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Short time ahead wind power production forecast.

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Abstract

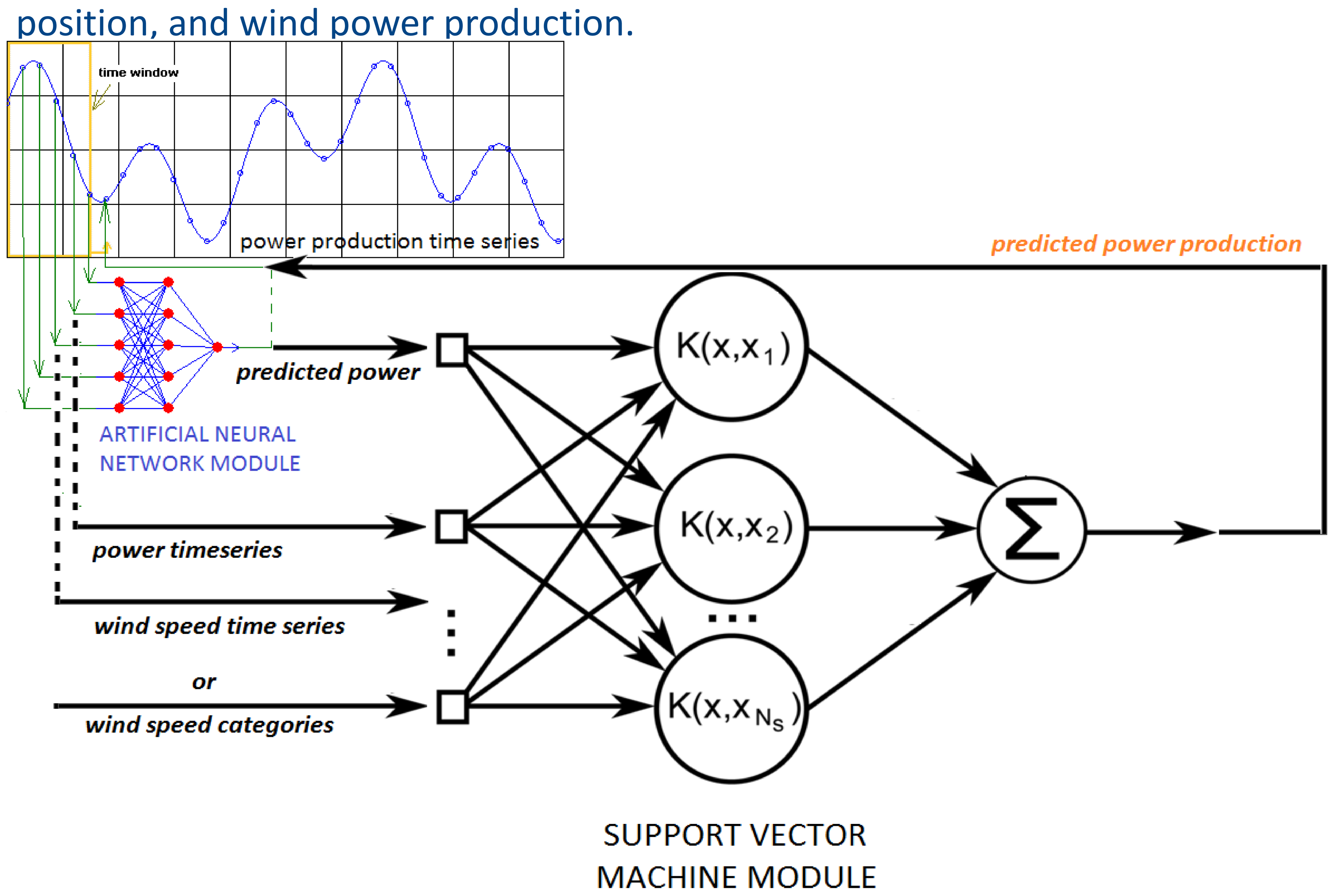
An accurate prediction of wind power output is crucial for efficient coordination of cooperative energy production from different sources. Long-term ahead (from 6 to 24 hours) prediction of wind power can be achieved by using coupled models that bridge mesoscale weather prediction data and computational fluid dynamics (as presented in [1]). When a forecast for shorter time horizon (less than 1 hour) is anticipated, an accuracy of predictive model that utilizes hourly mesoscale weather data is decreasing as the higher frequency fluctuations of the wind speed are lost when data is averaged over an hour. It is observed in [2] that wind speeds can vary up to 50% in magnitude over a period of 5 min and the analysis of wind speed fluctuations over periods from minutes to hours [3] shows that higher frequency variations of wind speed and direction have to be taken into account for accurate short-term ahead energy production forecast. In this work a new model to forecast wind power production 5- to 30-minutes ahead is presented. The model is based on machine learning techniques and categorization approach [4] and uses historical wind and power production time series to issue total power production of the park.

Objectives

The model allows accurate prediction of wind power output short time ahead. The model does not require NWP data for operation and is robust to uncertainty in the data sets. Therefore, it can be used for near real time prediction in the environment where the short periods of cutoffs can be expected.

Model

We suggest here a double-module model containing (1) Artificial Neural Network (ANN), that uses park power production time-series to predict power output 5 to 30 minutes ahead, and (2) Support Vector Machines (SVM), that utilizes output from ANN as one of the inputs along with time-series of registered wind speed, wind direction, nacelle speed, nacelle position, and wind power production.



Results

Model performances for short time ahead wind power forecast: prediction accuracy is not significantly affected by lack of NWP data for very short term ahead prediction, yet for longer prediction horizons, like 30 minutes ahead, NWP data helps to lower RMSPE.

Prediction horizon	5 minutes				10 minutes				30 minutes					
Power production time-series length, minutes	5	5	10	10	5	5	10	10	5	5	10	10	20	20
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

The model has been modified to employ categorization data (as described in [4]). The wind speed data were categorized and supplied as one of the input variables to the SVM module. The model that is using the categorization approach shows a better performance.

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

Suggested double-module model shows the best performance comparing to other models for 5 to 30 minutes prediction horizon.

Prediction horizon:	5 minutes	10 minutes	20 minutes	30 minutes
Single module ANN model error	7.9	8.1	8.6	8.9
Double-module model error	4.5	5.1	5.8	6.2
Persistence approach	14.2	17.1	19.2	26.2

Conclusions

The model uses NWP, historical wind speed and power production data and employs machine learning methods and categorization approach.

The best performance is shown for combination of ANN and kernel method for double-module model.

The model shows that use of NWP data does not significantly improve the accuracy for very short time ahead forecast (5-10 minutes ahead), yet is valuable for 30 (and longer) minutes ahead forecasts.

If categorization of an input variable is used, the better accuracy of the forecast can be achieved even with smaller number of 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 exactly 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 [5] the choice of methods for categorization is irrelevant to the generalization improvement therefore the generalization approach can be adapted for various input parameters.

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