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Development of neural network programme for automated testing of railway contact blocks

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ABSTRACT
A neural network model for automated testing of railway contact blocks was developed. The neural network computer programme allowed obtaining satisfactory results for relay diagnostics using "current-time" dependence during relay switching as an input diagnostic data.

KEYWORDS: automated testing, railway contact blocks, neural networks

1. Introduction

Increasing the reliability and safety of railway automatic systems by means of perfection of the relay-contact equipment maintenance is an important task. Although microprocessor systems have been used in railway automatics more widely in recent years, but a lot of signalling systems were executed on the basis of relay equipment till now.

The existing control technology of relay and relay blocks parameters includes many manual operations and has low accuracy with high subjectivity affecting the results of testing [5,8].

The relay and relay blocks are electromechanical systems and difficulties of their diagnostics are connected with measuring their mechanical parameters and characteristics without removing their cases. Railway automatic blocks contain different types of electromagnetic relays which electrical and mechanical parameters are varying in time in a wide range. The blocks contain other electric components (capacitors, resistors, semiconductor devices etc.) in which defects may also appear. Diagnostic tests for relay blocks usually were developed as sequence of elementary operations named elementary checks, which consist of supplying some test signals on the block inputs and measuring the output response [3, 5, 9]. The quantity of possible input combinations N is dependent on inputs quantity n: $N = 2^n$. This value N determines the maximal length of the trivial (not optimized) test sequence for discrete combinational logic blocks (without memory). However the railway automatics blocks contain feedbacks (for example, an automatic relay interlock circuits) and therefore have a memory. In this case output block responses depend on previous test signal combinations applied on block inputs. The additional output block response depends on time parameters of test signals. So the developing of detailed diagnostic tests for railway automatic blocks is a task difficult enough.

So the aim of this work is to develop a neural network model and computer programme for automated testing of railway contact blocks.

2. Neural network diagnostic tests for relay blocks

To develop an algorithm for relay blocks tests it is usually necessary to carry out the following basic stages:

- formal description of technical object of the diagnostics (relay blocks in our case) by means of logical operators taking in account feedback circuits and different time delays of signals in internal block circuits,

- developing of the model of technical object of diagnostics without defects,
- developing of the model of technical object of diagnostics with possible defects,
- providing simulation of operation of technical object with and without defects under different operating conditions,
- developing on the base of results of simulations the defect tables, tables of object technical state transitions, time diagrams,
- minimization of developed tables,
- formal representation of developed test tables as a computer programme,
- verification of the programme.

For complex technical objects such algorithms for tests developing are usually unpractical and in such cases the use of probabilistic test method is more reasonable. In probabilistic tests the stochastic or pseudo-stochastic test signal sequence is supplied on blocks inputs. The output response signal is compared with output signals obtained on blocks without defects. This method is usually used for objects with complex or unknown internal structure [3] and preliminary developing of the test algorithm is not necessary in such case. But disadvantage of the method is long-time testing for ensuring sufficient probability of defect detection.

The reduction of a testing time is possible due to application of mathematical processing of the diagnostic information based on artificial neural networks (ANN). The advantages of this method comprise the possibility of testing in fuzzy data conditions, finding of the hidden dependences object structure, automatic recognition of the output signal and system identification [1, 2]. However for object diagnostics it is necessary to develop the structure of neural network (NN), chose its parameters and then to train the NN model.

However, formalized recommendations on using some type of NN to attain necessary accuracy of diagnostics with rational NN training time for specified relay blocks are not described in the literature. So in this work a computer program was developed that allowed at the first stage to investigate the influence of artificial neural networks (ANN) configuration and its main key parameters on the accuracy of relay block testing. A two-layer perceptron was chosen as a basis of ANN model. The number of inputs ANN was chosen equal to the number of discrete diagnostic signals $(X_i,\ i=1..N)$, and the number of outputs (neurons in output layer) was chosen equal to the number of possible diagnostic object conditions $(Y_i,\ i=1..H)$. As it is well known input $\mathbf{X}$ and output $\mathbf{Y}$ vectors in ANN models are connected by equation.

$$\mathbf{X} = \mathbf{F}(\mathbf{W}, \mathbf{Y}) \tag{1}$$

where $\mathbf{W}$ is the matrix of weight factors, $\mathbf{F}$ is activation function. The neuron quantity in the hidden first layer was determined during computer investigations. Activation function was taken as a logic function (sigmoid)

$$f(x) = \frac{1}{1+e^{-\alpha x}} \tag{2}$$

where α is a parameter sigmoid function slope. The sigmoid function was taken due to simple expression for its derivative.

$$f'(x) = \alpha \cdot f(x) \cdot (1 - f(x)) \tag{3}$$

For ANN training the algorithm of back propagation of a mistake was used. Criterion of training is the minimum of a root-mean-square difference between responses obtained during ANN training and "ideal" theoretically obtained on control signal sampling. So it was necessary to ensure a minimum of criterion mistake function during ANN training

$$E(w) = \frac{1}{2}\sum_{j,p}(y_{j,p}^{(N)} - d_{j,p})^2 \tag{4}$$

where $y_{j,p}^{(N)}$ - an actual neuron state in j - layer when p -image data supplied on ANN inputs, and $d_{j,p}$ is a required neuron state as response to applied input signals.

Summation was carried out for all neurons in the input layer and for all data of images. Minimization was provided by a method of gradient decrease that means adjustment of weight factors as follows

$$\Delta w_{ij}^{(n)} = -\eta \cdot \frac{\partial E}{\partial w_{ij}} \tag{5}$$

where $W_{ij}^{(n)}$ is a weight factor synapse connection between i -neuron in $(n-1)$ -layer and j -neuron in n -layer, h – training rate factor $(0 < h < 1)$. Derivation in (4) was determined by equation

$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial y_j} \cdot \frac{dy_j}{ds_j} \cdot \frac{\partial s_j}{\partial w_{ij}} \tag{6}$$

where y_i - an output signal of j -neuron, and s_j is the sum of its output signals weights. The factor $\frac{\partial s_j}{\partial w_{ij}}$ is equal to output signals of previous $(n-1)$ -layer neurons.

The first factors in (5) can be presented as follows

$$\frac{\partial E}{\partial y_j} = \sum_k \frac{\partial E}{\partial y_k} \cdot \frac{dy_k}{ds_k} \cdot \frac{\partial s_k}{\partial y_j} = \sum_k \frac{\partial E}{\partial y_k} \cdot \frac{dy_k}{ds_k} \cdot w_{jk}^{(n+1)} \tag{7}$$

In this equation the summation was carried out for all neurons in $(n+1)$ -layer.

Using a new variable $\delta_j^{(n)} = \frac{\partial E}{\partial y_j} \frac{dy_j}{ds_j}$ we obtained the recursive formula for calculation of n -layer size from $\delta_j^{(n)}$ $(n+1)$ -layer size $\delta_j^{(n+1)}$

$$\delta_j^{(n)} = \left[\sum_k \delta_k^{(n+1)} \cdot w_{jk}^{(n+1)} \right] \cdot \frac{dy_j}{ds_j} \qquad (8)$$

For an output layer it was obtained

$$\delta_l^{(N)} = (y_l^{(N)} - d_l) \cdot \frac{dy_l}{ds_l} \qquad (9)$$

So expression (4) can be written as

$$\Delta w_{ij}^{(n)} = -\eta \cdot \delta_j^{(n)} \cdot y_i^{(n-1)} \qquad (10)$$

The training sample was shared on groups which quantity corresponds to possible relay technical states.

During the training (for one cycle) the discrete digital values corresponding to stochastic element training samples from certain group were applied to ANN inputs. As a result the ANN output response was:

$$y(n) = f\left[\sum_{h_1=0}^{H_1} w_{hi} f\left[\sum_{i=0}^{N} w_i x_i(n) \right] \right] \qquad (11)$$

Values of output response signal of ANN were compared with signals corresponding to a perfect state or to some defect states of the relay and on this basis the correction of weight factors for output (second) and hidden (first) layers were determined. Then the same procedure was carried out with random chosen element of the next group training sample and this procedure was repeated until all training samples were completed. Once the training sample was finished, the average root-mean-square difference between those obtained during ANN training and "ideal" responses on control signal sampling was compared with a prescribed value that was the criterion of ANN training finishing.

ANN model was realized in Delphi (using Object Pascal language). The program allowed changing an ANN layer quantity with the aim to investigate the influence of ANN parameters on the training rate and diagnostic accuracy. As a result the previously chosen parameters of ANN computer model were improved and that allowed obtaining satisfactory results on relay diagnostics using "current-time" dependence during relay switching as input diagnostic data.

3. Conclusions

A neural network model for automated testing of railway contact blocks was developed. The developed computer programme based on artificial neural networks model allowed investigating the influence of ANN configuration and its main key parameters on the accuracy of relay block testing. A two-layer perceptron was chosen as a basis of ANN model. The preliminary results for the application of neural networks for diagnostics of railway blocks with several input-output terminals and feedback circuits were described. A neural network computer programme allowed obtaining satisfactory results for relay diagnostics using "current-time" dependence during relay switching as an input diagnostic data.

Bibliography

[1] ARKATOV V.S., BAZHENOV A.I., DMITRENKO I.E., Remontno-tekhnologicheskijj uchastok SCB (Repair-technological division of railway signalling systems), Transport, Moscow 1987, (in Russian).

[2] DMITRENKO I.E., DJAKOV D.V., SAPOZHNIKOV V.V., Izmerenija i diagnostirovanie v sistemakh zheleznodorozhnojj avtomatiki, telemekhaniki i svjazi (Measurements and diagnostics in railway automatic and telecommunication systems), Transport, Moscow 1992, (in Russian).

[3] DMITRENKO I.E., Tekhnicheskaja diagnostika i avtokontrol` sistem zheleznodorozhnojj avtomatiki i telemekhaniki (Technical diagnostics and control of railway automatic systems), Transport, Moscow 1986, (in Russian).

[4] GALUSHKIN A.I. (ed.), Teorija nejjronnykh setejj (The theory of neural networks). IPJR-press, Moscow 2000, (in Russian).

[5] GAVRILJUK V.I., DUB V.Ju., Diagnostirovanie relejjno-kontaktnykh ustrojjstv zheleznodorozhnojj avtomatiki (Diagnostics of the relay-contact devices of the railway automatics), Dnepropetrovsk national university of railway transport bulletin, 2006, No12. p.3-7, (in Russian).

[6] KARIBSKI V.V., PARKHOMENKO P.P., SOGOMONJAN E.S., Osnovy tekhnicheskojj diagnostiki (Bases of technical diagnostics), Energija, Moscow 1976, (in Russian).

[7] PARKHOMENKO P.P., SOGOMONJAN E.S., Osnovy tekhnicheskojj diagnostiki (Bases of technical diagnostics), Energoatomizdat, Moscow 1981, (in Russian).

[8] SIMON HAYKIN, Neural Networks. A Comprehensive Foundation. Second Edition, McMaster University, Hamilton, Ontario, Canada 2005.

[9] SAPOZHNIKOV V.V., SAPOZHNIKOV VL.V., Osnovy tekhnicheskojj diagnostiki (Bases of technical diagnostics), Marshrut, Moscow 2004, (in Russian).