Fault Diagnosis of Pneumatic Actuator Based on Virtual Prototype Fault Simulation

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Aiming at the difficult problem of obtaining typical fault samples of pneumatic actuators in engineering practice and basing on the working principles of pneumatic diaphragm actuator, a model of pneumatic diaphragm actuator system was established by using DAMADICS. Then we simulated its common and typical faults and obtained a lot of samples. In this research, using KPCA to reduce the date dimension that obtained by the established system. We use the method of fault detection and diagnosis based on artificial immune algorithm to pneumatic diaphragm actuator's fault diagnosis. The experimental results indicate that the fault detection method based on artificial immune algorithm performs well.

Keywords: Virtual prototype; Pneumatic diaphragm actuator; Fault diagnosis; Artificial immune algorithm
Target audience: *Pneumatic Transmission, Fault Diagnosis, Fault Simulation*

1 Introduction

As the process control systems are becoming larger and more complex, its work environment is usually in high temperature and pressure, low temperature vacuum or flammable and explosive extreme conditions. If there is a fault in such a system, it will cause significant security incidents and serious environmental pollution. The actuator (also called the regulating valve) is the terminal execution device that executes the automatic control command in the process control system. Its performance is directly related to the fact that whether automatic control system can run smoothly and safely or not. Pneumatic diaphragm actuator, for example, once fault in operation is likely to cause major security incidents such as stopping production or a leakage of toxic substances. With the extensive application of pneumatic actuators, the fault diagnosis problem will become more and more prominent. So this research has a wide range of practical prospects.

In the engineering practice, the typical fault samples of the pneumatic actuators are difficult to obtain. Not only because the research on fault diagnosis of the pneumatic actuators often requires a lot of manpower and material resources, but the fault simulation method is limited. Therefore the research cannot be carried out. Establishing a virtual prototype to simulate the operating state of the real pneumatic actuator system. It can overcome the problems that fault samples are difficult to be obtained in practical engineering and the typical fault of the actuator is difficult to be simulated. This has higher application value.

2 The Establishment Principle of Virtual Prototype of Pneumatic Actuator

Pneumatic actuator systems are essentially non-linear systems. It is difficult to establish accurate mathematical models of pneumatic actuators due to the facts that gas inherent compressibility, low damping characteristics of pneumatic systems, non-linearity of valve port flow and some time-varying factors. Traditional modeling method cannot simulate typical faults of pneumatic actuators. As shown in Figure 1, the pneumatic actuator system consists of pneumatic actuators, regulating valves and valve positioner.

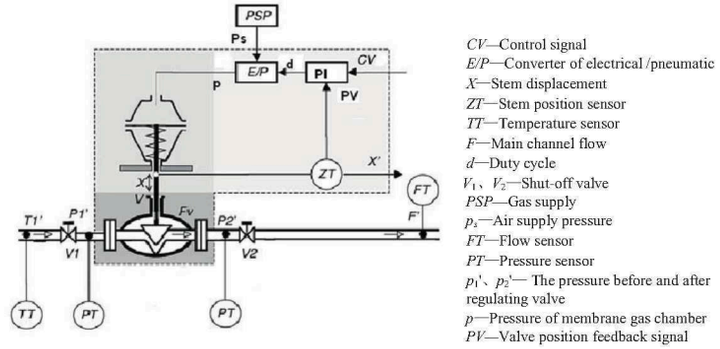


Figure 1. Composition of the pneumatic actuator system

In order to simulate the conditions of pneumatic actuator system in normal and under the faults and obtain the experimental data, the virtual prototype model of pneumatic actuators is built by using DAMADICS simulation platform under the environment of MATLAB/Simulink.

The simulation platform of DAMADICS is an actuator model library based on MATLAB / Simulink, which is developed by European Training Foundation (ETF). The model can effectively simulate the operation process as well as the input and output data of the pneumatic actuator. Each module has an interface of fault input. By connecting to the fault generation module, 19 typical faults of pneumatic actuator can be simulated that listed in Table 1.

Table 1. Typical faults of pneumatic actuator

NO.	Failure mode	Fault type	NO.	Failure mode	Fault type
1	Valve body obstruction	Jump failure	11	Spring failure	Jump failure
2	Core or seat deposits	Gradual failure	12	Electric/Pneumatic converter failure	Jump failure
3	Core or seat corrosion	Gradual failure	13	Position feedback signal sensor failure	Slow drift fault
4	The friction increases of the valve or bushing	Gradual failure	14	Pressure signal sensor failure	Jump failure
5	External leakage	Gradual failure	15	Locator spring failure	Jump failure
6	Internal leakage	Gradual failure	16	Air supply pressure drop	Gradual failure
7	Medium evaporation or critical flow	Jump failure	17	Valve body differential pressure abnormal change	Gradual failure
8	Stem bending	Jump failure	18	The bypass valve open	Jump failure
9	Membrane cap too tight	Random failure	19	Flow sensor failure	Jump failure
10	Membrane damage	Jump failure			

Pneumatic actuator system consists of three parts. We can divide the model into three basic functional units, namely pneumatic servo actuator unit, regulating valve unit and valve positioner unit. Then we can establish serval sub-modules according to the typical parts. Each sub-modules will be connected according to the relationship between input and output. Finally, we set up a complete virtual prototype model of pneumatic actuator. As shown in Picture 2.

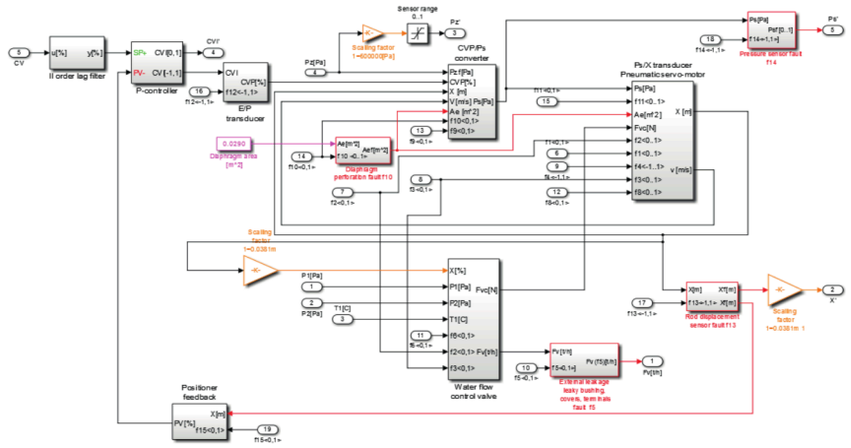


Figure 2. Virtual Prototype Model of Pneumatic Actuator

3 Typical Fault Simulation of Pneumatic Actuator

The entire pneumatic actuator system as shown in Figure 2 is packaged into a subsystem. The input and output parameters are set. Then the fault simulation model as shown in Figure 3 is established. The input of the simulation model is the control signal CV=25sin(0.02πt)+50. The upstream pressure of regulating valve is p_1=3.5MPa. The downstream pressure of regulating valve is p_2=2.6MPa. The fluid temperature in regulating valve is T_1=20℃. The output is set as a control signal CV. The stem displacement is X'. The difference pressure between front and rear of regulating valve is p_1'-p_2'. The fluid flow in regulating valve is F'. The control deviation is E.

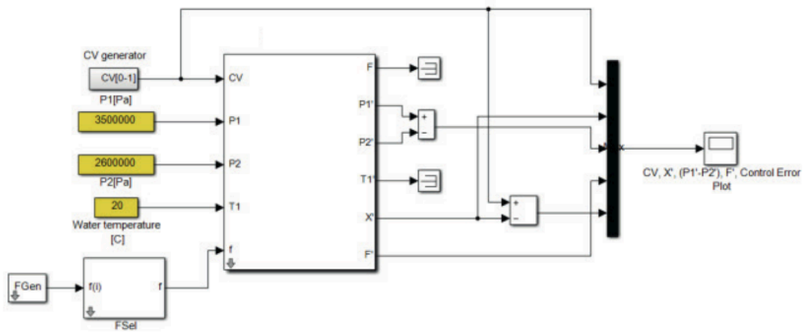
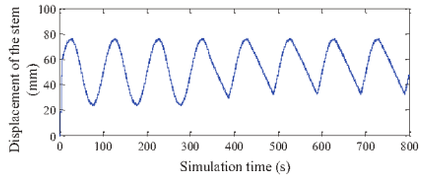


Figure 3. Failure Simulation Model of Virtual Prototype of Pneumatic Actuator

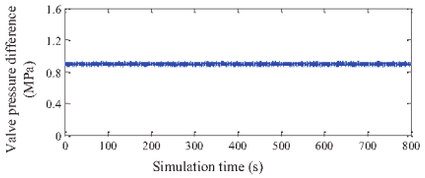
Setting the simulation time to 800 seconds. The fault type of the actuator system is selected by FSel module. The occurrence time and strength of the fault is set by FGen module.

In this paper, we have selected five conditions for fault diagnosis. They are the condition of normal operation condition, electrical/pneumatic converter blockage, position feedback sensor failure, valve body blockage and valve pressure difference abnormal. The fault occurred at the time of 300 seconds. The strength of fault is fs = 0.8. The simulation data of each fault mode is output to the working space of MATLAB. And 50 fault samples are extracted for each output variable after the fault. The corresponding fault sample set is formed. At the same strength of fault (fs = 0.8) for each failure mode to do two simulations. The sample set get from the first failure simulation serves as a training set for the production and training of antibodies. The sample set get from the second failure simulation serves as a test set for fault diagnosis.

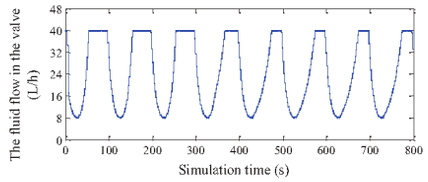
Figure 4 shows the waveforms of the four output signals of the simulation results of the electrical/pneumatic converter blockage. The pneumatic actuator is often operated in dusty and polluted conditions. If the gas source is not effectively filtered, there will be large particles of impurities in the air. The impurities will accumulate at the nozzle of the electrical/pneumatic converter, which will eventually lead to nozzle clogging. When this fault occurs, the gas cannot pass through the nozzle of the electrical/pneumatic converter into the membrane chamber. The valve stem of the pneumatic actuator cannot normally follow the control signal to do reciprocating motion. The valve fluid flow is also affected and the control deviation will become larger.



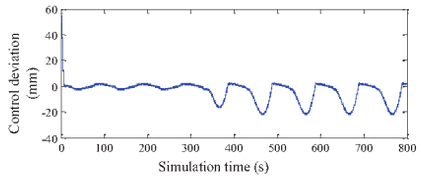
a) Displacement of the stem



b) Valve pressure difference



c) The fluid flow in the valve



d) Control deviation

Figure 4. Simulation results of electrical/pneumatic converter blockage fault

4 The Dimension Reduction of Actuator Failure Sample Based on KPCA

Tests are taken by using five kinds of data samples of the condition of normal operation condition, electrical/pneumatic converter blockage, position feedback sensor failure, valve body blockage and valve pressure difference abnormal. Each type of data samples contain control signals CV, stem displacement X', pressures p_1', p_2' before and after the valve, fluid flow F' in the control valve and fluid temperature T_1' in the regulating valve. The number of samples sampled in each state is 50.

The Kernel Principal Component Analysis (KPCA) method is used to process the fault sample data of the pneumatic actuator. The fault feature is extracted to reduce the dimension of the fault sample data [2]. The KPCA method uses the radial basis function as the kernel function. Selecting σ=10, and the result of the data processing is shown in Table 2:

Table 2. The processing results of KPCA

Eigenvalue number	λ_i	$\lambda_i \Big/ \sum_{i=1}^{n} \lambda_i$	Cumulative contribution rate
1	4.967	0.706	0.706
2	1.832	0.193	0.899
3	0.764	0.041	0.94
4	0.218	0.037	0.977
5	0.091	0.021	0.998
6	0.013	0.002	1.000

According to the results in the table, the cumulative contribution rate of the first two eigenvalues has exceeded 85%. Then the first and second principal elements are selected as the fault feature information. Finally, the fault sample data is reduced from six to two dimensions.

Figure 5 shows the projection of the first and second principal elements extracted by the KPCA method. The KPCA method not only greatly reduces the dimension of the feature set, but also makes a clear distinction between the samples of each fault state of the pneumatic actuator. It lays the foundation for the next fault diagnosis.

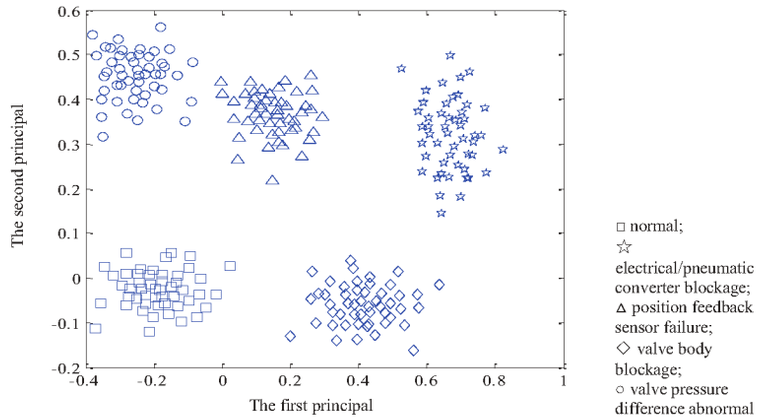


Figure 5.The projection of first and second principal elements extracted by KPCA

5 Fault Diagnosis of Pneumatic Actuator Based on Artificial Immune Mechanism

Inspired by the biological immune system, in recent years, the academic community setsup the artificial immune system (AIS) research boom which is more and more widely used to solve practical problems [3, 4]. The immune system has a strong information processing capabilities and many excellent features. The artificial immune system can enrich the theoretical system of fault diagnosis and engineering application and expand the research idea. The artificial immune system provides new theoretical and technical support for the research and development of fault diagnosis.

5.1 Antibody training

5.1.1 The design and coding of antigen and antibody

In an n-dimensional state space $\boldsymbol{S}^n$, the antibody and antigen are described by n normalized variables, ie, the antigen $\boldsymbol{Ag}=\{x_1,x_2,\cdots, x_n\}$ and the antibody $\boldsymbol{Ab}=\{y_1,y_2,\cdots, y_n\}$. x_i and $y_i(i=1,2,\cdots,n)$, respectively, known as the antigen $\boldsymbol{Ag}$ and antibody $\boldsymbol{Ab}$ gene, corresponding to the n eigenvalues of the state in fault diagnosis. The antigen and antibody sets are shown below: $\boldsymbol{AG}=\{\boldsymbol{Ag}_i|i=1,2,\cdots,M\}$, $\boldsymbol{AB}=\{\boldsymbol{Ab}_i|i=1,2,\cdots,N\}$. M and N are the number of antigens and antibodies.

Firstly, the fault feature samples after dimension reduction by KPCA method are normalized so that the values of all samples are between[0,1]. Each feature of each fault is defined as a different kind of antigen. In this paper, the antigens and antibodies are used in the form of real-number coding.

5.1.2 The calculation of affinity

In the n-dimensional state space $\boldsymbol{S}^n$, the affinity between the antigen $\boldsymbol{Ag}_i$ and the antibody $\boldsymbol{Ab}_i$ is expressed by the formula (1):

$$aff(\boldsymbol{Ag}_i, \boldsymbol{Ab}_i) = e^{-D_E} \tag{1}$$

D_E is the Euclidean distance of $\boldsymbol{Ag}_i$ and $\boldsymbol{Ab}_i$:

$$D_E = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \quad (1 \leqslant i \leqslant n) \tag{2}$$

By the formulas (1) and (2), it can be concluded that the amaller the Euclidean distance D_E, the greater the value of the affinity. The degree of matching of the antigen $\boldsymbol{Ag}_i$ with the antibody $\boldsymbol{Ab}_i$ will be better.

5.1.3 The definition of fitness function

The fitness function is a criterion for evaluating the quality of antibodies determined by the objective function. The fitness function is always nonnegative. The greater the value, the better the trained antibody. The fitness of antibody is the driving force of antibody in training process. While it's also one of the bases for natural selection of antibodies. In this paper, the fitness function is defined as:

$$f = \frac{1}{1 + D_E} \tag{3}$$

It can be seen from the formula (3) that the value of the fitness function f approaches the maximum value 1 when the value of the Euclidean distance D_E approaches zero.

5.1.4 The operation of genetic operator

To make the antibodies produced by the algorithm covering the areas of each type of antigen in the state space as much as possible, we introduced the selection, crossover and mutation operator operations from the genetic algorithm to accelerate the speed of antibody training and to increase the diversity of the antibody.

1. Selection

The antibodies that need to be cross-operated are selected from the initial antibody population . Firstly, the fitness value f_i of each initial antibody Ab_i was calculated according to the formula (3). In this paper, the Monte Carlo method is used to assign a

selection probability p_i to each antibody Ab_i in the initial antibody set. The probability that the antibody Ab_i is selected is expressed as:

$$p_i = \frac{f_i}{\sum_{i=1}^{N} f_i} \tag{4}$$

Where N is the size of the initial antibody population. $\sum_{i=1}^{N} f_i$ is called the cumulative fitness of N initial antibodies.

In this paper, the roulette selection method was used to select the initial antibody to be crossed. The fitness value f_i, the selection probability p_i of each antibody and the cumulative fitness in the initial antibody group were calculated. In order to select the cross individuals, multiple rounds of selection are required. Each round produces a uniform random number in the interval [0,1] as the selection pointer to determine the selected primary antibody.

2. Crossover

Crossover refers to the process of selecting any two parent individuals to produce new individuals by exchanging their partial genes. The real-coded chromosomes of the algorithmic training are used to obtain new antibodies by intermediate cross:

$$\boldsymbol{Ab}^{n+1} = \boldsymbol{Ab}_1^n + \alpha\left(\boldsymbol{Ab}_2^n - \boldsymbol{Ab}_1^n\right) \tag{5}$$

Where $\boldsymbol{Ab}_1^n$ and $\boldsymbol{Ab}_2^n$ represent the parent antibody 1 and 2. $\boldsymbol{Ab}^{n+1}$ represents the offspring antibody. α is a scale factor, which is generated by a random number evenly distributed over [0,1]. And a new α value is selected for each pair of cross antibodies.

3. Mutation

Mutation is a localized random search, which enables the immune algorithm to have a local random searching ability. Improving the diversity of antibody populations to prevent premature convergence (early maturity). According to the distance between any antibody $\boldsymbol{Ab}_i$ and the center of a certain antigen $\boldsymbol{Ag}_i$, take the antigen $\boldsymbol{Ag}_i$ as the center, take R_1 and R_2 as the radiuses. The antibody $\boldsymbol{Ab}_i$ was divided into three different areas of A, B and C. As shown in Figure 6.

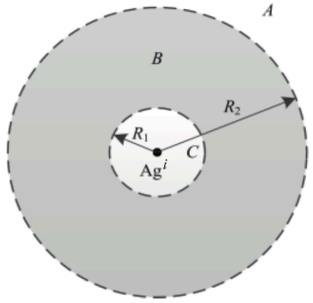


Figure 6. Division of antibody region variable

When the antibody $\boldsymbol{Ab}_i$ is located in the region A or C, The mutation operation does not performed; When the antibody $\boldsymbol{Ab}_i$ is located in the region B, according to formula (6) to perform mutation operation:

$$\boldsymbol{Ab}_i^{n+1} = \boldsymbol{Ab}_i^n + \beta(\boldsymbol{Ag}_i - \boldsymbol{Ab}_i^n) \tag{6}$$

Where β is the mutation rate. $\boldsymbol{Ag}_i$ is the antigen. $\boldsymbol{Ab}_i^n$ is the pre-mutation antibody. $\boldsymbol{Ab}_i^{n+1}$ is the antibody after mutation.

5.1.5 The promotion and inhibition of antibody

In the biological immune system, the number of each type antibodies will change dynamically with the stimulation of the antigens. When the concentration of some kind of antibodies is too high, the amount of the antibody will be inhibited. Whereas the amount of antibodies will be promoted so that the immune response can maintain a suitable strength[5].

The distance between the antibody $\boldsymbol{Ab}_i$ and any other antibody $\boldsymbol{Ab}_j$ in the antibody population (population number N) is D_E. Given a constant a_1 and a_1>0 as a similarity threshold. If $D_E > a_1$, the antibody $\boldsymbol{Ab}_i$ and antibody $\boldsymbol{Ab}_j$ are similar. In this paper, the concentration of antibody $\boldsymbol{Ab}_i$ is defined as L_i. The formula is as follows:

$$L_i = \frac{1}{N}\sum_{j=1}^{N} C_{ij} \tag{7}$$

In this formula, $C_{ij} = \begin{cases} 1, D_E \le a_1 \\ 0, D_E > a_1 \end{cases}$

The desired reproduction rate for the antibody $\boldsymbol{Ab}_i$ is defined as e_i, which can be expressed by:

$$e_i = I_{div}\frac{f_i}{L_i} \tag{8}$$

In the formula, I_{div} is the diversity index of antibody population and I_{div}=B/N. B is the number of groups after grouping of antibody group. N is the individual number of the antibody population. f_i is the fitness value of antibody $\boldsymbol{Ab}_i$.

From the formula (8), it can be concluded that the expected reproductive rate e_i of the antibody is proportional to the fitness f_i and is inversely proportional to the antibody concentration L_i. By introducing the expected reproductive rate of the antibody, both the antibody diversity can be maintained and the convergence speed of immune algorithm can be increased.

5.1.6 The update of memory antibody

Immune memory characteristic is an important feature of the immune system, which ensures that the host clears pathogens in the fastest and most effective way when re-infected. According to this characteristic, a memory threshold f_0 is set during the update of each generation of antibody population. When there is excellent individual and its fitness value $f_i > f_0$ in the population. It is added to the memory subgroup and the same individual in the original population are deleted. During each time the memory antibody is renewed, if the memory antibody population is full, the antibody with the worst fitness is replaced. And then check whether there is a good individual in the original population or not, if any, continue to add, otherwise stop the memory update operation.

5.1.7 The steps of antibody training

Antibody training process is shown in Figure 7, the specific steps are:

1. Initialization

Setting the size of antigen set $\boldsymbol{AG}$ and antibody set $\boldsymbol{AB}$ as N_{ag} and N_{ab}. The maximum cyclic algebra is g_{max}. The antigen and the antibody are encoded.

2. Creating the initial antibody

The initial antibody set $\boldsymbol{AB}^1$ is generated. If the number of memory antibodies is less than N_{ab}, the initial antibody is randomly produced to fill the memory antibody population. The antigen set $\boldsymbol{AG}$ consists of some type of training data.

3. The calculation of the indexes

For each antigen Ag_i in AG, the affinity of antigen Ag_i and all antibodies Ab_i in AB^1 are calculated according to formula (1). Calculating the fitness, antibody concentration and expected reproductive rate of antibodies and antigens,.

4. Producing new antibodies

The initial antibodies in AB^1 are first determined by the selecting operator. The antibodies in AB^1 are then executed crossover operator operation according to formula(5). Determining the parameters R_1 and R_2. Calculating the Euclidean distance D_E between antibody Ab_i and antigen Ag_i. When $D_E<R_1$ or $D_E>R_2$, the antibody Ab_i is not executed a mutation operation. When $R_1 \leqslant D_E \leqslant R_2$, the antibodies in AB^1 are mutated according to the formula (6) to obtain the progeny antibodies AB^2 of size N_{ab} are added to the parent antibodies to obtain the set AB^1 of size $2N_{ab}$.

5. Antibody promotion and inhibition

The value of the expected reproductive rate of the antibodies in AB^1 is calculated according to formula(8). Removing antibodies with low expected reproductive rates until N_{ab} antibodies are remained in AB^1.

6. Update the memory antibody group

The value of the fitness f_i of the antibody Ab_i is recalculated to determine the memory threshold f_0. When $f_i>f_0$, it is added to the subgroup M_i corresponding to the i -th antigen Ag_i, while the same individual in the original population are deleted.

7. Termination discrimination

Determine the termination condition, that is, whether to reach the maximum cyclic algebra g_{max} or not. If the condition is satisfied, stop the calculation. Otherwise, perform steps 3 to 6 until the termination condition is met.

8. The memory bank M_i corresponding to the antigen Ag_i are combined to obtain the antibody memory bank M.

9. Output the result M.

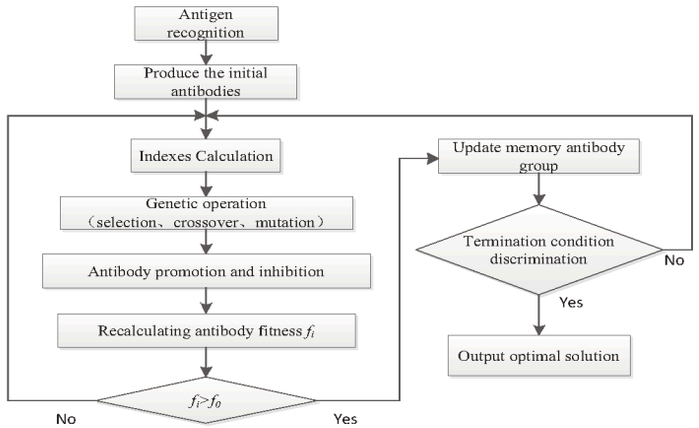


Figure 7. Antibody training process

The initial parameters of the algorithm are finally determined, as shown in Table 3:

Table 3. Initial parameters of the artificial immune algorithm

N_{ab}	g_{max}	α	f_0	β	R_1	R_2
500	200	0.1	0.96	0.3	0.025	0.15

The set of fault samples generated by the first simulation is extracted by KPCA method as a training set for the generation and training of antibody. Then the memory antibody library is obtained.

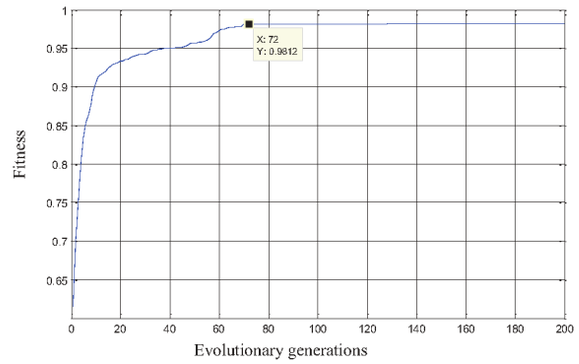


Figure 8 Antibody fitness function values for each generation

Figure 8 shows the changes of the fitness function value of each generation with the evolutionary algebra. It can be seen from the figure that when the algorithm is circulated to the 72nd generation, the value of the antibody fitness function reaches and in the maximum value of 0.9812. Indicating that the algorithm has a better ability to search for antibodies with the highest fitness less evolutionary algebra.

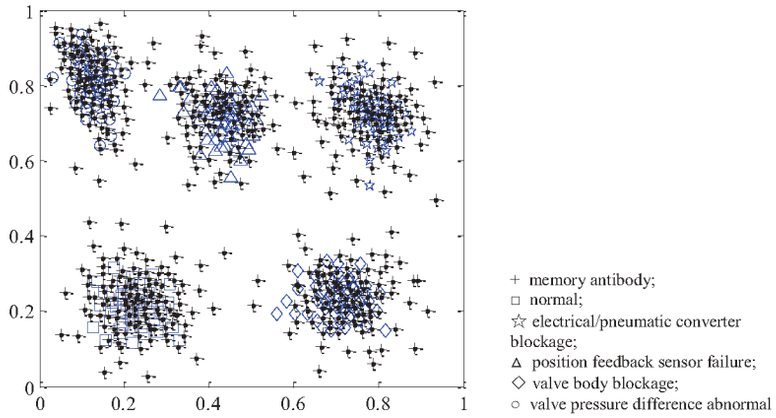


Figure 9 Memory antibody training results

Figure 9 illustrates that the algorithm is effective in learning the training samples and that the resulting memory antibodies can effectively cover the antigens. Besides, there is a clearer classification between each type antibodies.

5.2 The identification and diagnosis of faults

Fault identification and diagnosis are the second phase of the artificial immune algorithm, which is equivalent to the secondary immune response of the biological immune system.

The fault diagnosis concrete steps are as follows:

1. Getting and normalize the fault test samples. And the preprocessed test samples are set as antigens for input;

2. Setting a threshold upper limit y_0 based on the fault samples. Calculate the Euclidean distance D_E between each antigen and the memory antibodies of all fault types. If $D_E<y_0$, the memory antibody is considered to be activated by the antigen and copied into set $\boldsymbol{D}$. Circulating in this way, until all the activated memory antibodies are obtained in set $\boldsymbol{D}$;

3. The type of input fault is identified and diagnosed according to the type of failure to which the vast majority of the memory antibodies in set $\boldsymbol{D}$ belongs. The membership degree of the antigen belongs to a failure mode i is taken as the diagnostic accuracy of the corresponding fault [6];

$$\eta_i = \frac{C_i}{N_i} \tag{9}$$

In this formula, C_i is the number of antibodies that are activated by the antigen in the memory antibody set in failure mode i. N_i is the total number of antibodies in the memory antibody set in failure mode i.

Combining the memory antibody bank $\boldsymbol{M}$ of each type of failure. The KPCA method is used to extract the fault characteristics of the data generated by the second simulation. And then normalizing and constituting the test sample set as the antigen input. Identifying and diagnosiing it according to the above method. Setting the threshold is y_0=0.08. The final results are shown in Table 4:

Table 4 the results of troubleshooting

Working state	The number of test samples	Correct diagnosis number	Correct diagnosis rate
Normal	50	49	98%
Electrical/Pneumatic converter blockage	50	47	94%
Position feedback sensor failure	50	49	98%
Valve body blockage	50	45	90%
Valve pressure difference abnormal	50	46	92%

The diagnosis results show that the fault diagnosis algorithm based on artificial immune can effectively study the various types of fault samples of pneumatic actuators, generate the memory antibody group, and can accurately detect the type of fault that the test samples belongs to.

6 Conclusion

Based on the operation principle and characteristics of the pneumatic diaphragm actuator, a virtual prototype model of the pneumatic diaphragm actuator system is established under the DAMADICS software environment. The typical faults of the pneumatic diaphragm actuator are simulated according to the simulation. Obtaining a large number of fault samples. solving the problem that typical failure samples are difficult to be obtained in engineering practice.

The artificial immune algorithm is analyzed systematically and the KPCA technique is combined with the artificial immune algorithm. A method of artificial immune complex diagnosis is proposed, which is successfully applied to the fault diagnosis of pneumatic actuators. The validity of the method was verified by using the fault sample data of the virtual prototype of the pneumatic actuator. The experimental results indicate that the fault detection method performs well.

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