CHEMICAL ENGINEERING TRANSACTIONS

VOL. 62, 2017

A publication of AIDIC

The Italian Association of Chemical Engineering
Online at www.aidic.it/cet

Guest Editors: Fei Song, Haibo Wang, Fang He

ISBN 978-88-95608- 60-0; **ISSN** 2283-9216

DOI: 10.3303/CET1762203

Life Prediction of Automotive Electromagnetic Relay Based on Wavelets Neural Network

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After analysing the influencing factors on the life of automotive electromagnetic relays, this paper determines six performance degradation parameters as the input parameters for automobile electromagnetic relays, including contact resistance, pick-up time, super-path time, bounce time, arc time and release time. Then, three prediction models were proposed based on radial basis function (RBF), backpropagation (BP) network and wavelets neural network (WNN), considering the nonstationary nature of electrical performance parameters of relay. The models successfully predicted the original nonstationary parameter runoff series. Through comparative analysis, it is seen that the WNN-based life prediction method is the most accurate and suitable approach for relay life prediction.

1. Introduction

The traditional methods for life prediction of relays are mainly based on contact resistance (Rieder and Strof, 1990), surface roughness (Wei et al., 2006), loss quality and spectrum (Zhong, 2008). Each of these methods has its own merits, but all of them face some common problems: It is difficult for them to achieve a high accuracy based on existing prediction variables, and the measurement is too cumbersome to be practical. The typical studies on relay life prediction are as follows. Yao et al. (2007) took the dynamic contact resistance in the closure of relay contactor as the predictor, studied the statistical features of the predictor via repeated experiments, and then established a life prediction model based on time series analysis and the fuzzy theory. However, the predicted results may deviate from the actual life, due to the lack of versatility of the single parameter model. With super–time and pick-up time as the predictors, Zhai et al. (2002) proposed regression analysis and time series methods to establish the univariate and bivariate life prediction models based on super-time and pick-up time respectively.

Despite the simplicity of the prediction process, the models cannot guarantee the prediction accuracy when the variable fluctuates greatly, due to the fitting of predictors based on fixed function form. Shao et al. (2015) created a multi-parameter life prediction model via the polynomial least squares fitting. To a certain degree, the effect of the model is influenced by subjective factors, because the least squares method assumes that the performance parameter runoff series is linear. To solve the above problems, this paper introduces the performance degradation data into the life prediction of automotive electromagnetic relays, and predicts the relay life through quantitative analysis of the relationship between relay failure and performance degradation parameters, so that the predicted results are consistent with the actual data.

The key performance degradation parameters were determined as contact resistance, pick-up time, super-path time, bounce time, release time and arc time. Considering the nonstationary nature of electrical performance parameters of relay (i.e. the parameter values are difficult to form a constant or linear function), three life prediction methods were presented for automobile electromagnetic relay based on artificial neural network. The relay life is predicted by the nonlinear mapping ability of the network.

Specifically, the six performance degradation parameters are taken as the input data, the corresponding features are extracted by hidden layer nodes, and the predicted value is exported as the output data.

Please cite this article as: Jifeng Guo, Guoqiang Zhang, Yuxuan Bi, Yanjuan Li, 2017, Life prediction of automotive electromagnetic relay based on wavelets neural network, Chemical Engineering Transactions, 62, 1213-1218 DOI:10.3303/CET1762203

2. Analysis and selection of life degradation parameters

The performance degradation parameters should carry clear physical meanings (e.g. work status, life and reliability of the relay), be easy and stable in measurement, and exhibit a clear variation pattern over the time. In this paper, the key performance degradation parameters are determined as contact resistance, pick-up time, super-path time, bounce time, release time and arc time. These parameters are directly or indirectly affected by the contactor gap. The degradation parameters are defined as follows.
(1) Contact resistance: this parameter is mainly affected by the chemical composition of the contact surface and the contact pressure.
(2) Pick-up time: this parameter refers to the interval from the energization of the coil to the first contact between the movable contactor and dynamic resting static contactor, excluding the bounce time.
(3) Super-path time: this parameter stands for the interval from the first contact to the complete closure of the armature between the movable contactor and dynamic resting static contactor.
(4) Bounce time: this parameter means the interval from the first contact to the end of the contact bounce.
(5) Release time: this parameter is the interval from the de-energization of the coil to the first contact between the movable contactor and the static contactor, excluding the bounce time.
(6) Arc time: this parameter signifies the arc time of the release process between the moving contactor and dynamic resting contactor.

3. Neural network prediction algorithm

3.1 Principle and construction of BP neural network

The basic BP neuron network has n inputs, each of which is connected to a neuron. The inputs are assigned proper weights w_i *i=1, 2, …,* n_0 and outputted by the function $y = f(W \times X, \theta), \alpha = \sum_{i=1}^{n_0} w_i x_i$.The threshold θ of the neuron and the number of the input samples a are considered as the inputs of the activation function f. The threshold θis critical to the functioning of the network. It moves the graph of the activation function to the left and right, adding to the solvability of the problem.
The BP algorithm (Sadeghi, 2000) is a learning algorithm with a mentor. It is often used to calculate the steepest descent direction. In the network, the signals are propagated in both forward and backward directions. At the beginning, the learning samples are imported into the input layer, and transmitted to the output layer. The state of each neuron only affects the state of the next neuron. If the desired output is not obtained at the output layer, the error of the output layer will be calculated, marking the start of the error back-propagation phase. In that phase, the error signal is returned along the original connections from the output layer to the input layer, and the connection weights are adjusted to minimize the error.

3.2 Principle and construction of RBF neural network

The RBF network (Seshagiri and Khalil, 2000) consists of two layers, a hidden layer and an output layer. The neurons in the same layer are not connected, while those of two adjacent are fully connected. The function of the input layer nodes is to map the n0 inputs to the neurons in the hidden layer. Then, the hidden layer nodes nonlinearly map the inputs via the RBF. The hidden layer outputs are linearly weighted by output layer nodes.
The hidden layer of RBF network is usually activated by a Gaussian function:

$$\beta_j = \exp(-\left\|x - c_j\right\|^2 / \sigma_j^2),\ j = 1, 2, \cdots, n_1 \quad (1)$$

where ||•|| is the Euclidean norm; β_j is the j-th output of the hidden layer; x is the input; c_j is the *j-th* centre of the unit basis function; $\sigma_j^2$is the normalized parameter of the *j-th* hidden node. The output of the RBF network is a linear combination of its hidden nodes:

$$y_k = \sum_{k=1}^{m} w_{jk}\beta_j,\ j = 1, 2, \cdots ..., n_1,\quad k = 1, 2, \cdots ..., m \quad (2)$$

3.3 Principle and construction of the wavelets neural network (WNN)

The WNN (Vinay Kumar et al., 2008) replaces the Sigmoid function in the hidden layer of BP neural network with the wavelet function (the incentive function). The learning and training of the WNN are the same with those of the BP network.
The weights and the wavelet basis function parameters are modified by the gradient correction method. The correction is implemented in the following steps:
(1) Calculate the prediction error.

$$e = \sum_{k=1}^{m} y_n(k) - y(k) \tag{3}$$

where, $y_n(k)$ is the desired output; $y_n(k)$ is the predicted output of the WNN.
(2) Correct the weights and wavelet basis function coefficient according to the prediction error.

$$\omega_{n,k}^{(i+1)} = \omega_{n,k}^{i} + \Delta\omega_{n,k}^{(i+1)} \tag{4}$$

$$a_k^{(i+1)} = a_k^{i} + \Delta a_k^{(i+1)} \tag{5}$$

$$b_k^{(i+1)} = b_k^{i} + \Delta b_k^{(i+1)} \tag{6}$$

The $\Delta\omega_{n,k}^{(i+1)}, \Delta a_k^{(i+1)}, \Delta_k^{(i+1)}$ can be computed based on the prediction error:

$$\Delta\omega_{n,k}^{(i+1)} = -\eta \frac{\partial e}{\partial \omega_{n,k}^{(i)}} \tag{7}$$

$$\Delta a_k^{(i+1)} = -\eta \frac{\partial e}{\partial a_k^{(i)}} \tag{8}$$

$$\Delta b_k^{(i+1)} = -\eta \frac{\partial e}{\partial b_k^{(i)}} \tag{9}$$

4. Life prediction experiment

The HELLA/JD191 type normally open contact electromagnetic relays (Foshan Haila Electrical Co Ltd) was taken as the samples, and subject to a lift test on a designed test bench in the VW80932 standard working mode. The samples was energized for 2s and unenergized 3s, respectively. After working 104,088 times, the samples failed with the degradation trend recorded in the six parameters (Figure 1).

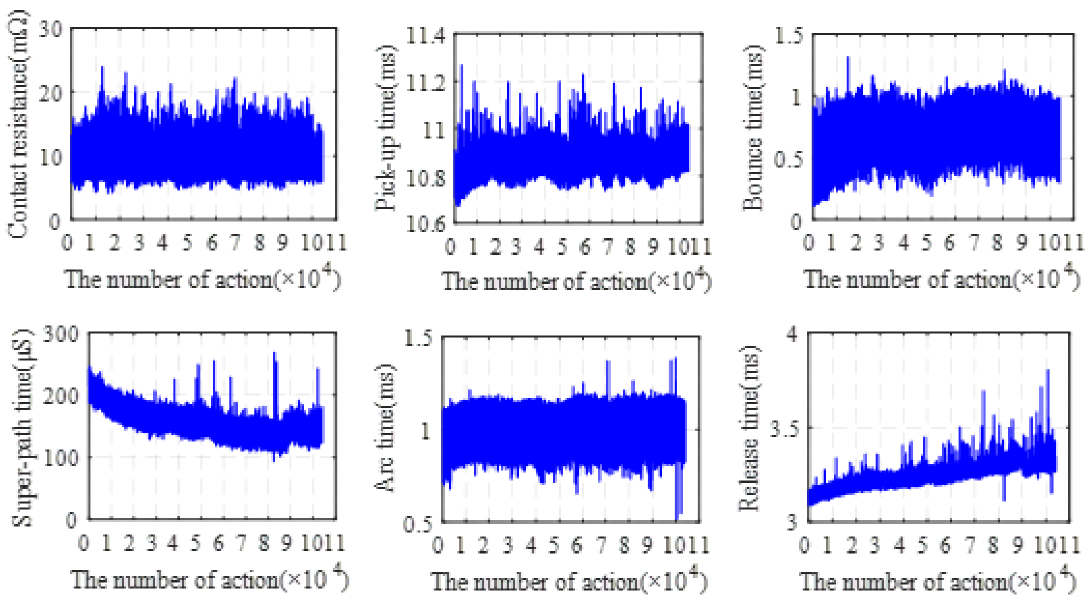

Figure 1: Regular diagram of the six key performance degradation parameters changes with the number of the action

4.1 Prediction accuracy and evaluation function

The prediction accuracy is expressed as:

$$\sigma_x = \left[1 - \frac{|X_t - X_r|}{X_t}\right] \times 100\% \tag{10}$$

Where X_t is the predicted value; X_y is actual value.
The root mean square error is obtained as follows:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i} - X_{model,i})^2}{n}} \tag{11}$$

where $X_{obs,i}$ is the *i-th* predicted value; $X_{mode,i}$ is the *i-th* actual value.

4.2 Life prediction and experimental verification

The BP neural network, RBF network and WNN were trained with 100, 500 and 1,000 training samples, respectively. The BP neural networks are denoted as NB1~3, the REF neural networks as NR1~3 and the WNNs as NW1~3.The same type of relays was selected to undergo the life tests. The degradation parameters at the 0, 10,000, 15,000, 30,000, 35,000, 45,000, 60,000, 70,000, 85,000, 90,000, 97,000 times are recorded in Table 1. The relay life was predicted by the 9 neural networks: NB1~3, NR1~3 and NW1~3, respectively. The predicted results are plotted in Figures 2~4.

Table 1: Parameters of the same type of relay for different life times

Serial number	Work times	Contact resistance (mΩ)	Pick-up time (ms)	Super-path time (μS)	Bounce time (ms)	Arc time (ms)	Release time (ms)
1	0	9.39	10.82	220.5	0.43	0.94	3.12
2	10000	11.96	10.85	184.1	0.59	0.98	3.16
3	15000	10.10	10.92	171.8	0.62	0.99	3.17
4	30000	9.47	10.87	158.2	0.57	0.97	3.22
5	35000	10.39	10.89	153.4	0.78	1.01	3.21
6	45000	9.40	10.85	153.5	0.63	0.98	3.25
7	60000	9.51	10.88	142.8	0.71	1.03	3.26
8	70000	9.92	10.85	132.1	0.74	0.99	3.29
9	85000	9.74	10.91	129.9	0.68	1.01	3.33
10	90000	9.95	10.86	146.8	0.71	1.02	3.29
11	97000	8.72	10.90	136.7	0.67	1.03	3.31

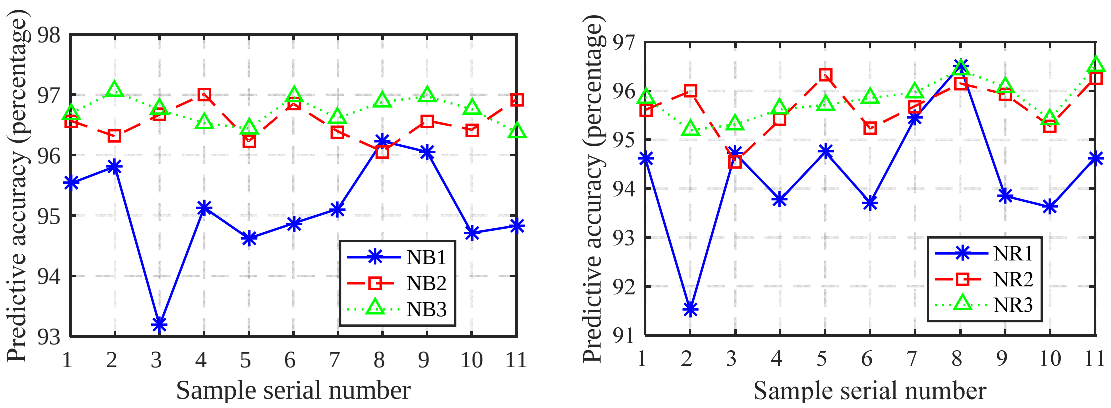

Figure 2: (a) Comparison of prediction accuracy of NB1 ~ 3 under different training samples; (b) Comparison of prediction accuracy of NR1 ~ 3 under different training samples

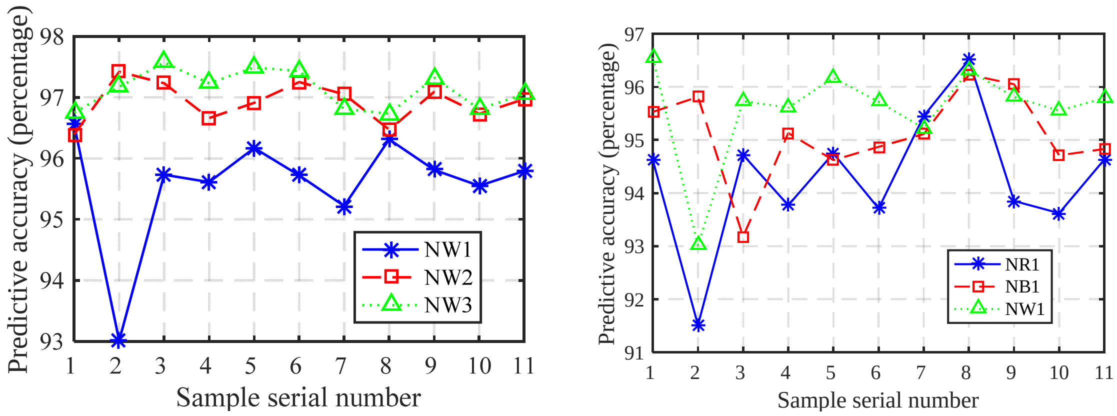

Figure 3: (a) Comparison of prediction accuracy of NW1 ~ 3 under different training samples; (b) Comparison of prediction accuracy of three models under 100 training samples

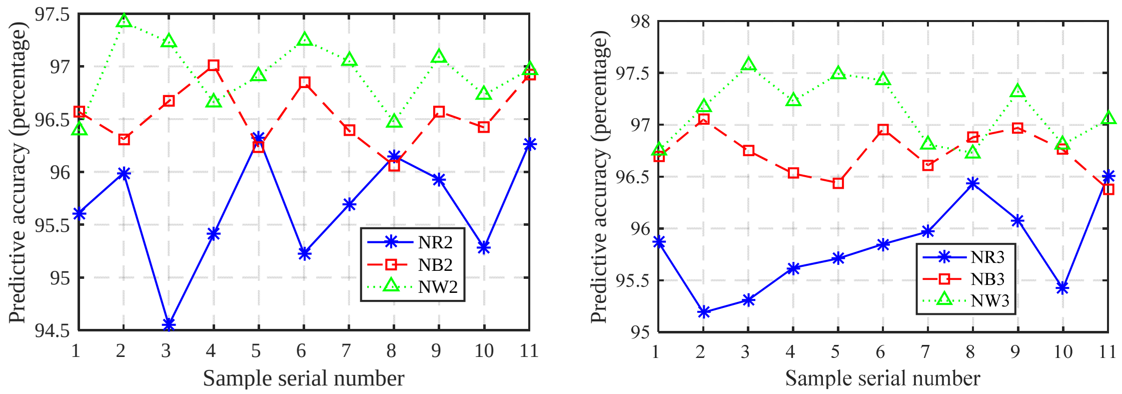

Figure 4: (a) Comparison of prediction accuracy of three models under 500 training samples; (b) Comparison of prediction accuracy of three models under 1000 training samples

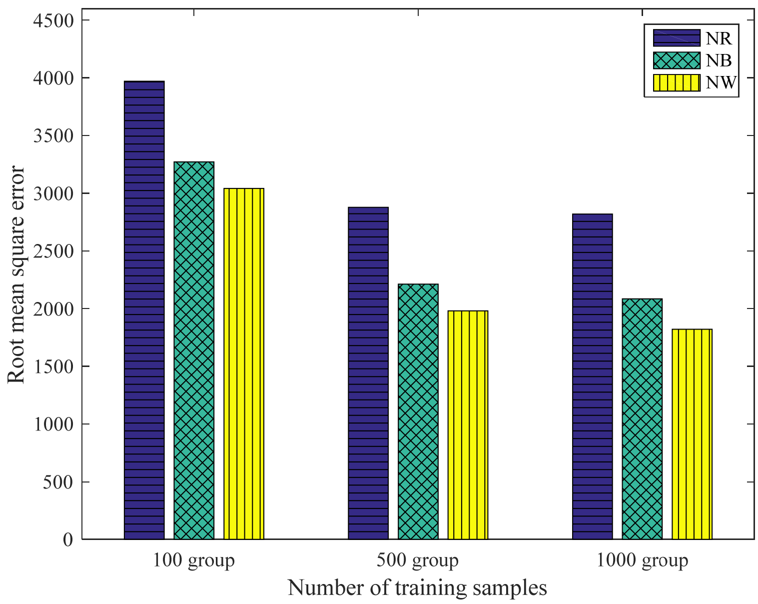

Figure 5: Comparison of prediction accuracy of 9 models under different group of training samples

It can be seen from Figures 2 ~4 that the prediction accuracy increased with the number of training samples. When the number of samples increased from 100 to 500, the prediction accuracies of the three networks (NR, NB and NW) grew by 1.45%, 1.39% and 1.33% respectively. However, the increase in prediction accuracy slowed down when there were more than 500 samples. When the number of samples increased from 500 to 1,000, the prediction accuracy only increased by 0.18%, 0.14% and 0.20%, respectively. To sum up, for the same type of neural networks, more training samples contribute to the improvement of prediction accuracy, but the contribution is not significant after the number of samples exceeds 500.
According to Figure 5, the WNN made more accurate prediction than the other two networks at the same number of training samples. With 100 training samples, the difference in prediction accuracy between BP and BR, and between BW and BP were 0.81% and 0.49%, respectively. The difference was 0.87% and 0.38%, respectively, with 500 training samples, and 0.91% and 0.39%, respectively, with 1,000 training samples.
Figure 8 compares the root mean square errors of the nine networks. The root mean square errors of NR, NB and NW are 3,969.64, 3,270.87 and 3,041.25, respectively, with 100 training samples, 2,877.97, 2,212.04 and 1,980.11, respectively, with 500 training samples, and 2,819.12, 2,084.92 and 1,820.91 with 1,000 training samples. The results confirm the positive correlation between prediction accuracy and the number of training samples. In general, the WNN boasts the best accuracy.

5. Conclusion

Based on artificial neural network, this paper presents a life prediction method for automotive electromagnetic relay, aiming to overcome the poor reliability and low accuracy for the existing relay life prediction methods. Taking six key parameters (i.e. contact resistance, pick-up time, super-path time, bounce time, release time and arc time) as the input and predicted life as the output, the non-linear mapping ability of artificial neural network was relied on to predict the non-stationary timing values of the performance degradation parameters of the relay. In this way, the author established three kinds of life prediction models based on BP, RBF and WNN. The experimental results show that the WNN-based model has achieved the best accuracy among all neural networks.

Acknowledgement

This work was supported by the Harbin Scientific and technological innovation special research funding projects (2016RAQXJ015) and the Fundamental Research Funds for the Central Universities (2572017CB33).

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