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A NEURAL NETWORK ALTERNATIVE TO TRADITIONAL MEASURE-CORRELATE-PREDICT ALGORITHMS IN WIND RESOURCE ASSESSMENT

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Abstract

In a typical wind resource assessment on-site measurements are only available for a limited time, perhaps one to three years. These in situ data are central to many facets of the wind resource assessment from project feasibility to micro-siting of turbines. It is thus crucial to understand what the measurement period represents in the context of the long-term wind climate at the site, and to correct and extrapolate the measurements where the measurements are not representative of long term climate.

The uncertainties resulting from seasonal and inter-annual variability embedded in on-site measurements are widely accepted to be reduced by careful long-term referencing of the measurements to nearby observations or model reanalysis data. There are various measure-correlate-predict (MCP) algorithms which are commonly used in the industry, and each has its own set of advantages and limitations. In this study an alternate approach to measure-correlate-predict using artificial neural networks (ANNs) is presented and compared with a linear regression MCP for several sites.

Method

The objective of this study was to compare results from traditional MCP methods to those achievable through the use of Artificial Neural Networks ANNs. The traditional method is a linear regression based MCP and the neural network method was developed in house to accomodate this comparison.

The neural network method uses the on-site data and long term reference data from a mesoscale model hindcast and/or nearby observation data, feed forward neural networks are used with the help of the MATLAB Neural Network Toolbox. The neural networks are trained in a supervised way using overlapping reference and observation time series, and the trained networks are then used to predict the observation series given only an extension of the reference series. A schematic of the network architecture is shown in Figure 1.

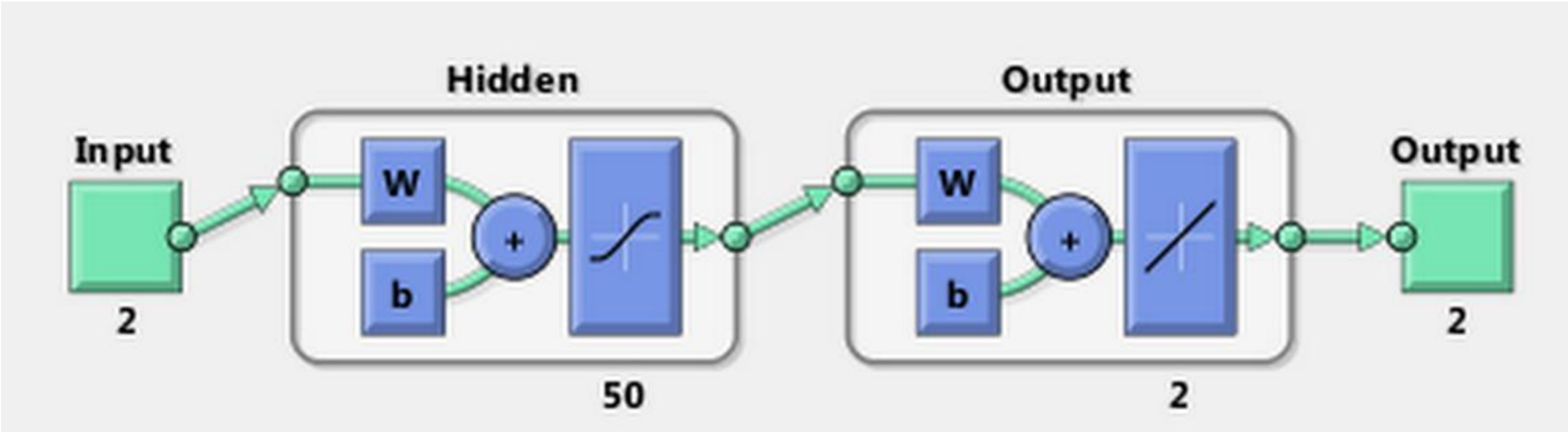

Fig. 1: Schematic showing the configuration of the feed-forward neural network used in this study. The inputs to the trained network are wind speed and direction from the reference time series and the outputs are predictions of the target time series.

For the purposes of comparison, the neural networks and the linear regression-based MCPs use the same 'training' period to establish correlations and network weights, and the same validation period from each site to create a predicted time series for a period in which observations exist, but have not been used in training. The results are summarized as comparisons between the respecive predicted time series and the validation observations.

Sites

Site 1:

A 50m mast in the Northeastern United States. Hourly averages of the measured wind speeds and directions are referenced with hourly time series from a meteorological model run in hindcast mode. The training period from the mast is April through December 2010, and the period used for validation is October 2009 through March 2010.

Site 2:

A 60m mast in the Western United states. Ten minute averages of the measured wind speeds and directions are referenced to the same for a nearby mast. The period for training is from January 2008 to February 2009 and the period used for validation is May through December 2007 and March 2009 through August 2010.

Site 3:

A 60m mast in the Western United states. Ten minute averages of the measured wind speeds and directions are referenced to the same from a nearby mast. The period for training is from January 2008 to February 2009 and the period used for validation is March 2009 to August 2010.

Results

Site 1	Mean Bias U [m/s]	RMSE U [m/s]	RMSE_Dir [deg]	R^2 U [-]	R^2 Dir [-]
NN	0.28	1.53	45.2	0.68	0.70
MCP	0.28	2.36	53.6	0.62	0.68
Site 2	**Mean Bias U [m/s]**	**RMSE U [m/s]**	**RMSE_Dir [deg]**	**R^2 U [-]**	**R^2 Dir [-]**
NN	-0.02	0.54	18.8	0.99	0.93
MCP	0.21	2.59	69.6	0.68	0.39
Site 3	**Mean Bias U [m/s]**	**RMSE U [m/s]**	**RMSE_Dir [deg]**	**R^2 U [-]**	**R^2 Dir [-]**
NN	0.00	0.98	17.4	0.96	0.93
MCP	-0.01	1.78	65.7	0.87	0.43

Table1: Summaries of the errors between the predicted and observed time series for the neural network and traditional MCP. R^2 and RMSE are hourly for Site 1 and for ten minute averages for sites 2 and 3.

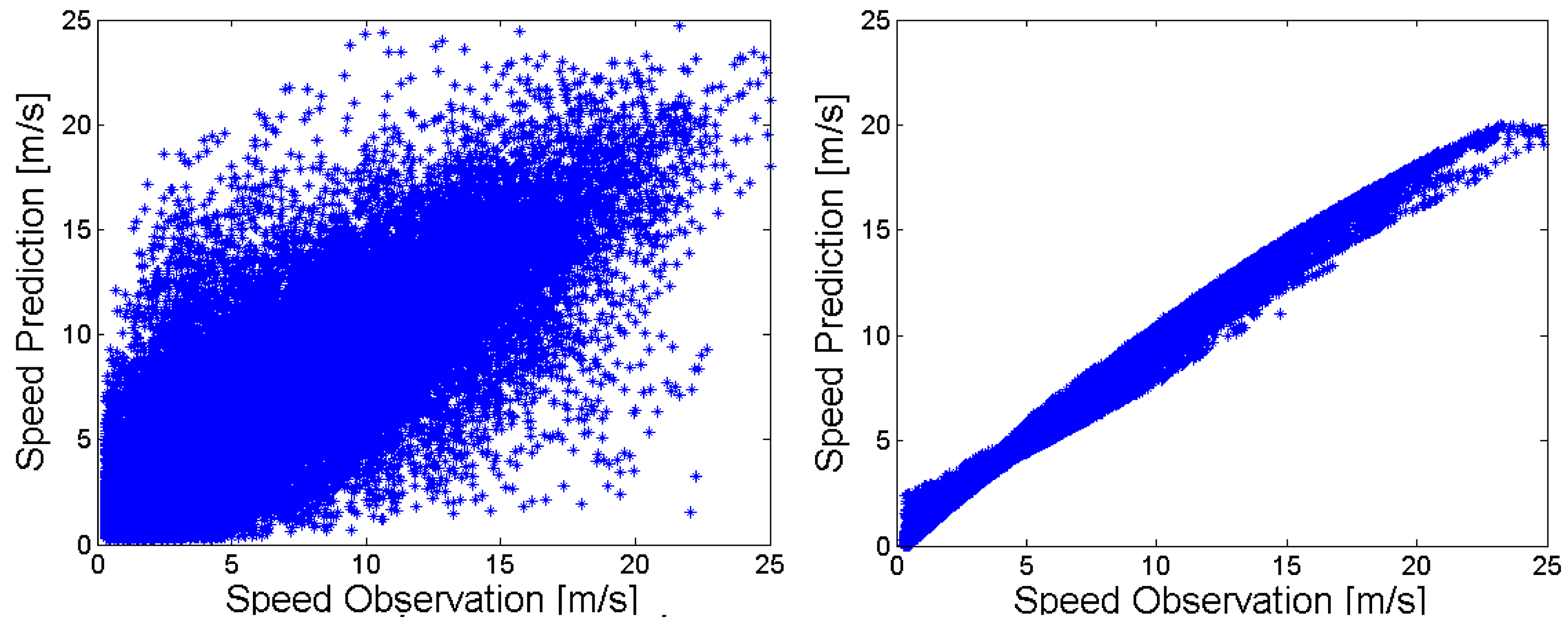

Fig. 2: Scatter plots of observed and predicted wind speeds for Site 2. The regression MCP scatter is on the left and the neural network method on the right.

Comparison of the results shows that for three the sites used in this comparison both the linear regression based method and the neural network method give satisfactory predictions for the mean wind speed in the validation period.

However the neural network method yields significantly lower root mean errors following the time steps of the time series, and also does better to reproduce the distribution of the wind speeds and directions in the validation periods. The scatter plots between observed and predicted wind speeds illustrate further that for individual time steps the neural networks out-perform the linear-regression method in terms of correlation between the predictions and observations values.

For all sites the neural network predictions correlate best with the observations in the middle of the range of wind speeds. This result can be explained in the lower range by the fact that at low wind speeds between the reference and observations sites are generally less correlated than higher wind speeds which are often driven by mesoscale meteorological phenomena. More extreme winds can be similarly local and thus more difficult to predict from reference time series.

Conclusions

A comparison in long-term correction in wind speeds was carried out between a traditional linear-regression based method and a method based upon artificial neural networks. The results were compared in terms of biases in the mean wind speed for a validation period, as well as RMS errors and correlations for the same period.

Both methods gave good estimates of the mean wind speed, but the neural networks outperformed the linear method in terms of root mean square errors, correlation coefficients and distribution of wind speed and direction.

Further work is needed to examine the impact that these differences would have on energy production as related to power curves for wind turbines, but the results reiterate the promise of using neural networks for long term correction of wind speeds which has been found in other studies.