

Kevin J. Brundage<sup>1</sup> and Stanley G. Benjamin

<sup>1</sup> NOAA Research -- Forecast Systems Laboratory, Boulder, Colorado

<sup>1</sup>[In collaboration with the Cooperative Institute for Research in the Atmosphere,  
Colorado State University, Fort Collins, Colorado

Marc N. Schwartz

National Renewable Energy Laboratory, Golden, Colorado

## 1. INTRODUCTION

Wind energy, the fastest growing energy technology, has become an important component of the nation's electrical power grid. Increased energy demands, combined with insufficient generation capabilities, underscore the importance of wind energy as a renewable alternative. The European Wind Energy Association predicts that by the year 2020, 10% of world energy needs will be provided by wind energy.

To effectively manage this growing resource, power managers require accurate estimates of power generation potential. To derive these estimates, energy planners require accurate forecasts of surface and near surface winds for a period from a few hours to several days. Accurate estimates of generation capacities provide energy planners and traders with critical planning tools.

In addition to accurate wind speed forecasts, planners desire a level of confidence associated with these forecasts. All forecasts are subject to some inaccuracies; however, some situations are more difficult to accurately predict than others. Parameters which quantify the uncertainties associated with a given forecast would improve the utility of those forecasts in the planning process.

A cooperative project was established in 2000 between NOAA's Forecast Systems Laboratory (FSL) and the DOE's National Renewable Energy Laboratory (NREL) to evaluate the use of forecasts from FSL's Rapid Update Cycle (RUC, Benjamin et al. 2001) forecast model in energy planning. This study was expanded in 2001 to explore the use of ensembles of forecasts as a predictor of forecast uncertainty. Preliminary results from this study, as presented here, support the use of ensembles as a basis in determining the degree of confidence associated with given forecasts.

The RUC model, currently running at NCEP with a 40-km resolution, was selected for this study for several reasons. The RUC model employs a 40-level hybrid sigma/isotropic vertical coordinate system with very high vertical resolution near the surface. A sophisticated multilevel soil/vegetation model improves the treatment of forecast surface fluxes. Additionally the RUC model was designed to run at a higher temporal frequency (hourly at NCEP), taking advantage of the volume of surface, profiler and aircraft reports available hourly.

*Corresponding author address:* Kevin Brundage, NOAA/FSL R/E/FS1, 325 Broadway, Boulder, CO, 80305-3328, kevb@fsl.noaa.gov.

## 2. PROCESSING

To facilitate this study, a 1-h 40-km test of the RUC/MAPS assimilation cycle was established including 36-h forecasts 4 times per day (at 0000, 0600, 1200, and 1800 UTC). Forecasts out to 12 h were run at 0300, 0900, 1500, and 2100 UTC. Datasets were assembled which included horizontal winds, temperature, and pressure interpolated to wind tower locations and heights for the period from May through August 2000.

## 3. FORECAST VERIFICATION

For verification purposes, NREL provided data from their National Wind Technology Center (NWTC) site at Golden, CO. These data includes wind speed measurements at 10, 25 and 40 m above the surface. Preliminary studies indicated that the NWTC site, located adjacent to the foothills south of Boulder, Colorado, was the most challenging of the 17 NREL wind tower locations to accurately predict, almost certainly due to its unique local terrain. However this site provided the most complete and accurate set of observations to study.

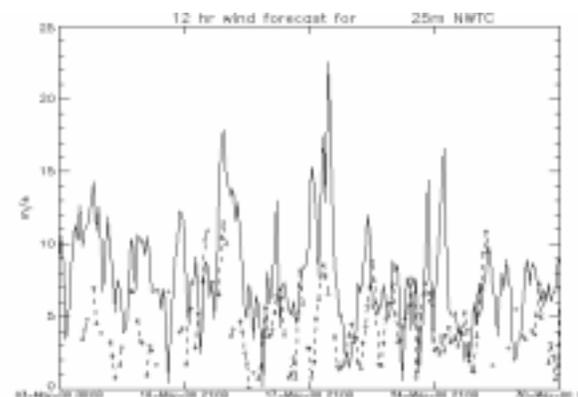


Figure 1. Observed wind speeds (solid), 12-h forecasts (dashed) - NWTC, Golden, CO

Figure 1 illustrates a typical time series of observed wind speed (solid line) versus forecast wind speed (dashed line) for a subset of the study period. Verification statistics us-

ing the NWTC observations compared with 12-h forecast wind speed produce RMS errors of approximately  $3 \text{ ms}^{-1}$  ( $2.96 \text{ m/s}$  at 10m,  $3.31 \text{ ms}^{-1}$  at 40 m). Note that although vector difference are typically calculated for determining errors in the horizontal wind field, for this study, only RMS differences in the wind speed are considered since wind turbines automatically rotate to face the current wind direction. Examining the time series more closely reveals intermittent, underforecast high wind events which explain the relatively large RMS errors at NWTC. On 17 May, for example, winds measured at the NWTC site exceed  $20 \text{ m/s}$  for a 4-h period, while the 12-h forecast winds were approximately  $7 \text{ ms}^{-1}$ . The observed winds from this case were from a local downslope wind event which was not fully captured by the model.

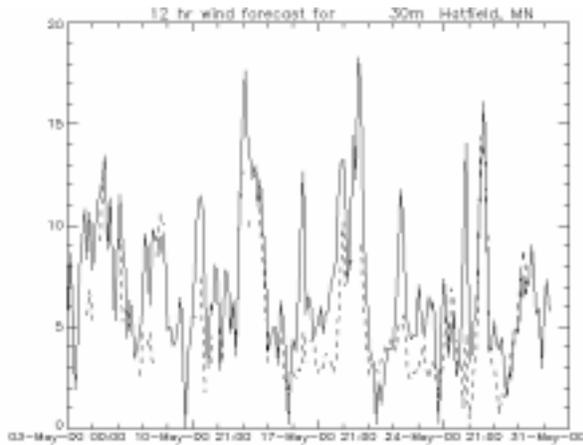


Figure 2. Observed winds (solid), 12-h forecasts (dashed) - Hatfield, MN

Data were also supplied for a Minnesota Department of Commerce 90-m tower located near Hatfield, Minnesota ( Fig. 2). Data was supplied for this site at 30, 60 and 90 m above the surface. Hatfield, MN, located near the South Dakota border, represents a site much less affected by terrain influences unresolved by the RUC model. The RMS error for 12-h forecasts at 30 m above the surface for the Hatfield site during the test period was  $2.49 \text{ m/s}$ . As expected, RMS errors in the wind speed at Hatfield are slightly better than those at the NWTC site.

#### 4. USE OF ENSEMBLE FORECASTS TO ASSESS FORECAST UNCERTAINTIES

Several methods were evaluated to determine an appropriate measure of confidence for a given forecast. It has been demonstrated that the variability of global model forecasts in an ensemble can be used as a predictor of forecast skill for variables such as 500-mb height (Kalnay and Dalcher 1987, Buizza 1997). However, similar techniques applied to precipitation forecasts showed little or no skill (Hamill and Colucci 1998), and only limited skill when applied to cyclone positions (Stensrud et al. 1999) using regional model ensembles.

For this study, ensembles of forecasts with common valid time, but differing initial times were considered. Each of these forecasts incorporate different synoptic observations from sources such as surface sites, profilers, and commercial aircraft reports. Consequently, each forecast has a slightly different initial condition.

For each of these ensemble sets, variance between the predicted wind speeds was calculated as a predictor of uncertainty. The computed variances were compared to differences between a given forecast (e.g. the 12-h forecast) and the measured wind speeds. A correlation coefficient was calculated to determine the applicability of ensemble variability as a measure of forecast accuracy.

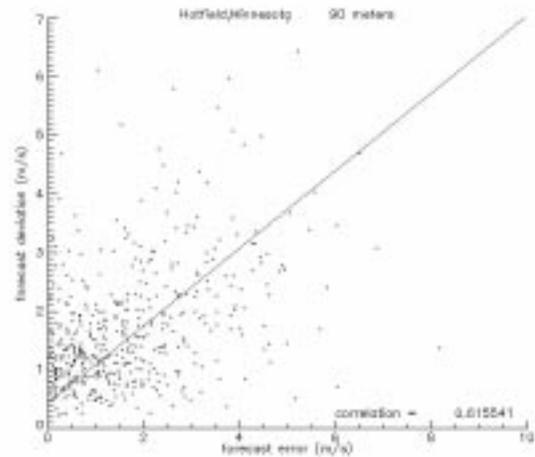


Figure 3. Scatter diagram: Ensemble variance vs. forecast error - Hatfield, MN

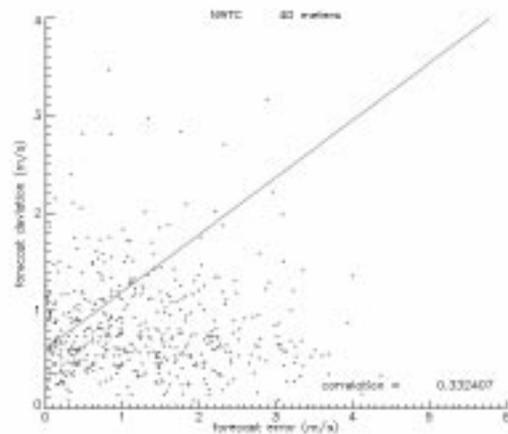


Figure 4. Scatter diagram: Ensemble variance vs. forecast error - NWTC site - Golden, CO

Figure 3 depicts a scatter diagram of variance in the ensemble versus the forecast error for 12 hour forecasts. This was

generated using observations from the Hatfield, MN. site. Although not a perfect fit, the correlation of 0.6 indicates a reasonably good fit between the ensemble variances and the actual observed forecast errors.

When a similar diagram is generated for the NWTC site (Fig. 4), the fit between the ensemble variance and the forecast errors is poorer (~0.3). As was noted in initial investigations, the NWTC site was difficult to forecast. When the NWTC statistics were stratified to include only verification times approximately corresponding to daytime (1200, 1500, 1800, 2100 UTC), the correlation coefficient between ensemble variance and forecast skill increased to 0.4, presumably because daytime mixing links near-surface winds more to larger-scale patterns.

## 5. CONCLUDING REMARKS

Preliminary results from tests using the ensemble method to estimate forecast confidence have been encouraging. Further refinements to this scheme are likely to improve these results and are currently being investigated. In addition to the confidence measured being demonstrated here, research is also being conducted to derive probabilistic measures, based on statistical distributions (climatology), forecasted wind speeds, and the ensemble variations.

Future areas of investigation include:

- Improvements attained through use of the 20-km RUC. The results shown in this paper are based on a 40-km 40-level version of the RUC. How much improvement can be attained with the new 20-km 50-level version (Benjamin et al. 2001), especially for sites such as NWTC with strong influence on wind climatology from local terrain effects?
- Would weighting various ensemble members differently improve the correlations between the weighted variance and the forecast errors?
- Initial investigation shows a diurnal variation in the accuracy of this confidence measurement. Correlations during the daytime (when lower-tropospheric winds are more deeply mixed), were much higher than those at night. Is there any seasonal variation in this predictor?

## 6. REFERENCES

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