The Prediction of the Elevator Fault Based on Improved PSO-BP Algorithm

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Abstract. In accordance with the problem of worst at the convergence of BP Neural Network, the elevator fault-prediction-model is proposed based on Improved PSO-BP Algorithm in this paper. The method uses mathematical operation mechanism to analyze the characteristic be studied. Then the prediction model of elevator fault based on the Improved PSO-BP Algorithm is established. This paper tests the same data by using different elevator fault prediction models. The experimental results show that the method has higher accuracy and convergence. This paper provides a method of fault prediction elevator reliability.

1. Introduction

The elevator is commonly selected as a standard piece of equipment for high-rise buildings. People would take a lift to down stairs, so reliability of the elevator becomes a crucial factor for public safety[1]. Several factors affect elevator safety, such as speed imbalance, abnormal vibration, acceleration fluctuations and force imbalance etc. In order to improve the safety of elevator, fault prediction has been extensively studied in recent years. For example, the BP Neural Network is used to predict faults [3], which aim at abnormal of door switch speed, abnormal of door opening and closing vibration in the elevator door system [2], but the selection of the research object is limit to the elevator door system. The operating parameters of the elevator control system and terminal system use BP Neural Network [4], but it is poor convergence in BP Neural Network. The learning efficiency and the momentum factor, it is modified the globally convergent adaptive quick back propagation algorithm [5], but the neural network algorithm has poor prediction accuracy for small data. The poor resolution in types of elevator fault is solved by the least square support vector machine and the feature state extraction is difficult [6], but the support vector machine can freely choose the kernel function and parameters. The algorithm of BP Neural Network is widely used in the establishment of system model. It is mostly used to solve the Model Prediction, Regression Analysis and other problems. The convergence speed of BP Neural Network is slow, and can not meet the requirements of the prediction accuracy of elevator fault.

In this paper, the fault-prediction-model of the elevator based on improved PSO-BP is proposed, which is optimized by improved particle swarm optimization algorithm, and to solve the problem of poor convergence of elevator-failure prediction. By means of the real-time data collected from the SCADA of the elevator, and then, the prediction model of the elevator fault is established. The model
achieves continuous training of error accuracy through training on elevator operating data, and the robustness of the system has been improved.

2. Methodology

2.1. The Characteristic Parameters Selection of Elevator

The elevator system consists of electrical and mechanical systems, and its complex structure can cause malfunctions [7]. The Big Data technology is used to analyze the data of elevator operation, and the elevator fault prediction and health management model is established [8]. Many data will be generated during the operation of the elevator, and the selection of appropriate research characteristic parameters is of great significance to model construction and elevator failure prediction.

According to the relevant standards of elevator safety-operation, the characteristic parameters of the ceiling fault or grounding fault may occur during the elevator operation are analyzed. The main parameters of characteristic to be analyzed include operating current of motor, voltage, temperature, traction rope friction, braking force, load, running speed, acceleration, vibration, etc. In Figure 1, the data of each elevator motion state is linearly normalized. According to covariance calculated the correlation coefficient attribute of each state and the elevator’s ceiling fault or grounding fault.

\[ C(R_w, Y_h) = \frac{1}{2} \left( \frac{\text{cov}(R_w, Y_1)}{\sqrt{\text{cov}(R_w, R_w) \cdot \text{cov}(Y_1, Y_1)}} + \frac{\text{cov}(R_w, Y_2)}{\sqrt{\text{cov}(R_w, R_w) \cdot \text{cov}(Y_2, Y_2)}} \right) \]  \(\text{(1)}\)

\( R_w \) is normalized state parameters, \( Y_h \) is normalized elevator crash data and fall failure data, \( Y_1 \) is the elevator hitting the ceiling fault, \( Y_2 \) is the elevator grounding fault.

| Characteristic parameter | R(1)  | R(2)  | R(3)  | R(4)  | R(5)  |
|--------------------------|-------|-------|-------|-------|-------|
| Elevator system          | Burden| Running speed | vibration | Working current | Friction |
| Weight balance system    | Electric drive system | Mechanica l system | Electric control system | Traction System |

In Table 1, Input parameters of the model, it selected the 5 most relevant state attributes, such as, R(1) is elevator burden, R(2) is running speed, R(3) is elevator z-axis vibration, R(4) is the traction machine working current and R(5) is friction between the traction sheave and the wire rope.

2.2. The Prediction Model of Elevator Fault Based on Improved PSO-BP Algorithm

In this study, the improved PSO algorithm is used to optimize the weights among the layers of the BP Neural Network. First, the basic PSO algorithm is improved by using non-linear decreasing inertia weights. And then, the weights of BP neural network algorithm are optimized to get the optimal value \( \text{Gbest} \) of each generation. The experiments show that it can improve system convergence and prediction accuracy.

In the paper, the input state is determined by calculation and the prediction accuracy and convergence of the model are improved by the optimization algorithm. Studying the correlation coefficient between feature of elevator operation and fault, then selected 5 representative characteristic parameters. The possibility of the elevator hit ceiling or touch ground is predicted.
Figure 1. The elevator fault prediction research based on Improved PSO-BP algorithm

In Figure 1, the flow chart of the improved PSO-BP model includes the determination of feature vector and the improved PSO-BP algorithm. In the first part, the feature parameters are selected by analyzing the correlation between each feature parameter and fault information. The second part, the particle swarm algorithm is initialized and calculate the Pbest and Gbest of the swarm. Then, the particle velocity and position are updated by nonlinear inertia weight. If the iterative condition is met, which the result is sent to the BP Neural Network weight. The iterative conditions are satisfied by the optimized BP Neural Network, and the elevator fault prediction results are output.

3. Results and discussion

3.1. Parameter setting of model

According to the actual operation data of a commercial elevator, the BP model, PSO-BP model and the improved PSO-BP model are established by the parameter analysis. In order to ensure the authenticity of the experimental results, the parameters of the same part of the three models are set in the same way. In order to improve the convergence of the model and improve the accuracy of the model. In this paper, the elevator operation data of the past year are randomly selected, and 60000 data samples are selected by random sampling method. In order to improve the accuracy of the model, 80% of the data is regarded as training data and 20% as test data. BP part is set to 1000 times for training times, 1e-4 for the training target, earning rate is 0.1 and the momentum factor is 0.8. The speed update of PSO to set to c1=c2=1.95, population size set to 100, iteration times are set to 300, maximum inertia factor set to ω max=0.9, minimum inertia factor set to ω min=0.4, maximum iteration times set to 100, and minimum adaptation value set to 0.1. In Table 2, it is shown that some of the research data.

| Table2. Determination of characteristic parameters. |
|---------|---------|---------|---------|---------|
| R(1)   | R(2)   | R(3)   | R(4)   | R(5)   |
| 1       | 0.9813 | 0.9015 | 0.4152 | 0.8514 | 0.2415 |
| 2       | 0.1462 | 0.1954 | 0.8104 | 0.7124 | 0.7531 |
| 3       | 0.8374 | 0.8252 | 0.6762 | 0.8065 | 0.5937 |

3.2. Weight optimization of PSO algorithm

The weight of Classical PSO algorithm is linear or fixed, which is not conducive to global search for the optimal value. Inertial weight is a variable that reflects the ability of particles to carry on the previous speed. Larger inertial weight is conducive to global search, while smaller inertial weight is conducive to
local search. In this paper, the adaptive weight optimization algorithm can improve the global search efficiency and the optimization ability of the algorithm.

\[ \omega_k = \omega_{\text{max}} - (\omega_{\text{max}} - \omega_{\text{min}}) \left( \frac{k}{T_{\text{max}}} \right)^2 \]  

(2)

\( \omega_k \) is current weight factor, \( k \) is current iteration number, \( T_{\text{max}} \) is the maximum number of iterations.

3.3. Improved BP algorithm

In this paper, the weights of BP Neural Network are updated by Gbest of improved PSO algorithm. The hidden layer nodes of BP Neural Network should be less than \( N-1 \) (\( N \) is the number of training samples), otherwise the network will have no generalization ability and lose the significance of prediction.

![Optimizing BP Neural Network](image)

**Figure 2. Optimizing BP Neural Network**

In Figure 2, the BP Neural Network contains five input parameters and two output variables. \( W_{ih} \) is the weight of input-hidden layer, \( W_{ho} \) is the weight of hidden-output layer.

\[
\begin{align*}
H_j &= \sigma(\sum_{i=1}^{n} W_{ih}R_i + d_j) \quad (j = 1, 2, \ldots, l) \\
Q_k &= \sigma(\sum_{j=1}^{l} W_{ho}H_j + d_k) \quad (k = 1, 2, \ldots, n)
\end{align*}
\]  

(3)

\( W_{ih} \) and \( W_{ho} \) are the prediction results of improved PSO algorithm, which they are used to optimize BP Neural Network. \( R_i \) is the input training data, \( H_j \) is the hidden layer output function, \( Q_k \) is the output layer output function, \( d_j \) is the hidden layer neuron bias, \( d_k \) is the output layer neuron bias, \( \sigma \) and \( \sigma \) are the activation function.

3.4. Experimental results

In order to verify the superiority of the improved PSO-BP model, there are established in this paper, such as, the BP Neural Network model, PSO-BP model and improved PSO-BP model. Using the same data, three models were used to predict, and the results were analyzed. The prediction results, convergence and error of the three models are analyzed. It is found that the Improved PSO-BP algorithm has the highest prediction accuracy and the fastest convergence speed.
In Figure 3, these curves are actual data curve, BP Neural Network prediction curve, PSO-BP Neural Network prediction curve and Improved PSO-BP Neural Network curve. The three prediction curves are close to the actual data curve, but the prediction accuracy is different. The Improved PSO-BP algorithm can improve the convergence and prediction accuracy. It is using the non-linear weight optimization particle swarm algorithm for BP Neural Network weight optimization. The curve makes the prediction result closer to the truth. In Figure 4, it is a partial enlarged view of the comparison image. The predicted result of the Improved PSO-BP algorithm model is closer to the true value.

In Figure 5, the improved PSO-BP model is trained about 100 times, which can reach the stable value and meet the accuracy requirements. However, the PSO-BP model needs to be trained about 150 times and the BP model needs to be trained about 450 times to meet the accuracy requirements. It proves that the Improved PSO-BP model has higher convergence than PSO-BP model and BP model.

| Relative errors | R(1) | R(2) | R(3) | R(4) | R(5) | Y(1) | Y(2) |
|-----------------|------|------|------|------|------|------|------|
| **BP algorithm** | 0.0040 | 0.0070 | 0.0050 | 0.0050 | 0.0060 | 0.0089 | 0.0100 |
| **PSO-BP algorithm** | 0.0032 | 0.0066 | 0.0045 | 0.0041 | 0.0067 | 0.0087 | 0.0083 |
| **Improved PSO-BP algorithm** | 0.0013 | 0.0032 | 0.0013 | 0.0036 | 0.0035 | 0.0047 | 0.0067 |

In Table 3, it shows prediction errors of the three algorithm models, BP algorithm, PSO-BP algorithm and Improved PSO-BP algorithm. The prediction error of the Improved PSO-BP algorithm model is only 0.0013, but the other models are 0.0040 and 0.0032, which is much smaller than the BP algorithm and PSO-BP algorithm. The calculation shows that the standard deviation of the errors of the three algorithms are 2.21e-3, 2.13e-3 and 1.89e-3. It can be found that the Improved PSO-BP algorithm has higher prediction accuracy.
4. Conclusion
The Improved PSO-BP algorithm is proposed to predict the Elevator Fault in this paper. Compared with BP model and PSO-BP models, the convergence rate of the improved PSO-BP model is increased by 35.47%, and the prediction accuracy is improved by 49.12%. Through the analysis of data samples, it is verified that the model has high prediction accuracy and convergence. Therefore, the elevator fault prediction model based on improved PSO-BP algorithm has a high application prospect in the field of elevator maintenance.

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