Subhourly Wind Forecasting Techniques for Wind Turbine Operations

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SUMMARY

Three models for making automated forecasts of subhourly wind and wind power fluctuations were examined to determine the models' appropriateness, accuracy, and reliability in wind forecasting for wind turbine operation. Such automated forecasts appear to have value not only in wind turbine control and operating strategies, but also in improving individual wind turbine operating strategies (such as determining when to attempt startup).

A simple persistence model, an autoregressive model, and a generalized equivalent Markhov (GEM) model were developed and tested using spring season data from the WKY television tower located near Oklahoma City, Oklahoma. The three models represent a pure measurement approach, a pure statistical method and a statistical-dynamical model, respectively.

Forecasting models of wind speed means and measures of deviations about the mean were developed and tested for all three forecasting techniques for the 45-meter level and for the 10-, 30- and 60-minute time intervals. The results of this exploratory study indicate that a persistence-based approach, using onsite measurements, will probably be superior in the 10-minute time frame. The GEM model appears to have the most potential in 30-minute and longer time frames, particularly when forecasting wind speed fluctuations. However, several improvements to the GEM model are suggested. In comparison to the other models, the autoregressive model performed poorly at all time frames; but, it is recommended that this model be upgraded to an autoregressive moving average (ARMA or ARIMA) model.

The primary constraint in adapting the forecasting models to the production of wind turbine cluster power output forecasts is the lack of either actual data, or suitable models, for simulating wind turbine cluster performance.

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1.0 INTRODUCTION

The planned large-scale use of wind turbine generators (WTGs) by several electric utilities has focused attention on problems associated with optimal unit commitment and dispatching when stochastic power sources are on-line. Control strategies for WTG clusters require decisions regarding power output to be made in the seconds-to-minutes time frame. Dispatching decisions are generally made in subhourly time frames; ideally, accurate forecasts of subhourly wind characteristics or resultant WTG power output should be available out to a time horizon equal to the startup times of conventional thermal generators (Dub and Pape 1981). Several studies (both completed and ongoing) have concluded that reliable wind and wind power forecasts would be valuable to utilities having a significant penetration of WTGs (Goldenblatt, Wegley and Miller 1983; Schlueter, Park and Bouwmeester 1983).

Dub and Pape (1981) and other investigators have demonstrated that wind is clearly a nonstationary stochastic phenomenon. Consequently, simple statistical techniques do not appear to be appropriate for forecasting the wind. Furthermore, such techniques may not be appropriate in forecasting WTG power output. This study was undertaken to explore and test some potential techniques capable of forecasting the subhourly wind and WTG power output fluctuations that are of concern to utility operations personnel.

There are three general approaches to the wind forecasting problem: statistical, dynamical, and statistical-dynamical hybrid forecasting techniques. As previously stated, simple statistical techniques appear to have intrinsic disadvantages when applied to wind forecasting. While such techniques are easy to apply and may exhibit some skill in very short time frames, there is no physically meaningful basis for their use. On the other hand, dynamic models of the atmosphere focus on physical processes. Such models generally require much computing power, are usually expensive to run (in terms of time and money) and often either their accuracy is limited by the simplifying assumptions made or their use is severely restricted by their complexity. Statistical-dynamical forecasting methods are defined in this report to include a combination of statistical techniques and physically meaningful predictors. Since this class

of techniques has worked well in predicting winds (Carter and Gilhousen 1979; Crisci, Carter and Hollenbaugh 1977; Miller, Whiton and Kelly 1977) and because, once developed, it can generally be implemented even on many microcomputers, this study focused primarily on statistical-dynamical forecasting techniques.

A second consideration in developing an approach to the subhourly wind forecasting problem is the WTG operating regime into which the forecast information will be incorporated. There are at least two general types of operating regimes: 1) open-loop control, which provides no feedback of information from the WTGs to the utility's central control, and 2) closed-loop control, in which such feedback is included for use in governing load frequency control and dispatching.

Reddoch et al. (1981) describe three possible operating strategies that would operate in an open-loop mode:

- use of wind as negative load with no WTG cluster control
- array ramp rate cluster control
- feed-forward cluster control.

Even with no cluster control, Goldenblatt, Wegley and Miller (1983) anticipate significant fuel savings for some utilities if sufficiently reliable 0- to 24-hour wind forecasts are incorporated into the daily operations planning (i.e., into the load forecast). If ramp rate control is imposed to help meet National Electric Reliability Council (NERC) guidelines, then forecast information on wind speed fluctuations in the 10-minute time frame will be needed. For feed-forward control, backup generation would be used to maintain a nearly constant output between the WTGs and their backup units. Again, in this operating strategy, wind speed information would be required for at least 10 minutes into the future.

Under closed-loop control, the central control of the utility is modified such that the WTGs are dispatched based upon current and forecast information about the WTGs' output. In this mode of operation detailed wind forecasts out to the startup time of some thermal generators (i.e., 3 to 6 hours) would be useful.

After considering the classes of wind forecasting techniques and the information requirements for the various WTG operating regimes, the following criteria for candidate subhourly wind forecasting techniques were established:

- techniques should be easily automatable (thus objective)
- techniques should have some physically meaningful bases
- any predictor(s) used must be available in real time
- techniques should be adaptable to a variety of forecast output formats to meet user needs
- techniques should be applicable for time frames ranging from ~ 10 minutes up to a few hours
- techniques should permit forecast updates to be made easily upon demand.

One versatile forecasting technique which appears to meet all the criteria is the Generalized Equivalent Markov (GEM) model (Miller 1979a). The GEM model has been developed and tested by the Techniques Development Laboratory of the National Weather Service specifically for forecasting weather elements in the 0 to 6 hour time frame. The favorable results of this testing lend much credibility to the GEM model's usefulness for producing subhourly wind forecasts.

Section 2 of this report describes the meteorological data used in this study, development of the GEM model on a carefully selected dependent data set, and two simpler models with which GEM forecasts were compared. Section 3 presents the forecast verification results on the independent data for all three models. Conclusions regarding the forecasting models tested are made in Section 4.

2.0 FORECAST MODELS TESTED

To provide a reasonable estimate of the usefulness and relative accuracy of the GEM model it is necessary to compare it to some standard(s). In the subhourly time frame, persistence effects are so strong that straight persistence was selected as a standard. The GEM model forecasts were also compared with an autoregressive (AR) model to examine the usefulness of physically meaningful predictors in subhourly wind forecasting. The dependent and independent data used, as well as the development of the three forecasting models, are discussed in the remainder of Section 2.

2.1 DEVELOPMENTAL DATA SET

The data set chosen for use in this study consisted of approximately 13 months of 10-second data (October 1976 through November 1977) collected from the 481-m-high WKY TV tower located 10 km northeast of Oklahoma City, Oklahoma. The site lies ~ 4 km northeast of the city's suburbs in gently rolling agricultural land. The ground cover is mostly low crops and grasses with some widely scattered areas of trees in the general vicinity of the site. (For further information on the tower site and instrumentation see Goff and Zittel [1974]). The WKY data set was selected because it contained high-quality high-speed data for a variety of meteorological variables at multiple heights on a tall tower.

Table 2.1 contains the raw meteorological data that were extracted for forecast development and verification. The basic 10-s data were averaged to make a 1-min averaged data set, which was then used to develop the set of wind forecasting predictors.

TABLE 2.1. Raw Developmental Data Extracted From the WKY Tower

<u>Data Element</u>	<u>Units</u>	<u>Height Above Ground</u>
Date/Time	month,day,yr/hr,min,s	---
Wind Speed	m/s	45 m
Wind Direction	degrees (from true north)	45 m
Temperature	degrees Celsius	Surface, 45 m
Pressure	millibars	Surface

Because of limited time and money it was necessary to limit the size of the dependent and independent data sets as well as the time spent exploring various potential predictors. Ideally a large set of predictors would have been developed from all the raw data and analysis of variance or screening regression would then have been performed to select the most promising set of predictors. A further constraint was that the site proved less windy (in terms of expected power from a large wind turbine) than was anticipated. Consequently, the dependent and independent data were drawn from only the windiest season of the year (February through April). Inclusion of other months had the effect of strongly biasing all forecasts toward light wind conditions that are not characteristic of a good WTG site.

The potential predictors shown in Table 2.2 were selected based upon subjective meteorological judgement rather than upon statistical analysis. Consequently, both the forecast technique development and the results are truly exploratory in nature and do not necessarily represent the state-of-the-art in short-term wind prediction.

TABLE 2.2. Potential Predictors Created From the Raw Developmental Data

<u>Predictor</u>	<u>Units</u>	<u>Time Intervals</u>	<u>Height</u>
Mean Speed	m/s	10,30,60 min	45 m
Stand. Dev. of Speed	m/s	10,30,60 min	45 m
Speed Trend	m/s	10,30,60 min	45 m
Stand. Dev. about Trend	m/s	10,30,60 min	45 m
Max Positive Speed Excursion in 2 Minutes	m/s	10,30,60 min	45 m
Max Negative Speed Excursion in 2 Minutes	m/s	10,30,60 min	45 m
2-Hour Pressure Change	mb	10,30,60 min	Surface
Stability (temp. change with height)	degrees C	10,30,60 min	45 m to Surface
Prevailing Wind Direction	quadrant	10,30,60 min	45 m
Hour of Day	---	10,30,60 min	---

Of the potential predictors shown in Table 2.2, the first four (mean, standard deviation, trend and maximum excursion of the speed) are of primary importance in predicting short-term fluctuations in WTG power output. The mean and standard deviation provide much of the required information as they can be used to estimate the mean power output and the fluctuation about that mean over a predetermined time interval. However, the speed trend and maximum excursion, if they can be predicted reasonably well, are also valuable. If the trend is known, then the deviations about the trend form a Gaussian distribution from which the character of the power output variability can be determined more accurately and used to advantage in both the operation and simulation of WTG clusters (Chan et al. 1983). The maximum wind speed excursion is related to the maximum ramping rate and thus is important in determining and maintaining load following, operating reserves and unloadable generation requirements. Averaging intervals of 10, 30 and 60 min were used in the developmental data to test the sensitivity of wind forecasting accuracy to the time resolution factor.

2.2 THE GEM FORECASTING MODEL

The GEM model was first considered for operational weather forecasts by R. G. Miller (1968). It was further explored by Whiton (1977) and Miller (1979a). The model is a logical extension of the traditional use of conditional climatology as a forecasting tool. In the past, forecasters have been given tables of categories of weather elements and the associated probabilities that the same, or other categories, will occur some number of time steps into the future. Such guidance has proven useful in short-term weather forecasting.

Upon examination of the conditional climatology described above, it becomes obvious that use of this type of information is really the use of a Markhov model. A Markhov model is one in which the predictand consists of a set of possible states and the probability of a transition to any other state is specified in a transition matrix or a state diagram (see EssenWanger [1976] or Whiton [1977] for a more detailed mathematical description of Markhov processes and models). Obviously the "ideal" transition matrix would provide probabilities of state transitions for all possible states of the atmosphere; but, the size

of such a matrix would be unmanageable. Even when one limits the description of the states of the atmosphere to just a few, as in the case of the subhourly wind forecasting data described in Section 2.1, a classical Markhov model may easily require 50 factorial or more states to provide sufficient resolution of the predictand categories. Though the number of states is finite, it is computationally unmanageable.

A primary advantage of the GEM model over classical Markhov models is that the large number of states is reduced to a computationally manageable number. For example, a 50! by 50! matrix (required by the Markhov model) is reduced to a 50 by 50 matrix of regression coefficients. The method of development by which this is made possible is illustrated in Figure 2.1 and explained in the following discussion.

*Each predictand must also be a predictor

FIGURE 2.1. Development of the Generalized Equivalent Markhov (GEM) Model

2.2.1 Input Predictors

The predictors selected for the test application of the GEM model were those listed in Table 2.2. Though the predictands of interest in predicting short-term WTG performance are primarily the mean speed, standard deviation of speed, speed trend and maximum excursion of speed, any available/measurable meteorological data that are physically related to the predictands are candidate predictors.

The dependent data set was defined to be the first 19 days of February, March 6-25, and April 11-30. These data were extracted from the 3 months of developmental data (February through April 1977). The remainder of these data were designated as independent data for forecast verification (see Section 3). The rationale for this division of the data was to keep the dependent data set as large as possible while still allowing sufficient independent data to make a reasonable estimate of forecasting accuracy and to avoid any seasonal biases by evenly distributing both the dependent and independent data over the period of record.

2.2.2 Categorizing Predictors

To provide discrete predictors with some degree of resolution, the predictors were categorized as shown in Tables 2.3, 2.4 and 2.5. Categorization was performed semiobjectively by plotting the frequency distributions of the 10 predictors and dividing each distribution into categories having approximately the same probability of occurrence (for a particular predictor). If one category of a predictor has a much higher probability of occurrence than any other category of that predictor this will be reflected by rapid convergence of the forecast for that predictor to the most probable category (see Section 2.3 for further explanation). The actual number of categories was selected based upon a subjective judgement about the degree of resolution needed. For example, for stability an attempt was made to separate the stable, neutral and unstable atmospheric cases; therefore, only three categories were used for stability. In any future work it is recommended that a more objective approach to categorization be employed to maximize the forecasting performance (such as that of Miller and Best 1979).

TABLE 2.3. Categories for 10-Minute Wind Predictors

Predictor	#Cats.	Category Intervals
Mean Speed (m/s)	6	0.0 to 3, >3 to 5, >5 to 7, >7 to 9, >9 to 12, >12
Std. Dev. about Mean Speed (m/s)	4	0.0 to 0.3, >0.3 to 0.6, >0.6 to 1.0, >1.0
Speed Trend (m/s)	6	<-0.17, -0.17 to <-0.07, -0.07 to <-0.01, -0.01 to <0.05, 0.05 to <0.13, >=0.13
Std. Dev. about Speed Trend (m/s)	4	0.0 to 0.3, >0.3 to 0.6, >0.6 to 1.0, >1.0
Max Positive Speed Excursion in 2-min	3	0.0 to 0.5, 0.5 to 1.5, >1.5
Max Negative Speed Excursion in 2-min	3	0.0 to -0.5, -0.5 to -1.5, <-1.5
2-Hour Pressure Change (mb)	5	<-0.6, -0.6 to -0.07, -0.07 to <0.07, 0.07 to 0.6, >=0.6
Stability (temp. difference in °C, 45 m - surface)	3	<-0.6, -0.6 to 0.4, >0.4
Wind Direction (90° quadrant)	4	NE, SE, SW, NW
Hour of Day (Local Standard)	8	>00-03, >03-06, >06-09, >09-12, >12-15, >15-18, >18-21, >21-24

TABLE 2.4. Categories for 30-Minute Wind Predictors

Predictor	#Cats.	Category Intervals
Mean Speed (m/s)	6	0.0 to 3, >3 to 5, >5 to 7, >7 to 9, >9 to 12, >12
Std. Dev. about Mean Speed (m/s)	4	0.0 to 0.4, >0.4 to 0.7, >0.7 to 1.1, >1.1
Speed Trend (m/s)	6	<-0.05, -0.05 to <-0.02, -0.02 to <0.0, 0.0 to >0.02, 0.02 to <0.05, >=0.05
Std. Dev. about Speed Trend (m/s)	4	0.0 to 0.4, >0.4 to 0.7, >0.7 to 1.1, >1.1
Max Positive Speed Excursion in 2-min	3	0.0 to 1.0, 1.0 to 2.0, >2.0
Max Negative Speed Excursion in 2-min	3	0.0 to -1.0, -1.0 to -2.0, <-2.0
2-Hour Pressure Change (mb)	5	<-0.6, -0.6 to -0.035, -0.035 to <0.035, 0.035 to 0.6, >=0.6
Stability (temp. difference in °C, 45 m - surface)	3	<-0.6, -0.6 to 0.4, >0.4
Wind Direction (90° quadrant)	4	NE, SE, SW, NW
Hour of Day (Local Standard)	8	>00-03, >03-06, >06-09, >09-12, >12-15, >15-18, >18-21, >21-24

TABLE 2.5. Categories for 60-Minute Wind Predictors

Predictor	#Cats.	Category Intervals
Mean Speed (m/s)	6	0.0 to 3, >3 to 5, >5 to 7, >7 to 9, >9 to 12, >12
Std. Dev. about Mean Speed (m/s)	4	0.0 to 0.5, >0.5 to 0.8, >0.8 to 1.2, >1.2
Speed Trend (m/s)	6	<-0.028, -0.028 to <-0.0035, -0.0035 to <0.0035, 0.0035 to >0.02, 0.02 to <0.036, >=0.036
Std. Dev. about Speed Trend (m/s)	4	0.0 to 0.4, >0.4 to 0.8, >0.8 to 1.1, >1.1
Max Positive Speed Excursion in 2-min	3	0.0 to 1.3, 1.3 to 3.0, >3.0
Max Negative Speed Excursion in 2-min	3	0.0 to -1.3, -1.3 to -3.0, <-3.0
2-Hour Pressure Change (mb)	5	<-0.7, -0.7 to -0.035, -0.035 to <0.035, 0.035 to 0.5, >=0.5
Stability (temp. difference in °C, 45 m - surface)	3	<-0.35, -0.35 to 0.35, >0.35
Wind Direction (90° quadrant)	4	NE, SE, SW, NW
Hour of Day (Local Standard)	8	>00-03, >03-06, >06-09, >09-12, >12-15, >15-18, >18-21, >21-24

2.2.3 Regressing Predictors on Predictions

The method by which the probabilities of one-time-step-ahead categories of a predictand are produced is through the development of a multiple linear regression equation for the probability of each predictor-predictand. Such equations were developed by first placing the dependent data in the format shown in Table 2.6.

The general form for the multiple linear regression is:

$$\mathbf{Xb}=\mathbf{Y}$$

where: **X** = the matrix of categorized observations at time zero

b = the matrix of regression coefficients (to be determined)

Y = the matrix of categorized observations one time step into the future

and all Xs and Ys are binary values (0 or 1). The use of binary values for the categorized predictor-predictands is sometimes called the use of "dummy variables" (see Draper and Smith 1966).

TABLE 2.6. Format of Dependent Data for Development of GEM Model Regression Estimates of Event Probabilities

Obs#	$x(a)$			$y(a)$		
	Observed Categorized Predictor-Predictands at Time T0			Observed Categorized Predictor-Predictands at Time T0+dt		
	X0	X1	X2.....X46	Y0	Y1	Y2.....Y46
1	1	X(1,1)	X(2,1)....X(1,46)	1	Y(1,1)	Y(1,2)...Y(1,46)
2	1	X(2,1)	X(2,2)....X(2,46)	1	Y(2,1)	Y(2,2)...Y(2,46)
3	1	X(3,1)	X(3,2)....X(3,46)	1	Y(3,1)	Y(3,2)...Y(3,46)
.	.	. . .		.	. . .	
.	.	. . .		.	. . .	
.	.	. . .		.	. . .	
n	1	X(n,1)	X(n,2)....X(n,46)	1	Y(n,1)	Y(n,2)...Y(n,46)

(a) Note that $Y(1,1)=X(2,1)$, $Y(1,2)=X(2,2)$ etc. because all predictands (Y) are simply predictors (X) one time step into the future.

Solving for the regression coefficient matrix, **b**, yields the following:

$$\mathbf{b} = (\mathbf{X}^T * \mathbf{X})^{-1} * \mathbf{X}^T * \mathbf{Y}$$

where: $\mathbf{X}^T$ is the transpose of the **X** matrix

$(\mathbf{X}^T * \mathbf{X})^{-1}$ is the inverse of the product of **X** and **X** transpose.

Since **X** transpose **X** results in a 46 by 46 matrix (46 is the total number of categories in the case studied) the matrix inversion becomes manageable.

Obtaining $\mathbf{X}^T * \mathbf{X}$, however, will be time-consuming on most computers.

The use of the vector of 1s (in X0 and Y0) leads to singular matrices, preventing the required matrix inversion. This problem was avoided by leaving out the column vector of one predictor and then back-calculating to obtain the vector of the corresponding regression coefficients. This technique is explained in detail by Whiton (1977).

An important result of the use of categorized dummy variables is that the constant term for each regression equation is equal to the climatological probability of occurrence of the event for which the equation was developed. It is

also important to note that the regression coefficients themselves are directly interpretable (i.e., they are proportional to the part of the probability of occurrence of a predictand attributable to the predictor). Thus the importance of each predictor can be seen by the value of its coefficient.

2.3 PRODUCING FORECASTS USING THE GEM MODEL

Figure 2.2 shows the general method by which forecasts are generated using the regression coefficient matrix described in Section 2.2.3. For example, if the input predictors are 10-min values for the 10 observed predictors of Table 2.2, the category limits of Table 2.3 would be imposed to create a vector of 47 binary values (the predictors observed at time T0 plus the constant term, unity). The predictors would be multiplied by each row of the regression coefficient matrix to produce forecast probabilities of each predictand.

In the test application of the GEM technique, the forecast category for each predictand was selected (that is, set equal to 1) for that category of the predictand having the highest forecast probability of occurrence. All other categories of the predictand were set to zero. This produces a set of forecasts for each predictand for one time step into the future. By retaining the forecast probabilities and using them in conjunction with the regression coefficient matrix, one can iterate ad infinitum to produce forecasts out to any number of time steps; but, since the probabilities of occurrence of any category of predictor are all less than unity, each successive iteration yields smaller contributions to the total forecast probability for all but the constant term (the climatological probability of occurrence) which is always multiplied by 1. This means that the process of iteration will eventually converge to the climatological probability of occurrence of each category of predictand. Beyond that convergence point only seasonal and diurnal effects (if they are inherent in the regression coefficients) will be seen. The convergence of the forecasts to climatology is a desirable quality of the GEM forecasts as it is consistent with the fact that forecasting skill (for any technique) deteriorates with time and eventually becomes no more skillful than climatology.

FIGURE 2.2. Forecast Production Using the GEM Technique

The iterative nature of the GEM technique permits updating of the forecast whenever new observations (predictors) are available; this is a desirable capability for use in WTG operations. Also, the forecasts can be issued as deterministic (specified) categorical forecasts or the probabilities can themselves be displayed and decisions made based upon cost/loss ratios and the probability of occurrence of events (see Murphy 1977). An alternative approach is to empirically, or statistically develop threshold probabilities above which forecasts of a category of predictor will be made (regardless of the probability of occurrence of other categories of the predictor). This approach is usually used in conjunction with cost/loss considerations.

2.4 THE AUTOREGRESSIVE FORECASTING MODEL

In order to compare the GEM technique to a strictly statistical approach (having no physical basis) an AR model was developed for the following predictands for the 10-, 30- and 60-min time intervals:

1. mean speed
2. standard deviation of speed about the mean
3. speed trend
4. standard deviation of speed about the trend.

Analysis of variance showed that almost nothing was gained by going beyond a fifth-order AR model; thus, the fifth-order model was developed for the four predictands listed above.

The time series of uncategorized predictors for the same dependent data set used for the GEM model was used for the AR model development. The form of the fifth-order AR model used was:

$$X_{t+1} = b_0 + b_1 * X_{t-4} + b_2 * X_{t-3} + b_3 * X_{t-2} + b_4 * X_{t-1} + b_5 * X_t$$

where X_t is the current observation, X_{t-1} is the previous observation, etc., and b values are regression coefficients. Forecasts were produced using the same independent data set used in the GEM model verification and forecast values were categorized using the same category intervals as for the GEM model. Forecast verification results are presented in Section 3.

2.5 THE PERSISTENCE MODEL

Most meteorological phenomena that are routinely forecast show very strong persistence in the short (subhourly) time frames. Consequently, persistence has become one standard used to measure forecast accuracy. The persistence model used simply held the initially observed category of each predictor constant for the forecast period. Results of the persistence forecast verifications are contained in Section 3.

3.0 FORECAST VERIFICATION RESULTS

Due to the exploratory nature of this study, the limited resources and limited amount of suitable data, all work was limited to a single site and data from a single year at that site. Though a data set of MOD-2 simulated power output (using the model of Miller and Formica 1984) was developed, it was not possible to analyze those data at this time. Consequently, all verification results are for forecasts of wind speed fluctuations that are associated with WTG power output fluctuations (as described in Section 2) rather than for power output itself.

Two measures of forecasting accuracy/skill were used to compare forecasts: 1) the fraction of correct forecasts and 2) the Heidke Skill Score. The fraction of correct forecasts is simply the number of forecasts of the correct category divided by the total number of forecasts. The Heidke Skill Score (Brier and Allen 1952) attempts to measure the actual skill of the forecasts by eliminating the fraction of correct forecasts that would have been obtained by chance (guessing with no skill). A simple 2 by 2 matrix of forecast versus observed values is shown in Figure 3.1 to illustrate the Heidke Skill Score (SS). The term $(X*L)+(Y*M)/Z$ is the climatological probability of the event. The number of correct forecasts is $(A+D)$ and Z is the total number of forecasts. The SS ranges from -1 (negative skill) to +1 the greatest possible skill. A SS of 0 denotes no improvement over climatology. The method of computation can be generalized to an N by N matrix of forecast and observed categories of events.

		Forecast Wind Speeds		
		Category 1	Category 2	Total
Observed Wind Speeds	Category 1	A	B	X
	Category 2	C	D	Y
	Total	L	M	Z

$$\text{Heidke Skill Score} = \frac{(A+D) - ((X*L) + (Y*M))/Z}{Z - ((X*L) + (Y*M))/Z}$$

FIGURE 3.1. Computation of the Heidke Skill Score

As implied in Section 2.3, the GEM model is well suited for the production of probability forecasts; however, the forecasts were output and verified only as categorical forecasts for this study.

The remainder of Section 3 provides a comparison of the 10-, 30- and 60-min forecasts for the GEM, autoregressive, and persistence models as well as discussion of some of the interesting characteristics of the GEM forecasts (such as time required for convergence to climatology).

3.1 COMPARISON OF GEM, AUTOREGRESSION AND PERSISTENCE FORECASTER

In actual application it is doubtful that either the 10-, 30- or 60-min forecasts would be used beyond six time steps into the future. In fact it is very possible that a set of hybrid forecasting equations might be used to predict, for example, 10-min intervals for the first half-hour, half-hour intervals for the following 1-1/2 hours (out to hour 2) and hourly intervals for the remainder of the forecast (3 to 6 hours). For this reason all comparisons of verification statistics for the three time intervals and three models were limited to six time steps into the future.

The independent data (see Section 2.2.1) consisted of approximately 4 weeks of observations from portions of February, March and April. These periods of time were appended to provide a data set from which six time interval forecasts were made end-to-end (i.e., there was no overlap in time between successive forecasts; thus, no redundant use of the independent data). All discontinuities in time (caused by missing data) were flagged and forecasts were truncated at the time step at which the discontinuity occurred. Such discontinuities interrupted only a very small fraction of the forecasts and thus did not introduce any significant biases into the forecast verification results.

3.1.1 Overall Forecasting Skill and Accuracy

Before skill scores for the forecasts of mean speed were computed, certain categories of speed were combined. This was done to reflect the importance of operating characteristics of large WTGs. For example, there is very little

importance (for verification purposes) in discriminating between wind speed categories such as 0 to 3 and 3 to 5 m/s if the cut-in wind speed of the WTG exceeds 6 m/s. For this reason the six original categories of mean speed (see Tables 2.3, 2.4 and 2.5) were reduced to four by combining the first three speed categories, which are, for the most part, below cut-in for a large WTG. This recategorization was not done before developing the regression equation for the GEM model because it would have strongly biased the forecasts by introducing a large climatological probability for the three combined categories, thereby causing the iterative forecasting generation procedure to converge rapidly to the large speed category.

Tables 3.1 through 3.3 present the comparison of the three forecasting model results (all time steps combined) for the 10-, 30- and 60-min forecasts, respectively.

TABLE 3.1. Comparison of 10-Minute Forecasts for All Time Steps Combined

	GEM		AR Model		Persistence	
	<u>Skill Score</u>	<u>Fraction Correct</u>	<u>Skill Score</u>	<u>Fraction Correct</u>	<u>Skill Score</u>	<u>Fraction Correct</u>
Mean	0.60	0.76	0.46	0.70	0.63	0.73
Std. Dev. about Mean	0.38	0.53	0.19	0.38	0.38	0.54
Trend	0.08	0.22	0.00	0.11	0.04	0.21
Std. Dev. about Trend	0.38	0.55	0.19	0.41	0.39	0.55

Note that only four of the six predictands of interest are compared. The two other predictands, maximum and minimum excursions, were originally developed for 2-min time periods. Since National Electric Reliability Council (NERC 1981) guidelines require that operating reserves must be effective within a 10-min period (Reddoch et al. 1981), 10-min excursions in wind speed would be more appropriate predictands. The 2-min wind speed excursions used in this study can not be used to infer the predictability of 10-min excursions and therefore are not included in the Skill Score tables.

TABLE 3.2. Comparison of 30-Minute Forecasts for All Time Steps Combined

	GEM		AR Model		Persistence	
	<u>Skill Score</u>	<u>Fraction Correct</u>	<u>Skill Score</u>	<u>Fraction Correct</u>	<u>Skill Score</u>	<u>Fraction Correct</u>
Mean	0.49	0.70	0.27	0.61	0.53	0.72
Std. Dev. about Mean	0.41	0.56	0.11	0.32	0.37	0.53
Trend	0.05	0.23	0.00	0.13	0.00	0.10
Std. Dev. about Trend	0.40	0.55	0.09	0.32	0.42	0.57

TABLE 3.3. Comparison of 60-Minute Forecasts for All Time Steps Combined

	GEM		AR Model		Persistence	
	<u>Skill Score</u>	<u>Fraction Correct</u>	<u>Skill Score</u>	<u>Fraction Correct</u>	<u>Skill Score</u>	<u>Fraction Correct</u>
Mean	0.36	0.64	0.25	0.60	0.38	0.63
Std. Dev. about Mean	0.31	0.49	0.01	0.25	0.22	0.43
Trend	0.03	0.33	0.00	0.14	0.00	0.21
Std. Dev. about Trend	0.36	0.55	0.05	0.35	0.28	0.48

Before drawing conclusions about the data in Tables 3.1, 3.2 and 3.3, the reader is reminded that both the GEM model and the autoregressive model can be improved. Several recommendations for improvements to the application of the GEM technique are made in Section 4. The AR model could be improved somewhat by developing an autoregressive moving average (ARMA) model to better fit the dependent data. Persistence, however, cannot be improved upon.

There is a second aspect of the verification results: hindsight shows that the trend was divided into too many categories. Consequently, it was difficult to discriminate between the categories. This resulted in poor skill and accuracy in forecasting the trend for all three forecasting models.

With the information discussed above in mind one can now begin to make some general statements about the skill (SS) and the accuracy (fraction correct)

of the three models and of their performance as a function of time interval. The first conclusion is that for the mean speed, the effects of persistence are very strong and they gradually decrease with increasing time interval. Therefore, for very short time frames (~ 10 min) a persistence-based forecast made from onsite observations may perform well for some dispatching decisions and for WTG cluster control operations. Thus, recommendations by Schleuter, Park and Bouwmeester (1983) for using on-, or near-, site instrumentation as part of the power system operating strategy appear well founded. However, refinements to the way in which the GEM model was applied could make it significantly superior to the other two approaches to short-term wind forecasting. (Specific refinements are discussed in Section 4).

A second conclusion is that both SS and the fraction of correct forecasts, in general, grow small with increasing time averaging interval. This is particularly true for forecasts of the mean speed.

Finally, the GEM and persistence models appear to be considerably more skillful and accurate than the simple autoregressive model.

Since SS and fraction correct are very highly correlated^(a), especially for the same length of time interval, only SS statistics will be presented for the remainder of this section.

3.1.2 Forecasting Skill as a Function of Projection Time

Tables 3.4, 3.5 and 3.6 show the variation of forecasting skill with time for the three forecasting models and for the 10-, 30- and 60-min time intervals, respectively.

The results are, for the most part, expected. For example, for the predictands that were categorized reasonably well (this excludes the speed trend), forecasting skill for all three models decreases rather steadily with increasing projection time. As in the overall comparison (Tables 3.1, 3.2 and 3.3 of the previous section) the AR model is significantly less skillful than persistence or the GEM forecasts.

(a) For SS versus fraction correct, $r^2 = 1.0, 0.98, 0.86$ for 10-, 30- and 60-min intervals, respectively.

TABLE 3.4. Ten-Minute Forecasting Heidke Skill Scores as a Function of Projection Time

		Time Step					
		1 (0-10 Min)	2 (10-20 Min)	3 (20-30 Min)	4 (30-40 Min)	5 (40-50 Min)	6 (50-60 Min)
Mean	Persistence	0.76	0.67	0.63	0.62	0.56	0.52
	AR	0.67	0.55	0.44	0.43	0.34	0.30
	GEM	0.76	0.67	0.63	0.59	0.51	0.44
Std. Dev. about Mean	Persistence	0.40	0.41	0.41	0.42	0.35	0.32
	AR	0.39	0.33	0.21	0.13	0.08	0.04
	GEM	0.42	0.43	0.38	0.39	0.35	0.33
Trend	Persistence	0.03	0.02	0.03	0.07	0.03	0.04
	AR	-0.02	-0.02	0.00	0.00	0.00	0.00
	GEM	0.13	0.07	0.09	0.07	0.04	0.06
Std. Dev. about Trend	Persistence	0.45	0.41	0.41	0.41	0.35	0.33
	AR	0.39	0.35	0.21	0.12	0.07	0.03
	GEM	0.46	0.42	0.37	0.41	0.31	0.33

TABLE 3.5. Thirty-Minute Forecasting Heidke Skill Scores as a Function of Projection Time

		Time Step					
		1 (0-30 Min)	2 (30-60 Min)	3 (60-90 Min)	4 (90-120 Min)	5 (120-150 Min)	6 (150-180 Min)
Mean	Persistence	0.58	0.60	0.56	0.49	0.47	0.38
	AR	0.50	0.32	0.26	0.20	0.16	0.15
	GEM	0.68	0.60	0.54	0.41	0.41	0.30
Std. Dev. about Mean	Persistence	0.45	0.45	0.36	0.36	0.31	0.27
	AR	0.31	0.16	0.28	0.09	0.06	0.05
	GEM	0.60	0.54	0.39	0.40	0.28	0.27
Trend	Persistence	0.00	0.02	-0.02	0.00	0.02	0.01
	AR	0.00	0.00	0.00	0.00	0.00	0.00
	GEM	0.11	0.04	0.03	0.03	0.01	0.09
Std. Dev. about Trend	Persistence	0.60	0.51	0.43	0.39	0.36	0.26
	AR	0.37	0.07	0.10	0.03	0.01	0.00
	GEM	0.63	0.52	0.37	0.31	0.31	0.25

TABLE 3.6. Sixty-Minute Forecasting Heidke Skill Scores as a Function of Project Time

		Time Step					
		1 (Hr)	2 (Hr)	3 (Hr)	4 (Hr)	5 (Hr)	6 (Hr)
Mean	Persistence	0.61	0.54	0.36	0.25	0.30	0.24
	AR	0.37	0.30	0.30	0.18	0.21	0.14
	GEM	0.61	0.50	0.31	0.26	0.23	0.24
Std. Dev. about Mean	Persistence	0.41	0.27	0.24	0.20	0.10	0.11
	AR	0.09	0.01	-0.01	-0.01	0.00	0.00
	GEM	0.46	0.38	0.31	0.30	0.20	0.23
Trend	Persistence	-0.06	0.01	-0.04	0.10	0.02	-0.02
	AR	0.00	0.00	0.00	0.00	0.00	0.00
	GEM	0.09	0.08	-0.02	0.04	-0.03	-0.01
Std. Dev. about Trend	Persistence	0.44	0.43	0.32	0.22	0.12	0.17
	AR	0.25	0.00	0.00	-0.01	0.00	0.00
	GEM	0.46	0.41	0.36	0.30	0.27	0.33

For the first three time steps (and for all three averaging intervals) the effects of persistence are so strong that GEM showed very little improvement over persistence. This indicates that one of the following is true:

- 1) possibly persistence cannot be improved upon in the very short term, or
- 2) that the hastily assembled subjective GEM model requires refinement, or
- 3) perhaps other models should also be investigated. The good results displayed by GEM when sufficient developmental data were used (Miller 1979a) indicate that refining the GEM model would probably be a fruitful approach.

Furthermore, when high resolution is required in the very short-term categorical forecasts, GEM appears to show its skill even in the crude GEM model used in this study. This is evidenced by the 10- and 30-min skill score for the trend (see Tables 3.4 and 3.5) for the first three time steps. (The trend was divided into six very narrow categories.)

For the 10-minute time frame it appears from Table 3.4 that the effects of persistence are very nearly as strong as the statistical-physical relationships modeled using the GEM approach. With this in mind, one can only expect improvements if more physically significant predictors are found that can be used to discriminate between the many occurrences of no change and the smaller number of cases of predictand category change.

3.2 RATE OF CONVERGENCE OF GEM FORECASTS TO CLIMATOLOGY

As discussed in Section 2.3 the method of development and application of the GEM model insures that the forecasts (if projected far enough into the future) will converge to the event(s) having the highest climatological probability of occurrence. This phenomenon was examined to further evaluate GEM forecasting skill for the three different time intervals used in the study. The results of this examination for mean wind speed are shown in Figures 3.2, 3.3 and 3.4 for 60-, 30- and 10-min time intervals, respectively. Similar results were obtained for the other predictands, excluding the trend (which had too narrow categories). The cases examined are ones for which the initial conditions differed significantly from climatology, thus they seem to better illustrate the nature of the convergence.

FIGURE 3.2. Convergence of GEM 60-Minute Forecasts

FIGURE 3.3. Convergence of GEM 30-Minute Forecasts

FIGURE 3.4. Convergence of GEM 10-Minute Forecasts

Two effects of repeated use of the regression estimates of event probabilities in the GEM method can be seen in the figures. First, in the time horizon examined the forecast probability approaches (but does not always converge exactly to) the climatological probability. The probability versus time step plots in Figures 3.2 and 3.4 show this to be the case. Second, even when the forecast probability approaches the climatological probability, the most probable event is not always forecast. This is demonstrated in the top portion of Figure 3.4. Wind speed category 4 is forecast initially; but after 36 time steps the climatological wind speed (category 2) was still not forecast. The lack of convergence to the expected value in the 10-minute forecast shown in Figure 3.4 demonstrates the strong effect of persistence in this very short time frame and the need for a larger developmental data set, improved method of predictor selection, and an improved categorization scheme.

It is interesting to note that the 30- and 60-min forecasts converge to both the climatological probability of event occurrence and to a forecast of the most probable category in 10 to 15 time steps. Several cases were examined for each time averaging interval. Approximately 12 time steps was the mean number required for convergence. Preliminary examination of skill scores for more than the six time steps examined in Section 3.1 indicates that the skill of the 30- and 60-min GEM forecasts approaches zero at 10 to 12 time steps. There is an implication that the GEM model, even in the crude form used in this study, will exhibit skill out to at least 10 time steps when only onsite observations are used as predictors. If further testing and analysis upholds this implication then 30-min forecasts could be useful in providing half hourly resolution out to 3 to 5 hours and 60-min forecasts to 6 to 10 hours. There is still a great deal of uncertainty regarding the ability to provide 10-min wind forecasts that will perform better than persistence-based wind forecasts.

4.0 CONCLUSIONS AND RECOMMENDATIONS

The exploratory nature of the work in this study dictates that the results be interpreted only as indications of the approaches to subhourly wind forecasting that might be most appropriate. At present it appears that, regardless of the WTG operating regime used, wind measurements will be required at or near a WTG site(s) for control and forecasting purposes. Based upon the verification results of Section 3, both a persistence-based approach and a carefully constructed GEM model are promising approaches to subhourly wind forecasting. Some recommended refinements to the forecasting models are the use of:

- a larger dependent data set
- a better categorization scheme
- a better selection technique for predictors
- threshold probabilities in forecast production
- more carefully selected physically meaningful predictands
- prediction of WTG power output for WTG clusters.

Both the persistence-based and the GEM model approaches could benefit from a larger dependent data set. In the test case, the GEM dependent data set, due to lack of suitable data, was only about 5% of the recommended size for development of the GEM forecasting equations (Miller 1979a). This certainly degraded the skill and accuracy of the GEM forecasts. In addition, a larger dependent data set would make it possible to replace straight persistence by some simple persistence probability tables. Whenever the site climatology indicates a very strong probability of a change in category, then a deviation from straight persistence could be made. This type of forecast may prove to be an effective and practical means of producing very short-term (< 10 minute) forecasting for WTG cluster control.

The remainder of the recommendations made apply primarily to the GEM model; however, all three of the forecasting approaches used in the study could benefit from most of these recommendations. For example, a better categorization scheme would help to optimize the tradeoff between the need for resolution in certain predictands and the ability to forecast skillfully the predictand. The wind speed trend forecasts made in this study would certainly have benefited from such refinements (see Section 3.1.1).

The GEM model performance will improve if more physically significant predictors are selected. It is strongly recommended that screening regression or discrete likelihood functions (Miller 1979b) be used to select predictors. Screening regression will undoubtedly select a better set of predictors than the subjective approach used in this study because screening selects predictors based upon the sums of explained squares due to the regression. Discrete likelihood functions could further improve the GEM forecasts by taking into account some of the interdependence between predictors.

To make the forecasts more useful to the end user, the utility, it is recommended that any future work use the 10-min maximum positive and negative excursions in WTG power output as a predictand. Furthermore, all predictands of interest (i.e., means, standard deviation, trends and excursions) should be forecast and verified in terms of WTG power output (actual if possible, or else model-simulated). If suitable WTG cluster/array models become available, then they should be used for future forecasting and subsequent verification. Intuitively one would expect that the filtering effects of the operating strategy of a single WTG, and to a much greater extent the time and space averaging of multiple machines, would make power output a more "forecastable" quantity than the wind itself. For this reason, and due to the widespread availability of appropriate software, future work in short-term wind power forecasting should also examine autoregressive moving average (ARMA or ARIMA) models.

The use of operational models for the MOD-OA and MOD-2 WTGs (Miller and Formica 1983) revealed possible improvements in the individual WTG operating strategy. Such improvements include more intelligent startup/shutdown decisions and "motoring" the WTG through brief lulls in the wind rather than shutting it down. Accurate short-term wind predictions could be used to advantage in optimizing these aspects of WTG operating strategies, thereby improving energy capture. Consequently, it is recommended that future work in short-term forecasting include such predictands as run duration probabilities. Verification of these forecasts would help quantify the economic value of modifying WTG operating strategies.

There appears to be much to be gained from reliable predictions of sub-hourly wind variations. The primary constraint in providing such information

is the lack of actual WTG cluster performance data and, in the absence of that, the lack of appropriate high speed meteorological data to accurately simulate performance of a cluster of wind turbine generators. Collection of actual or appropriately simulated cluster performance data should be performed as soon as is practical.

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