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 in order to simulate the conditions of the 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](image)

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

![Figure 1. Composition of the pneumatic actuator system](image)
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 several sub-modules according to the typical parts. Each sub-module 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.

![Picture 2. Virtual Prototype Model of Pneumatic Actuator](image)

**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\(^2\)=25sin(0.02\(\pi\)t)+50. The upstream pressure of regulating valve is \(p_1'=3.5\) MPa. The downstream pressure of regulating valve is \(p_2'=2.6\) MPa. The fluid temperature in regulating valve is \(T_1=20\) ℃. The output is set as a control signal \(CV\). The fluid flow in regulating valve is \(F\). The control deviation is \(E\).

![Picture 3. Failure Simulation Model of Virtual Prototype of Pneumatic Actuator](image)

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 gain from the first failure simulation serves as a training set for the production and training of antibodies. The sample set gain 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.

![Figure 4. Simulation results of electrical/pneumatic converter blockage fault](image)

**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 [23]. The KPCA method uses the radial basis function as the kernel function. Selecting \(\sigma=10\), and the result of the data processing is shown in Table 2.
5 Fault Diagnosis of Pneumatic Actuator Based on Artificial Immune Mechanism

Inspired by the biological immune system, in recent years, the academic community has set up the artificial immune system (AIS) research boom which is more and more widely used to solve practical problems \(^{10,9}\). 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 \(S^n\), the antibody and antigen are described by \(n\) normalized variables, i.e., the antigen \(Ag = ([x_1, x_2, ... , x_n])\) and the antibody \(Ab = ([y_1, y_2, ... , y_n])\), \(x_i = 1, 2, ... , n\), respectively, known as the antigen \(Ag\) and antibody \(Ab\) gene, corresponding to the \(n\) eigenvalues of the state in fault diagnosis. The antigen and antibody sets are shown below:

\[
Ag = \{[x_1, 1], [x_2, 1], ... , [x_n, 1]\},\ Ab = \{[y_1, 1], [y_2, 1], ... , [y_n, 1]\}.
\]

The antibody that needs to be cross-operated are selected from the initial antibody population. First, the fitness value is calculated. The fitness function is defined as:

\[
f = 1 + D_e = 1 + \sqrt{\sum_{i=1}^{n}(X_i - Y_i)^2} \quad (1 \leq i \leq N).
\]

By the formulas (1) and (2), it can be concluded that the smaller the Euclidean distance \(D_e\), the greater the value of the affinity. The degree of matching of the antigen \(Ag\) with the antibody \(Ab\) will be better.

#### 5.1.2 The calculation of affinity

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

\[
aff(Ag, Ab) = e^{-D_e^2}.
\]

#### 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 degree of matching of the antigen \(Ag\) with the antibody \(Ab\) will be better.

#### 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 \(f\) of each initial antibody \(Ab\) 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 $f_i$ 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:

$$Ab^{+} = Ab_i + \alpha (Ab^{*} - Ab_i) \tag{5}$$

Where $Ab_i$ and $Ab^*$ represent the parent antibody 1 and 2; $Ab^{+}$ represents the offspring antibody, $\alpha$ is a scale factor, which is generated by a random number evenly distributed over $[0,1]$. And a new $\alpha$ 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 (earlly maturity). According to the distance between any antibody $Ab_i$ and the center of a certain antigen $Ag$, take the antigen $Ag$ as the center, take $R_1$ and $R_2$ as the radius. The antibody $Ab_i$ was divided into three different areas of A, B and C. As shown in Figure 6.

![Figure 6. Division of antibody region variable](Image 34x647 to 69x664)

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

$$Ab^{\star} = Ab_i + \beta (Ag_i - Ab_i) \tag{6}$$

Where $\beta$ is the mutation rate. $Ag_i$ is the antigen. $Ab^{\star}_i$ is the pre-mutation antibody. $Ab_i^{+}$ 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. The distance between the antibody $Ab_i$ and any other antibody $Ab_j$ in the antibody population (population number $N$) is $D_{ij}$. Given a constant $a_i$ and $a_j$ as a similarity threshold. If $D_{ij} > a_i$, the antibody $Ab_i$ and antibody $Ab_j$ are similar. In this paper, the concentration of antibody $Ab_i$ 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, $C_{ij}$ can be chosen as $D_{ij}$, if $0, D_{ij} > a_i$.

The desired reproduction rate for the antibody $Ab_i$ is defined as $e_i$, which can be expressed by:

$$e_i = L_{i} \frac{f_i}{\sum_{i=1}^{N} f_i} \tag{8}$$

In the formula, $L_{i}$ is the diversity index of antibody population and $L_{i} = B/N$, $B$ 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 $Ab_i$.

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 $f_{th}$ is set during the update of each generation of antibody population. When there is excellent individual and its fitness value $f_i > f_{th}$ 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 $AG$ and antibody set $AB$ 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 $AB$ is generated. If the number of memory antibodies is less than $N_{m}$, the initial antibody is randomly produced to fill the memory antibody population. The antigen set $AG$ consists of some type of training data.

3. The calculation of the indexes
Table 3. Initial parameters of the artificial immune algorithm

<table>
<thead>
<tr>
<th>Nab</th>
<th>gmax</th>
<th>α</th>
<th>f₀</th>
<th>β</th>
<th>R₁</th>
<th>R₂</th>
</tr>
</thead>
<tbody>
<tr>
<td>500</td>
<td>200</td>
<td>0.1</td>
<td>0.96</td>
<td>0.3</td>
<td>0.025</td>
<td>0.15</td>
</tr>
</tbody>
</table>

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.

Figure 9 Memory antibody training results

The memory antibody library is obtained.
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. Get the normalized fault test samples. 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 $D$. Circulating in this way, until all the activated memory antibodies are obtained in set $D$;
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 $D$ belongs. The membership degree of the antigen belongs to a failure mode $i$ is taken as the diagnostic accuracy of the corresponding fault [5].

$$\eta = \frac{C_i}{N_i} \quad (9)$$

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 $M$ of each type of failure. The KPCA method is used to extract the fault characteristics of the data generated by the second simulation. Then normalizing and constituting the test sample set as the antigen input.

Identifying and diagnosing it according to the above method. Setting the threshold is $y_0 = 0.08$. The final results are shown in Table 4:

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

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.

Acknowledgement

This work is supported by the National Natural Science Foundation of China (51475405).

References