Short time ahead wind power production forecast.

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Abstract. An accurate prediction of wind power output is crucial for efficient coordination of cooperative energy production from different sources. Long-time ahead prediction (from 6 to 24 hours) of wind power for onshore parks can be achieved by using a coupled model that would bridge the mesoscale weather prediction data and computational fluid dynamics. When a forecast for shorter time horizon (less than one hour ahead) is anticipated, an accuracy of a predictive model that utilizes hourly weather data is decreasing. That is because the higher frequency fluctuations of the wind speed are lost when data is averaged over an hour. Since the wind speed can vary up to 50% in magnitude over a period of 5 minutes, the higher frequency variations of wind speed and direction have to be taken into account for an accurate short-term ahead energy production forecast. In this work a new model for wind power production forecast 5- to 30-minutes ahead is presented. The model is based on machine learning techniques and categorization approach and using the historical park production time series and hourly numerical weather forecast.

1. Introduction

Currently, the wind energy plays a significant role in total electricity production in Europe. Therefore it is vital to predict the wind energy output timely and accurate. The variability of the wind is the primary challenge for obtaining an accurate forecast minutes to hours ahead.

Many studies have been devoted to the improvements of wind forecasting techniques with a number of models developed and launched. These models are based on physical [1,2], statistical [3,4] or hybrid approaches [5,6].

The physical approach focuses on integrating well-known physical aspects into the model, such as information about surrounding terrain and properties of the wind turbines. Statistical approaches relies more on historical observations and their statistical relation to meteorological predictions as well as measurements from Supervisory Control And Data Acquisition (SCADA). Statistical models are usually built around Numerical Weather Prediction (NWP) at tens-of-kilometers resolution.

But NWP-based models are failing to provide site-specific short time ahead forecasts at satisfactory accuracy due to a relatively coarse resolution of the NWP model.

For site-specific forecasts, the mesoscale-microscale coupling model was proposed in [7], where the artificial intelligence methods were used to issue 1 to 3 hours ahead wind speed forecast from NWP data, and later the CFD module was used to calculate the flow at finer scales [8]. The accuracy of the coupled model [7] was found to be superior comparing to that based on polynomial fittings as well as AutoRegressive Moving Average (ARMA) models, although the accuracy for shorter-than-one-hour forecast remains unsatisfactory.

Very short-term models (less than 9 hours) used for wind power forecasting usually consists of statistical methods like Kalman Filters, ARMA, Auto-Regressive with Exogenous Input, Box-Jenkins etc. Inputs to these models are historical observations of wind speed, wind directions, temperature, etc.

Machine learning methods used in this area include Neural Networks [9], Support Vector Machines [10], Nearest Neighbour Search [11], Random Forests, etc. Summarizing the reports for very-short time ahead forecast the error of 12% of the total rated power can be stated as the state-of-the-art. [12,16]

2. Model selection

In this work, the model proposed in [7] has been adapted to forecast a wind power output for less than one hour ahead by utilizing time series of historical power production in addition to NWP data. Adapted model also uses a data categorization approach, as described in [13]. There the information obtained from the categorization of a single variable (wind speed, for instance) is supplied as an additional input to the model.

The model for short-time ahead prediction of the wind power is based on time series analysis of the historical park production and NWP data. The quality of the forecast depends on the ability of the model to predict the wind flow near the ground in the complex terrain, where the roughness and complexity affect the flow at microscale. Therefore the model employs machine learning techniques as those are proven to be efficient for nonlinear multivariable functions approximation when explicit physical-based models have a limited application or not available.

In this work, a combination of artificial neural networks (ANN) module and kernel module (support vector machine, SVM) has been used to forecast the total wind park power production 5- to 30-minutes ahead. The modules are trained, tested and validated on 4-months historical data from several onshore wind parks from Sweden and Norway.

To forecast the wind power production 5- to 30-minutes ahead a feed-forward (FF) ANN with a single hidden layer and single output neuron has been built.

Two different sets of the input variables were used for ANN training. One ANN received the historical power production values as inputs and obtained the total power production minutes ahead as output. Another ANN received time-series of multiple environmental variables as inputs (registered wind speed and direction time-series and hourly NWP data) in addition to historical power production time-series.

The length of a time window was two times longer than the prediction horizon. For example, for 5-minutes ahead prediction, the last 10-minutes park power production records (averaged over 1 minute) were used as inputs.

The pre-processing included data cleaning, normalization, and time averaging. The data was averaged by 1-minute for 5- to 10-minutes ahead prediction, and 5-minutes averages were used for 15- to 30-minutes ahead prediction. The dataset split in the ratio 70:20:10 for training, testing, and validation correspondingly. After cleaning, the total number of records available for the model training was 129600 for 1-minute averaging intervals and 25920 for 5-minutes averaging intervals.

To measure the differences between values predicted by the model and the values observed the normalized root-mean-square error (root-mean-square percentage error, RMSPE) had been calculated:

$$RMSPE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i-y_{ipredict}}{y_i}\right)^2} ,$$

where y denotes the observed value and $y_{predict}$ denotes the corresponding prediction.

As in RMSPE the negative and positive errors don't cancel out each other and the higher weight is given to larger errors it makes an excellent general purpose error metric for numerical predictions: the smaller the RMSPE, the better fit of the model. RMSPE for ANN models for validation data sets is shown in Table 1.

Backpropagation training method as provided by Encog Workbench open source software package [15] has been used.

Table 1. Root-mean-square percentage error of wind power production forecast performed by ANN-module.

Prediction time-window	Hourly weather forecast and historical power production time series	Historical power production time series
5 minutes ahead prediction	12.2	8.2
15 minutes ahead prediction	14.9	9.7
30 minutes ahead prediction	15.1	9.5

Because of the lower prediction error, the ANN trained only on historical power production time series has been selected for further modification.
From a theoretical point of view, one can approximate almost any function with one layer neural network. Therefore, the most of the literature suggests that a single layer neural network with a sufficient number of hidden neurons will provide a good approximation for most problems and that adding a second or third layer yields little benefit. Here a new double-module model has been suggested to improve the model's accuracy. One single hidden layer FF ANN has been used to issue a "coarse" prediction and the output from the first module has been submitted to the second machine learning unit (a "correcting" module) to issue a more accurate forecast. With the suggested double-module approach when the output of the coarse predictor has been used as additional input to the fine predictor, RMSPE has been lowered to 7.9 and 8.9 for 5 minutes ahead and 30 minutes ahead predictions respectively.
The accuracy of the "correcting" module based on single hidden layer FF ANN is compared to the one based on kernel method (SVM). RMSPE for different "correcting" module architectures is provided in Table 2.

Table 2. Root-mean-square percentage error of wind power production forecast performed by "correcting" module.

Prediction time-window	ANN module	SVM module
5 minutes ahead prediction	7.9	6.4
30 minutes ahead prediction	8.9	7.9

The performance of double-module model has been compared to data categorization approach based model. This method is described in [13] and suggests that the entire dataset should be grouped into several discrete categories. Here, the wind speed data has been split into nine categories according to the turbine power curve characteristics (with categories' names similar to Beaufort scale) as shown in Table 3. Obtained numerical attribute of the category has been fed as an additional input to "coarse" module FF ANN.

Table 3. Wind speed ranges and corresponding numerical attributes used for categorization.

Wind speed range, m/s	<0.5	0.5-1	1-3	3-7	7-10	10-15	15-20	20-25	>25
Category	Failed record	Wind calm	Light breeze	Gentle breeze	Fresh breeze	Strong wind	Near gale	Gale	Cut off
Numerical attribute	1	2	3	4	5	6	7	8	9

Previously it was shown [14] that the selection of methods for categorization is not critical, so in this work, the wind speed was categorized. RMSPE on validation data set for all the models mentioned above summarized in Table 4.

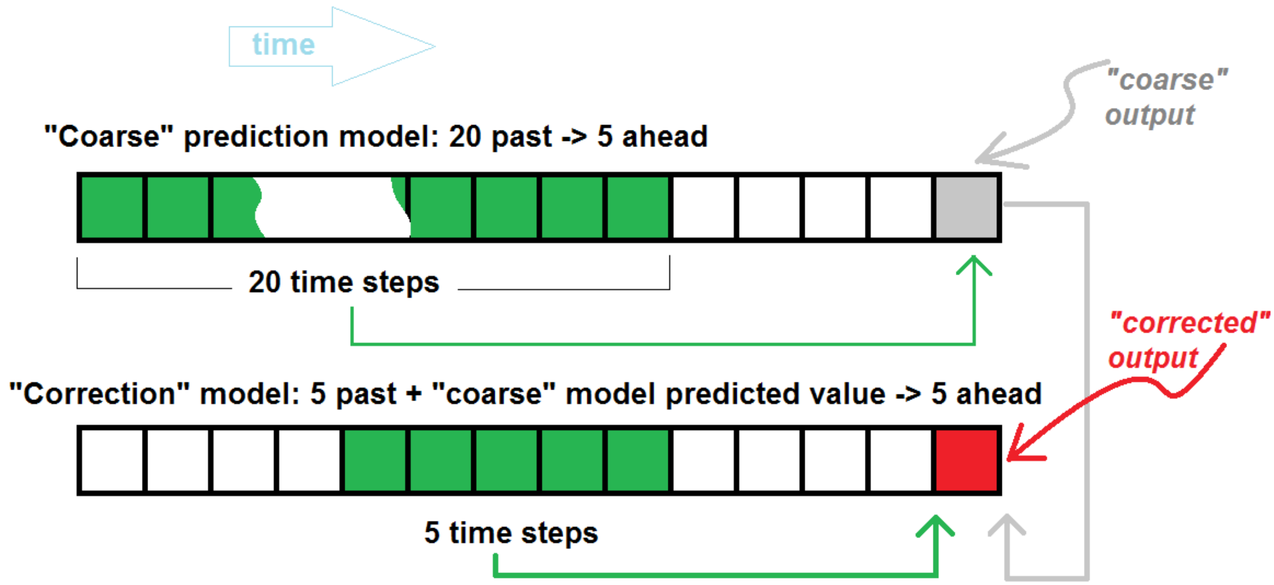
Table 4. Root-mean-square percentage error of 30 minutes ahead power output forecast for different model architectures.

Single-module, ANN model	Double-module, ANN based model	Double-module, ANN and SVM based model	Double-module model with data categorization approach
14.9	8.9	7.9	7.5

3. Results

The suggested double-module model comprise of (1) ANN that uses park power production time-series to predict power output 5- to 30-minutes ahead, and (2) SVM that utilizes output from ANN as one of the inputs along with NWP data and the wind power production time-series. Schematic description of the model shown in Figure 1.

Figure 1. Double-module model: "coarse"-predicting module is using longer time-series of a single variable; the output from "coarse" module is utilized by "correcting" module along with shorter time-series of multiple variables.



ANN architecture and performance for various length of time-windows and prediction horizons is summarized in Table 5.

Table 5. ANN modules' architectures and root-mean-square percentage error of wind power production forecast performed by corresponding modules.

Prediction horizon	5 minutes			10 minutes			20 minutes			30 minutes		
Time-series window interval, minutes	10	20	30	20	30	40	30	40	60	40	60	90
Number of hidden neurons	10 to 30	20 to 60	30 to 90	20 to 60	30 to 90	40 to 100	30 to 90	40 to 100	60 to 100	40 to 100	60 to 100	90 to 100
Validation error (RMSPE)	14.9	9.7	7.9	15.1	12.2	8.1	18.1	12.4	8.6	16.2	8.9	8.9

The output from the ANN module along with other inputs has been submitted to SVM to predict the power output same time ahead. With the double-module approach, RMSPE for 10 minutes ahead forecast has been lowered from 7.9 to 5.9. The SVM module performance is shown in Table 6.

Table 6. SVM modules' architectures and root-mean-square percentage error of wind power production forecast performed by corresponding modules.

Prediction horizon	5 minutes				10 minutes				30 minutes					
Power production	5	5	10	10	5	5	10	10	5	5	10	10	20	20

time-series length, minutes														
NWP data used	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Wind speed and direction time-series, minutes	5	5	5	5	5	5	5	5	10	10	10	10	10	10
Validation error (RMSPE)	6.6	6.7	5.9	5.9	6.9	6.8	6.1	6.2	9.1	9.4	8.6	9.2	8.2	8.5

SVM module performance is not significantly affected by the lack of NWP data for very short term ahead prediction, yet for longer prediction horizons, like 30-minutes ahead, using NWP data as input helps to lower RMSPE.
Finally, the model has been modified to employ the categorization data (as described in [4]). The wind speed data were categorized and supplied as one of input variables to SVM module. The model that is using categorization approach shows better performance, as shown in Table 7.

Table 7. SVM module performances for the short time ahead wind power forecast with and without categorization approach.

Prediction horizon	5 minutes		10 minutes		30 minutes		
Power production time-series length, minutes	5	10	5	10	5	10	20
Wind speed and direction time-series, minutes	5	5	5	5	10	10	10
RMSPE for model without categorization approach	6.7	5.9	6.8	6.1	9.1	8.6	8.2
RMSPE for model with categorization approach	4.5	4.6	5.1	5.1	6.5	6.2	6.2

4. Conclusions

In this work a new model to forecast the wind power production 5- to 30-minutes ahead is presented.
The model uses NWP, historical wind power production data and employs machine learning methods and categorization approach. The best performance is observed for the combination of ANN and kernel methods. The proposed model provides 10-minutes ahead prediction with RMSPE 4.5 and 30-minutes ahead prediction RMSPE 6.2 which is much better than reported state of the art for less than one hour ahead prediction [12, 16].
It is shown that use of NWP data does not significantly improve the accuracy of very short time ahead forecast (5-10 minutes ahead), yet it is valuable for 30-minutes ahead forecasts.
If categorization approach is used, better accuracy of the forecast can be achieved even with smaller number input variables. It is observed that model's generalization arises from the model's ability to find similarity in the training data that usually consists of continuous numeric data. Since numbers are rarely the same from one example to the next, the model can fail in selecting the margins for identical properties. In this case, the generalization can be improved by classification. As shown in [14] the choice of methods for categorization is irrelevant to the generalization improvement. Therefore, the generalization approach can be adapted to various input parameters.

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