J. Wind Eng. Ind. Aerodyn. 136 (2015) 201–210

Contents lists available at ScienceDirect

Journal of Wind Engineering and Industrial Aerodynamics

journal homepage: www.elsevier.com/locate/jweia

A selection of time series models for short- to medium-term wind power forecasting

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ARTICLE INFO

Article history:
Received 22 July 2014
Received in revised form
16 November 2014
Accepted 17 November 2014
Available online 8 December 2014

Keywords:
Mycielski algorithm
WPPT
GWPPT
Wind power
Wind energy
Forecasting
Prediction

ABSTRACT

In this paper we investigate the short- to medium-term prediction performance of several recent wind power forecasting models. In particular, we analyze the Wind Power Prediction Tool (WPPT), which is a successfully employed model in Denmark, its generalization (GWPPT, generalized WPPT), an adaptation of the Mycielski approach, a nonparametric regression model and several univariate time series benchmarks. In the longer forecasting horizon scenario, GWPPT performs best, while the time series models are still strong competitors in the short-term setup. Our findings are in line with the majority of the literature. They support the results by Croonenbroeck and Dahl (2014). The Mycielski approach is a successfully employed wind speed forecaster and usually returns well results. However, its performance as a wind power forecasting model is somewhat limited, showing that the adaptation to this new operational area leaves an opportunity for additional work in the future.

1. Introduction

For the last two decades, energy production has been characterized by renewables. Conventional power is deterministic, and as such, easy to predict. Wind power, however, possesses stochastic features, so prediction has proven to be a tough task. Literature holds a wide range of wind power forecasting model propositions. Giebel et al. (2011) provide an overview. Simple universal forecasting algorithms such as the persistence model (i.e. $\hat{x}_{t+k} = x_t$) or the Mycielski algorithm (as provided by Ehrenfeucht and Mycielski, 1992) can be adopted for wind power forecasting. Hocaoglu et al. (2009) and Gan et al. (2012) attain good results from using the Mycielski approach for hourly rounded wind speed predictions. Soman et al. (2010), Jiang et al. (2010), Pourmousavi Kani (2011) and Özgonenel and Thomas (2012) use the model as a benchmark procedure. Jiang et al. (2010) achieve good results from the Mycielski approach for 7-day ahead forecasts. Wen et al. (2011) and Fidan et al. (2012) improve the theory basis and Lee et al. (2013) attain good results in a unique setting.

Still, models in even broader use are generally more advanced. For example, WPMS (Wind Power Management System) is based on Artificial Neural Network (ANN) modeling. Ernst and Rohrig (2002) describe it in detail. ANN models are mostly used for short-term prediction. However, they are oftentimes outperformed by highly persistent models. Moreover, they are prone to overfitting.

Lange and Focken (2006) introduce the Prediktor model, which is an approach based upon physics. Such models perform well in longer-term scenarios, where persistence and periodicity are of less importance. Finally, stochastic modeling is used mostly for short- (up to 1 h) to medium-term forecasting (up to 48 h ahead), as Lei et al. (2009) point out. Many models are available, capturing several stochastic properties of wind power. For example, spatial-temporal interdependencies between multiple turbines are investigated by Hering and Genton (2010). These models are often based on univariate or multivariate time series modeling.

The Wind Power Prediction Tool (WPPT), as discussed by Nielsen et al. (2007), is one of the most successful multi-variable stochastic models. This model is put to wide use in Denmark, the worldwide leader in wind energy harvesting (Giebel et al., 2011). The model explains wind power production by local wind speed. It captures diurnal periodicity by means of a Fourier series model component and incorporates lagged variables, depending on the forecasting horizon. Still, the model has its drawbacks. As it is linear in the estimation, it neglects the turbine's both-sided limited power range, an important ex ante available information. Furthermore, as locally perceived wind direction is influenced by the turbine's immediate surroundings, this variable provides important additional model structure, but WPPT ignores it. The aforementioned shortcomings are eliminated within the generalized WPPT (GWPPT). Croonenbroeck and Dahl (2014)

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http://dx.doi.org/10.1016/j.jweia.2014.11.014
0167-6105/

recently introduce GWPPT in great detail. Moreover, they point out the benefits of GWPPT and compare the approach to WPPT and a persistent benchmark.

However, a broad comparison is not provided. Therefore, the gap this paper is intended to fill is the lack of a more thorough study concerning the forecasting performance of WPPT, GWPPT and several other approaches. We use a different turbine data set than Croonenbroeck and Dahl (2014). Our data even stem from a different turbine type and from a different manufacturer (Fuhrländer FL MD 77 instead of Vestas V90). Certainly, our turbines are placed at different locations. Thus, we use a unique data set of four turbines to compare GWPPT to its antecessor, WPPT, as well as several benchmark models. Finally, we evaluate each model's behavior at different forecasting horizons.

The selection of benchmark models is based on two main aspects: first, comparison models should be well known and established and second, they should be easy to implement. The first, well known and easy approach is the persistence forecaster. Slightly more flexible and still pretty simple, AR and VAR models are used. Next, we implement the famous and yet rather simple Nadaraya/Watson type kernel based nonparametric estimator. Lastly, the Mycielski approach is rather common in the wind speed forecasting literature. Its pattern search algorithm is easy to implement and is known for good results. To the best of our knowledge, the approach has never been applied to wind power forecasting before.

The paper is organized in the following way. A description of the analyzed data is given in Section 2. Thereafter, Section 3

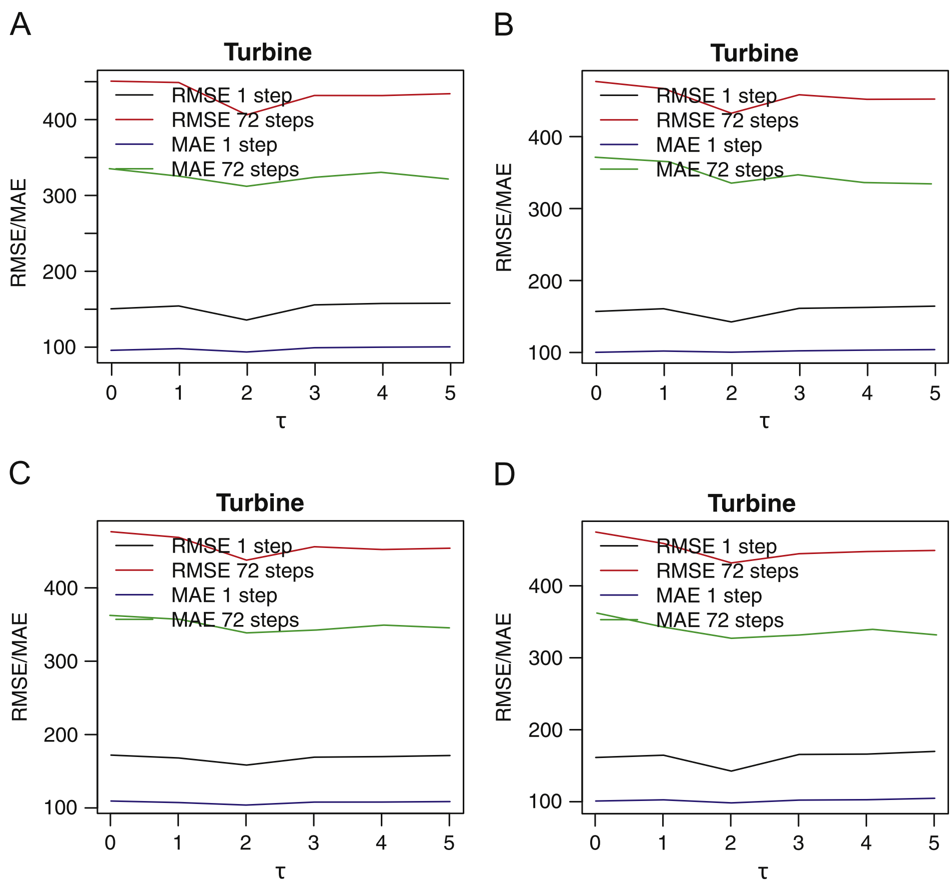

Fig. 1. Behavior of RMSE and MAE dependent on τ, Turbines A–D, 1 step and 72 steps ahead, time frame December 08, 2011 to January 04, 2012.

Table 1
Average length of Mycielski chains dependent on τ and percentage inflation of chain length in comparison to previous chain length $(\tau-1)$.

Model	$\tau=0$	$\tau=1$	$\tau=2$	$\tau=3$	$\tau=4$	$\tau=5$
Turbine A						
1 step	1.00	1.75 (+75.31%)	2.38 (+35.54%)	2.57 (+8.24%)	2.77 (+7.61%)	2.91 (+5.12%)
72 steps	1.00	1.75 (+75.34%)	2.38 (+35.54%)	2.60 (+9.24%)	2.77 (+6.62%)	2.91 (+5.15%)
Turbine B						
1 step	1.00	1.73 (+73.45%)	2.34 (+34.68%)	2.53 (+8.41%)	2.73 (+7.76%)	2.88 (+5.35%)
72 steps	1.00	1.73 (+73.25%)	2.33 (+34.39%)	2.55 (+9.33%)	2.72 (+6.90%)	2.88 (+5.40%)
Turbine C						
1 step	1.00	1.72 (+72.18%)	2.33 (+35.27%)	2.52 (+8.34%)	2.72 (+7.70%)	2.86 (+5.15%)
72 steps	1.00	1.72 (+72.09%)	2.32 (+35.02%)	2.53 (+9.03%)	2.71 (+7.09%)	2.85 (+5.17%)
Turbine D						
1 step	1.00	1.74 (+73.53%)	2.39 (+37.64%)	2.58 (+7.95%)	2.77 (+7.37%)	2.91 (+5.00%)
72 steps	1.00	1.73 (+73.42%)	2.38 (+37.31%)	2.59 (+8.78%)	2.76 (+6.64%)	2.90 (+5.03%)