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# Evaluation and Prediction of Mechanical Equipment Operation Status based on PCA and GA-BP Model

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## Abstract

**For the evaluation and the prediction of mechanical equipment operation status, a new method based on Principal Component Analysis (PCA), Genetic Algorithm (GA) and BP neural network is proposed in this paper. This method optimizes the initial weight and the threshold with GA. Moreover, the output error of the training data is explotied as the objective function. During the process of evaluation, the time domain features of the signals is collected, and constructed as a comprehensive index with PCA. During the process of prediction, the comprehensive index is used to train the BP neural network which is optimized by GA to construct a prediction model. The results of numerical simulations show that the proposed method in this paper is better than the traditional BP neural network in the convergence precision.**

## Keywords

**Time Domain Feature; Principal Component Analysis; Genetic Algorithm; BP Neural Network; Mechanical Equipment; Operation Status.**

## 1. Introduction

Recently, lots of computational methods have been developed to solve the practical engineering problems [1-5], especially in the field of fault diagnosis. Accurate prediction for the operating status of equipment is an important part of equipment health monitoring and fault diagnosis. The intelligent prediction theory has made a lot of research results in the evaluation of equipment operating conditions and the prediction of performance degradation trends, and this has played a positive role in preventing and repairing early failures of mechanical equipment [6]. The Models based on neural networks and the support vector machines are more commonly used. References [7-8] used neural network and the correlation vector machine to complete the prediction of equipment operation reliability, and achieve good results.

This paper proposes a new method based on PCA and GA-BP models. The GA-BP model is constructed using GA to optimize the BP neural network, and 6 time domain features are integrated into a comprehensive index using the PCA method, and the evaluation and prediction of the equipment operating status is finally completed. Compared with the traditional BP neural network, the proposed method in this paper has better performances.

## 2. PCA Method

PCA is a data processing and analysis method that reduces the dimensionality and noise. It is a mathematical method that maps the high-dimensional data space to the low-dimendional space through the orthogonal transformation [9]. Suppose $X$ is a matrix of $n$ samples and $p$ variables, we have

$$X=(x_{ij})_{n*p}=(x_1,x_2,\cdots,x_p) \tag{1}$$

where $x_j=(x_{1j},x_{2j},\cdots,x_{nj})^T$ is $j-th$ variable. The steps of PCA are given as follows:

(1) Normalize the data as follows:

$$x=\frac{x_{ij}-\overline{x}_j}{s_j},\ i=1,2,\cdots,n,\ j=1,2,\cdots,p \tag{2}$$

(2) Compute the covariance matrix $V$ of the normalized matrix $\tilde{X}$.

(3) Find the $p$ of the eigenvalues of $V:\lambda_1\geq\lambda_2\geq\cdots\geq\lambda_p$ and the corresponding eigenvectors:

$$U=(u_1,u_2,\cdots,u_p) \tag{3}$$

(4) Calculate the contribution rate of the first $m$ principal components:

$$\phi(m)=\sum_{i=1}^{m}\lambda_i/\sum_{i=1}^{p}\lambda_i \tag{4}$$

(5) Find the first $m$ principal components:

$$Y=U^TX \tag{5}$$

## 3. GA-BP Model

Because the initial weight and the initial threshold of the BP neural network are randomly generated, it is easy to fall into a local minimum during the training process. GA is a method that can adaptively search the optimized solution from a global perspective [10], which can overcome the shortcomings of BP neural network. This paper introduces GA on the basis of BP neural network to construct GA-BP model, the steps of GA-BP are given as follows:

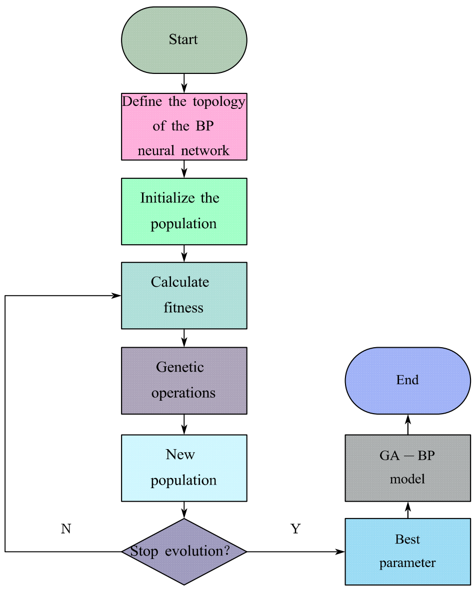


**Figure 1.** The flowchart of GA-BP algorithm

Firstly, we need to determine the structure of the BP neural network, including the number of network layers and the number of nodes in each layer. Secondly, we take the optimization targets as genes and compose a chromosome, and then randomly generate several chromosomes. Then, the fitness function is defined as the error between the output of the neural network training data and the ideal output. Under the guidance of fitness, we carry out the operations such as selection, crossover and mutation until get a target with the best fitness. Finaly, the weight and the threshold optimized by GA are input into the BP neural network, and the GA-BP model is completed. The flowchart is shown as Figure 1.

## 4. Example Analysis

### 4.1. Data Processing

The data comes from the measured data of the IEEE PHM 2012 Prognostic challenge provided by the FEMTO-ST Institute, and its experimental device is shown in Figure 2. In the experiment, the artificial acceleration is used to simulate the full life data of 17 bearings from normal to failure under 3 operating conditions. In this paper, the bearing 3-3, which is more in line with the trend of bearing degradation, is selected as the experimental object. The full life data is shown in the Figure 3, and it can be seen from Figure 3 that the bearing enters the performance degradation stage at about 3000s and enters the failure stage at about 4200s.

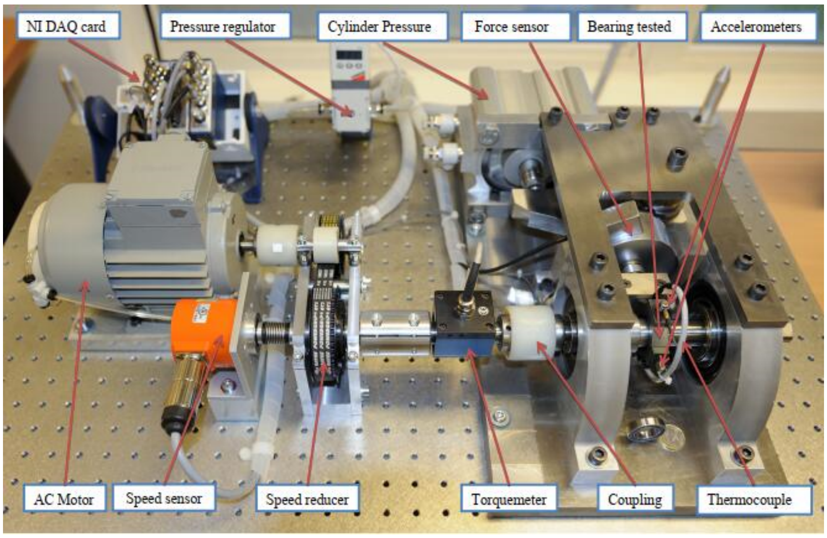


**Figure 2.** The experimental device

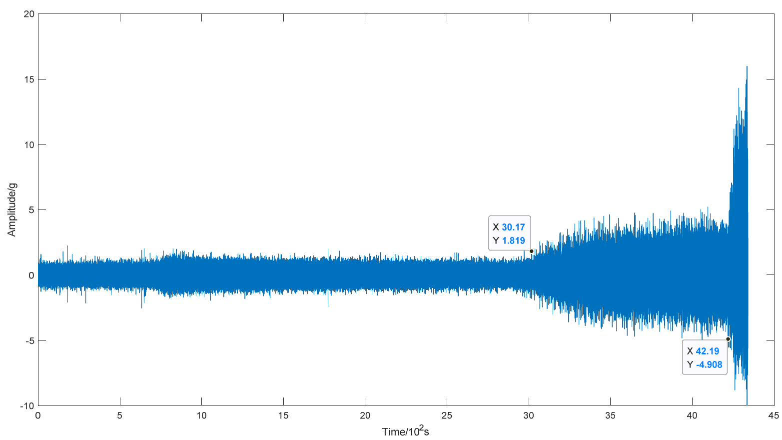


**Figure 3.** The full life data of the bearing 3-3

## 4.2. The Evaluation of Operation Status

The signal is divided into 2170 segments, the peak value, root mean square value, kurtosis, waveform factor, mean value and margin factor of each segment are calculated, and then PCA is used to integrate them into a one-dimensional comprehensive index. The normalized comprehensive index is shown in the Figure 4.

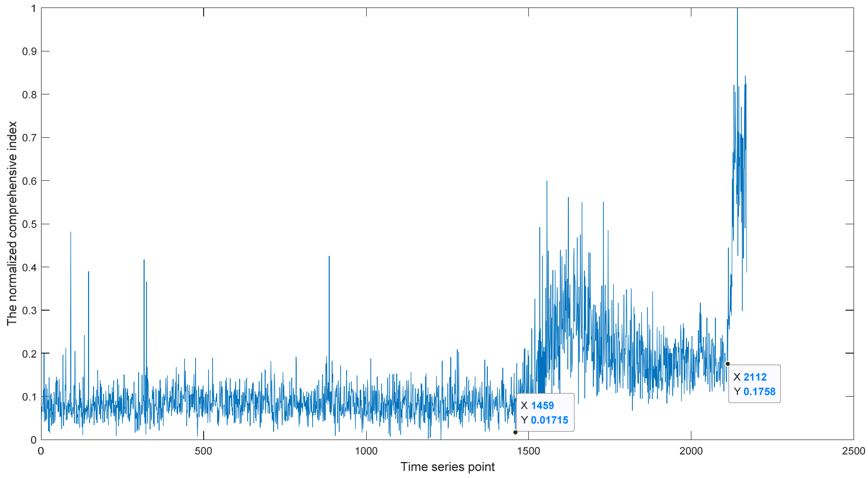


**Figure 4.** The normalized comprehensive index of the bearing 3-3

It can be seen from Figure 4 that the comprehensive index is stable before about 1459 points, indicating that the bearing is in a normal operating state. Between 1460 and 2112 points, it experiences a rise and then a steady phase, which indicates that it is in a performance degradation stage. After 2112, the comprehensive index rises sharply, which indicates that the bearing has entered the failure stage. We can evaluate the running status of the bearing according to the change of the comprehensive index.

## 4.3. Prediction of Operation Status

**Table 1.** Evaluation indexes of two models

| Model | The average of RMSE | The average of MAE |
|---|---|---|
| BP | 0.0346 | 0.0123 |
| GA-BP | 0.0085 | 0.0045 |

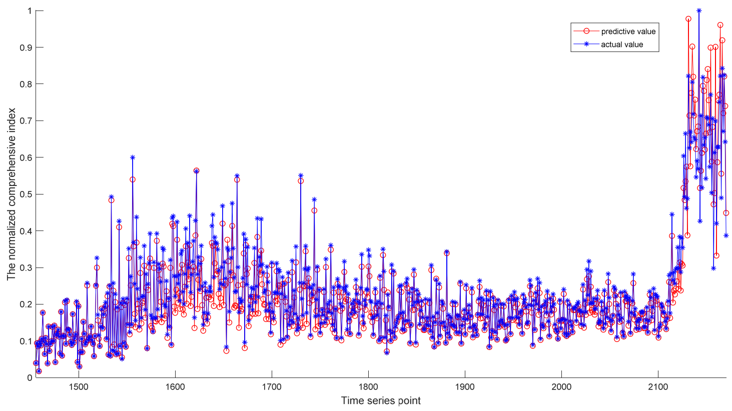


**Figure 5.** The prediction result of BP Model

A one-step advance prediction technique with a regression step size of 5. The comprehensive index before 1459 points is used as training data to input into the GA-BP model, and the model is trained and saved. Taking the comprehensive index after 1460 points as the test data, the BP model and the GA-BP model 5 are tested 5 times. The average of Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE) are shown in Table 1. And Figures 5-6 show the best prediction charts of the two models.

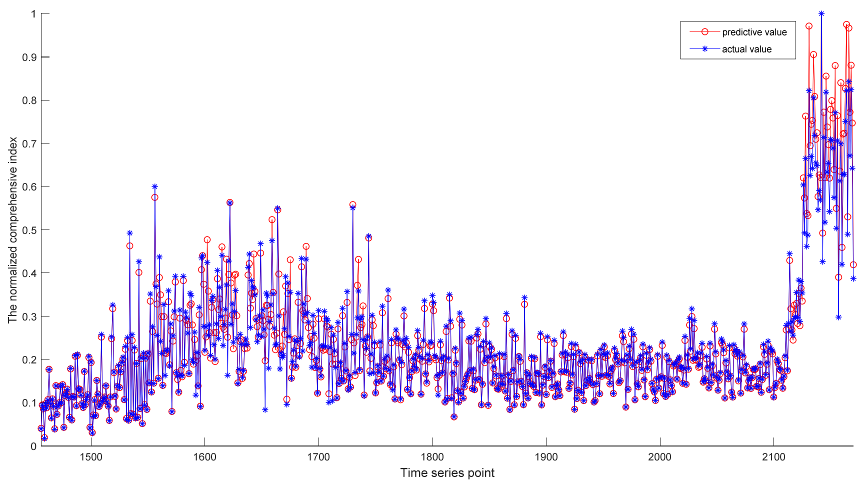


**Figure 6.** The prediction result of GA-BP Model

Table 1 and Figures 5-6 show that both models perform very well in predicting bearing operating conditions, but the GA-BP model has lower RMSE and MAE, which means that the GA-optimized BP model is better than the BP model in the convergence accuracy, and it can effectively predict the status of equipment operation.

The time periods between 1460 points to 1664 points are sensitive when the bearing enters the degradation stage. In order to show the prediction effect more clearly, the prediction results of this time period are enlarged. The results are shown in Figures 7-8. We can also see that the GA-BP model has better performances.

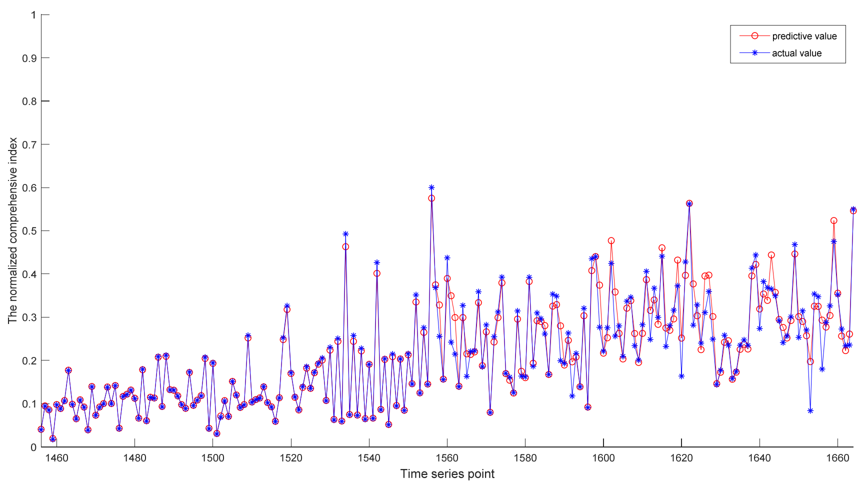


**Figure 7.** The prediction result of GA-BP model from 1460 to 1664 points

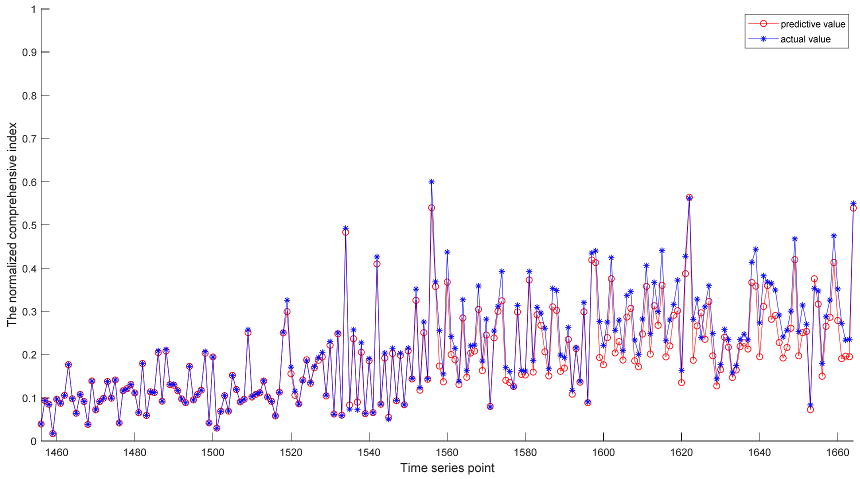


**Figure 8.** The prediction result of BP model from1460 to 1664 points

## 5. Conclusion

Aiming at the problem about the evaluation and prediction of equipment operation state, a new method based on PCA and GA-BP model is proposed, and the following conclusion can be drawn:

(1) By extracting the time domain features of the equipment's operating vibration signal and using the PCA method to merge it into a comprehensive index, the operating status of the equipment can be correctly evaluated.

(2) The GA is used to optimize the BP neural network and it is applied to the prediction of the operating status of the equipment. Both models have very good performances, but the BP neural network optimized by the GA has better convergence accuracy.

(3) This method can effectively predict the operating status of equipment and provide an effective method for equipment health monitoring and fault diagnosis.

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