Using Reanalysis Data for Hourly Wind Resource Estimates

Kashif Gill, Dennis Moon and Bruce Lee
WindLogics Inc.

Abstract

The current work demonstrates a temporal downscaling scheme from 6-hourly wind/power estimates to hourly estimates. The 6-hourly estimates are generated as part of the Enhanced-Measure-Correlate-Predict (E-MCP) [1] study conducted on the wind farm sites. The E-MCP study employs the National Center for Environmental Prediction (NCEP)'s global reanalysis I (RNL) dataset. The RNL data is available from 1948-present at a temporal resolution of 6-hours, and a spatial resolution of 2.5 degrees.

Finer (than 6-hourly) scale estimates contribute directly to more accurate wind and energy resource assessment studies, which has wide applications for the renewable industry. In the present paper, a downscaling methodology to estimate long-term hourly wind speed and energy predictions is developed. This temporal downscaling model uses a combinatorial algorithm employing high-level computational learning machines and multi-objective evolutionary strategies. The results are compared against a simpler approach employing spline interpolation.

Methodology

The current research develops a scheme using a combinatorial approach employing Support Vector Machine (SVM) [2] and multi-objective evolutionary optimization (MOEO) algorithm [3, 4, 5]. SVM is a powerful machine learning tool that has applications in a wide range of scientific disciplines. Windlogics primarily employs SVM for building regression models for assessing and forecasting wind resources. The multi-objective evolutionary algorithm is used to optimize the SVM hyper-parameters. It allows more than one objective to be minimized (or maximized) simultaneously in optimization and thus provides a *trade-off surface* between various objectives. The methodology employs a *Pareto ranking* strategy to rank the population according to the superiority of the solutions in the multi-objective space, which eventually guarantees a well-populated *trade-off surface*.

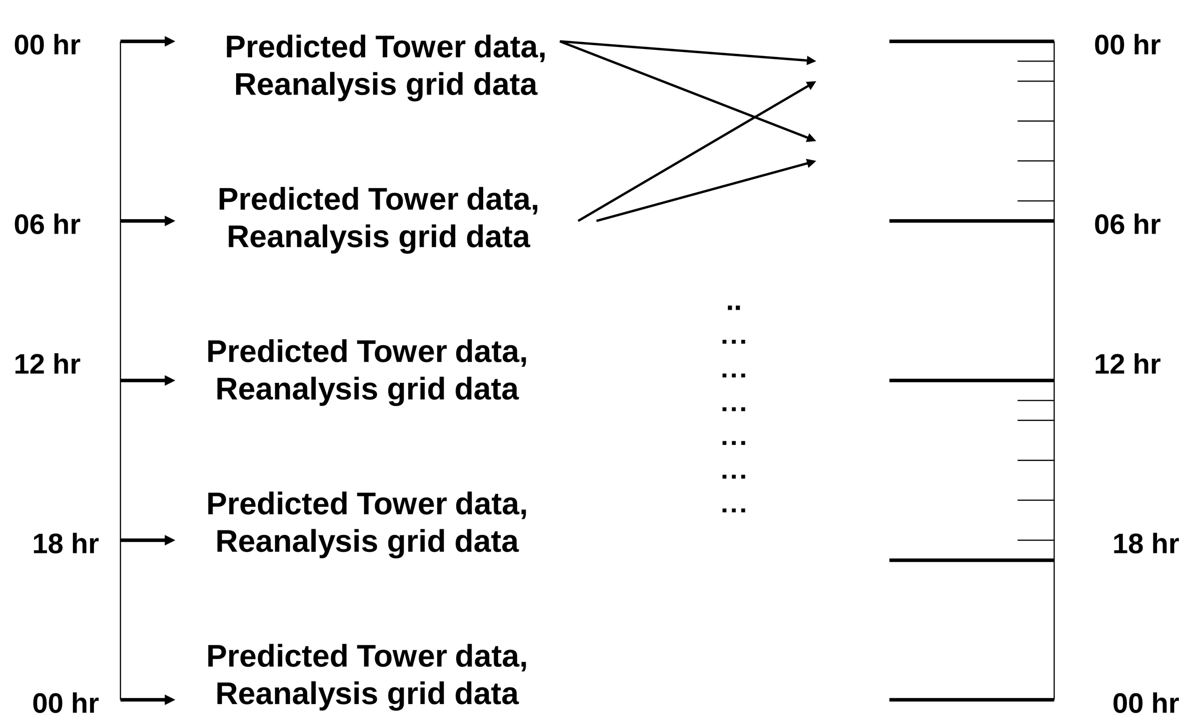

Figure 1: Hourly estimates from 6-hourly data

The downscaled estimates are produced using the data available at the nearest (in time) 6-hourly nodes, as shown in Figure 1. The input to the SVM for the intermediate hourly predictions is the reanalysis data at the two nearest 6-hourly nodes. The tower data values which are predicted via the E-MCP study at the two nearest 6-hourly nodes are also included as inputs for the hourly data estimates. The output is the observed tower data value at the intermediate hourly node. The proposed prediction/downscaling strategy is tested on two sites namely "A" and "B" in the U.S. for the downscaling of 6-hourly wind estimates to the hourly time step.

Results

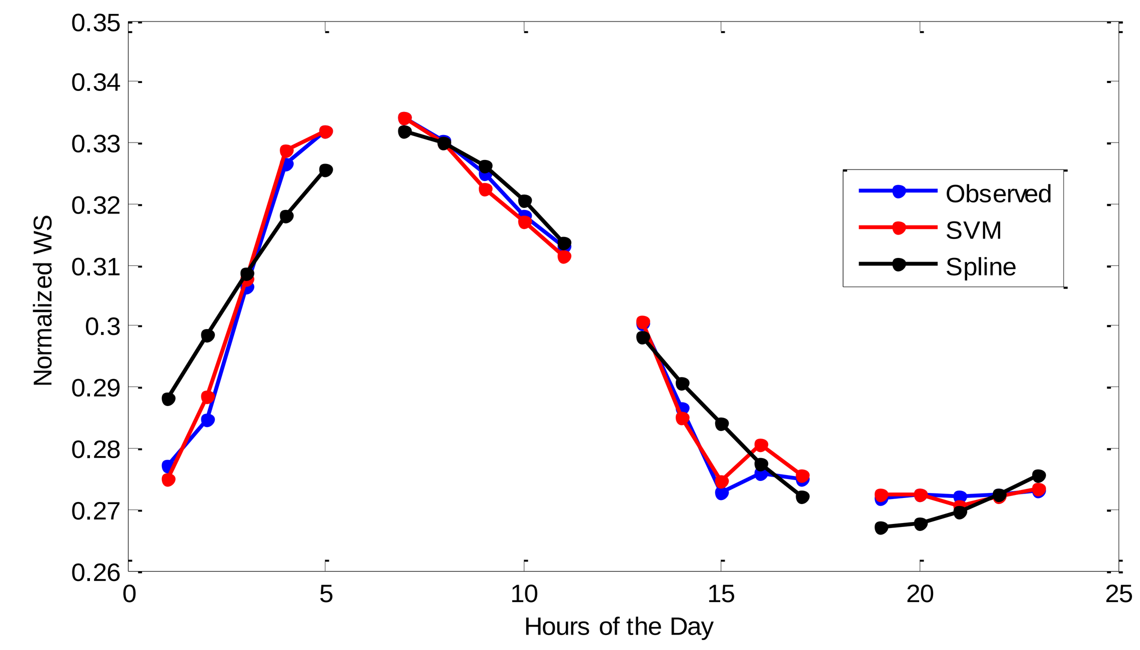

Figure 2: Mean hourly wind speeds at site 'A'

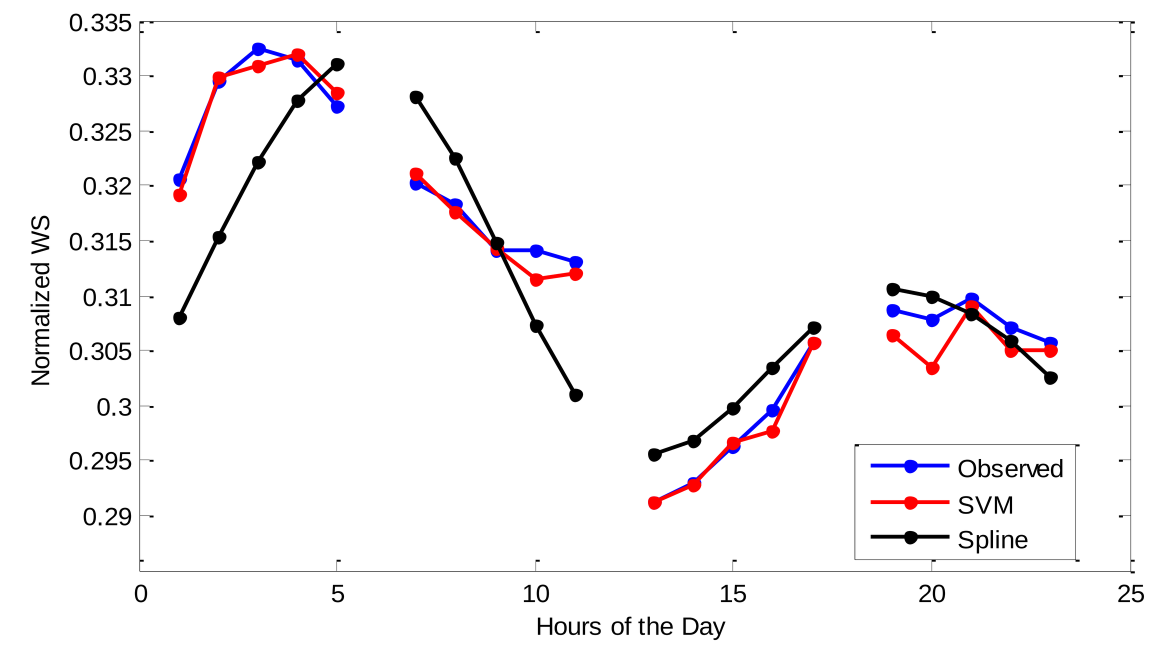

Figure 6: Mean hourly wind speeds at site 'B'

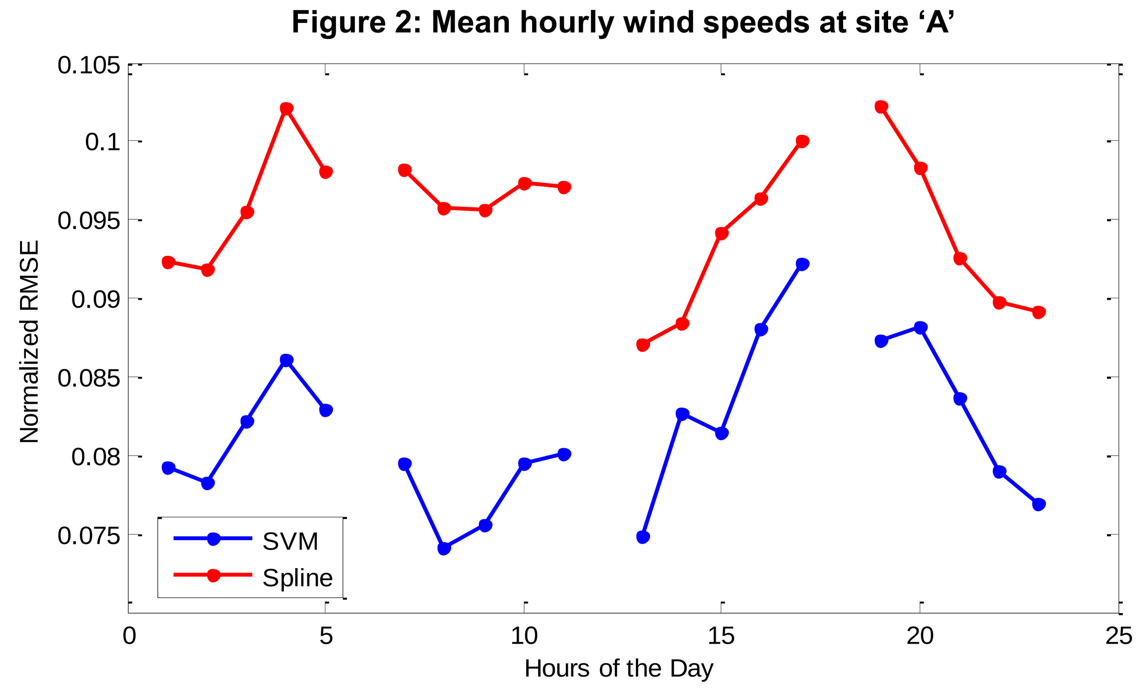

Figure 3: RMSE values for wind speeds by hour at site 'A'

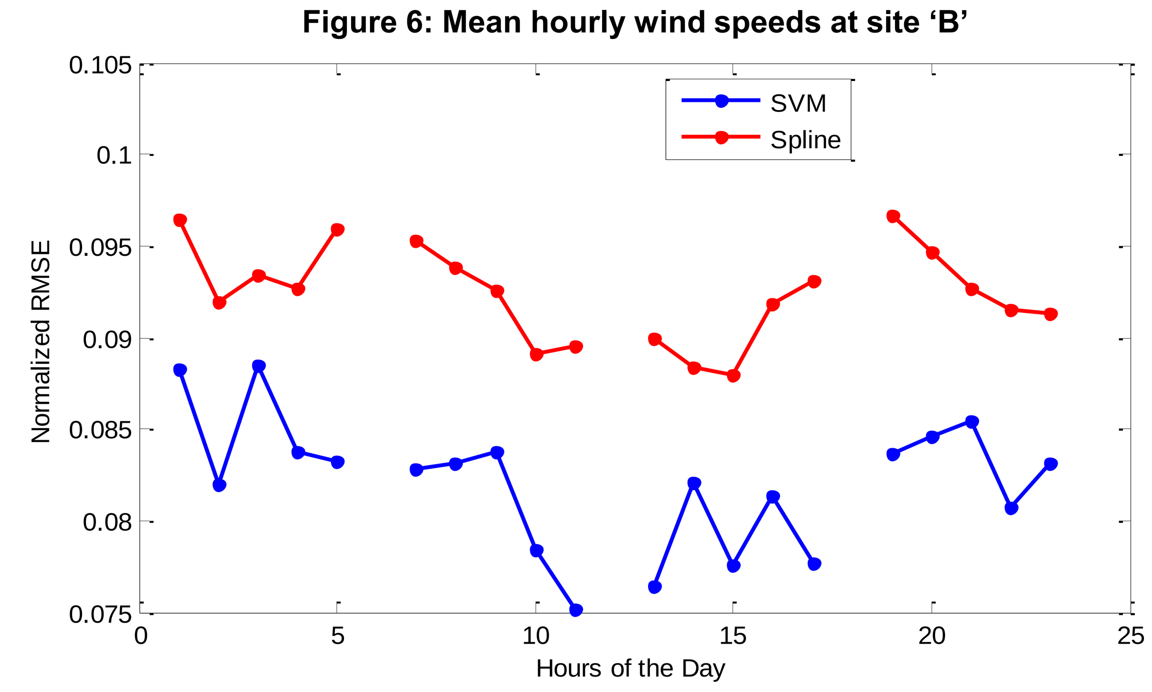

Figure 7: RMSE values for wind speeds by hour at site 'B'

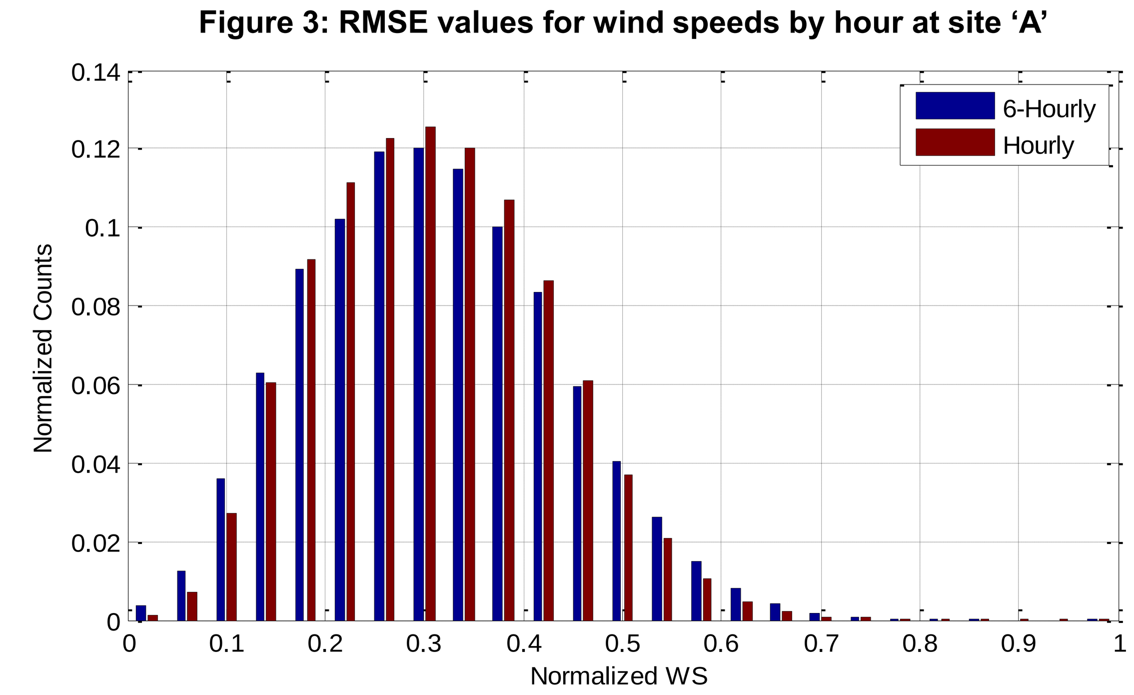

Figure 4: Long-term wind speeds histogram at site 'A'

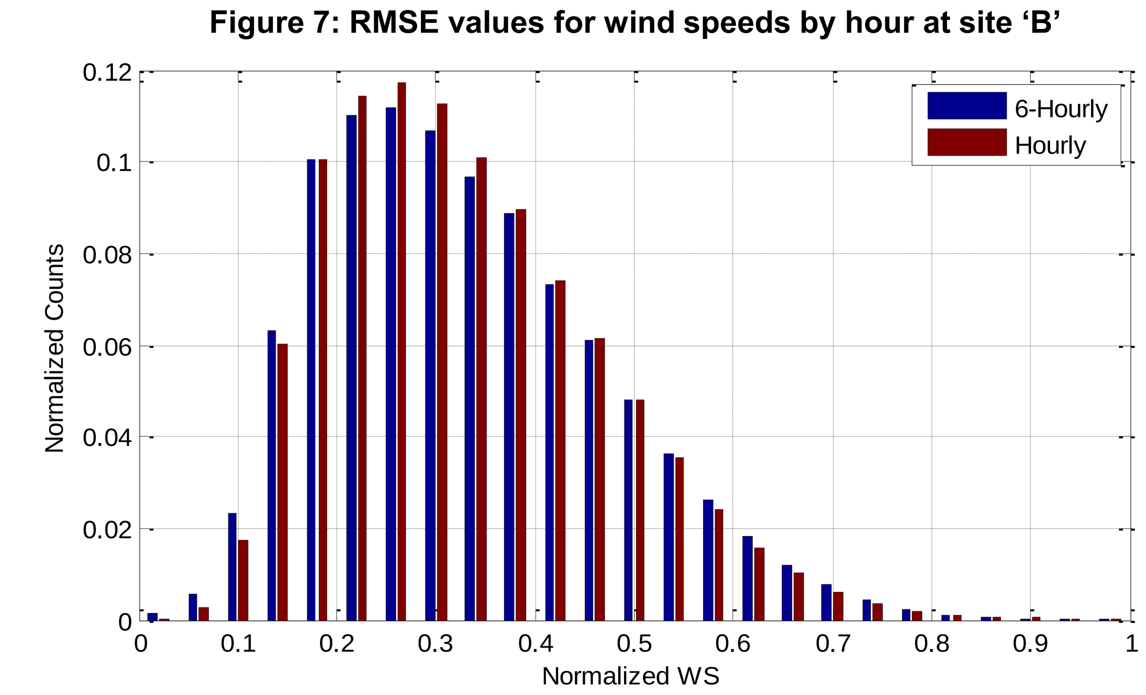

Figure 8: Long-term wind speeds histogram at site 'B'

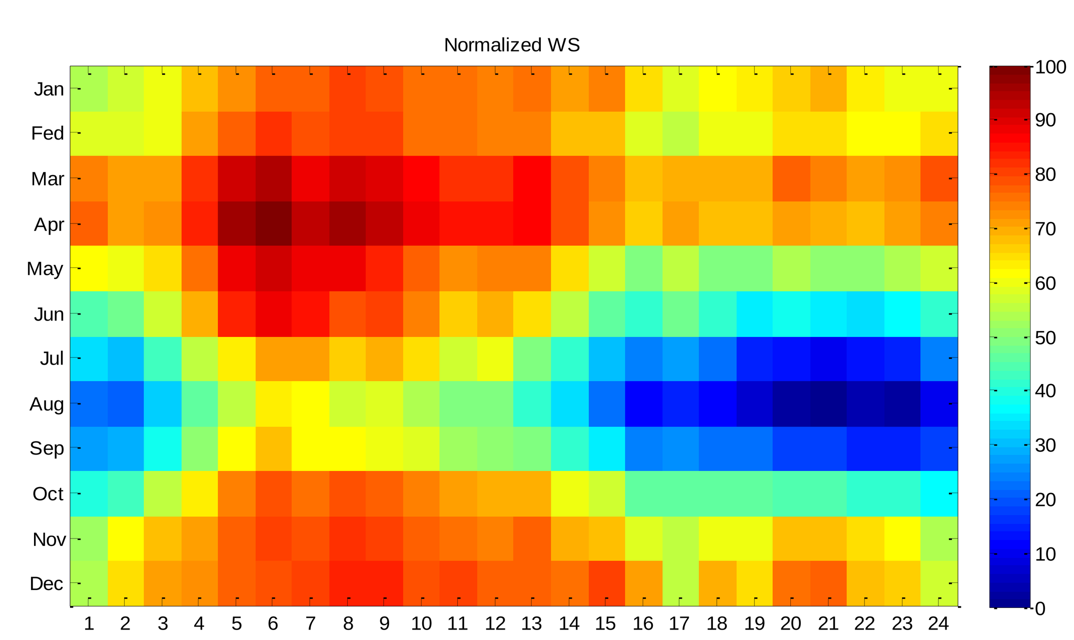

Figure 5: 12x24 plot for wind speeds at site 'A'

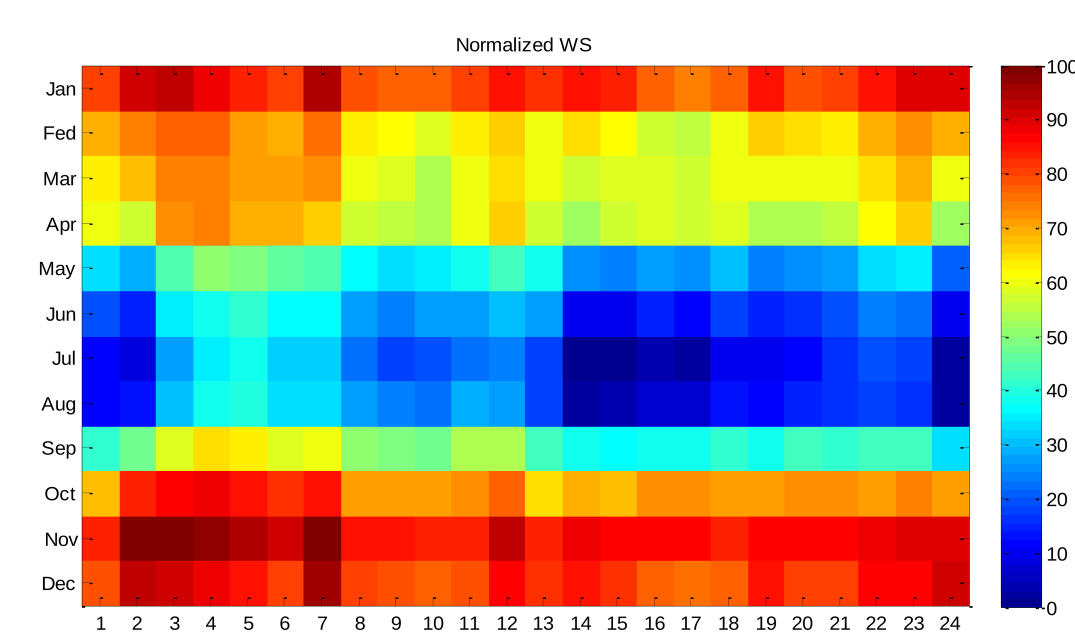

Figure 9: 12x24 plot for wind speeds at site 'B'

Figures 2-3, 6-7 and Table 1 provide short-term (training phase) results for the downscaling scheme using SVM and spline interpolation for the two sites. SVM trained on short-term tower data (usually 1-2 years), is used to produce an hourly time series for the 40 years. A long-term hourly wind speed histogram is shown along with 6-hourly wind speed histogram in Figures 4 and 8 for the two sites. A joint monthly/diurnal plot (also known as 12x24 plot) is shown in Figures 5 and 9. The 12x24 plot shows the long-term wind speeds based on 40-years of predictions and helps to understand the windiness at the site.

Table 1: Goodness-of-fit results

Sites	A		B	
Method	SVM	Spline	SVM	Spline
RMSE	0.08	0.10	0.08	0.09
Overall Bias (%)	0.10	0.26	-0.24	-0.39
Overall MAE (%)	6.51	7.37	6.35	7.09
COD / R^2	0.60	0.49	0.69	0.62

Conclusions

The downscaling method presented here employs 6-hourly RNL nodes to make predictions at the intermediate hourly time steps. The method has been tested for two sites in the U.S. for prediction of wind speed. The results in the training phase have been compared with the observed data and a reasonable agreement has been found. The current paper only presents the results for wind speed but similar results have been found for power estimation.

References

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[4] Gill, M. K., D. Moon, B. Lee, and D. Elliott, (2008), Wind Power Predictions using Swarm Intelligence and Machine Learning, In Proceeding (633) Intelligent Systems and Control, Nov. 16-18, Orlando, FL.

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