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Review

Current status of wind energy forecasting and a hybrid method for hourly predictions

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ABSTRACT

Generating accurate wind energy and/or power forecasts is crucially important for energy trading and planning. The present study initially gives an extensive review of recent advances in statistical wind forecasting. Numerous prediction methods for varying prediction horizons from a few seconds to several months are listed. Then in the light of accurate results in the literature, the present study combines the adaptive neuro-fuzzy inference system (ANFIS) and an artificial neural network (ANN) for 1 h ahead wind speed forecasts. The performance results show the mean absolute percentage errors (MAPE) of 2.2598%, 3.3530% and 3.8589% at three different locations for daily average wind speeds.

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1. Introduction

Fossil fuel usage is being planned to be restricted and alternative renewable energy resources such as solar, wind, biomass and geothermal are having a growing part in the energy production. The wind energy, which is one of the most popular clean resources, has significant advantages and is widely used around the world. Nevertheless, due to chaotic nature of the wind, generating accurate wind energy forecasts stays problematic. Improving the predictions is in high demand and developing superior forecasting models is a subject of intense research [1–14].

The study initially provides an extensive review of recent studies in statistical wind speed and power forecasting in Section 2. It reviews the intensive effort for more accurate predictions and shows the recent improvements owing to the advanced machine learning techniques. The review focuses on statistical prediction methods. It differs from most of the surveys in extent by tabling prediction errors with respect to the forecast horizon. Detailed tables present recent obtained results along with the method used or developed. Study groups the prediction methods in four categories as pre-processing, non-hybrid, hybrid and post-processing. The review also lists the previous studies by their prediction horizons.

Section 3 gives a hybrid method. The adaptive neuro-fuzzy inference system (ANFIS) and the feed-forward artificial neural network (FNN) techniques are chosen to be combined in an adaptive way. This combination can be one of the most accurate candidates for hourly predictions in the light of literature review. And the method gives markedly low prediction errors in terms of three different error measures.

2. Literature review

The recent advances in wind energy and power prediction are reviewed in this section. This section gives the current methods

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with their reported accuracies and identifies enduring challenges in terms of forecast accuracy for different prediction horizons. Wind blows randomly and by definition it is not possible to predict its speed exactly. Accuracy of predictions and performance of the prediction methods are critically important for usage of wind energy. Results on the performance of methods in literature depend on the target location and tested data. And determining the ultimate best approach is difficult. The goal of this survey is twofold. The first is to reveal the range of prediction error in respect to the horizon obtained by the latest methods. And secondly, to list the approaches or techniques that can be favorable for a specific predication horizon.

In general, if historical data are preprocessed for a specific location and for a given prediction horizon, predictions improve. The reported studies show that hybrid methods combining several techniques mostly outperform the non-hybrid methods. Vast variety of methods and ongoing researches for different prediction horizons together with corresponding errors are demonstrated in Tables 1–3.

Table 1 lists the prediction errors of recent studies along with their horizons. Table compares the prediction errors in terms of different error measures including the mean absolute percentage error (MAPE), the mean absolute error (MAE), the mean squared error (MSE) and the root mean square error (RMSE) values. Studies are grouped by whether wind speed or power data are used. Table 1 reveals that wind power forecasting might be more accurate than the wind speed forecasting. The table includes the previous studies which report both the prediction error and horizon clearly. Also the references using non-conventional error measures are excluded since they are not comparable.

Table 2 presents the vast variety of methods employed in forecasting. The abbreviation list of method names is given alongside the table. The methods are classified as "hybrid" if they combine different techniques. The methods are put into separate groups when they are used for preprocessing or post-processing. Both pre and post-processing improve the predictions in general. In preprocessing, input data are manipulated, for example wind speeds are extrapolated to a hub height, or data are decomposed into representative components such as wavelet or principal components. In post-processing, the output data are classified to render the results or modified according to other available predictions such as from the numerical weather forecasts.

In Table 3, the previous studies are grouped by their prediction horizons as very short-term, short-term, medium-term, long-term and very long-term. The very short-term predictions cover a period from a few seconds to 30 min, the short-term predictions are from 30 min to 6 h, the medium-term predictions are from 6 h to 24 h, the long-term predictions are from 24 h to 72 h and the very long-term predictions are for 72 h and longer. This classification is made in regard to the drop in prediction accuracy and the focus of different business sectors. The review shows that most of the studies tackle with the short-, medium- and long-term forecasts. However, being accurate for these terms is particularly difficult. And if a prediction horizon inside any of these terms increases, the accuracy characteristically gets down. Table 3 gives the list of prediction horizons along with a reference list.

Wide variety of methods are being used and developed for predictions. The studies reviewed here are arranged by their horizon from very-short to long-term. *For the very short-term predictions*, a new artificial neural network (ANN)-Markov chain (MC) model is described in [15]. For wind speed predictions, study investigates data patterns of different time scales. A set of data of 175 min is used for examining the accuracy of the proposed model and predicting the wind speeds up to 7.5 s ahead. The MAPE values for the ANN-MC model are obtained as 3.14%, 8.03% and 11.33% for 2.5, 5 and 7.5 s ahead predictions, respectively. Errors show that abrupt behavior of wind reduces the accuracy in this horizon. Another time series model that is integrating the concepts of structural breaks and the Bayesian inferences is introduced in [16]. This approach, however, gives 0.165 MAE and 2.266 MAE for 1 min and 1 h ahead forecasts, respectively.

By deriving the optimal loss functions from different error models, a uniform model of ν-support vector regression in connection with the general noise model (N-SVR) is investigated in [17]. Study compares three different N-SVR models, namely ν-SVR, GN-SVR

Table 1
Errors in recent studies against the prediction horizon.

Refs.	Input data	Prediction Horizon	Error
[15]	Wind speed	2.5-s 5-s 7.5-s	3.14% MAPE 8.03% MAPE 11.33% MAPE
[16]	Wind speed	1-min 1-h	0.165 MAE 2.266 MAE
[17]	Wind speed	10-min 1-h	3.79% MAPE 12.40% MAPE
[18]	Wind speed	10-min 30-min 1-h 2-h	8.01% MAPE 15.99% MAPE 23.85% MAPE 34.70% MAPE
[19]	Wind power	10-min 12-h	70.25 MAE 101.26 MAE
[20]	Wind speed	15-min (Site 1) 30-min (Site 2)	7.75% MAPE (Site 1) 9.84% MAPE (Site 2)
[21]	Wind speed	15-min	11.5% MAPE
[22]	Wind power	1-h	4.3678 NMAE
[23]	Wind speed	30-min 60-min 90-min	1.61% MAPE 3.33% MAPE 5.08% MAPE
[24]	Wind power	1-h	3.513% MAPE
[25]	Wind speed	1-h 3-h 5-h	0.051 RMSE 0.074 RMSE 0.100 RMSE
[26]	Wind power	1–6 h 24-h	Between 2.70 and 7.82 MAE 8.64 MAE
[27]	Wind power	3-h	3.75% MAPE
[28]	Wind speed	4-h	5.71% MAPE
[29]	Wind power	6-h	13.02% MAPE (Ave.)
[30]	Wind speed Wind power	24-h	Around 2.65 m/s MAE (WS) Around 0.19% NMAE (WP)
[31]	Wind power	1–24 h	Range from 8.96% to 11.66% MAPE
[32]	Wind power	24-h	5.41% MAPE
[33]	Wind speed	24-h	21.61% MAPE (Exp.1) 22.93% MAPE (Exp.2) 19.83% MAPE (Exp.3)
[34]	Wind power	24-h	23.73% MAPE (Ave.)
[35]	Wind speed Wind power	24-h	Around 1.85 m/s MAE Around 69 kW MAE
[36]	Wind power	24-h Weekly	11.91% MAPE (Ave.) 15.38% MAPE (Ave.)
[37]	Wind power	48-h	3.0 MAE (Ave.)
[38]	Wind power	12-h 84-h	12.41 MAE 11.62 MAE
[39]	Wind power	48-h	8.90 NMAE
[41]	Wind speed Wind power	72-h	1.66 MAE (WS) 146.50 MAE (WP)
[42]	Wind power	5-day	0.096 sMAPE (Station A) 0.069 sMAPE (Station B)
[44]	Wind speed	Quarter-yearly	15.32% MAPE