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RESEARCH ARTICLE

The Investigation of Data Voting Algorithm for Train Air-Braking System Based on Multi-Classification SVM and ANFIS

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Abstract — The pressure data of the train air braking system is of great significance to accurately evaluate its operation state. In order to overcome the influence of sensor fault on the pressure data of train air braking system, it is necessary to design a set of sensor fault-tolerant voting mechanism to ensure that in the case of a pressure sensor fault, the system can accurately identify and locate the position of the faulty sensor, and estimate the fault data according to other normal data. A fault-tolerant mechanism based on multi-classification support vector machine (SVM) and adaptive network-based fuzzy inference system (ANFIS) is introduced. Multi-classification SVM is used to identify and locate the system fault state, and ANFIS is used to estimate the real data of the fault sensor. After estimation, the system will compare the real data of the fault sensor with the ANFIS estimated data. If it is similar, the system will recognize that there is a false alarm and record it. Then the paper tests the whole mechanism based on the real data. The test shows that the system can identify the fault samples and reduce the occurrence of false alarms.
Keywords — Multi-classification support vector machine, Adaptive network-based fuzzy inference system, Train air braking system, Fault-tolerant voting, Multi-sensors.
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I. Background

Automatic train protection (ATP) is an important part of modern train operation control system. The core component used in the train ATP system is the safety computer, which needs to receive data from the on-board sensor and make judgments after fusion. In practice, heterogeneous and multi-sensor methods are usually used to complete the sampling of a certain data.

Due to the influence of external conditions, sensor error and environmental factors, the results of two sensors (especially heterogeneous sensors) are difficult to be absolutely consistent. When processing the results of multiple sensors, the safety computer needs to judge whether the sampling results belong to "nearly consistent". In the existing practice, the threshold method is usually used. The setting of threshold is important: if the threshold is too small, some normal data may be recognized as abnormal, resulting in frequent alarms and affecting the availability of the system; If the threshold is too large, some abnormal data may be labeled as normal, which will affect the safety. How to balance the availability and safety has become the key to the performance of the safety computer.

Taking these disadvantages into consideration, there are several new ways for fault detection except the

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threshold-based method, like the fuzzy-rule based method, the statistics-based method and so on [1]–[5].

In order to realize the fault detection and isolation (FDI), the analysis method based on SVM is proposed in paper [6] to identify the fault location in wireless sensor networks. The result of verification with actual data is that for offset (the difference between the sensor reading and the actual value is fixed as a constant), gain (the sensor reading is a linear function of the actual value), fixed value (the sensor reading is a fixed constant), overrun (the sensor reading exceeds the normal value range of physical quantity). The recognition rate of random faults is more than 95%, but SVM belongs to two classification algorithm, so the test is only carried out individually in this paper. At the same time, the literature does not involve the recognition of soft failure. The soft failure is a special kind of failure, the device or system with soft failure can still function, but with lower service qualities.

In terms of soft failure identification, a new data-driven algorithm for sensor fault identification is designed in reference [7]. The specific way is to build virtual sensors based on multi-layer observer Using using high reliable sensor data to correct low confidence sensor data, and using air quality monitoring system consisting of five different sensors, the results show that the whole system can achieve simultaneous interpreting simultaneous interpreting. Darvishi*et al.* then described the details in paper [4], The algorithm is described in detail, and verified by using two kinds of fault data: deviation and drift in hard failure and soft failure of air quality, wireless sensor network and permanent magnet synchronous motor. It is compared with two existing algorithms: SVM classification algorithm and FCC neural network. During the test, SVM, FCC and the new algorithm have high recognition accuracy for hard deviation, which are 92.3%, 99.7% and 99.8% respectively; however, the recognition accuracy for soft deviation is 34.9%, 15.9% and 58.1%, respectively [8].

After completing the FDI process, the safety computer should estimate the real value corresponding to the faulty sensor based on the existing conditions. The existing methods are mainly divided into two categories: estimation methods based on analytical model and data-driven estimation methods [9].

Among them, the estimation method based on analytical model is represented by Kalman filter and its extension method [10], [11]. In reference [12], the application of two out of three voting and Kalman filter in train integrated positioning system is analyzed, and various sensors are divided into three groups, each group includes a GNSS receiver and an inertial navigation IMU unit (or an axle speed sensor). The three groups output the position information after fusion based on extended Kalman filter, the 3 groups of position information are processed by Kalman filtering and two out of three structure based on threshold decision, and finally output. The verification results based on the actual data show that the accuracy (expressed in 95% confidence interval), availability and MTTF value of the two out of three voting system are better than Kalman filter, but the voting failure can not occur because the difference between the three data is too large. Similarly, the same is true in the analysis of soft failure of train integrated positioning system in literature [13] and the analysis of low-speed positioning of road vehicles in literature [14]. The estimation method based on analytical model requires users to have a deep understanding of the analyzed system.

For systems with complex internal structure or the relationship between system variables is difficult to be described by formula, data-driven estimation methods can often achieve good results. Reference [15] introduces the design of monitoring mechanism for hydraulic pump based on ANFIS. In this paper, an ANFIS model is trained for the three faults of piston leakage, discharge blockage and filter damage of hydraulic pump; Finally, the accurate identification and diagnosis of hydraulic pump fault are realized. The motor fault-tolerant control strategy based on ANFIS in reference [16] and the fault-tolerant strategy for sensor errors in wastewater treatment equipment based on ANFIS reasoning in reference [17].

The data within train control system includes switching value and continuous data. The discrimination of continuous data is relatively difficult because the algorithm needs to solve the following three problems:

1) Non-linearity. There are relationships between input data, but these relationships may be difficult to be expressed in the form of functions.

For example, in the integrated train positioning system [5], [6] (as shown in the Figure 1), in phase I, the system needs to process the information from GNSS and the speed information from ODO, which are not strictly linear correlation. In phase II, the 2-out-of-3 unit needs to process the fused position information. Under normal conditions, The correlation coefficient between any two input data should be close to 1.

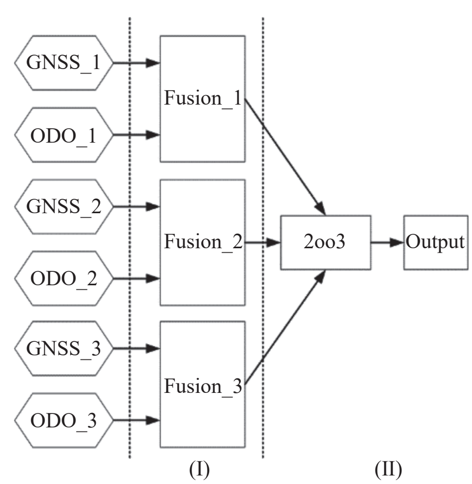

Figure 1 Example of the Integrated location system.

2) Dynamic. Under normal conditions, the "correct value" of data is constantly changing.

3) Unreliability. All data may be "unreliable". The safety computer should treat input values "equally", rather than assume that the reliability of some input values exceeds other input values.

In reference [1], an algorithm of fault detection based on intervariable variance(IVV) is designed which is good at solving problem 2) and 3). In the paper, the data of air pressure in train brake cylinders are used to form a decision vector $\boldsymbol{x}_k = [x_1, x_2, \ldots, x_m]^T$, and then the IVV detection criterion is designed as follows:

$$IVV(\boldsymbol{x}_k) = \sum_{i=1}^{m}(x_i - \bar{x})^2 \tag{1}$$

Here, the $x_1, x_2, \ldots, x_m$ means the air pressure in m braking cylinders, $\bar{x}$ is their average pressure, if all the datas are in normal condition, the $IVV(\boldsymbol{x}_k)$ should be small, if they are in abnormal condition, the $IVV(\boldsymbol{x}_k)$ will be bigger. The $IVV(\boldsymbol{x}_k)$ can be seen as the L2-norm of the $IVV(\boldsymbol{x}_k)$. On the basement of this paper, the paper [15] used the ∞-norm, which is more sensitive for tiny changes. But all the algorithms are available on the condition that the input variables are almost synchrous, or the correlation coefficient of any two variables is close to 1, which is not good at solving problem 1).

References [4], [7] designed the sensor fault detection, isolation and accommodation algorithm based on multi-layer perceptron,. In these papers, virtual sensors based on multi-layer perceptron are designed and sensors with high dependability are used as inputs for accommodation of sensors with low dependability. The results show that it is good at solving problem 1) and 2), but not able to deal with problem 3), as they have separated sensors into "trusted" and "untrusted" before data processing.

As far as we know, the algorithm which is able to deal with problem 1), 2) and 3) are still not accessible, which is still worth studying.

The contributions of this paper include:

i) For the purpose of fault tolerance, the fault identification and location of train braking system under redundant sensors are realized based on multi classification SVM algorithm. ii) Based on ANFIS inference algorithm and taking the train brake handle as the discrimination basis, the fault sensor data of the train brake system is estimated to ensure that the system can still be accurately predicted when the steady state of the system changes

II. Correlation Theories

1. Support vector machine

Support Vector Machine (SVM) is a classical algorithm for binary classification of data according to supervised learning. It is one of the most classical algorithms to realize the classification function based on machine learning [6], [18]–[23].

Figure 2 shows the difference of hyperplane position obtained by SVM training when the number of two training samples are the same and different. Where, the hyperplane M1 represents the hyperplane position trained by SVM algorithm when the number of samples labeled "+1" is strictly equal to the number of samples labeled "−1"; Hyperplane M2 represents the hyperplane position trained by SVM algorithm when the number of samples labeled "−1" remains unchanged and the number of samples labeled "+1" decreases. It is not difficult to see from the figure that when the sample data used for training are obviously different, the position of the hyperplane obtained by training may shift to the side with less samples.

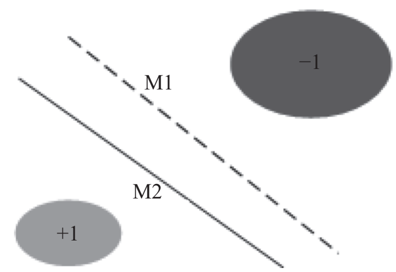

Figure 2 Influence of different classification training samples on classification effect.

In practical application, if the hyperplane M2 is used to classify the real data, the system may have false alarm (that is, the normal data is mistaken for the fault data), but the probability of missing alarm (that is, the fault data is mistaken for the normal data) will be reduced. Therefore, in order to ensure the fault-tolerant performance of the system, the number of fault samples is more than the number of normal samples.

2. Multi-classification algorithm based on SVM

In order to realize multi classification, the combination of different SVMs are often used. The existing combination methods mainly include 1-against-rest (Figure 3), 1-against-1 (Figure 4), etc.

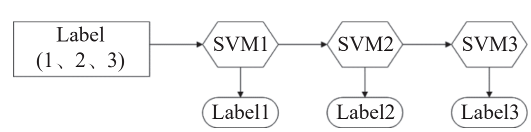

Figure 3 one-against-rest multi-classification algorithm.

Practice shows that the 1-to-1classification method has higher accuracy [21], but the number of SVM classifiers required increases with the increase of the number of categories n. when the value of n is large, the amount of computation is large.

3. Adaptive network-based fuzzy inference system (ANFIS)

ANFIS is developed on the basis of traditional fuzzy

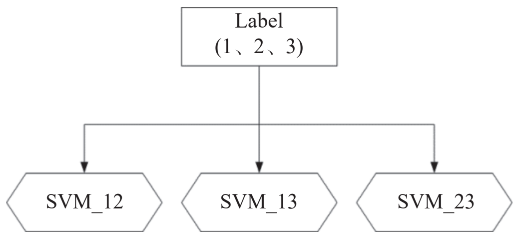

Figure 4 one-against-one multi-classification algorithm.

inference system [24]–[26]. The core part of the traditional fuzzy reasoning system is fuzzy rules. One of its standard forms is "if a is m, then B is n". Here a and B are input variables and output variables respectively, and m and N are their corresponding membership functions respectively. In the traditional fuzzy inference system, the fuzzy rules often come from the experience summary of the designer, in which human factors may affect the effect of the final decision. The ANFIS introduces the self-learning ability of the neural network, so that the whole network can self-learn through the sample data, so as to "deduce" the appropriate fuzzy rules by itself, It is suitable for characteristic modeling of complex systems.

A typical ANFIS network can be roughly divided into five layers: input layer (I), fuzzification layer (II), product layer (III), normalization layer (IV), de fuzzification layer (V) and total output layer (VI), as shown in Figure 5.

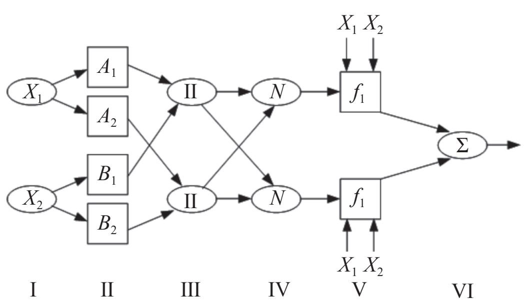

Figure 5 System structure of a typical ANFIS network.

4. Overall description of the whole algorithm

The overall fusion algorithm flow of pressure data of train braking system is roughly shown in Figure 6.

The functional requirements for the algorithm mainly include: 1) how to judge whether there are errors in the field collected data and how to locate if there are any; 2) How to estimate the true value of fault data according to the values of other normal data when it is determined that there is an error on site. At the same time, the performance requirements of the algorithm mainly include: 1) Ensure the fault data detection rate as much as possible; 2) The estimated value of fault data shall be as accurate as possible; 3) In case of previous misjudgment (i.e., normal data value is judged as fault ones), the algorithm can make corrections and keep them in the correct ones.

Specifically, the algorithm is mainly divided into three parts: 1) Based on the principle of multi classification SVM, classify the data to determine whether it is correct or not; 2) Estimate the error data based on ANFIS algorithm; 3) In step 1), when determining the SVM hyperplane, the sample size of normal data and fault data is artificially set to be different, resulting in a certain false alarm rate. Therefore, the possibility of false alarm is minimized in this link. Specifically, after the estimation is completed, the estimated value is compared with the original data value. If the two are similar (e.g., the difference is less than 20 kPa), it is considered that there is a misjudgment before, and the original data is used as the output value, otherwise the estimated value is output.

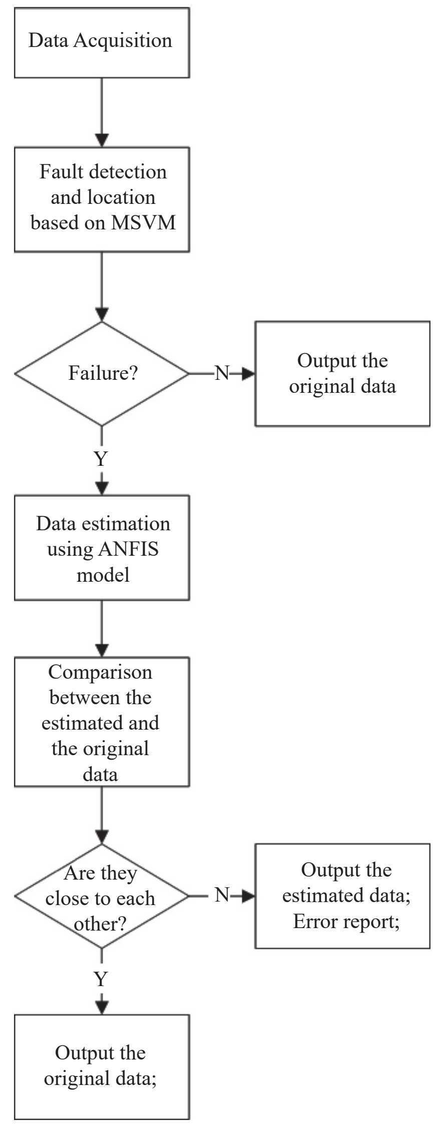

Figure 6 Flow chart of data fusion algorithm based on SVM-ANFIS algorithm.

Fault identification and location based on multi classification SVM is the focus of this algorithm. The specific process is shown in Figure 7.

In order to ensure the recognition rate of fault data, SVM is trained and unbalanced samples were deliberate-

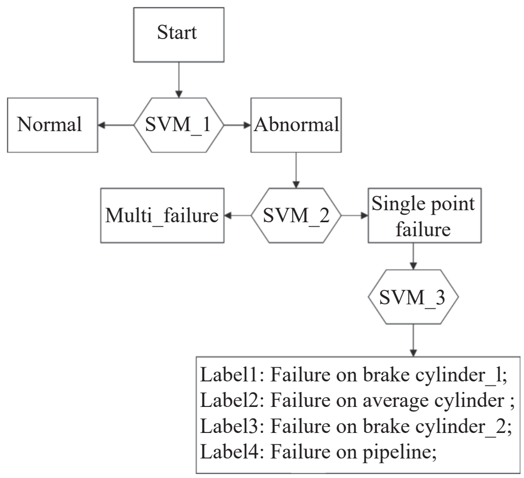

Figure 7 Fault detection and location algorithm based on SVM.

ly selected. Specifically, 140 groups of samples in the normal state and 156 groups of samples in the fault state of the system, so as to ensure that the hyperplane obtained by training is closer to the "normal" side. The "missed detection rate" of the system for fault data is reduced.

III. Calculation and Analysis

In order to verify the effectiveness of the algorithm, this paper collects the real data from the air braking system of 3 ordinary speed trains to train the multi classification SVM and ANFIS model, and then verifies the accuracy of the final result by artificially introducing intermittent faults in a certain route, The BP neural network are used as a comparison to verify the advantages of the new algorithm.

1. Fault location based on multi-classification SVM

The fault detection and location algorithm based on multi-classification SVM algorithm is mainly responsible for the recognition of fault state and the location of fault sensor. According to the above, the sample data selected when training three SVM classifiers are shown in Table 1.

Table 1 List of training samples

SVM	Classification	Train data
SVM1	Binary	Normal sample: 140 Abnormal sample: 156
SVM2	Binary	1 Failure: 39 Multiple failures: 39
SVM3	Multiple	Brake1 failure: 39 Average failure: 39 Brake2 failure: 39 Pipe failure: 39

When measuring the effect of multi-classification SVM, precision and recall are used. The two indexes measure the recognition rate of the classifier for a certain kind of data and the accuracy of the recognition results. Specifically, it is assumed that the classification effect of a set of three classification SVM needs to be measured. The real attributes and classification results of the test data are shown in Table 2.

Table 2 Example of result from a MSVM

		Classified label		
		1	2	3
Real	1	A	B	C
	2	D	E	F
	3	G	H	I

Take the label 1 as an example, the calculation formula for the $P_{precision}$ and the P_{recall} are as follows:

$$P_{\text{precision}} = \frac{A}{A+D+G} \tag{2}$$

$$P_{\text{recall}} = \frac{A}{A+B+C} \tag{3}$$

Using the hyper classification algorithm, the classification results are listed in Table 3.

Table 3 The $P_{\text{precision}}$ and the P_{recall} of the algorithm

	$P_{\text{precision}}$	P_{recall}
Type 1 : normal	0.35	0.8
Type 2 : failure on brake cylinder1	1	1
Type 3 : failure on average cylinder	1	1
Type 4 : failure on brake cylinder2	0.87	1
Type 5 : failure on braking pipe	0.54	1

For the comparison, the results using the one-versus-one and the one-versus-rest are listed in Table 4.

Table 4 The results for the 1-v-1 and the 1-v-rest

	One-versus-one		One-versus-rest	
	$P_{\text{precision}}$	P_{recall}	$P_{\text{precision}}$	P_{recall}
Type 1 : normal	0.5	0.75	0.6	0.7
Type 2 : failure on brake cylinder1	0.8	1	0.5	1
Type 3 : failure on average cylinder	1	1	1	0.5
Type 4 : failure on brake cylinder2	1	0.75	1	0.75
Type 5 : failure on braking pipe	1	0.5	1	0.54

For the multi-classification SVM, the 1-versus-1 algorithm should come up with $C_5^2 = 10$ binary SVM classifiers, the 1-versus-rest algorithm has a lower accuracy, but needs only 5 classifiers; the new classification algorithm included in this paper needs $(1+1+C_4^2=8)$ binary SVM classifiers, reducing the amount of calculation while ensuring the similar classification effect.

2. Data estimation algorithm based on ANFIS

After fault location, it is necessary to use the "normal" data of the remaining sensors to estimate the real value of the fault data.

This paper chooses to train different ANFIS networks according to the different positions of the brake handle because the position information of the brake handle is reliable.

Taking "train pipe pressure sensor fault" as an example, in practical application, select the sample data under normal operation, manually set the column of "train pipe data" to 0 intermittently, and compare the estimated value with the real value after training ANFIS network to analyze its error.

Firstly, the correlation coefficients of the air pressure data variables (brake cylinder1, average cylinder, brake cylinder2, pipeline, main cylinder) are calculated, and the results are shown in Table 5.

Table 5 The correlation coefficient calculation results

Brake cylinder1	Average cylinder	Brake cylinder2	Main cylinder	Braking pipe
−0.5377	−0.5371	0.2095	0.0889	0.2208
1	0.9997	−0.6891	−0.1433	−0.6930
0.9997	1	−0.6910	−0.1429	−0.6953
−0.6891	−0.6910	1	0.0624	0.9857
−0.1433	−0.1429	0.0624	1	0.0595

From the correlation coefficient of pressure data, the pressure values of brake cylinder1 and equalizing cylinder are highly linearly correlated, brake cylinder2 and train pipe are highly linearly correlated, and the pressure of main air cylinder is basically irrelevant to other values. Therefore, brake cylinder1, equalizing air cylinder, brake cylinder2 and train pipe pressure are selected to realize the voting function.

It is unlikely that the position data of train brake handle will be abnormal in the acquisition process. Therefore, taking the position data of train brake handle as a reference, different ANFIS models are trained according to the position of train brake handle.

The actual braking process includes: 1) No braking: the pressure of brake cylinder 1 is 0; 2) Apply braking: the pressure of brake cylinder 1 rises; 3) Low braking: the pressure of brake cylinder 1 remains between 300–400 kPa; 4) High braking: the pressure of brake cylinder 1 is maintained above 400 kPa and remains stationary; 5) Brake release: the pressure of brake cylinder 1 decreases; 6) Adjustment: the pressure of brake cylinder 1 fluctuates and does not exceed 100 kPA. At this time, the pressure of pipe remains unchanged at 600 kPa;

When no braking is applied, the air pressure in brake cylinder and the average cylinder should be 0, and the air pressure in brake cylinder 2 and pipeline should be 600 kPa. Therefore, the value between two records (0, 0, 600, 600) in the actual data is selected as a cycle, and the value between the highest point of the pressure value of brake cylinder 1 and (350, 460) in all cycles is guaranteed as far as possible. The ANFIS models' parameters are listed in Table 6. The AnfisNo is the ANFIS model referring to the condition in which no braking is applied, and the AnfisChange is the ANFIS model referring to the condition in which braking is applied. The "Membership" in Table 6 means the fuzzy membership functions. For example, the [4 4] means there are 2 input variables each one is fuzzified by 4 triangle member functions.

Table 6 Some parameters of ANFIS model

	AnfisNo	AnfisChange
Membership	[4 4]	[5 5 5]
Input variables	Brake cylinder2 Main cylinder	Brake cylinder1 Average cylinder Brake cylinder2
No. of rules	16	125

The comparison between the train air duct pressure value after training and the real value is shown in Figure 8. In Figure 8, the horizontal axis refers to the number of air pressure samples, and the vertical axis refers to the air pressure of train pipe, the blue is the estimated value and red is the real value.

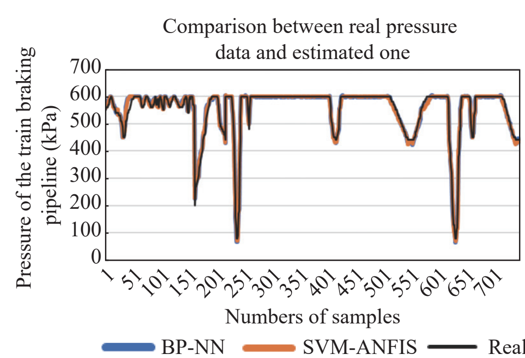

Figure 8 Comparison between real value and estimated value.

Figure 8 shows an extreme case, in which the pressure sensor of the train braking pipeline is in abnormal condition and the pressure data of the braking pipeline is completely unaccessible. The estimated pressure data and the real pressure data is displayed separately.The error between the two models and the real ones are shown in Figure 9.

The RMSE of the estimation error between the calculated and real data using BP model is 8.12, while the RMSE of the SVM-ANFIS model is 8.20. The average value of the BPmodel is 5.83 and the average value of the SVM-ANFIS model is 5.60. The SVM-ANFIS model has a lower average estimation error, judging from Figure 9 it could be seen that the highest error using the SVM-ANFIS is the 31st sample, 40.63 for detail, the biggest error using the BP-neural network is the 38th sample, −62.23 for detail. In real applications, users are more concerned about the absolute value of the error than the positive and negative. The SVM-ANFIS model

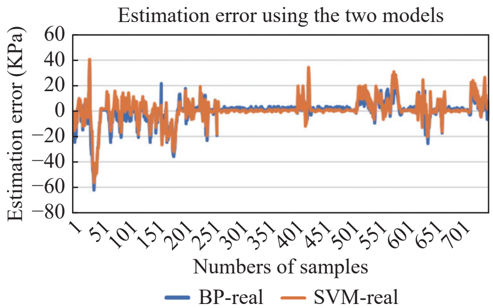

Figure 9 The estimation error of the two models.

has a lower average estimation error, judging from Figure 8(b) it could be seen that the highes error using the BP model is over 60, 62.22 for detail; and the highest error using the SVM-ANFIS model is less than 60, 51.08 for detail. It could be seen from above that the SVM-ANFIS model has smaller fluctuation peak and smaller average value.

IV. Conclusion

In this paper, a fault-tolerant voting mechanism is designed for the pressure sensor fault of the train air braking system. Firstly, the multi-classification SVM classifier is used for FDI; Then, the ANFIS algorithm is used to estimate the data of the fault sensor. Finally, the estimated value of the sensor data is compared with the actual data of the fault sensor. If the two values are close, it is recognized as the system false alarm and the real data is output. The results show that the whole set of fault-tolerant voting algorithm can identify the single point fault and accurately estimate the fault value. In case of intermittent fault of a sensor, the system can still ensure the correctness of the data. It is of great significance to improve the quality of pressure data collected by train air braking system.

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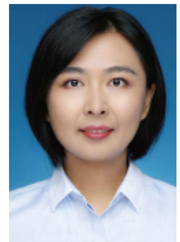

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