Real-time Online Prediction of Data Driven Bearing Residual Life

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ABSTRACT. In order to realize the predictive maintenance of key components under massive vibration data, real-time online prediction of the remaining life of different types of bearings, a data driven real-time online prediction method for bearing residual life is introduced. The method realizes the construction of the data-driven bearing residual life prediction model by selecting the bearing vibration data Spearman characteristic parameter selection, principal component analysis (PCA), health index fusion, and BP neural network fitting. The built model is continuously updated by real-time online acquisition of data to achieve real-time online prediction of bearing residual life. The accuracy and feasibility of the method for predicting the remaining life of different types of bearings are verified by experiments. Using this method to predict the remaining life of the bearing helps to achieve predictive maintenance of critical components, reduce unplanned downtime, increase production efficiency, and reduce production costs.

1. INTRODUCTION

Bearing is one of the key components in the production process of some mechanical equipment. Bearing failure often leads to the immediate stop of production in this section, while causing huge losses in production. In recent years, it is difficult to access, process critical or very expensive mechanical installation sensors. The goal is to find defects in equipment and components early and eliminate or reduce production losses caused by unplanned downtime through available and reliable equipment. With the real-time online state data of bearings in industrial equipment becoming easy to obtain and analyze and process, it has become a trend to predict the real-time online life of bearings in mechanical equipment [1].

At present, researchers at home and abroad have done research on the prediction of the residual life of bearings. In order to establish the bearing degradation model, Hu Yaogang et al. [2] proposed a method based on Wiener process to establish the bearing performance degradation. In order to adapt the degradation model to the real-time changing conditions, a real-time parameter estimation method was proposed. Shen et al. [3] proposed an evaluation method of bearing degradation after analyzing the bearing degradation data. A method for predicting bearing life based on MSPSO algorithm and MK-LSSVM was proposed by Zhang et al. [4]. Wavelet packet is used to describe the degradation of bearings. Zhou Jianmin et al. [5] proposed a bearing vibration data prediction model based on ARMA model, which was not suitable for long-term prediction. Shi Yiming et al. [6] proposed a new bearing life prediction method. Bearing life prediction method based on WLR and PSO-AFS-SVR model, in which...
the degradation process of bearings was partitioned and PSO-AFS is used to optimize the SVR parameters; Wu Qianhui et al. [7] proposed SVD to describe the degradation index of component state to realize the residual life prediction of key components of equipment; Wang Fengtao et al. [8] proposed a KPCA-based method. Jiyun et al. [9] proposed a DPMM-CHMM-based bearing degradation assessment method, which could effectively identify the real-time operation degradation state of bearings. The current bearing residual life prediction method can be used for axles. The residual life of bearings can be predicted [5-9] or the degradation state of bearings can be identified in real time [2-4], but it is difficult to predict the residual life of bearings on-line in real time [2-9]. To solve these problems, Real-time Online Prediction of Data Driven Bearing Residual life is proposed in this paper.

2. Establishment of Bearing Residual Life Prediction Model

The methods of bearing residual life prediction mainly include data cleaning and segmentation, variable selection and principal component analysis, fusion of health indicators, model generation, performance evaluation and residual life prediction [10]. When extracting degradation factor, fusing health index based on PCA and constructing residual life prediction model [11], a real-time online method is adopted to extract degradation factor, fuse health index and fit the residual life prediction model of bearing with BP neural network [12].

**Step 1.** Data cleaning and data segmentation. In the process of model building, the data collected by sensors need to be pre-processed, including data cleaning and data segmentation. Its main purpose is to make the original data suitable for model building.

**Step 2.** Data are filtered and smoothed. The sliding mean filter is used to effectively eliminate and suppress the noise in the data collected by the sensor. The main process of the algorithm is to establish a data buffer in RAM, store N times of sampled data in order, calculate the arithmetic average value of the RAM buffer, remove the earliest data when a new data is stored, and then calculate the arithmetic average value of the RAM buffer. The calculation formula is as follows:

\[ \overline{y_n} = \frac{1}{N} \sum_{i=0}^{N-1} x_{n-i}, \quad \overline{y_{n}} \text{ is the output of the nth sampling} \]  \(1\)

**Step 3.** Variable selection. In the process of model building, the method based on Pearman is used to select the characteristic parameters with obvious monotony [14]. The aim is to derive a simplest possible model that can explain the past and predict the future. Spearman algorithm steps are:

Let two vectors \(X\) and \(Y\), \(X\) and \(Y\) of length \(N\) contain \(N\) elements, and calculate the correlation between the two vectors \(X\) and \(Y\).

1) The elements \(X_i\) and \(Y_i\) corresponding to vectors \(X\) and \(Y\) are converted into rankings in their column vectors, which are denoted as \(R(X_i)\) and \(R(Y_i)\).

2) Calculate the difference \(d\) between \(R(X_i)\) and \(R(Y_i)\) of the corresponding elements in two column vectors \(X\) and \(Y\), and add them together.

\[ d = \sum_{i=1}^{N} |R(X_i) - R(Y_i)| \]  \(2\)

3) Calculate the correlation \(R_s\) between the two column vectors.

\[ R_s = 1 - \frac{6\cdot d}{N\cdot(N^2-1)} \]  \(3\)

\(R_s>0\) indicates that the two column vectors are positively correlated, and \(R_s<0\) indicates that the two column vectors are negatively correlated.

**Step 4.** Principal Component Analysis (PCA). Its overall goal is data simplification and data fusion, with fewer variables instead of more variables. In this case, the information in the first \(k\) components is almost as much as that in the original \(P\) variable. Geometrically, this process corresponds to rotating the original \(p\)-dimensional space with a linear transformation, and then selecting only the first \(k\)-dimension of the new space.

PCA algorithm steps [15]:

1) Form the original data into column matrix \(Y\) of row \(A\) and column \(B\).

2) Centralization of features. That is to say, the average value of each dimension is subtracted from the data of each dimension, so that the average value of each dimension is 0.
\[ x_{ij} = \frac{y_{ij} - \overline{y}_j}{n-1}, \quad i = 1, 2, \ldots, n, \quad j = 1, 2, \ldots, k. \] (4)

Where:

\[ \overline{y}_j = \frac{1}{n} \sum_{i=1}^{n} x_{ij}; \] (5)

\[ \delta_j = \frac{1}{n-1} \sum_{i=1}^{n} (y_{ij} - \overline{y}_j)^2 \] (6)

Matrix after feature centralization

\[
X = \begin{bmatrix}
x_{11} & x_{12} & \cdots & x_{1k} \\
x_{21} & x_{22} & \cdots & x_{2k} \\
\vdots & \vdots & \ddots & \vdots \\
x_{n1} & x_{n2} & \cdots & x_{nk}
\end{bmatrix}.
\]

3) Calculate the covariance matrix.

\[ R = \frac{1}{n-1} X^T X. \] (7)

4) Calculate the eigenvalue \( \lambda \) of the covariance matrix and the corresponding eigenvectors.

\[ \alpha_i = (\alpha_{i1}, \alpha_{i2}, \ldots, \alpha_{ik})^T, \quad i = 1, 2, \ldots, k. \] (8)

5) Find the data after dimensionality reduction. Take out the required dimension as needed. For example, if we take the data after dimensionality reduction to \( K \) dimension, we select the corresponding matrix \( p \), then the data after dimensionality reduction is \( y = px \).

6) PCA cumulative contribution rate \( \eta \).

\[ \eta(k) = \frac{\sum_{k=1}^{p} \lambda_k}{\sum_{k=1}^{n} \lambda_k} \] (9)

Step 5. Fusion of health indicators, including normalization, transformation and health indicators. Spearman calculates the monotonicity of the eigenvalues, extracts the good monotonicity of the eigenvalues, fuses the extracted eigenvalues, and uses PCA to reduce the dimensionality of the fused eigenvalues to fuse the health indicators.

Step 6. Model generation, including BP neural network modeling, trend analysis, performance evaluation and residual life prediction.

BP neural network has linear function and non-linear function, which can well fit linear model or non-linear model [16-17]. Real-time online prediction model of bearing residual life is constructed by health index and BP neural network. The main characteristics of BP algorithm are forward and backward transmission of signals and errors respectively. The training of BP neural network is to make the final output of BP neural network as close as possible to the expected output by constantly adjusting the network weight value. It is the most effective learning method of multi-layer neural network learning method [18].

Multilayer neural network structure and its description. Usually a multi-layer neural network consists of \( L \)-layer neurons, where: the first layer is called the input layer, the last layer (the \( L \)-th layer) is called the output layer, and the other layers are called the hidden layer (the second layer ~ the first \( L-1 \) layer).

Input vector:

\[ \mathbf{x} = [x_1, x_2, \ldots, x_i, \ldots, x_m], \quad i = 1, 2, \ldots, m \]

Output vector:

\[ \mathbf{y} = [y_1, y_2, \ldots, y_k, \ldots, y_n], \quad k = 1, 2, \ldots, n \]
Neuronal output of the lth hidden layer: 
\[ h^{(l)} = [h_1^{(l)} \ h_2^{(l)} \ldots h_{s_l}^{(l)}], \quad j=1, 2, \ldots, s_l \]

Where, \( s_l \) is the number of neurons in layer 1.
\( b_i^{(l)} \) is the bias of the first neuron in the first layer, and the connection weight between the \( j \)-th neuron in the \( L-1 \) layer and the \( i \)-th neuron in the \( L \) layer is \( w_{ij}^{(l)} \) rule.

\[ h_i^{(l)} = f(\text{net}_i^{(l)}) \]

\[ \text{net}_i^{(l)} = \sum_{j=1}^{s_{l-1}} h_{ij}^{(l-1)} + b_i^{(l)} \quad (10) \]

Where, \( \text{net}_i^{(l)} \) is the output of neurons and \( f(\text{net}_i^{(l)}) \) is the non-linear activation function of neurons. Two kinds of nonlinear activation functions of BP neural network:
\[ f(x) = \frac{1}{1+e^{-x}}; f(x) = \frac{1-e^{-x}}{1+e^{-x}} \quad (11) \]

BP algorithm process description. The weights and biases of BP neural network are updated by batch updating method.

Step 1: First, let \( \Delta M^{(j)} = 0, \Delta N^{(j)} = 0 \) be all layers \( 2 \leq j \leq J \), where \( \Delta M^{(j)} \) and \( \Delta N^{(j)} \) are all zero matrices and all zero vectors, respectively.

Step 2: For \( i = 1:k \),

Calculating the gradient moments \( \Delta M^{(j)}(i) \) and \( \Delta N^{(j)}(i) \) of weights and biases of neurons in each layer:

1. Calculating \( \Delta M^{(j)} = \Delta M^{(j)}(j) \) \quad (12)
2. Calculating \( \Delta N^{(j)} = \Delta N^{(j)}(i) \) \quad (13)

Step 3: Update the weights and biases:

1. Calculating \( M^{(j)} = M^{(j)} - \frac{1}{k} \Delta M^{(j)} \) \quad (14)
2. Calculating \( N^{(j)} = N^{(j)} - \frac{1}{k} \Delta N^{(j)} \) \quad (15)

Step 7. Performance evaluation and residual life prediction. After fitting the model with BP neural network, the trend analysis and performance evaluation of the output of the model can be carried out through historical data, and the model can be further optimized according to the evaluation situation, so that the model can better realize the residual life prediction of bearings[19].

3. Real-time on-line Residual Life Prediction Process of Bearings
The residual life can be predicted after the optimization of the model. When new data are collected, the model can be updated according to the new data to realize real-time online prediction of bearing residual life.

![Flow chart for real-time on-line residual life prediction of bearings](image)

4. Test Verification
In order to verify the feasibility of the real-time online prediction method for the residual life of rolling bearings, the proposed method was verified by the rolling bearing life data set. The data set collects the
vibration acceleration signal of the bearing with a life cycle of 50 days. The sampling frequency of the bearing vibration signal is 97,656 Hz.

Fig. 3 Vibration Data Acquisition Site of Rod Bearing

4.1 Data Processing

The data collected by sensors are processed, including data cleaning, data segmentation, data smoothing and filtering. Its main purpose is to make the original data after processing fit for the model establishment.

Fig. 4 shows the whole life time domain signal diagram of the bearing from normal state to failure. The time domain signal of bearing life shown in Fig. 4 shows the increasing trend of signal pulse.

Fig. 4 time domain diagram of full life of bearings

After processing and calculating the vibration acceleration signal, 10 time domain signals and 4 frequency domain signals are obtained. In order to reduce the influence of noise on time-domain signal and frequency-domain signal, sliding mean algorithm is used to smooth the time-domain signal and frequency-domain signal.

4.2 Feature Extraction

Feature extraction. Statistical feature sets obtained from time domain signals and spectral kurtosis are extracted. Noise with opposite trend can sometimes be harmful to the prediction of the residual life of bearings. Therefore, a filter is applied to filter the extracted features, and the window size is 5. The monotonicity of feature is analyzed based on Pearman method, and the required feature values are extracted.

4.3 PCA Dimensionality Reduction and Feature Fusion

PCA is used for dimensionality reduction and feature fusion. Among them, PCA must use Spearman to select the feature parameters before the feature parameters are reduced. The aim is to make the fused feature parameters monotonous and can be used to construct health indicators. Spearman was used to select the characteristic parameters of the data set, and seven characteristic parameters with large monotonic characteristics were selected. Then PCA-based methods are used to perform PCA dimensionality reduction and feature fusion on the characteristic parameters with large monotonic
characteristics. Part of the data of the one-dimensional PCA1 is fused by the partial feature parameters and characteristic parameters after the selection of the Spearman feature parameters, as shown in FIG. 5.

The number of PCA principal components depends on the amount of information that can reflect more than 85% of the original variables, that is, when the cumulative contribution rate is more than 85%.

Table 1 Principal Component Analysis

| PCA     | characteristic value | Proportion | Gradual increase |
|---------|----------------------|------------|------------------|
| PCA1    | 0.3099               | 93.8861%   | 93.88610%        |
| PCA2    | 0.0196               | 5.9%       | 99.85242%        |
| PCA3    | 0.00042              | 0.13%      | 99.97916%        |
| PCA4    | 0.00006              | 0.018%     | 99.99754%        |
| PCA5    | 0.000006             | 0.002%     | 99.99938%        |

The contribution rate of PCA1, the first principal component in Table 1, is 93.886% and more than 85%. Therefore, it is hopeful that the first principal component can be fused into a health indicator.

Fig. 6 shows the health indicators generated by the data fusion of bearing life cycle. From Fig.6, it can be seen that the health indicators of bearings increase monotonously with the increase of the running time of bearings.

Fig. 6 Health Indicators Generated by Visual Fusion

4.4 Real-time Online Prediction of Bearing Residual Life

By fitting the health index with BP neural network, the real-time online model of bearing residual life is finally constructed. Because the fitting of BP neural network to health indicators is unstable, a screening method is adopted to fit health indicators. The BP neural network model with high fitting degree is retained to realize the prediction of the remaining life of bearings. The stability and accuracy of the BP neural network model are improved. The process flow chart is shown in Figure 7.

Fig. 5 Partial data before and after feature parameter fusion
Figures 8 to 11 show the residual life of bearings predicted by the residual life prediction model on the 25th, 35th, 40th and 45th day of operation respectively.

Figure 8 residual life prediction of BP model

Figure 9 residual life prediction of BP model

Figure 10 residual life prediction of BP model

Figure 11 residual life prediction of BP model

According to the design life and health index threshold of the bearing itself, the prediction model of the residual life of the bearing is generated by the state data of the bearing. Based on the design life of the bearing and the threshold of the health index of the bearing, the health index of the bearing is predicted according to the current state data of the bearing, and then the health index of the bearing is predicted. The residual life of the bearing is predicted. Through the research and analysis of the prediction results of the generated bearing residual life prediction model and the actual results corresponding to the data set, the model can predict the bearing residual life online in good real-time based on the bearing state data.

In order to further validate the practicability of the method, another set of data sets of rolling bearings of different types are used to validate the method. The signal sampled by the data set is the acceleration...
signal. The sampling frequency is 25.6 kHz. A total of 32768 data points are recorded with 62 sampling times. Using the same method to process the data set.

Fig. 12 time domain diagram of full life of bearings

Figures 13 to 15 show the residual life of bearings predicted by the residual life prediction model on the 35th, 45th and 50th day of operation respectively.

Fig. 13 residual life prediction of BP model

Fig. 14 residual life prediction of BP model

Fig. 15 residual life prediction of BP model

Through the research and analysis of the prediction results of the generated bearing residual life prediction model and the actual results corresponding to the data set, the prediction results of the model are consistent with the actual results corresponding to the data set. The bearing residual life can be predicted on-line in good time according to the bearing state data, and the predictive maintenance of the bearing can be achieved.

5. Concluding Remarks

Aiming at the construction of real-time online prediction model of bearing residual life, a method is proposed in this paper, and the feasibility of this method is verified by two examples. The model generated by this method can be updated continuously through real-time online acquisition of data. The model has been verified by experiments: it can adapt to the new situation very well; it can predict the residual life of different types of bearing; it has strong practical significance for predictive maintenance of bearing.
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