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Machine learning for short time ahead wind power forecast

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Abstract

With wind power generation growing new complications are introduced to wind energy producers: in order to work effectively changes in the wind power have to be anticipated. This is only possible with accurate wind predictions.

Wind speed and wind direction can be forecasted with quite accuracy for onshore wind parks located in complex terrain with models based on a coupling between artificial neural networks (ANN) and mesoscale weather predictions, and computational fluid dynamics (CFD).

While generally the combination of ANN and CFD ensures high accuracy of the forecast, some weather regimes remain unresolved. The accuracy of the forecast for wind speed and wind direction improved significantly when categorization information was added as an input to the artificial neural network. The improved model was able to resolve extreme events and converged faster with significantly smaller number of hidden neurons.

Objectives

In this work we predict wind speed, wind direction and total energy yield for wind park from one to 3 hours ahead.

In order to forecast the wind flow near the ground in the complex terrain, where roughness and complexity affect the flow at microscale the ANN is employed to predict nonlinear multivariable functions in the environment where explicit physics-based models either have limited application or are not available.

ANN based model's generalization arises from its ability to find similarity in the training data consisting of continuous numeric data. Since numbers are rarely exactly the same from one data sample to the next, the model can fail in selecting the margins for identical properties. In this case, the generalization can be improved by classification. When the training data is limited or incomplete a *categorization* approach can be used.

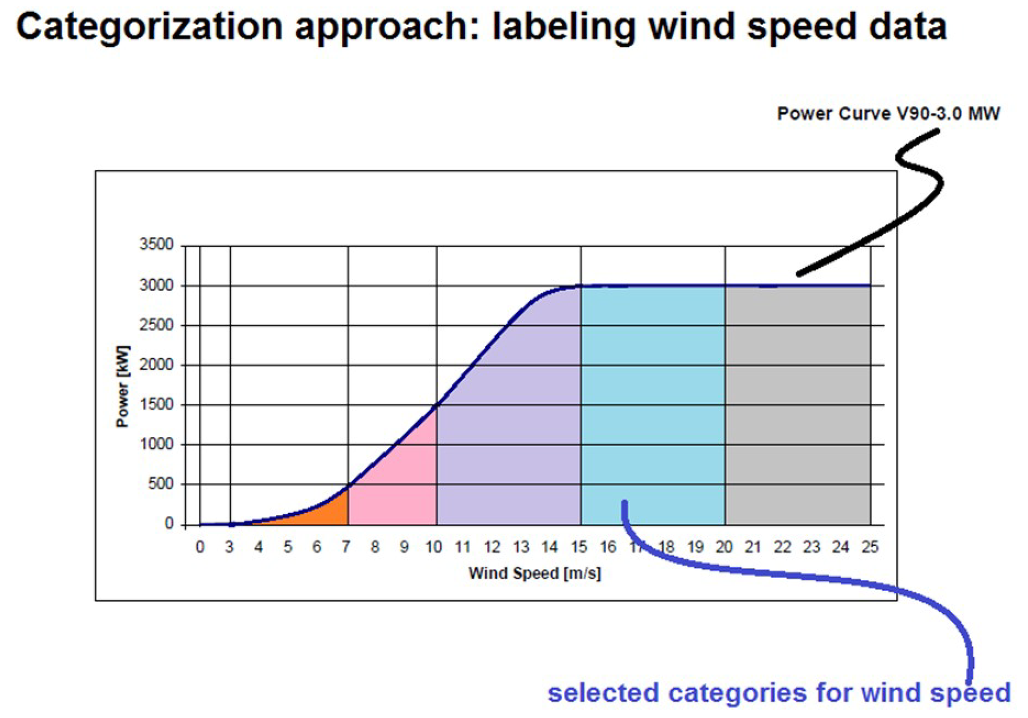
Methods and Model

The mesoscale-microscale coupling model uses NWP time-series for temperature, pressure, relative humidity, wind speed, and wind direction to issue a site-specific forecast.

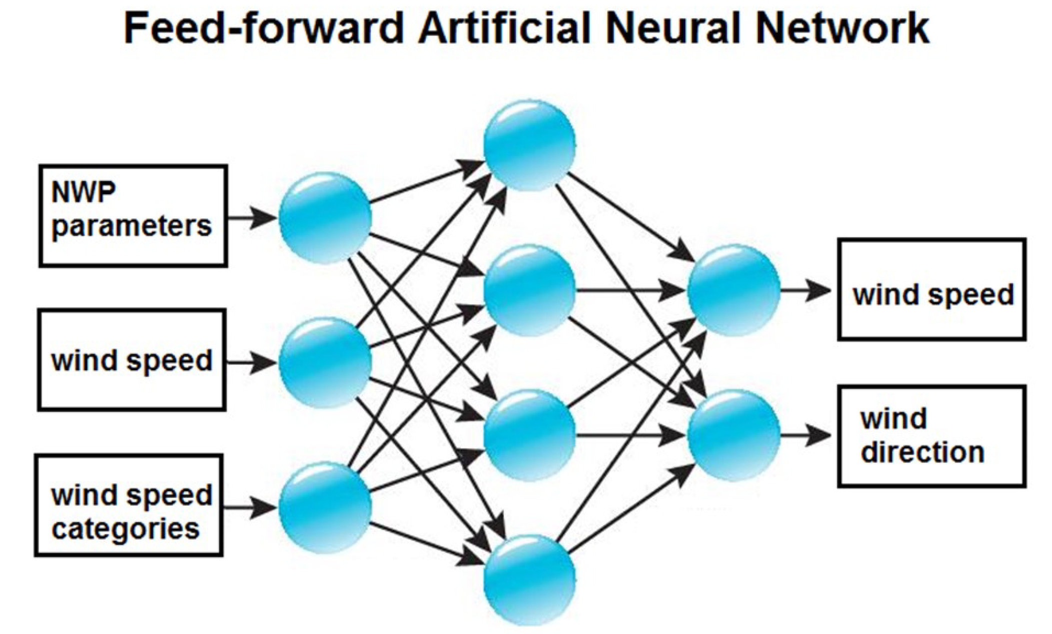
ANN is trained against historical observations of wind speed and direction and corrects the NWP forecasts of mean hourly wind speed and direction.

To categorize the continuous numeric data each wind speed value has been labeled similar to typical human concepts (e.g. “calm wind”, “fresh breeze”, “strong wind”, etc.). The relation between categories and wind speed ranges is shown below.

Categorization approach: labeling wind speed data



The information obtained from categorization of a wind speed variable has been supplied to the ANN input along with NWP variables, as shown on model's scheme below.



Data

In this work the data from ERG Wind Farm located in Molise in central Italy was used. The farm location is in a wide area between the town of Ururi and Montelongo, situated in complex terrain of different ridges and is about 10 km wide. The wind farm layout is composed by 20 Vestas V90 turbines. The anemometer used as a reference, located in a central position of the wind farm at 30 m height.

The NWP data provided by Meteogroup is a forecast of five days delivered four times a day. The wind speed, wind direction, temperature, pressure, density and relative humidity forecasted at 80 m and 30 m heights.

Prior usage, the anemometer registered values were cleaned from invalid data. Then the measured and forecasted values were pre-processed and normalized.

Results

wind speed	temperature	<NWP parameters>	wind speed category label, numerical		wind speed predicted	wind speed actual
8.3	30.35		"breeze",	3	7.6559172161	7.36
6.2	16.51		"breeze",	3	6.7288569885	8.68
1.54	19.48		"calm",	2	2.7145615158	2.48
6.46	28.52		"calm",	2	3.8186234012	4.37
5.87	13.84		"breeze",	3	6.9018778585	8.22
8.52	32.19		"calm",	2	3.7441752731	4
1.57	8.43		"none",	0	-0.9305498312	-1
8.93	11.32		"strong",	4	11.450469544	10.17

The table above shows model's input values, including category values (both as a label and numerical form) and predicted vs actual values for wind speed [m/s] one hour ahead.

Performance of new model with categorization has been compared to non-categorization model and classification model where input variables (excluding category variable) have been enhanced by classification identification obtained from self-organizing maps. The comparison is shown in table below:

Model	With categorization	Non-categorization I	Non-categorization II	Classification
ANN architecture with winning performance	4 input, 9 hidden, 1 output neurons	2 input, 30 hidden, 1 output neurons	36 input, 60 hidden, 1 output neurons	4 input, 30 hidden, 1 output neurons
Training time required to reach 0.01 % training error, number of iterations rounded to thousands	20,000	240,000	2,185,000	438,000
Mean absolute percentage error	2.4 %	4.6 %	4.1 %	5.0 %
Root mean square percentage error (RMSPE)	5.4 %	9.8 %	8.8 %	10.4 %
Coefficient of determination (R^2)	0.83	0.74	0.77	0.69
Correlation	0.87	0.62	0.79	0.67

Conclusions

The ANN-based model for mesoscale-microscale coupling has been improved by employing categorization approach.

It is observed that a model with added categorization information has nearly twice as low RMSPE (root mean square percentage error) than a regular model (5.4% vs 9.8%) with the number of hidden neurons lowered twice in the categorization model.

The model with categorization shows MSE =1.1 m/s for wind speed prediction on the test data sets and resolves all weather regimes at the same level of accuracy.

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