01 Sep 2001

Using Neural Networks to Estimate Wind Turbine Power Generation

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***Abstract*—This paper uses data collected at Central and South West Services Fort Davis wind farm to develop a neural network based prediction of power produced by each turbine. The power generated by electric wind turbines changes rapidly because of the continuous fluctuation of wind speed and direction. It is important for the power industry to have the capability to perform this prediction for diagnostic purposes—lower-than-expected wind power may be an early indicator of a need for maintenance. In this paper, characteristics of wind power generation are first evaluated in order to establish the relative importance for the neural network. A four input neural network is developed and its performance is shown to be superior to the single parameter traditional model approach.**

***Index Terms*—Estimation, neural network, wind power generation.**

I. Introduction

ADVANCES in wind turbine technology [1] and rich wind resources in many areas improve prospects for the wind power industry [2], which motivates the analysis of wind power generation and wind turbine performance. However, because turbines are distributed over a wide area in a wind farm, the power generated by each is usually different due to variations in wind direction and speed. In fact, measured wind data is seldom identical to that seen at the generator for a variety of reasons, including the expense of obtaining and maintaining that data, and topographical constraints.

It is important to be able to estimate wind power generation as a diagnostic tool. However, this estimation must be made even in the absence of ideal wind data, because topographical conditions often make gathering ideal data impractical. (Ideally, wind should be measured at a distance roughly two to six turbine diameters, upwind of the generator, and at hub height of the turbine [3].) This may require an impractical height for the anemometer tower. Furthermore, features such as mountains can cause the wind profile to deviate significantly from ideal cases. Fig. 1 implies that both these issues will be constraints for our example. Many, if not most, wind farms will be subject to similar limitations to wind speed measurement. Therefore, the estimation must be based on wind speed and direction measurements, and not merely an extrapolation of past readings, in order to have diagnostic value.

Manuscript received September 8, 2000. This work was supported by Central and South West Services, the National Science Foundation, the Center for Energy Research on Texas Tech, EPRI, and Zond Inc.

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Publisher Item Identifier S 0885-8969(01)07333-8.

The estimation of power generation for diagnostic purposes is currently accomplished by comparing generated power to the manufacturers ratings for a given wind speed. Fig. 2 shows the manufacturers rating with measured power generation plotted over it. The deviation from rated power production is not sufficient to use for diagnostic purposes except in extreme circumstances, because the manufacturers rating does not anticipate the lack of ideal conditions described above. Nevertheless, this method is the current state of practice.

This paper uses unpublished data from Central and South West's Fort Davis wind farm. The data come from two meteorological towers, which give wind velocities and directions at 5 second and 10 minute averages. The power produced by each turbine is also available for the same periods. Although some turbines near the meteorological towers generate power from wind similar to that predicted by the manufacturers rating, for most others the estimated power based on the recorded wind is usually different from the actual power generated. While several published accounts exist using short-term wind farm data [6], [16], [17], we are not aware of work using such long-term results as presented here.

Below we discuss characteristics of wind power generation and the construction and training of neural networks to estimate the power.

II. Analysis of Wind Power Generation for Actual Measured Data

At the Fort Davis wind farm, there are 12 towers for turbines numbered no. 1 to no. 12 and 2 towers for meteorological measuring equipments (Fig. 1). The twelve turbines at Fort Davis are located in one long North South line on slightly offset ridge lines and two meteorological towers are located on East and West. Data received from the wind farm can be divided into two parts. The first contains data from two meteorological towers, such as wind velocities and directions. The second contains detailed information about wind turbine power generation such as average power outputs, voltages and currents.

A. Influence of Wind Turbine Power Generation by Wind Velocity

The turbine will follow the power generation curve of Fig. 2 if the following conditions are met:

1) The wind speed at the height of the turbine's hub is as indicated on the horizontal axes.
2) The wind speed is uniform horizontally across the face of the turbine.

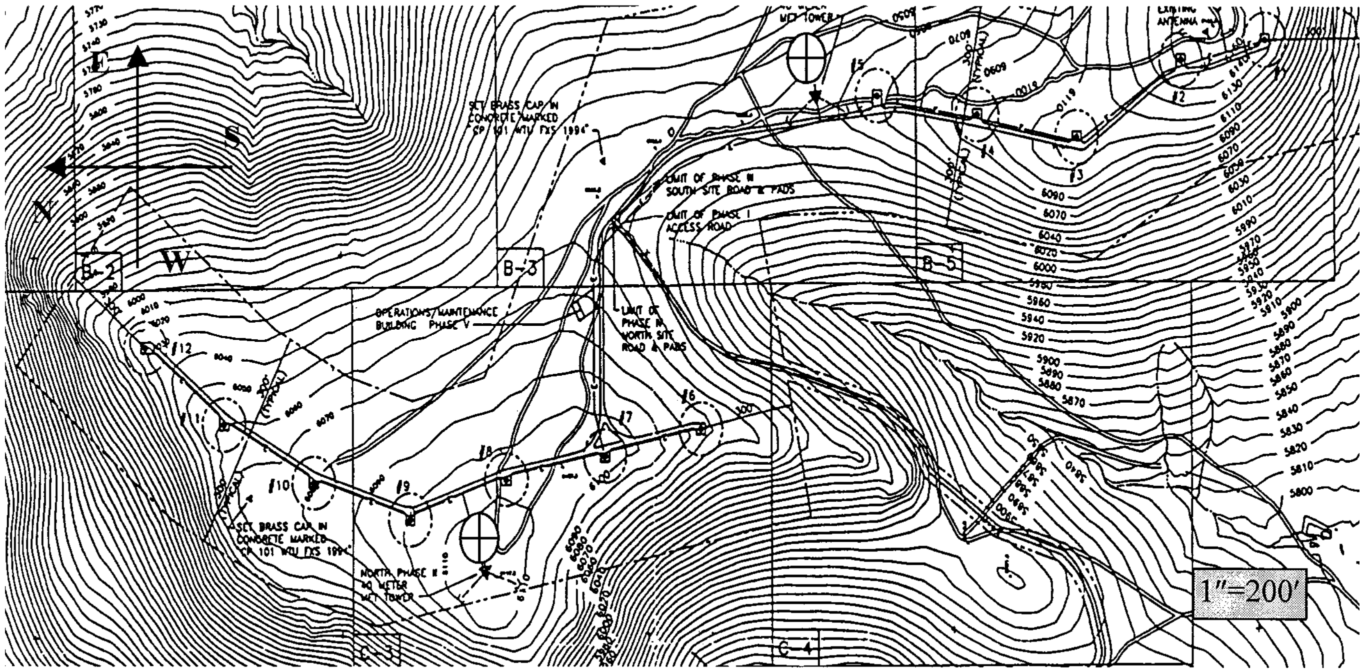

Fig. 1. Central and South West renewable project small wind farm, Fort Davis, Texas (The two meteorological towers indicated with "Q" symbol are the sites for measurement of wind speed and direction. Each dotted circle is the location of a wind turbine).

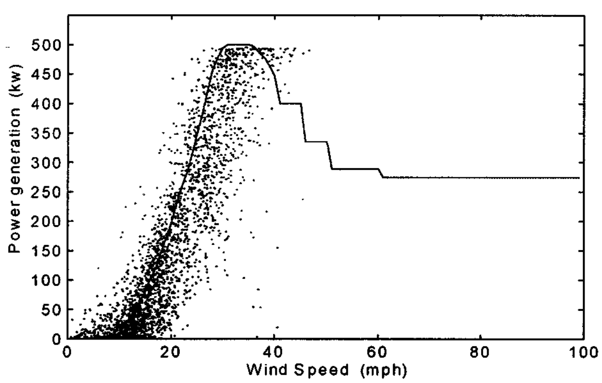

Fig. 2. Wind power generation vs. wind speed (turbine no. 5). (The big power difference under the same wind speed implies the influence of turbine power by other factors.)

3) The vertical wind speed profile is the same as that experienced during the calibration of the turbine.
4) The air density is the same as that during the calibration.

These conditions are seldom met at a wind farm for each turbine, especially in the mountains when the wind speed used is from a met tower that is some distance from the turbine. A second factor is that typically the wind speed is an averaged value over a long enough period that the individual valves may vary significantly. The 10-minute average values used here typically come from 50 or more instantaneously recorded values. There is also the possibility of miss representing the power generated when using an averaged wind speed since the power is proportional to the cube of the wind speed.

Looking at Fig. 1, it can be seen that while the east met tower is near turbine no. 5 the west tower is over 500 feet away and 100 feet higher. It is probable that average wind speed recorded for the east tower will more accurately represent the actual hub height wind speed of turbine no. 5 for winds from the east than the west tower does for winds from the west direction. The dots in Fig. 2 represent the 10 minute generated power of no. 5 at the same time period of the averaged wind speed, where the wind value is either from the east or west tower depending upon the direction.

From the above there are two general reasons for the wide range in values seen in Fig. 2 for the power generated at any selected velocity, these are: the speed from the met tower does not represent the actual average wind speed at the hub height experienced by a turbine, and the actual wind did not meet the four criteria listed. A comment relating to the density is that these turbines were made and calibrated in southern California and the manufacturer corrected the performance curve to account for the 6100-foot elevation at the Ft. Davis site. The power is directly proportional to the air density, thus as the density varies during the day the power produce will also vary slightly.

In Fig. 2, at 500 KW the output curve is level and is at its maximum value. The current generated is proportional to the generator shaft torque. The shaft is connected through a gear train to the hub of the turbine. The output power is limited by controlling the torque produced by the turbine blades. This is accomplished by using ailerons at the tip of the blades to reduce the blade lift. This is necessary during high winds in order to protect the equipment.

B. Influence of Wind Turbine Power Generation by Wind Direction

The direction of wind also influences power generation. However, compared with wind velocity, wind direction has less influence on power output because each turbine is built to face into the wind when operating. Generally, at the same wind speed, there is no great difference in the power generation for different

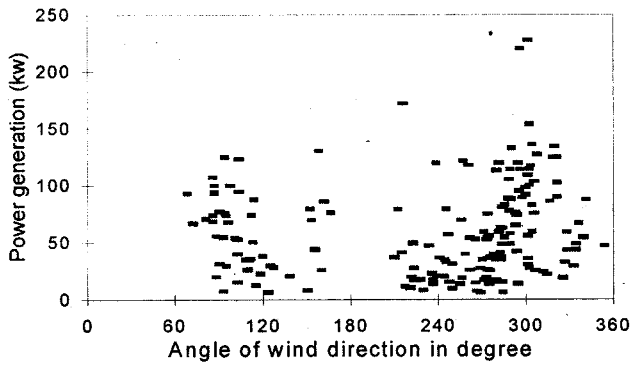

Fig. 3. Influence of wind power generation by wind direction (11 mph < wind speed < 12 mph, turbine no. 5). (Strong wind usually comes from certain direction but low wind can come from much wider direction.)

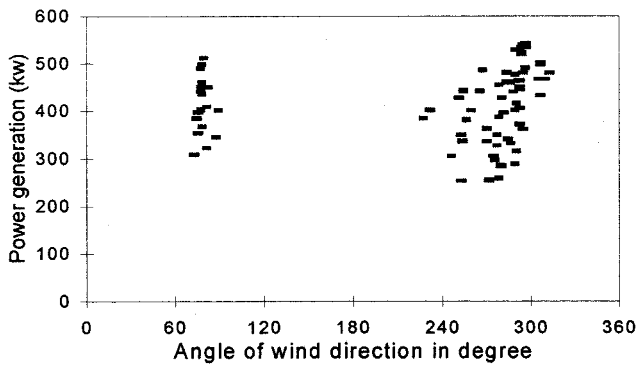

Fig. 4. Influence of wind power generation by wind direction (25 mph < wind speed < 26 mph, turbine no. 5). (Strong wind usually comes from certain direction but low wind can come from much wider direction.)

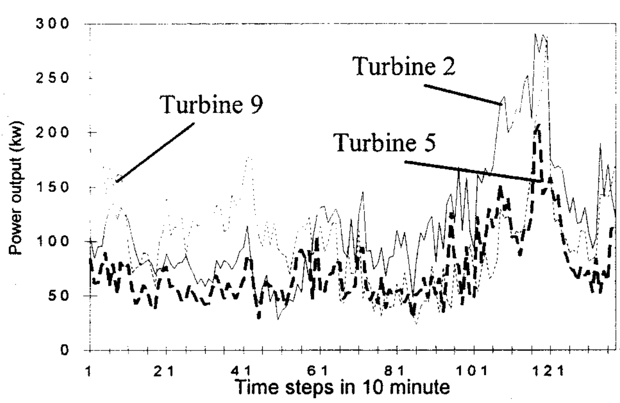

Fig. 5. Comparison of wind power generation by different turbines (4/1/96). (Topographic condition makes the power generated by different turbine to be very different even under the same weather circumstance.)

wind directions. But, for lower power generation, the variation in wind direction is greater (Fig. 3) than for higher power generation, where wind comes mainly from the east or the west (Fig. 4).

C. Wind Power Generation by Different Turbines

Even though the Fort Davis wind farm has only twelve turbines, at any one instance or for 10 minute averaged values, there can be large differences between the recorded output power for the turbines. This can be seen in Fig. 5, where the 10 minute

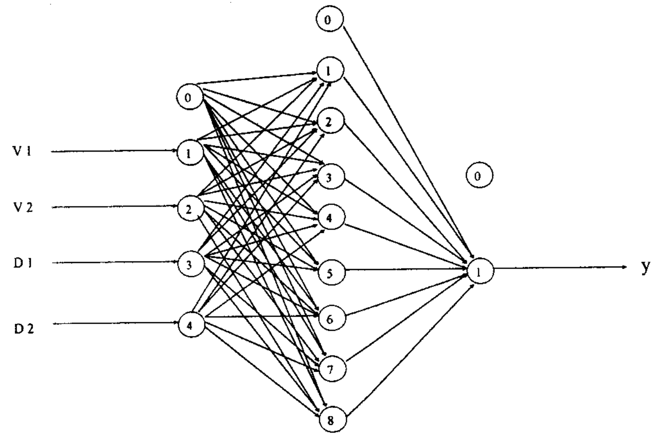

Fig. 6. Multi-layer neural network for turbine power generation estimation.

power output for three turbines are shown. The period of data shown covers almost 24 hours. All of these observations motivate us to design a suitable neural network for each turbine to predict its performance.

III. Neural Network for Wind Power Generation Estimation

A. A Suitable Neural Network for Wind Power Generation Estimation

Several motivations exist for using a separate neural network for each turbine. First, this scheme can greatly reduce the size and complexity of the neural network. (Training time scales with the number of weights, not nodes in a network. Thus, twelve small networks train better than one big one.) Second, the operation of a wind farm usually requires some of the wind turbines to be off-line. The scheme of a neural network for each turbine will not be influenced by the cases that some turbines are off-line. Third, this approach scales better for large wind farms.

The input–output mapping desired for this problem lends itself to the multilayer perceptron of Fig. 6. The relatively compact design, 4-8-1, plus bias nodes at the input and hidden layers, was chosen based on a combination of trial-and-error and extensive prior experience. It ensures relatively fast training with good representational accuracy. Preprocessing and activation function selection are other design parameters, the choice of which are described in Sections III-B and III-C below.

B. Patterns and Data Processing

The neural networks (NN) developed for each turbine will all use the same input: ten minute averages of wind velocity and direction from the two meteorological towers.

This input data, termed input patterns, is represented as V_1, V_2, D_1, and D_2 in Fig. 6. The network outputs are the power generated by each turbine. Thus, each of the twelve NN developed use the same four input patterns but are individually trained in the training processes for each turbine by the corresponding power generated by that turbine for the given input patterns.

The velocity of the wind is the most important factor affecting the power generated. Because of the very wide variation in the hub height wind velocity across the wind farm, it is possible

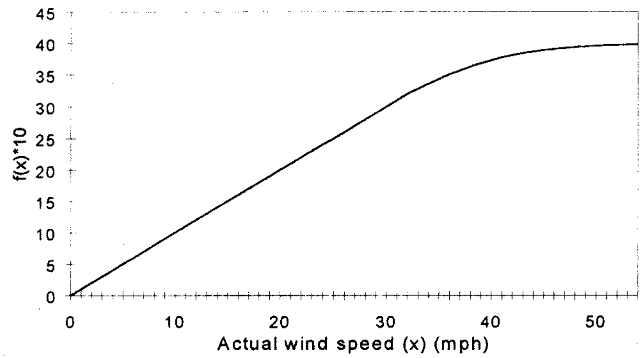

Fig. 7. Compressing function for wind speed.

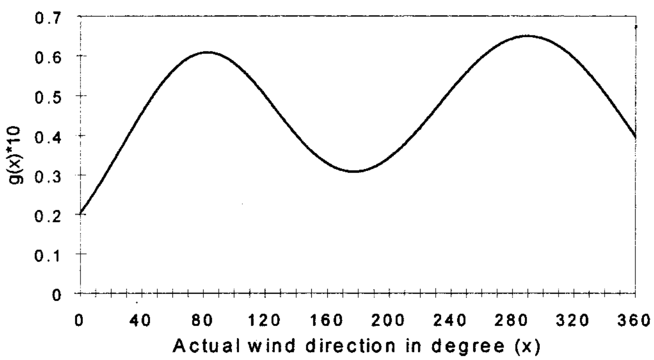

Fig. 8. Compressing function for wind direction.

for the meteorological towers to record velocity of zero to one or two miles per hour and yet some of the turbine show a high power output. The cut in speed of the turbine is 8 mph. To assist in the NN learning process "weighting" the "raw" (which is measured velocity in mph) pattern is important. This is called preprocessing. Similar concepts about data preprocessing can also be found in [18] in which the authors obtained a better trained neural network than their previous network [19]. The preprocessing in this paper uses the concept of a compressing function which is shown in Figs. 7 and 8. This new scale for the input patterns enable the NN to learn faster (i.e., less learning iterations) and produce a smaller difference between the predicted output and the measures output for each turbine.

The changing range of wind velocity is limited within the range of 0 to 5 and the compressing function used can somewhat reflect the limitation on power output of a wind turbine when the wind is strong (Fig. 7). On the other hand, the wind turbine power output is less influenced by wind direction. So, the changing range of wind direction (0° to 360°) is compressed into a much more limited range compared with that of wind velocity, and the compressing function selected can increase the influence of wind direction at certain directions and decrease the influence at other directions (Fig. 8). In other words, between the wind velocity and direction, we want to improve the influence by wind velocity but decrease the influence by wind direction and we want to amplify the influence of wind direction at certain ranges of degree. This approach is appropriate because the twelve turbines at Fort Davis are located in one long North South line onto slightly offset ridge lines and the predominant winds are either from the East or West. In our case, the compressing functions were created by trial and error. The functions $f(x)$ and $g(x)$ in Figs. 7 and 8 are:

$$f(x) = \begin{cases} x/10 & x < 32 \\ \left(32 + 8\dfrac{1 - e^{-0.2(x-32)}}{1 + e^{-0.2(x-32)}}\right) \Big/ 10 & x \geq 32 \end{cases} \tag{1}$$

$$g(x) = \left(0.6e^{-5/3 \cdot 10^{-3} \cdot (x-80.5)^2} + 0.65 \cdot e^{-10^{-3} \cdot (x-290)^2}\right) \Big/ 10. \tag{2}$$

The purpose of the compressing functions used in this paper is to help the NN to learn and perform better. When selecting a compressing function three points are considered. First, it should reflect some of the system properties that we know so that the network does not need to learn it. Second, it should preserve important differences between patterns. For the compressing function of wind direction, because the patterns we have are integers in degree, we can make the compressed wind direction to be different for different patterns through selecting the locations of two maximums in Fig. 8. Third, it is not necessary for a compressing function to be very precise. The compressing function merely provides an improved data representation and is the same for all the turbines, and all the other properties are left for the neural network to learn.

Like the processing for input patterns, the desired output is not measured wind turbine power output, which could change from 0 kw to 500 kw, but is a ratio of measured wind turbine power output to its rated power. This can easily be converted to the actual power by a postprocessing operation if desired.

C. Activation Function in NN

We note that an asymmetric activation function typically learns faster [7]. Therefore, a hyperbolic activation function

$$\varphi(v) = a \cdot \left(1 - e^{-bv}\right) / \left(1 + e^{-bv}\right) \tag{3}$$

is used, with $b = 1.2$ at the output layer and $b = 0.8$ at input and hidden layers, which is chosen by trail and error. The gain a is set to 1 and at the output layer a coefficient is added to the function to keep the estimated power positive.

IV. Training with Back Propagation

We trained with the aforementioned design of Fig. 6. Including more neurons in the hidden layer was also tested with no significant improvement on NN learning rates or performance. The input patterns are processed measured data for wind velocities and directions. The desired outputs are the processed power outputs for each wind turbine. The available measured data for Fort Davis used came from March 1996. For each turbine, 1500 sets of 10 minute average data are selected in March, which represented the wind turbine performance.

Pattern mode training is used here to train the NNs. In order to achieve a well performed NN, besides the criteria in [8], both the training and testing are combined into the software design of NN training. For each turbine, the training is based only on the 1500 sets of data but the testing will cover all the effective data in the month. Because of the techniques used in III, the mean

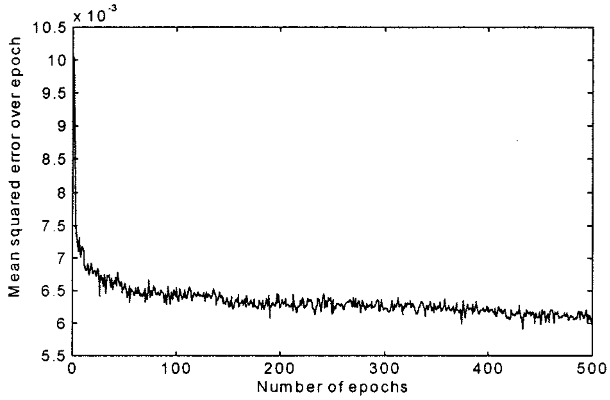

Fig. 9. Mean squared error of turbine no. 5.

squared error stabilizes quickly but this does not always guarantee satisfactory testing results. Randomly generated initial weights can lead to unsatisfactory NN performance even after thousands of training epochs but reinitializing the weights and retraining the NN after several hundred training epochs is effective if the test result is not good. For most of the turbines, the training and successful testing can be finished in 30 minutes on a Pentium 150 MHz computer, but some of them needed several hours. The training curve in Fig. 9 shows the learning process of the NN of turbine no. 5 for a successful testing. During training, the mean squared error decreases gradually and becomes stable.

V. Wind Power Generation Estimation by Traditional and NN Models

In order to understand the NN performance, two models used on Fort Davis wind farm are discussed and compared here in estimating wind turbine power generation.

1) Traditional Model: Traditional models are usually based on turbine's power curves or based on the modeling or simulation of wind turbine generators [5], [9], [10]. The traditional model used on Fort Davis wind farm is chiefly based on the manufacture's power curve (Fig. 2) in which turbine power P is only a function of wind speed V, i.e., $P = f(V)$. Because there are two meteorological towers on the wind farm, we need to decide which tower's measurements should be used in the function. In this model the possible topographic influence on different turbines is considered in two ways. First, wind speed is selected based on which direction the wind comes from, i.e., if the wind comes from east, the measured wind speed from east tower will be selected; if the wind comes from west, the measured wind from west tower will be used. Second, a correction coefficient k_{id} for each turbine under east or west wind is introduced into the power curve function, i.e.,

$$P_i = k_{id} \cdot f(V_d) \qquad i = 1, \ldots, 12 \quad d = \text{“East” or “West”} \tag{4}$$

where i represents turbine ID number and d represents the direction wind comes from. Note that each turbine has only a single parameter based on wind directions. These parameters are fixed for each turbine once a trial iteration is performed to select the best output comparison result.

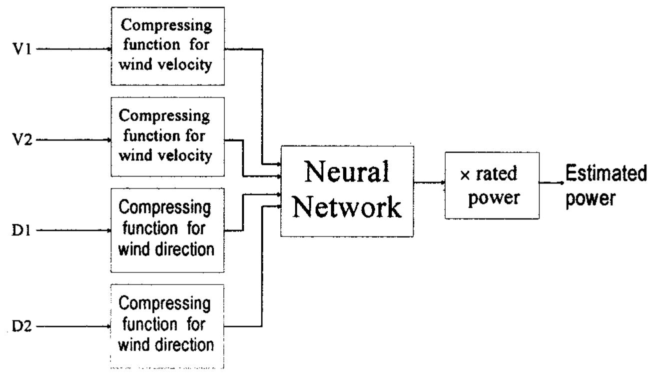

Fig. 10. Neural network model for wind power.

TABLE I
ESTIMATION OF WIND POWER GENERATION IN MARCH

Turbine No.	P_M (kwh)	P_N (kwh)	P_T (kwh)	D_{MN} %	D_{MT} %
5	75982	75168	88534	1.082	-16.520
6	93723	92989	97060	0.802	-3.561
7	76398	76128	90979	0.352	-19.086
8	91117	90841	99469	0.303	-9.166

TABLE II
ESTIMATION OF WIND POWER GENERATION IN APRIL

Turbine No.	P_M (kwh)	P_N (kwh)	P_T (kwh)	D_{MN} %	D_{MT} %
5	87230	86567	112315	0.76	-28.76
6	115225	112489	120875	2.37	-7.45
7	2757	2645	2987	4.06	-8.34
8	100636	98462	103864	2.16	-3.21

2) Neural Network Model: The trained NN in Section IV can be used to estimate the wind turbine power generation directly based on wind velocity and direction information (Fig. 10). The NNs are trained with 1500 patterns from March 1996 and the comparison in Tables I and II use all of the March data and then the April data.

Table I gives: the measured power generation P_M, the estimated power generation by neural network model P_N, the estimated power generation by traditional model P_T, the percentage difference between measured and NN estimated $D_{MN} = (P_M - P_N)/P_M\%$, and the percentage difference between measured and traditional model estimated $D_{MT} = (P_M - P_T)/P_M\%$ for turbines no. 5 to 8 in March 1996. Even though the traditional method uses coefficients reflecting actual wind speed relationships among the turbines and reference anemometers, there is still a large difference between the measured and estimated wind power. This occurs because it does not reflect the dynamic performance of a wind turbine under changing wind conditions and many other factors. The superior neural network results are due to its ability to learn such factors.

Table II is the estimation results in April 1996 for Fort Davis wind farm using the NNs trained by March data. The estimation

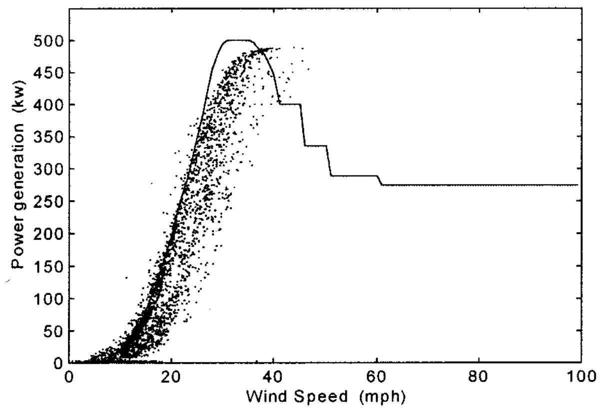

Fig. 11. Wind power generation vs. wind speed (turbine no. 5).

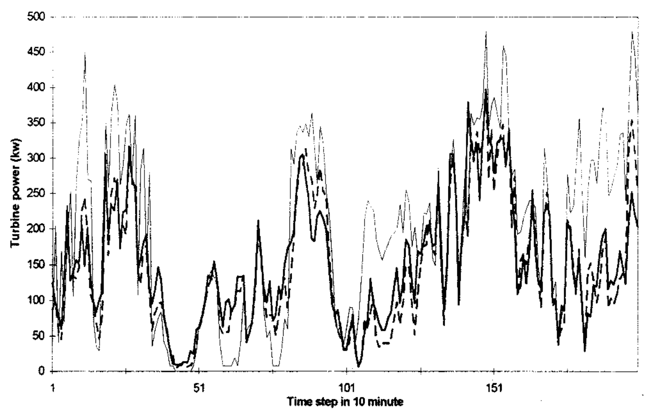

Fig. 12. Estimated and measured power output (turbine no. 5).

using neural network is again good. Tables I and II show that a well trained NN can succeed if the data set can properly represent the characteristics of a system. The percent differences between the estimated and the measured power generation for all the turbines at Fort Davis are basically around 1% in March and around 2% in April, which indicates the effectiveness of the NN's in the estimation of wind power generation.

Fig. 11 shows the estimated 10 minute wind turbine power generation by neural network using the measured wind data for March 1996, which are plotted over the manufacture's curve as in Fig. 2. Compared with that, it is seen that the neural network learned the overall turbine performance for different turbines. Fig. 12 shows the comparison of measured, traditional model estimated, and NN model estimated 10 minute turbine power generation in the following month (i.e., April 1996) over a selected period of 200 continuous time steps (10 minutes each step), in which (where heavy solid line is measured power, dashed line is NN model estimated, and light solid line is traditional model estimated). The large difference between the measured power and the traditional model estimated power can be seen clearly. But the estimation based NN model performs well. It is necessary to point out that the similar situations as shown in the figure is very typical for the data we achieved on Fort Davis wind farm from 1996 to 1997. Studies on the measured wind data from the two meteorological towers show there are many cases where the measured wind speeds from the two towers have large differences and there are also many instances where the measured wind directions from the two towers are quite different. This reflects some of the complicated wind dynamics in the mountain area like Fort Davis wind farm. Under the sophisticated wind dynamics, it is very difficult for a single parameter traditional model to correctly estimate the power produced. However, the neural network tries to learn it. Thus we claim that the neural network technique is to be preferred.

VI. Summary and Conclusions

The power generated by a wind turbine is mainly influenced by wind velocity and direction. Generally, the higher the wind speed, the higher is the power generated. However, the wind power production are also influenced by other factors such as wind direction, air density, vertical wind profile, and variability in both wind speed and wind direction, making the power generated by wind fluctuates rapidly.

Wind direction has much less influence on wind turbine power generation than wind velocity. However, at a certain geographical environment, high power is usually generated by wind coming from certain directions. But for low power generation, wind comes from a much wider range of directions.

As shown, neural networks can be used to estimate wind power generation efficiently as a diagnostic tool. The compressing function is a valuable preprocessing step. The resulting neural network can also allow wind power prediction over time. Experience from the body of research in time series forecasting is relevant in [13], [14]. For wind energy, a recurrent neural network [15] for the prediction of wind cascaded with the neural network discussed in this paper could make the prediction of the expected performance of wind power generation system [6] in another way, which would benefit power system forecasting and management.

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