Fault Diagnosis of Elevator Safety Circuit Based on Deep Forest

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Abstract. There exist some problems in the current diagnosis methods of elevator faults, including complicated calculation, numerous parameters and difficulties in effectively processing information of the faults' feature . This paper proposes a method of diagnosing the faults of elevator's safety loop, and designs a structure of the faults' diagnosis model. Further more, on this basis a collection system of elevator's fault signals is developed, with which, the parameters of corresponding feature can be obtained, and then the information of elevator faults' feature can be extrated through Multi-Grained scanning. At last, diagnosing the faults of elevator safety loop is realized through Cascade Forest. The experiment result shows that with this method the diagnosis accuracy is 4% higher and the model operation time is 99.1% faster than BPNN.

Keywords: elevator, fault diagnosis, deep forest

1.QUOTES

With the accelerating modernization process of today's cities and the increasing level of China's national economy, elevators are widely used in people's daily lives. However, the wear and aging of internal components caused by long time use of elevators and uncivilized behavior of passengers have led to the occurrence of elevator failures, which can seriously threaten the lives and properties of passengers [1]. Therefore, condition monitoring and fault diagnosis of elevators are extremely important.

Frequent failures of elevators include safety circuit failures, elevator door machine system failures, door lock circuit failures, inverter failures [2], etc. The most frequent failures are elevator safety circuit [3] and elevator door machine system failures [4].. Above all, elevator safety circuit failures are the main cause of the elevator emergency stop failures. In the process of elevator operation, if a safety circuit failure occurs, the elevator will immediately stop sharply at the current running position, which directly endangers the personal and property safety of elevator passengers, so the diagnosis of elevator safety circuit failure will help improve the safety of elevator passengers.

At present, related scholars have achieved some results in elevator fault diagnosis and prediction. Zong Qun et al [5] established a model tree -based elevator fault system diagnosis model based on fault tree analysis method and combined with expert system structure, which can analyze the system defects of elevator by expert diagnosis basis. Bao G Y [6] used a manual knowledge acquisition method with a fault tree analysis algorithm and a forward reasoning strategy to locate the possible causes of system faults. Chang L et al [7] used a decision tree classification algorithm to classify faults and establish a fault diagnosis model in accordance with elevator operation theory. Pei H [8] created a fault tree analysis model to improve the accuracy of fault diagnosis, which quantitatively and qualitatively derived various faults that are prone to occur in elevators and the reasons for their occurrence. Wang G W [9] established an elevator fault tree triggered by fire and analyzed the situations leading to the occurrence of fire accidents, thus proposing relevant measures to reduce the risk of elevator operation under fire conditions. Zhao C G et al [10] introduced rough set theory for improvement based on decision trees and proposed an intelligent fault diagnosis method to construct an elevator fault diagnosis system. Bai D S et al [11] used a mathematical operation mechanism to analyze the features under study, and then built an elevator fault prediction model based on the improved PSO-BP algorithm. Liu L [12] designed a wireless sensing network based on Zigbee protocol to collect elevator car pressure signals, and proposed an improved BP neural network algorithm SA-CG-BP to overcome the shortcomings of BP algorithm which tends to fall into local minima and overfitting, and completed elevator fault diagnosis with this algorithm. Cheke Lin [13] combined fuzzy system and neural network to establish an elevator fault diagnosis model, followed by fuzzifying the input parameters, determining the affiliation functions of different parameter fuzzification, designing a BP neural network model on this basis, and then using genetic algorithm to optimize the neural network. Li Weihe et al [14] used kernel principal component analysis combined with random forest to apply to elevator emergency stop fault diagnosis for the problems that traditional analysis methods cannot significantly reflect the inconspicuous and nonlinear attributes of elevator

Fig.1 Laboratory elevator model

Table 1 Composition of the elevator model and the role of each componen

Elevator system components	The main components and devices of the composition	Role
Guidance System	Car, counterweight rail and its rail frame	The freedom of movement of the car and counterweight is limited, and the car and counterweight can only move up and down along the rail.
Security Protection System	Speed limiters, safety clamps, buffers, etc.	Ensure the safe use of elevators and prevent all accidents that may endanger personal safety
Carriage	Car frame, car body	Components used for transporting passengers and cargo
Door system	Car doors, floor doors, door locks, etc.	Passenger and cargo import and export
Weight balancing system Power dragging system	Counterweight and weight compensation devices, etc. Traction motor, power supply system, speed feedback device, etc.	It can balance the weight of the car and compensate the length of the traction rope of the high-rise elevator Powering the elevator and controlling the speed of the elevator in real time
Electrical control system	Operation device, position display device, layer selector, etc.	Control and operate elevators
Traction system	Guide pulley, traction machine, wire rope, etc.	Output and transmission of power to power elevator operation

emergency stop fault feature samples.

Although the above-mentioned related scholars have achieved some results in elevator fault diagnosis and

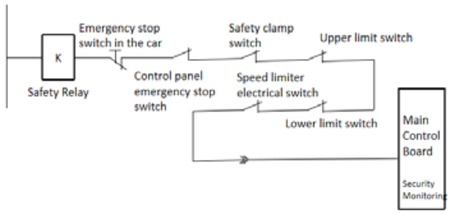

Fig.2 Elevator electrical safety circuit

prediction, traditional neural networks have the disadvantages of high data demand and the need to set more hyperparameters; for complex systems, the preparation of fault trees has more steps and complicated calculations, which makes it difficult to conduct qualitative and quantitative analysis; and for small data or low-dimensional data, random forests cannot produce a good classification. To address the shortcomings of neural networks, fault trees, and random forests, ZHOU Z H et al [15] proposed a deep forest model (Deep Forest for short), which is built on the random forest [16] algorithm and uses a deep structure similar to deep learning. The literature [17] evaluated the Deep Forest algorithm as a model with controllable parameters and the ability to adapt to data of different sizes. Deep forests are currently achieving comparable results to deep neural networks in cancer disease diagnosis [18] and recommendation systems [19].

This paper proposes a deep forest algorithm for elevator safety loop fault diagnosis. Compared with neural networks, fault trees and random forests, the deep forest algorithm is efficient and scalable, and supports small-scale training data.

2.SYSTEM DESCRIPTION AND MODEL STRUCTURE DESIGN

2.1.Composition of the research object system

Elevator is a kind of electrical equipment with complex structure, and its structure is divided into two major parts, namely, mechanical system and electrical system. After decades of development, most of the elevators in the market

Table 2 Sensors and the elevator faults corresponding to the collected

Sensors	Output signal range	Normal value range
Current Sensor	0-30(A)	30 (less than 23A abnormal)
Voltage Sensor	0-380 (V)	380 (less than 353.4V abnormal)
Acceleration sensor	0-1.5（m/s²）	<= 0.65
Speed sensors	0-2 (m/s)	<=1.5

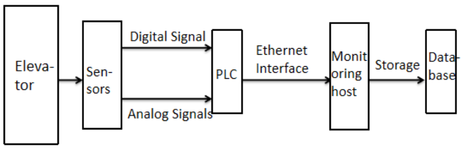

Fig.3 Block diagram of data acquisition

today are AC traction elevators, so this paper focuses on the construction of fault diagnosis model for AC traction elevators. The research object of this paper is a six-story, six-station model elevator in the Beijing Key Laboratory of Building Big Data Intelligent Processing Methodology of Beijing University of Architecture, whose structure is shown in Figure 1. The composition of the elevator model and its basic roles are shown in Table 1.

To ensure safe operation, the elevator is equipped with several safety components. Only when each safety component is in proper condition can the elevator operate, otherwise the elevator will stop immediately. Since the safe operation of the elevator is related to the safety of people's lives, the safety circuit is of vital importance in the elevator. The safety circuit is equipped with a safety switch in each safety part of the elevator, and all the safety switches are connected in series to control a safety relay. Common safety circuit switches are: control panel emergency stop switch, safety clamp switch, up and down limit switch, etc. Only when all safety switches are on, can the safety relay be activated and the elevator be powered to run.

Elevator safety circuit is an important control circuit and execution circuit to realize the safety protection function of elevator. This paper mainly studies the fault diagnosis model of elevator safety circuit. When abnormal door switch, up and down limit failure, emergency stop switch failure and main contactor failure occur, the safety circuit failure will be triggered.

2.2.Structure design of elevator safety circuit fault diagnosis model

The Deep Forest is a deep integrated learning model inspired by convolutional neural networks, with the advantages of few hyperparameters and a strong adaptive model structure, which mainly consists of two parts: multi-grain scanning technique and cascade forest structure. The cascade forest is used to classify normal and faulty elevator operation data.

The original features required for the deep forest-based

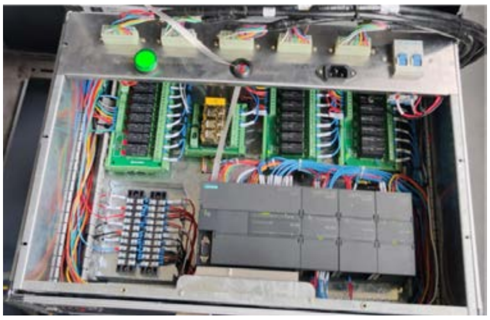

Fig.4 S7-200 smart PLC

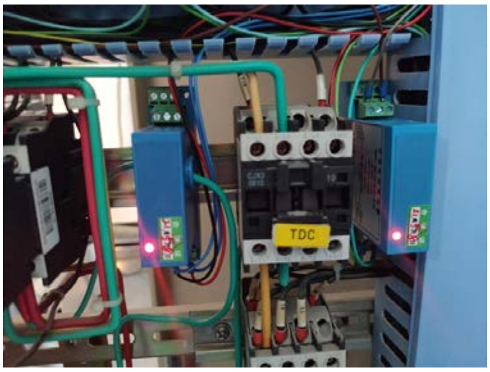

Fig.5 Current and voltage sensors

elevator fault diagnosis model can be changed or enhanced in the multi-granularity scanning stage. When an elevator fails in the safety circuit, six parameters, namely elevator car position, elevator car speed, elevator car acceleration, inverter output current, inverter output voltage and door signal, will be abnormal compared with the normal operation state of the elevator. Therefore, the fault diagnosis model uses the above six parameters as model inputs. According to the experiments, the output of the fault diagnosis model is divided into different fault types, and the collected data are then labeled, so the fault types of elevators include normal operation (0), safety circuit failure on floors 1-2 (1), safety circuit failure on floors 2-3 (2), safety circuit failure on floors 3-4 (3), safety circuit failure on floors 4-5 (4) and safety circuit failure on floors 5-6 (4). In this paper, the above six states are used as the six output parameters of the fault diagnosis model. After the model is constructed, the Deep Forest can exploit and learn the fault feature information and identify the fault type through cascade forest .

3.DATA ACQUISITION AND PROCESSING

3.1.Data acquisition scheme

Fig.6 Rotary encoder

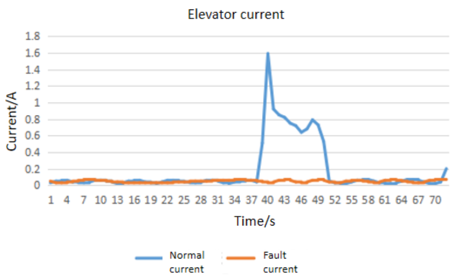

Fig.7 Elevator current line graph

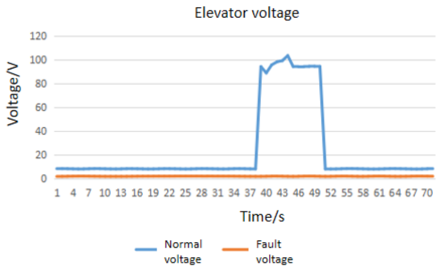

Fig.8 Elevator voltage folding line graph

The data acquisition system consists of S7-200 smart PLC, current sensor, voltage sensor, rotary encoder (for measuring speed and acceleration), and monitoring host. The system structure is shown in Figure 3, the structure of each component is shown in Figures 4-6, and the information of each sensor is shown in Table 2. The data acquisition system first collects the digital and analog signals of elevator operation through sensors and transmits them to the PLC, then transmits the collected elevator signal data to the monitoring host through the Ethernet interface, and finally stores these historical operation data in the database.

3.2.Data Analysis

In this paper, 3530 sets of elevators' normal and safety circuit fault data were collected. Table 3 shows some of the collected elevator operation data, among which the data with serial number 1 and fault signal 0 indicate that the elevator is normal, and according to the position, speed and acceleration signals, the elevator can be judged to be the original position stationary state; the data with serial number 2006 and fault signal 3 indicate that the elevator has a safety circuit fault between floors 3 and 4. According to the remaining six signals, it can be judged that the elevator is stopped between 3 and 4 floors at this time.

The current and voltage curves of the elevator during normal and fault times, obtained from the collected data, are shown in Figure 7 and Figure 8, respectively.

From the elevator current line graph, the elevator current rises from 0 A to 1.6 A and then drops to 0 A during normal operation, and stays at 0 A when the safety circuit fails.

From the voltage line diagram of the elevator, the voltage is about 8 V when the elevator remains stationary, and the voltage will gradually increase to about 100 V with the movement of the elevator, and then the voltage will drop to the normal, about 8 V when the elevator stops; from Figure 8, we can see that the voltage is 2 V when the elevator has a safety circuit failure. Therefore, when the voltage of the elevator is about 2 V, taking account of the signal of the door area and the location of the car, it can be judged that there is a safety circuit failure causesing the elevator to stop.

3.3.Feature parameter pre-processing

In this paper, the operations of elevator include normal condition, 1-2 floor emergency stop failure, 2-3 floor emergency stop failure and other conditions. In the data pre-processing of the elevator historical operation data, in order to prevent the situations that the absolute error of larger data is larger and the absolute error of smaller data is smaller, this paper normalizes the historical data to ensure that the elevator model training data are all between [0, 1]. The normalization process is given by the formula

$$x = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{1}$$

x_{max} reprents the maximum value of the collected data, and each type of data takes a different maximum value. For example, the maximum position data in the original data is 243.48cm, the maximum velocity data is 10.04cm/s, etc..

x_{min} reprents that the minimum value of the collected data are 0.

x_i reprents the current value of the collected data.

In this paper, we use[0,1] standardized approach to normalize the collected data, and some of the processed data are shown in Table 4.

4.DEEP FOREST FAULT DIAGNOSIS MODEL CONSTRUCTION

After the data pre-processing work is completed, the Deep Forest model is trained with the obtaied normalized data in order to construct the fault diagnosis model.

4.1.Model Construction Process

Table 3 Part of the elevator operation data collected

Serial number	Location	Speed	Acceleration	Current	Voltage	Door signals	Fault Signals
1	0	0	0	0.03	8.36	1	0
2006	116.57	0	0	0.06.	1.99	0	3
2239	165.82	0	0	0.04	1.99	0	4
2475	208.07	0	0	0.06	2.19	0	5
18	25.3	8.88	0.95	0.82	99.47	0	0
220	37.02	3.68	-4.36	0.72	94.52	0	0
22	43.28	3.08	-0.1	0.68	94.58	1	0

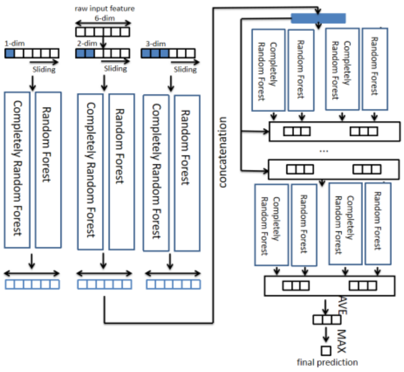

Fig.9 Schematic diagram of deep forest diagnosis model

In this paper, the training and test sets are divided in the ratio of 8:2 according to the model testing requirements, on the basis of which, the feature extraction and feature conversion are performed by using the multi-grained scanning of the deep forest model, and the final feature vectors train the completely random forest and random forest in the cascade forest. Then the model performance is tested by the test set, and the Multi-Grained Scanning feature extraction and cascade forest are continuously performed until the accuracy of the fault diagnosis reaches a stable level, then the iteration is terminated. Finally, the maximum value of the final class vector is taken to identify the fault state of the elevator. The schematic diagram of the deep forest-based elevator safety loop fault diagnosis model constructed in this paper is shown in Figure 9.

4.2. Multi-grained scanning

In the multi-grained scanning stage, the model uses three sizes of sliding windows for sampling to obtain more subsamples of elevator operation features. Suppose the input is aq dimensional original feature, the sliding window size is$n$ dimensional and the sliding step size is$d$, the sliding window scans the original input features to extract feature information, which will generate$N$$n$dimensional feature instances.

$$\boldsymbol{N = (q - n)/d + 1} \tag{2}$$

After random forest and completely random forest training, each forest outputs s dimensional class probability vectors, and then all class probability vectors are concatenated into$L$ dimensional transformed feature vectors.

$$\boldsymbol{L = 2 \times [(q - n)/d + 1] \times s} \tag{3}$$

In this paper, the original input features are 6-dimensional, and the scale of the transformed feature vector obtained by multi-granularity scanning is much larger than the original input features, so that more feature information can be extracted.

4.3.Cascade forests

Each layer of the cascade forest is constructed by a completely random forest and an ordinary random forest . In this model, it is assumed that each the complete random forest and the ordinary random forest containsT_1 and T_2, where each complete random forest and ordinary random forest contains t_1 and $t_2$decision trees. A feature in the completely random forest is randomly selected and partitioned in each node of the decision tree until each node contains only the same class. Similarly, in the ordinary random forest, we randomly select $\sqrt{\boldsymbol{q}}$ features as candidates. Then the information gain value is calculated and ranked. At last the information gain value is analyzed to select the best splitting feature for the growth of the decision tree. The information gain is shown in Equation (4).

$$\boldsymbol{Gain(W|z_i) = H(W) - H(W|z_i)} \tag{4}$$

W represents the set of data features, and z_i represents the i feature, and H(W) represents the entropy of the feature setW, and H(W|z_i) represents the z_i the empirical conditional entropy under the given conditions W.

To reduce the risk of overfitting, the model validate class vectors generated by each random forest via k-fold cross algorithm (K-fold Cross Validation). In addition, after extending a new layer, the performance of the entire cascade is evaluated on the validation set, and the training process is terminated if the accuracy of the classification no longer increases.

4.4.System model parameters

The deep forest model is experimentally validated by specifying the parameters of the default multigranularity scan structure, and for the original data with$d$ dimensional features,the feature windows of$d$/16 ,d/8 and$d$/4 are used for scanning [9], which maximizes the computational efficiency while ensuring the diversity of the generated samples. The elevator operation data set studied in this paper contains position, velocity, acceleration, current, voltage, and door signals. Therefore, there are 6 dimensions of the original input features. In the process of multi-grained scanning, the model scans the original features using three different size scanning windows with window sizes of 1, 2 and 3 , and the rest of the parameters are determined according to the default values, such as the window sampling step size of 1, the number of decision trees used in each random forest and completely random forest is 30, and the decision tree growth rule is that the leaf node purity is optimal. Then, in the process of the cascade forest,the

Table 4 Selected training data after normalization

Location	Speed	Acceleration	Current	Voltage	Door signals
0	0.73333333	0.46587927	0.01265823	0.06053407	1
0	0.73333333	0.46587927	0.00632911	0.06186449	1
0	0.73333333	0.46587927	0.01898734	0.06290982	1
0	0.73333333	0.46741032	0.16455696	0.88225791	1
0	0.73333333	0.46587927	0.20253165	0.88358833	1

Table 5 Safety circuit fault diagnosis model model performance

Output parameters	Precision	Recall	F1-score	support
0.0	1.00	0.82	0.90	282
1.0	0.80	1.00	0.89	61
2.0	0.88	1.00	0.94	60
3.0	1.00	1.00	1.00	91
4.0	1.00	1.00	1.00	78

model determines the number of forests in each cascade layer is 4, including two completely random forests and two ordinary random forests, and the number of decision trees contained in each forest is 101, and the decision tree growth rule is that the leaf node purity reaches the optimum. The cascade process is automatically terminated if there is no significant performance improvement of the model during training within 3 consecutive layers, and all experimental results are obtained by K-fold cross-validation.

4.5.Diagnostic model training

The fault diagnosis model training steps are as follows.

(1) Initialize the elevator feature data setW. There are t1 decision trees in T1 completely random forests, t2 decision trees in T2 ordinary random forests and K values.

(2) Calculate the elevator feature dataset to obtain the information gain value, then perform feature ranking, training T1 andT2 random forests, K fold cross-validation as well as computational accuracy.

(3) The class probabilities output by the two decision trees t1 and t2 in the two random forests are summed and then averaged using the averaging strategy to form the class probability vector.

(4) Splice the class probability vector with the original feature vector and input it to the next layer.

(5) Iterate the second and third steps above, and stop the training when the accuracy of the classification no longer rises.

Through the above steps, the elevator fault diagnosis model is finally obtained.

5.EXPERIMENTAL STUDY

5.1.Model performance evaluation criteria

In this paper, the effectiveness of the deep forest for elevator fault diagnosis is assessed with the use of two evaluation metrics(*Accuracy* and *weighted-F_1*). The

Table 6 Correctness of safety circuit fault diagnosis model with weighted macro average

Accuracy	weighted-F_1
92%	92%

formulas are as follows:

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TN+TP}}{\boldsymbol{TN+TP+FP+FN}} \qquad (5)$$

$$\boldsymbol{P} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FP}} \qquad (6)$$

$$\boldsymbol{R} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}} \qquad (7)$$

In the above equation, F_1 is the weighted average of precision and recall rate, where F_1 value reaches the best value at 1 and the worst value at 0. When both precision and recall rate are high, and the F_1value is also high, it indicates that the model is more robust. Therefore, this paper uses weighted- F_1 indicator , and for each category*i* the binary classification formula is used to calculate the F_1, denoting as $F_1 i$,Then the multipleF_1i are given different weights for calculation. weighted- F_1 is defined as shown in equation (8).

$$\boldsymbol{F_1} = \sum_{i=1}^{k} \boldsymbol{W_i} \cdot \boldsymbol{F_{1i}} = \sum_{i=1}^{k} \boldsymbol{W_i} \cdot \frac{\boldsymbol{2P_iR_i}}{\boldsymbol{P_i+R_i}} \qquad (8)$$

k represents the number of categories, W_i represents the proportion of samples in each category, *P* represents the precision, *R* represents the recall rate, and *TP* (True Positive) represents the number of positive cases predicted correctly, *FP* (False Positive) represents the number of negative prediction errors, *FN* (False Negative) represents the number of positive prediction errors and *TN* (True Negative) represents the number of positive prediction errors.

5.2.Analysis of experimental results

In this paper, the historical operation data of elevators are classified into six types, namely, elevator is normal, 1-2 floors safety circuit failure, 2-3 floors safety circuit failure, 3-4 floors safety circuit failure, 4-5 floors safety circuit failure and 5-6 floors safety circuit failure. The test results of the fault diagnosis model are shown in Figure 5 and Table 6.

According to Table 5, it can be seen that the accuracy of the fault diagnosis model of the elevator emergency stop established in this paper is 92%. The diagnosis results are organized to produce the confusion matrix, as shown in

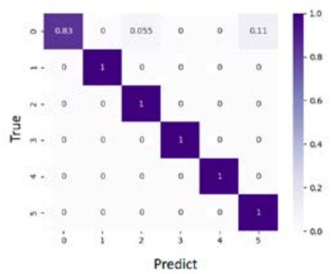

Fig.10 Troubleshooting confusion matrix

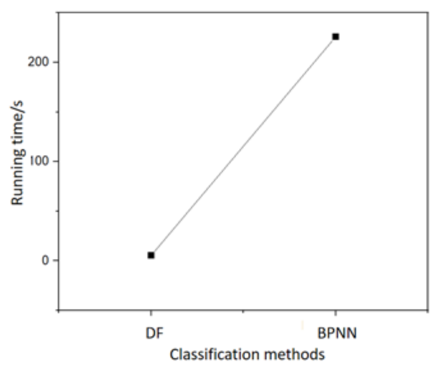

Fig.11 BPNN operation time and depth forest operation time line graph

Figure 10.

In the fault diagnosis confusion matrix, the horizontal coordinate shows the predicted status category, and the vertical coordinate shows the actual status category, "0-5" in the figure indicates the normal elevator and the well-functioning elevator between floors. As can be seen in the gragh, 5,5% and 11% of the normal operations are predicted to be the safty circuit failures between floors 2-3 and 5-6 respectively. There is a certain uncertainty in the identification only when the elevator is in normal operation, and the overall classification performance is good and the error is slight.

In order to verify the model performance, this paper uses the feature data set as the input feature parameter of the back propagation neural network (BPNN) model for the fault diagnosis analysis of elevator emergency stop. The BPNN model has 3 layers, the activation functions of hidden and output layers are Sigmoid functions, the learning rate is 0.01, the maximum number of training is 10000, and the final accuracy of the BPNN model is 88%.

The difference in computing time between BPNN and deep forest models is more obvious, as shown in Figure 11.

In the line graph of BPNN operation time and Deep Forest operation time, we can see that the Deep Forest operation time is about 2s, while the BPNN operation time is about 240s, so the Deep Forest model is more efficient than BPNN.

6.SUMMARY

In this paper, a fault diagnosis model of elevator safety circuit based on a deep forest is constructed to address the problems of complicated calculation, numerous parameters and difficulties in effectively processing information of the fault features in current methods of elevator fault diagnosis. Firstly,this paper analyzes the fault characteristics of elevator safety circuit and designs the fault diagnosis model structure. Secondly, on this basis, a fault characteristic data collection system is designed and developed. Thirdly, the elevator safety circuit fault diagnosis model is constructed based on the deep forest.Through the mode, the collected data is pre-processed, the fault characteristics are extracted by multi-granularity scanning, and then the fault type is identified by cascade forest. The experimental results show that the accuracy of the constructed fault diagnosis model is improved by 4% compared with the BPNN model, and the computational speed is improved by 99.1%, and the complicated tuning process of neural network can be avoided.

The next step of this paper is to study how to realize the early warning function of elevator safety circuit failure based on deep forest, and to realize the early prediction of failure to meet the demand of remote alarm and fault prediction through intelligent fault diagnosis method.

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