Spatio-temporal wind speed predictions for Germany

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Abstract. *State of the art wind forecasting models, like Numerical Weather Predictions utilize huge amounts of computing time. Some of them have rather low spatio-temporal resolution. Time series prediction model accomplish good results in high temporal settings. Moreover, their consumption of computing capacities is relatively low and return accurate short-term to medium-term forecasts. The recent literature shows increasing interest in the topic of spatial interdependence. This article deals with a spatial and temporal model for wind speed. We describe the temporal model structure independently on spatial correlations. Therefore, seasonality and a huge correlation structure are included. Subsequently, the model is extended and a spatial structure is included. The data set includes ten minute observations of several measurement stations in Eastern Germany. The validation procedure shows that the model is reliable.*

Keywords. *Wind speed; Forecasting; Spatio-temporal; Periodicity; Autocorrelation.*

1 Introduction

The European Wind Energy Association (2014) finds that the cumulative capacity installation for renewables has a total share of 72%. The World Wind Energy Association (2014) indicates that especially the wind energy capacity within Europe increases from 2.4% in 2000 to 14.1% in the year. This indicates the growing relevance of renewable energies for the European market. In particular the European Wind Energy Association (2014) recognises the need for a European Energy Union and the importance of wind energy which is displayed in different wind energy scenarios for 2020. In Europe the wind energy installation is expected to meet about one sixth of the total energy consumption (e.g., European Wind Energy Association, 2014). The Berkhout et al. (2013) point out that about 8% of the German electricity mix is based on wind energy.

Models for the description and prediction of wind speed are of outstanding importance. However, the accuracy of those models differ severely. The characteristics of wind speed and wind energy makes it challenging to forecast the underlying processes precisely. The uncertainty in the data set which remains, maintain the necessity to develop and optimise forecasting methods.

Beside models like Numerical Weather Predictions (NWP) and Artificial Neural Networks (ANN), there exists a huge scope of time series approaches. A new field of research are hybrid models. They combine two or more types of wind forecasting approaches. We combine temporal and spatial modelling. Damousis et al. (2004) combine a spatial model with a genetic algorithm for model fitting and forecasting. Han and Chang (2010) describe a simulation study to analyse the impact of spatial and temporal correlation on wind power forecasting accuracy. Moreover, Benth and Šaltyte (2011) evolve a spatial and temporal model. Primarily, they model the temporal structure by using a periodic autoregressive moving average model (ARMA) and a heteroscedastic variance. Accordingly, they use Gaussian random fields to cover the spatial dependence. Hering and Genton (2010) as well as Zhu et al. (2014) cover spatial dependence structure by regime switching models. Following this research, Díaz et al. (2014) comment on the importance of spatial composition according to the spread and wake effect of wind generators over a small geographical areas. Another important aspect of spatial wind modelling is related to the characterization of wind resources at specific regions where sufficient information is not available. In this situation, kriging can be applied. Thus, spatio-temporal models are useful indicators to perform wind energy potential assessments at sites without measurements (e.g Jung and Broadwater, 2014).

The article is structured in the following way. Section 2 describes the data set. Besides, we analyse the spatial structure. The novel spatio-temporal model is introduced in Section 3. Section 4 provides a small outlook of our results.

2 Wind speed data in Eastern Germany

In Figure 1 the measurement stations of the considered wind speed data are shown. They are located in Brandenburg and Berlin. This article focuses on Eastern Germany according to the homogeneity of this region. This area is rural and plain and perfect for wind parks. The data is provided by the "Deutscher Wetterdienst" (DWD) and reaches from January 2009 to December 2011. For model fitting, a time span of one years is used and the remaining months (January 2011 to December 2011) are used for out-of-sample forecasts. The wind speed $(W_t)_{t\in\{1,\cdots,T\}}$ is measured in m/s in a 10-minute interval.

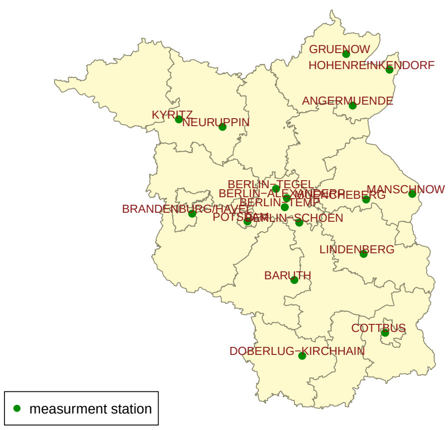

Figure 1: Meterological measurement stations in Berlin and Brandenburg which provide 10min data

3 A spatio-temporal wind speed model

Univariate time series models for wind speed modelling have been considered by Ambach and Schmid (2015). They are based on a periodic temporal model structure. Nevertheless, such models are unable to predict the wind speed at stations where no measurement is observed. Therefore, spatio-temporal models provide a beneficial contribution. The here described methodology, is an extension of Ambach and Croonenbroeck (2015) and is able to capture the spatial and temporal auto-correlation structure of the wind speed data and the cross-correlation with other variables.

We consider a periodic space-time autoregressive model with external regressors for the wind speed (e.g. Cressie and Wikle, 2011). The vector of observations at time t and all locations is denoted by $\boldsymbol{W}_t = (W_{1t},...,W_{nt})$. Let $\{W_{st} : s = 1,...n; t = 1,...,T\}$ denote the collection of data. Therefore, we obtain the following model equation

$$\boldsymbol{W}_t = \boldsymbol{\alpha}_t + \sum_{j=1}^{p} \boldsymbol{\phi}_{tj} \boldsymbol{W}_{t-j} + \boldsymbol{X}_t \boldsymbol{\beta} + \boldsymbol{\delta} \boldsymbol{v_t} + \boldsymbol{\epsilon}_t, \tag{1}$$

$$\boldsymbol{\alpha}_t = \boldsymbol{\vartheta_0} + \boldsymbol{U}_1 \sum_{i=1}^{K} \boldsymbol{\vartheta}_i B_i^{\boldsymbol{s}}(t), \tag{2}$$

$$\boldsymbol{\phi}_{tj} = \boldsymbol{U}_2 \boldsymbol{\phi}_{0j} + \boldsymbol{U}_3 \sum_{i=1}^{K} \boldsymbol{\phi}_{ij} B_i^{\boldsymbol{s}}(t), \tag{3}$$

where $\{\boldsymbol{\epsilon_t}\} \sim N_n\big(\boldsymbol{0}, \boldsymbol{\sigma_\varepsilon^2 I}\big)$ is an $n \times 1$ column vector. The measurement errors $\boldsymbol{\epsilon_t}$ follow a Gaussian white noise in space and time. Furthermore, $\boldsymbol{v_t}$ is an $n \times 1$ vector which contains spatial random effects and $\boldsymbol{X_t}$ is a matrix of external variables (e.g. Finazzi et al., 2013). These effects are time independent, but provide the following spatial correlation structure $\boldsymbol{v_t} \sim N_n\big(\boldsymbol{0}, \boldsymbol{\Sigma(H,\theta)}\big)$. The spatial covariance matrix $\boldsymbol{\Sigma}$ is determined by $\boldsymbol{H}$, which is a matrix of pairwise geographic distances and a spatial covariance function $(C(s_h, s_l, \theta))_{h,l=1,...n}$. Moreover, $\boldsymbol{\vartheta_0}$ is an $n \times 1$ intercept vector and $\boldsymbol{\vartheta}_{i_1}$ are $n \times 1$ periodic coefficient vectors. $\boldsymbol{\phi}_{0j}$ is an $n \times n$ parameter matrix of autoregressive parameters for lag j and $\boldsymbol{\phi}_{j_1 j}$ are $n \times n$ parameter matrices of periodic AR parameters for lag $(j)_{j \in \mathbb{N}}$. Furthermore, $\boldsymbol{U}_1$, $\boldsymbol{U}_1$ and $\boldsymbol{U}_3$ are known spatial weight matrices of dimension $n \times n$. De Boor (1978) and Eilers and Marx (1996) define the fundamentals for the periodic B-spline basis functions which is given by $B_i^{\boldsymbol{s}}(t)$. Therefore, it is important to define the set of equidistant knots κ. The daily periodicity is $s = 144$. Cubic B-splines are an attractive approach, because they are twice continuously differentiable.

In this study we use a model which is able to perform predictions for a certain regions. Moreover, it is able to capture the temporal structure of our wind speed data set. We include the aforementioned periodicities as well as other known regressors. Especially, the terrains roughness, natural vegetal cover, and meteorological variables. The meteorological variables are not deterministic, but we are able to use the temporal lagged information. Hence, we are able to include linear mixed effects to introduce more spatial and temporal structure.

4 Outlook

The main objective of this article is to provide a model for wind speed which is easy to use and provide reliable prediction in both space and time. We recommend a simple periodic space-time autoregressive model with external regressors model which seems powerful enough to describe the wind dynamics in both dimensions. The model contains periodic B-spline functions and space and time autoregressive components. Although, the wind speed is a noisy meteorological variable, which makes it hard to model, the described model provides a useful procedure to predict the spatio-temporal wind speed structure.

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