Application of extension theory to vibration fault diagnosis of generator sets

M.-H. Wang

Abstract: An extension diagnosis method based on the matter-element model and extended correlation function is presented for vibration fault diagnosis of steam turbine generators. First, the matter-element models of the vibration fault are built according to diagnostics derived from practical experience and then, vibration faults in steam-turbine generators can be directly identified by relation indices. The applications of this new method to generator sets in China have given promising results.

1 Introduction

Generator sets are the most important and valuable devices in power systems. A generator fault not only damages the generator itself, but also causes a break in power supply and loss of profits. It is of great importance to recognise internal failures in generator sets as early as possible, so that it is possible to switch them safely and improve the reliability of power systems.

The steam-turbine generator set consists of turbine and generator; the turbine can also be divided into high-pressure (HP), intermediate-pressure (IP) and low-pressure (LP) turbine, all of these sections are girdled by the bearings. Generally, the generator set is well constructed and robust, but the possibility of incipient faults is inherent due to stresses involved in the conversion of mechanical to electrical energy [1–3]. For example, the machine bearings may be subject to excessive damage caused by inadequate lubrication, impure lubrication, or incorrect loading [4, 5]. Hence, the diagnostic information supplied by the power spectrum of the vibration signals can be a valuable source of information as to the condition of the generators [6]. Fault diagnosis can produce significant cost saving by scheduling preventive maintenance and preventing extensive downtime periods caused by extensive failure [7–9].

In the past, various fault diagnosis techniques have been proposed, including expert systems [4], neural networks [NN] [2, 8], fuzzy logic approaches [5] and fuzzy neural networks (FNN) [3, 6]. The expert system and fuzzy logic approaches can take human expertise, and have been successfully applied in this field. However, there are some intrinsic shortcomings, such as the difficulty of acquiring knowledge and maintaining a database. These may vary from utility to utility due to the heuristic nature of the method and no general mathematical formulation can be utilised. Neural networks can directly acquire experience from training data and exhibit highly nonlinear input-output relationships. This can overcome some of the shortcomings of the expert system. However, the training data must be sufficient and compatible to ensure proper training. A further limitation of the NN approach is its inability to produce linguistic output, because it is difficult to understand the content of network memory.

In this paper, a novel extension diagnosis method is presented for vibration fault diagnosis in steam turbine generator sets. The concept of extension theory was first proposed by Cai to solve contradictions and incompatibility problems in 1983 [10]. Extension theory consists of two parts, matter-element model and extended set theory. The extension theory has given promising results in many fields [11–14], but in fault diagnosis applications extension theory is adopted scarcely. To the knowledge of the author, this paper is the first application of extension theory to generator set diagnosis. The proposed diagnosis method uses a set of matter-element models and a modified extended correlation function, then the vibration fault type in a generator set can be directly identified by the degrees of extended correlation. Results from applications to some steam turbine generators show that the proposed method is suitable as a practical solution to this problem.

2 Outline extension theory

In the real world, there are some problems that cannot be directly solved by given conditions, but the problem may become easier or solvable through some proper transformation. For example, if there exists no solution for problem Q under the condition h, we can find a transformation T, such that problem Q becomes solvable under condition $T(h)$. The Laplace transformation is one of the commonly used techniques in engineering fields, and the concept of fuzzy sets is a generalisation of well-known standard sets to extend application fields. Extension theory tries to solve incompatibility or contradiction problems by the transformation of the matter element. The extension set extends the fuzzy set from [0, 1] to $(-\infty, \infty)$ [10]. As a result, it allows us to define a set that includes any data in the domain. On the other hand, extension set theory assigns a membership grade with any real value to points, with the convention that grades below -1 apply to points that definitely cannot be in the set, grades between -1 and 0 are for points that are

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The author is with the Institute of Information and Electrical Energy, National Chin-Yi Institute of Technology, 35, 215 Lane, Sec. 1, Chung Shan Road, Taiping, Taichung, Taiwan, Republic of China

Table 1: Three different sorts of mathematical sets

Compared item	Crisp set	Fuzzy set	Extension set
Research objects	Data variables	Linguistic variables	Contradictory problems
Model	Mathematics model	Fuzzy mathematics model	Matter-element model
Descriptive function	Transfer function	Membership function	Correlation function
Descriptive property	Precision	Ambiguity	Extension
Range of set	$C_A(x) \in \{0,1\}$	$\mu_A(x) \in [0,1]$	$K_A(x) \in (-\infty, \infty)$

apparently outside the set but could be members of the set. Grades above 0 denote degrees of membership in the set. The comparisons of crisp sets, fuzzy sets and extension sets are shown in Table 1. Some definitions of extension theory are introduced in the following Section.

2.1 Matter-element theory

In extension theory, a matter-element contains three fundamental elements, if we define the name of the matter N, one of the characteristics of the matter by c, and the value of c by v. The matter-element can be described as follows [10, 14]:

$$R = (N, c, v) \tag{1}$$

On the other hand, if we assume that $\boldsymbol{R} = (N, \boldsymbol{C}, \boldsymbol{V})$ is a multidimensional matter-element, $\boldsymbol{C} = [c_1, c_2, \ldots c_n]$ a characteristic vector and $\boldsymbol{V} = [v_1, v_2, \ldots, v_n]$ a value vector of C, then a multidimensional matter-element is defined as

$$\boldsymbol{R} = (N, \boldsymbol{C}, \boldsymbol{V}) = \begin{bmatrix} R_1 \\ R_2 \\ \cdots \\ R_n \end{bmatrix} = \begin{bmatrix} N, c_1, v_1 \\ c_2, v_2 \\ \cdots\cdots \\ c_n, v_n \end{bmatrix} \tag{2}$$

where $R_i = (N, c_i, v_i)(i = 1, 2, \ldots n)$ is defined as the sub-matter-element of $\boldsymbol{R}$. For example,

$$\boldsymbol{R} = \begin{bmatrix} \boldsymbol{Wang}, \boldsymbol{Height}, \mathbf{179cm} \\ \boldsymbol{Weight}, \mathbf{76kg} \end{bmatrix} \tag{3}$$

This can be used to state that Wang's height is 179 cm, and his weight is 76 kg. A matter may have many characteristics; the same characteristics and values may also belong to some other matter. Some basic formulations in extension theory can be expressed as follows:

***Theory* 1:** If a matter has many characteristics, it can be written as:

$$N \dashv (N, c, v) \dashv \{(N, c_1, v_1), (N, c_2, v_2), \ldots, (N, c_n, v_n)\} \tag{4}$$

The symbol"⊣" indicates the mean of the extension.

***Theory* 2:** If some matters have the same characteristic, they can be written as:

$$(N, c, v) \dashv \{(N_1, c, v_1), (N_2, c, v_2), \ldots, (N_n, c, v_n)\} \tag{5}$$

***Theory* 3:** If some matters have the same value, they can be written as

$$(N, c, v) \dashv \{(N_1, c_1, v), (N_2, c_2, v), \ldots, (N_n, c_n, v)\} \tag{6}$$

Using the matter-element model, we can describe the quality and quantity of a matter, which is a new concept in mathematical territory.

2.2 Summary of extension set theory

2.2.1 Definition of extension set

Let U be a space of objects and x a generic element of U, then an extension set $\tilde{A}$ in U is defined as a set of ordered pairs as follows:

$$\tilde{A} = \{(x, y) | x \in U, y = K(x) \in (-\infty, \infty)\} \tag{7}$$

Where $y = K(x)$ is called the correlation function for extension set $\tilde{A}$. The $K(x)$ maps each element of $\boldsymbol{U}$ to a membership grade between $-\infty$ and ∞. An extension set $\tilde{A}$ in U can be denoted by:

$$\tilde{A} = A^+ \cup J_o \cup A^- \tag{8}$$

Where

$$A^+ = \{(x, y) | x \in U, y = K(x) > 0\} \tag{9}$$

$$J_o = \{(x, y) | x \in U, y = K(x) = 0\} \tag{10}$$

$$A^- = \{(x, y) | x \in U, y = K(x) < 0\} \tag{11}$$

In (9) and (10), A^+ is called a positive domain in $\tilde{A}$, it can describe the degrees to which x belongs to X_o. A^- is called a negative domain in $\tilde{A}$, it describes the degree to which x does not belong to X_o. J_o is called a zero boundary.

2.2.2 Primitively extended correlation function

The correlation functions have many forms dependent on application. If we set $X_o = \langle a, b \rangle$, $X = \langle a_p, b_p \rangle$ and $X_o \in X$, then the extended correlation function can be defined as follows:

$$K(x) = \frac{\rho(x, X_o)}{D(x, X_o, X)} \tag{12}$$

Where

$$\rho(x, X_o) = \left| x - \frac{a+b}{2} \right| - \frac{b-a}{2} \tag{13}$$

$$D(x, X_o, X) = \begin{cases} \rho(x, X) - \rho(x, X_o) & x \notin X_o \\ -1 & x \in X_o \end{cases} \tag{14}$$

The correlation function can be used to calculate the membership grade between x and $\boldsymbol{X_o}$. The extended correlation function is shown in Fig. 1. When $K(x) \geq 0$, this indicates the degrees to which x belongs to X_o. When $K(x) < 0$ it describes the degree to which x does not belong to X_o. When $-1 < K(x) < 0$, it is called the extension domain, which means that the element x still has a chance to become part of the set if conditions change.

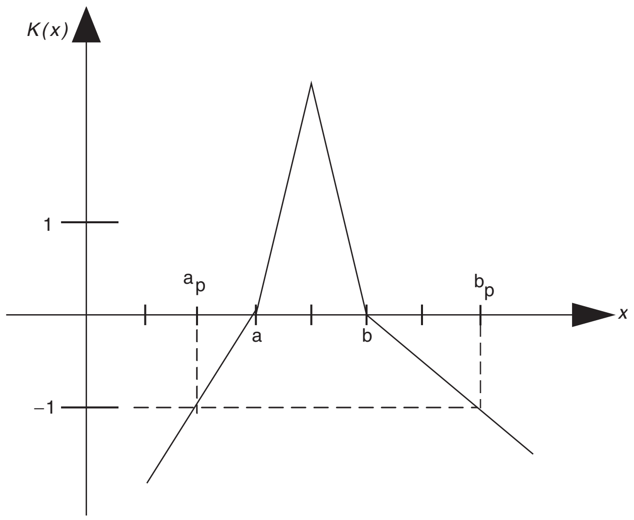

Fig. 1 *Extended correlation function*

3 Proposed vibration fault diagnosis method

Figure 2 shows a simplified schematic diagram for a steam-turbine generator. It consists of three parts: turbine, generator and exciter. All of these sections are girdled by the bearings that supply most of the diagnostic information. The vibration diagnosis is based on the principle that components in engineering systems and plants produce vibration during operation. If a generator set is operating properly, vibration conditions are usually small and constant, but when faults grow or some of the dynamic processes in the machine change, the vibration signature also changes [2, 3]. Hence, diagnostic information can be supplied by the spectrum of the vibration signal as shown in Fig. 3. The proposed method is by collecting the power spectrum of the vibration signals from some generator sets and performing detailed analysis to detect features for vibration fault diagnosis. In agreement with past studies [2, 3], the typical six values (amplitude of $<0.4f$, $0.4f \sim 0.5f$, f, $2f$, $3f$ and $>3f$) are selected for vibration fault diagnosis. First, we need to develop matter-element models of the vibration fault types, and then vibration faults of the tested steam-turbine generator set can be identified directly by the degrees of the relation.

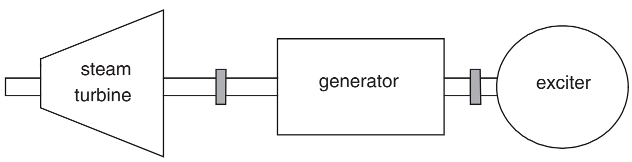

Fig. 2 *Schematic diagram of steam turbine generator*

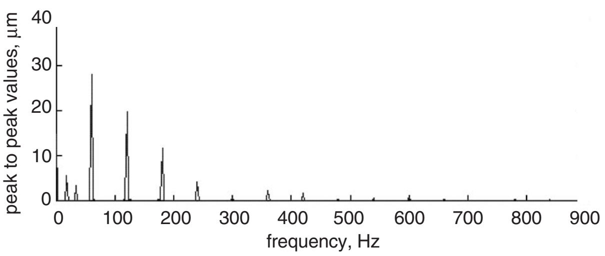

Fig. 3 *Power spectrum of the vibration signals*

3.1 Matter-element model of vibration fault diagnosis

The first step of the extended fault diagnosis method is to formulate matter-element models of fault types. According to field-test records [2, 3], the matter-elements of four fault types are shown in Table 2. Where R_i is the matter-element of four fault types, where $F = \{F_1, F_2, F_3, F_4\}$ is the fault set, F_i is the ith fault type. The value range and classical domains of every characteristic are set according to low bounds and up bounds of field-test records. The neighbourhood domain of every characteristic, defined as the possible range of every vibration spectrum, is set as

$$\boldsymbol{R}_p = (F_p, \boldsymbol{C}, \boldsymbol{V}_p) = \left\{ \begin{array}{ll} F_p, <0.4f, & \langle 0,7 \rangle \\ 0.4f \sim 0.5f, & \langle 0, 54 \rangle \\ f & \langle 0, 60 \rangle \\ 2f, & \langle 0, 27 \rangle \\ 3f, & \langle 0, 22 \rangle \\ >3f, & \langle 0, 22 \rangle \end{array} \right\} \quad (15)$$

The range of neighbourhood domains can be directly obtained from previous experience, or determined from

Table 2: Fault matter-element models of generator sets

Fault types	Matter-element model
F_1: oil- membrane oscillation	$R_1 = (F_1, C, V_1) = \left\{ \begin{array}{ll} F_1, <0.4f, & \langle 2.7,6.5 \rangle \\ 0.4f \sim 0.5f, & \langle 43, 54 \rangle \\ f, & \langle 11, 19 \rangle \\ 2f, & \langle 1.1, 4.9 \rangle \\ 3f, & \langle 0.8, 2.4 \rangle \\ >3f, & \langle 0.5, 3.8 \rangle \end{array} \right\}$
F_2: unbalance	$R_2 = (F_2, C, V_2) = \left\{ \begin{array}{ll} F_2, <0.4f, & \langle 0.54,2.7 \rangle \\ 0.4f \sim 0.5f, & \langle 1.1, 3.8 \rangle \\ f, & \langle 38, 54.5 \rangle \\ 2f, & \langle 2.7, 6.8 \rangle \\ 3f, & \langle 0.54, 4.1 \rangle \\ >3f, & \langle 0, 2.7 \rangle \end{array} \right\}$
F_3: no orderliness	$R_3 = (F_3, C, V_3) = \left\{ \begin{array}{ll} F_3, <0.4f, & \langle 0.54,1.9 \rangle \\ 0.4f \sim 0.5f, & \langle 0.8, 2.2 \rangle \\ f, & \langle 22, 30 \rangle \\ 2f, & \langle 22, 26.5 \rangle \\ 3f, & \langle 14, 19.5 \rangle \\ >3f, & \langle 5.4, 16.2 \rangle \end{array} \right\}$
F_4: no fault	$R_4 = (F_4, C, V_4) = \left\{ \begin{array}{ll} F_4, <0.4f, & \langle 0, 0.54 \rangle \\ 0.4f \sim 0.5f, & \langle 0, 0.54 \rangle \\ f, & \langle 0, 8.6 \rangle \\ 2f, & \langle 0, 3.3 \rangle \\ 3f, & \langle 0, 3.3 \rangle \\ >3f, & \langle 0, 1.6 \rangle \end{array} \right\}$

maximum and minimum values of every characteristic in field-test records. After the element-matter model of fault diagnosis is formulated, the vibration fault diagnosis of generator sets can be initiated.

3.2 Extension fault diagnosis method

The proposed extension diagnosis method has been successfully implemented using PC based software for fault diagnosis of generator sets. The extension fault diagnosis method is described as follows:

Step 1: Formulating the matter-element of every fault type as Table 2. The ranges of class domains can be directly obtained from the field-test data. It also can be determined from previous experience.

Step 2: Formulating the vibration matter-element of the tested generator set as follows:

$$\boldsymbol{R}_t = (F_t, \boldsymbol{C}, \boldsymbol{V}_t) = \begin{Bmatrix} F_t, <0.4f, & v_{t1} \\ 0.4f \sim 0.5f, & v_{t2} \\ f, & v_{t3} \\ 2f, & v_{t4} \\ 3f, & v_{t5} \\ >3f, & v_{t6} \end{Bmatrix} \tag{16}$$

where $\boldsymbol{V}_t = [v_{t1}, v_{t2}, \ldots, v_{t6}]$ a value vector of spectrum signal.

Step 3: Calculating the relation degree of the tested generator set with the faulted characteristic by the proposed extended correlation function as follows:

$$K_{ij}(v_{tj}) = \begin{cases} \dfrac{-2\rho(v_{tj}, V_{ij})}{|b_{ij} - a_{ij}|}, \text{if } v_{tj} \in V_{ij} \\ \dfrac{\rho(v_{tj}, V_{ij})}{\rho(v_{tj}, V_{pj}) - \rho(v_{tj}, V_{ij})}, \text{if } v_{tj} \notin V_{ij} \end{cases} \tag{17}$$

$i = 1, 2, \ldots, 4$; $j = 1, 2, \ldots, 6$

where

$$V_{ij} = \langle a_{ij}, b_{ij} \rangle \tag{18}$$

$$V_{pj} = \langle a_{pj}, b_{pj} \rangle \tag{19}$$

The proposed extended correlation function can be shown as Fig. 4, where $0 \le K(v) \le 1$ corresponds to the normal fuzzy set. It describes the degree to which v belong to V. When $K(v) < 0$, it indicates the degree to which x does not belong to X_o, which is not defined in the fuzzy theory.

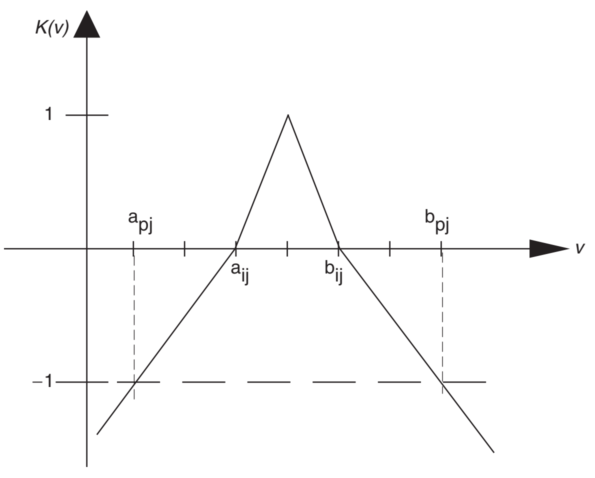

Fig. 4 *Proposed extended correlation function*

Step 4: Setting the weights of the fault pattern, W_{i1}, $W_{i2}, \ldots, W_{i6}$, depending on the importance of every fault features in the diagnosis process. In this paper, all six weights are set at 1/6.

Step 5: Calculating the relation indices for every fault type:

$$\lambda_i = \sum_{j=1}^{6} W_{ij} K_{ij}, \; i = 1, 2, \ldots, 4 \tag{20}$$

Step 6: Normalising the values of the relation indices into an interval between –1 and 1 as in (21), this process will be beneficial for fault diagnosis:

$$\lambda_i' = \frac{2\lambda - \lambda_{\min} - \lambda_{\max}}{\lambda_{\max} - \lambda_{\min}}, i = 1, 2, \ldots, 4 \tag{21}$$

Where

$$\lambda_{\max} = \max_{1 \le i \le 4} \{\lambda_i\} \tag{22}$$

$$\lambda_{\min} = \min_{1 \le i \le 4} \{\lambda_i\} \tag{23}$$

Step 7: Ranking the normalised fault indices and find the maximum value of the relation index (or 1) to detect the fault type of the tested generator set. The fault diagnosis rule is shown as follows:

$$\text{if } (\lambda_k' = 1), \text{ then } (F_t = F_k)$$

Note the proposed method can determine the main fault severity compared to other types, and identify the fault likelihood by the fault indices. It is most helpful in the diagnosis of multiple vibration faults.

Step 8: Going back to step 2 for the next generator when the diagnosis of one has been completed, until all have been done.

The main advantage of the proposed method is that it can provide more detailed information about vibration faults of the generators by relation fault indices. Moreover, the proposed method does not need to learn or to tune any parameters, and a simple software package can easily implement it.

4 Case studies and discussions

Generally, fault records are very rare at general power companies. To demonstrate the effectiveness of the proposed extension fault diagnosis method, 20 sets of field-test data from steam-turbine generator sets in China [2, 3] were tested (the data are shown in Table 3). The input data include the six amplitude values of the vibrational spectrum, where f is the frequency of the generator rotor. It is clear that vibration diagnosis in steam-turbine generator sets is a most complicated and nonlinear classification problem.

The diagnosis results of the proposed method with the vibration relation indices λ_j' are shown in Table 4. It is very easy to diagnose fault types in generator sets from Table 4. For example, in generator number 1, the relation index with fault type F_1 equals 1 (or maximum value), which is indicative of fault type F_1, or oil- membrane oscillation faults. In comparison, the relation indices with other fault types are very small. Hence, generator number 1 does not need to be checked in the future. Moreover, the proposed method cannot only diagnose the main fault types of generator sets, it can also provide useful information for future trend analysis by the relation indices. For example,

Table 3: Tested data of generator sets

Generator number	Input data						Actual fault types
	<0.4f	0.4f∼0.5f	1f	2f	3f	>3f	
1	3.35	46.6	12.15	1.94	2.3	3.67	F_1
2	4.43	51	11.02	3.02	1.3	2.43	F_1
3	3.29	50	11.61	1.24	0.9	1.3	F_1
4	5.72	46.3	12.31	3.62	1.5	0.59	F_1
5	6.32	45.8	15.23	3.56	2.3	3.19	F_1
6	1.51	3.29	52.92	6.59	2.5	2.54	F_2
7	2.43	1.19	54.49	4.64	0.8	1.78	F_2
8	0.54	2.92	48.82	6.64	3.9	1.51	F_2
9	0.81	1.73	52.00	6.43	3.6	1.89	F_2
10	1.24	1.35	49.79	4.64	1.0	2.27	F_2
11	1.78	1.46	22.46	23.8	19	8.59	F_3
12	0.92	1.24	30.08	22	16	5.67	F_3
13	0.65	2.11	21.98	26.2	18	11.1	F_3
14	1.13	0.92	24.46	22.3	15	15.8	F_3
15	0.92	1.40	26.08	26	20	11.4	F_3
16	0.54	3.24	37.80	2.7	2.7	0.0	F_2, F_1
17	3.24	48.6	42.66	2.16	1.1	0.54	F_2
18	1.08	0.54	20.52	25.4	17	11.9	F_3
19	0.54	0.54	8.10	2.7	2.7	1.08	F_4
20	0.27	0.27	8.64	1.08	1.1	0.54	F_4

Table 4: Relation indices λ_i' by the proposed method and diagnosis results

Generator number	Relation indexes λ_i'				Diagnosis results
	F_1	F_2	F_3	F_4	
1	1.00	−1.00	0.01	−0.03	F_1
2	1.00	−1.00	0.70	0.74	F_1
3	1.00	−1.00	0.60	0.54	F_1
4	1.00	−1.00	0.60	0.53	F_1
5	1.00	−1.00	0.02	−0.12	F_1
6	−1.00	1.00	0.62	−0.25	F_2
7	−1.00	1.00	0.88	0.40	F_2
8	−0.92	1.00	0.37	−1.00	F_2
9	−1.00	1.00	0.60	0.51	F_2
10	−1.00	1.00	0.69	0.23	F_2
11	−0.74	−0.46	1.00	−1.00	F_3
12	−1.00	−0.06	1.00	−0.80	F_3
13	−1.00	−0.49	1.00	−0.96	F_3
14	−1.00	−0.70	1.00	−1.00	F_3
15	−1.00	−0.42	1.00	−0.86	F_3
16	0.50	1.00	0.83	−1.00	F_2
17	−0.76	1.00	0.71	−1.00	F_2
18	−0.58	−1.00	1.00	−0.83	F_3
19	0.70	−1.00	0.79	1.00	F_4
20	0.61	−1.00	0.67	1.00	F_4

generator number 7 was diagnosed to have main fault type F_2 (unbalance fault). On the other hand, the relation index of F_3, about 0.88, also shows that this generator had a high possibility of fault type F_3, i.e. no orderliness. Conversely, owing to a negative relation index, generator number 7 had a very low possibility of fault type F_1 or oil-membrane oscillation.

To compare diagnosis performance, the partial diagnosis results with two different classification methods [2, 3] are shown in Table 5, there are only three outputs to indicate

Table 5: Partial diagnosis results using different methods

generator number	MLP [2] structure: 6-13-3			FNN [3] structure: 6-13-3			Diagnosis results
	F_1	F_2	F_3	F_1	F_2	F_3	
1	0.87	0.21	0.06	0.97	0.83	0.80	F_1
2	0.90	0.28	0.21	0.96	0.87	0.81	F_1
6	0.13	0.95	0.09	0.81	0.99	0.83	F_2
7	0.10	0.96	0.06	0.83	0.99	0.86	F_2
11	0.15	0.12	0.89	0.70	0.84	0.89	F_3
12	0.13	0.14	0.91	0.79	0.88	0.89	F_3

Note: 1. MLP: multilayer perceptrons.

2. FNN: fuzzy neural network.

3. Training times of MLP = 976 epochs.

4. Training times of FNN = 900 epochs.

the fault types. The two methods were capable of pointing toward faults, but the fault conditions of generators are not easy to identify by the two methods, due to very similar output values. For example, if we use the FNN for fault diagnosis of generator number 12, the output values of F_2 and F_3 are about 0.88 and 0.89, respectively. In addition, both methods need to learn about 976 and 900 epochs before fault diagnosis. In opposition, use of the proposed method most clearly diagnoses the vibration fault of generator number 12 as shown in Table 4. Moreover, the proposed method permits a quickly adaptive process to significant new information and does not need to relearn, and it also could be easily implemented by computer software.

5 Conclusions

This paper presents a vibration-fault-diagnosis method based on the extension theory for steam-turbine generator sets. Compared with other traditional AI methods, the proposed method does not require particular artificial parameters and learning processes. In addition, the calculation of the proposed diagnosis algorithm is fast and very simple. It can be implemented easily by PC software. Test results shows that the proposed method can not only diagnose the main fault types of generator sets, it can also detect useful information for future trends and multi-fault analysis by the relation indices. This paper is the first application of extension theory on generator sets. This approach merits more attention, because extension theory deserves serious consideration as a tool in this field. The author hope's this paper will lead to further investigation.

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