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A New Approach Using Targeted Observations to Improve Short-Term Wind Power Forecasts in the Tehachapi Pass of California

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Introduction

Balancing authorities (BA) often make critical decisions on how to most reliably and economically balance load and generation in time frames ranging from a few minutes to six hours ahead. At higher levels of wind power generation, there is an increasing need to improve the accuracy of 0- to 6-hour ahead wind power forecasts. Forecasts on this time scale have typically been strongly dependent on short-term trends indicated by the time series of power production and meteorological data from a wind farm. Additional input information is often available from the output of Numerical Weather Prediction (NWP) models and occasionally from off-site meteorological towers.

A proposed method to improve short-term forecasts is deployment of off-site meteorological towers at locations upstream from the wind generation facility in order to sense approaching wind perturbations. While conceptually appealing, it turns out that, in practice, it is often very difficult to derive significant benefit in forecast performance from this approach. The difficulty is rooted in the fact that the type, scale, and amplitude of the processes controlling wind variability at a site change from day to day if not from hour to hour. Thus, a location that provides some useful forecast information for one time may not be a useful predictor a few hours later. Indeed, some processes that cause significant changes in wind power production operate predominantly in the vertical direction and thus cannot be monitored by employing a network of sensors at off-site locations. Hence, it is very challenging to determine the type of sensors and deployment locations to get the most benefit for a specific short-term forecast application.

Two tools recently developed in the meteorological research community could help determine the locations and parameters to measure in order to get the maximum positive impact on forecast performance for a particular site and short-term look-ahead period. Both tools rely on the use of NWP models to assess the sensitivity of a forecast for a particular target location to measurements made at a prior time (i.e. the look-ahead period) at points surrounding the target location. The fundamental concept is that points and variables with high sensitivity are good candidates for measurements since information at those points will have the most impact on the forecast for the desired parameter and location.

One approach is called the adjoint method (Errico and Vukicevic, 1993; Errico, 1997) and the other newer approach is known as Ensemble Sensitivity Analysis (ESA; Ancell and Hakim, 2007; Torn and Hakim, 2008). Both approaches have been tested on general large scale atmospheric prediction problems (e.g. forecasting pressure or precipitation over a relatively large region 24 hours ahead) but neither has been applied to the problem of 0- to 6- hour ahead forecasting of winds near the surface of the earth. A number of factors suggest that the ESA approach is better suited for the short-term wind forecasting application. One of the most significant advantages of the ESA approach is that it is not necessary to linearize the mathematical representation of the processes in the underlying atmospheric model as required by the adjoint approach. Such a linearization may be especially problematic for the application of short-term forecasting of boundary layer winds in complex terrain since non-linear shifts in the structure of boundary layer due to atmospheric stability changes are a critical part of the wind power production forecast problem. Therefore, AWS Truewind has decided to explore the value of observation targeting information that can be obtained from ESA approach for short-term (0- to 6-hour head) wind forecasting in the Tehachapi Pass of California. It should be kept in mind that, prior to this project, the ESA approach had only been applied to large-scale, day-ahead or longer predictions of pressure, temperature and precipitation. This is the first attempt to apply this approach to the forecasting of near-surface winds for very short (0- to 6-hour) look-ahead periods.

Objective

The broad objective of the project that is the subject of the proposed paper and presentation is to demonstrate that the ESA approach can provide valuable guidance for the targeting of observations on the space and time scales associated with 0 to 6 hour ahead wind forecasting problem. The specific objective of the project is to identify measurement locations and variables that have the greatest positive impact on the accuracy of wind forecasts in the 0- to 6-hour look-ahead periods for the wind generation area of California's Tehachapi Pass during the warm (high generation) season.

Method

The ESA approach uses data generated by a set (ensemble) of perturbed NWP simulations for a sample time period to statistically diagnose the sensitivity between a specified forecast variable for a target location (the forecast target metric) to parameters at other locations and prior times [the initial condition (IC) state variable]. The ensemble of NWP simulations are produced by starting with a single initial state at the beginning of the analysis period and introducing statistical perturbations into the initial and lateral boundary conditions. This process generates a set of initial states that differ from each other due to the perturbations. The number of initial states must be large enough to produce a statistically significant sample for the sensitivity calculations. Generally, 40 or more ensemble members are needed to obtain statistically significant results.

Each of these initial states is then used as the starting point for an NWP simulation. The NWP simulations are marched forward in time with periodic assimilation of observational data for a representative period of time referred to as the analysis period. The periodic assimilation of measurement data serves to keep the model state from drifting too far the actual atmospheric conditions. However, the assimilation process must be carefully managed to prevent the individual ensemble members from becoming very similar since they are all assimilating the same measurement data.

The ensemble of simulations produces a large volume of three-dimensional data from each ensemble member at periodic intervals throughout the analysis period. A statistical analysis is then performed on this data to determine the sensitivity (dF/ds) of a target forecast metric (F) to selected IC state variables (s) from prior simulated times at all points in the model domain. This relationship can be expressed as:

$$\frac{\partial F}{\partial s} = \frac{\mathrm{cov}(F,s)}{\mathrm{var}(s)}$$

where the covariance (cov) and variance (s) are computed over all ensemble members.

In the Tehachapi Pass application, the forecast metric (F) was the average 80-m wind speed over a rectangular area encompassing most of the wind generation resources in the Pass. A variety of IC state variables (s) were evaluated. The simulations were generated on a 3-dimensional grid matrix of 200 by 200 horizontal points and 38 vertical layers that covered most of southern California (area depicted in Figure 3). They were produced with the Weather Research and Forecast (WRF) atmospheric model (version 2.2) and observational data was assimilated every 6 hours using an ensemble Kalman filter data assimilation procedure. A total of 48 ensembles members were used in the analysis. The analysis period extended from 7 July 2008 to 25 August 2008 and was selected as a representative period for warm season conditions in Tehachapi Pass.

Results

The output data from the ensemble of simulations provide a large volume of information about the space-time connection of atmospheric variability within the simulation domain and can potentially be analyzed in many different ways. The approach used in this project follows that employed by Torn and Hakim (2008) in their analysis of forecast sensitivity of day-ahead forecasts over western portion of the state of Washington. In their approach, the sensitivity of the forecast metric variable to a particular IC state variable for a specific forecast time and look-ahead period is determined by constructing a linear relationship between the forecast metric values (F) and the values of a specific IC state variable (s) at a particular model grid point based on data from all ensemble members. Figure 1 illustrates an example of the data from all of the ensemble members and the resulting linear relationship for F defined as the average 80-m wind speed in a rectangular area in Tehachapi Pass for 0300 UTC (8 PM PDT) 10 August 2008. In this case, the IC state variable is the 80-m wind speed three hours earlier at grid point (82,144), which is located in the central valley to the northwest of Tehachapi Pass. Each data point denotes the value of the 80-m wind speed at point (82,114) from 0000 UTC and the average 80-m wind speed in the Tehachapi Pass target area at 0300 UTC from one of the 48 ensemble members.

The plot indicates that there is well-defined relationship between the changes in the 80-m wind speed at point (82,114) from 0000 UTC and changes in the average 80-m wind speed in the forecast target area three hours later. The slope of the regression line through these points defines the sensitivity of the forecast metric to the specific IC variable and location for the specific date, time, and look-ahead period under consideration. The interpretation of the regression line is that a 1 m/s change in the 80-m wind speed at point (82,114) will be associated with a 1.94 m/s change in the 80-m wind speed in the Tehachapi Pass target area three hours later.

Another set of data from the ensemble members for the same date and time is shown in Figure 2. The forecast metric is the same (80-m wind speed in the Tehachapi Pass target area) but the IC state variable is the 80-m wind speed at a different model grid point (19,28) which is located over Pacific Ocean just to the west of the California coast. For this point, there is essentially no relationship between changes in the 80-m wind speed at 0000 UTC and the 80-m wind speed three hours later in the Tehachapi Pass target area. This result is indicated by the fact that slope of the regression line associated with this data is essentially zero.

A spatial representation of the sensitivity patterns for a particular date and time can be created by constructing a contour map of the sensitivity values (i.e. the slopes of the regression lines between each grid point and the target area). The map for 0300 UTC 10 August 2008 is shown in Figure 3. The forecast target region (i.e. the eastern side of Tehachapi Pass) is represented by the white box. The map indicates that there is a region of high sensitivity in the central valley to the north and northwest of Tehachapi Pass.

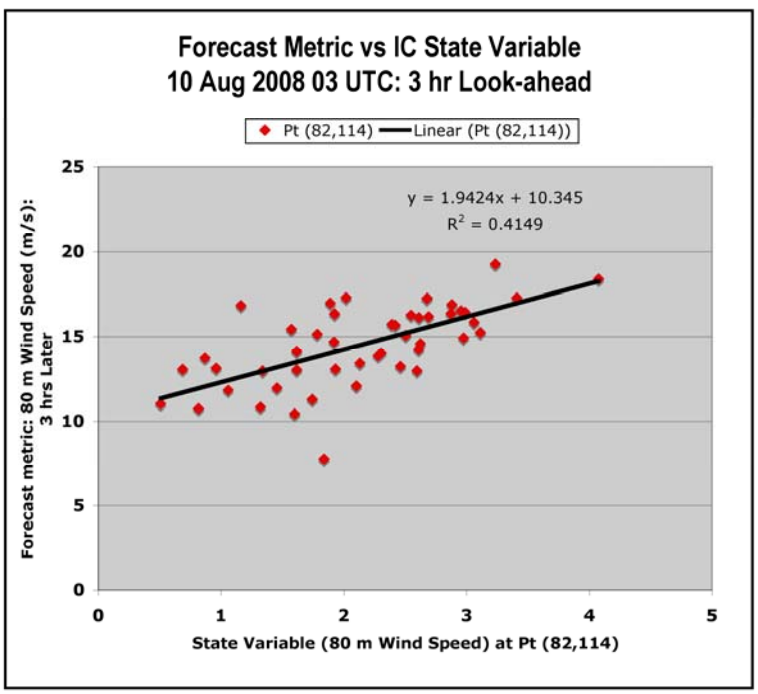

Figure 1. Initial condition state variable and forecast metric data from each of the 48 ensemble members and an associated regression line for model grid point (82,114) at 0300 UTC 10 August 2008.

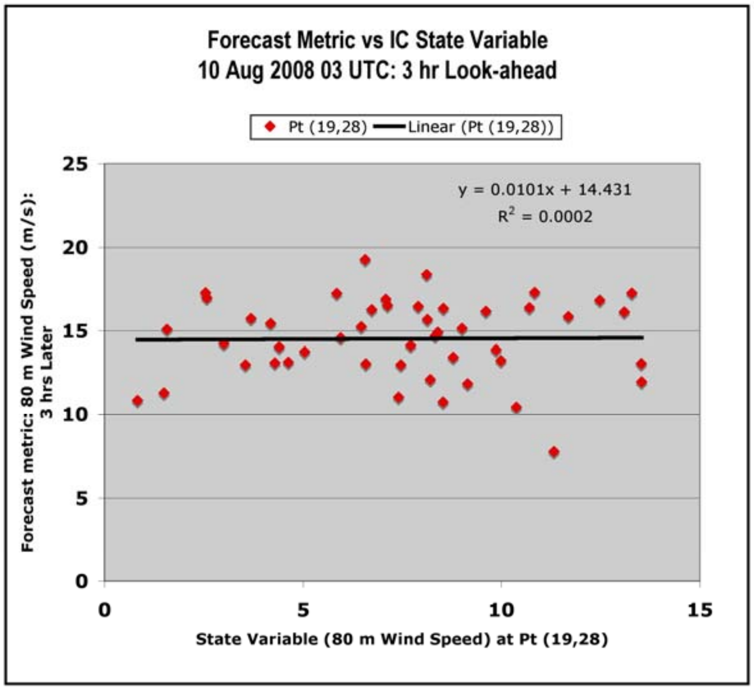

Figure 2. Initial cond ition state variab le and forecas t m etric data fro m each of the 48 ensemble mem bers and an associated regr ession line for m odel grid point 19,28 at 0300 UTC 10 August 2008.

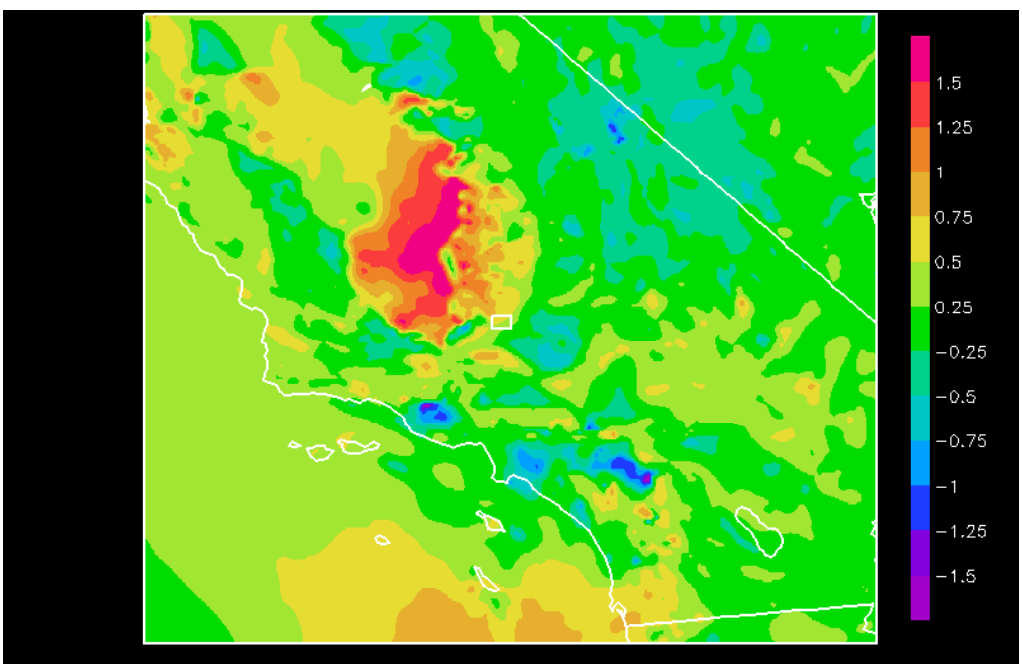

Figure 3. Sensitivity of the average 80-m forecast wind speed in white b ox at 0300 UTC 10 August 2008 (8 PM PDT 9 August) to 80-m wind speed elsewhere in the domain three hours earlier.

The map in Figure 3 represents the sensitivity for only one date and time for a specific look-ahead period. In order to make inferences about the best measurement locations and variables to improve forecast performance, it is necessary to construct some type of statistical composite of the sensitivity values over a representative sample of cases. The simplest composite is an average although this statistic may not be the most meaningful or useful parameter for a particular application. The average could be constructed for all dates and times in the analysis period to obtain information about which areas have the highest average sensitivity over all cases. The average could also be constructed by time of day to obtain a representation of any diurnal cycles in the sensitivity patterns. In addition, the average could be computed for specific subsets of the analysis period – such as those date and times which experiences large ramps in wind power production. This approach would yield information about the locations and variables that have the most sensitivity for those types of events.

An example of an average sensitivity map is shown in Figure 4. This map illustrates the average forecast sensitivity of the 80-m wind speed for 0300 UTC (8 PM PDT) in the target region (white box) to 80-m wind speeds three hours earlier over a 4-week period. This map indicates that there are areas of high average sensitivity to the north and northwest of Tehachapi Pass. The average sensitivity over much of the domain is near zero indicating that 80-m wind speed measurements in most locations would have little value for 3-hour ahead forecasts of 80-m wind speed in the target region.

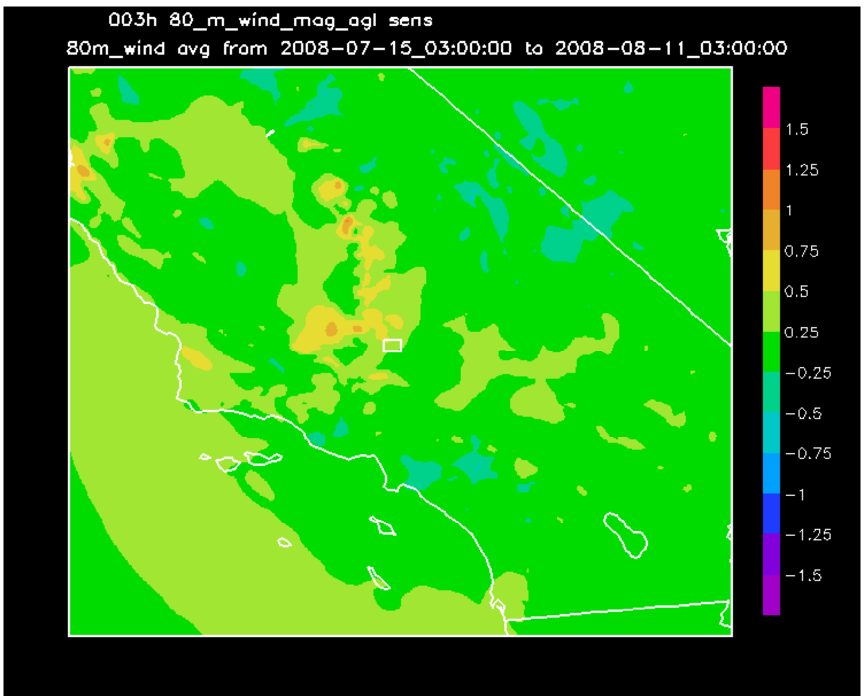

Figure 4. Four-week average sensitivity values of 80-m wind speed (m/s) within the white target box throughout the entire grid domain for 8 PM PDT (0300 UTC). The color contours indicate the change in the average 80-m wind speed in the white target box associated with a 1 m/s change in 80-m speed at a point three hours earlier.

It is also important to note that the sensitivity analysis can generated from the ESA dataset for any IC state variable or combination of IC state variables (pressure, temperature, humidity, different height levels etc.) that are available from the model output dataset for any look-ahead period that is consistent with the length of the model simulation segments between data assimilation times. An example of the sensitivity of the 80-m wind speed forecast for Tehachapi Pass to a variable other than 80-m wind speed is shown in Figure 5.

This map illustrates the sensitivity of the 80-m wind speed in the white box to 3-hour earlier values of the vertical temperature difference between 25 m above ground level (AGL) and 1 km AGL. This temperature difference is essentially a stability index of the near-surface atmosphere. The patterns on this map indicate that there is a well-defined fairly large region of high positive sensitivity to this IC state variable in an area to the northwest of Tehachapi Pass. Increases in the 25 m to 1 km temperature difference in this area are associated with significant increases in the 80-m wind speed in the target region three hours later. Interestingly, there is a small area of negative sensitivity (dark blue) to the north-northeast of the target area. The negative values indicate an inverse sensitivity (i.e. a decrease in the 25-m to 1-km temperature difference in this area is associated with an increase in the 80-km wind speed in the target area three hours later).

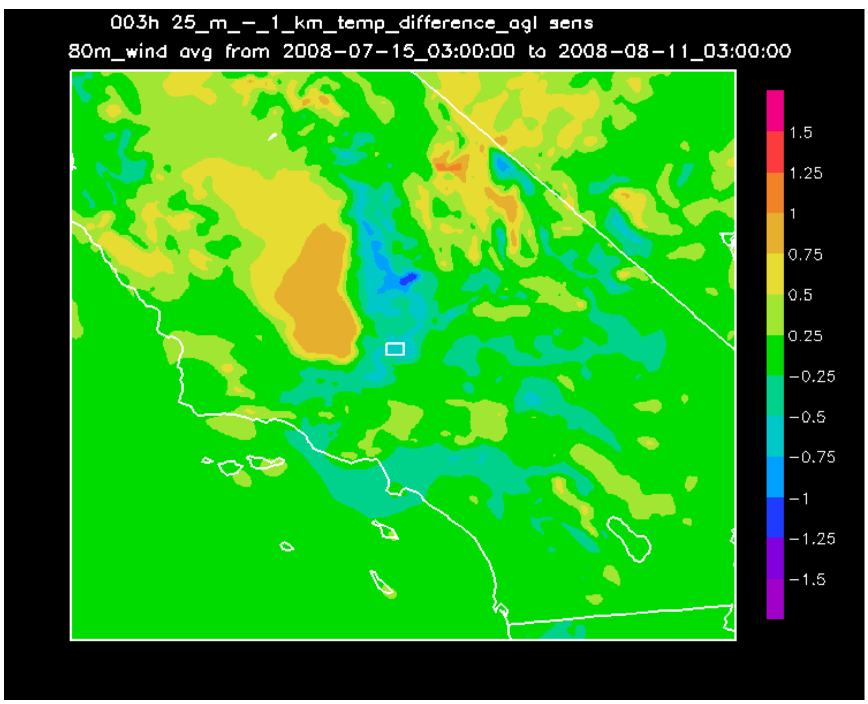

Figure 5. Four-week average sensitivity values of 80-m wind speed (m/s) within the white target box throughout the entire grid domain for 8 PM PDT (0300 UTC). The color contours indicate the change in the average 80-m wind speed in the white target box associated with a 1°C change in the temperature difference between 25 m and 1 km at a point three hours earlier.

Next Steps

The ESA procedure produces a large volume of forecast sensitivity data. Many of the sensitive locations and variables are highly correlated and hence they provide similar information about the variability of the forecast metric. There is not much additional value in making measurements at locations whose sensitivity is highly correlated with other sensitive locations and variables that are already measured. The challenge is to extract a set of measurement locations and variables from the sensitivity maps that in combination produce the greatest amount of benefit to the targeted forecast variable and look-ahead period. A procedure is currently under development that will account for the correlations between sensitive areas and variables as well as select an optimal combination (i.e. based on a specified optimization criteria) of variables and locations to measure for a specific forecast application. This procedure will be used to provide guidance for the development of a sensor deployment strategy for a particular region and forecast application.

There is also a need to validate this approach for this type of application, in general, and the sensitivity patterns for the Tehachapi Pass application, in particular. The validation can be accomplished by demonstrating that data included or excluded in the sensitive areas as part of the forecast experiments does indeed have the impact on the forecast as indicated by the sensitivity maps. However, since most existing measurement sites are not in sensitive areas, a more complete and rigorous test of this approach for the wind forecasting applications will require a field campaign in which sensors are deployed near the locations with highest sensitivity.

Summary

A recently formulated approach called ESA, which is designed to analyze the sensitivity of forecasts to prior changes in atmospheric state variables, has been applied to 0- to 6-hour ahead forecasts of the 80-m wind speed in Tehachapi Pass. The method is based on the statistical analysis of data from a relatively large ensemble of NWP model simulations for an analysis period that is representative of the weather regimes in the area of interest. The members of the ensemble differ from each other due the introduction of perturbations in the initial and boundary conditions of the numerical atmospheric simulations. The introduction of the perturbations permits an analysis of the forecast sensitivity for individual dates and times. A composite of the sensitivity for individual dates and times can then be generated to provide information about the climatological sensitivity patterns. These patterns can, in turn, be used as guidance on where to deploy meteorological sensors to achieve the greatest impact on forecast performance for the desired variable and look-ahead period. This method has previously been applied to large-scale weather prediction but not to short-term wind forecasting.

The application of this approach to Tehachapi Pass produced well-defined, localized patterns of high sensitivity for a number of prior state variables. The patterns were coherent, temporally stable, and consistent with the existing knowledge of the basic physical processes that drive the wind patterns in the Tehachapi area. The development of a method to determine the optimal combination of measurement locations and variables from the multitude of spatially-correlated sensitivity patterns produced by the ESA is in progress. This method will provide more precise guidance for the design of the best meteorological sensor deployment strategy for a specific forecast application.

The proposed presentation will provide an overview of the ESA method, some of the details of its application to Tehachapi Pass area, the results for Tehachapi Pass forecast application, and the implications for sensor deployment strategies as well as the potential impact on the performance 0- to 6-hour ahead forecasts of the hourly or sub-hourly average wind power production as well as the characteristics (start time, magnitude, duration etc.) of large wind ramp events.

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