Research on Fault Diagnosis Method of Electric Vehicle Battery System Based on Wavelet-RBF Neural Network

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Abstract. Combining the good pattern recognition performance of neural network and the data processing performance of wavelet decomposition, this paper combines wavelet analysis with neural network and uses particle swarm optimization radial basis function neural network to diagnose the fault of electric vehicle battery. In this paper, for large data volume and redundant data, wavelet decomposition is used to process signal processing, including data noise reduction and feature vector extraction. In the fault diagnosis of electric vehicle battery system, a radial basis function RBF neural network based on particle swarm optimization (PSO) optimization is proposed. Finally, the reliability and feasibility of the proposed algorithm are proved by simulation.

1. Introduction

With the continuous enhancement of social environmental awareness and the rapid development of modern battery technology, emerging energy vehicles represented by electric vehicles are booming. As an important part of the electric vehicle system, the battery system plays a decisive role in the normal operation of electric vehicles. Therefore, research on the battery management system of electric vehicles has become a key topic for many research institutes. The monitoring and diagnosis structure of electric vehicle battery systems is as shown in Figure 1.
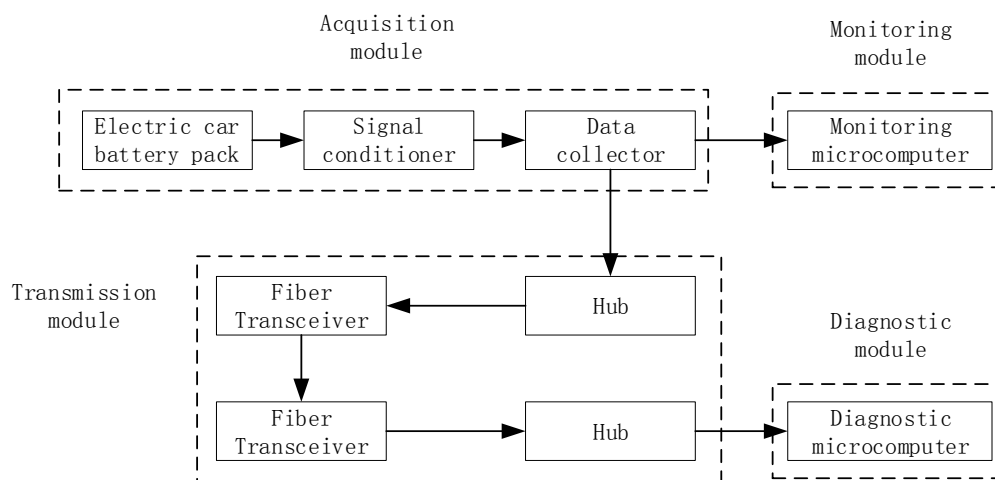

Figure 1. Electric vehicle battery system monitoring and diagnosis structure block diagram

In order to ensure the normal operation of electric vehicles, domestic and foreign experts have used DS evidence theory, Petri net, BP neural network algorithm, SVM fault diagnosis algorithm and other theoretical algorithms for the fault diagnosis of battery management system [1-4], and optimized the fault diagnosis model of electric vehicle battery. Based on the analysis of previous algorithms, this paper proposes a fault diagnosis method based on wavelet-RBF neural network for electric vehicle battery system.

2. Battery pack status signal acquisition

The basis for battery system state analysis and detection is the acquisition of raw data. In this paper, the disturbance signal of the battery pack is collected to analyze the operating state of the battery system. If the measurement system is in disrepair or the maintenance is not timely, the signal accuracy may not be high. In addition, the measurement position and sampling frequency may also affect the signal quality. Battery pack status signal acquisition system is shown in Figure 2.
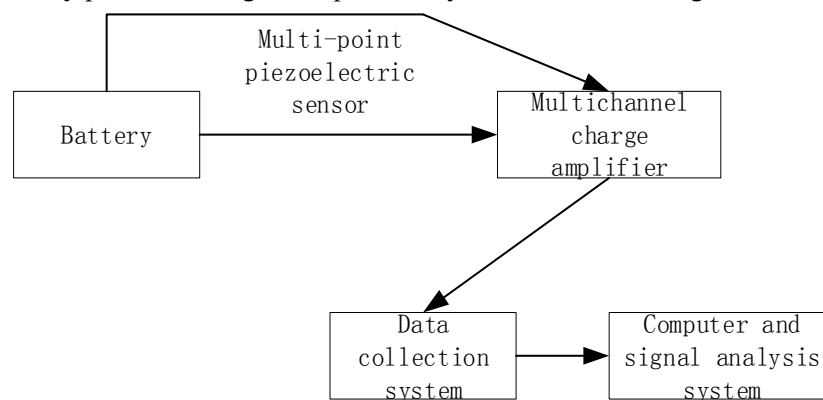
Figure 2. Battery pack status signal acquisition system block diagram

3. Wavelet Denoising of Signals and Extraction of Feature Vectors

3.1. Experimental data denoising

In the experiment, we set the sampling frequency of the battery disturbance signal to be, the number of sample points is, so the frequency resolution of the signal is. As shown in Figure 3 as its time domain diagram, it can be seen from the time domain diagram of the original signal that the signal is subject to severe noise interference. Therefore, noise is eliminated by signal preprocessing, including high-pass filtering and averaging, and db10 compactly supported wavelet base and 4-layer wavelet are selected for noise reduction.
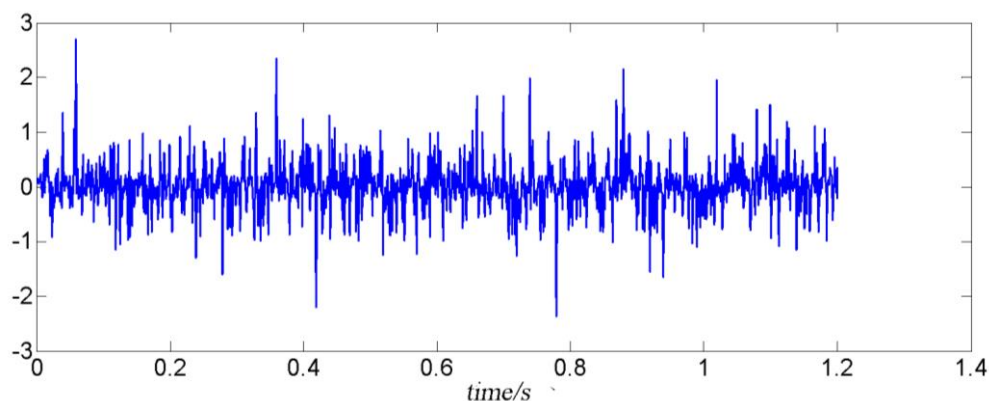
Figure 3. The original vibration signal

In matlab, the signal is decomposed by wavelet, and the four layers of wavelet coefficients are respectively decomposed into a layer and the wavelet is approximated to a4. As shown in Figure 4, the decomposition signals of each layer are shown.
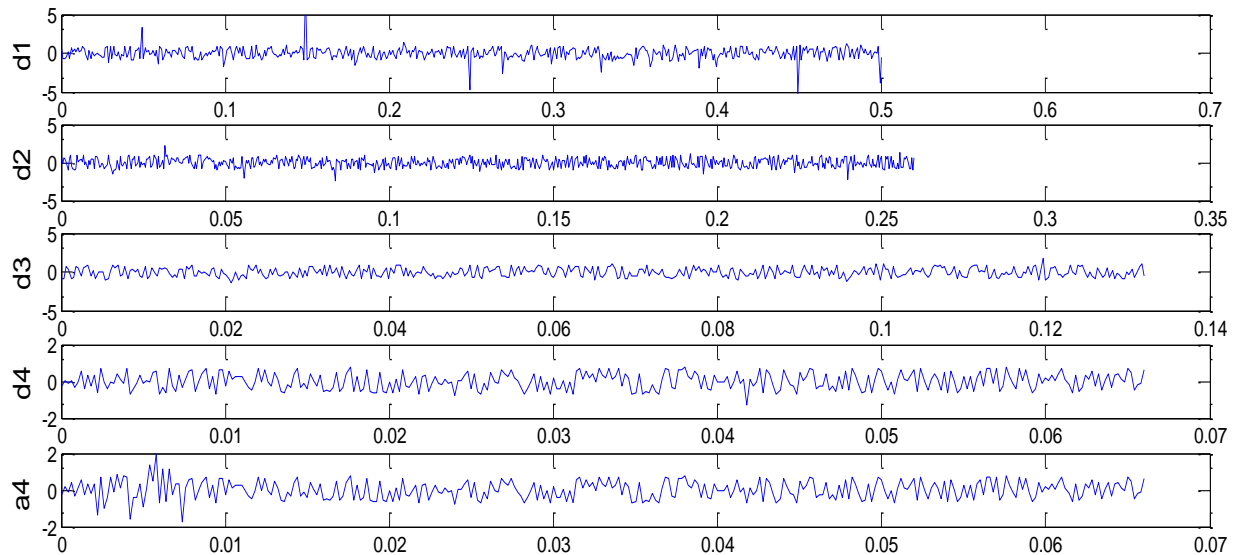

Figure 4. Wavelet denoising of battery pack disturbance signal

When the data is denoised, the noise reduction threshold is obtained for each layer of the wavelet signal according to the default threshold algorithm, thereby obtaining the corrected noise reduction threshold, and finally, the corrected threshold is substituted into the wavelet coefficient, and the reconstruction is performed. The signal is already denoised, as shown in Figure 5.
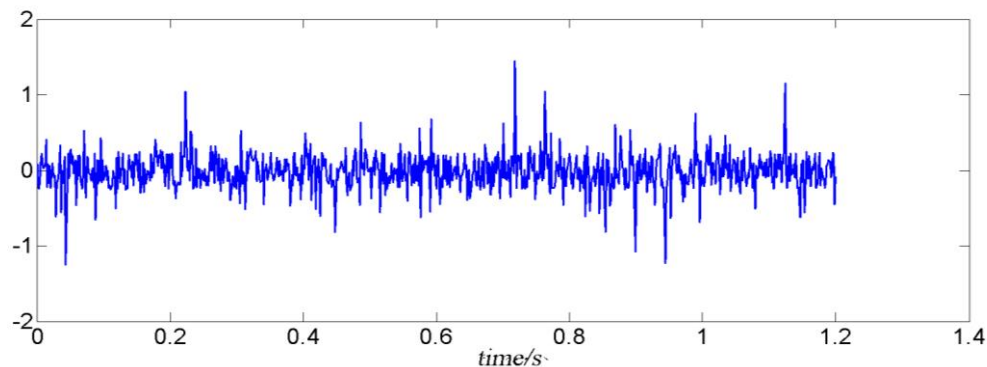

Figure 5. Signal after noise reduction

3.2. Time domain fault feature extraction

For signal analysis, time domain waveforms are usually used when the requirements are not high, because the time domain waveform can visually display the characteristics of the signal, which is convenient for the observer to analyze, especially the disturbance waveform when the fault occurs, and different faults. The resulting waveform has a different shape, such as when the external vibration or voltage is unstable, an impact signal is generated in the waveform.

The range parameter values include dimension range parameters and dimensionless range parameters. The former includes peak value, root mean square value, and kurtosis. The latter includes waveform indicators and pulse indicators. The time domain analysis is based on these range parameters, and they perform certain mathematical processing to analyze the data [5].

3.3. Frequency domain fault feature extraction

Although it is more intuitive to observe the operating state of the device with the signal, the natural frequency of the device is usually affected when the fault occurs, so the dynamics of the device can be observed through frequency domain analysis. The failure of the battery pack usually causes a change in the frequency component of the system signal, so frequency domain analysis is indispensable in the fault diagnosis of the battery system. There are many methods for frequency domain analysis, and the common methods used in engineering are detailed spectrum analysis and power spectrum analysis [6].

The random distribution of signal energy can be reflected by the signal power spectrum. The center position of the power spectrum changes with the energy ratio of the frequency components in the signal. Moreover, the power spectrum energy distribution will be more as the signal frequency component increases. concentrated. That is to say, the change of the position of the center of gravity of the spectrum and the degree of dispersion of the spectral energy distribution can be used as the basis for analyzing the signal products and features.

4. Fault Diagnosis of RBF Neural Network Based on PSO Optimization

The general idea of neural network applied to fault diagnosis is to obtain the process parameters of the device under set fault and no fault, respectively, and normalize it into network input; then use the known data to train the weight parameters of the neural network [7].The next step is the performance test of the neural network. The input symptom vector is output, and the output data is processed to obtain the fault result. Figure 6 is a troubleshooting flowchart.
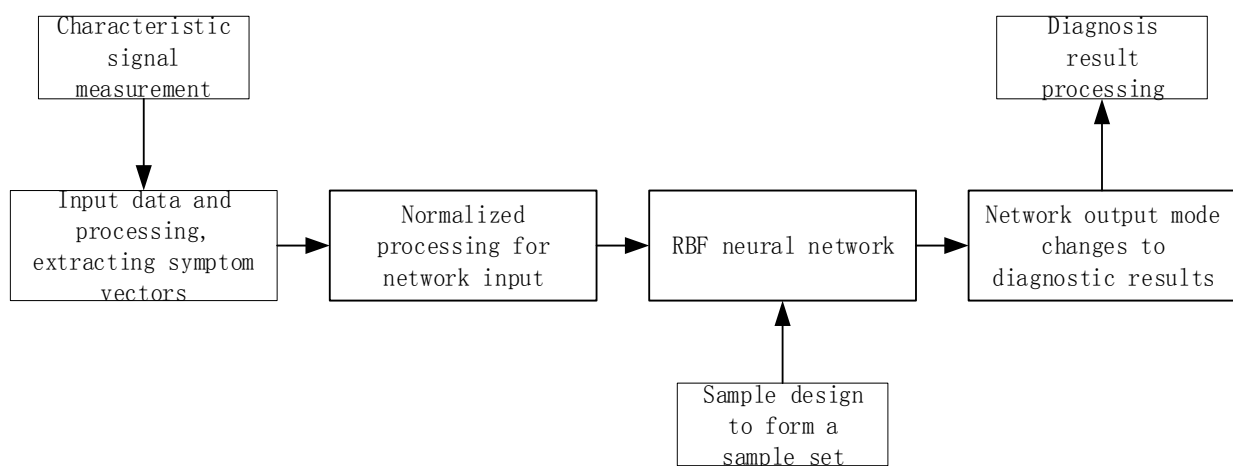

Figure 6. Neural network troubleshooting flowchart

4.1. The coding and fitness function of PSO optimized neural network algorithm

In the PSO algorithm, the particles are in one-to-one correspondence with the feasible solutions. Therefore, the center value and width of the basis function and the fitness of the particle velocity should be included in the particle coding. Suppose there is a center, each center is dimensioned, the position of the particle is dimension, and the corresponding particle velocity is also dimensioned, plus a fitness. The coding structure of the particles is as follows:

$$Z_{11}Z_{12}\cdots Z_{lk}\sigma_i\cdots Z_{21}Z_{22}\cdots Z_{1k}\sigma_1\cdots Z_{m1}Z_{m2}\cdots Z_{mk}\sigma_m\cdots \quad V_1 V_2 \cdots V_{m\times(k+1)}$$

(1)

The training of neural networks is mainly to minimize the parameter errors in the network, so the fitness function selects the average squared error. Then the fitness of the first individual is:

$$f_i = R_i$$

$$R_i = \frac{1}{N}\sum_{k=1}^{N}\left(y_k - \hat{y}_k\right)^2$$

(2)

4.2. Determination of neural network sample set

In order to facilitate the observer to understand the fault of the equipment, we divide the fault of the equipment into four levels, namely 0, 1, 2, and 3, and the fault degree from 0 to 3 is getting higher and higher, 0 The level is no fault and the third level is a serious fault. Then the network output is set to the following:

If $0.85 < S < 1.50$, then $S=3$ (serious failure);

If $0.50 < S < 0.85$, then $S=2$ (medium failure);

If $0.15 < S < 0.50$, then $S=1$ (slight failure);

If $S < 0.15$ or $S > 1.50$, then $S=0$ (no fault);

4.3. Comparison of diagnostic results of neural networks

In order to reflect the superiority of neural network based on particle swarm optimization, we use the same training sample set to train the original neural network and particle swarm optimization neural network, and input the test data into two neural networks respectively. comparing. In the particle swarm optimization neural network, the number of particles is set to 40, and the maximum number of iteration steps is 300. The fitness function curve at this time is shown in Figure 7.
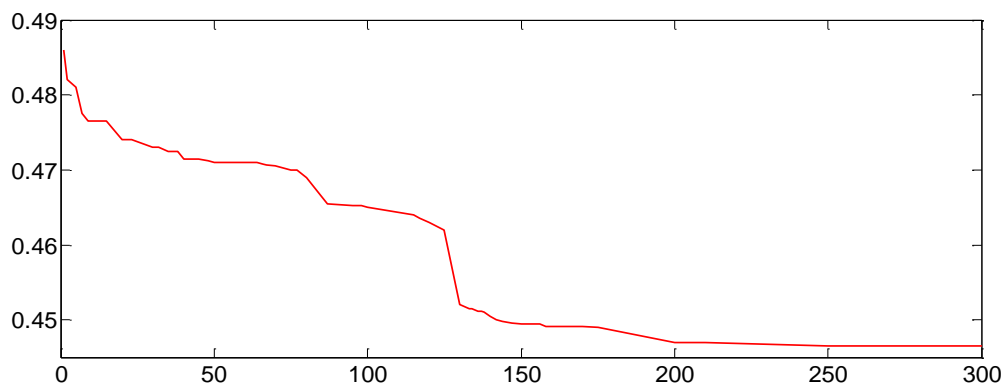

Figure 7. The curve of optimal fitness function

It can be seen from the diagnostic simulation that both neural networks have achieved rapid training and accurate diagnosis of the fault. However, comparing the two neural networks, it can be seen that the neural network diagnosis by particle swarm optimization is more accurate. The original neural network will have errors when the diagnostic data is large, such as the fault diagnosis error or fault type of the same fault type. Diagnostic errors, etc.,[8] and the particle network-optimized neural network has greatly improved the accuracy of diagnosis.

5. Conclusion

Through the fault diagnosis analysis of the battery system. Firstly, the battery pack fault diagnosis system is designed. [9] It is a local area network consisting of four parts: acquisition module, transmission module, monitoring module and diagnostic module. Then the wavelet analysis is performed on the collected data to denoise the experimental data, and the collected neural network is optimized by the particle swarm optimization algorithm, and some data is used for performance verification of the neural network. It is concluded that the radial basis function neural network optimized by the particle swarm optimization algorithm shows good performance in fault diagnosis.

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