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Fault Status Information Monitoring Technology for Large Complex Electromechanical System

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Abstract

In order to improve the accuracy of fault state monitoring of electromechanical system, a fault state informatization monitoring technology for large complex electromechanical system is proposed. Based on the standard PD (Partial Discharge) signal expression derived from the traditional communication theory, the characteristic value of the fault signal is calculated, and the feature of the fault state signal is extracted by using the functions of the time and frequency of the fault state of the electromechanical system. Experimental results show that compared with the information monitoring technology based on support vector machine, the proposed fault monitoring technology has a higher monitoring accuracy.

Keywords: complex electromechanical; system fault state; informatization; monitoring technology;

1. Introduction

Large-scale complex electromechanical systems in modern engineering are gradually developing towards the direction of complicated structure, intelligent operation and process automation. Such electromechanical features make not only the components within each single device very closely interconnected, but also the different devices are very closely interconnected, and through such close structural and functional interconnections, a complete device operating system is constructed [1]. Due to the high load capacity, high transmission accuracy and the relevant characteristics of constant power transmission of large complex electromechanical systems, large complex electromechanical systems, as an indispensable component of electromechanical equipment, are widely used in modern equipment such as aviation, agricultural electromechanical equipment, factories, mines, military equipment, power systems, and metallurgical electromechanical equipment, etc. [2, 3].

If the mechanical and electrical system of a moving car breaks down, it will directly affect the life and safety of the people inside the car; for some machinery and equipment that are in a state of continuous operation for a long time, such as generating units in the electric power industry, and machine power for ore collection and transportation in the mining industry, the whole production process will be stopped due to the mechanical and electrical failure, which will cause incalculable economic losses [4]. For example, in 1988, the main axle of the power plant in Qinling Mountain area was broken, and the national economy suffered a loss of over 100 million yuan, and affected the local normal electricity use, and affected people's normal life. Our country once used a scientific survey ship to go to sea for scientific research. After a period of navigation, due to a partial breakage of the main retarder, the research ship had to slow down and move forward. As a result, the whole fleet did not arrive at the designated scientific survey area on schedule, and the scientific survey action was seriously affected [5]. In 1986, a generator unit at the Chernobyl nuclear power plant in the former Soviet Union was vibrating because of a serious mechanical and electrical failure, which led to nuclear leakage, more than 2,000 deaths, and economic losses of $3 billion. The consequences of the accident, which caused severe environmental pollution and threatened the safety of human life, were incalculable [6].

As early as one hundred years ago, people began to study the fault and fault information state of large complex electromechanical systems. However, the fault state monitoring technology for large complex electromechanical systems has become a scientific component of the equipment fault monitoring technology, which can arouse people's great attention. In 1986, the British scholar H. Optiz published some research curves of great significance in the fault monitoring of large complex electromechanical systems, and discussed that the vibration and noise generated by electromechanical systems are functions of power and error generated by electromechanical transmission [7]. There are two kinds of methods to monitor the faults of electromechanical system: one is to process the dynamic data of vibration and noise by signal processing method, the other is to detect the faults of electromechanical system by analyzing and processing the lubricating oil used in the process of working. At present, the vibration signal is widely used in electromechanical system fault monitoring, and the technology is mature, but the vibration fault

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monitoring method has its own shortcomings. In addition, among the existing fault monitoring methods, there are many cases of using acoustic emission technology to realize fault monitoring, but the scientific research applied to the fault monitoring of electromechanical systems is not very extensive. However, due to the characteristics of high sampling accuracy and fast collection speed, the application of acoustic emission signals to the fault monitoring of electromechanical systems still has high scientific research value [8-10].

To sum up, it can be found that the fault monitoring technology of electromechanical system has a long history at home and abroad, and in some areas of electromechanical fault monitoring and technology is relatively mature [11, 12]. But from the technical level, it can be seen that the current fault monitoring technology of electromechanical system is mainly used to collect and analyze signals by means of vibration, but because vibration signals in the operation of large electromechanical equipment will produce a lot of noise, it is easy to submerge useful vibration signals in noise. Another point is that vibration sensors pick up mechanical and electrical systems only when they are in deep trouble, making them difficult to detect in the early stages of a failure [13]. With the development of science and technology, AE signal acquisition system has been developed. Because AE signal has the characteristics of high acquisition precision and high signal frequency, it is easy to collect the fault information in the early stage of signal occurrence, and because of the high frequency of AE signal, it is easy to shield the noise information generated by electromechanical equipment. So, it is found that the use of AE signal to achieve fault monitoring of electromechanical system has a little scientific research value by reference to the summarized literature. Based on the above background, the research on fault monitoring of electromechanical system can realize the fundamental transformation of electromechanical system from accident maintenance, regular maintenance to real-time maintenance according to the operation of electromechanical system, and can reduce some unnecessary economic losses, thus produce greater economic benefits and social benefits. Therefore, fault monitoring of electromechanical system is of great significance in people’s real life.

2. Design of Fault State Information Monitoring Technology for Large Complex Electromechanical System

2.1. Extracting fault state signal characteristics of electromechanical systems

The traditional fault monitoring method based on discharge current pulse is based on the IEC60270 standard. The frequency band is limited to 10-200 kHz. The measurement is the total amount of local discharge. Finally, the spectrum of Yi-Q-N (discharge phase - discharge quantity - discharge times) is drawn to identify the discharge types. This method is insufficient to obtain sufficient local discharge and noise in the information area and different types of local discharge, and the anti-noise ability is weak [14].

PD Check converts the actual time of the PD signal into the equivalent time, so that the length of the signal can be linked to other information about the signal. Formula (1) is a standardized PD signal expression based on the traditional communication theory.

$$\tilde{s}(t) = \frac{s(t)}{\sqrt{\int_0^T s(t)^2 \, dt}} \tag{1}$$

In the formula, $s(t)$ represents the transformation of PD signal standardization (t is time), calculates the signal characteristics, and obtains the function of time and frequency:

$$\sigma_T = \sqrt{\int_0^T (t-t_0)^2 \, \tilde{s}(t)^2 \, dt} \tag{2}$$

$$\sigma_F = \sqrt{\int_0^\infty f^2 \left|\tilde{s}(f)\right|^2 df} \tag{3}$$

Formula (2) and (3) are the standard deviation of $s(t)$ in formula (1) in time domain and frequency domain. $S(f)$ is the Fourier transform of $s(t)$, t_0 is the time center of the standard signal, and t_0 expression is:

$$t_0 = \int_0^T t\tilde{s}(t)^2 \, dt \tag{4}$$

The feature of a PD signal is transformed into some digital quantities, which preserve the time and frequency information of the signal. The signals generated by the same PD source are very similar, usually the collected data contains more than one signal source, and the stronger noise signal will cover the internal PD signal. In order to separate and record the source of the signal and eliminate the interference, the fuzzy logic method is applied to obtain the classification of PD pulse [15]. Different types of signals can be separated according to the characteristics of different types of impulses, which plays a vital role in the noise separation and type analysis. Then, the noise interference of fault signal is eliminated, which provides the basis for fault monitoring of electromechanical system.

2.2. Eliminating noise interference of fault signal

Through calculation and classification, the fault signals with different characteristics can be divided into different parts. This step is to remove the noise signals from different parts of the signals. For the general fault state noise signals, due to the randomness of the fault state signals, their phases are not necessarily related to the phases of the applied voltage, which is very obvious in the local spectrograph, that is, the points representing these noise pulses are scattered over all time periods without any rules, and we can easily eliminate the fault state noise signals after classification [16]. Another kind of fault state noise signal is fixed in one or several phases, they have relatively fixed phase angle, such as AC/DC rectifier. This recurrence of the periodic appearance in the same phase of the signal spectrum can also be obtained through the Fourier transform. Choose different parts, observe the discharge spectrum, we can find out the noise signal.

The aim of fault state signal type recognition is to find out the PD signal's PD source accurately and judge its harm. In principle, the more samples collected, the more accurate the analysis. However, due to a variety of noises and local sources that consistently emit fault state signals, too many signals can lead to overlap, making it difficult to separate fault state signals [17]. Therefore, the number of fault state signal acquisition can only be guaranteed to extract a complete fault state signal characteristics.

When the fault state signals are separated, the PD signals can be statistically calculated to obtain the standard parameters and the distributed parameters of the PD pulses, which can help identify the types of fault state signals [18-20].

The PDCheck system is equipped with a powerful expert identification system, in which a huge database of fault state characteristics is included. For each discharge pulse waveform analysis software, dozens of fault state characteristics are extracted according to certain steps, and then the fault state characteristics are compared with the fault state in the expert database. The fuzzy logic method is used to determine the similarity between the tested fault state type and the known fault state type, so as to reach the corresponding judgment conclusion [21]. The recognition of a signal can be divided into two levels, the first level is to judge the type of PD, which is mainly divided into internal failure state, surface failure state and corona failure state. This step is judged by the analysis of the random characteristics of the fault state signals [22]. Among the parameters that represent the signal characteristics, only the very appropriate and accurate signal characteristics can be defined as the characteristic database of the fault state signals.

2.3. Monitoring the failure state of electromechanical systems

The KELM (Kernel Extreme Learning Machine) theory is used to monitor the fault state of electromechanical system. When the KELM algorithm is used to monitor the collected health state data of electromechanical system, the test results are not stable because of the unstable performance caused by the random initialization weight. Differential evolution algorithms can be used to solve optimal input weights, but because iterative evolution takes a lot of time, there is no guarantee that the optimal network structure will be obtained [23]. In order to make the performance of the KELM algorithm more stable, the concept of kernel function is introduced according to the SVM (Support Vector Machine), and the nonlinear kernel mapping is introduced into the KELM algorithm.

Many engineering practices show that it is feasible to combine kernel functions with KELM, which improves the stability of KELM algorithm and has better nonlinear approximation ability [24]. The kernel functions commonly used in SVM are linear kernel function and polynomial kernel function. These can be applied to KELM as a kernel function.

Given any N different samples (x_i, t_i), the specific fault monitoring process is as follows:

1. Step 1: Get fault characteristic samples of electromechanical systems in different health states, and normalize the samples;
2. Step 2: Train KELM. The normalized characteristic data of electromechanical system is composed of training samples (x_i, t_i) and $i = 1, 2, \cdots, N$, and the kernel function is selected to obtain the optimal classification function:

$$f(x) = \begin{bmatrix} K(x_1, t_1) \\ K(x_2, t_2) \\ \vdots \\ K(x_N, t_N) \end{bmatrix}^T \left(\frac{I}{C} + \Omega_{ELM} \right)^{-1} \quad (5)$$

In the equation, $K(\cdot)$ represents the kernel function, I represents the fault current, C represents the fault normalized characteristic parameter, Ω_{ELM} represents the fault information entropy.

3. Step 3: Fault monitoring of mechanical and electrical systems with a constructed KELM fault monitoring model.

To sum up, according to the standardized PD signal expression derived from the traditional communication theory, the characteristic value of the fault signal is calculated, and the feature extraction of the fault state signal of the electromechanical system is completed by using the functions of the time and frequency of the fault state of the electromechanical system; on the basis of eliminating the noise interference of the fault signal, the fault state monitoring of the electromechanical system is realized through the fault monitoring algorithm design.

3. Comparative analysis of experiments

3.1. Experimental Research on Fault State Information Monitoring Technology of Electromechanical System Based on SVM

3.1.1. Sample selection

Aiming at the research object of large-scale complex electromechanical system, 590 sets of experimental data are used as training test data in the four states A_1, A_2, A_3 and A_4 of large-scale complex electromechanical system, of which 400 sets are selected as normal state A_1, A_2 50 groups of data are selected as training data for each of the three fault states A_3 and A_4, and 10 groups of data are selected as test data for each state. So, we get 550 sets of training data and 40 sets of test data.

3.1.2. Selecting kernel functions and classifiers

Compared with other kernel functions of SVM, such as linear kernel function, RBF can deal with the samples with nonlinear characteristics, and RBF needs fewer parameters than polynomial kernel function.

In addition, in the selection of classifiers, the first problem to be solved by SVM is the problem of two classifications. As we know, there are four fault modes of electromechanical system, which belong to the problem of multiple classifications.

3.1.3. Fault monitoring training and result analysis

After analysis, seven parameters are selected to represent the running state of the engine, including low-pressure rotor speed (N_1), high-pressure rotor speed (N_2), exhaust temperature after turbine (T_4), engine inlet temperature (T_2), gearbox vibration (B_1), engine inlet pressure (P_2), compressor outlet pressure (P_3), as the characteristic parameters of the mechanical and electrical system. The mechanical and electrical system failure modes are expressed as a set of four, i.e. $\{A_1, A_2, A_3, A_4\}$, in which mode A_1 refers to the operation of mechanical and electrical system in normal state; mode A_2 refers to the bearing damage failure of mechanical and electrical system;

mode A_3 refers to the regulator failure of mechanical and electrical system; mode A_4 refers to the failure of exhaust temperature and speed exceeding the limit value when the throttle lever is pushed from idle state to intermediate state.

Four failure modes $\{A_1, A_2, A_3, A_4\}$ of electromechanical system are classified and trained, in which normal state A_1 sample is represented by 1; A_2 failure is represented by 2; A_3 failure is represented by 3; A_4 failure is represented by 4. After the monitoring test, the monitoring results as shown in Figure 1 are obtained.

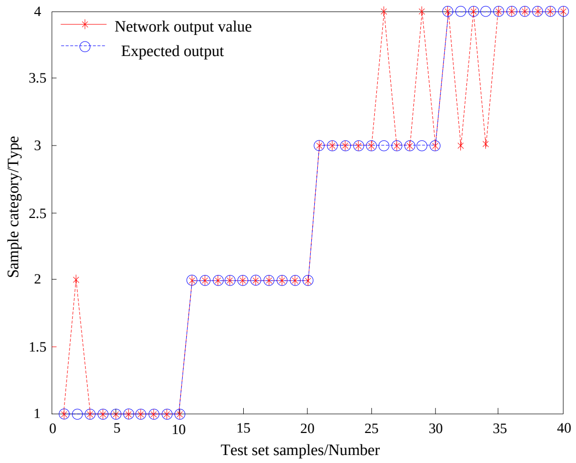

Figure 1. Support vector machine monitoring test results

From the test results of Figure 1, we can get the specific test results of 40 sets of test data in 4 states of electromechanical system, as shown in Table 1.

Table 1. Test results of four failure modes

Failure mode	Number of test samples	Number of correct monitoring	Correct monitoring rate
A_1 fault	10	9	90%
A_2 fault	10	10	100%
A_3 fault	10	8	80%
A_4 fault	10	8	80%

To sum up, the general process of fault monitoring is as follows: use SVM fault monitoring model to train 550 groups of data, then use 40 groups of data to test and monitor the trained SVM fault monitoring model, and finally correctly monitor 35 groups of data, including 1 group of A_1 status data misdiagnosed as A_2 fault, 2 groups of A_3 fault status data misdiagnosed as D fault, 2 groups of C fault status data misdiagnosed as A_4 fault The data of group A_4 is misdiagnosed as failure A_3, so it can be concluded that the final failure monitoring rate is 87.5% by testing and monitoring 40 groups of test data.

3.2. Test and Research on information monitoring technology of mechanical and electrical system fault state

Aiming at the research object of electromechanical system, 590 sets of experimental data are used as training test data under the four states of electromechanical system A_1, A_2, A_3, A_4, of which 400 sets are selected as normal state A_1, A_2 50 groups of data are selected as training data for each of the three fault states A_3 and A_4, and 10 groups of data are selected as test data for each state. So, we get 550 sets of training data and 40 sets of test data.40 groups of samples are used to test the fault monitoring model trained by the limit learning machine. Table 2 shows the output results of ELM (Extreme Learning Machine) monitor.

Table 2. Description of ELM monitor output results

Monitor output				health status
A_1 Failure mode status	A_2 Failure mode status	A_3 Failure mode status	A_4 Failure mode status	
0	0	0	1	Healthy
0	0	1	0	A_2 fault
0	1	0	0	A_3 fault
1	0	0	0	A_4 fault

In this paper, the fault monitoring of electromechanical system based on ELM is carried out on the platform of MATLAB. Because the selected characteristic parameters of electromechanical system are 7, the number of input neurons should be set to 7; the fault mode of electromechanical system is 4, that is, the number of output neurons is set to 4, and the Sigmoid function is selected as the activation function. In addition, the connection weights between input layer and hidden layer and the offset b of neurons in hidden layer are initialized randomly, and the number of neurons in hidden layer is 75. The identification results of Limit Learning Machine fault monitoring are shown in Figures 2 to 5.

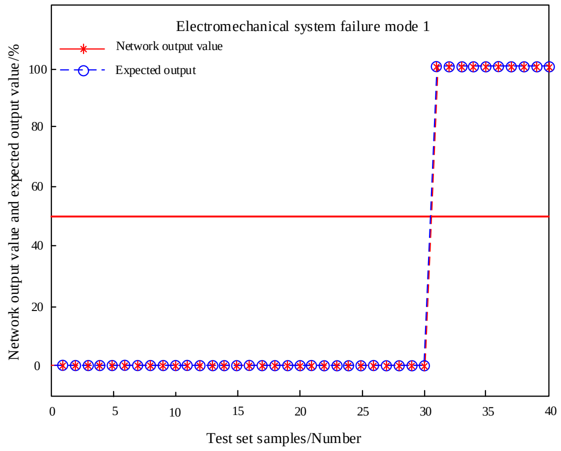

Figure 2. Output result of mode 1

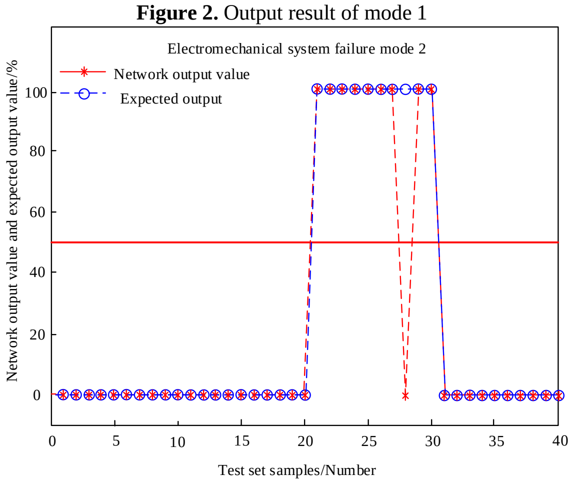

Figure 3. Output result of mode 2

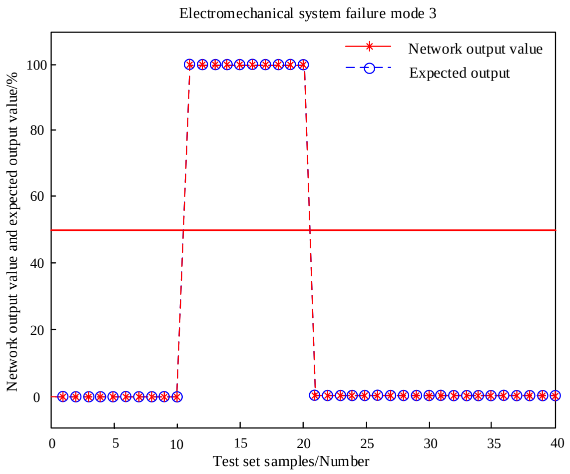

Figure 4. Output result of mode 3

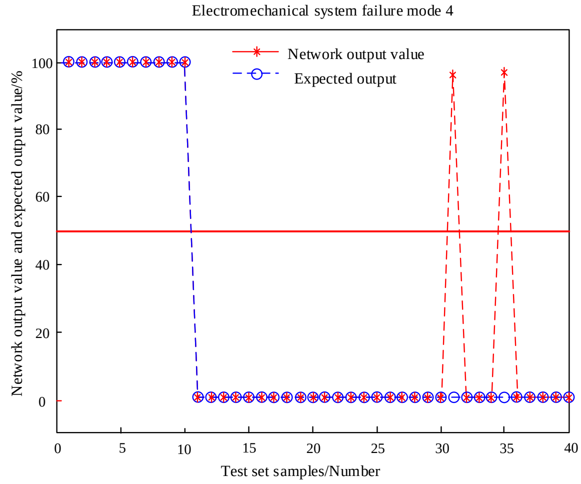

Figure 5. Output result of mode 4

It can be seen from Fig. 2 to Fig. 5 that by using the trained elm model to monitor each fault type with 10 groups of test data respectively, according to the principle that the previously set test output results are changed into binary codes, comparison and sorting are carried out, and the monitoring results of four types of large-scale complex electromechanical systems A_1, A_2, A_3, A_4 can be obtained respectively in Table 3 to Table 6.

Table 3. Monitoring results of mechanical and electrical system A_1 status

	Actual output value				Expected output			
1	0.41537	0.00005	0.00000	0.58458	0	0	0	1
2	0.40981	0.00004	0.00000	0.59015	0	0	0	1
3	0.39747	0.00003	0.00000	0.60250	0	0	0	1
4	0.37752	0.00002	0.00000	0.62246	0	0	0	1
5	0.35416	0.00001	0.00000	0.64583	0	0	0	1
6	0.34794	0.00001	0.00000	0.65205	0	0	0	1
7	0.35293	0.00001	0.00000	0.64706	0	0	0	1
8	0.35829	0.00001	0.00000	0.64169	0	0	0	1
9	0.36357	0.00001	0.00000	0.63641	0	0	0	1
10	0.36830	0.00001	0.00000	0.63168	0	0	0	1

It can be seen from Table 3 that the actual output value and expected output value of the test are compared with the output specified in the original training. The number of correct data groups monitored by these 10 groups of test data is 10, and the number of data groups monitored by the wrong fault type is 0. Therefore, the monitoring rate of A_1 state of electromechanical system is 100%.

Table 4. Monitoring results of mechanical and electrical system A_2 status

	Actual output value				Expected output			
1	0.00000	0.00000	1.00000	0.00000	0	0	1	0
2	0.00000	0.00000	1.00000	0.00000	0	0	1	0
3	0.00000	0.00000	1.00000	0.00000	0	0	1	0
4	0.00000	0.00000	1.00000	0.00000	0	0	1	0
5	0.00000	0.00000	1.00000	0.00000	0	0	1	0
6	0.00000	0.00000	1.00000	0.00000	0	0	1	0
7	0.00000	0.00000	1.00000	0.00000	0	0	1	0
8	6.4900000000000e-321	1.0436945140000e-314	1.00000	0.00000	0	0	1	0
9	0.00000	0.00000	1.00000	0.00000	0	0	1	0
10	0.00000	0.00000	1.00000	0.00000	0	0	1	0

It can be seen from Table 4 that the actual output value and expected output value of the test are compared with the output specified in the original training. The number of correct data groups monitored by these 10 groups of test data is 10, so the monitoring rate of A_2 state of electromechanical system is 100%.

Table 5. Monitoring results of mechanical and electrical system A_3 status

	Actual output value				Expected output			
1	0.00202	0.77226	0.00000	0.22571	0	1	0	0
2	0.00588	0.72855	0.00000	0.26557	0	1	0	0
3	0.00000	0.98448	0.00000	0.01552	0	1	0	0
4	0.00000	0.84964	0.00000	0.15035	0	1	0	0
5	0.00003	0.84336	0.00000	0.15661	0	1	0	0
6	0.00019	0.85666	0.00000	0.14315	0	1	0	0
7	0.00001	0.95109	0.00000	0.04890	0	1	0	0
8	0.01001	0.49985	0.00000	0.49013	0	1	0	0
9	0.00008	0.95084	0.00000	0.04908	0	1	0	0
10	0.00083	0.61570	0.00000	0.38347	0	1	0	0

It can be seen from Table 5 that the actual output value and expected output value of the test are compared with the output specified in the original training. The number of correct data groups monitored by these 10 groups of test data is 9, and the number of data groups monitored by the wrong fault type is 1. Therefore, the monitoring rate of A_3 state of electromechanical system is 90%.

Table 6. Monitoring results of mechanical and electrical system A_4 status

	Actual output value				Expected output			
1	0.48547	0.00303	0.00000	0.51150	0	0	0	1
2	0.50065	0.00330	0.00000	0.49606	1	0	0	0
3	0.53875	0.00115	0.00000	0.46010	1	0	0	0
4	0.52609	0.00223	0.00000	0.47168	1	0	0	0
5	0.47410	0.00195	0.00000	0.52395	0	0	0	1
6	0.54764	0.00134	0.00000	0.45102	1	0	0	0
7	0.50009	0.00160	0.00000	0.49831	1	0	0	0
8	0.55583	0.00195	0.00000	0.44222	1	0	0	0
9	0.50777	0.00140	0.00000	0.49083	1	0	0	0
10	0.53284	0.00216	0.00000	0.46500	1	0	0	0

It can be seen from Table 6 that the actual output value and expected output value of the test are compared with the output specified in the original training. The number of correct data groups monitored by these 10 groups of test data is 8, and the number of data groups monitored by the wrong fault type is 2. Therefore, the monitoring rate of A_4 state of electromechanical system is 80%.

To sum up, the ELM fault monitoring model is used to train 550 sets of data, and 40 sets of data are used to test and monitor the trained ELM fault monitoring model. The final result is that 37 sets of data are correctly monitored, and 3 sets of data are monitored incorrectly.

3.3. Comparison and analysis of effects of different fault monitoring technologies

The selection and comparison methods are based on the support vector machine monitoring technology. The 550 groups of data under the above-mentioned four failure states of the mechanical and electrical system are used for training, and 40 groups of data are used to test the monitoring technology based on the support vector machine. The results are as shown in Table 7.

Table 7. Monitoring results of different states of electromechanical system based on support vector machine method

Failure mode		Actual output value				Expected output			
A_1	1	0.56734	0.00001	0	0.64972	0	0	0	1
	2	0.69734	0.00002	0	0.59346	0	0	0	1
	3	0.56701	0.00003	0	0.66795	0	0	0	1
	4	0.36974	0.00003	0	0.63697	0	0	0	1
	5	0.34219	0.00001	0	0.65647	0	0	0	1
	6	0.32577	0.00001	0	0.62367	0	0	0	1
	7	0.34524	0.00002	0	0.66379	0	0	0	1
	8	0.32472	0.00003	0	0.65937	0	0	0	1
	9	0.35274	0.00001	0	0.79416	0	0	0	1
	10	0.35277	0.00001	0	0.69734	0	0	0	1
A_2	1	0	0	1	0	0	0	1	0
	2	0	0	1	0	0	0	1	0
	3	0	0	1	0	0	0	1	0
	4	1	0	0	0	0	0	1	0
	5	0	0	1	0	0	0	1	0
	6	0	0	1	0	0	0	1	0
	7	0	0	1	0	0	0	1	0
	8	1.34697	1.9465	1	0	0	0	1	0
	9	0	0	1	0	0	0	1	0
	10	0	0	1	0	0	0	1	0
A_3	1	0.04527	0.45277	0	0.25427	0	1	0	0
	2	0.00452	0.75277	0	0.27527	0	1	0	0
	3	0	0.9272	0	0.01752	0	1	0	0
	4	0	0.72752	0	0.72772	0	1	0	0
	5	0	0.452	0	0.7527	0	1	0	0
	6	0.00012	0.84527	0	0.14224	0	1	0	0
	7	1	1	0	0.04527	0	1	0	0
	8	0.01042	0.54277	0	0.40204	0	1	0	0
	9	0.0004	0.9204	0	0.02752	0	1	0	0
	10	1	0.2044	0	0.34527	0	1	0	0
A_4	1	0.25752	0.0427	0	0.5115	0	0	0	1
	2	0.45427	0.0033	0	0.49606	1	0	0	0
	3	0.54277	0.02425	0	0.4601	1	0	0	0
	4	0.54275	0.04205	0	0.47168	1	0	0	0
	5	1.357	0	0	0.57257	0	0	0	1
	6	0.42752	0.00134	0	0.45102	1	0	0	0
	7	0.500427	0.04074	0	0.49831	1	0	0	0
	8	0.57257	0.04024	0	0.44222	1	0	0	0
	9	0.51527	0.0014	0	0.49083	1	0	0	0
	10	0.5727	0.042	0	0.465	1	0	0	0

Based on the analysis of the above data, the number of monitoring errors in A_1 fault state is 2, the number of monitoring errors in A_2 fault states is 1, the number of monitoring errors in A_3 fault states is 1, and the number of monitoring errors in A_4 fault states is 1. The results of the two methods are summarized and compared as shown in Table 8.

Table 8. Comparison of results of different monitoring techniques

Monitoring technology	Total number of test samples	Correctly identify the number of samples	Number of error identification samples	Correct recogniti on rate
Monitoring technology based on SVM	40	35	5	87.5%
Proposed monitoring technology	40	37	3	92.5%

From Table 8, we can see that the proposed monitoring technology is the best, the correct recognition rate is 92.5%, while the correct recognition rate of the monitoring technology based on SVM is 87.5%. Therefore, the proposed monitoring technology has a higher monitoring accuracy.

4. Conclusions

Large complex electromechanical system is a device with complex structure in electromechanical equipment. In addition, large complex electromechanical system plays the role of transmitting power in the operation of equipment, so it carries more forces. In addition, the general large complex electromechanical system is running in the environment of poor external conditions, so it is also a component prone to failure. Once a large complex electromechanical system failure will cause the most direct impact on the reliability of the entire operation of electromechanical equipment and will lead to reduced efficiency and precision. With the development of large scale, complicated and automatic, the failure of large complex electromechanical system will make the industrial production and even the whole society run normally. Based on the feature of fault state signal, the noise interference of fault signal is eliminated, and the fault state monitoring flow is combined to realize the fault state monitoring of electromechanical system. The results show that the proposed fault monitoring technology in different modes of fault monitoring, the accuracy of fault monitoring reaches 92.5%, far higher than the failure rate of other methods, indicating that the design method can effectively improve the accuracy of fault monitoring. Although this paper has basically achieved the expected goal of graduation design, but because of the limited number of test samples, the results and conclusions can only be used as a technical guidance in practical application.

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