

Research Article

Gear Fault Detection in a Planetary Gearbox Using Deep Belief Network

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Traditional prognostics and health management (PHM) methods for fault detection require complex signal processing and manual fault feature extraction, and the accuracy is low. To address these problems, a fault diagnosis method of planetary gearbox based on deep belief networks (DBNs) is proposed. Firstly, the vibration signals of the planetary gearbox are collected and analyzed in the time domain and the frequency domain. Then, the DBN model and optimal parameters are determined to meet the task requirements. Finally, the vibration data is divided into training set and test set and input into the DBN model, which can realize the automatic feature extraction and fault recognition of vibration signals. The results show that the identification accuracy reaches 97% under five working conditions of planetary gearbox.

1. Introduction

Under harsh working environments, cracks, broken teeth, and other faults may appear in internal planetary gears, sun gears, and other components of planetary gearboxes. Thus, it is important to monitor the health condition of planetary gearboxes via typical signals. The vibration data is one of the most widely used signals since some characteristics of vibration signals will change with the appearance of faults in the planetary gearbox [1, 2]. Zhang et al. [3] improved the DBN fault diagnosis method and improved the fault pattern recognition ability of the model. Li et al. [4] proposed a gear fault diagnosis method based on DBN and information fusion, and achieved good experimental results. Chen et al. [5] analyzed the collected signals in the time domain and the frequency domain, and applied discrete wavelet transform and the convolutional neural network to gearbox fault diagnosis. Ren et al. [6] combined variational modal decomposition (VMD) with DBN for fault diagnosis and revealed the characteristic law of the fault vibration signal. Zhao et al. [7] proposed a fault feature extraction and

diagnosis method based on DBN, which could extract and diagnose a variety of fault features from the original signal. Yu et al. [8] combined the improved wavelet packet transform technology with DBN to extract the bearing fault features and identify the fault state. Li et al. [9] used a particle swarm optimization algorithm to optimize the DBN network structure, extracted low-dimensional fault features from the original vibration signals, and used softmax classifier for fault pattern recognition. Zhang et al. [10] used Laplace feature mapping and semisupervised model of DBN to extract the features of vibration signals, used a small number of labeled samples and a large number of unlabeled samples to mine fault features twice, and constructed softmax classifier for pattern recognition. Xu et al. [11] combined DBN with fuzzy C-Means (FCM) for fault diagnosis, extracted the vibration signal of rolling bearing by DBN, then reduced the dimension of the vibration signal characteristics by principal component analysis, and selected the first two principal components as the input of FCM for fault identification. Gai et al. [12] combined grasshopper optimization algorithm (GOA) with DBN to establish a

gearbox fault diagnosis model, which effectively improved the adaptive feature extraction ability and fault diagnosis accuracy of the model.

Traditional signal processing methods need to extract fault features manually, which require some professional knowledge and experience in vibration signal processing [13]. Compared with traditional signal processing methods, the advantage of the AI method is that it can automatically extract fault features. Only by inputting the original data into the model, it can intelligently complete the whole process of feature extraction and classification and recognition so as to achieve the purpose of fault diagnosis [14, 15]. Chen et al. [16] input the frequency signal obtained from the simulated experimental data by fast Fourier transform into DBN and successfully classified seven fault types. Li et al. [17] analyzed different gradient optimization algorithms, selected the best design scheme of the DBN model, and successfully extracted fault features. Li et al. [18] applied DBN to the processing of bearing original vibration signals to realize the classification and identification of bearing faults. Liu and Xu [19] applied DBN to wind turbine gearbox fault diagnosis, input the original time-domain signal data into DBN for training, and achieved good results. Zhang et al. [20] used the DTCWT method to decompose the bearing vibration signal, used the DBN small sample classification model to classify the bearing fault, and accurately identified different fault types. Yang et al. [21] proposed a DBN model based on an adaptive learning rate, which was applied to the fault diagnosis of the planetary gearbox, and achieved good results. Shao et al. [22] proposed a convolutional deep belief network (CDBN) and proved the effectiveness of this method through experiments. Yang et al. [23] studied the problem that DBN still needs to manually set the network structure and proposed a structure adaptive deep belief network (SADBN). This method has been proved to be effective in adaptively determining the network structure of DBN so as to improve the diagnosis accuracy. Xing [24] improved the sigmoid activation function of the DBN network, accelerated the parameter update speed, and the diagnostic accuracy reached more than 95%. Wen [25] applied DBN to the fault diagnosis of rolling bearing, evaluated the DBN model through a variety of performance parameters, and achieved good classification results. Yang [26] combined the Nesterov momentum method with an adaptive learning rate, proposed an improved DBN method, and successfully applied it to the fault diagnosis of rotating machinery. Liang [27] applied DBN to rolling bearing fault diagnosis, and the fault recognition accuracy reached 97.96%.

In recent decades, numerous outstanding studies have been carried out; for example, Liu et al. [28] proposed a fault diagnosis method using the finite element method (FEM) simulation and ELM to detect faults in gears and achieved high classification accuracy. Gao et al. [29] proposed a novel fault detection scheme to build a bridge between AI and real-world running mechanical systems. Public datasets of bearings have been used to verify the effectiveness of the proposed scheme. Gao et al. [30] presented a hybrid fault classification approach by combining the finite element method (FEM) with generative adversarial networks

(GANs) for rotor-bearing systems, which could be guided to solve insufficient fault sample problems in more complex mechanical systems with agreeable fault classification accuracy. Zhang et al. [31] proposed a tripartition state alphabet-based sequential pattern (Tri-SASP) for MTSSs, which has important reference value for processing time series. Ran et al. [32] developed a novel K-means clustering algorithm based on a noise algorithm to capture urban hotspots. Five datasets have been selected to test and verify the effectiveness of the proposed noise K-means clustering algorithm. Wang et al. [33] employed a simulation-determined band pass filter to improve the performance of minimum entropy deconvolution (MED) for the fault diagnosis of axial piston pump bearings. The case confirmed the effectiveness of the proposed method for detecting bearing faults in axial piston pumps. Deng et al. [34] proposed an enhanced fast NSGA-II based on a special congestion strategy and an adaptive crossover strategy, namely ASDNSGA-II, and its effectiveness was proved. Wang et al. [35] proposed a method using deep belief networks (DBNs) to detect multiple faults in axial piston pumps. The classification accuracy ratio is 97.40%. Shao et al. [36] developed a novel method called an adaptive deep belief network (DBN) with dual-tree complex wavelet packet (DTCWPT). The results confirmed that the proposed method was more effective than the existing methods. Han et al. [37] proposed a new intelligent fault diagnosis framework, i.e., deep transfer network (DTN), which generalized a deep learning model to domain adaptation scenario. Liu et al. [38] proposed a novel method for bearing fault diagnosis with RNN in the form of an autoencoder. The experiment results indicated that the proposed method achieves satisfactory performance. Han et al. [39] presented a framework for the comparison of different Intelligent diagnosis methods to find the most efficient one. The results suggested that random forest is a promising pattern recognition method for the intelligent diagnosis of rotating machinery. Li et al. [40] proposed a novel deep learning-based method for anomaly detection in mechanical equipment. The results showed that the proposed approach could detect anomaly working condition with 99% accuracy. Ma and Chu [41] proposed an ensemble deep learning diagnosis method based on multiobjective optimization. The multiobjective optimization algorithm was used as the ensemble strategy in this method to realize the effective diagnosis of rotor and bearing faults for rotating machinery. Wang and Xiang [42] presented a novel minimum entropy deconvolution (MED)-based convolutional neural network (CNN) to classify faults in axial piston pumps. The experimental data were performed to manifest the superiority of the present method. Liu et al. [43] proposed a personalized diagnosis fault method to activate the smart sensor networks using finite element method (FEM) simulations. The personalized diagnosis method was effective to detect faults. Shao et al. [44] developed an auxiliary classifier GAN (ACGAN)-based framework to learn from mechanical sensor signals and generate realistic one-dimensional raw data. Induction motor vibration signal datasets were utilized to investigate the effectiveness of the proposed framework. Zhao et al. [45] proposed a novel bearing fault diagnosis

method based on switchable normalization semisupervised generative adversarial networks (SN-SSGANs). Experimental results showed that the proposed method has a desirable 99.93% classification accuracy. Han et al. [46] proposed a novel deep adversarial convolutional neural network (DACNN). The studies on the fault dataset demonstrated the applicability of the proposed method. Li et al. [47] proposed a model based on the generative adversarial network (GAN) as pretreatment to improve the accuracy of reliability classification. Simulations on gear data showed that the proposed model outperforms other methods on operational metrics. Zhao et al. [48] proposed a motor fault diagnosis method based on the stacked denoising autoencoder. The results showed that the method is efficient and intelligent. Jiang et al. [49] proposed an intelligent deep learning method, named the improved deep recurrent neural network (DRNN). The proposed method was verified with experimental rolling bearing data.

This paper proposes a planetary gearbox fault diagnosis model based on DBN, which directly takes the vibration signal as the input to realize the planetary gearbox fault diagnosis. The model can automatically extract fault features and has high fault identification accuracy. It has important engineering value for reducing vehicle maintenance cost and improving vehicle operation reliability.

2. Theoretical Introduction

2.1. DBN Structure. Deep belief network (DBN) is one of the classical algorithms of deep learning. It can automatically extract various features from data through nonlinear transformation. DBN is a multihidden layer neural network composed of a restricted Boltzmann machine (RBM) [50]. Its core is to optimize the connection weight of the neural network through layer by layer greedy learning algorithm. The unsupervised layer by layer training method is used to extract the fault features in the data. On the basis of adding the corresponding classifier, the structure of DBN is optimized through reverse supervised fine tuning. The optimization process of DBN is shown in Figure 1.

RBM contains a hidden layer $h = (h_1, h_2, h_3, \dots, h_m)$ and a visible layer $v = v_1, v_2, v_3, \dots, v_n$. The two layers are connected through the weight matrix $W_{n \times m}$; each unit in the same floor is not connected. The basic structure of RBM is shown in Figure 2.

In terms of the DBN structure, the energy functions of the hidden layer h and the visible layer v are

$$E(v, h; \theta) = - \sum_{i=1}^m b_i v_i - \sum_{j=1}^n c_j h_j - \sum_{j=1}^n \sum_{i=1}^m w_{ij} v_i h_j. \quad (1)$$

Here, $\theta = \{w_{ij}, v_i, h_j\}$, w_{ij} is the connection weight between dominant neuron v_i and recessive neuron h_j , b_i is the bias of visual layer neuron v_i , and c_j is the bias of the hidden layer neuron h_j .

The joint probability distribution of all variables in DBN is

$$p(v, h; \theta) = \frac{e^{-E(v, h; \theta)}}{Z(\theta)}, \quad (2)$$

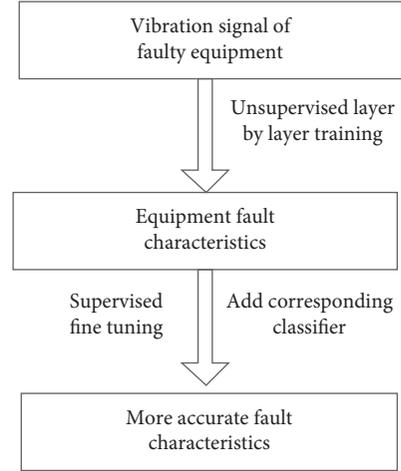


FIGURE 1: Optimization process of DBN.

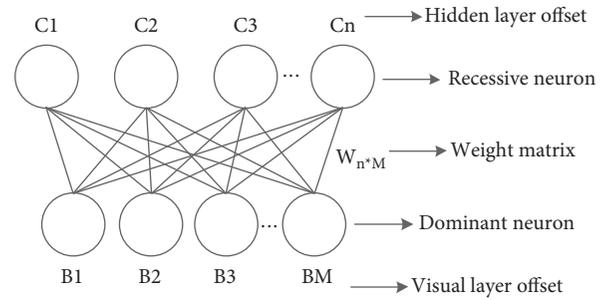


FIGURE 2: Structure of RBM.

where

$$Z(\theta) = \sum_v \sum_h e^{-E(v, h; \theta)}. \quad (3)$$

When the state V of dominant neurons in the visual layer is given, the activation function of hidden layer neurons is

$$p(h_j = 1/v) = \text{sig} \left(c_j + \sum_{i=1}^m v_i w_{ji} \right). \quad (4)$$

When the state h of recessive neurons in the hidden layer is given, the activation function of visual layer neurons is

$$p(v_i = 1/h) = \text{sig} \left(b_i + \sum_{j=1}^n h_j w_{ji} \right), \quad (5)$$

where sig is the sigmoid function and is defined as

$$\text{sig}(x) = \frac{1}{1 + e^{-x}}. \quad (6)$$

When training RBM, the parameters are adjusted by maximizing the log likelihood of the training set. The partial derivative of the connection weight w_{ij} is

$$\frac{\partial \ln(p(v))}{\partial w_{ij}} = \langle v_i h_j \rangle_d - \langle v_i h_j \rangle_m, \quad (7)$$

where $\langle v_i h_j \rangle_d$ and $\langle v_i h_j \rangle_m$ are the expectations of data distribution and model distribution. The computational

complexity of $\langle v_i h_j \rangle_m$ is high, the contrastive divergence-k (CD-k) can be used for gradient estimation, and the connection weight w_{ij} can be updated by the following formula:

$$Vw_{ij} = \eta(\langle v_i h_j \rangle - \langle v_i h_j \rangle_r), \quad (8)$$

where $\langle v_i h_j \rangle_r$ is the distribution expectation of visual layer reconstruction, η is the learning rate, and b_i and c_j are the offset values and can be updated in the same way.

q_1, q_2 are the fault signals, and the corresponding fault label is p_1 ; taking softmax as the loss function, the final loss function L_s is as follows:

$$L_s = \frac{1}{B} \sum_{i=1}^B -1g \frac{e^{\|W_i\| \|X\| \cos \theta_i}}{\sum_{j=1}^N e^{\|W_j\| \|X\| \cos \theta_j}}, \quad (9)$$

where B is the number of training samples, N is the number of fault categories, X is the hidden layer output, and W is the weight matrix, and θ is the included angle. Softmax loss is related to signal amplitude. DBN has strong ability of feature extraction and classification, and is widely used in fault diagnosis.

2.2. Training Process of RBM. RBM is trained by the CD-k method, in the CD-k method, when the value of k is 1, only one Gibbs sampling can achieve good results; therefore, the CD-1 method can be used to obtain the unbiased estimation of log likelihood function. The training process is as follows: first, initialize the data $v^{(0)}$, sample from $h(0) \sim p(h|v^{(0)})$, then sample from $h^{(0)} \sim p(v^{(0)}|h)$, and finally sample from $h(0) \sim p(h|v^{(0)})$. The training process is shown in Figure 3.

2.3. Training Process of DBN. After the pretraining of vibration data, the parameters of RBM in each layer are initialized. The preliminary structure of DBN has been formed and makes backward fine tuning training for DBN. The BP algorithm is used to adjust the network parameters of DBN. The main adjustment contents are the weight and offset between each layer. The BP algorithm of DBN searches the weight parameter space, which has shorter convergence time and faster training speed than the forward neural network. The training process of DBN is shown in Figure 4.

3. Verification of Experimental Data of Planetary Gearbox

The effect of DBN fault diagnosis is verified by using the experimental data of a planetary gearbox. As shown in Figure 5, the planetary gearbox test-bed is mainly composed of planetary gearbox, motor, hydraulic station, main control platform, sensor, and data line. The speed and torque of the motor output are adjusted by the frequency conversion cabinet. The power is input into the planetary gearbox through the bevel gear transmission box. The function of the bevel gear transmission box is to change the transmission direction of force and make the overall layout of the test-bed reasonable. The output terminals on both sides of the planetary gearbox are connected with the speed torque

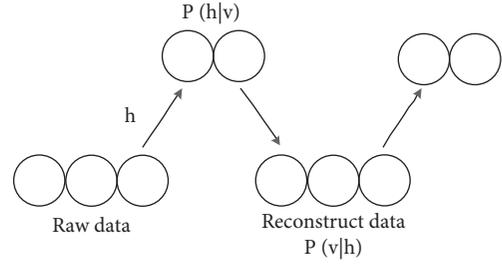


FIGURE 3: Training process of RBM.

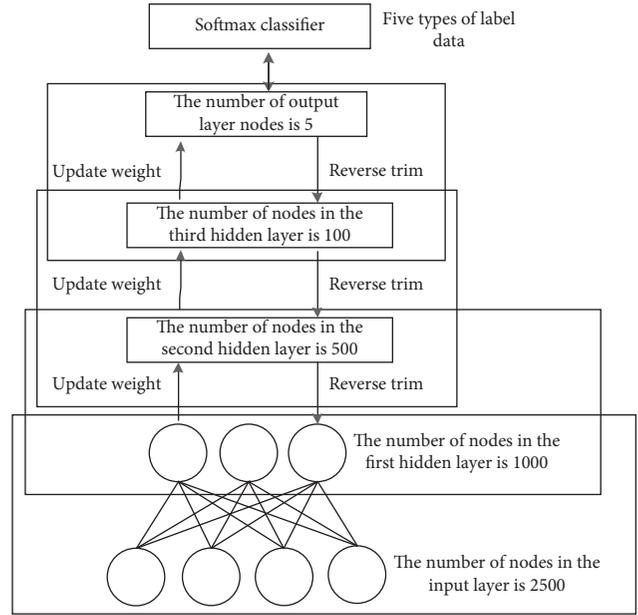


FIGURE 4: Training process of DBN.

meter, and the generator is used to load it. The hydraulic station provides lubricating oil pressure and shift pressure to the planetary gearbox. In this paper, the research object is the planetary gearbox. As shown in Figure 6, gear failures are processed by cutting. In the process of the experiment, four faults are set as follows: the sun gear with 31 teeth is broken, the sun gear with 30 teeth is broken, the planetary gear with 18 teeth is broken, and the planetary gear with 15 teeth is broken.

The main control platform is used to control the start and stop, speed regulation, and experimental conditions of the planetary gearbox. The load is set to 900 Nm, the output shaft speed is 1500 r/min, when the test bench is running, and the measurement system is used to complete data acquisition. The measurement system is mainly composed of measurement hardware platform, measurement software platform, vibration sensor, power supply, and signal cable. The hardware of the measurement system is a 32 channel solid data acquisition system, and the sampling frequency of each channel can reach 100 kHz. The measurement system software is a multichannel online test software for equipment status information, which has the functions of online acquisition, characteristic quantity calculation, data storage, and conversion. The measuring points are set on the surface of the box, and the vibration

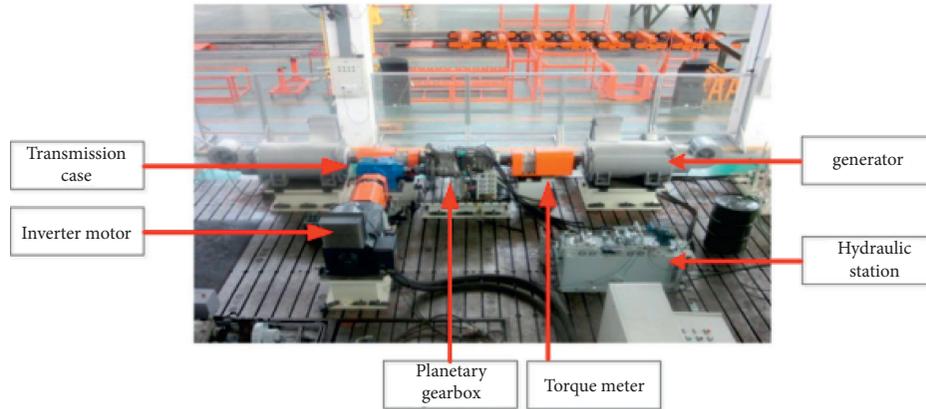


FIGURE 5: Planetary gearbox test bench.

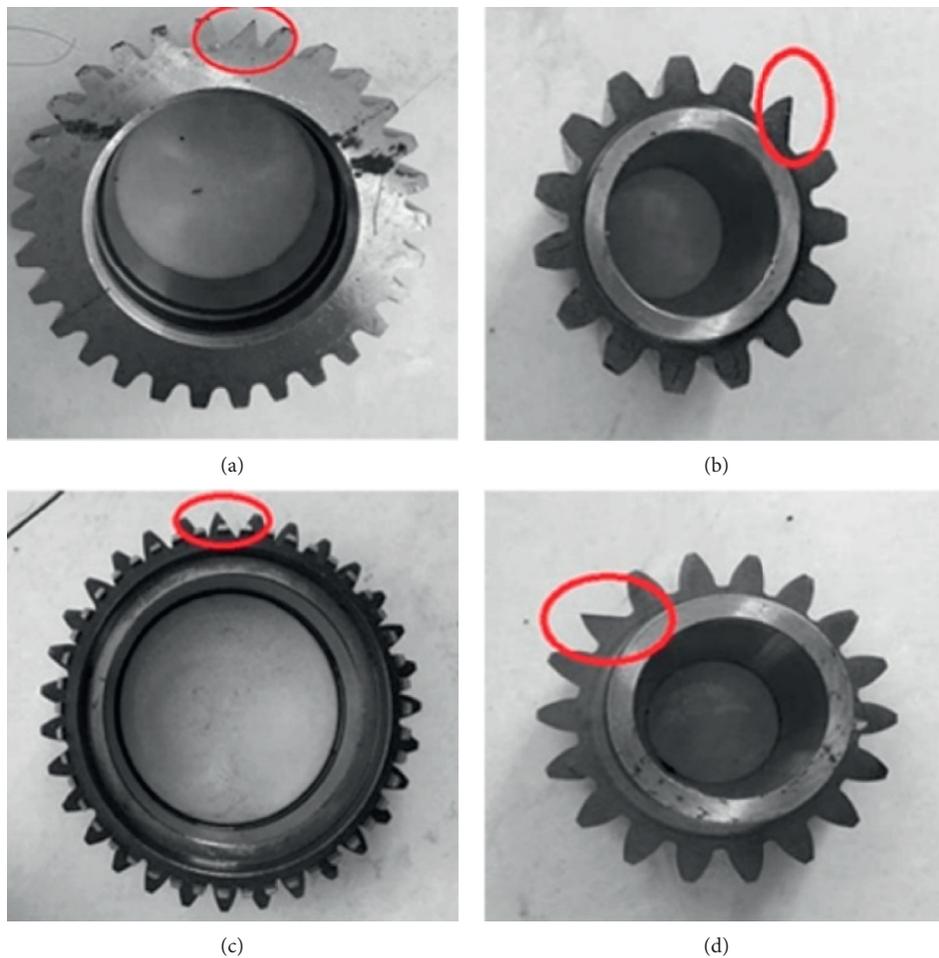


FIGURE 6: Planetary gearbox fault-type setting (teeth broken): (a) sun gear $Z = 30$, (b) planetary gear $Z = 15$, (c) sun gear $Z = 31$, and (d) planetary gear $Z = 18$.

acceleration sensors are used to collect the vibration data of each measuring point of the box. The one-way and three-way vibration sensors adopt 127-3215M1 general acceleration sensor and 127-3023M2 three-way acceleration sensor produced by DYTRAN instrument company, respectively. The sensitivity of both vibration sensors is 10 mv/g, and the

maximum range is 500g; the sampling frequency is set at 20 kHz. The vibration signal experimental data are collected under five conditions: normal gear (normal), the sun gear with 31 teeth is broken (z31), the sun gear with 30 teeth is broken (z30), the planetary gear with 18 teeth is broken (z18), and the planetary gear with 15 teeth is broken (z15).

In order to ensure the accuracy of fault diagnosis and the speed of DBN calculation, the number of sampling points (1,835) including the whole cycle sampling time of each gear is selected. When the number of sampling points is greater than 1,835, the sampling points of one revolution of other gears must be included. 2,500 points are taken as a section for signal segmentation, which is divided into 280 sections, and each working cycle is 0.125 s. Among the five working conditions, the amount of z30 experimental data is 704,512, and the amount of experimental data for the other four working conditions is 700,416. In order to facilitate calculation, the first 700,000 data points are intercepted. Therefore, the data input into the DBN network is divided into 280 segments, and the data dimension is 2,500.

The technical route adopted in this paper is shown in Figure 7. The vibration signals of the planetary gearbox are collected and grouped, analyzed in the time domain and the frequency domain, and then the signals are normalized. The DBN model is established, and its network parameters are determined. Vibration signals are divided into training set and test set. DBN uses the training set for feature extraction and classification recognition. The test set is used to verify the ability of DBN feature extraction. The dimension of the input data sample determines the number of nodes in the input layer, and the fault category determines the number of nodes in the output layer.

The collected vibration data are analyzed in the time domain and the frequency domain. Due to the high sampling frequency, the regularity of time domain waveform is not obvious. Fourier transform is performed to obtain the spectrum of the data. The time domain diagram and frequency domain diagram of the data are shown in Figure 8.

In order to intuitively reflect the learning situation of DBN on different fault characteristics, the clustering effect of fault features in DBN is analyzed by t-distributed stochastic neighbor embedding (t-SNE) [51]; t-SNE is an effective nonlinear dimensionality reduction method. Based on the probability distribution of random walk on the proximity graph, the structural relationship can be found in the data. It is concerned with learning to maintain the local structure of data and reduce the dimension to two-dimensional space to preserve the popular structure of data. The fault features of input layer, hidden layer, and full connection layer are visualized in two dimensions, and the results are shown in Figure 9.

It can be seen from the figure that as the data pass through the hidden layer and the full connection layer, the distribution boundaries of different fault categories are gradually clear, the five states are gradually separated, and the separability is gradually strengthened. The classification distance of the five states does not represent the real classification distance of the features but is just a clustering diagram. The five states are basically separated in the full connection layer. The data features have good clustering effect in the model.

Multiple sets of data are obtained through the planetary gearbox test-bed. Under different grouping ratios of training set and test set, there is a certain difference between the

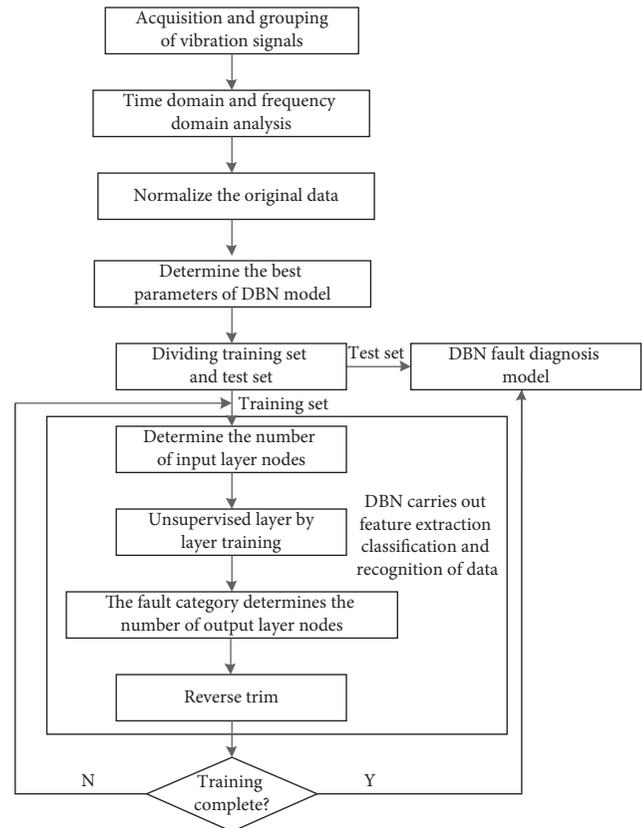
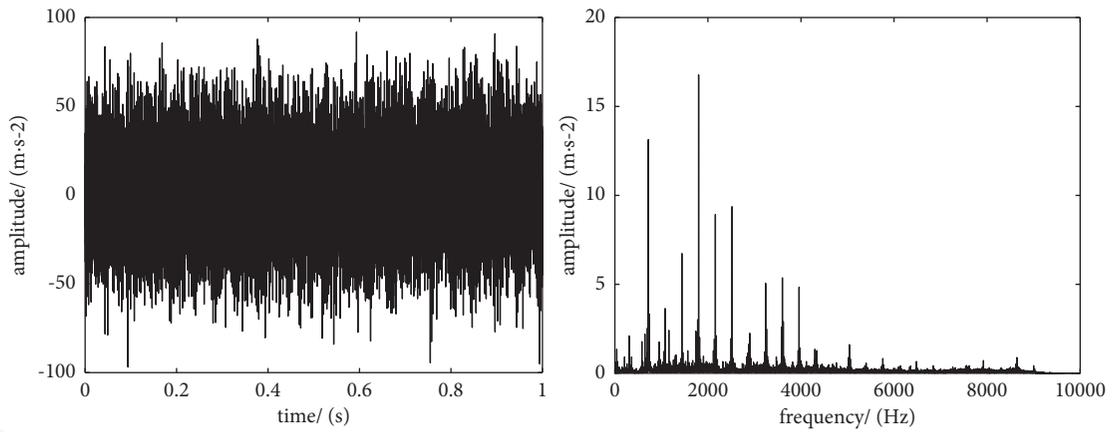


FIGURE 7: Technology roadmap.

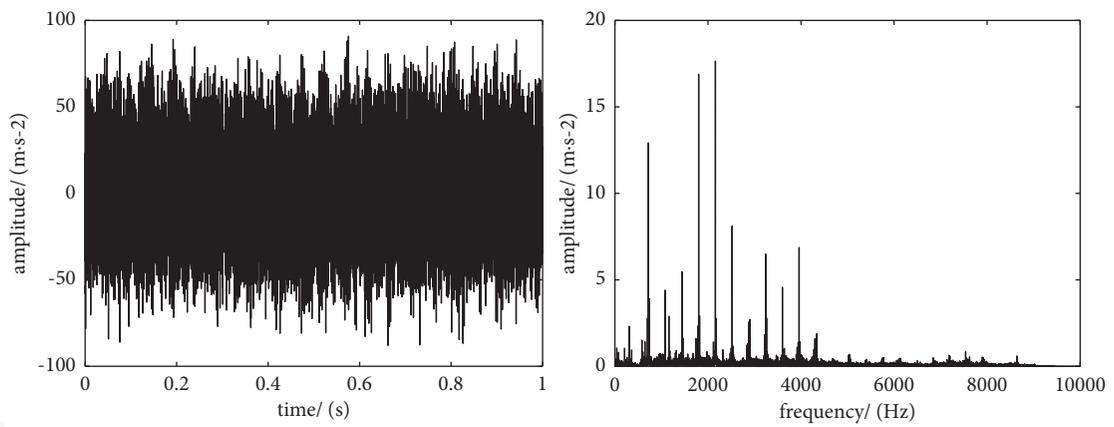
average accuracy of training set and the average accuracy of test set. With the increase of grouping ratio of the training set, the average accuracy first increases and then decreases, and the average running time continues to increase. The average accuracy under different grouping ratios is shown in Figure 10. It can be seen that when the grouping proportion of the training set is 80% and the grouping proportion of the test set is 20%, the average accuracy is the highest, and a better fault identification effect can be achieved.

In order to prove the fault diagnosis effectiveness of DBN, the training set is the first 80% of the 280×5 data, i.e., 1,120 groups of data, and the last 20% is the test set, i.e., 280 groups of data, and then the DBN model is trained and tested. The accuracy rate and loss curve of a training are shown in Figure 11. The confusion matrix of the classification results of the test samples is shown in Figure 12. The vertical axis represents the real situation, and the horizontal axis represents the prediction situation. The accuracy of classification and recognition is 97%.

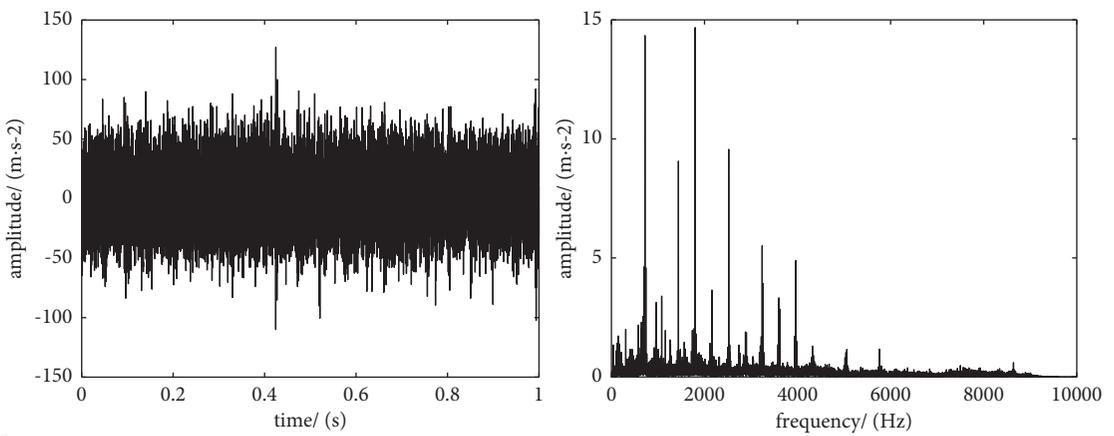
It can be seen from the training result curve that the proper selection of iteration times can obtain the best fitting effect and have the minimum time cost. The structure of DBN is (2500, 1000, 500, 100, 5). The learning rate is 0.2, and the initial weight and bias value are 0. With the increase of the number of iterations, the recognition accuracy continues to improve and the loss function gradually decreases. When the number of iterations reaches 150, the recognition accuracy is basically stable, which shows the effectiveness of DBN fault recognition.



(a)



(b)



(c)

FIGURE 8: Continued.

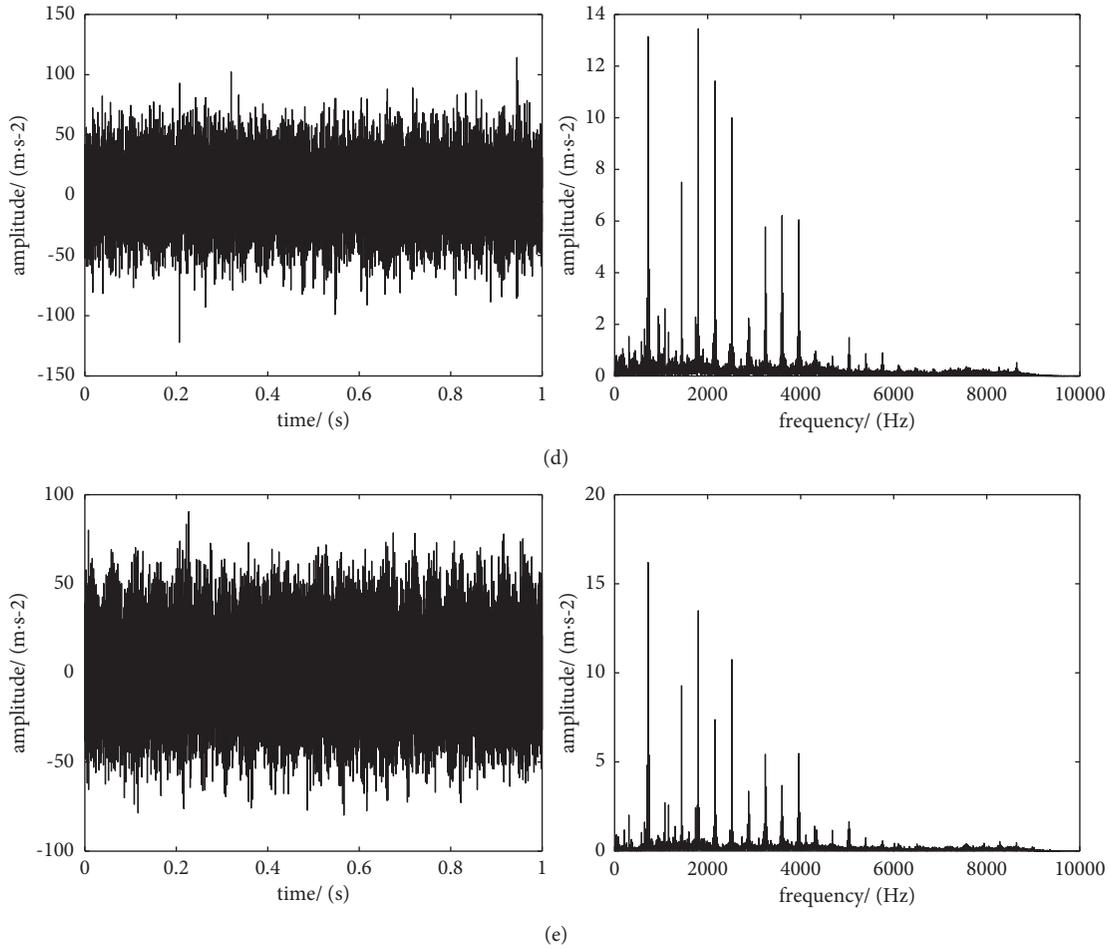


FIGURE 8: Time domain and frequency domain diagram of vibration signal. (a) Normal state. (b) z15 broken tooth. (c) z18 broken tooth. (d) z30 broken tooth. (e) z31 broken tooth.

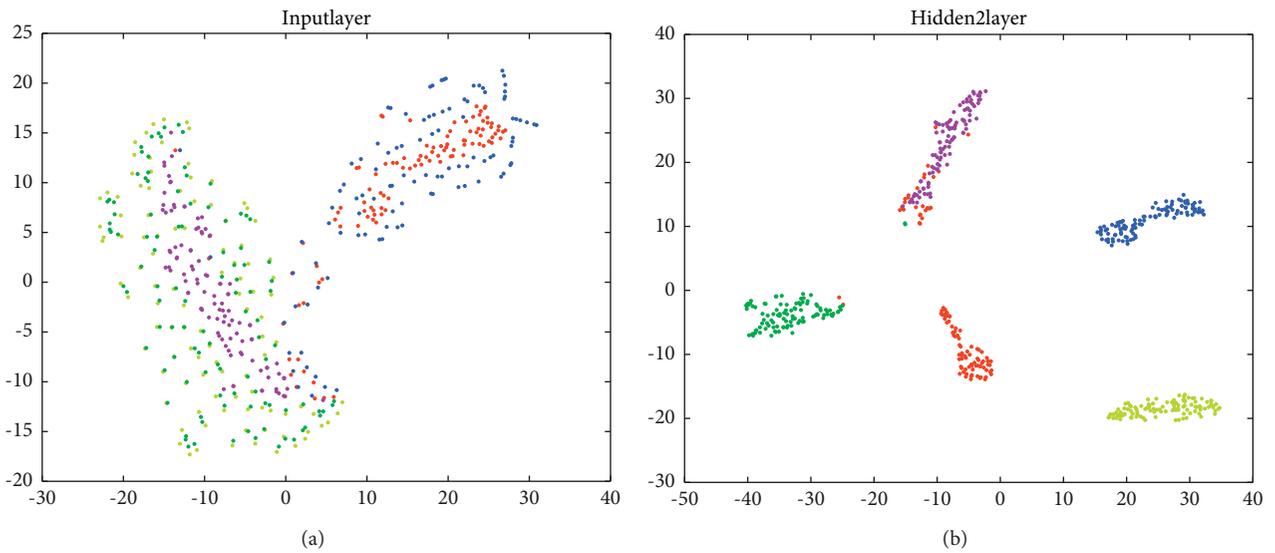


FIGURE 9: Continued.

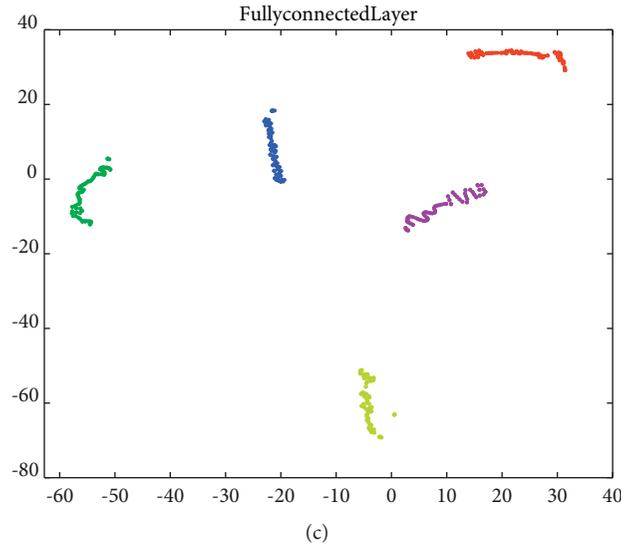


FIGURE 9: t-SNE visualization of data features. (a) Input layer. (b) Hidden layer. (c) Full connection layer.



FIGURE 10: Accuracy under different grouping proportions.

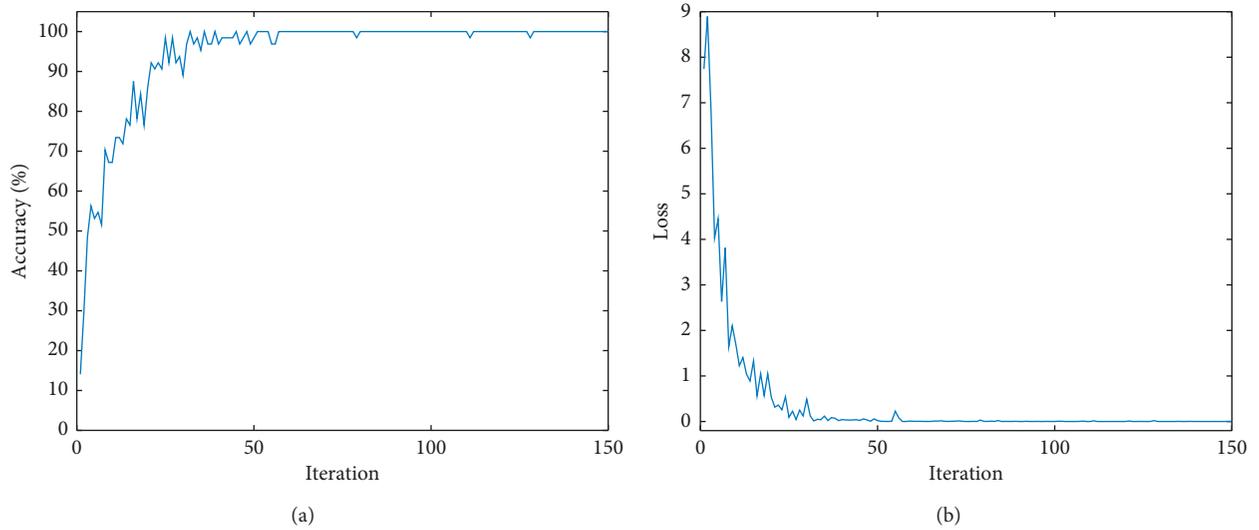


FIGURE 11: Training result curve. (a) Accuracy curve. (b) Loss curve.

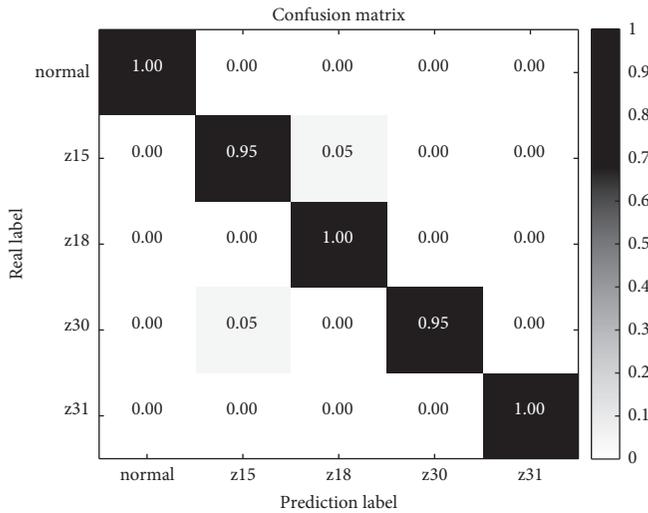


FIGURE 12: Confusion matrix of classification result.

4. Result Discussion

Planetary gear train is the core structure of the planetary gearbox. Planetary gear train includes sun gears and planetary gears with different numbers of teeth. Setting fault in each kind of gear can ensure the completeness of fault samples. Experimental results show the effectiveness of fault diagnosis based on DBN. When the grouping proportion of the training set is 80% and the test set is 20%, the average value of fault diagnosis accuracy is the highest. The five states are well classified and recognized, which shows that DBN has excellent classification and recognition ability. On the problem of parameter selection of DBN, the paper uses a large number of experiments to verify the selection, and how to determine a more intelligent optimization selection method is a problem worthy of discussion.

5. Conclusion

The data characteristics of a planetary gear box are complex. The DBN model is established, and its network parameters are determined for fault diagnosis and classification. The classification accuracy of DBN is verified by the experimental data of the planetary gear box. The collected fault data are analyzed in the time domain and the frequency domain. The data are divided into training set and test set. DBN is input to complete feature extraction and fault recognition.

After calculation, with the improvement of the grouping proportion of the training set, the classification accuracy first increases and then decreases. When the grouping proportion of the training set is 80%, the classifier accuracy reaches 97%. It can be seen that the data grouping proportion will affect the classification results. The DBN model can be used for fault diagnosis with high accuracy.

Data Availability

The data used to support the study are included in the Supplementary Materials.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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