Research Article

Piezoelectric Active Sensor Self-Diagnosis for Electromechanical Impedance Monitoring Using *K*-Means Clustering Analysis and Artificial Neural Network

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Piezoelectric sensor is a crucial part of electromechanical impedance technology whose state will directly affect the effectiveness and accuracy of structural health monitoring (SHM). So carrying out sensor self-diagnosis is important and necessary. However, it is still difficult to distinguish sensor faults from structural damage as well as identify the cases and degrees of sensor faults. In the study, three characteristic indexes of admittance which have different indication intervals for damages of structure and sensors were selected from six indexes after comparison. To improve the discrimination effect, three principal components (PC) were extracted by principal component analysis (PCA). And the damage information represented by PCs was clustered by the *K*-means algorithm to identify the cases of damage. Then, the degrees of sensor damages were classified with the artificial neural network (ANN). The results show that the *K*-means clustering analysis based on admittance characteristics can accurately distinguish and identify the structural damage and four kinds of sensor damages, namely, pseudosoldering, debonding, wear, and breakage. The trained ANN model has a good recognition effect on the damage degrees and the accuracy of recognition reaches 100%. This study has a certain reference value for piezoelectric sensor self-fault identification.

1. Introduction

Electromechanical impedance technology using piezoelectric materials has aroused extensive attention in structural health monitoring (SHM) [1, 2]. Piezoelectric lead zirconate titanate (PZT), as one of the most common piezoelectric materials, has a wide application to many structures [3–6]. The tested structures are usually under various external impacts and environmental condition changes. It is non-ignorable that such changes will also affect the PZT patches coupled with the structure which may result in sensor faults. Sensor faults include pseudosoldering at welding spot and wear of PZT surface caused by adverse weather environment, debonding between sensor and structure during the long-term monitoring, and breakage after external impact or improper operation on fragile material PZT. If the sensor faults are not identified and then excluded, it will lead to the

inaccurate identification of structural damage or even more serious problems such as the misjudgment of the structure state. Therefore, the diagnosis of PZT state is the premise to ensure the effectiveness of the SHM system.

Data mining algorithm integrates the techniques of machine learning, statistics, pattern recognition, artificial intelligence, database system, and so on [7, 8]. It shows a good prospect in the data processing of impedance signals as it can reveal the hidden, previously unknown, and potentially valuable information from a large number of data in the database. At present, there are many methods combining electromechanical impedance and data mining algorithms that have been used to solve practical application problems. Naidu et al. [9] incorporated a Bayesian network model for damage location identification after discussing the issues of variable selection, variable dependency, probabilistic inference, and error modeling, which eliminated the model error

and realized the accurate damage location. Min et al. [10, 11] proposed a technique for autonomous selection of damage-sensitive frequency range with an artificial neural network (ANN) and examined the approach performance by detecting the loose bolts and cracks. In further study, the neural network algorithm was embedded into a wireless impedance sensor node to successfully detect the real damage of a full-scale bridge. Sepehry et al. [12] considered a steel plate and gas pipe with bolted joints as two cases and confirmed that the proposed method using ANN based on radial basis function (RBF) can be effectively utilized to compensate for the temperature change. Shuai et al. [13] devised a prescreening scheme that reduces the fault parameter space. Then a Bayesian inference method is introduced to determine the fault location and severity with high computational efficiency. Park et al. [14] verified the effectiveness of the method which incorporates the principal component analysis (PCA) and *K*-means clustering in the practical application of electromechanical impedance-based wireless SHM system. Taking the bolts on the aluminum plate as the research object, Zhang et al. [15] used LibSVM to process a large number of impedance data and realized the accurate recognition of the loose bolt from 12 possible positions. Selva et al. [16] presented a method relying on ANNs for in situ damage and localization in carbon fiber reinforced plates (CFRPs). The result shows that ANN can serve as a tool for the prediction of a single damage in-plane position. Lim et al. [17] developed an impedance damage detection technique using Kernel principal component analysis (KPCA). The method is proved effective after detecting bolt loosening within a metal fitting lug. Zhang et al. [18] used 51 impedance values as a set of input data and 11 different ice thicknesses as the output. Through the trained ANN model, the accuracy of the ice thickness evaluation achieves 100%.

The above studies show that the data mining algorithms are feasible in dealing with impedance data and solving

practical problems. Most of the existing monitoring systems are not intelligent enough to distinguish the signal changes caused by structural damage and sensor faults. After PZT is damaged, it is impossible to identify the cases and degrees of sensor damages with the current study. To tackle these issues, we studied the admittance signals of structural damage and four kinds of PZT faults (pseudosoldering, debonding, wear, and breakage) under three PZT fault degrees. Three PCs were obtained after the PCA of three selected admittance spectrum characteristics. Then the *K*-means algorithm was used to cluster different cases of damages represented by the PCs. Finally, the degrees of four PZT damages were identified by the ANN model.

2. Electromechanical Impedance-Based Damage Detection Method

When the piezoelectric material is deformed by an external force, the polarization phenomenon will appear in the material, and the positive and negative charges will gather on its two opposite surfaces to form the potential difference. The conversion of mechanical energy into electrical energy is called the direct piezoelectric effect. On the contrary, when the electric field acts on the polarization direction of piezoelectric materials, it will cause mechanical strain. This phenomenon of converting electrical energy into mechanical energy is called the inverse piezoelectric effect. Due to its unique piezoelectric effect, piezoelectric materials are often used in various driving and sensing applications [19, 20].

Liang et al. [21] first proposed that the coupling system of PZT and the host structure can be simplified into a one-dimensional model of stiffness-mass-damping (SMD) when only considering axial deformation. They then concluded that the admittance of PZT is related to the mechanical impedance of the structure under test and PZT. The expression of admittance is as follows:

$$Y(\omega) = \frac{I_0}{V_i} = G(\omega) + jB(\omega) = j\omega a \left(\bar{\epsilon}_{33}^T - \frac{Z_s(\omega)}{Z_s(\omega) + Z_a(\omega)} d_{3x}^2 \hat{Y}_{xx}^E \right), \quad (1)$$

where $Y(\omega)$ denotes the admittance (a complex number); ω denotes the excitation angular frequency at work; V_i denotes the input voltage to PZT; I_0 denotes the output current from PZT; $G(\omega)$ denotes the conductance; $B(\omega)$ denotes the susceptance; j denotes the imaginary part of a complex number; a denotes the geometry constant; $\bar{\epsilon}_{33}^T$ denotes the dielectric constant at zero stresses; $Z_s(\omega)$ and $Z_a(\omega)$ denote the mechanical impedance of the host structure and PZT; d_{3x} denotes the piezoelectric coupling constant at zero stresses; and $\hat{Y}_{xx}^E$ denotes the complex Young's modulus of PZT at zero electric fields.

After the PZT coupled with the structure is applied with the alternating electric field, the PZT vibrates due to the inverse piezoelectric effect, thus causing the vibration of the structure. Then the vibration of the structure will, in turn,

deform the PZT. The sensor will generate an electrical signal because of the direct piezoelectric effect. The admittance signal will change when structural damages or PZT faults occur. The damage state of the structure or sensor can be studied through the comparative analysis of the signal and the benchmark obtained by the healthy PZT when the structure is intact [22, 23]. The detection schematic diagram is shown in Figure 1.

3. Experimental Investigation on EMI-Based Sensor Self-Diagnosis

3.1. Experimental Setup. At a constant temperature of 26°C, an experiment was carried out to study the effects of structural damage and PZT faults on the admittance signal.

FIGURE 1: Detection schematic diagram of PZT coupled with the host structure.

We used a Wk6500B impedance analyzer to extract and process the signal. Four PZT patches (PZT-5A) numbered 1–4# were pasted on the diagonal symmetrical position of an aluminum plate. The distance from each PZT to the center of the plate is the same. The positive and negative electrodes led out from the PZT surface were connected with the clamp of the analyzer, as shown in Figure 2. The plate is 200 mm in length, 200 mm in width, and 2 mm in thickness. The density, Young's modulus, and Poisson's ratio of the plate are 2750 kg/m^3 , 70 GPa, and 0.35, respectively. The density of the piezoelectric wafer is 7750 kg/m^3 , and the diameter and thickness of the wafer are 16 mm and 2 mm. The total weight of the plate with coupled PZT is 232 g.

When setting the structural damage, we placed different numbers of specimens (coins, nuts, and steel blocks) with various shapes and mass in the center of the plate to simulate structural damage conditions as the added mass will result in the change of structure mechanical impedance [24, 25]. The size, weight, and placement scheme of each specimen are shown in Table 1 and the settings of structural damage are shown in Figure 3. Based on the different range of mass addition after superimposing coins, nuts, and steel blocks, the superposition effect of the three specimens is equivalent to mild damage, moderate damage, and severe damage, correspondingly.

As for the setting of PZT faults, three degrees of pseudosoldering, debonding, wear, and breakage were introduced to 1–4# PZT, respectively. When pseudosoldering occurs, it will mainly increase the contact resistance between the wire and the PZT. To study the principal aspects of the problem, resistances (20 Ω , 200 Ω , and 2000 Ω) were connected in series with the positive electrode of the PZT to simulate three levels of pseudosoldering (mild pseudosoldering, moderate pseudosoldering, and severe pseudosoldering). The setting of each sensor fault is shown in Figures 4–7 (Figures 4–7 are reproduced from Jiang et al. [26]).

We set the upper limit output voltage 1 V of the analyzer as the excitation voltage for the higher excitation voltage in a certain range can significantly improve the detection sensitivity of EMI [27, 28]. In terms of selecting the test frequency range, Yan and Chen [29] proposed that when the excitation frequency is set at 30 kHz–400 kHz, it can sensitively detect minor changes in structural integrity. Yang et al. [30] concluded that high-frequency signal also contains the information of damage. After the trial and error method

[31], we selected 400 sample points in the frequency range of 30 kHz–1 MHz to conduct the experiment. The specific steps of the study are as follows: firstly, extract the initial admittance signals of the healthy structure and intact PZT as the benchmark; secondly, use 1–4# undamaged PZT to measure the admittance of the structure under 1–9# working condition; finally, collect the admittance of healthy structure when the 1–4# PZT patches are set with different degrees of pseudosoldering, debonding, wear, and breakage.

3.2. Admittance Analysis of Structural Damage and PZT Faults. The conductance and susceptance under different damage conditions are shown in Figures 8–12. The X-axis represents the serial number of the signal. The Y-axis represents the frequency and the Z-axis represents the value of conductance or susceptance. The last curve on the YOZ plane is the projection of four signals.

Take the cases when the structure is under 7–9# working conditions as examples to study the effects of structure damages on signal changes. Figures 8(a) and 8(b) depict the conductance and susceptance (30 kHz–1 MHz) under three degrees of severe structural damage. It can be seen from Figure 8(a) that the conductance of the damaged structure has similar characteristics to the benchmark in frequency, amplitude, and change trend which shows a strong correlation. Structural damages sharply change the susceptance peaks at 187 kHz and 365 kHz, while having no obvious effect on susceptance in other frequency ranges. It is concluded that the peak of the susceptance has a sensitive indication effect on the change of the structure state.

Figure 9 displays the changes of conductance and susceptance with the increasing degree of pseudosoldering. It is observed in Figure 9(a) that the mild pseudosoldering decreases the peak of conductance more greatly than the valley of conductance in the frequency range of 250 kHz–1 MHz. At the same time, the curve still has the same local characteristics as the benchmark. As the level of pseudosoldering increases, the conductance decreases further as a result of which it is difficult to determine the frequency of peak and valley by direct observation. When 1# PZT is in severe pseudosoldering condition, the conductance is approximately a straight line from which we can judge that 1# PZT is invalid. In Figure 9(b), the susceptance peak changes obviously when pseudosoldering occurs which indicates that the peak of susceptance is also sensitive to the pseudosoldering.

It can be seen from Figure 10(a) that, with the increase of debonding area from 10% to 30%, the conductance does not increase or decrease significantly compared with the benchmark. Different debonding conditions slightly change the magnitude and frequency of conductance at the extreme value while keeping the same trend as the benchmark. According to Figure 10(b), the main effect of debonding is altering the values of the two peaks at 140 kHz and 360 kHz.

Figure 11 shows the conductance and susceptance of 3# PZT under mild, moderate, and severe wear conditions. In Figure 11(a), the conductance of mild wear has a relatively high similarity with the benchmark which suggests that mild wear

FIGURE 2: Experimental setup includes an impedance analyzer and an aluminum plate bonded with 1–4# PZT.

TABLE 1: Size and mass of specimens.

Specimen	Mass (g)	Size	Stacked on the plate	Mass addition (%)	Working condition
Coin	6	$\Phi 25 \text{ mm} \times 2 \text{ mm}$	2 coins	5	1#
			4 coins	10	2#
			6 coins	15	3#
Nut	109	Internal diameter: M18 mm $\times$ 1.5 mm External dimension: 28 mm Length: 35 mm	1 nut	47	4#
			2 nuts	94	5#
			3 nuts	141	6#
Steel block	1012	$40 \text{ mm} \times 40 \text{ mm} \times 80 \text{ mm}$	1 block	440	7#
			2 blocks	880	8#
			3 blocks	1320	9#

FIGURE 3: Settings of structural damage.

has little influence on the detection ability of PZT. With the degree of wear increase, the conductance decreases correspondingly in the frequency range of 230 kHz–1 MHz, and the difference between the peak and the valley also decreases further. As for the susceptance in Figure 11(b), the wear reduces the magnitude of the peak and slope of the curve.

For the effect of PZT breakage on signal, the conductance and the susceptance were measured in the frequency range of 30 kHz–1 MHz in Figures 12(a) and 12(b). The conductance characteristics of damaged PZT are completely dissimilar from that of the benchmark. Besides, the admittance of PZT with 10%, 20%, and 30% breakage area is

also greatly different from each other. The changes shown in Figure 12(a) are not consistent with the conclusion drawn by Huynh et al. [32] that the conductance goes down when the breakage area of PZT rises. The reason may be that the sensor breakage not only lessens the effective bonding area between the PZT and the structure but also causes secondary vibration due to the various roughness of the broken PZT edge. In Figure 12(b), PZT breakage changes the value of susceptance peak at 183 kHz and makes the peak at 631 kHz disappeared.

By making a comparison with Figures 8–12, it is found that there are different characteristic change rules between

FIGURE 4: Pseudosoldering of 1# PZT including mild pseudosoldering ($20\ \Omega$), moderate pseudosoldering ($200\ \Omega$), and severe pseudosoldering ($2000\ \Omega$).

FIGURE 5: Debonding of 2# PZT. (a) 10% debonding; (b) 20% debonding; (c) 30% debonding.

FIGURE 6: Wear of 3# PZT. (a) Mild wear; (b) moderate wear; (c) severe wear.

FIGURE 7: Breakage of 4# PZT. (a) 10% breakage; (b) 20% breakage; (c) 30% breakage.

FIGURE 8: (a) The conductance and (b) the susceptance of 1# undamaged PZT when the structure is in healthy and different severe damage conditions.

FIGURE 9: (a) The conductance and (b) the susceptance of 1# PZT under healthy and different pseudosoldering conditions.

FIGURE 10: (a) The conductance and (b) the susceptance of 2# PZT under healthy and different debonding conditions.

FIGURE 11: (a) The conductance and (b) the susceptance of 3# PZT under healthy and different wear conditions.

FIGURE 12: (a) The conductance and (b) the susceptance of 4# PZT under healthy and different breakage conditions.

signal under various damages of structure and PZT and benchmark. Combined with the feature of the curves, the following six indexes are taken to further extract and quantify the changes of the admittance spectrum caused by different damages. The six indexes coded as 1–6# include the correlation coefficient between the tested signal and the benchmark of conductance, the average frequency shift of the conductance peak, the average change of the conductance peak, the root mean square deviation (RMSD) of the susceptance, the slope change of the linear fitting curve of the susceptance, and the RMSD of the conductance. Five bands (30 kHz–200 kHz, 200 kHz–400 kHz, 400 kHz–600 kHz, 600 kHz–800 kHz, and 800 kHz–1 MHz) divided from the test frequency range are studied with 2# and 3# indexes to avoid inaccurate results due to the improper selection of frequency range. RMSD is a commonly used statistical index for damage evaluation [33, 34]. The expressions of RMSD [35] in 4# and 6# are in

$$\text{RMSD}_B = \sqrt{\frac{\sum_N (B_i - B_i^0)^2}{\sum_N (B_i^0)^2}}, \quad (2)$$

$$\text{RMSD}_G = \sqrt{\frac{\sum_N (G_i - G_i^0)^2}{\sum_N (G_i^0)^2}}, \quad (3)$$

where N denotes the number of samples. For the i th frequency point, B_i^0 and B_i denote the susceptance of the PZT at the baseline and the changed condition, and G_i^0 and G_i denote the conductance of the PZT at the baseline and the changed condition, respectively.

A damage index with good distinguishing ability should have a nonoverlapping characterization range for different kinds of damage. According to this standard, 1–6# indexes

were analyzed and compared. As illustrated in Table 2, the indication ranges of six indexes to five damages cases vary from each other. Since PZT breakage seriously destroys the characteristic of the conductance, the indication ranges of 1–6# index for breakage are wider than that of the other four cases of damage. Among the six indexes, the range of 3# index for debonding is included in the indication range for breakage. The indication range of 4# index for wear is also included in the indication range for breakage. The large-scale overlap of indication intervals will lead to inaccurate or even wrong damage identification. It is worth noting that PZT breakage makes the frequency of conductance peak shift greatly and the 2# index indication interval for breakage (marked data in Table 2) is obviously different from that for other damages. Therefore, when the 2# index is abnormally large, it can be judged that the PZT fault is breakage. The following is a discussion on the distinguishing effect of the 1–6# indexes on structural damage, pseudosoldering, debonding, wear, and breakage. The results show that there is a large overlap between the indication range of 1# index to pseudosoldering and debonding. The coincidence rate of indication range of 2# index to debonding and wear is high. In addition, it is impossible to distinguish structural damage and sensor wear by the value of the 5# index. As for 3#, 4#, and 6# indexes, 4# index has different indication intervals of noncoincidence for each damage; meanwhile, there is only a small part of the indication intervals of 3# and 6# index overlap. A conclusion can be drawn that the three indexes have a good ability to distinguish the various damage cases.

After comparison, 3#, 4#, and 6# indexes were selected for further study. As there is a large difference among the value of the three indexes, if the original data are extracted and used directly without being processed dimensionlessly, the large index will be highlighted and the small index will be excluded in cluster analysis. Therefore, we used the extreme value normalization formula to compress the data between $[0, 1]$. The expression of the formula is as follows:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}. \quad (4)$$

In the formula, x and x' denote the original data and the normalized data and $x_{\min}$ and $x_{\max}$ denote the minimum value and the maximum value of the original data, separately.

The distinguishing effect on structural damage, pseudosoldering, debonding, and wear with the normalized 3#, 4#, and 6# indexes is shown in Figure 13(a). Four damage cases are located in different areas of the three-dimensional figure which means that it is feasible to distinguish different types of damage with the three indexes. As the location distribution of the same damage cases is relatively wide, the classification accuracy will be affected if the clustering analysis is carried out directly. To make the four damage cases more distinguishable, PCA was used to deal with the three indexes. PCA has the advantage of eliminating the correlation between the evaluation indexes and extracting independent PCs [36, 37]. After analysis, we took the PC1 as

x-axis, PC2 as y-axis, and PC3 as z-axis, respectively, in Figure 13(b). Through the comparison of Figures 13(a) and 13(b), the PCA of damage indexes can be used to improve the discrimination of different damage. However, for the experimental data under unknown damage conditions, it is still unable to automatically identify the damage types after extracting the signal features. In view of this, the *K*-means algorithm is used for the data clustering.

4. Clustering Analysis of Damage Data Based on *K*-Means Algorithm

K-means algorithm [38] is a vector quantization method that originated from signal processing and now is more popular in data mining as a clustering analysis method. The purpose of the algorithm is to divide n points into k clusters by the standard that each point belongs to the cluster corresponding to the shortest distance to the mean of the cluster, that is, the cluster center [39]. Suppose that there are 20 known samples, and each sample has two characteristics. The characteristics of each sample are shown in Table 3. Taking two-dimensional clustering as an example, the specific steps of clustering analysis are as follows:

- (1) Set $k=2$; select the initial cluster center, $\mathbf{Z}_1(1) = x_1 = (0, 0)^T$ and $\mathbf{Z}_2(1) = x_2 = (1, 0)^T$, as shown in Figure 14(a).
- (2) Calculate the distance between x_1 and two cluster centers, $\|x_1 - \mathbf{Z}_1(1)\| = \left\| \begin{pmatrix} 0 \\ 0 \end{pmatrix} - \begin{pmatrix} 0 \\ 0 \end{pmatrix} \right\| = 0$ and $\|x_1 - \mathbf{Z}_2(1)\| = \left\| \begin{pmatrix} 0 \\ 0 \end{pmatrix} - \begin{pmatrix} 1 \\ 0 \end{pmatrix} \right\| = 1$. As $\|x_1 - \mathbf{Z}_1(1)\| < \|x_1 - \mathbf{Z}_2(1)\|$, $x_1 \in \mathbf{Z}_1(1)$. Then calculate the distance between x_2 and two cluster centers, $\|x_2 - \mathbf{Z}_1(1)\| = \left\| \begin{pmatrix} 1 \\ 0 \end{pmatrix} - \begin{pmatrix} 0 \\ 0 \end{pmatrix} \right\| = 1$ and $\|x_2 - \mathbf{Z}_2(1)\| = \left\| \begin{pmatrix} 1 \\ 0 \end{pmatrix} - \begin{pmatrix} 1 \\ 0 \end{pmatrix} \right\| = 0$. As $\|x_2 - \mathbf{Z}_2(1)\| < \|x_2 - \mathbf{Z}_1(1)\|$, $x_2 \in \mathbf{Z}_2(1)$. Similarly, all the sample distances are calculated and divided into two clusters: $\mathbf{G}_1(1) = (x_1, x_3)$ and $\mathbf{G}_2(1) = (x_2, x_4, x_5, \dots, x_{20})$.
- (3) Establish the new cluster center according to the two new clusters, $\mathbf{Z}_1(2) = 1/N_1 \sum_{x_i \in \mathbf{G}_1(1)} x_i = 1/2(x_1 + x_3) = (0, 0.5)^T$ and $\mathbf{Z}_2(2) = 1/N_2 \sum_{x_i \in \mathbf{G}_2(1)} x_i = 1/18(x_2 + x_4 + x_5 + \dots + x_{20}) = (5.67, 5.33)^T$, shown in Figure 14(b).
- (4) If the former cluster centers and the latter ones are not the same, go to step (2) and update the cluster centers until the former and the latter ones are consistent, as shown in Figure 14(c).

Set $k=4$; that is, after mixing the four types of training data, four standard clustering centers are obtained through the calculation of the *K*-means clustering analysis model. Based on the principle of similar selection, the mixed signals will be clustered into four categories. If the four clusters have no overlap or a small proportion of overlap, it is considered

TABLE 2: The value range of 1–6# indexes under different damage conditions.

Index	Structural damage		Pseudosoldering		Debonding		Wear		Breakage	
	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
1#	0.9932	0.9995	0.8136	0.9736	0.8235	0.9781	0.6734	0.9811	0.1285	0.8358
2#	0	3.7215	2.4810	15.3431	7.6785	32.2560	7.4435	35.9775	119.0978	270.4510
3#	0.0001	0.0003	−0.0106	−0.0064	−0.0027	0.0017	−0.0063	−0.0024	−0.0033	0.0080
4#	0.0010	0.0102	0.0212	0.0341	0.0504	0.1385	0.2472	0.6802	0.0726	6.2370
5#	−0.0778	0.0850	−0.0065	0.0512	−0.0016	0.0385	−0.0332	−0.0118	−0.0089	0.0590
6#	0.0018	0.0360	0.3824	0.8599	0.0366	0.0792	0.1017	0.4664	0.1402	0.7484

FIGURE 13: The effect of different damages differentiation (a) before and (b) after PCA.

TABLE 3: Sample characteristics.

Sample	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}	x_{17}	x_{18}	x_{19}	x_{20}
Characteristic 1#	0	1	0	1	2	1	2	3	6	7	8	6	7	8	9	7	8	9	8	9
Characteristic 2#	0	0	1	1	1	2	2	2	6	6	6	7	7	7	7	8	8	8	9	9

to achieve good damage identification and classification. Structural damage data (a 180×3 matrix) and PZT faults data (a 45×3 matrix) where column represents the three PCs were mixed and then input to the K -means clustering analysis model. The classification effect of the clusters is shown in Figure 15.

As can be seen from Figure 15 and Table 4, all 180 groups of data in structural damage are divided into cluster 1# and the center of cluster 1# is $(-0.4848, -0.0363, -0.0256)$. 15 groups of pseudosoldering samples, 15 groups of debonding samples, and 15 groups of wear samples are divided into clusters 2–4# and the cluster centers are $(-0.1243, 0.4620, -0.0326)$, $(-0.4055, -0.0220, 0.0340)$, and $(-0.0746, -0.0008, 0.3108)$, respectively. The accuracy of the classification is 100%. The result shows that the K -means clustering model can be used to identify the damage cases and have a good distinguish performance on the structural damage, pseudosoldering, debonding, and wear which proves the feasibility of the algorithm in identifying the unknown damage.

5. Identification of Damage Degrees Using ANN

After obtaining the information of damage types, it is often necessary to further master the degree of damage. Specifically, damage degree identification is a pattern recognition problem. In the field of pattern recognition, a very successful method is ANN, which is a mathematical model that simulates the behavior characteristics of animal neural networks and carries out distributed parallel information processing [40, 41]. In this section, damage data are processed by ANN to directly identify the degree of damage. The model of ANN composed of the input layer, hidden layer, and output layer is shown in Figure 16.

The hyperbolic tangent function $\tanh(x) = (e^x - e^{-x}) / (e^x + e^{-x})$ is used as the activation function for the hidden layer and the softmax function; that is, $\text{softmax}(x) = e^x / \sum(e^x)$ serves as the activation function for the output layer [42]. The three PCs of the same damage case in different degrees were taken as a set of input

FIGURE 14: Schematic diagram of K-means algorithm: (a) set the initial cluster center; (b) establish a new cluster center; (c) determine the clustering results.

FIGURE 15: Effect of K-means cluster analysis.

TABLE 4: The corresponding relationship between clustering results and different kinds of damage.

Damage types	Cluster 1#	Cluster 2#	Cluster 3#	Cluster 4#
Structural damage	180	0	0	0
Pseudosoldering	0	15	0	0
Debonding	0	0	15	0
Wear	0	0	0	15

FIGURE 16: ANN model for sensor damage degrees identification.

FIGURE 17: Classification effect of ANN model: (a) confusion matrix of pseudosoldering; (b) confusion matrix of debonding; (c) confusion matrix of wear; (d) confusion matrix of breakage.

data. For PZT faults, the output of the ANN model consists of three damage degrees, which are set as (1, 0, 0), (0, 1, 0), and (0, 0, 1) from mild level to severe level. Considering the quality of the training model and computational efficiency, it is found that a hidden layer training model with 20 nodes has

a good recognition effect. To train the ANN model, the proportion of the training set, validation set, and testing set is 70%, 15%, and 15%. That is to say, the training set contains 11 groups of data; the test set and the training set each contain 2 groups of data. Set the output class as the vertical

axis and the target class as the horizontal axis; the confusion matrixes of four PZT faults are shown in Figure 17.

After 25, 27, 20, and 23 iterations, the error calculated by the cross entropy reaches $4.09e-7$, $2.78e-7$, $1.86e-7$, and $2.03e-7$. The observation from Figure 17 shows that all damage degrees of four PZT faults are accurately classified. We can conclude that the extracted PCs not only have a good effect to identify different damages but also contain the degree information of the same damage case. The PCA method is of great significance in the signal processing of electrical admittance. In the model training, the accurate classification is achieved by only using few data which indicates the strong practical application ability of the method. By building a large database of different damage cases in various degrees in advance, the scope of damage degree identification will be further expanded and the efficiency and accuracy will also be greatly improved.

6. Summary and Conclusions

In the actual environment, the accurate recognition of PZT fault is the key to improve the ability of long-term SHM based on the electromechanical impedance method. This paper proposes a PZT self-diagnosis method based on K -means clustering analysis and ANN given in the existing study cannot achieve the intelligent identification and evaluation of the cases and degrees of sensor faults. By clustering the admittance spectrum characteristics under different damages, the PZT fault can be distinguished from structural damage, and the damage types of PZT can be classified and identified. Then we used the ANN trained model to realize the accurate evaluation of the damage degree. The specific conclusions are as follows:

- (1) Combined with the characteristics of conductance and susceptance, six damage indexes are used to extract the signal feature under different damage conditions. By comparing the index indication interval of the five damage cases, it is found that the PZT breakage can be determined by the large shift of the conductance peak frequency. In addition, three indexes with good damage indication effect were screened out, including the average change of conductance peak, the RMSD of susceptance, and the RMSD of conductance.
- (2) K -means cluster analysis is used to classify the damage types. After normalizing the selected indexes, the PCA method is used to get three PCs with higher discrimination for different damages, and the damage information represented by the PCs is used as the input parameters of the K -means cluster model. The results show that the same kind of damage is correctly divided into the same cluster which realizes the intelligent classification of damage cases.
- (3) The ANN is used to solve the problem of damage degree identification. Three PCs under various damages are used as input data of neural network and the output corresponds to three different

damage degrees. With the trained model, the accuracies of four PZT faults all reach 100% which proves the feasibility of ANN in identifying the degree of sensor damage. By establishing a large database of sensor damage degrees, the recognition range and accuracy will be further improved.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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