more often
  - Redispatch of conventional power plants becomes necessary
  - Wind farms have to be disconnected from the grid
  - …
- Probabilistic wind power forecasts:
  - Allow to assess the range of future system states and make comparisons to deterministic models
  - Help to prepare remedial measures in advance in order to maintain system security
  - Could be the basis for an enhanced OPF

Agenda

I. Methodology

II. Case study

III. Results

IV. Conclusions and further research

METHODOLOGY

Required properties of probabilistic wind power forecasts

- Spatial resolution
  - Grid node level in order to use the spatio-temporal interdependences that is inherent in weather/wind forecasts
- Temporal resolution
  - Depends on the TSO, but at least hourly in order to make use of forecast error's autocorrelation
- Time-adapative behavior
  - New information should be processed as fast as possible
- Conditional properties
  - Use of explanatory variables in order to sharpen the forecast interval
  - Forecast uncertainty should be conditional on the look-ahead time
- Information content
  - Ideally the entire probability distribution function (pdf)

Approaches for probabilistic wind power forecasting

Approach	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)

→So far, only applications to single wind farms
→Complete pdf is only provided by (C)KDE

Kernel density estimation

- Nonparametric method to estimate *f(x)*:
  - by counting all observations that fall into the interval [x-h,x+h]
  - and weighting them depending on the previously chosen kernel function *K*

$$f(x) = \frac{1}{nh} \sum_{i=1}^{n} K(u) \qquad u = \frac{x - X_i}{h}$$

- Kernel functions:
  - Uniform: $\frac{1}{2} I(|u| \leq 1)$
  - Epanechnikov: $\frac{3}{4}(1-u^2) I(|u| \leq 1)$
  - Gaussian: $\frac{1}{\sqrt{2\pi}} \exp(-\frac{1}{2}u^2)$

Nadaraya-Watson estimator*

Static estimator

$$\hat{f}(y|X=x) = \frac{\hat{f}_{XY}(x,y)}{\hat{f}_X(x)} = \frac{\sum_{i=1}^{N} K_{h_y}(y-Y_i)K_{h_x}(x-X_i)}{\sum_{i=1}^{N} K_{h_x}(x-X_i)}$$

Time-adaptive estimator according to Bessa et al. (2012b)

CKDE1: $$\hat{f}_t(y|X=x) = \frac{\lambda\hat{f}_{t-1}(y,x)+(1-\lambda)\left[K\left(\frac{y-Y_i}{h_y}\right)K\left(\frac{x-X_i}{h_x}\right)\right]}{\lambda\hat{f}_{t-1}(x)+(1-\lambda)K\left(\frac{x-X_i}{h_x}\right)}$$

Time-adaptive estimator according to Jeon et al. (2011)

CKDE2: $$\hat{f}(y|X=x) = \frac{\sum_{i=1}^{N} \lambda^{N-i}K_{h_y}(y-Y_i)K_{h_x}(x-X_i)}{\sum_{i=1}^{N} \lambda^{N-i}K_{h_x}(x-X_i)}$$

* Sometimes referred to as Rosenblatt estimator

Quantile-copula estimator

Static estimator (Faugeras, 2009)

$$\hat{f}(y|X=x)=\hat{f}(y)\hat{c}(u,v)$$

$$\hat{c}(u,v)=\frac{1}{Nh_u h_v}\sum_{i=1}^{N}K_{h_u}\left(\frac{u-F_X^e(X_i)}{h_u}\right)K_{h_v}\left(\frac{v-F_Y^e(Y_i)}{h_v}\right)$$

$$u=F_X(x), v=F_Y(y)$$

Quantile-copula estimator

Time-adaptive estimator (Bessa et al., 2012b)

CKDE3:

$$\hat{f}_t(y|X = x) = \hat{f}_t(y)\hat{c}_t(u, v)$$

$$\hat{f}_t(y) = \lambda \hat{f}_{t-1}(y) + \frac{1-\lambda}{h_y} K\left(\frac{y-Y_t}{h_y}\right)$$

$$\hat{c}_t(u, v) = \lambda \hat{c}_{t-1}(u, v) + \frac{1-\lambda}{h_x h_y}\left[K_{h_x}\left(\frac{u-F_X^e(X_i)}{h_x}\right) K_{h_y}\left(\frac{u-F_Y^e(Y_i)}{h_y}\right)\right]$$

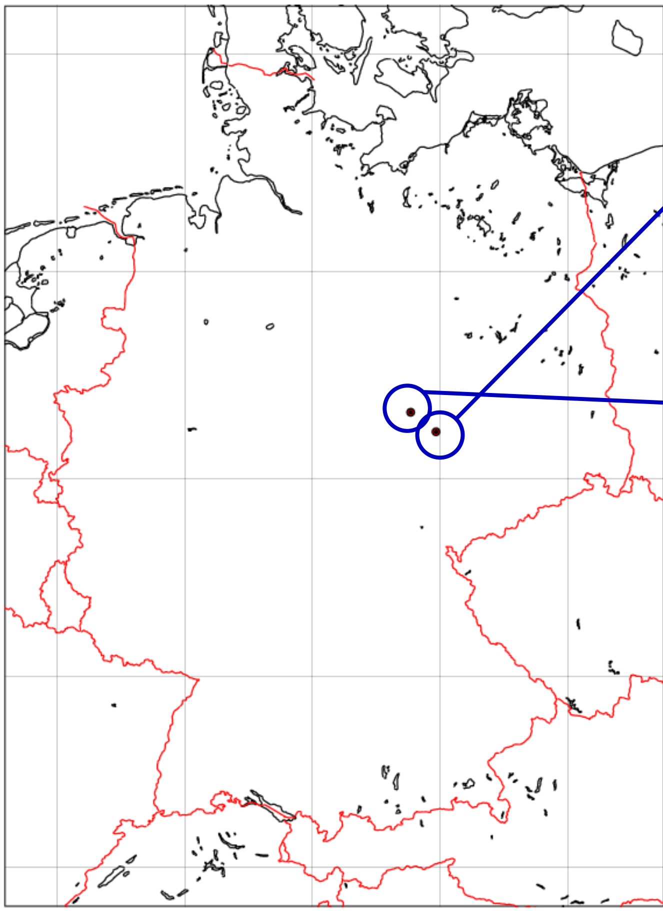
$$0 \leq \lambda \leq 1$$

CASE STUDY

Data

- Grid and wind farms:
  - >5700 wind farms accounting for 27 GW installed capacity in Germany
  - All German transmission grid nodes included
- Time frame:
  - Training data set (in-sample): July 2011 – April 2012 (10 months)
  - Evaluation data set (out-sample): May 2012
- Forecasts:
  - Hourly values from an European-wide NWP model with a spatial resolution of 7km
  - > 230 weather station measurements provided by the German weather service
  - Basic W2P model with randomly assigned power curves depending on the rated power, if the exact power curve was unknown (56 %)

Case study data



Grid node of interest (y)

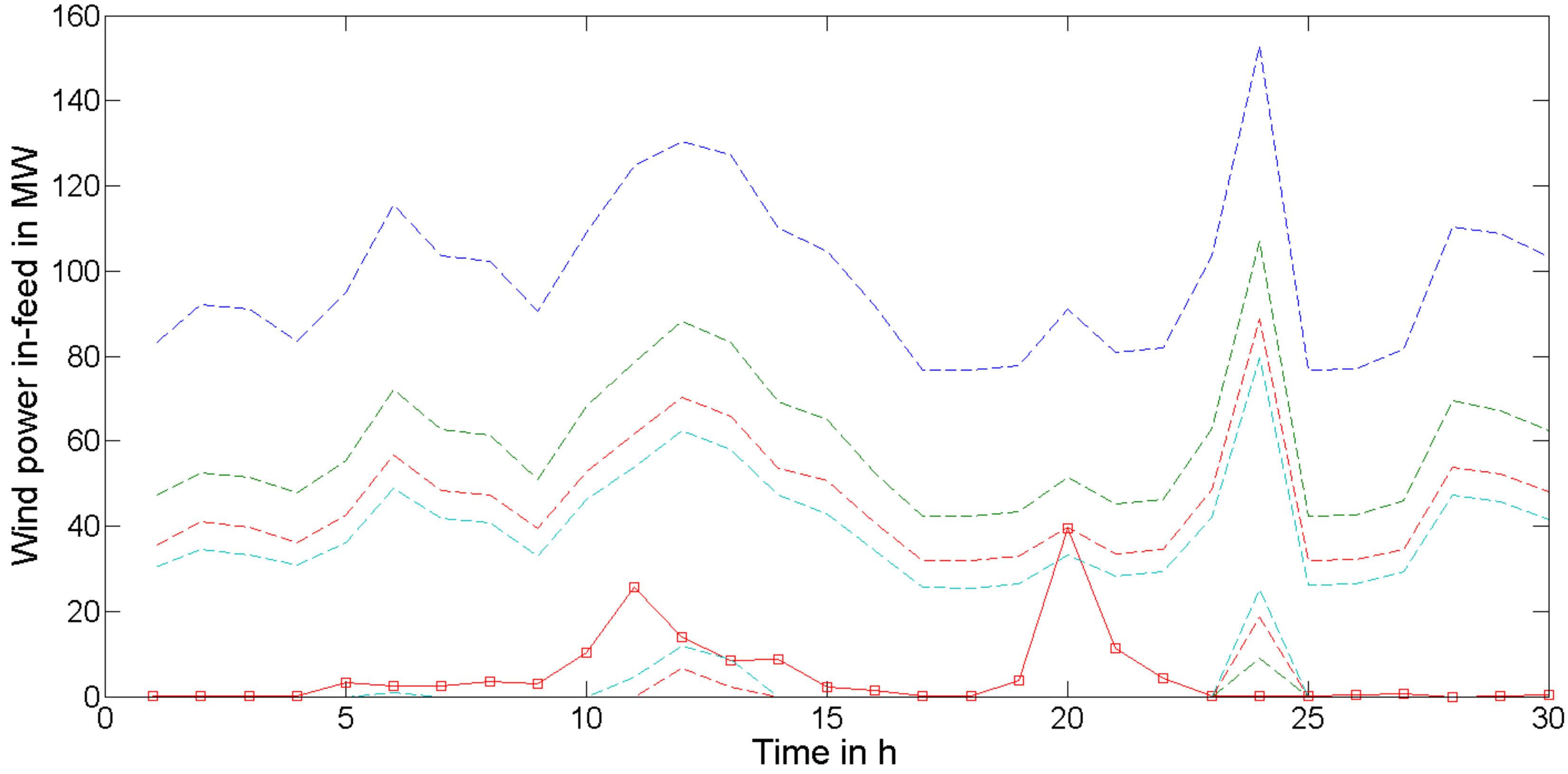
→400.38 MW installed wind power capacity

Grid node that is used within the set of explanatory variables (x)

→ 743.19 MW installed wind power capacity

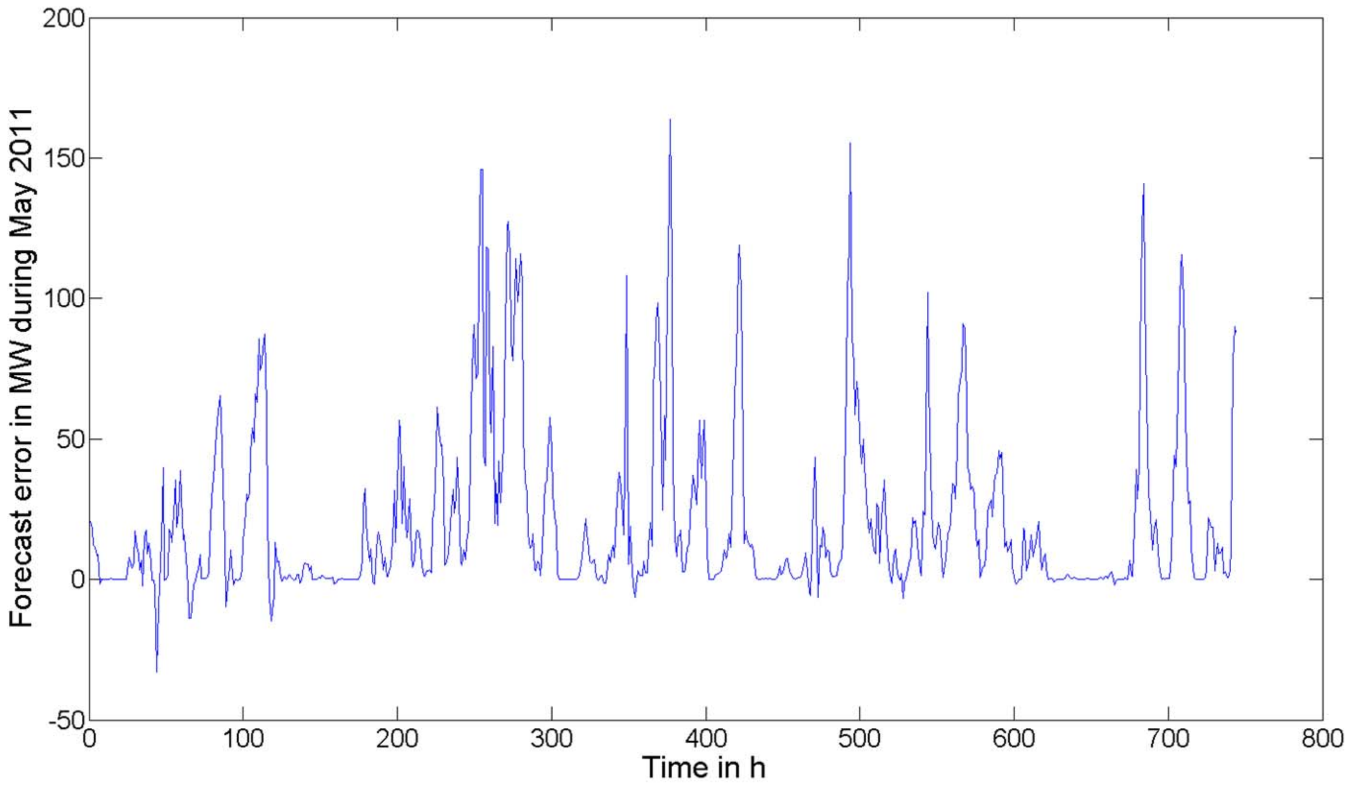
RESULTS

Example

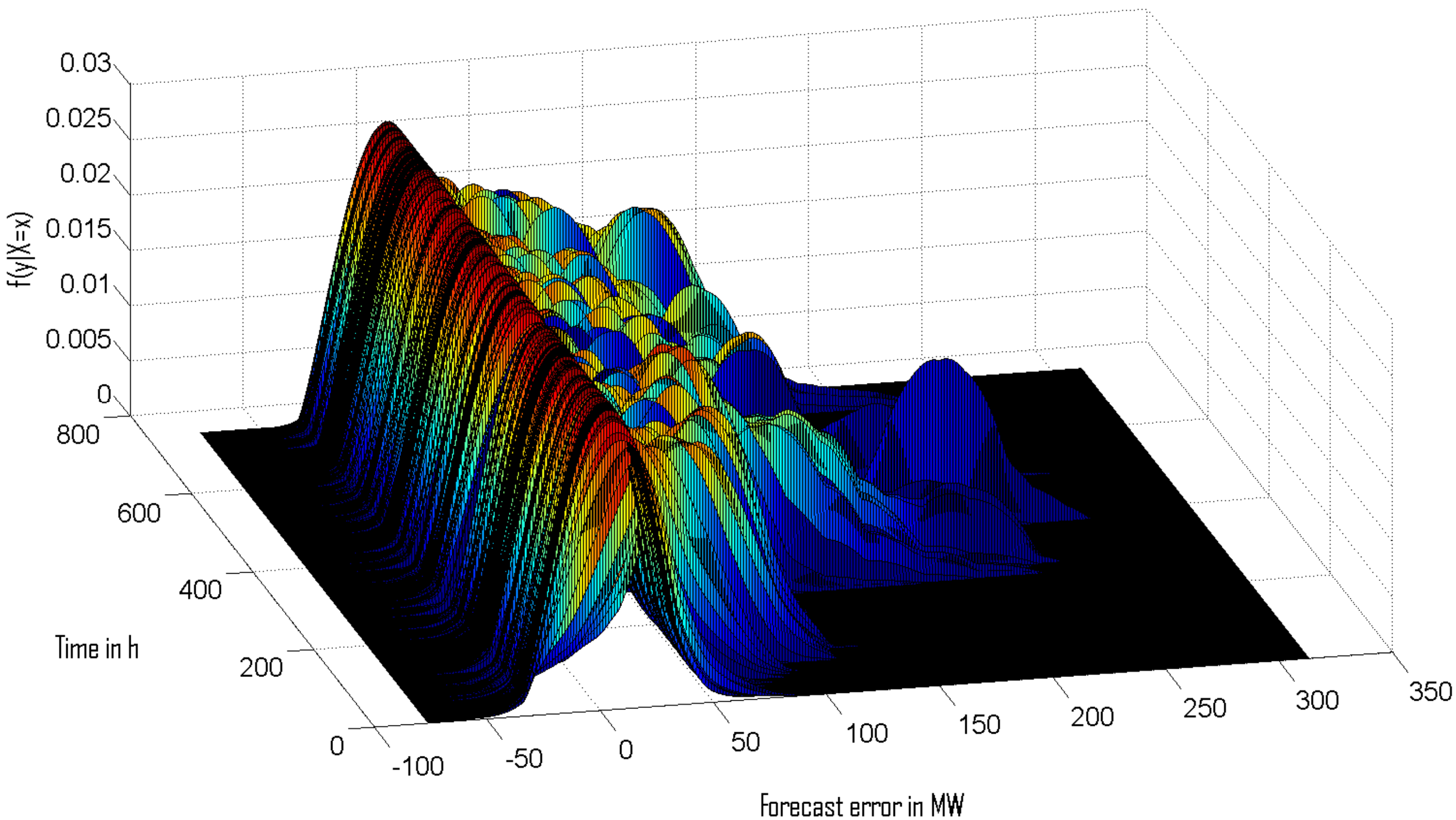

Wind power in-feed in MW
160
140
120
100
80
60
40
20
0
0
5
10
15
20
25
30
Time in h

Forecast error

Mean=20.22 MW, SD=29.82 MW

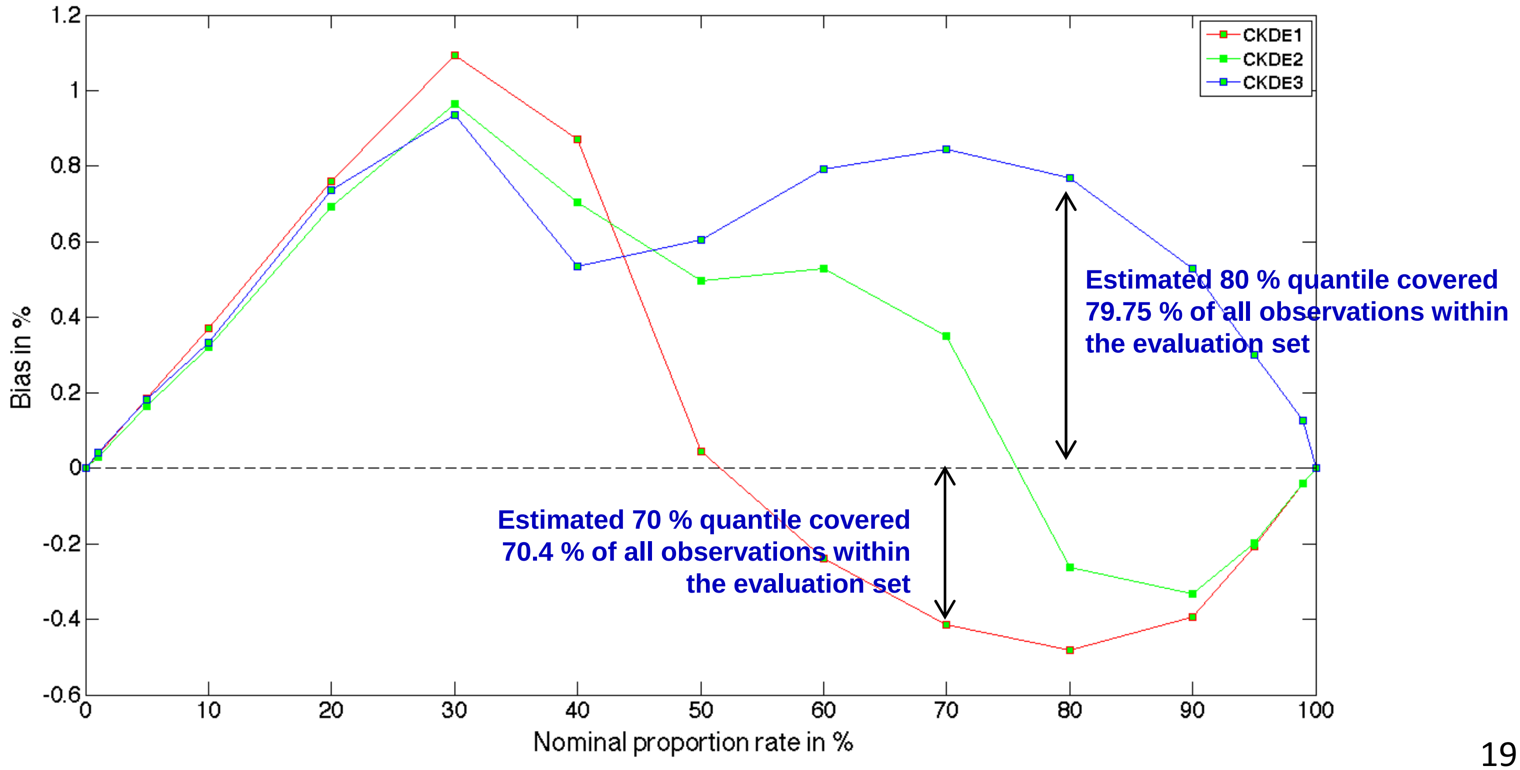


Conditional pdf



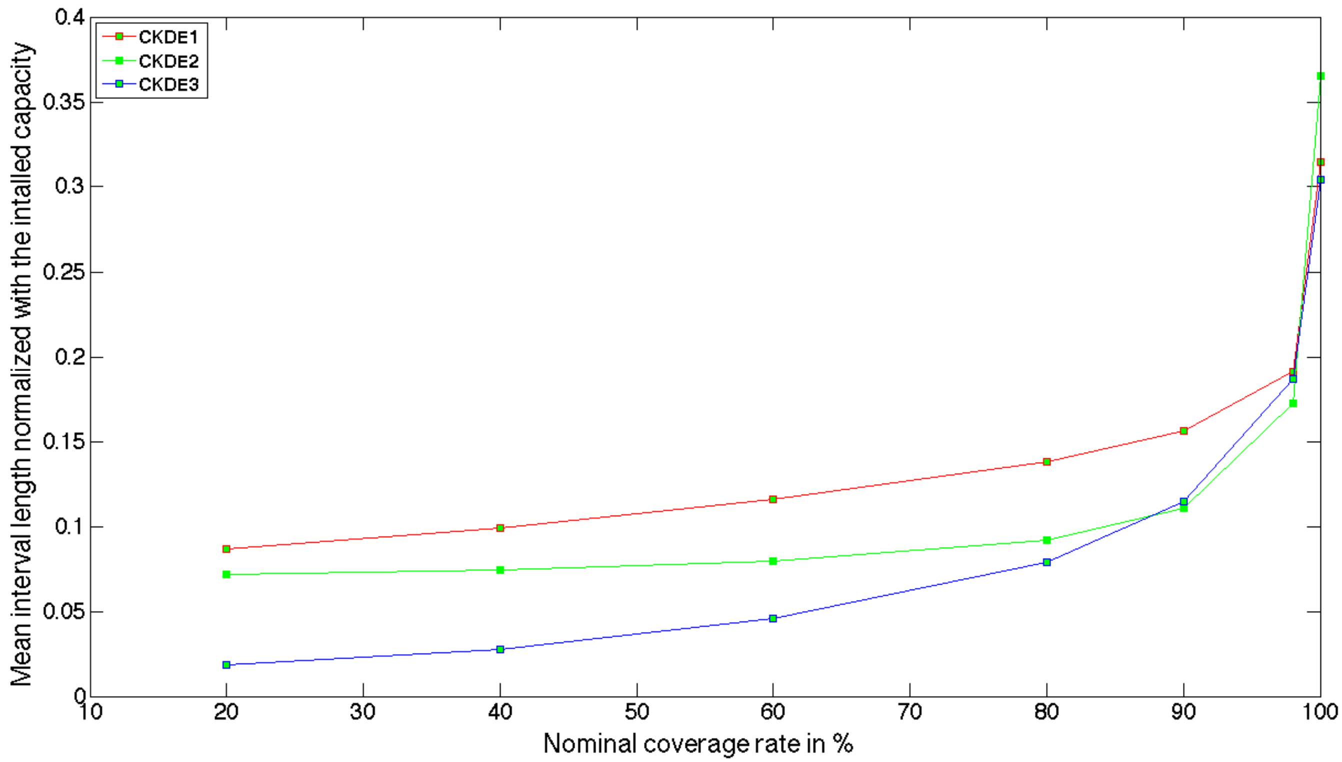
Reliability

Calculates the bias between the estimated quantile and the realizations within a evaluation set



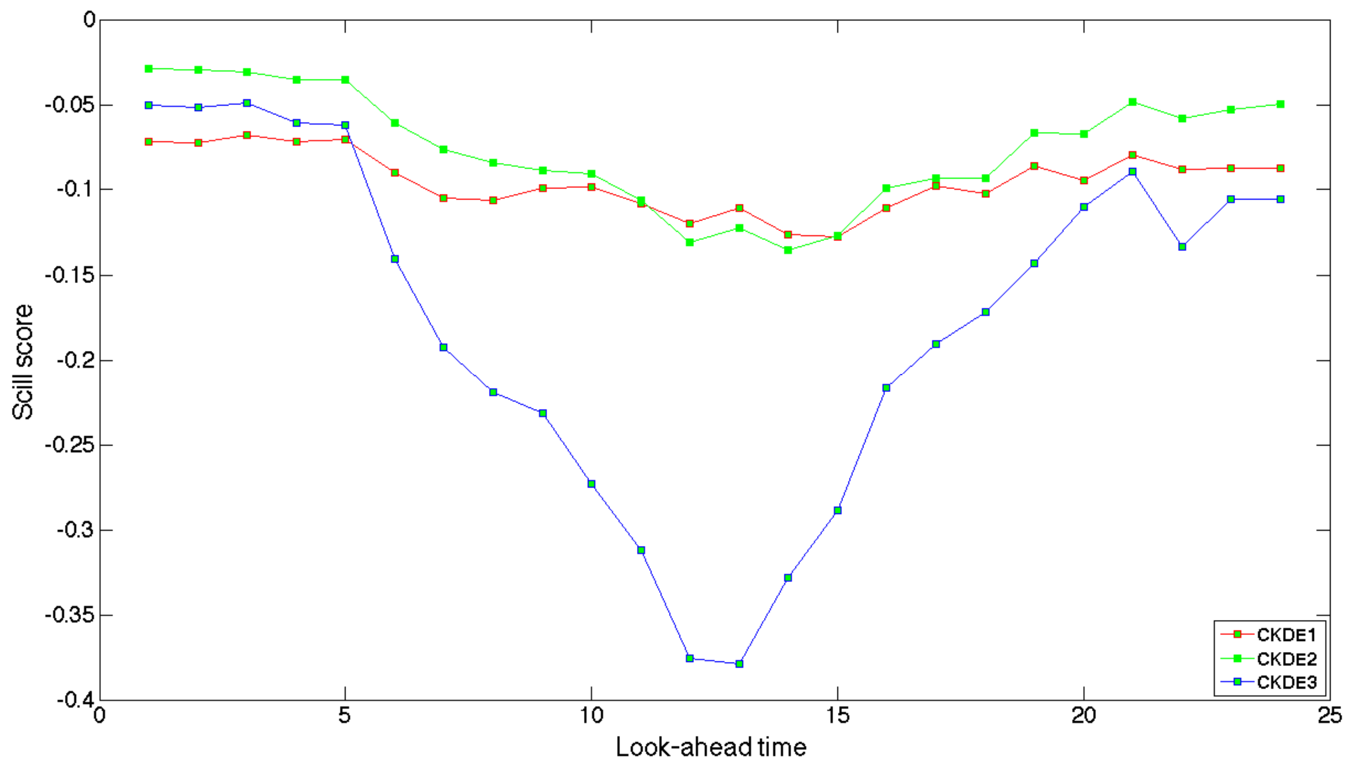
Sharpness and Resolution

Provides information about the average interval length → Important for operational issues



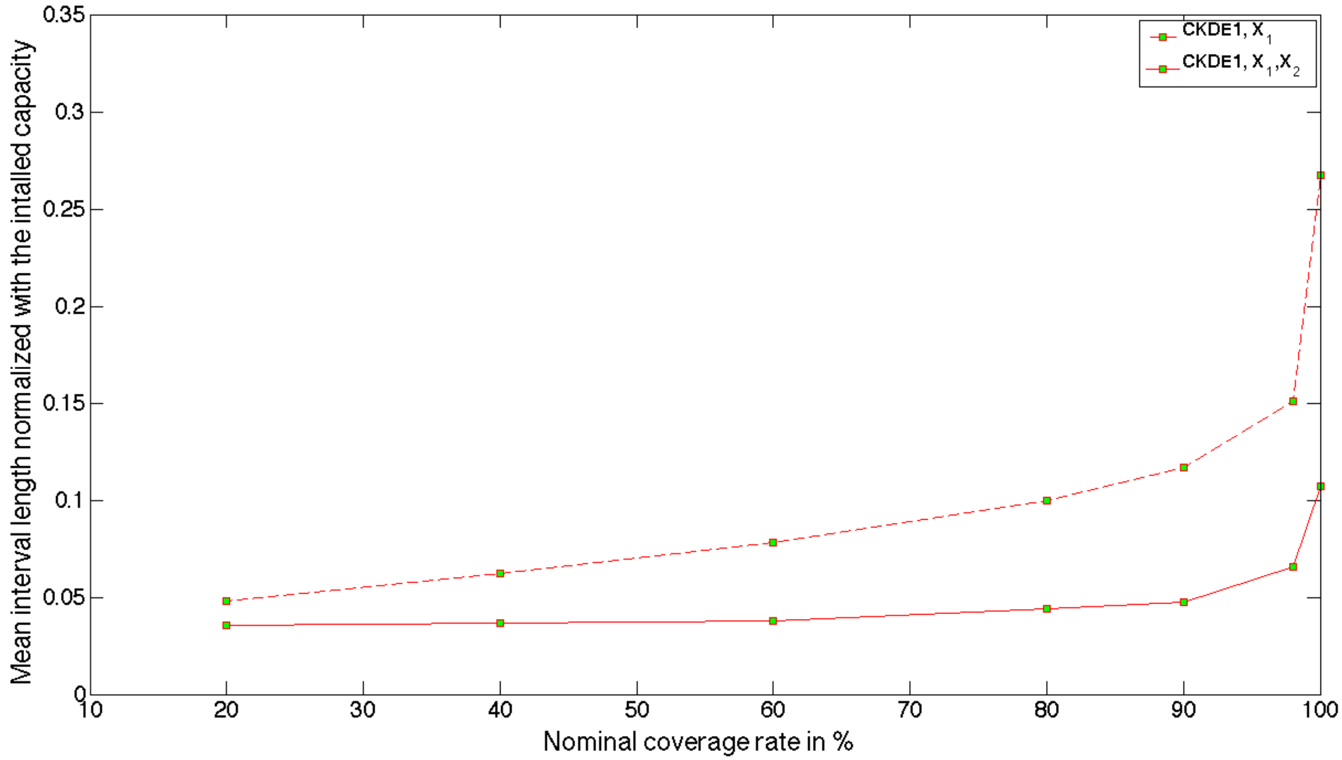
Skill Score

Combines reliability and sharpness indicators, so that 0 would be a perfect forecast



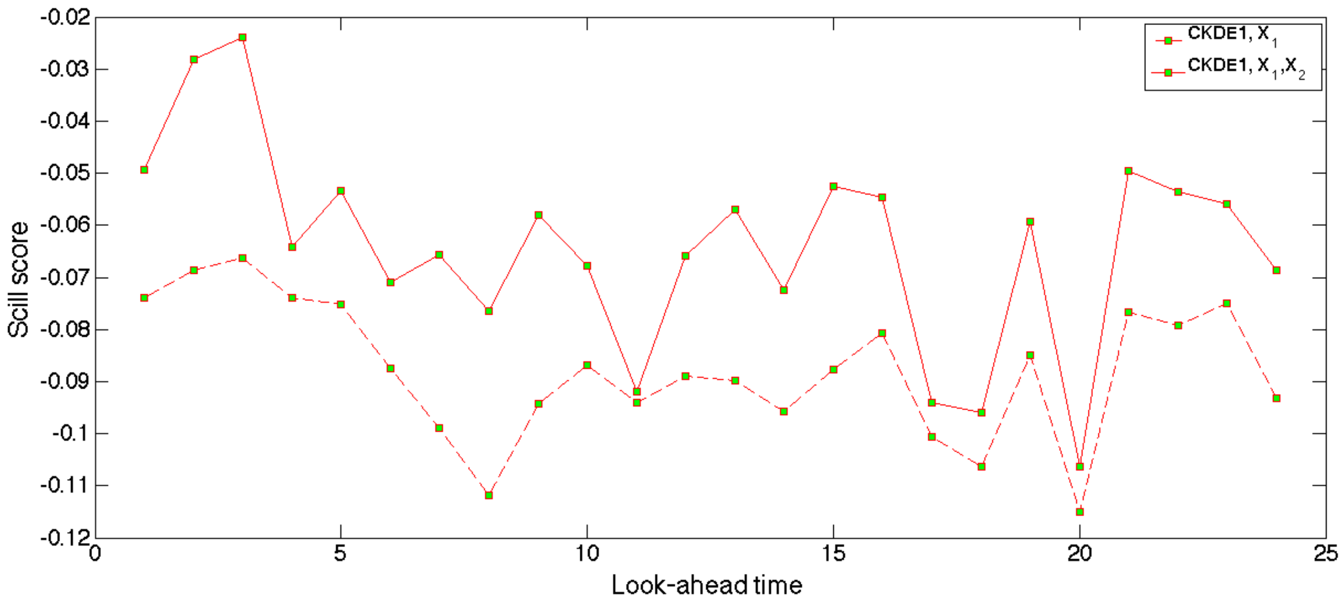
Sharpness and Resolution (2)

Provides information about the average interval length → Important for operational issues



Skill Score

Combines reliability and sharpness indicators, so that 0 would be a perfect forecast



Conclusions and further research

Conclusion:

- CKDE is able to provide useful additional information for the TSO
- Including information from nearby grid nodes narrows the forecast interval
- The method requires only point forecasts of surrounding wind farms

Next steps:

- Test the additional value of integrating more grid nodes in the set of explanatory variables
- Find estimation methods that can handle large data sets and explanatory variables

Thank you for your attention

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APPENDIX

Bandwidth selection

Least squares cross-validation (CV) minimizes the integrated square error (ISE):

1. One-dimensional case

$$CV(h) = \frac{1}{n^2 h}\sum_i \sum_j K * K\left(\frac{X_j - X_i}{h}\right) - \frac{2}{n(n-1)}\sum_i \sum_{j \neq i} K_h(X_i - X_j)$$

2. Multi-dimensional case

$$CV(\mathbf{H}) = \frac{1}{n^2 \det(\mathbf{H})}\sum_i \sum_j K * K\{\mathbf{H}^{-1}(X_i - X_j)\} - \frac{2}{n(n-1)}\sum_i \sum_{j \neq i} K_{\mathbf{H}}(X_i - X_j)$$

(Härdle, 2004)