Research on Fault Diagnosis of Metro Bearing Based on Wavelet Neural Network

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Abstract: Bearings are critical rotating components in subway vehicles, and their health directly affects the safety of train operation. Traditional bearing fault diagnosis heavily relies on simplistic signal processing techniques, which struggle to achieve high precision fault recognition. Therefore, this paper proposes a novel method for subway bearing fault diagnosis based on Wavelet Neural Networks (WNN). The paper analyzes the basic principles of wavelet transform and details the structural design of Wavelet Neural Networks. In the experimental section, vibration signals from subway bearings under different operating conditions are collected and analyzed using Wavelet Neural Networks to validate the effectiveness of the proposed method. Experimental results demonstrate that the fault diagnosis method based on Wavelet Neural Networks can accurately identify early bearing faults with higher precision compared to traditional methods.
***Keywords*:** subway bearings; fault diagnosis; Wavelet Neural Network; vibration signals; intelligent diagnosis

1. Introduction

With the deepening urbanization, subways play a crucial role in urban transportation, and their safety has garnered widespread attention. Bearings, as critical rotating components of subway vehicles, directly impact subway operation safety. Hence, the development of efficient subway bearing fault diagnosis technology is crucial. Traditional methods rely on vibration analysis techniques, which have limitations in practical applications such as strong dependence on specialized personnel and limited diagnostic accuracy. In recent years, driven by the rapid development of artificial intelligence, data-driven intelligent diagnostic methods have become a research hotspot. Wavelet Neural Networks (WNN), as a hybrid model combining wavelet transform and neural network advantages, show significant potential in signal processing. Wavelet transform extracts local features of signals, while neural networks possess strong nonlinear mapping capabilities. By integrating these strengths, a robust bearing vibration signal fault recognition model is constructed. This paper aims to explore the subway bearing fault diagnosis method based on Wavelet Neural Networks and verify its effectiveness through experiments [1].

2. Basic Principles of Wavelet Transform

Wavelet Transform is a mathematical transformation method widely used in signal processing, image processing, data compression, and other fields. Compared with traditional Fourier transform, Wavelet Transform provides accurate time and frequency localization information, making it particularly suitable for processing non-stationary signals. The fundamental idea of wavelet transform generally involves representing a signal using a family of wavelet basis functions, which are derived from a mother wavelet function through translation. The mother wavelet is a function with finite energy, satisfying expected orthogonality and compactness conditions. Wavelet transform is divided into Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT). CWT performs continuous scale and translation transformations on signals, while DWT discretely translates the signal and is typically implemented using Multi-Resolution Analysis (MRA). This decomposition divides the signal into multiple sub-bands of different frequencies, each corresponding to a different scale. In practical DWT operations, signals are decomposed into low-frequency (approximate) and high-frequency (detail) parts. High-pass and low-pass filters are used to filter the signals, obtaining high-frequency details and low-frequency approximations. Subsequently, down-sampling filters are applied to reduce data volume [2].

3. Wavelet Neural Network Fault Diagnosis Model

3.1 Establishing the Fault Diagnosis Model

Bearings are critical components of subway vehicles, directly impacting the operational efficiency of trains. Developing an efficient and accurate bearing fault diagnosis model is crucial for ensuring the stable operation of subway systems. Therefore, this paper proposes a novel subway bearing fault diagnosis model that fully utilizes the advantages of Wavelet Packet

Transform (WPT) and improved Backpropagation (BP) neural networks to further enhance fault diagnosis efficiency. (1) Feature Extraction and Recording.Researchers employ Wavelet Packet Transform (WPT) to extract vibration signals from bearings, which helps directly reflect the bearing's condition. Additionally, WPT effectively decomposes signals into different frequency bands, capturing local features such as energy and entropy. These features are crucial for subsequent neural network training, especially in identifying subtle bearing faults. (2) Training of Wavelet Neural Network and Determination of Optimal Parameters:Following feature extraction, an enhanced BP neural network model is constructed, integrating traditional BP neural network advantages with momentum terms and adaptive learning rates to accelerate training. Researchers use the extracted features as inputs and conduct extensive network training with experimental data. Cross-validation methods are employed to determine optimal network parameters, including the number of hidden layer nodes, learning rate, momentum coefficient, etc. (3) Application of the Trained Model to Actual Bearing Fault Diagnosis:Once network training is complete, the model is applied to diagnose actual bearing faults by extracting new vibration signal features. These features are input into the trained neural network to accurately output the type and severity of bearing faults. The model's diagnostic accuracy is validated by comparing it with actual fault records. Experimental results demonstrate that the model accurately identifies various bearing fault modes, including wear, cracks, looseness, etc., with higher accuracy than traditional diagnostic methods (as shown in Figure 1).

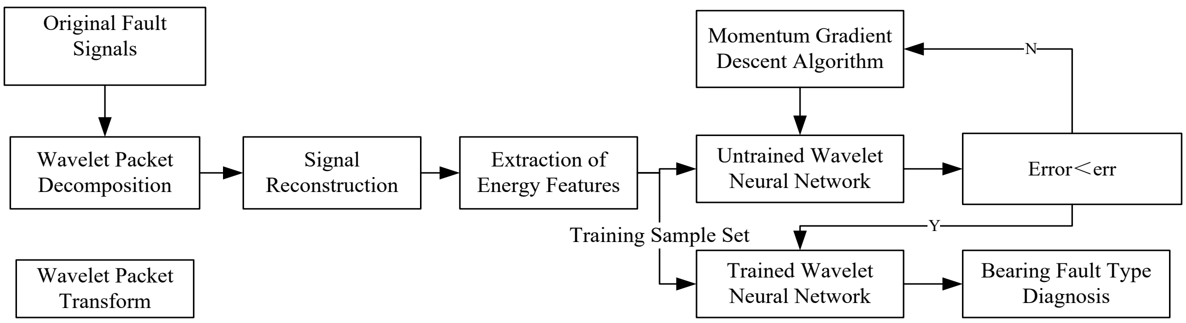

Figure 1. Architecture Diagram of the Wavelet Neural Network Fault Diagnosis Model

3.2 Selection of Neural Network Structure Parameters

When establishing the Wavelet Neural Network (WNN), it is crucial to determine the network's size, the number of nodes per layer, the input layer nodes, and the input data quantity based on the network structure. The number of hidden layer nodes should be calculated using relevant formulas, while the output layer nodes depend on the output structure.In this study, researchers based their parameter selection on the features extracted from Wavelet Packet Decomposition. They employed high-pass conjugate orthogonal filters and low-pass filters to process the signal content separately, generating corresponding signal components. Research revealed that during filter operation, signal length tends to decrease as the decomposition layers increase, significantly impacting frequency band resolution. Moreover, the number of decomposition layers in the original signal's Wavelet Packet Decomposition is influenced by factors such as sampling frequency and bearing fault characteristic frequencies. The study found that stopping at 5 layers resulted in a higher error rate compared to 3-layer decomposition. Therefore, the study adopted a 3-layer decomposition approach, calculating that the input signal comprises 8 components.

In this case, the researchers extracted feature vectors with normalization capability, where the input layer has 8 nodes and the output layer has 4 nodes. For determining the number of nodes in the hidden layer, the following formula was used:

$$n_h = \sqrt{n_i + n_o} + a \tag{1}$$

Here,

n_h represents the number of nodes in the hidden layer,

n_i is the number of nodes in the input layer, which is 8,

n_o is the number of nodes in the output layer, which is 4,

a is a constant parameter, with a value of 9.549 in this study.

Applying these values to the formula, the researchers obtained n_h=13.

4. Model Testing

4.1 Data Collection

In this experiment, data were sourced from the bearing fault experimental database at Case Western Reserve University (CWRU). Accelerometers were positioned at the 12 o'clock position on the motor rotor drive end to facilitate real-time monitoring by the researchers. The experimental design included scenarios of fault-free conditions, inner race faults, outer race faults, and rolling element faults. Experimental conditions were set at a speed of 1797 r/min (equivalent to 30 Hz) under zero load conditions (0 hp). The diameter of the faulty bearings was set to 0.5334 mm. During data collection, a sampling frequency of 12 kHz was utilized, with a sampling duration of 10 seconds.

4.2 Data Processing and Feature Extraction

The study involved key operations in extracting energy feature vectors for the four fault modes: (1) Dataset Partitioning. The 120,000 original vibration signals for each fault mode were divided into training and testing datasets in a 3:1 ratio, with each set containing 300 samples. This partitioning ensured diverse representation in the dataset, laying a solid foundation for subsequent model training. (2) 42 signal sets were decomposed using conjugate orthogonal filters, with a decomposition level of 3 layers. After the reconstruction process, 8 signals were generated. This approach utilized wavelet transforms to extract time-frequency characteristics from the signals, providing rich information for fault diagnosis. (3) The reconstructed signals underwent normalization to enhance the model's convergence speed and accuracy. Normalization ensured numerical comparability among different feature vectors, aiding the model in accurately identifying fault modes and obtaining energy feature vectors. These vectors were used as input data for training and validating the wavelet neural network model [5].

4.3 Wavelet Neural Network Model Construction

The wavelet neural network combines the multiscale analysis capability of wavelet transforms with the nonlinear mapping capability of neural networks. In this model, the input layer receives feature vectors, the hidden layer uses wavelet basis functions for feature mapping, and the output layer predicts the fault types. The network is trained using the training dataset, and network parameters are adjusted to optimize classification performance (as shown in Figure 2).

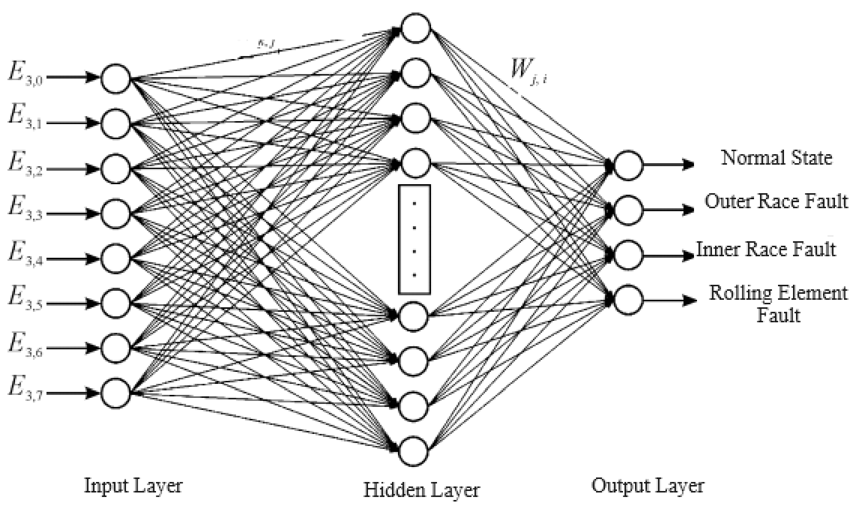

Figure 2. Network Topology Diagram

4.4 Model Validation

The model is validated using experimental data provided by CWRU. Different types of data are categorized into training and testing sets. By comparing actual fault types with model predictions, metrics such as accuracy, recall, and F1 score are calculated to scientifically evaluate the model's performance [6].

4.5 Results and Discussion

The experimental results demonstrate that the wavelet neural network-based fault diagnosis model effectively distinguishes between four different bearing conditions with high accuracy and robustness. Particularly in handling nonlinear and non-stationary vibration signals, the wavelet neural network shows superior performance. When the number of training iterations reaches 2583, the model achieves the desired target error accuracy, with an accuracy of over 95% on the test set, indicating the model's ability to correctly identify various bearing fault types. Additionally, the researchers enhanced the training error accuracy requirement of the wavelet neural network to 0.01. Experimental results show that with 607 training iterations, the model also meets the preset accuracy requirement. By adjusting the training error accuracy, the model's performance is maintained while significantly reducing the time and computational resources required for training. By comparing training iterations and model performance under different training error accuracies, it was found that increasing training accuracy can accelerate model convergence but may also increase the risk of overfitting. Therefore, in practical applications, it is crucial to scientifically select the appropriate training error accuracy based on specific requirements and data characteristics [7].

5. Conclusion

In summary, this paper extensively explores subway bearing fault diagnosis technology based on wavelet neural networks. By combining the time-frequency analysis capability of wavelet transforms with the nonlinear mapping capability of neural networks, an accurate fault diagnosis model is constructed. This model effectively identifies various fault types in subway bearings, providing robust technical support for the safe operation of subway systems. Future research can further optimize network structures, explore more efficient training algorithms, and develop more intelligent fault prediction and health management strategies.

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