Research on Life Prediction of Railway Relays Under Vibration Conditions (Postprint)

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Abstract

Reliability and safety in railway relay operation are essential requirements for ensuring the normal functioning of various railway equipment and play a crucial role in train control. This paper develops an accelerated life test scheme for railway relays under vibration stress based on accelerated testing principles and conditions, and obtains contact voltage drop data of railway relay contacts through accelerated life testing. Contact voltage drop is selected as the characteristic parameter for relay performance degradation, the wavelet threshold method is employed to denoise the obtained contact voltage drop data, and an EEMD-RBF prediction model is established to predict relay life. A comparative analysis of the errors between EEMD-RBF and RBF demonstrates that the EEMD-RBF model achieves higher prediction accuracy. Finally, based on the predicted life, the inverse power law equation is utilized to predict the life of railway relays under normal vibration stress levels.

Full Text

Preamble

Study on Life Prediction of Railway Relay under Vibration

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Abstract

The reliability and safety of railway relays during operation are essential requirements for ensuring the normal functioning of various railway equipment, playing a critical role in train control systems. This paper develops an accelerated life test scheme for railway relays under vibration stress based on accelerated testing principles and experimental conditions, and obtains contact voltage drop data for railway relays through accelerated life testing. Contact voltage drop is selected as the characteristic parameter for relay performance degradation. Wavelet threshold denoising is applied to process the obtained contact voltage drop data, and an EEMD-RBF prediction model is established to predict relay lifespan. Comparative analysis of errors between the EEMD-RBF and RBF models demonstrates that the EEMD-RBF model achieves higher prediction accuracy. Finally, based on the predicted lifespan values, the inverse power law equation is employed to extrapolate the lifespan of railway relays under normal vibration stress levels.

Keywords: Railway relay, vibration stress, degradation test, wavelet threshold denoising, EEMD-RBF life prediction

1 Introduction

Railway relays are primary switching devices in railway equipment, serving as specialized multi-circuit switches that close or disconnect control circuits. With the rapid advancement of modern industrial capabilities in recent years, many machines are developing toward higher speeds, pressures, and temperatures. While technological levels have improved rapidly, factors contributing to engineering failures have also increased, with vibration and fatigue being among the most significant. Environmental factors now exert greater influence on relay lifespan, leading to stringent railway requirements for relays: long service life and the ability to maintain high electrical insulation strength despite changes in external conditions such as vibration and temperature [1].

This study employs accelerated life testing methodology to investigate performance degradation and lifespan prediction of railway relays in vibration environments. The research object is a specific type of railway signal relay, as shown in [Figure 1: see original paper].

[Figure 1: see original paper] Railway signal relay

2 Working Principle of Railway Signal Relays

Signal relays refer to the general category of relays used in railway signaling systems and represent indispensable components in railway signal control systems. Their basic structure is illustrated in [Figure 2: see original paper].

[Figure 2: see original paper] Schematic diagram of signal relay structure

The electromagnetic system and contact system constitute the two major structural components of signal relays. The electromagnetic system comprises a coil, fixed iron core, yoke, and movable armature. The coil is horizontally mounted on the iron core, divided into front and rear windings. Dual-winding design enhances the adaptability and flexibility of control circuits, allowing selection of single or dual-coil control based on circuit requirements in practical applications. The iron core utilizes soft magnetic materials with high magnetic flux density and low residual magnetism. The armature is fixed to the yoke blade by a butterfly steel wire sheet, primarily functioning to convert electromagnetic energy into mechanical energy. Notably, unlike typical electromagnetic relays, the armature of signal relays is riveted with weight plates to increase its mass, enabling gravity to forcibly disconnect the front contacts when the coil is de-energized.

The contact system includes movable and stationary contacts. Each contact group of a non-polarized relay comprises front, middle, and rear contacts, employing a two-row longitudinal linkage structure with eight contact groups operating synchronously.

3 Constant Acceleration Testing of Railway Relays under Vibration

Accelerated degradation testing, which has emerged in recent years, provides new means for relay reliability assessment [2]. Due to the long service life of railway relays, this paper adopts accelerated life testing methodology, characterizing test results by failure time to complete experiments with a small number of samples in relatively short periods. Since constant acceleration testing offers relatively simple implementation, straightforward data analysis, and accurate lifespan assessment results [3-4], this study employs a constant acceleration test scheme.

The test samples are a specific type of railway relay. Before testing, qualified products were randomly selected and inspected to ensure transparent and clear relay housings and that all components were free from surface defects or detachment [5]. A total of 20 samples were used in this test, evenly divided into four groups of five samples each for accelerated life testing under different vibration stress levels.

3.1 Determination of Failure Criteria and Stress Levels

First, failure criteria must be established before testing. The determination of failure criteria significantly impacts test results, as different criteria lead to different experimental outcomes and subsequent data analysis. Based on relay operating principles, the most vulnerable component in electromagnetic relays is the contacts, with excessive contact resistance being the primary failure mode [6]. Therefore, according to relay reliability test method specifications and project partner requirements, this paper selects contact voltage drop exceeding 0.5 V as the failure criterion to guide the testing process.

Second, accelerated stress levels must be determined. The stress type in this test is vibration stress at room temperature. Literature review indicates that sinusoidal vibration testing primarily simulates transportation and usage processes of electrical and electronic products, and is used to study vibration environment effects. Therefore, this study employs fixed-frequency sinusoidal vibration. According to GB/T7417—2010 specifications and product manuals, the vibration amplitude is 0.45 mm, the minimum vibration frequency is 20 Hz, and the vibration direction is vertical sinusoidal motion. Per enterprise requirements, the maximum vibration frequency is set at 100 Hz. Following the principle of equal stress distribution, two intermediate stress levels, xm1 and xm2, are added between the maximum stress level xk and minimum stress level x1:

xm1 = (2x1 + xk) / 3 = 46.67
xm2 = (2xk + x1) / 3 = 73.33

For experimental convenience, the four vibration frequency levels are adjusted to 20 Hz, 47 Hz, 73 Hz, and 100 Hz. Considering practical test conditions and time constraints, and lacking sufficient preliminary 摸底 test data, if no obvious failure occurs after more than one month of testing for each group under different vibration stress levels, the test may be terminated. Degradation parameter data are collected at one-hour intervals.

3.2 Test Equipment

The vibration environment for this test is provided by a specific model of electrodynamic vibration table, as shown in [Figure 3: see original paper], which supplies accelerated stress for the railway signal relay accelerated life test. The electrodynamic vibration table is critical equipment for mechanical environment testing, primarily consisting of a vibration table body, vibration controller, power amplifier, and cooling device. Railway signal relays are placed on the vibration table as test specimens for vibration acceleration testing to evaluate their reliability.

[Figure 3: see original paper] Vibration table

4 Preprocessing of Railway Relay Contact Voltage Drop Data

The railway relays studied in this paper have 16 contact pairs, including eight normally open and eight normally closed contacts. Under vibration stress, failure of any single contact pair causes entire relay failure. Since this test measures contact voltage drop, relay lifespan depends on the contact with maximum contact resistance among its multiple contacts. During testing, external factors such as industrial interference or internal factors like thermal agitation within components introduce noise and interference into the test data. The presence of this noise information is unreasonable and significantly impacts modeling accuracy. Therefore, preprocessing of predictive variables is necessary to reduce interference effects [7].

Wavelet analysis is currently a common denoising method [8-9], primarily including three approaches: correlation denoising, modulus maximum denoising, and wavelet threshold denoising algorithms [10]. This paper employs wavelet threshold denoising to smooth noise in the railway relay maximum contact voltage drop time series.

(1) This study selects db4 as the wavelet function for three-level decomposition of noise signals. The high-frequency fluctuation sequences from levels 1 to 3 are denoted as d1, d2, and d3, while the low-frequency trend sequence from level 3 is denoted as a3. The three-level decomposition model is shown in [Figure 4: see original paper].

[Figure 4: see original paper] Three layers decomposition model

(2) The "Rigrsure" unbiased likelihood estimation threshold type is used to select thresholds for each level.

(3) Signal-to-noise ratio (SNR) and root mean square error (RMSE) are used to evaluate denoising effectiveness. Using the contact voltage drop signal of sample #1 under 100 Hz vibration frequency as an example, partial denoising results after wavelet denoising are shown in .

Partial denoising results

Table 2 presents the denoising evaluation metrics for five samples' contact voltage drops under 100 Hz vibration frequency stress.

Denoising evaluation index

As shown in Table 2, the calculated SNR for wavelet threshold denoising reaches 55.9156 dB with an RMSE of 0.0222, indicating good denoising effectiveness that contributes to improved prediction accuracy in subsequent processes.

5 EEMD-RBF Neural Network Prediction Model

5.1 EEMD Decomposition

Empirical Mode Decomposition (EMD) offers the multi-resolution advantages of wavelet transform while overcoming the difficulty of selecting wavelet bases and decomposition scales. However, when analyzed data are not purely composed of white noise, EMD decomposition suffers from mode mixing—manifesting as chaotic decomposition. To address this, this paper proposes an improved algorithm: Ensemble Empirical Mode Decomposition (EEMD). The fundamental principle of EEMD utilizes the statistical properties of noise to effectively avoid mixing phenomena. Gaussian white noise following a (0, ( )^2) normal distribution is superimposed on the original signal, followed by multiple EMD decompositions. The Gaussian white noise cancels out across numerous trials, while useful signals from the original signal are retained as the mean after repeated white noise addition experiments [11]. Thus, EEMD represents a significant improvement over EMD.

The EEMD decomposition process for railway relay contact maximum voltage drop time series X(t) is as follows:

(1) Add white noise to the X(t) signal.

(2) Perform multiple EMD decompositions on the noise-added sequence to obtain IMF sequences.

(3) Repeat steps (1) and (2) with different white noise sequences added each time.

(4) Use the mean of each IMF obtained from decomposition as the final result.

5.2 EEMD Simulation Results

Using the contact voltage drop signal of a sample under 100 Hz vibration frequency as an example, EEMD decomposition is performed on the contact maximum voltage drop sequence, with results shown in [Figure 5: see original paper]. The figure demonstrates that EEMD divides the signal into eight layers, effectively suppressing mode mixing.

[Figure 5: see original paper] EEMD decomposition results

5.3 Construction of EEMD-RBF Neural Network Prediction Model

Radial Basis Function Neural Networks (RBFNN) exhibit optimal approximation and global optimization performance, widely applied in function approximation and classification problems. RBF neural networks are efficient feedforward neural networks with a topological structure comprising input, hidden, and output layers. The mapping from input to output is nonlinear, while the mapping from hidden layer space to output space is linear. RBF networks achieve nonlinear transformation from input to output space through linear combination of nonlinear basis functions. The RBF in the hidden layer typically uses Gaussian functions with radial symmetry and attenuation around center points. Compared with BP neural networks, RBF networks offer significantly faster learning speeds and effectively avoid local minima.

Using RBF neural networks, this study predicts each decomposed IMF and RES sequence separately and superimposes the results. The decomposition sequence prediction model flowchart is shown in [Figure 6: see original paper].

[Figure 6: see original paper] Predictive flow chart

This paper constructs the RBF network using Matlab's Neural Network Toolbox. The model is built as follows:

(1) Training and prediction sample sets are selected. This study uses 900 samples for RBF neural network training and 59 samples for network validation.

(2) Network parameter settings. The `newrb()` function in Matlab is called to construct the RBF network. The `newrb()` function establishes a radial basis neural network with the format: `net = newrb(P, T, goal, spread, MN, DF)`. The network's mean square error goal is set to 0.001. The spread parameter controls the network' s performance: larger spread values require more hidden neurons and produce smoother function fitting, while very small spread values degrade network performance and may cause overfitting. Therefore, different spread values must be tested iteratively until requirements are met. After multiple debugging iterations, a spread value of 10 yields the highest prediction accuracy. The maximum number of neurons MN and radial basis function distribution constant DF use default values.

5.4 Simulation Results Analysis

To analyze the results, the following definitions are used:

$SSE = \Sigma(f(i) - \hat{f}(i))^2$
$MSE = (1/n)\Sigma(f(i) - \hat{f}(i))^2$

To verify the impact of EEMD decomposition on RBF neural network prediction model accuracy, predictions using only RBF neural networks without EEMD decomposition on the original sequence are added for comparison. Figures 7-14 show RBF neural network prediction results for IMF sequences, while Figure 15 compares RBF predictions with and without EEMD decomposition. Table 3 displays errors for both models, using Sum of Squared Errors (SSE) and Mean Squared Error (MSE) as metrics.

[Figure 7: see original paper] The IMF1 forecast compared to the real value
[Figure 8: see original paper] The IMF2 forecast compared to the real value
[Figure 9: see original paper] The IMF3 forecast compared to the real value
[Figure 10: see original paper] The IMF4 forecast compared to the real value
[Figure 11: see original paper] The IMF5 forecast compared to the real value
[Figure 12: see original paper] The IMF6 forecast compared to the real value
[Figure 13: see original paper] The IMF7 forecast compared to the real value
[Figure 14: see original paper] The RES forecast compared to the real value
[Figure 15: see original paper] The comparison of the two models' prediction results

The error of the two models

Simulation results demonstrate that all metrics for the EEMD-RBF model predictions are significantly superior to those of the RBF model without EEMD decomposition. This indicates that EEMD' s data stabilization processing substantially improves RBF model prediction accuracy. Therefore, this paper selects the EEMD-RBF model for cyclic rolling prediction of sample data under four different vibration stress points in the railway relay vibration accelerated life test, obtaining lifespan values under each stress condition, as shown in .

Life prediction of railway relay under different vibration stress (Unit: h)

During multi-step rolling prediction, prediction errors increase with the number of prediction steps. When all inputs to the prediction model are predicted values rather than measured values, prediction effectiveness deteriorates further. As model complexity increases, data processing volume grows and time consumption extends, making it difficult to obtain product storage lifespan prediction results within short timeframes.

5.5 Life Prediction under Normal Vibration Stress

According to the product manual for the railway relay model used in this study, the normal working environment requires vibration frequency not exceeding 15 Hz and amplitude not exceeding 0.45 mm. Under these conditions, relay degradation proceeds extremely slowly, resulting in long test cycles and often yielding no failure data. To obtain lifespan values under normal stress, accelerated life testing is used to establish a relay degradation regression prediction model for extrapolating lifespan under normal stress levels.

Under vibration stress, the inverse power law equation for railway relay failure lifespan is:

t = d · S^(-)

Taking logarithms of both sides yields:

ln t = ln d - · ln S

Where T = ln t and a = -ln d. This shows a linear relationship between the logarithm of lifespan and the logarithm of vibration stress. To ensure relatively conservative predictions, the minimum predicted lifespan under each vibration stress level is used. Least squares method yields parameter estimates of a = -ln d = 13.9179 and = 1.0145. The relationship between relay lifespan and vibration stress is given by Equation (5), with the accelerated life curve shown in [Figure 16: see original paper].

[Figure 16: see original paper] Accelerated life curve

Using this derived equation, the lifespan of railway relays under normal vibration stress can be extrapolated. The final extrapolation yields lifespan values of 72,802 h, 109,440 h, and 219,680 h (approximately 8.3107 years, 12.4932 years, and 25.0777 years) for vibration frequencies of 15 Hz, 10 Hz, and 5 Hz, respectively, at 0.45 mm amplitude.

6 Conclusion

This study employs accelerated life testing methodology under vibration stress to investigate railway relays, obtaining performance degradation data of contact voltage drops and predicting relay lifespan. Wavelet threshold denoising preprocesses the contact voltage drop data. Ensemble Empirical Mode Decomposition (EEMD) deeply mines and decomposes the characteristics of contact voltage drop sequences, and an EEMD-RBF prediction model is established for relay parameter prediction. Comparison between EEMD-RBF and RBF prediction models demonstrates that the EEMD-RBF prediction model achieves higher accuracy. Finally, this model performs rolling predictions for relays under four vibration stress levels, and the derived inverse power law equation extrapolates the lifespan of railway relays under normal vibration stress levels.

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Note: Figure translations are in progress. See original paper for figures.