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Exhibit No. 24.05

WINDNAVIGATOR

Methods and Validation

AWS Truepower, LLC

Information Services

May 2010

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INTRODUCTION

windNavigator® is a web-based platform developed by AWS Truepower, LLC (formerly AWS Truewind, LLC), for delivering high-resolution wind resource data and maps to customers in the wind industry. The first version of windNavigator was released in May 2008. windNavigator v. 2.0 became available in February 2010. The new version contains several enhancements, including revised and updated wind resource maps and data sets as well as a new product, wind resource reports. The system presently covers the United States, Canada, and India.

This report describes the methods and models behind windNavigator and the validation and accuracy of the windNavigator data products.

METHOD AND MODELS

There are three types of data available through windNavigator: wind resource maps, wind resource distribution charts and tables, and virtual met masts (VMMs). The following sections describe the methods and models used to create these products.

Wind Resource Maps: MesoMap®

windNavigator provides maps of estimated mean wind speed at heights of 30 m, 60 m, 80 m, and 100 m above ground. These maps are created with AWS Truepower's MesoMap system. They are subsequently fine-tuned with direct measurements from a large network of wind monitoring stations. Figure 1 illustrates the process.

MesoMap is a combination of two atmospheric models: a mesoscale numerical weather prediction model (MASS[1]) and a microscale wind flow model (WindMap[2]). The mesoscale model simulates weather conditions for a representative meteorological year (366 days sampled from a recent 15-year period) on a horizontal grid of 2.5 km. The microscale model then refines the wind fields from the mesoscale model to capture the local influences of topography and surface roughness changes at a resolution of 200 m.

The atmospheric models use meteorological and geophysical data from a wide variety of sources. The mesoscale simulations are initialized by the NCAR/NCEP Global Reanalysis (NNGR) database, which provides a snapshot of weather conditions every 6 hours on a 2.5-degree resolution grid. NNGR incorporates weather observations from many thousands of platforms around the world, including surface stations, rawinsonde stations (instrumented balloons that provide soundings from the surface to high in the atmosphere), satellites, aircraft, and others. In the course of the simulations, MASS also assimilates observations directly from rawinsonde stations. The geophysical data include topography, land cover, sea-surface temperatures, and soil temperatures and moisture.

The objective of the fine tuning is to minimize discrepancies between predicted and observed mean wind speeds. To accomplish this AWS Truepower has created a data base of long-term mean wind speeds for just over 2000 weather stations and tall towers (about 1600 in the United States and 400 in Canada). (A similar database for India is under development.) The data come from a wide range of sources, including the US National Weather Service, Environment Canada, various state-level wind resource assessment programs, and clients of AWS Truepower. Where possible, the mean speeds from short-term measurement programs are adjusted to represent long-term conditions; stations with periods of record of less than one year are not considered. Surface weather stations not equipped with the automated surface observing system (ASOS) are excluded because it has been found that they tend to overstate wind speeds, especially in low-wind areas.

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[1] Manobianco, J., J. W. Zack and G.E. Taylor, 1996: Workstation-based real-time mesoscale modeling designed for weather support to operations at the Kennedy Space Center and Cape Canaveral Air Station. Bull. Amer. Meteor. Soc., 77, 653-672. Embedded equations are described in Zack, J., et al., 1995: MASS Version 5.6 Reference Manual. MESO, Inc., Troy, NY.

[2] Brower, M.C., 1999: Validation of the WindMap Model and Development of MesoMap, Proc. of Windpower 1999, American Wind Energy Association, Washington, DC.

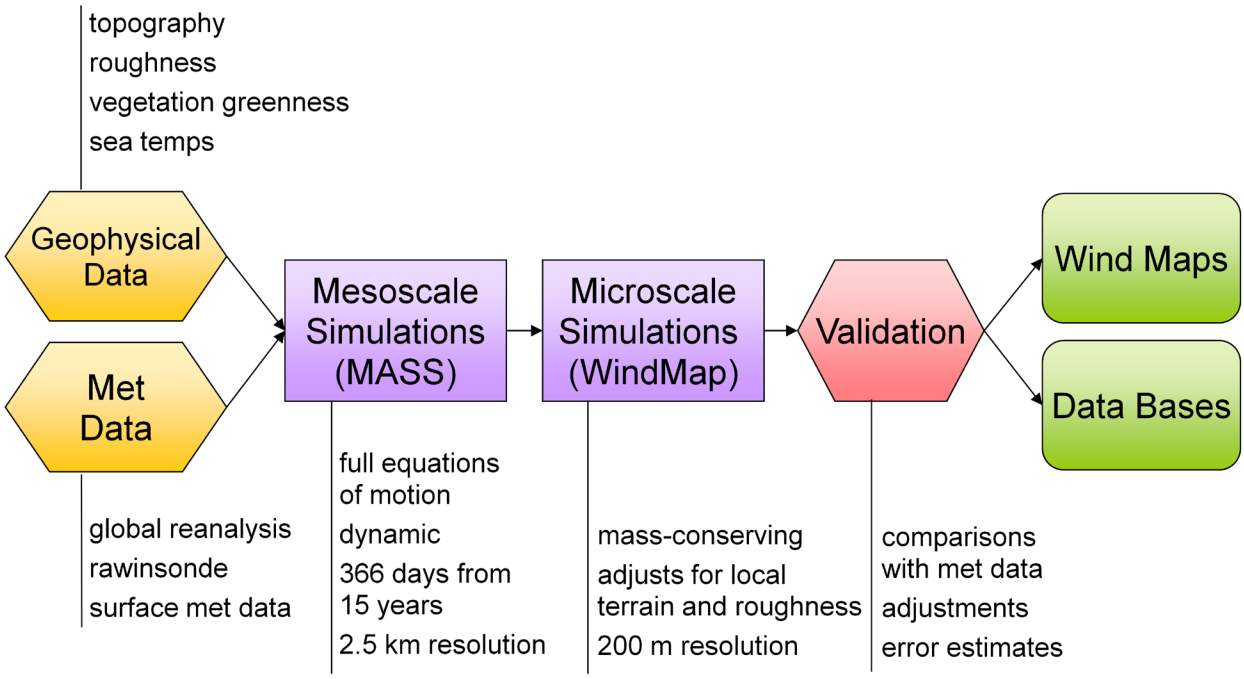

Figure 1. Schematic of the MesoMap process.

For each station, the mean speed is projected to the map height using either the observed wind shear exponent (where available), an exponent derived from modeling, or an exponent estimated from regional experience and local land cover and topography. A bias is then calculated between the raw (unadjusted) wind map and the extrapolated-observed speed for each station.

Finally, a software program developed by AWS Truepower interprets the biases to create a bias-correction map, and applies the correction to create the final wind map. This process does not eliminate the bias at every station, as this could produce unreasonable adjustments in some areas. Instead, it is designed to eliminate spatially correlated biases affecting regions of a significant size (roughly the mean spacing between stations, about 50-100 km).

Wind Resource Distributions and Virtual Met Masts: *windTrends*

In addition to wind maps, windNavigator provides access to wind resource distribution data and VMMs. Both types of data are generated from windTrends, AWS Truepower's data base of weather conditions for the conterminous United States, Canada, and India.

windTrends is created in two stages. First, the MASS model is run in a sequence of two-week simulations from 1997 to the present. As in the the MesoMap system, the simulations are initialized from NNGR data, and rawinsonde data are assimilated every 12 hours to control model drift. To accommodate the multi-year simulations, however, the grid resolution is 20 km rather than 2.5 km. In addition, the rawinsonde stations are carefully selected to ensure that wind and other weather trends are consistent through time. In the second stage, the WindMap model is applied to correct for local topographic and land cover influences, and the resulting speeds are scaled so that the mean speed matches the wind resource map.

The result is a time series of hourly wind speed, direction, temperature, and pressure values for a selected location and height above ground. From this VMM, frequencies by speed and direction are derived, along with mean speeds by time of day and time of year. Other statistics, such as interannual variability, wind power density, and maximum speeds, are also calculated.

VALIDATION

Wind Resource Maps

To produce an objective estimate of the map accuracy, each station in AWS Truepower's database is withheld in turn from the fine-tuning procedure and the difference between the map speed and the observed speed at that station is determined. Then all the deviations are analyzed and error statistics are derived.

Based on this procedure, the mean bias of the high-resolution wind maps of the United States and Canada is found to be virtually zero, while the standard error (after accounting for uncertainty in the data) is 0.35 m/s.[3] In Figure 2, a scatter plot comparing the predicted mean wind speeds with the observed after projection to the 80 m map height is presented for the United States. Error statistics by US region are summarized in Table 1. Errors tend to be larger in the Northeast and West, where the terrain and vegetation cover are more complex, and smaller in the Midwest and Plains states.

A similar error analysis has not yet been performed for India. For the present, AWS Truepower estimates the standard error of the high-resolution India maps to be 0.75 m/s. However, in all cases AWS Truepower recommends that the wind resource be measured on-site before committing funds to a wind energy project of a substantial size.

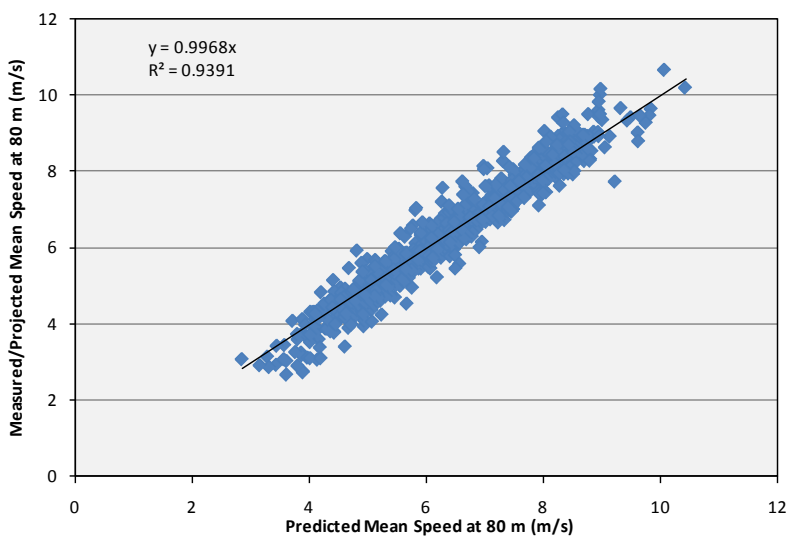

Figure 2. Scatter plot of predicted speeds from the adjusted US wind map and observed/extrapolated mean wind speeds at 80 m.

[3] The 2.5 km resolution wind maps have a much greater error margin because of their coarser spatial resolution. The estimated standard error for these maps is 0.75 m/s.

Table 1. Mean and standard deviation of biases, in m/s, for the adjusted 80 m US wind map.

Northeast	Mean	0.02
	Std Dev	0.43
Southeast	Mean	0.05
	Std Dev	0.31
Midwest	Mean	0.01
	Std Dev	0.20
Plains	Mean	0.04
	Std Dev	0.28
West	Mean	-0.03
	Std Dev	0.51
US	Mean	0.00
	Std Dev	0.42

Wind Resource Distributions and VMMs

The accuracy of the wind resource distributions and VMMs derived from windTrends is evaluated according to three criteria of relevance to the wind industry: consistency of speed trends over time, accuracy of long-term climate adjustments of short-term observations (measure-correlate-predict, or MCP), and accuracy of energy production estimates based on VMMs.[4]

Speed Trends

Annual and monthly mean wind speeds from the windTrends data set have been compared with data from other sources for a number of locations and for the entire United States. Figure 3 demonstrates that on the whole, the windTrends speeds track ASOS quite closely, and more closely than do two leading climatological data bases, NNGR and the North American Regional Reanalysis (NARR). Both the ASOS and windTrends anomalies fluctuate about zero in similar ways and with little trend. NNGR exhibits a small but noticeable downward trend, while there is a marked discontinuity in the NARR data from 2001 to 2002, which AWS Truepower associates with a change in procedures for assimilating rawinsonde data in that period.

Climate Adjustments

To assess the accuracy of windTrends for climate adjustments, AWS Truepower identified ten tall towers in wind resource areas around the United States with at least four years of high-quality wind speed measurements. For different 12-month sub-periods within each data set, a measure-correlate-predict (MCP) analysis was performed using windTrends, ASOS, and NNGR data. The predicted mean speeds for the entire period of record of each tower were then compared with the observed, and error statistics were derived for each data set.

The results of the analysis are presented in Figure 4. At most sites, the windTrends standard error is comparable to or smaller than those derived from ASOS and NNGR. The only site where windTrends performs substantially worse than ASOS is Mast 6, which is located in a California mountain pass where the wind climate is not well resolved by the mesoscale simulations. These findings confirm both the consistency through time of the windTrends data set and the relatively good correlation between windTrends and observed wind speeds. The average correlation coefficient (r^2) with the tall tower data was 0.75 for windTrends, 0.72 for ASOS, and 0.55 for NNGR.

[4] Validation of the windTrends data set is described in greater detail in Taylor, M. A. et al., Using Simulated Wind Data from a Mesoscale Model in MCP, Proceedings of Windpower 2009, American Wind Energy Association.

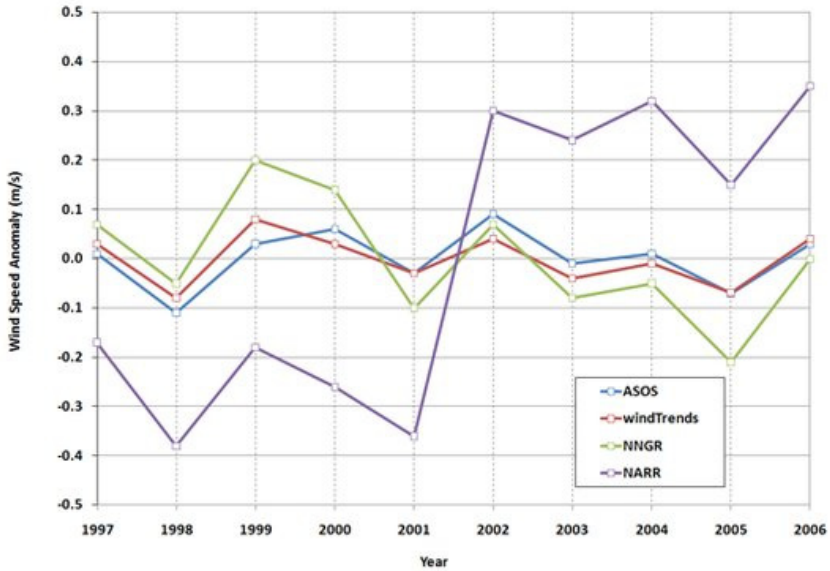

Figure 3. Annual mean wind speed anomalies for 1997 to 2006 according to windTrends, ASOS, NNGR, and NARR data, for 198 representative ASOS station locations in the United States. The wind anomaly is the difference between the mean wind speed in a given year and the 1997-2006 average.

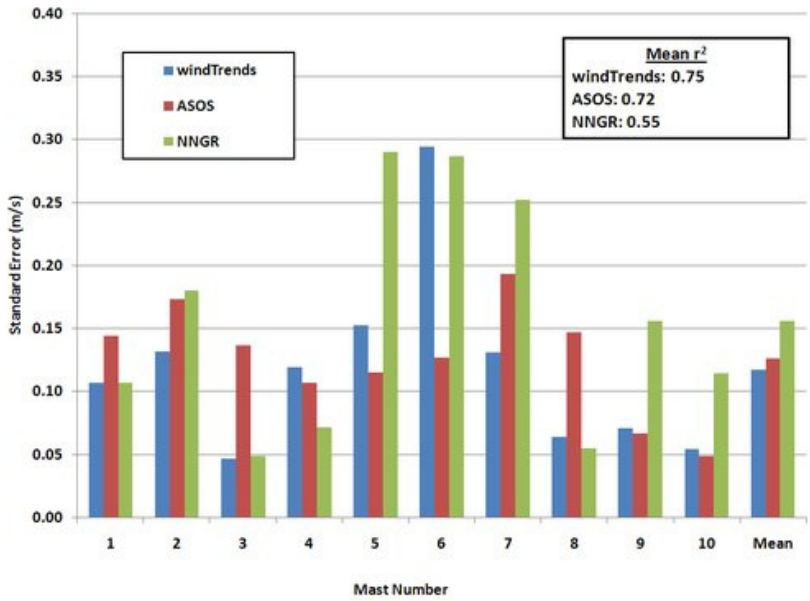

Figure 4. Standard errors of MCP long-term speed estimates using windTrends, ASOS, and NNGR.

Energy Production Estimates

Energy production estimates based on windTrends VMMs are compared with estimates derived from observed wind speeds at ten sites across the United States. (The sites are not the same as those used for the MCP analysis.) The simulated speed distributions are scaled so their means match the observed means. Both sets of data are passed through a generic IEC Class II power curve (a composite of three commercial wind turbine power curves), and the bias (predicted minus observed production) is calculated. This approach provides a direct test of the accuracy of the speed frequency distributions independent of errors in the mean speed.

The results are shown in Table 2. Over all sites, the standard deviation of the biases as a percent of average energy production is 5.7%. This result is dominated by a relatively poor prediction at Site 3; excluding this site, the standard deviation is 2.3%. Site 3 is a mountain pass with a low mean speed but very strong summer winds associated with a mesoscale circulation pattern, which the windTrends simulations do not adequately resolve.

Table 2. Capacity factors derived from windTrends and observed speed distributions for the same mean speeds. The capacity factor is the average output divided by the rated capacity.

Site	windTrends	Observed	Error (% of Rated)	Error (% of Energy)
Site 1	47.7%	47.9%	-0.3%	-0.5%
Site 2	43.6%	43.8%	-0.2%	-0.5%
Site 3	29.5%	35.4%	-5.9%	-16.7%
Site 4	47.0%	47.1%	-0.1%	-0.2%
Site 5	23.5%	24.1%	-0.5%	-2.2%
Site 6	39.8%	37.9%	1.8%	4.8%
Site 7	38.8%	38.4%	0.4%	1.0%
Site 8	38.2%	37.6%	0.6%	1.7%
Site 9	42.9%	43.0%	-0.1%	-0.3%
Site 10	57.3%	54.8%	2.5%	4.6%
Site 11 (Offshore)	48.9%	48.8%	0.1%	0.2%
Mean			-0.2%	-0.7%
Std Dev			2.1%	5.7%
Mean (excl. Site 3)			0.4%	0.8%
Std Dev (excl. Site 3)			1.0%	2.3%

Combined with the uncertainty in the mean speed, AWS Truepower estimates the overall uncertainty in gross energy production to be about 10% for capacity factors over 35%, increasing to 15% for capacity factors of about 25%. The uncertainty is larger in low-resource areas both because the mean speed uncertainty is proportionately larger, and because the turbines tend to operate more often on the steepest part of the power curve where small errors in speed produce large differences in power output.

It should be stressed that errors may be larger in some areas, and that the uncertainty does not consider deviations from ideal turbine production, including wake-related and other losses.