Research on Urban Rail Train Passenger Door System Fault Diagnosis Using PCA and Rough Set

Lin Shuai¹, Jia Limin*¹, Qin Yong¹, Yu Bo² and Wang Yanhui¹

¹Beijing Jiaotong University, Beijing, 100044, China
²Locomotive and Car Research Institute, China Academy of Railway Sciences, Beijing 100081, China

Abstract: Train passenger door is the key system for operation and maintenance on urban rail train. In this paper, we analysis passenger door system of urban rail train working process and establish the mathematical model. Firstly, we use the method of parameter estimation to get physical parameters of doors on different working condition. Then fault diagnosis experiment is done to train passenger door with principal component analysis and rough set theory. In the end, we verify fault diagnose accuracies under different time settings of opening and closing profile with the test rig.

Keywords: Door control system, fault diagnosis, principal component analysis (PCA), rough set.

1. INTRODUCTION

With increasing operation tasks, passengers congestion happens during peak time, extrusions and manhandles on the door affecting doors’ normal working process, causes doors fault, trains delay, even rescue. The way to improve operation efficiency and quality of urban rail train by using real-time data, is a big issue for metro operation department. Door system is one of most frequently damaged system on urban rail train, while the passenger doors are the main objects for maintenance personnel to receive complaints in case of its large quantity and high frequency utilization.

All along, the domestic and foreign research scholars’ research mainly focused on analysis through historical data, whose methods are lack of real-time and effective. The studies of urban rail trains electric door are limited to the reliability analysis because of real-time data acquisition difficulties, they usually use methods such as reliability block diagram, bias methods, fault tree network [1, 2], GÖ [3] and FMECA [4], but the applications of these methods require a large number of prior knowledge, and did not make full use of the state data real time train operation, so they are not feasible to new train lines or new model of equipment. Migueláñez & Lehrasab [5, 6] proposed a dynamic neural network fault diagnosis method for the pneumatic door, Dassanayake [7] proposed a parameter identification method for vehicle door motion state, the motor inductance, resistance and other parameters are estimated to guide the diagnosis of the door system, but this method is more applicable to the door system as fault review (Table 1).

The traditional fault diagnosis methods of pneumatic door are often limited to vehicle opening and closing time [8]. The modern urban rail train passenger doors use closed loop control principle, fault information is difficult to judge from significant information under the closed loop control of EDCU (Electronic Door Control Unit) as motor voltage, current, and the identification of opening, closing time and so on. The real-time working data is restored in the EDCU, which can be transmitted to the fault diagnosis computer through MVB. Based on the urban rail train passenger door working model, we can do parameter estimation based on EDCU data to check if there are sudden changes as fault happens. Then we use the time domain analysis method for the fault isolation experiments, under different working conditions and configurations the accuracy of this method is verified.

2. ANALYSIS AND MODELING FOR URBAN RAIL TRAIN COMPARTMENT DOORS

2.1. Analysis of Urban Rail Train Doors Working Process

The working mode of urban rail train doors is very similar to ball screw table and gear drive, the structure of main working parts (door suspension) can be simplified, as shown in Fig. (1).

Fig. (1). Simplified view of urban rail train passenger door.

Open/close commands are sent by drivers loading the open/close button in the cab. TCN transmits control signals to electronic door control unit (EDCU), EDCU starts motor and drives screw in a preset delay.

2.2. Urban Rail Train Passenger Compartment Door Model

As shown in Fig. (1), the train compartment doors of wire rod is divided into two parts, screw rotate in opposite directions, respectively, for opening and closing the left door leaf. The screw rod of each part is divided into three
2.3. Passenger Door Model Symbols Definition

Table 1. Parameters of passenger door model.

<table>
<thead>
<tr>
<th>Param</th>
<th>Description</th>
<th>Param</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Q$</td>
<td>Axial load</td>
<td>$\psi$</td>
<td>Screw helix angle</td>
</tr>
<tr>
<td>$d_2$</td>
<td>Screw thread pitch diameter</td>
<td>$\rho$</td>
<td>Wire rod friction angle</td>
</tr>
<tr>
<td>$P$</td>
<td>Motor power</td>
<td>$r_1$</td>
<td>Motor drive wheel radius</td>
</tr>
<tr>
<td>$r_2$</td>
<td>Radius of wheel screw drive</td>
<td>$J_2$</td>
<td>The moment inertia of drive wheel</td>
</tr>
<tr>
<td>$T$</td>
<td>Screw torque</td>
<td>$c$</td>
<td>Friction coefficient</td>
</tr>
<tr>
<td>$h$</td>
<td>Slide ball lead</td>
<td>$m$</td>
<td>Door frame and door mass</td>
</tr>
<tr>
<td>$x(t)$</td>
<td>Working table displacement</td>
<td>$M_f$</td>
<td>Moment force of failure</td>
</tr>
<tr>
<td>$i$</td>
<td>Armature current</td>
<td>$\omega$</td>
<td>The motor shaft angular velocity</td>
</tr>
<tr>
<td>$L_d$</td>
<td>Armature inductance</td>
<td>$J$</td>
<td>The total resistance of inertia</td>
</tr>
<tr>
<td>$P(t)$</td>
<td>Output power of motor</td>
<td>$\alpha_{0/c}$</td>
<td>Friction torque of door opening</td>
</tr>
<tr>
<td>$T(t)_fric$</td>
<td>The sum of the screw rod friction</td>
<td>$R_h$</td>
<td>Armature resistance</td>
</tr>
<tr>
<td>$\beta_{0/c}$</td>
<td>The static friction torque of door</td>
<td>$K_e$</td>
<td>The back EMF constant of motor</td>
</tr>
<tr>
<td>$\nu$</td>
<td>The armature voltage</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

sections, respectively, working section with helix angle greater than friction angle, locking section with helix angle less than the friction angle, the transition section between the two. A typical portal velocity is shown in Figs. (2, 3).

Electric door opening and closing speed can be adjusted in the system between 2.5 and 4 seconds by the train control system. Each motor shaft is provided with a high resolution optical encoder, optical encoder can measure the displacement and rotation of the motor, the motor position acquisition, optical encoder and EDCU with closed-loop control door opening and closing the door, so judging only from the working time door fault is not feasible.

Actually, as there is difference between short and long operation mode in running time and running speed, but the working distance, namely graph covering trapezoidal 3 in the area, are the same.

According to the Darren Bell principle, sliding screw working torque can be described in formula (1) [9]:

$$T = \left[ J_x + \left( \frac{h}{2\pi} \right)^2 \frac{d}{dt} \left( \frac{2\pi}{h} x(t) \right) \right] + c \left( \frac{h}{2\pi} \right) \frac{d}{dt} \left[ \frac{2\pi}{h} x(t) \right]$$  \hspace{1cm} (1)

Considering the axial load and failure caused by the torque, we can get

$$9550 * P(t)/2\pi \omega(t) = \frac{r_1}{r_2} T + Q \tan(\psi + \rho) d_2 + M_f$$  \hspace{1cm} (2)

If we take into consideration of the motor, although there are many none-linear factors to motor running state, according to the linear theory of localization [10], we can ignore the impact on the result of the nonlinear facts. When the doors are opening, the friction force will impact on the operation of the joint between each component and motor rotary inertia, so the electrical of door model can be expressed as:
\[ v(t) = R_2 i(t) + L \frac{d i(t)}{dt} + K \omega(t) \]

\[ P(t) = R_2 i^2(t) + L \frac{d i(t)}{dt} + K \omega(t)i(t) \]

\[ P(t) = L \frac{d i(t)}{dt}i(t) + K \omega(t)i(t) \] (3)

This model shows that, when doors’ roller guide slots, screw rods and drive nuts fail, they will affect the motor load, motor rotary inertia and friction torque. Under the control of EDCU, the motor speed will keep stable but the motor driving torque and motor power will increase or decrease, so that the power ride comfort changes. Power ride comfort under different mode of door machinery fault will show different characteristics, we can identify the fault categories according to this principle.

During the working process, as it does not involve gravity acting, the motor output is mainly used to overcome the friction torque and the load, the model (1), (2) can be simplified as follows.

\[ J \frac{d^2 \omega(t)}{dt^2} = K_i i(t) - T(t) \]

\[ T(t) = \left[ \frac{K^2}{R_o} + \alpha_\omega \right] \frac{d \omega(t)}{dt} + \beta_\omega \cdot d(t) \] (4)

\[ d(t) = \begin{cases} 1, & \text{Opening parameter} \\ -1, & \text{Closing parameter} \end{cases} \]

\( J \) contains rotary inertia between motor and the motor rotor, door leaf, screw rod and nuts on the door indirectly from the inertia moment, the fault causes numerical changes of \( J \cdot \alpha_\omega \cdot \beta_\omega \), so the changes of these values can reflect directly to the fault influence on door.

3. PCA BASED FAULT DETECTION

3.1. Signal Pretreatment of Urban Rail Train Doors

In order to get concrete numerical value of \( J \cdot \alpha_\omega \cdot \beta_\omega \), we use collected data to do parameter estimation according to formula (3). For the convenience of treatment, the system (3) can be transformed into

\[ \frac{d^2 \omega(t)}{dt^2} = \frac{K}{J} \cdot \frac{I}{J} - \frac{\alpha'}{J} \frac{d \omega(t)}{dt} - \frac{\beta_\omega}{J} \cdot d(t) \]

\[ \alpha' = \frac{K^2}{R_o} + \alpha_\omega \] (5)

On the basis of the input and output of passenger door system (i.e. formula (4)) of the continuous analog signal, we use integral filter circuit to do fast integral, and discrete digital signals output to do signal processing. Integral filter circuit’s principle is shown in Fig. (4) [11].

The passenger door test rig.

The formula (4) is formed by two times of piecewise integral

\[ \Gamma_i \cdot y(k) = b_2 \cdot \Gamma_i \cdot i(k) - a_1 \cdot \Gamma_i \cdot y(k) + b_2 \cdot \Gamma_i \cdot d(k) + \text{err}(k) \] (6)

\[ \Gamma_i \cdot y(k) = \phi(k) \cdot \theta + \text{err}(k) \]

Among which

\[ \phi(k) = \left( \Gamma_i \cdot i(k), \Gamma_i \cdot y(k), \Gamma_i \cdot d(k) \right)^T \]

\[ \theta = \left( b_2, -a_1, b_2 \right)^T \]

For the integral time constant \( \Gamma_i \ (i = 0,1,2) \), \( \text{err}(k) \) is higher order than the integral window, when the sampling interval is short enough, it can be regarded as a constant or ignored, and \( \Gamma_i \) is considered known, the physical parameters of the passenger compartment door can be calculated as follows

\[ J = \left( \frac{1}{b_{21}} \right) \cdot K_e \cdot \alpha' = \left( \frac{a_1}{b_{21}} \right) \cdot K_e \cdot \beta = \left( \frac{b_2}{b_{21}} \right) \cdot K_e \]

\( \phi(k) \) is the discrete signal piecewise integrated by linear integral filter LIF (Linear Integral Filter), it can be seen that the output of LIF is a linear signal, we use recursive least square method with fast convergence rate to estimate parameters in time domain (RLS) [12], while the real-time physical parameters of the door can be obtained.

In consideration of the differentiation of parameter estimates of dimension and size, we choose the obtained parameter estimates ratio data offset as the criterion of fault detection, as shown in Table 2, the calculation method is the offset divided by the normal data of parameter estimation.

3.2. Fault Detection Algorithm

Principal component analysis based fault detection method can transform multi variable sample space into the principal component variables, which is a lower dimensional projection subspace and a corresponding residual subspace.
Table 2. The door fault detection features.

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( R_{oc} )</td>
<td>Standardized moment of inertia data of closing door</td>
</tr>
<tr>
<td>( R_{oc} )</td>
<td>Standardized moment of dynamic friction torque of closing door</td>
</tr>
<tr>
<td>( R_{oc} )</td>
<td>Standardized moment of static friction force of closing door</td>
</tr>
<tr>
<td>( R_{ic} )</td>
<td>Standardized moment of inertia data of opening door</td>
</tr>
<tr>
<td>( R_{io} )</td>
<td>Standardized moment of dynamic friction torque of opening door</td>
</tr>
</tbody>
</table>

Respectively the structure can reflect the spatial variation of the statistics in two spaces, then the observation vector were projected to two subspaces, and the corresponding statistic index is calculate for process monitoring. S. Joe Qin et al. [13-14] has done a lot and very fruitful work on the fault diagnosis method based on PCA, such as the optimization index, the optimal number of principal components method etc. Without considering the main element selection, fault detection algorithm of PCA can be realized according to the following three steps.

**Step 1. Data normalization for door fault feature**

With no fault, door parameter can be obtained after \( N \) times sampling to data matrix \( X \in R^{nxn} \). Do standard treatment to \( X \), as the mean value is 0, variance of 1 sequences of multivariate data, standardized way:

\[
\begin{align*}
    r_i &= \frac{x_i - x_{mean}}{x_{std}} \quad (8)
\end{align*}
\]

For the raw data \( x_i \) as the i time sampling value, \( x_{mean} \) as the average of the original data, \( x_{std} \) as the variance of the original data, \( r_i \) for the standardized data. Data matrix normalized is represented for:

\[
\begin{align*}
    R = \begin{bmatrix} r_1^T \\ \vdots \\ r_n^T \end{bmatrix} \in R^{nxn} \quad (9)
\end{align*}
\]

**Step 2. Decomposition of covariance matrix**

The covariance matrix is

\[
\Sigma_n = \frac{1}{N} R^T R \quad (10)
\]

By doing SVD (singular value decomposition) or EVD (EVD), covariance matrix can be decomposed into the following form:

\[
\frac{1}{N} R^T R = P\Lambda P^T \quad (11)
\]

**Step 3. Online fault detection**

When the door complete a opening or closing procedure, we can obtain the new data for door operation. Firstly, by doing standardization, we can get the data \( y \in R^n \). In this way, the fault detection index and can be obtained by the following formula.

\[
\begin{align*}
    SPE &= y^T P_{rev} \Lambda_{rev} y \quad (13) \\
    T^2 &= y^T P_{pc} \Lambda_{pc} y \quad (14)
\end{align*}
\]

Assume fault threshold for SPE and \( T^2 \) were \( J_{\alpha,SPE} \) and \( J_{\alpha,T^2} \). Then the corresponding threshold for SPE with a degree of confidence \( \alpha \) [15] is

\[
J_{\alpha,SPE} = \theta_i \left[ \frac{h_{\alpha} \sqrt{2\theta_i}}{\theta_i} + 1 + \frac{\theta_i h_{\alpha} (h_{\alpha} - 1)}{\theta_i^2} \right]^{\frac{1}{\theta_i}} \quad (15)
\]

where in \( \theta_i \) = \( \sum_{j=1}^{m} \lambda_j^i \), \( i = 1, 2, 3 \), \( \lambda_i \) is the ith singular value of a covariance matrix.
The corresponding confidence threshold for $T^2$ with a degree of confidence $\alpha$ [16] is

$$J_{th,T^2} = \frac{(m-l)(N^2-1)}{N(N-m+1)}F_{m-l,N-m+l}$$

(16)

Wherein $F_{m-l,N-m+l}$ is the probability density distribution function $F$ with a degree of belief $\alpha$, freedom $m-1$ and $N-m+1$.

The available fault diagnosis rules as follows:

$$\begin{align*}
\text{SPE} & \leq J_{th,SPE} \quad \text{AND} \quad T^2 \leq J_{th,T^2} \rightarrow \text{No fault} \\
\text{Otherwise} & \rightarrow \text{Fault}
\end{align*}$$

(17)

In actual application of two kinds of evaluation indexes, the sensitivities are not identical, in the actual test, we found the using of square prediction error has a higher sensitivity, this article uses the index as the basis of judging fault.

4. FAULT DIAGNOSIS BASED ON ROUGH SET

A. Fault recognition method based on Rough Set

Rough set theory is proposed by Poland scholar Z. Pawlak in 1982, its characteristics are as follows [17]:

1. It can handle a variety of data, including incomplete data and data with multi variables;
2. It can deal with imprecise data, including deterministic and non-deterministic situation.
3. It can reveal the simple concept and easy operation mode from the data;
4. It can produce accurate, easy to check and confirm formation rules, especially rules in intelligent control.

Take door physical parameters changing with fault into account, and the typical door failure is always happen due to mechanical parts damaging caused by aging, each mode for door parameter weights and in different ways, the using of PCA based fault detection method can judge whether fault occurs, but not for fault identification, as data get from the integrator is discrete, the numerical calculation results with the inevitable error, this paper using rough set method to detect fault characteristics of the train doors.

Rough set knowledge representation methods exist in the form of decision table. Where in

$U$ : A finite set of objects;

$A$ : The finite set of attributes, $A = C \cup D, C$ is the condition attribute subset, $D$ is the decision attribute subset;

$V_i$ is the domain of attribute $P_i$ ;

$f : U \times A \rightarrow V$ is a total function, s.t. $\forall x_i \in U , q \in A$ , $f(x_i,q) \in V_q$ ;

Do derivation to formula(2), we get

$$\left(P'(t)\right) = L_p \left( \frac{d^2i(t)}{dt^2} \right) + L_d \left( \frac{di(t)}{dt} \right) + K_1 \omega(t) \frac{di(t)}{dt}$$

(18)

We use the numerical differentiation to get each sampling points derivative, namely power change rate. By doing arc tangent to the absolute value of the change rate, we have sample points’ angel to the horizontal plane, and the angle of discrete data can be divided based on discrete degree, collecting the sample data scattered in various areas as condition attributes subset, then we found out it have a great relationship between the discrete degree of accuracy and fault recognition. Discrete degree too small will cause the fault isolation not enough, while too large with difficulty to generate effective fault judgment rule, fault separation accuracy will be reduced. Condition attributes of train door are continuous, we need to discretize these attributes to do attribute reduction. There are many discretization method in rough set attribute reduction [18], we choose dynamic clustering algorithm for continuous attributes discretization with more reasonable and effective performance.

The decision attributes in the decision table set $D$ is shown in Table 3.

Table 3. Decision attribute of train door fault diagnosis.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F(1)$</td>
<td>Roller failure</td>
</tr>
<tr>
<td>$F(2)$</td>
<td>Drive nut fault</td>
</tr>
</tbody>
</table>

Doors fault identification algorithm as follows.

Step 1: Acquire screw speed and current signals at different operating conditions.

Step 2: Do three order spline interpolation to current to get numerical differential signal.

Step 3: Get the motor power changing rate

Step 4: Calculate the angle of changing rate with the horizontal axis, and do classification to equal angle.

Step 5: Use the dynamic hierarchical clustering method for object classification of finite sets into 3 discrete series.

Step 6: Do attribute reduction and generate fault recognition rules.

The first five steps of passenger door fault recognition method are the same to the fault recognition rules generation algorithm, the followed steps are as follows.

Step 1: Generate discrete dynamic hierarchical clustering method according to the sample conditions attributes;

Step 2: Judge fault mode according to the fault diagnosis rules generation algorithm.

B. Algorithm for fault diagnosis

Urban rail train passenger door fault diagnosis algorithm can be summarized as follows

Step 1: Generate fault judgment rule base on sample data.
Step 2: Use the PCA based fault detection methods for fault detection initial conditions.

Step 3: When fault detected, use passenger door fault recognition method for fault identification.

5. RESEARCH AND ANALYSIS OF EXPERIMENTAL SIMULATION

In order to simulate the actual working environment, we set up the experimental platform, the structure as shown in Fig. (5). With Tektronix TPS2014 oscilloscope (Fig. 5a) and IMC-Cronos-PL3 (Fig. 5b) we can get resolved data initially, the German company IMC modular number is used for data acquisition, data pretreatment, and data transmission. The screw rod motor test bench and signal processing, acquisition unit as shown in Fig. (6). Passenger door experiment appearance as shown in Fig. (7).

(A) (B)

Fig. (5). The picture of passenger door experiment platform.

Fig. (6). Outside view of passenger door experimental platform.

With of the signal sampling interval $T_o = 4096 \mu s$, when we use the 3 seconds open configuration, after normalization of a normal case closing procedure, signals as shown in Fig. (8).

We can see from the chart that the process of passenger door working process is divided into three sections, respectively are accelerating, decelerating and stable operation period. The peak of signals occurred in process of opening end stage and the door closing start stage, we can infer from the two figures that the further distance between the door frame and lead screw, particularly the motor, the larger motor damping torque is. This phenomenon is caused by the process of lubrication and load imbalance or screw problem.

![Normalized signal of door opening procedure.](image)

Fig. (7). Normalized signal of door opening procedure.

![Normalized signal of door closing procedure.](image)

Fig. (8). Normalized signal of door closing procedure.

Attention should be paid that the passenger door only works in the train station, we almost don’t need to consider the efficiency of computer operation in the process of failure diagnosis, thus we can reduce the sampling interval for fault diagnosis to obtain more precise parameter estimation and fault diagnosis results.

In consideration of that there are more the acceleration and deceleration section of the dynamic information, so we select the stable operation period (0.8 - 2.2s) for parameter estimation. With sampling interval of $T_o = 256 \mu s$, the 3 conditions of 20 simulation trials were averaged with the door opening procedure, with integral window of 20 times of the sample rate, we got the door opening and closing procedure estimation of the physical parameters, as shown in Table 4.

We specify physical parameters for fault detection, $J_c$, $\alpha_c$, $\beta_c$ as the fault detection sequence when the door is
When the door is closing, use PCA based fault detection algorithm.

During the procedure of rough sets based fault identification, the sample data set number of each failure mode choices should be moderate, with the selection of too many groups may result in too little fault identification rules while with too little groups will cause the judgment rule inaccurate. Through repeated tests, when the discrete degree is 10, select 3 groups of motor power changing rate angle classification data for each condition, the results are the best. According to the 9 objects composed finite set of opening procedure in 3S conditions, Through the dynamic hierarchical clustering algorithm[19] on the change rate of power angle classified data, discretized decision table as shown in Table 5.

Before the generation of fault judge rules, we only select the fault data as condition attributes for reduction and rules generation, so that we can improve the recognition rate.

According to the attribute reduction for condition attributes which is shown in Table 2, we get 4 reductions for doors fault diagnosis, \( \{A_0, A_2\} \),  \( \{A_2, A_4, A_4\} \),  \( \{A_2, A_4, A_6, A_7\} \),  \( \{A_1, A_4, A_7\} \). Do attributes reduction and generate fault diagnosis rules separately for each attribute reduction set, we can obtain the fault isolating rules which are shown in Table 6.

Simulate three kinds of working status to the door in the 4 opening/closing duration profiles, we do 50 times of each working scheme, the testing accuracy of the statistical results as shown in Table 7.

As can be seen, for the two kinds of fault, the longer opening and closing duration makes the door fault judgment and fault recognition more accurate, so it is more efficient if we choose long model for fault diagnosis on urban rail train electric door, but the common 3 seconds factory configuration can basically meet the demand of fault diagnosis. From the average recognition ratio we can see that the use of PCA fault diagnosis method can meet the demand of fault detection for different fault level. When we are doing failure analysis on experimental platform showed in this chapter, fault recognition accurate for wire rod, a driving nut

Table 4.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Fault Mode</th>
<th>Normal</th>
<th>Roller Failure</th>
<th>Drive Nut Fault</th>
</tr>
</thead>
<tbody>
<tr>
<td>( J_c )</td>
<td>( kgm^2 )</td>
<td>0.00643</td>
<td>0.00741</td>
<td>0.00844</td>
</tr>
<tr>
<td>( \alpha_c )</td>
<td>( Nm ) ( (rad s^{-1})^{-1} )</td>
<td>0.0056</td>
<td>0.0080</td>
<td>0.0041</td>
</tr>
<tr>
<td>( \beta_c )</td>
<td>( Nm )</td>
<td>1.272</td>
<td>1.681</td>
<td>1.370</td>
</tr>
<tr>
<td>( J_o )</td>
<td>( kgm^2 )</td>
<td>0.00785</td>
<td>0.00771</td>
<td>0.00443</td>
</tr>
<tr>
<td>( \alpha_o )</td>
<td>( Nm ) ( (rad s^{-1})^{-1} )</td>
<td>0.0038</td>
<td>0.0067</td>
<td>0.0039</td>
</tr>
<tr>
<td>( \beta_o )</td>
<td>( Nm )</td>
<td>1.28</td>
<td>1.63</td>
<td>1.31</td>
</tr>
</tbody>
</table>

Table 5. Discretized decision table.

<table>
<thead>
<tr>
<th>Sample</th>
<th>( A_0 )</th>
<th>( A_1 )</th>
<th>( A_2 )</th>
<th>( A_3 )</th>
<th>( A_4 )</th>
<th>( A_5 )</th>
<th>( A_6 )</th>
<th>( A_7 )</th>
<th>( A_8 )</th>
<th>( A_9 )</th>
<th>( F )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>6</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>7</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>8</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>9</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>2</td>
</tr>
</tbody>
</table>
is more precise than that for roller, guide rail, so if it is hard to confirm the fault situation we will check on the latter.

6. CURRENT & FUTURE DEVELOPMENTS

The research of fault diagnosis for urban rail train door is a weak field both home and abroad. This paper shows a real-time fault diagnosis method for urban rail train doors. First of all, we introduced the working process for the train doors, respectively from the door opening and closing movement and the door motor working angle we established its mathematical model. For the electrodynamic model, we used integral filter circuit for signal preprocessing, and used the parameter estimation method to get the door physical parameters. In order to realize the real-time fault diagnosis, we considered the influence of fault on fault recognition, proposed PCA based method for fault detection, and then used the rough set based method for fault diagnosis. Through the experiment on the test rig, we verified the accuracy of this method. Compared with the traditional off-line fault diagnosis methods based on probability theory and mathematical statistics, this method is more real-time and effective for urban rail trains’ passenger doors’ real-time monitoring.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

ACKNOWLEDGEMENTS

This work was supported in part by The National High Technology Research and Development Program of China (Grant No. 2012AA112001-07).
REFERENCES


