

# Fault Diagnosis Technology for Complex Mechanical Systems Based on Deep Learning

Zijian Guo

Jinan Xinhang Experimental Foreign Language School, Jinan, China

**Abstract.** Traditional fault diagnosis methods are usually based on expert knowledge and experience, but this method often relies on manual analysis and judgment, which is time-consuming and inaccurate. Deep learning has become a hot spot because of the development of optimization algorithms and computer hardware, and has achieved great success in many applications. In the field, neural network, as a popular tool, can establish a feature recognition system between perceptron and classifier through training. This system includes the representation process of input layer, the promotion process of hidden layer and output layer. While ensuring the safe, stable and reliable operation of equipment and personal safety, improving the production efficiency of enterprises and enhancing the international competitiveness and influence of the industry are the new development trends of the design, production and maintenance guarantee system of manufacturing industry worldwide. At the same time, comprehensive testing and evaluation records of the operating status of the transmission equipment of the rolling mill can provide reliable reference for the diagnosis of faults and major and medium repairs of this type of rolling mill in the future. In practical engineering, due to different working conditions and complex environments, the types of faults that occur are unpredictable, which may result in a lack of samples available for training fault diagnosis models. This article mainly discusses and analyzes in depth the fault diagnosis technology of complex mechanical systems based on deep learning algorithms.

**Keywords:** Deep learning; Complexity; Machinery; Fault diagnosis.

## 1. Introduction

Fault diagnosis technology for mechanical systems, especially complex mechanical systems, plays an important role in ensuring the safety of mechanical equipment, improving product quality, saving maintenance costs, and preventing environmental pollution [1]. Applying probabilistic reasoning and statistical theory to Bayesian networks enables dynamic modification and reconstruction of the network and improves the accuracy of fault diagnosis. Traditional fault diagnosis methods are usually based on expert knowledge and experience, but this method often relies on manual analysis and judgment, which is time-consuming and inaccurate [2]. Deep learning has become a hot topic due to the development of optimization algorithms and computer hardware, and has achieved great success in many applications. Deep learning has made rich achievements in fault detection, location and identification, especially in the field of rotating machinery and chemical process [3]. In the field, neural network, as a popular tool, can establish a feature recognition system between perceptron and classifier through training [4]. This system includes the representation process of input layer, the promotion process of hidden layer and output layer. The effectiveness of the proposed method is verified by empirical analysis, so as to improve the intelligent level of system fault diagnosis and fault tolerance.

Manufacturing industry is the foundation of national economy, while high-end manufacturing industry marks the core competitiveness of a country [5]. While ensuring the safe, stable and reliable operation of equipment and personal safety, improving the production efficiency of enterprises and enhancing the international competitiveness and influence of the industry are the new development trends of the design, production and maintenance guarantee system of manufacturing industry worldwide [6]. Therefore, the research on condition monitoring and fault diagnosis of complex mechanical systems has become a very concerned issue for researchers and engineers all over the world. At the same time, the comprehensive test and evaluation record of the running state of the



rolling mill transmission equipment can provide reliable reference for the fault diagnosis and major and medium repair of this type of rolling mill in the future [7]. Machine learning algorithms predict the probability of failure by analyzing and modeling large amounts of mechanical system sensor data [8]. In engineering practice, due to different working conditions and complex environments, the types of faults that occur are unpredictable, which may result in no samples available for fault diagnosis model training. This article mainly conducts an in-depth discussion and analysis of fault diagnosis technology for complex mechanical systems based on deep learning algorithms.

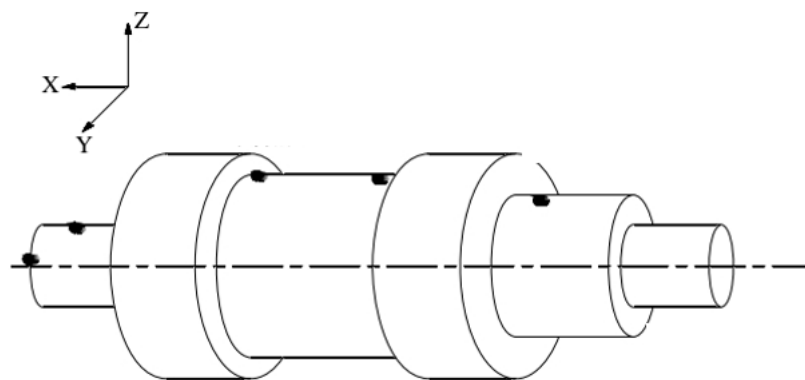
## 2. Data Collection and Preprocessing

### 2.1 Collection and Storage of Sensor Data in Mechanical Systems

In the automatic mechanical system, sensors play a key role, which are used to measure and monitor various parameters of the mechanical system, including temperature sensors, pressure sensors, vibration sensors and so on [9]. One disadvantage of deep neural network is that the network training process needs a lot of sample data. In the real scene, we often encounter the situation that the available data is insufficient or nonexistent, and it is no exception in the field of fault diagnosis [10]. To extract process related low dimensional features from high-dimensional data, linear regression method can be used, as follows:

$$\gamma = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n \quad (1)$$

Compared with traditional machine learning methods, deep learning has achieved great success in processing various data such as speech, images, videos, and texts. Backpropagation uses the chain rule of differential calculus. In the chain rule, the gradient of the error value corresponding to the weight of the last layer is first calculated, and then the gradient value is used to calculate the gradient of the penultimate layer. If the working time is too long, the steel ball will begin to wear, and the preload acting on the steel ball will begin to weaken, which may lead to radial runout. The right winding motor is shown in Figure 1.



**Figure 1.** Layout of Right Roll Motor

Through the research of multi-sensor information fusion and new hybrid classifier, the separability of multi-faults is improved, and the accurate location and real-time tracking of multi-faults are realized. Wavelet analysis method is a time-frequency localization analysis method with fixed window size but changeable shape, and both time window and frequency window can be

changed. These data should be organized and stored in chronological order, and need to have high-speed read and write capabilities for subsequent data analysis and modeling.

## 2.2 Data quality evaluation and preprocessing method

The quality of sensor data is crucial for the accuracy and reliability of fault diagnosis and prediction. Firstly, embed the objects into BN to establish functional models for each sub object, and then utilize the functional transfer relationships between the objects to form an OOBN that describes the overall system functionality. For stuck faults, since the output cannot be adjusted, a backup actuator must be used to ensure normal performance. Taking the vibration signal as an example, its convolution operation is defined as:

$$f_{ij} = \sigma(\omega \cdot f_{i-1,j} + \beta \cdot f_{i-1,j} + \varepsilon) \quad (2)$$

The model output similarity is:

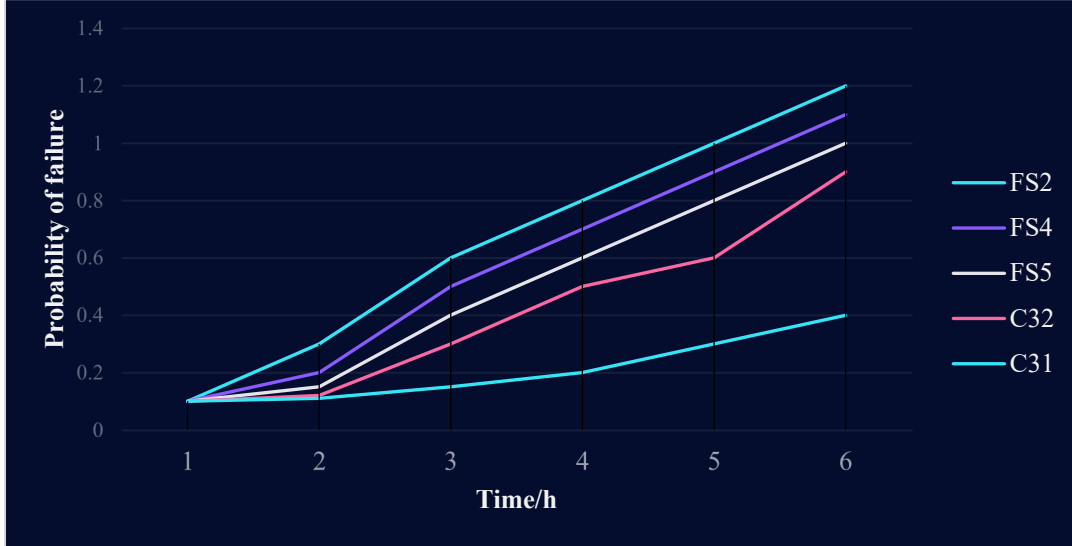
$$d(x_1, x_2) = \|f(x_1) - f(x_2)\|_2^2 \quad (3)$$

During the process, it is necessary to design fault diagnosis algorithms to identify fault categories. The training data is used for model training, the validation set is used for hyperparameter tuning, and the test set is not involved in training but is used to evaluate the generalization performance of the final model. There are connections between each neuron node in adjacent layers, and in each layer, the neuron nodes remain unconnected to each other. The end effect will increase the additional losses of the linear motor feed system, reduce the efficiency of the linear motor feed system, and especially cause thrust fluctuations in the motor. However, most people focus on the research of signal processing methods, fault feature extraction and fault symptom judgment on this basis. However, the problem of fault information content of information source determined by parameter selection and multi-sensor position configuration is ignored. Feature selection is to select the most relevant and important features from the extracted features, so as to reduce the dimensions and improve the effect of the model.

## 3. Experiment and Result Analysis

### 3.1 Introduction to experimental setup and data sets for automated mechanical systems

In the experimental setup, a representative automatic mechanical system can be selected as the research object, and relevant sensor data can be collected. The theoretical and experimental methods of establishing fault dynamics model of mechanical system and transfer function matrix between multi-fault sources and multi-sensors are studied, and the zoning criterion of complex mechanical system is studied as the basis of multi-sensor grouping optimization. During the working process, as the motor is hardly subjected to axial force, only deep groove ball bearings are used to provide axial support for the motor shaft. Probability of important node states. As shown in Figure 2.



**Figure 2.** Input Node State Probability

The other is the bottom-up modeling method. Firstly, the system is decomposed to determine the objects in the system, and the internal properties of the objects are described by BN. Using the information transfer relationship between the sub-networks of the objects to connect the objects, it embodies the modular modeling idea. Once it is found that the loss in the training process continues to decline, but the performance of the verification set tends to saturation or even decline, it usually means that the model has begun to be fitted. We optimized the model structure and proposed a multi-layer feature fusion method, which fully utilizes the extracted features of each layer to improve the recognition ability of the model. The verification experiment proved that the model improved the recognition accuracy and achieved reliable and effective qualitative and quantitative identification of bearing faults.

### 3.2 Performance evaluation and result analysis of machine learning methods in fault diagnosis and prediction

In order to evaluate the performance of machine learning methods in fault diagnosis and prediction, first, some common evaluation indicators can be used, such as accuracy, recall, F1 value, etc. Among them, the quality of fault feature extraction directly affects the effect of the zero-shot classification method designed in this article. The experimental results fully demonstrate the high accuracy, robustness and real-time performance of the designed system in fault detection and diagnosis. Normalization is beneficial to simplify the subsequent calculation, and can avoid gradient explosion and gradient disappearance to some extent. The confusion matrix is shown in Table 1. It can be seen that the sensor fault detection effect is the best.

**Table 1.** Confusion Matrix

Predicted/Actual	Sensor offset	Signal drift	Valve stuck	clogged pipes	Controller failure	Communication interruption
Sensor offset	0.95	0	0	0	0	0
Signal drift	0	0.90	0	0.01	0	0.01
Valve stuck	0	0	0.87	0.06	0	0
clogged pipes	0	0.04	0.03	0.90	0	0
Controller failure	0	0	0	0	0.93	0
Communication interruption	0	0.02	0	0	0	0.93

In addition, band-pass filtering is carried out in the model to enhance texture features and reduce the influence of noise. Considering the actual situation of different machining accuracy requirements and different users, the performance threshold of dividing the health status of linear motor feed system is not fixed. That is to say, users can set the threshold of health status division by themselves through software according to working conditions, operating conditions or key points and their own judgment standards. These models are established through theoretical analysis, fault simulation, observation data analysis, online identification and other methods, and trained and modified through machine operation. Finally, based on the comprehensive experimental results and analysis, it can be concluded that which machine learning method performs the best in fault diagnosis and prediction, and has better adaptability to different types of faults.

#### 4. Conclusion

In summary, through machine learning-based methods, in-depth research has been conducted on fault diagnosis and prediction of complex mechanical systems. A relational network is used to compare known fault samples with defined unknown fault descriptions. The framework makes full use of the feature learning and modeling capabilities of deep learning to build a high-precision diagnosis system. However, with the continuous updating of technology and the continuous development of society, the demand for research objects will continue to increase due to limitations of time and technical conditions. Based on the analysis of typical fault diagnosis methods and remaining service life prediction methods and key technologies of complex mechanical equipment, the advantages and existing problems of existing methods are summarized. This fault analysis model has hierarchical and dynamic characteristics, introduces the impact of component functional degradation on the system's functional state, describes the real-time state information of the system, and ensures the consistency between node state probability and the real system. The research on fault diagnosis and prediction of complex mechanical systems based on machine learning has broad application prospects and will provide important support for achieving intelligent manufacturing and fault prevention.

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