Hindawi Publishing Corporation
Mathematical Problems in Engineering
Volume 2012, Article ID 194091, 12 pages
doi:10.1155/2012/194091

Research Article

Application of ENN-1 for Fault Diagnosis of Wind Power Systems

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Received 20 March 2012; Accepted 20 May 2012

Academic Editor: Jitao Sun

Maintaining a wind turbine and ensuring secure is not easy because of long-term exposure to the environment and high installation locations. Wind turbines need fully functional condition-monitoring and fault diagnosis systems that prevent accidents and reduce maintenance costs. This paper presents a simulator design for fault diagnosis of wind power systems and further proposes some fault diagnosis technologies such as signal analysis, feature selecting, and diagnosis methods. First, this paper uses a wind power simulator to produce fault conditions and features from the monitoring sensors. Then an extension neural network type-1- (ENN-1-) based method is proposed to develop the core of the fault diagnosis system. The proposed system will benefit the development of real fault diagnosis systems with testing models that demonstrate satisfactory results.

1. Introduction

The opposition to the establishment of thermal power or nuclear energy plants is because of growing awareness of environmental protection. The price of fossil fuel energy is rising, the research for better and new sources of renewable energy is one way to settle present energy problems [1, 2]. Currently, wind power is one of the most popular green energies; most large-scale wind turbines are installed in remote or offshore locations, making it difficult to arrange maintenance [3]. Wind turbines must be maintained and repaired consistently to prevent or fix failures that may occur. The maintenance and management of large-scale wind power is critical for continuous operations.

With the growing use of wind turbines, fault diagnosis technology for wind generator systems can have a positive effect on power systems by locating faults earlier. Wind generator systems will operate safely and reliably. A fault is an event that leads to the entire system or part of the functions of the system to fail [4–6]. The framework for wind power fault diagnosis systems includes the following: (1) analyzing the fault pattern: this is based on the mathematical model of wind power that precedes development of simulation systems by analyzing the relationship between failure types and characteristics, (2) selecting detectors and placing them in the best location: selecting and designing detectors is critical for fault diagnosis. All failure signals are collected with additional signals for limited detecting spots. Additionally, selecting the best detector position can affect accuracy and reliability for failure diagnosis; the system must also be able to capture and condition the relevant data automatically; (3) transforming fault signals by installing detectors on the wind power systems to assemble the fault signals with the Fourier analysis or wavelet theory that can be effectively be used for fault signal analysis [7, 8]; (4) to develop fault diagnosis methods—the core of the fault diagnosis system develops a knowledge-based method to classify the relationships between fault signals and the fault types.

The primary goal of this paper is to develop the fault diagnosis method and system frame for large-scale wind power systems, because as proprietary information, fault records are rarely reported by wind power companies. A historical database is limited. First, this paper uses wind power simulators to produce fault conditions that give typical fault types. Then, this paper proposes using an ENN-1-based method to diagnose faults for proposed wind power systems. This paper simulates 8 different fault conditions for wind power systems and proposes 9 different features as input signals for fault diagnosis systems. The system simulates a variety of fault features with different operating conditions by using sensors that receive the characteristic signals. The results indicated that the proposed ENN-1-based method not only has a high identification accuracy rate and superior toleration capability but also made quick calculations. This proposed diagnosis method and diagnosis system structures merit greater attention, because they provide the technologies related to design for practical fault diagnosis for larger-scale wind power systems.

2. Extension Neural Network Type 1

The extension neural network type 1 (ENN-1) introduced by this author [9], is a new pattern classification system based on concepts from extension theory and neural networks. The ENN-1 is well suited to the classification of problems: problems where there exists the pattern with a wide range of continuous inputs and a discrete output indicating which class the pattern belongs to. The ENN-1 is a relatively new neural network model and has been shown to be successful as a classifier using the well-known Iris dataset and the more complex problems [10–13].

2.1. Structure of the ENN-1

Successfully applied to fault diagnosis of actual cases, the schematic structure of the ENN-1 is depicted in Figure 1. It comprises both the input layer and the output layer. The nodes in the input layer receive an input feature pattern and use a set of weighted parameters to generate an image of the input pattern. In this network, there are two connection values (weights) between input nodes and an output node, one weight w_{kj}^{L} represents the lower bound for this classical domain of the features and the other weight w_{kj}^{U} represents the upper bound. This image is further enhanced in the process characterized by the output layer. Only one output node in the output layer remains active to indicate a classification of the input pattern. The learning algorithm of the ENN-1 is discussed in the next section.

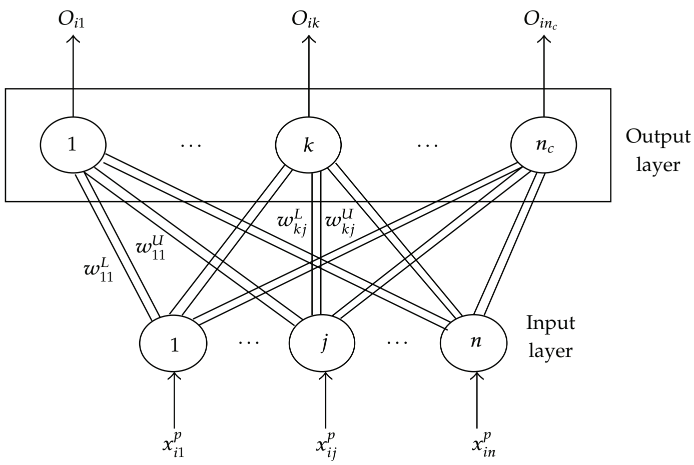

Figure 1: The structure of extension neural network (ENN-1).

2.2. Learning Algorithm of the ENN-1

The learning of the ENN-1 is a supervised learning. Before the learning, several variables have to be defined. Let training pattern set be $X = \{x_1, x_2, \ldots, x_{Np}\}$, where N_p is the total number of training patterns. The ith pattern is $X_i^P = \{x_{i1}^P, x_{i2}^P, \ldots, x_{in}^P\}$, where n is the total number of the features, and the category of the ith pattern is p. To evaluate the clustering performance, the total error number is set as N_m, and the total error rate E_T is defined below:

$$E_T = \frac{N_m}{N_p}. \tag{2.1}$$

The detailed supervised learning algorithm can be described as follows.

Step 1. Set the connection weights between input nodes and output nodes. The range of classical domains can be directly obtained from previous requirement as follows:

$$w_{kj}^L = \max_{i \in P}\left\{x_{ij}^k\right\}, \qquad w_{kj}^U = \min_{i \in P}\left\{x_{ij}^k\right\} \tag{2.2}$$

$$Z_{kj} = \frac{\left(w_{kj}^L + w_{kj}^U\right)}{2}, \tag{2.3}$$

for $i = 1, 2, \ldots, N_p$, $j = 1, 2, \ldots, n$, $k = 1, 2, \ldots, n_c$, where n_c is the total number of the clusters.

Step 2. Read the ith training pattern and its cluster number p:

$$X_i^p = \left\{x_{i1}^p, x_{i2}^p, \cdots, x_{in}^p\right\}, \quad p \in n_c. \tag{2.4}$$

Step 3. Use the extension distance (ED) to calculate the distance between the input pattern X_i^p and the kth cluster as follows:

$$\mathrm{ED}_{ik} = \sum_{j=1}^{n}\left[\frac{\left|x_{ij}^{p} - z_{kj}\right| - \left(w_{kj}^{U} - w_{kj}^{L}\right)/2}{\left|\left(w_{kj}^{U} - w_{kj}^{L}\right)/2\right|} + 1\right], \quad \text{for } k = 1, 2, \ldots, n_c. \tag{2.5}$$

It can be graphically presented as Figure 2. It can describe the distance between the x and a range $\langle W^L, W^U\rangle$. From Figure 2 it can be seen that different ranges of classical domains can arrive at different distances due to different sensitivities. This is a significant advantage in classification applications.

Step 4. Find the m, such that $\mathrm{ED}_{im} = \min\{\mathrm{ED}_{ik}\}$. If $k^* = p$ then go to Step 7, otherwise Step 6.

Step 5. Update the weights of the pth and the k^*th clusters as follows:

$$\begin{aligned}
w_{pj}^{L(\text{new})} &= w_{pj}^{L(\text{old})} + \eta\left(x_{ij}^{p} - z_{pj}^{\text{old}}\right),\\
w_{pj}^{U(\text{new})} &= w_{pj}^{U(\text{old})} + \eta\left(x_{ij}^{p} - z_{pj}^{\text{old}}\right),\\
w_{k^*j}^{L(\text{new})} &= w_{k^*j}^{L(\text{old})} + \eta\left(x_{ij}^{p} - z_{k^*j}^{\text{old}}\right),\\
w_{k^*j}^{U(\text{new})} &= w_{k^*j}^{U(\text{old})} + \eta\left(x_{ij}^{p} - z_{k^*j}^{\text{old}}\right), \quad \text{for } k = 1, 2, \ldots, n_c,
\end{aligned} \tag{2.6}$$

where η is the learning rate and set as 0.1 in this paper. The result of tuning two cluster weights shown in Figure 3 clearly indicating the change of $\mathrm{ED_A}$ and $\mathrm{ED_B}$. The cluster of pattern X_{ij} is changed from cluster A to B due to $\mathrm{ED_A} > \mathrm{ED_B}$ From this step, we can clearly see that the learning process is only to adjust the weights of the pth and the k^*th clusters. Therefore, the ENN-1 has a rapid speed advantage over other supervised learning algorithms and can quickly adapt to new information.

Step 6. Repeat from Step 2 to Step 5, if all patterns have been classified, then a learning epoch is finished.

Step 7. Stop if the clustering process has converged, or the total error rate E_t has arrived at a preset value, otherwise, return to Step 2. It can produce meaningful output after the learning, because the classified boundaries of the features are clearly determined. It can carry on the recognition or sort when the ENN-1 completes a learning procedure.

2.3. Operation Phase of ENN-1

Step 1. Read the weight matrix of ENN-1.

Step 2. Calculate the initial cluster centers of every cluster using (2.3).

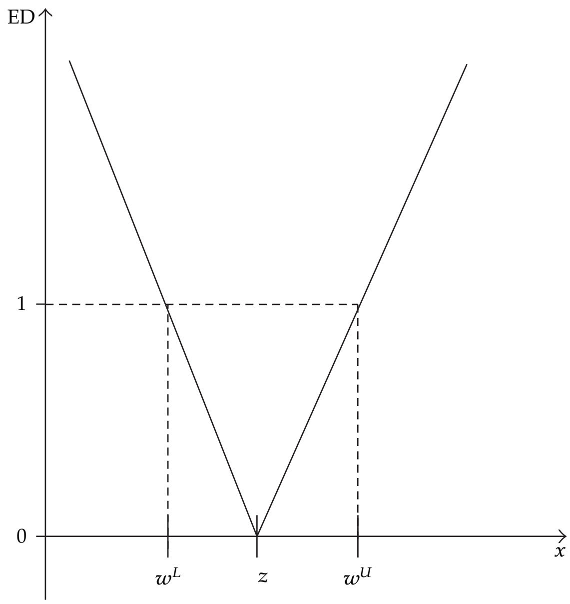

Figure 2: The proposed extensions distance (ED).

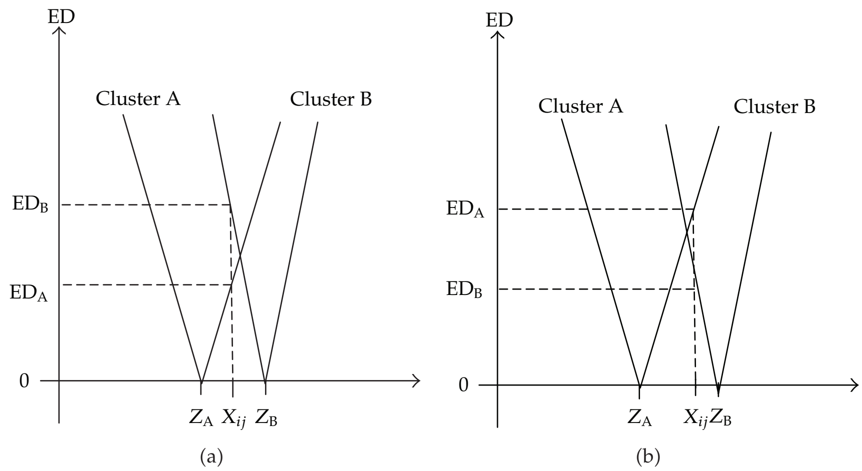

Figure 3: The results of tuning cluster weights—(a) original condition; (b) after tuning.

Step 3. Read the tested pattern.

$$X_t = \{x_{t1}, x_{t2}, \ldots, x_m\}. \tag{2.7}$$

Step 4. Use the proposed extension distance (ED) to calculate the distance between the tested pattern and every existing cluster by (2.5).

Step 5. Find the k^*, such that $\mathrm{ED}_{ik^*} = \underset{k\in n_c}{\mathrm{MIN}}(\mathrm{ED}_{ik})$ and set $O_{k^*} = 1$ to indicate the cluster of the tested pattern.

Step 6. Stop if all the tested patterns have been classified, otherwise go to Step 3.

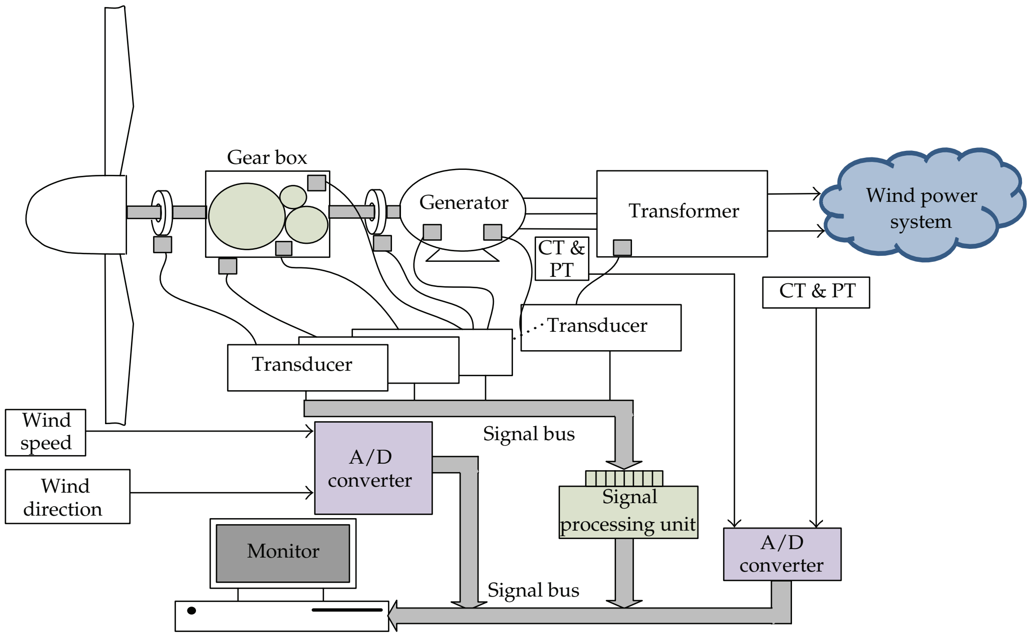

Figure 4: The structure of the wind turbine condition monitoring system.

3. Fault Diagnosis for Wind Power Systems

Condition monitoring for power systems is becoming critical because the need to increase system reliability and decrease production caused system breakdowns. Detecting specific failures for wind power systems early is critical for safe switching and improved reliability. A good diagnosis system must have automatic explication for condition data to identify specific faults and for basic advice for the operations engineer. This paper designs wind power system units that simulate fault models and operation signals using sensor monitoring, because of the difficulty in collecting fault models for large-scale wind power systems. The proposed hardware architecture of wind power fault diagnosis systems is shown in Figure 4, it includes sensors, transducers, signal processes, and the diagnosis system. This system can diagnose a fault in the simulated system with the fault diagnosis software because they deal with signals and the software interface. The hardware for simulation systems is shown in Figures 5 and 6. The software interface for the wind power fault diagnosis system uses the LabVIEW. The sensor signals include generator voltage, generator current, motor speed, generator speed, vibration sensors, temperature sensors, and oil level pressure, among others. The A/D card provides the feedback characteristics and commands.

3.1. Introduction to the Characteristics for the Fault Diagnosis System

The fault detection system uses vibration analysis that is based on different sensors. The most commonly used sensor is the acceleration sensor. If the vibration signal is transformed by the frequency domain, the signal can be analyzed by the status messages of the facilities. The conditions of the gearbox operations cause attrition between the gears that

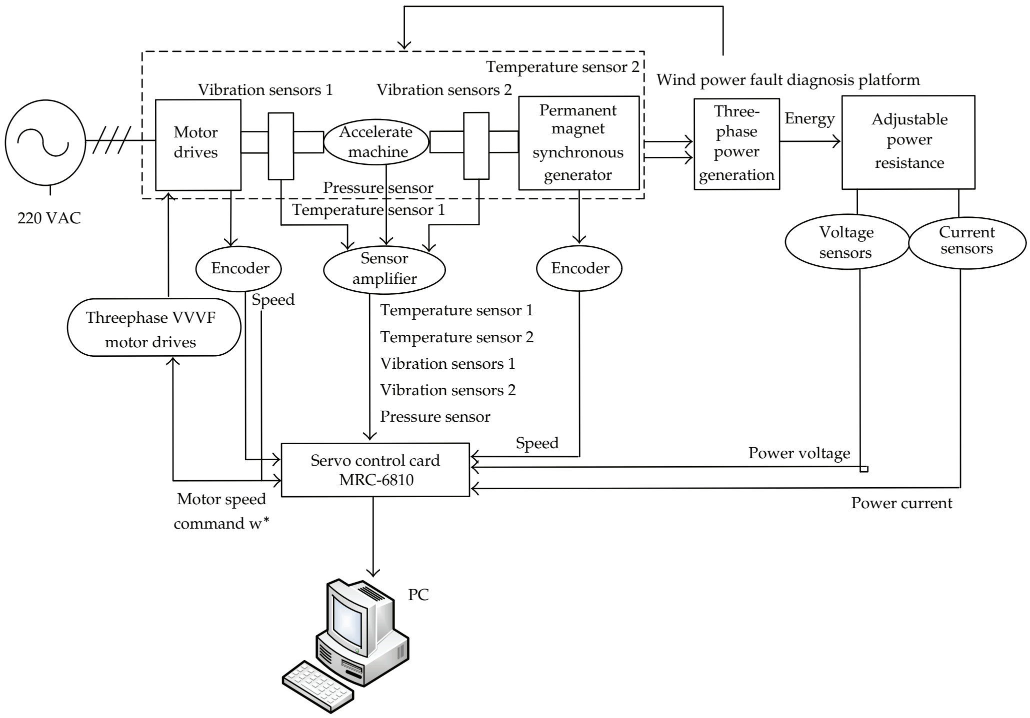

Figure 5: The structure of the simulated fault diagnosis system.

Figure 6: Actual hardware structure of the proposed fault diagnosis simulator.

decreases the output efficiency of the wind turbines. The oil level and the oil temperature are either normal or abnormal, which is important for normal operations of the gearbox. The monitoring system of the gearbox checks the lubricant oil level, oil temperature signal, and the gear vibration signal, among others. The main component is the generator that transforms mechanical energy into electrical energy. The generator needs to take into account the output voltage, current, and phase relative to the wind speed at that time. The generator removes electrical signals to be used as diagnostic signals.

This paper uses a wind power fault diagnosis simulation system that simulates eight different fault conditions and uses 9 different features to allow the ENN-1 to diagnose the fault types. The 9 features are the blade speed (C_1), generator speed (C_2), generator output voltage (C_3), generator output current (C_4), generator output power (C_5), amplitude of

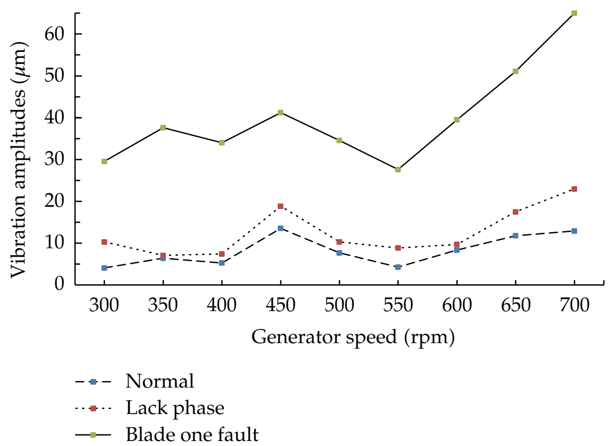

Figure 7: Vibration amplitudes of the blade bearing for the different faults and the generator speed.

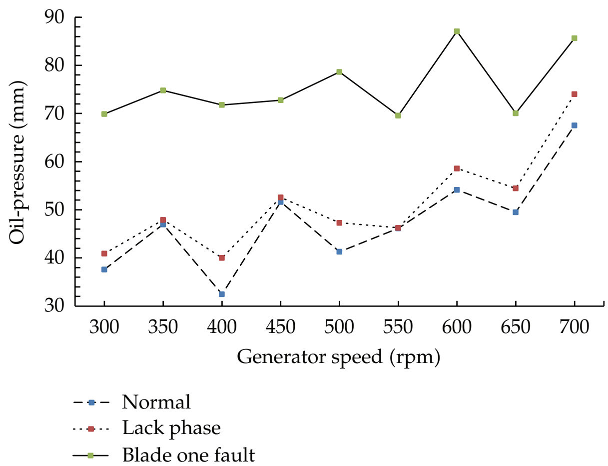

Figure 8: Oil pressure of the gearbox for different faults and the generator speed.

leaves bearing (C_6), the amplitude of gear box bearing (C_7), gear box oil temperature (C_8), and oil pressure (C_9).

3.2. Description of the Types of Fault Diagnosis

To obtain fault diagnosis information, the system simulates 300 rpm to 700 rpm as the main speed of the wind generator. The system obtains the testing data after the rotational speed becomes stable. There are eight simulated fault statuses in this paper, they include the normal (F_1), one blade break (F_2), two blade breaks (F_3), lacks of the phase (F_4), gearbox oil insufficient (F_5), gearbox temperature higher (F_6), gearbox oil temperature higher (F_7), and bearing misalignment fault (F_8). Two typical curves are shown in Figures 7 and 8, they show the oil pressure of the gearbox and the vibration amplitude of the blade bearing at different speeds. Clearly identifying broken blade or normal state will have obvious differences, but

Table 1: Some parts of the typical learning data.

	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8
C_1	342.0	348.6	330.1	348.9	334.6	339.7	334.4	350.2
C_2	1021	1051	999	1048	1010	1026	1008	1055
C_3	18.49	21.78	18.31	22.08	18.12	17.45	17.97	23.48
C_4	4.908	4.835	4.782	4.507	4.585	4.556	4.640	4.456
C_5	157.2	182.4	151.6	172.4	143.9	137.7	144.4	181.3
C_6	3.73	6.25	10.59	15.70	4.38	3.45	5.69	6.73
C_7	2.93	3.54	7.29	14.4	4.82	1	4.68	3.96
C_8	33.68	33.39	33.59	32.07	34.4	36.02	35.54	33.06
C_9	51.25	42.4	38.8	50.58	32.81	51.27	50.07	56.3

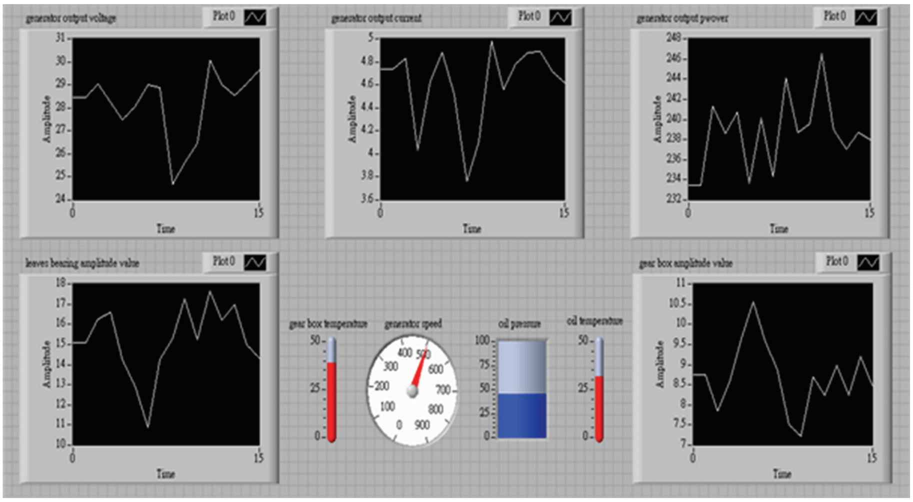

Figure 9: Typical sensor value of the simulated system.

the lack of the phase for the wind generator and the normal state are not different. A different characteristic to diagnose the fault in the wind power system must be used.

4. Test Results and Discussion

To demonstrate the effectiveness of the proposed extension fault diagnosis method, the paper uses sensors installed on the simulated system to collect information and then uses ENN-1 to design the core of the diagnosis system. There are 3,600 sets of testing data from the simulated diagnosis system. This paper uses 1,800 data sets for learning and the other 1,800 data sets for testing the fault diagnosis. Table 1 shows some of the learning data. When the learning stage of the ENN-1 has been completed, then the identifying stages with ENN-1 can be started for fault diagnosis. The human-machine interface for fault diagnosis uses LabVIEW to design the programs. Beginning with LabVIEW, the sensing data are collected and waveform control monitoring is shown in Figure 9. Then the collected data will be collected to be learned. The learning program of the diagnosis system is shown in Figure 10. Finally, the diagnosis system can pass through the input features to diagnose the fault quickly and shows the fault condition, as shown in Figure 11.

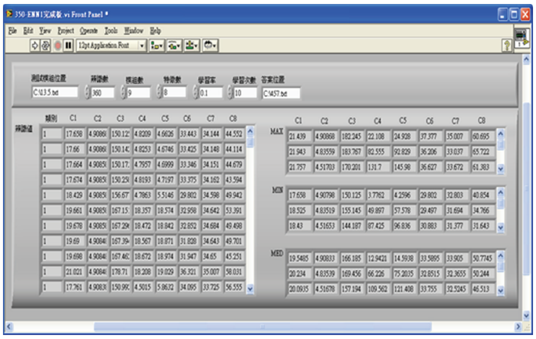

Figure 10: Learning program of the fault diagnosis system.

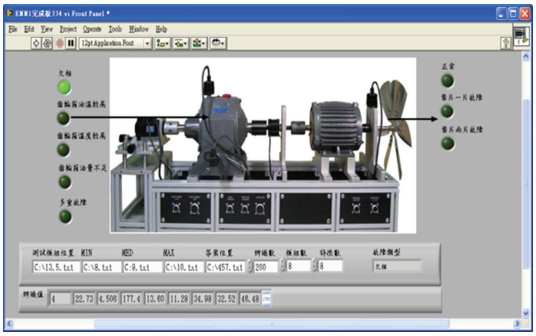

Figure 11: User interface of the fault diagnosis system.

The simulation results were compared with other traditional methods as shown in Table 2. *K* means [14] accuracy and fuzzy *C* means [15] accuracy less than 70%. The accuracy of extension method [16, 17] was only 85%. The maximum accuracy was 99% in multilayer neural networks. The accuracy of the proposed ENN-1-based method was 100%. It should be noted that the structure of the proposed ENN-1 was simple, as only 17 nodes and 144 connections were needed. Contrarily, the structure of the MNN-based method needed approximately 27 nodes and 170 connections. Moreover, the proposed ENN-1-based method permits fast adaptive processing for large amounts of training data or new information, because the learning of ENN-1 was to tune lower bounds and upper bounds of the excited connections. In addition, the proposed ENN-1 had a shorter learning time than the traditional neural networks, and ENN-1 only took six epochs to complete. Although the fault diagnosis system was trained offline, the training time was not a critical factor for evaluation. However, an index implied some degree of efficiency for the algorithm developed, which was beneficial for implementation fault diagnosis methods with a microcomputer for a real-time fault detecting device or as a portable instrument.

The input data for fault diagnosis systems will contain some uncertainties and noise. The sources of errors include environmental noise, transducers, and human mistakes, among others, which can lead to data uncertainties. When considering the noise and uncertainties, 1,800 sets of testing data were created by adding ±5% to ±15% of random, uniformly distributed errors to the training data for appraisal of fault-tolerant abilities for the proposed

Table 2: Recognized performances of different methods.

Test method	Learning times (epochs)	Accuracy (%)
K-means	No	61
Fuzzy C-means	No	64
Extension methods	No	85
Neural network (9-6-8)	1000	77
Neural network (9-8-8)	1000	98
Neural network (9-10-8)	1000	99
ENN-1 (9-8)	6	100

Table 3: Recognized performances of the proposed method with different percentages of errors added.

Error percentage	Accuracy
±0%	100%
±5%	94%
±10%	88%
±15%	75%

method. The test results with various added errors are given in Table 3. Typically, error-containing data degraded the recognition capabilities in proportion to the number of errors added. Table 3 shows that these methods all bear remarkable tolerance to the errors contained in the data. The proposed method shows good tolerance for added errors with a high accuracy rate of 75% with extreme errors ±15%.

5. Conclusions

This paper presented a novel fault diagnosis method based on ENN-1 for a wind power system. Compared with existing methods, the structure of the proposed ENN-1 is simpler with a faster learning time than other methods. We can quickly and reliably receive diagnostic results. The feasibility to implement the proposed method using a computer as a portable fault-detecting device is strong. According to simulation results, the proposed method had a significantly high degree of diagnosis accuracy and showed good tolerance for the errors added. With the simulation of a wind turbine fault diagnosis system, this new approach merits more attention, because it can understand the technologies related to designing actual systems. We hope that this paper will lead to further investigation for industrial applications.

Acknowledgment

The authors gratefully acknowledge the support of the National Science Council, Taiwan, for financial support under Grant no. NSC-98-2221-E-167-028.

References

[1] J. Wood, "Under pressure renewable energy generation," *IEEE Power Engineer*, vol. 19, no. 2, article 12, 2005.

[2] P. Li, "Energy storage is the core of renewable technologies," *IEEE Nanotechnology Magazine*, vol. 2, no. 4, pp. 13–18, 2008.

[3] H. Li and Z. Chen, "Overview of different wind generator systems and their comparisons," *IET Renewable Power Generation*, vol. 2, no. 2, pp. 123–138, 2008.

[4] B. C. Ummels, M. Gibescu, E. Pelgrum, W. L. Kling, and A. J. Brand, "Impacts of wind power on thermal generation unit commitment and dispatch," *IEEE Transactions on Energy Conversion*, vol. 22, no. 1, pp. 44–51, 2007.
[5] V. Akhmatov and P. B. Eriksen, "A large wind power system in almost island operation—a Danish case study," *IEEE Transactions on Power Systems*, vol. 22, no. 3, pp. 937–943, 2007.
[6] A. S. Zaher and S. D. J. McArthur, "A multi-agent fault detection system for wind turbine defect recognition and diagnosis," in *Proceedings of the Power Technology Conference*, pp. 22–27, Lausanne, Switzerland, July 2007.
[7] M. H. Wang and C. P. Hung, "Extension neural network and its applications," *Neural Networks*, vol. 16, no. 5-6, pp. 779–784, 2003.
[8] W. Yang, P. J. Tavner, and M. R. Wilkinson, "Condition monitoring and fault diagnosis of a wind turbine synchronous generator drive train," *IET Renewable Power Generation*, vol. 3, no. 1, pp. 1–11, 2009.
[9] M. H. Wang, "Extension neural network for power transformer incipient fault diagnosis," *IEE Proceedings: Generation, Transmission and Distribution*, vol. 150, no. 6, pp. 679–685, 2003.
[10] M. H. Wang, "Partial discharge pattern recognition of current transformers using an ENN," *IEEE Transactions on Power Delivery*, vol. 20, no. 3, pp. 1984–1990, 2005.
[11] K. H. Chap, C. G. Li, and M. H. Wang, "A maximum power point tracking method based on extension neural network for PV systems," in *Proceedings of the 6th International Symposium on Neural Networks (ISNN '09)*, Lecture Notes in Computer Science, pp. 745–755, 2009.
[12] K. S. Cho, J. Y. Shin, Y. S. Lee, H. J. Lee, and J. W. Hong, "Partial discharge classification and diagnosis of power cable joint by statistical processing," in *Proceedings of the 6th International Conference on Condition Monitoring and Diagnosis (CMD '08)*, pp. 1232–1235, Beijing, China, April 2008.
[13] Q. Zhou, C. W. Chan, and P. Tontiwachiwuthikul, "Development of an intelligent system for monitoring and diagnosis of the carbon dioxide capture process," *Journal of Environmental Informatics*, vol. 18, pp. 75–83, 2011.
[14] S. C. Wang and P. H. Huang, "Fuzzy C-means clustering for power system coherency," in *Proceedings of the IEEE Systems, Man and Cybernetics Society*, pp. 2850–2855, October 2005.
[15] M. H. Wang, "A novel extension method for transformer fault diagnosis," *IEEE Transactions on Power Delivery*, vol. 18, no. 1, pp. 164–169, 2003.
[16] M. H. Wang and C. Y. Ho, "Application of extension theory to PD pattern recognition in high-voltage current transformers," *IEEE Transactions on Power Delivery*, vol. 20, no. 3, pp. 1939–1946, 2005.
[17] S. Khomfoi and L. M. Tolbert, "Fault diagnostic system for a multilevel inverter using a neural network," *IEEE Transactions on Power Electronics*, vol. 22, no. 3, pp. 1062–1069, 2007.