Research on relay safety output control method based on BP neural network

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Abstract. With the continuous improvement and expansion of the metro network, the issues of train safety capacity, transportation effi-ciency and maintenance cost will become increasingly prominent. As an indispensable switching and controlling device of train safety control system, the health status of relay is the foundation of low-cost, high safety and efficient development of subway. This paper designs and proposes a BP neural network based relay safety output control method, this method utilizes BP neural net-work on the basis of improved two-take-two hardware structure to do fault prediction and safety state management with real-time retrieved detection signals, finally uploads operation and mainte-nance logs to the platform to guide subsequent fault trouble-shooting and maintenance.

Keywords: Condition prediction; neural network; train safety protection; intelligent control.

1. Introduction

In the safety control system of rail transportation, relays have a wide range of applications, such as emergency stop control system, safety door lock control system, turnout indication control system, traffic light control system, etc [1]. All of them use the switching characteristics of relays to complete the corresponding control functions. There are about hundreds of relays in a subway train. Once a relay malfunctions such as high contact resistance, insufficient over-travel, or sticking in electric shock, the safety output control system will make a wrong judgment, which will eventually lead to a series of safety accidents. At the same time, the current train safety status belongs to the passive safety detection mode, whose working process is "Fault alarm and then emergency disposal" or "Timed maintenance when the train stops running", the passive safety detection model will not be able to meet the current requirements of increasing networked line tracks and train operating frequency, and will not be able to provide critical constraints on sudden failures. In this paper, a relay safety output control system based on BP neural network is proposed, which not only improves the conventional two-take-two hardware circuit structure which increases the safety power supply circuit, suicide circuit, monostable circuit, dual-relay series re-output circuit, and dual-channel processor mutual detection circuit, etc., but also utilizes the powerful nonlinear mapping capability and self-correcting capability of BP neural network to do the prediction of relay state and life span with the high-speed and real-time retrieval of the characteristic signals. Using a large amount of back-mining data for training, this method will ultimately obtain a high accuracy prediction model, which will be used to nonlinearly fit the real-time collected back-inspection feature signals and set the threshold interval to realize the active safety mode "Fault prediction-Advance processing". This method reduces the cost of operation and maintenance on the basis of improving the safe operation of trains, and the massive data self-learning not only improves the intelligent train safety prediction capability, but also provides the basis for informationized operation and maintenance.

2. Hardware Design of Relay Safety Output System

2.1 General architecture of the system hardware

The structure of the safe output system is shown in Figure 1 and includes two processor modules, two drive control modules, two acquisition modules, two monostable modules, two relay modules, a safe power conversion module and a suicide module. When the system needs to perform output, CPU1 and CPU2 first open the power conversion switch by outputting monostable pulse signals through the IO pins to convert the normal power supply to safe power output; CPU1 and CPU2 then output the drive control signals to make the relays suction up, while CPU1 and CPU2 collect the output drive control signals and the time of the node action signals through their respective acquisition modules, which are recorded and saved in the CPU [2]:

Safeguard 1: CPU1 or CPU2 turns off the respective drive control.

Safeguard 2: CPU1 or CPU2 stops the monostable pulse signal output and cuts off the normal power supply to the safety power supply.

Safeguard 3: CPU1 or CPUer2 enables the suicide circuit.

The following circuits will not do the conventional two-take-two structure of too much discussion [3], this paper will introduce the newly added monostable circuit module and the suicide circuit module, which prevents the drive circuit from being disturbed, chip defects, or relay sticking after the non-safe output of the system.

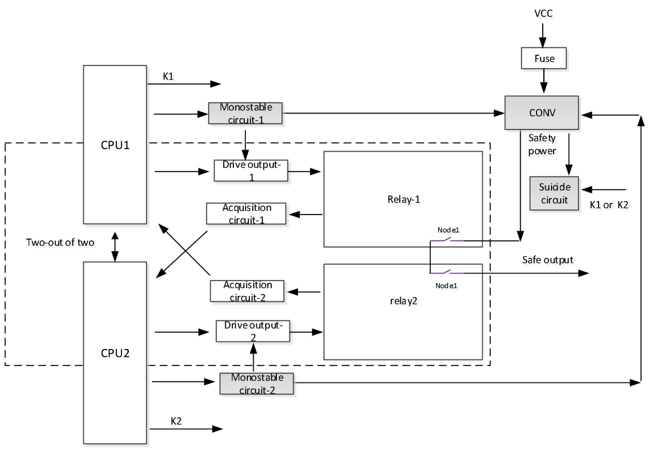

Fig. 1 The structure of the secure output system

2.1.1 Monostable Circuit Module

Monostable circuit is a basic pulse unit circuit with two operating states, steady state and transient. When triggered by no applied signal, the circuit is in steady state; when triggered by an applied signal, the circuit flips from steady state to transient state and automatically returns to steady state after a period of time. Using the properties of monostable circuits, this system defines steady state as no output from the system and transient as output from the system. Fig. 2 below shows the operating time sequence for different pulse cycles.

The monostable circuit module design includes a front stage monostable circuit and a back stage monostable circuit, the output of the front stage monostable circuit is connected to the input of the back stage monostable circuit, and the output of the back stage monostable circuit is connected to the enable driver control module and the enable safety power output module. The steady state time is set by RC respectively, with Tw1 for the front stage and Tw2 for the back stage, where Tw1 is less than Tw2. When the pulse frequency output from the processor IO pin is lower than Tw1 or higher than Tw2, the monostable circuit module cannot output correctly, and the monostable circuit module outputs correctly only when the pulse frequency output from the processor IO pin is greater than Tw1 and lower than Tw2. Compared to the direct output of the processor's pins, this prevents the processor from being interfered with and remaining at an active output, which would result in incorrect operation of the relay.

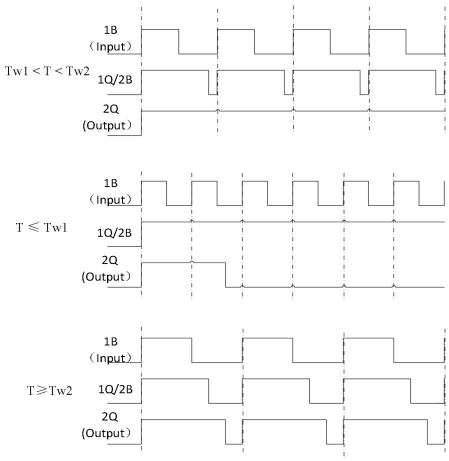

Fig. 2 Two-stage monostable flip-flop operating sequence

2.1.2 Suicide circuit modules

When multiple faulty abnormalities occur in the control system hardware, such as the failure of the acquisition module and the simultaneous failure of the driver module, the processor is not only unable to know whether there is an output or not, but also unable to know whether the output has been turned off or not.

Suicide circuits mainly contain power resistors and PMOS tubes. Fuses are usually designed on the input side of a normal power supply to ensure that if an overcurrent condition (e.g. short circuit or overload) occurs at the back end of the circuit, the fuse blows and cuts off the current, preventing the power conversion module or relay module from being damaged due to excessive current. Using the characteristics of the fuse blowing system oriented safety, the power resistor and PMOS tube in the suicide circuit are connected in parallel to the output of the safety power supply. When the processor discovers that the system has multiple faults, it will blow the fuse by activating K1 or K2, which will conduct the positive and negative terminals of the safety power supply through the power resistor and the PMOS tube, which simulates an abnormally high current situation.

2.1.3 Relay status acquisition circuit

The relay acquisition circuit includes contact suction time, contact release time, overtravel time, contact resistance, contact voltage drop and contact open circuit voltage. The collected data are calculated by the processor of the other channel respectively, realizing dual-channel processor mutual checking and improving system reliability and fault tolerance [4].

2.2 Relay Failure Prediction Based on BP Neural Networks

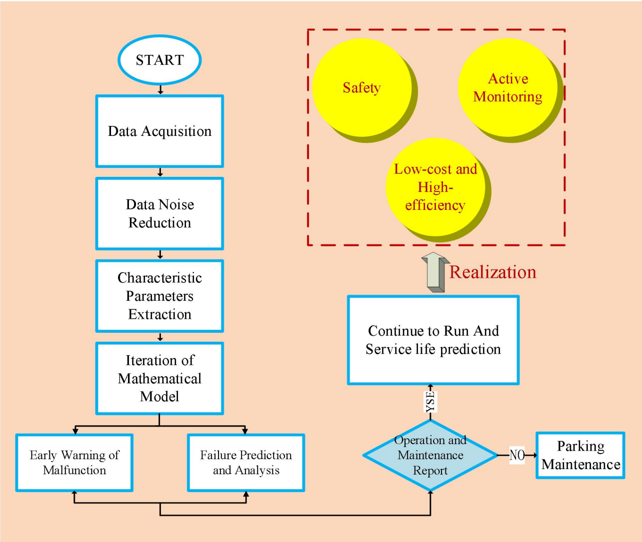

Fig. 3 Schematic diagram of fault prediction and decision management work

While strengthening the safety of the relay safety output system, this study also does real-time detection of the relay return node and completes the real-time failure prediction through the data fusion algorithm. The working principle of its failure prediction and decision-making management is shown in Fig. 3.

2.2.1 Data Acquisition and Selection of Characteristic Parameters

Failure prediction accuracy of relay safety output systems greatly depends on data acquisition and selection of characteristic parameters, the main reasons for the failure of relays in train systems are as follows:

1) Contact delay caused by physical factors such as vibration, thermal stress and so on.
2) The contact resistance is too high and the movable and static contacts do not engage properly.
3) Excessive suction and release times due to aging relays.

Analyzing the above three main causes of failure, it can be seen that the three dynamic characteristic quantities of contact release or suction time, overtravel time, and contact resistance can characterize the different failure states of the relay. In addition, the easily measurable contact voltage drop and open circuit voltage can also serve as characteristic parameters for relay monitoring. Therefore, these six signals are made data fusion and used as input variables of the prediction model in this paper to realize the accurate prediction of the safety performance of the relay [5].

2.2.2 Data filtering

Affected by the train operating environment, the collected data signals are highly susceptible to contamination, and the noise has a great probability of masking the useful signals, which ultimately affects the prediction results. Therefore, before doing the failure prediction, the six acquired signals need to be noise reduced. This article will use wavelet denoising method to extract features from the six collected signals mentioned above[6]. This method not only reduces high-frequency noise interference, but also preserves signal features well after wavelet denoising[7]. The flowchart is shown in the Fig. 4.

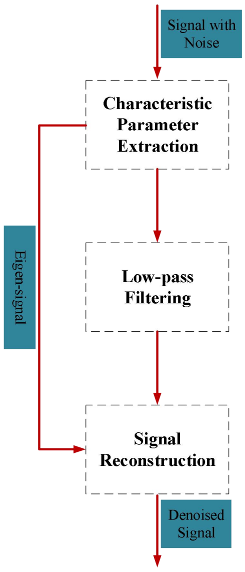

Fig. 4 Wavelet denoising process

This paper use the root mean square error R and the signal-to-noise ratio S as the judgment indexes of the noise reduction effect, which is calculated by the formula:

$$R = \sqrt{\frac{1}{q}}\sqrt{\sum_{i=1}^{q}(f_i - f_i^{'})^2} \tag{1}$$

$$S = \sqrt{\frac{1}{q}}\sqrt{\sum_{i=1}^{q}(f_i - f_i^{'})^2} \tag{2}$$

where fi is the ith value of the original signal; fi' is the ith value of the signal after noise reduction; and q is the original signal length. In addition to this, the smoothness index is also introduced as a judgment index for evaluating the noise reduction effect, Eq. 3 is the formula for its calculation:

$$r = \sum_{i=1}^{q-1}(f_{i+1}^{'} - f_i^{'})^2 / \sum_{i=1}^{q-1}(f_{i+1} - f_i)^2 \tag{3}$$

In Eq. 3, r is the smoothness index, the value range is [0,1], the closer r is to 0, the better the noise reduction effect, and the smoother the fitted curve.

2.2.3 Failure to predict

In terms of the structure and learning algorithms of artificial neural networks, BP neural network refers to a multilayer forward network that employs an error back propagation algorithm [8]. The BP neural network structure used in this paper is shown in Fig. 5 below, which contains three neuron levels including input layer, hidden layer, and output layer, w, v are the weights, β , λ are the biases. For this paper there are six parameters in the output layer, contact release time, suction time, overtravel time, contact resistance, contact voltage drop and open circuit voltage, these six input parameters will be characterized from the input layer through the hidden layer to the output layer, the output value will be back propagated with the input value in the form of a mean-square error, and according to the error to gradually adjust the weights between the layers and parameters, so that the network output prediction is constantly close to the desired real value.

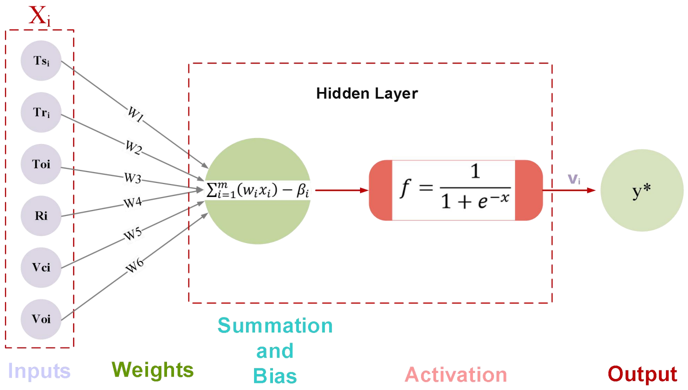

Fig. 5 BP neural network structure diagram

From the structural diagram of the BP neural network in Fig. 5 above, we assume that the full lifetime of a register is N, and the number of switching actions per time is noted as i (0 < i < N). Suction time is ts1, ts2, ts3⋯txi; release time is tr1, tr2, tr3⋯tri; overtravel time is to1, to2, to3⋯toi; contact resistance R1, R2, R3 ⋯ Ri; contact Ri; contact voltage Vc1, Vc2, Vc3 ⋯ Vci; open-circuit voltage Vo1, Vo2, Vo3⋯Voi; the above txi, tri, toi, Ri, Vci, Voi are input layer characteristic parameters. It is worth noting that in order to improve the prediction speed and efficiency of the BP neural network, the data are normalized before reusing the input parameters to map the data to smaller intervals . Since this paper expects the output parameter to be the failure probability, the interval is chosen as [0,1], and the activation function is chosen as the sigmoid function. The derivation equation is as follows:

$$\begin{cases} q_1 = ts_1 w_{11} + ts_2 w_{21} + ts_i w_{i1} \cdots - \beta 1 \\ q_2 = tr_1 w_{11} + tr_2 w_{21} + tr_i w_{i1} \cdots - \beta 2 \\ q_3 = to_1 w_{11} + to_2 w_{21} + to_i w_{i1} \cdots - \beta 3 \\ q_4 = R_1 w_{11} + R_2 w_{21} + R_i w_{i1} \cdots - \beta 4 \\ q_5 = Vc_1 w_{11} + Vc_2 w_{21} + Vc_i w_{i1} \cdots - \beta 5 \\ q_6 = Vo_1 w_{11} + Vo_2 w_{21} + Vo_i w_{i1} \cdots - \beta 6 \end{cases} \tag{4}$$

Summarizing and organizing is available:

$$q_i = x_1 w_{1i} + x_2 w_{2i} - \beta_i \tag{5}$$

$$h_i = f(x_1 w_{1i} + x_2 w_{2i} - \beta_i) \tag{6}$$

where f is the sigmoid activation function with the expression:

$$f = \frac{1}{1+e^{-x}} \tag{7}$$

From this we can derive the following equation:

$$\mu = h_1 \cdot v_1 + h_2 \cdot v_2 + \cdots h_6 \cdot v_6 - \lambda \tag{8}$$

$$y^* = f(h_1 \cdot v_1 + h_2 \cdot v_2 + \cdots h_6 \cdot v_6 - \lambda) \tag{9}$$

$$Loss = \frac{1}{2}\sum_i (y_i - y_i^*)^2 = \frac{1}{2}(y_i - y_i^*)^2 \tag{10}$$

where Loss is the loss function, y is the expected value, and y* is the output value. In this paper, λ has been derived as an example, where φ is the learning efficiency:

$$\Delta\lambda = -\varphi \cdot \frac{\delta Loss}{\delta \lambda} \tag{11}$$

$$\frac{\delta Loss}{\delta \lambda} = \frac{\delta Loss}{\delta y^*} \cdot \frac{\delta y^*}{\delta \lambda} \tag{12}$$

Substituting into the above equation (10), we finally get:

$$\Delta\lambda = -\varphi \cdot (y - y^*) \cdot y^* \cdot (1 - y^*) \tag{13}$$

According to the chain rule to update v, β, w and do a number of iterations, so as to obtain the optimal weights and bias, get the results of the output layer after Softmax processing for the probability of value, and through the loss of cross-entropy to quantify the strengths and weaknesses of the current network, so as to determine whether the predicted value is accurate or not. In this case, the formula for cross entropy is to find the negative of the logarithm.

The ultimate purpose of utilizing BP neural network in this paper is to predict the safety/failure state of the relay, for the convenience of data processing in this paper the failure probability of the relay will be used as the output of the network, the failure probability is divided by the number of switching times divided by the full life. The use of BP neural network to predict the safety state of the relay is not described by a specific mathematical expression, when we establish the above three-layer neuron structure, the acquisition of feature signals will do a finite number of times of self-learning training, so that the output layer of the network for the proximity of the real expectations and constantly adjust the weights and expression function, and ultimately to obtain a fixed-value mathematical models. Once the mathematical model has been established, a nonlinear fit can be performed on the feature signals acquired in real time, and the failure probability is finally obtained, when the monitored probability of failure is greater than the set non-safety threshold, the relay safety output control system will upload a failure warning to provide decision-making guidance for subway operations and maintenance personnel. The data will be uploaded in real time through the infinite transmission module in the system to the upper computer system of safety monitoring, which has data saving, visual waveform display, and real-time recording of the occurrence points of fault prediction. This system will further improve the intelligent maintenance capability of subway trains, and realize the all-round safety guarantee such as multi-layer hardware barrier protection, real-time condition monitoring and failure prediction of train relay fault-oriented safety.

3. Summary

The safety and dynamic monitorability of the relay safety output control system is of great significance in guaranteeing the safe operation of trains. In this paper, we design multi-layer protection circuits based on the conventional two-take-two circuit structure, so as to ensure that when the system encounters a fault, it can be directed to the safety in time. At the same time, in order to accomplish the dynamic monitoring and failure prediction of relays, which are the most important devices in the relay safety output control system. We adopted wavelet noise reduction is used to effectively extract six feature signals from environmental noise, the feature signals are used as inputs to the BP neural network and derivation is done, and self-learning of the failure prediction mathematical model is accomplished through the collection of a large amount of data to obtain the optimal weights and bias, and ultimately, the best failure prediction model is obtained.

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