Research on Fault Diagnosis Method for Speed Sensor of High-Speed Train

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***Abstract*—Speed sensors installed on the axes of high-speed train will lead to faults due to the vibration and electromagnetic interference during train operation. At present the braking system can't detect all faults of speed sensor but misdirect the axle lock fault, which affects the safety of train operation. Therefore, this paper proposes an integral intelligent fault diagnosis method for speed sensor of high-speed train brake system, which realizes real-time detection of speed sensor anomalies and accurate location of the axis of the speed sensor fault. Firstly, the traditional principal component analysis method is improved by proposing a comprehensive monitoring statistic to realize real-time fault detection of speed sensor. Then, the modified reconstruction based contribution plot based on the idea of combination maximization is adopted to achieve accurate fault location of speed sensor. In addition, the fault injection experiments are conducted, the results prove the method can diagnose the fault of speed sensor accurately and effectively, and solve the hidden trouble of high-speed train operation.**

Keywords—speed sensor; fault diagnosis; improved principal component analysis (IPCA); improved reconstruction -based contribution plots (IRBCP)

I. INTRODUCTION

The braking system of high-speed train applies braking and anti-skid control to the vehicle according to the axle speeds collected by the speed sensors, thus the accuracy of the signals output by speed sensors directly influences the safe operation of train. Because of the complicated operation environment of train and the existence of factors like vibration and electromagnetic interference during operation, it might cause the fault of output signal of speed sensor. And during the operation of existing high-speed train, brake system has already occurred many false detection of axle lock faults due to faults of speed sensor [1], which causes the delay of train operation. Therefore, it has important significance to the safe of train by research on the fault diagnosis method of speed sensor.

In order to solve above-mentioned problems, the researchers have carried out the cause analysis of axle lock fault and the exploratory study of fault diagnosis method of speed sensor. Reference [2-4] analyze the axle lock faults in CRH2, CRH3 and CRH380BL, which are mainly caused by faults of speed sensors, thus they have already proposed the maintenance measures like cancel the mounting bracket of speed sensor and apply dual-speed sensor which improves the reliability of speed sensor, but the fault identification of speed sensor still relies on the personal experience. Reference [5-6] propose the fault diagnosis method of speed sensor of locomotive and metros based on the Radial Basis Function neural network. Reference [7] proposes the fault diagnosis method of single and multiple speed sensors based on the information fusion of Kalman filtering. The existing research is all on-line diagnosis, which relies on a large number of training of sample data under all working conditions, and has certain requirements for computing power. At the same time, they only realize the function of fault detection, and have not yet realized the accurate fault location.

Therefore, this paper proposes a fault detection and location method for the speed sensor of braking system in high-speed train. Firstly, the traditional principal component analysis method (PCA) is improved to realize the fault detection of speed sensor by proposing a comprehensive monitoring statistic so as to overcome the inconformity defect of detection results that caused by traditional two different kinds of monitoring statistic. And the improved reconstruction based contribution plot (RBCP) based on the idea of combination maximization is adopted to realize the accurate location through repeated iteration judgment. In addition, the operation data and fault-injection simulation test data of the speed sensor are performed to training and verification of diagnosis algorithm, the results prove the validity of such method, and the method can solve the hidden trouble of high-speed train operation.

II. WORKING PRINCIPLE

The high-speed train brake system applies current-type and switch-type Hall speed sensor. As shown in Fig. 1, speed sensors are mounted at the axle end of wheels with gear plate. When wheel rotates, the rotating gear will change the air-gap magnetic field around the front of speed sensor. The speed sensor outputs the pulse frequency signal of 7mA low current and 14mA high current.

Fig. 1. Speed sensor mounted at axle end

The working principle of high-speed train brake system is shown in Fig. 2. According to the input of brake instructions,

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speed frequency signals of four axles, and vehicle weight, the electronic brake control unit calculates the requested brake force in real time, and drives the air brake control unit to generate brake air pressure. Brake clamp converts brake air pressure into brake power for the train. At the same time, the electronic brake control unit judges whether the axles have sliding or not based on the sliding criteria of deceleration, velocity difference and slip rate, and controls anti-skid valves to inflate or exhaust brake pressure, so as to realize the brake force adjustment under the sliding condition. Therefore, the research on fault diagnosis of speed sensor is helpful to improve the safety and reliability of brake system.

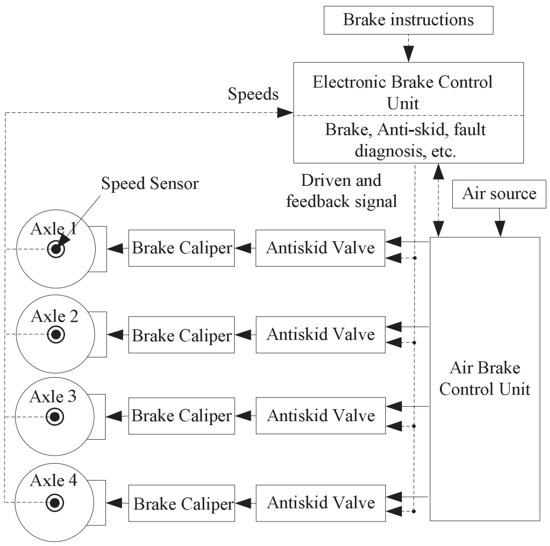

Fig. 2. Working principle of high-speed train brake system

In order to realize the fault diagnosis of the speed sensor, PCA is improved to realize the fault detection of speed sensor according to the overrun judgment of comprehensive monitoring index. Then apply the RBCP to realize the accurate location of failed axle through repeated iteration judgment.

III. FAULT DETECTION

Fault detection is the first step of fault diagnosis. When using PCA model to perform fault detection, it usually applies Squared Prediction Error (SPE) and Hotelling's T^2 to detect whether the system has failures. However, the metrics of these two monitoring statistic are different which is easy to cause inconformity of monitoring results. Therefore, the comprehensive index φ, which applies both T2 and SPE, is proposed to realize the fault detection.

A. Selection and Pre-processing of Detection Data

Since the brake system is of vehicle-control mode, the detection data will take the speeds of four axles of one car as an integral. And it shall take pairwise speed difference of four axles as observable variable to avoid the influence to fault diagnosis from each working condition of speed. Then the detection data is represented as:

$$X = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \end{bmatrix}^T = \begin{bmatrix} |v_{axle1} - v_{axle2}| \\ |v_{axle1} - v_{axle3}| \\ |v_{axle1} - v_{axle4}| \\ |v_{axle2} - v_{axle3}| \\ |v_{axle2} - v_{axle4}| \\ |v_{axle3} - v_{axle4}| \end{bmatrix}^T \tag{1}$$

In the formula: X is the observable variable, v_{axle1} , v_{axle2} , v_{axle3} , v_{axle4} are the speed of 4 axles of 1 car.

In order to reduce the influence from the measurement interference of speed sensor, it shall perform de-noising to the data before fault detection. Therefore, please refer to the below for the training sample data X_train and the detection sample data X_test after pre-processing:

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nm} \end{pmatrix} \tag{2}$$

In the formula: X is matrix of $n \times m$, i.e., n samples, m observable variables. In this case, m is 6, and n shall be determined according to actual working conditions.

B. Data Standardization

In order to avoid some particular variables occupy the leading role during detection, it shall perform standardization processing to the sample data X_train and test data X_test , including centralization and dimensionless process of data. Please refer to the formula below:

$$\hat{x}_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j}, \quad i = 1, 2, \cdots, n \quad j = 1, 2, \cdots, m \tag{3}$$

In the formula: μ_j and σ_j are respectively the mean value and the standard deviation of each variable of the training sample data X_train . Please refer to the formula below:

$$\mu_j = \frac{1}{\mathrm{n}} \sum_{i=1}^{n} x_{ij} \tag{4}$$

$$\sigma_j = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (x_{ij} - \mu_j)^2} \tag{5}$$

C. PCA Modeling

Suppose the matrix after standardization is $\bar{X}$, the covariance matrix of standardized matrix $\bar{X}$ is:

$$S = \mathrm{cov}(\bar{X}) = \frac{1}{n-1}\bar{X}^T * \bar{X} \tag{6}$$

Make eigenvalue decomposition to the covariance matrix, and sort the eigenvalue from the largest to the smallest, derive the eigenvalue $\lambda_1, \lambda_2, \cdots, \lambda_m (\lambda_1 > \lambda_2 > \cdots \lambda_m)$ and their eigenvector $p_1, p_2, \cdots p_m$.

D. Determination of numbers of principal components, and their eigenvalue and the eigenvector

Apply cumulative variance contribution rate to determine the numbers of principal components. The cumulative variance contribution rate of fist k principal components shall be:

$$q = \frac{\sum_{i=1}^{k} \lambda_i}{\sum_{i=1}^{m} \lambda_i} \tag{7}$$

When the cumulative variance contribution rate of fist k principal components reaches to 90%, take the number of principal components as k. After k is determined, it will derive k eigenvalues $\lambda_1, \lambda_2, \cdots, \lambda_k (\lambda_1 > \lambda_2 > \cdots \lambda_k)$ and corresponding eigenvector $p_1, p_2, \cdots p_k$.

E. Statistic SPE and T^2

SPE measures the variation of the projection of sample vector in residual space:

$$SPE_i = \left\| (I - P \cdot P^T) \cdot x_i \right\|^2 \le \delta_\alpha^2 \tag{8}$$

In the formula: x_i is the ith data of observable variables of detection sample, δ_α^2 refers to the control limit with confidence coefficient α. This control limit δ_α^2 is calculated with training sample. Please refer to the formula below:

$$\delta_\alpha^2 = \theta_1 \left(\frac{C_\alpha \sqrt{2\theta_2 h_0^2}}{\theta_1} + 1 + \frac{\theta_2 h_0 (h_0 - 1)}{\theta_1^2} \right)^{1/h_0} \tag{8}$$

In the formula: $\theta_i = \sum_{j=k+1}^{m} \lambda_j^i (i = 1,2,3)$, $h_0 = 1 - \frac{2\theta_1\theta_3}{3\theta_1^2}$, λ_j^i is the eigenvalue of covariance matrix of $\bar{X}$, C_α is the threshold value with standard normal distribution under confidence coefficient α. In this paper, the confidence coefficient α is 90%.

Hotelling T^2 is the standard sum of square of score vector, which measures the variation of sample vector in principal component space. Please refer to the formula below:

$$T_i^2 = t_i \lambda^{-1} t_i^T = x_i P \cdot \Lambda^{-1} \cdot P^T x_i^T \le T_\alpha^2 \tag{9}$$

In the formula: t_i is the ith row of score matrix, $\Lambda = diag\{\lambda_1, \lambda_2, \cdots \lambda_k\}$, T_α^2 is the control limit of T^2 with confidence coefficient α.

Suppose when speed sensor is normal and the samples comply with the normal distribution, the control limit value T_α^2 can be calculated through training samples with the formula below:

$$T_\alpha^2 = \frac{k(n^2 - 1)}{n(n-k)} \cdot F_{k, n-k : \alpha} \tag{10}$$

In the formula: $F_{k, n-k : \alpha}$ is critical value of F distribution with freedom degree k and $n-k$ and the confidence coefficient α.

F. Comprehensive index φ

In order to avoid the inconformity of detection results caused by different values of SPE and T^2, this paper proposes a comprehensive index φ, which weighs both SPE and T^2. Please refer to the formula below:

$$\varphi_i = \frac{SPE_i}{\delta_\alpha^2} + \frac{T_i^2}{T_\alpha^2} \le \zeta_a^2 \tag{11}$$

In the formula: ζ_a^2 refers to the control limit with confidence coefficient α. Please refer to its calculation formula as below:

$$\zeta_a^2 = g\chi_{h,\alpha}^2 \tag{12}$$

In the formula: $g = \frac{tr(S.M)^2}{tr(S.M)}$, $h = \frac{[tr(S.M)]^2}{tr(S.M)^2}$, $M = \frac{I - P.P^T}{\delta_\alpha^2} + \frac{P.\Lambda^{-1}.P^T}{T_\alpha^2}$, S is the covariance matrix of training sample $\bar{X}$.

Therefore, put the detection sample into above-mentioned statistic calculation formula, it will derive the comprehensive index φ. Then compare with the control limit calculated by training sample. Detect in real-time if there is any fault for speed sensor during operation. When there is fault, record the time when fault occurred.

IV. FAULT LOCATION

It can detect the time when fault occurred through PCA but without the information that which axle has occurred fault. RBCP can locate the failed axle and is applicable for the case when multiple variables failed simultaneously.

It is not necessary to consider in advance the numbers of failed variables when apply RCBP. Meanwhile, in order to eliminate the influence to non-fault variables to avoid smearing, it will only solve RBC value of each variable of the test sample at the time when fault occurred. It will collect the number of times of largest RBC value of each variable at the time when fault occurred, the variable with highest number of times is the fault variable, thus realize the location of fault variable, and make judgment if the monitoring index of reconstruction sample exceed the control limit. It realizes the location of multiple fault variables one by one through such repeated iteration judgment until all the reconstruction index of sample are lower than control limit.

In consequence, the main fault location steps are as follows:

1）Define the set of fault variables as X_f , and initially it is null, the number of fault variables is k with initial default as 0.

2）Regarding the test sample data at the time when fault occurred, it calculate the RBC values of fault variable X_f and non-fault variable $x_i(i=1,2,...m-k)$, and obtain the maximum value. The variable with the largest number of maximum values is the fault variable. Put the fault variable into X_f . Please refer to the formula below for the calculation of RBC value.

$$
\begin{aligned}
RBC_i &= \left\|\xi_i f_i\right\|^2_M = \left\|\xi_i(\xi_i^T M\xi_i)^{-1}\xi_i^T Mx\right\|^2_M \\
&= x_i^T M\xi_i(\xi_i^T M\xi_i)^{-1}\xi_i^T Mx_i
\end{aligned} \tag{13}
$$

In the formula: $M=\frac{I-P.P^T}{\delta_\alpha^2}+\frac{P.\Lambda^{-1}.P^T}{T_\alpha^2}$, ξ is the unit matrix made up of fault direction.

3）Numbers of fault variables: k=k+1. It calculate the monitoring index $Index(x_i)$ of reconstruction sample of fault variable set X_f ,and make judgment whether it is smaller than control limit, if yes, location completed, if not, return back to step 2, and repeat the cyclic location. Please refer to the formula below for the monitoring index of reconstruction sample.

$$Index(x_i)=(x_i-f_i.\xi^T)M(x_i-f_i.\xi^T)^T \le \zeta_a^2 \tag{14}$$

In the formula, ζ_a^2 is the control limit of comprehensive index φ . $f_i=(\xi_i^T M\xi_i)^{-1}\xi_i^T Mx_i$ is the fault amplitude of fault variables.

4）Locate all faults through repeated cyclic literation until all monitoring index of reconstruction sample of fault variable set X_f are lower than control limit.

5）solve specific speed sensor of specific axle exists fault according to the fault variable set X_f .

V. Algorithm Verification

In order to make fully verification to the fault diagnosis algorithm, it shall obtain the sample data under each kind of failure mode of speed sensor. Since the measured data of current vehicle cannot cover all the failure modes, it has set up the test environment for the speed sensor and performed each kind of simulation test with fault injection, such as normal mode, broken wire, weak connection, high-low temperature, EMI and vibration. Fig. 3 is a simulation test by applying vibration test bench to perform vibration, and heat gun to make local heating to speed sensor.

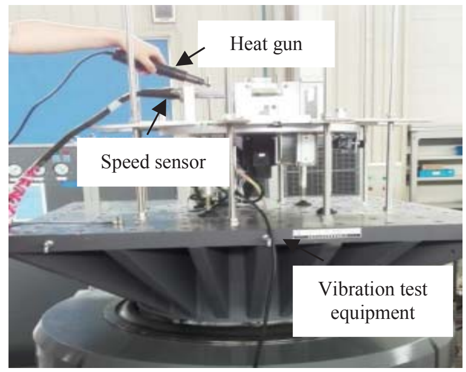

Fig. 3. Fault simulation test of speed sensor

In consequence, there are 84 sets of typical sample data of speed sensor through simulation test and measured data of current vehicles. Fig. 4 is the data curve under normal working conditions. The speeds of four axles gradually reduce from 225km/h to 160km/h, and the data acquisition period is 10ms.

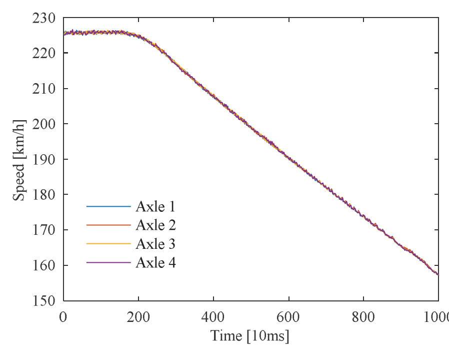

Fig. 4. Speed curve of four axles under normal working conditions

Fig. 5 is the data curve when axle 1 appears wire broken fault. The speed of axle 1 suddenly drops to 0 at around the time 120.

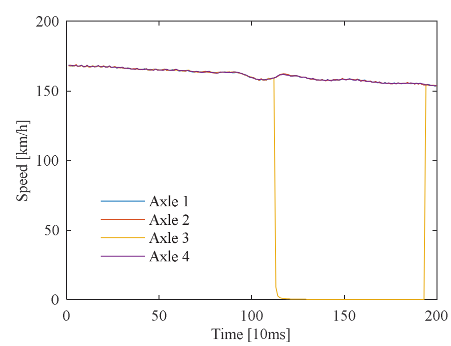

Fig. 5. Speed curve of four axles with wire broken fault

We apply matlab to realize the modeling of fault diagnosis method of speed sensor, including fault detection and location of failed axle. 84 sets of data are applied to perform training and verification to the models, the results prove the accuracy and validity of such fault diagnosis algorithm. Take Fig. 5 as the example, its diagnosis result is as follows:

A. Fault Detection

The training samples apply the data of four axles of one car under normal working conditions, and its curve is as Fig. 4. The key parameters of training samples obtained by model algorithm are shown in Table I.

TABLE I. THE KEY PARAMETERS OF TRAINING SAMPLES

Critical Parameter	Calculation Result
Mean Value μ_j	[0.2990 0.2127 0.2830 0.2817 0.2458 0.2753]
Standard Difference σ_j	[0.2285 0.1658 0.2040 0.2078 0.1942 0.2060]
Quantity of principal component k	5
Corresponding load vector P	[-0.3884,0.0775,0.5185,-0.1567,0.4850; 0.0392, -0.0748,0.3410,0.9244,0.1021; -0.6085,-0.3228,-0.3937,0.0479,0.4592; 0.4629,-0.0412,0.4032,-0.2894,0.4866; 0.0067, 0.8926,-0.2914,0.1368,0.3064; 0.5128, -0.2930,-0.4607,0.1271,0.4612]
Confidence coefficient α	99%
Control limit of index T^2	20.8005
Control limit of index SPE	1.7953
Control limit of comprehensive index φ	1.5991

During fault detection, the PCA algorithm calculates the comprehensive index φ of testes sample according to the critical parameters of training samples. As shown in Fig. 6, the control limit of comprehensive index φ obtained from training sample is 1.5991, and at the time [54,77，113:193], the comprehensive index φ of tested sample has already exceeded the control limit which means fault appears, thus realize the fault detection, and then record the time period when fault appeared.

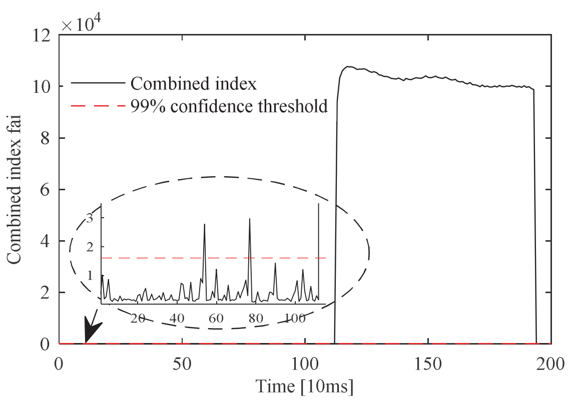

Fig. 6. Comprehensive index curve of tested sample

B. Fault Location

During fault location, the RBCP algorithm calculates the RBC values of 6 variables at each moment and counts the number of times with the maximum RBC for each variable in the time period [54, 77, 113:193], and the variable who has the most number is fault variable. As shown in Fig. 7, at first location diagnosis, the number of times when 6 variables are located as fault variable are respectively 1, 81, 1, 0, 0 and 0, so, the fault variable set is $X_f = \{2\}$, thus realize first fault location.

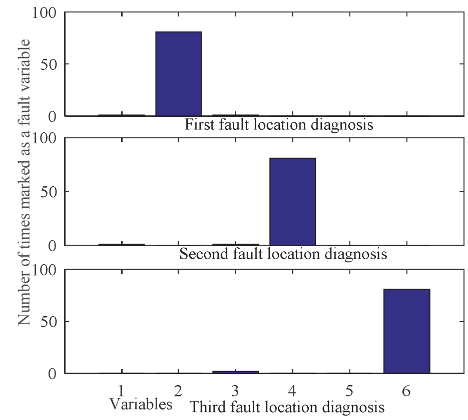

Fig. 7. Bar graph of fault quantity of 6 variables

Each time when 1 variable is located, calculate the monitoring index of reconstruction sample, and make judgment if it exceeds control limit φ. As shown in Fig. 17, the control limit is 1.5991, after first reconstruction, the monitoring index of reconstruction sample within time period [54,77，113:193] exceed the control limit, therefore, it shall continuously perform RBC calculation and fault variable judgment. After 3 times of literation judgment, all monitoring index of reconstruction sample are less than control limit, thus fault location completed, and all fault variables are located. As shown in Fig. 16, the fault variable set is $X_f = \{2,4,6\}$, according to the concept of combination maximization and the relationship between variable and axle, derive the fault axle is axle 3, thus realize the accurate location of fault axle.

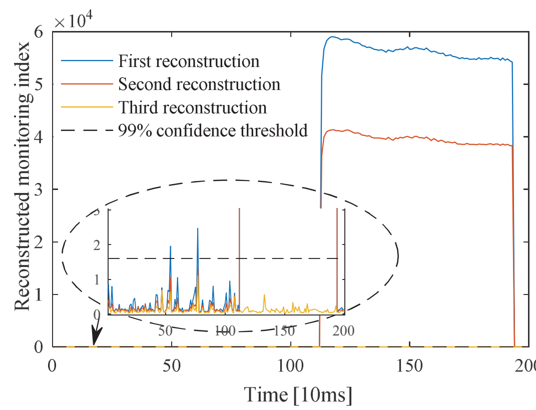

Fig. 8. Reconstruction monitoring index curve of tested Sample

VI. CONCLUSION

This paper proposes an integral intelligent diagnosis method for the speed sensor of high-speed train brake system. This method realizes the real-time detection of fault and accurate location of failed axle. On the basis of PCA, real-time detection of fault of speed sensor is realized by judging whether the comprehensive monitoring indicators of test samples exceed the limit, which effectively avoid the inconformity defect of detection results that caused by traditional two different kinds of monitoring statistic. Then RBCP is applied to realize the accurate location of specific failed axle through repeated literation judgment, which is applicable for the location of multi-variable fault, and decreases the influence to non-fault variables to avoid smearing. And training and verification of speed sensor diagnosis algorithm are performed based on the operation data and fault-injection simulation test data, the results show that the method is effective. And this method can solve the false report problem of current vehicles and improve the safety and maintainability of brake system, and lays a foundation for subsequent research on automatic recognition of fault type and fault oriented security treatment of speed sensor.

REFERENCES

[1] Liu Binpu, Zhang Yongming, Tian Peng. "Reason Analysis and Optimization Scheme for Locked-brake Failure on Type CRH2 EMU, " Electric Locomotives & Mass Transit Vehicles. China, vol. 39, no. 2, pp. 66–69, March 2016.

[2] Yang Biao. "Analysed Reasons and Improved Suggestions About the CRH2 Axle Failure, " Railway Locomotive & Car. China, vol. 35, suppl 1, pp. 106–107, May 2015.

[3] Yin Fang, Yang Yongqin, Cui Hushan. "Solution to misinformation failure in axle lock braking detection of EMU," Electric locomotives & Mass Transit Vehicles. China, vol. 36, no. 1, pp. 83–84, January 2013.

[4] Zhang Xiaojun. "Brief introduction of fault tree analysis for CRH380BLEMU,"Railway locomotive & car. China, vol. 34, no. 6, pp. 87–90, June 2014.

[5] Zhou Guifa, Wang Jian. "Research on Locomotive Speed Sensor Fault Diagnosis Method Based on Neural Network," Electric Drive for Locomotives. China, vol. 1, pp. 36–38, January 2010.

[6] Song Yun, Zhu Mingnian. "Subway Sensor Fault Diagnosis Based on Radial Neural Network," Urban Mass Transit. China, vol. 5, pp. 94–101, May 2014.

[7] Lv Feng, Du Hailian, Wang Zhanfeng. "The Study of the Fusion Estimation and the Fault Diagnosis Method Based on Multi-speed Sensor," 2009 WRI World Congress on Computer Science and Information Engineering. Los Angeles, California, USA,vol. 7, pp. 176–180, March 2009.