Research on Life Prediction of Motor Bearing Based on Vibration Signal

Qingchuan Fan*, Fei Yu and Min Xuan

College of Electrical Engineering, Naval University of Engineering, Wuhan, Hubei, 430033, China

*Corresponding author’s e-mail: whhgdnue.edu.cn

Abstract. In order to solve the problem of motor bearing life prediction, a model of Long and short time memory (LSTM) network remaining life prediction based on genetic algorithm (GA) optimization is proposed. Firstly, the time-domain and time-frequency domain features of vibration signals are extracted. Secondly, the super-parameters of LSTM network are optimized by GA algorithm. Finally, the trained LSTM network is used to predict the remaining life of motor bearings. The results show that the model established in this paper can effectively predict the remaining life of motor bearings, which is of great significance to the study of health management and life prediction of motors.

1. Introduction

In the production process of each enterprise, the motor bears the main power, and once it breaks down, it may seriously affect the whole production process. With the continuous development of motor products and the continuous improvement of insulation strength, the breath faults of motor are greatly reduced. However, according to the statistics of motor fault data, about 70% of motor faults are caused by the damage of motor bearings.

The vibration signal of motor bearing contains a lot of information, and the analysis method based on the vibration signal of motor bearing has always been the most efficient method in the research of motor bearing condition detection. It is an important way to study bearing life prediction by extracting its characteristic parameters from bearing vibration signals and establishing a bearing life prediction model based on artificial intelligence technology. At present, scholars at home and abroad have made remarkable progress in the research of bearing vibration signals. For example, literature [1] takes the vibration signal of subway fan as the research object, and through vibration monitoring and computer technology, analyzes the time-frequency and frequency-domain characteristics of the vibration signal of fan bearing to realize the fault diagnosis of fan bearing. Literature [2] puts forward a life prediction model of rolling bearing based on feedforward neural network, which can output the state detection value of a kind of equipment, such as vibration amplitude. In reference [3], two hidden layer neuron structures are used to establish a prediction model, and the current life and several detected variables are taken as model inputs, and the remaining life is taken as model output, thus completing the prediction of the remaining life of rolling bearings. Literature [4] constructs a support vector machine (SVM) model optimized by particle swarm optimization (PSO), thus completing the prediction of bearing degradation trend. In order to effectively extract the feature information of motor bearing vibration signals and achieve the purpose of bearing life prediction, this paper proposes a motor bearing life prediction model based on time domain features and GA optimized LSTM, which takes
the time domain features of vibration signals as input and the remaining life of bearings as output to test the accuracy of the proposed model.

2. Feature vector extraction

2.1. Time domain feature extraction
The vibration signals of motor bearings have strong time domain characteristics. Therefore, some important time domain indexes extracted from vibration signals in this paper include average value, root mean square value, peak value, kurtosis, etc. These indexes are widely used in the fields of state detection, fault diagnosis and life prediction of mechanical equipment. These indicators and their calculation formulas are shown in Table 1.

![Table 1. Time domain index calculation formula](image)

The root mean square value of these characteristic parameters can effectively reflect the degree of failure, and can be used to describe the change of signal trend. Kurtosis, peak value and margin factor are obvious for early bearing failure.

2.2. Integrated empirical mode decomposition
Empirical Mode Decomposition (EMD) is a new adaptive decomposition method, which has obvious advantages when dealing with nonlinear signals. When EMD processes the signal, it decomposes an original signal into multiple IMF's and a residual. However, due to the mode aliasing and other problems, its practical performance is reduced. Therefore, the EEMD algorithm is proposed to effectively suppress and eliminate the mode aliasing in EMD, so that the decomposed signal can reflect the physical information of the signal more objectively. In the EEMD algorithm, specific white noise is included in the acquisition signal, so that there is a unified reference frame in the analysis time domain, and each time scale can be fully decomposed to form an effective binary recorder set, which is more conducive to data decomposition in EMD [5]. The basic steps are as follows:

Step 1: A group of white noise is inserted into the original signal $y(t)$ to obtain the target signal $y_m(t)$:

$$y(t) = kn_m(t) = y_m(t)$$  \hspace{1cm} (1)

Step 2: The EMD algorithm is used to decompose $y_m(t)$, and the IMF components of the target signal are obtained;

Step 3: Add M different white noises to the target signal and repeat the above two steps;

Step 4: Calculate the average value of the IMF for each trial;

Step 5: Take the corresponding IMF mean as the final IMF parameter.
3. LSTM model based on GA optimization

3.1. LSTM algorithm
LSTM network is an excellent variant of recurrent neural network (RNN), which solves the problem of gradient explosion or gradient disappearance of RNN. LSTM network with memory module has strong advantages when dealing with the prediction and nonlinear mapping of time series. There is a memory module in the LSTM network structure, which helps it to have memory function. The LSTM network structure is shown in Figure 1.

\[
\begin{align*}
C_t &= f_t C_{t-1} + i_t \sigma(W_f h_{t-1} + b_f + x_t) \\
\tilde{C}_t &= \sigma(W_c h_{t-1} + b_c + x_t) \\
\tilde{H}_t &= \tanh(\tilde{C}_t) \\
H_t &= f_t C_{t-1} + i_t \tilde{H}_t \\
o_t &= \sigma(W_o h_{t-1} + b_o + x_t) \\
O_t &= \sigma(W_o h_{t-1} + b_o + x_t)
\end{align*}
\]

Figure 1. LSTM network architecture

LSTM network calculation process is as follows:

Step 1: The forgetting gate decides whether to keep the state information \( C_{t-1} \) at the previous moment. The forgetting gate inputs the cell hidden state \( h_{t-1} \) at the previous moment and the newly input data \( x_t \), and outputs the forgetting gate value \( f_t \):

\[
f_t = \sigma(W_f h_{t-1} + b_f + x_t)
\]

Step 2: The input gate calculates the information that can be learned from the input \( x_t \), the previous state \( h_{t-1} \) and the output \( f_t \) of the forgetting gate, and determines the value \( i_t \) of the information to be used and saved, and the current cell state \( \tilde{C}_t \):

\[
i_t = \sigma(W_i h_{t-1} + b_i + x_t)
\]

\[
\tilde{C}_t = \tanh(W_c h_{t-1} + b_c + x_t)
\]

Step 3: According to the input \( x_t \), the hidden layer state \( h_{t-1} \) of the previous time and the cell state of the current time, the output gate calculates the cell state \( h_t \) at the current time and outputs \( o_t \):

\[
h_t = o_t \cdot \tanh(C_t)
\]

\[
o_t = \sigma(W_o h_{t-1} + b_o + x_t)
\]

Where, \( W_f, W_i, W_c, W_o, b_f, b_i, b_c, b_o \) respectively correspond to the weight matrix and deviation of each gate, and \( \sigma \) stands for sigmoid function.

3.2. The GA optimization LSTM
GA is a typical heuristic swarm optimization algorithm based on biological evolution theory, which simulates the target as the process of biological evolution. GA algorithm simulates biological crossover, heredity, mutation and other operations to generate new individuals, individuals with low fitness will be eliminated, and individuals with high practicability will be retained. The specific steps of genetic algorithm are referred to Literature [6].

The performance of LSTM network is mainly determined by its super parameters, among which the learning rate and the number of hidden layer neurons play the most important roles. This paper is helpful for GA algorithm to find the best combination of these two parameters and further improve the nonlinear mapping ability of LTM. The GA optimized LSTM process is shown in Figure 2.
4. Motor bearing life prediction experiment

4.1. Introduction to the experimental platform

The experimental data of motor bearings studied in this paper comes from the XJTU-SY bearing data set of Xi’an Jiaotong University[7]. The bearing full life cycle test bench is shown in Figure 3.

The motor speed is 2100r/min. A PCB 352C33 acceleration sensor is installed in the horizontal direction and the vertical direction of the bearing. The DT9837 portable vibration signal collector is used to collect vibration signals. The sampling frequency is 25.6kHz, the sampling interval is 1min, and each sampling time is 1.28s[8].

4.2. Results and analysis

The selected vibration signal of the full life cycle of the bearing is shown in Figure 4. It can be seen from the figure that the bearing is in normal working condition at first, and the amplitude of the vibration signal changes after a period of operation. At this time, the bearing has a slight failure and enters the degradation stage. The amplitude of vibrations eaten every week during the degeneration phase increases rapidly.
5. Conclusion
Aiming at the motor bearing vibration data set, this paper builds a bearing life prediction model based on GA optimized LSTM. Through the model proposed in this article, the remaining service life of motor bearings can be accurately predicted, which has certain engineering significance and research value. The main conclusions of this paper are as follows:

1) The EEMD noise reduction method based on filter processing is very effective for the vibration signal of the motor bearing. It can well retain the effective components of the vibration signal while removing the noise.

2) The hyperparameters of the GA optimized LSTM network are proposed, and the experimental data is analyzed and compared with other methods. The prediction results show that the prediction accuracy of the model in this paper is higher and it is more suitable for the prediction of bearing life.
References
[1] Li, G., Chow, J.X. (2018) Research on Fault Diagnosis of Metro Fans Based on Vibration Monitoring. Transportation and environmental protection, 14: 16-18.
[2] Gebraeel, N., Lawley, M., Liu, R., Parmeshwaran, V. (2004) Residual life predictions from vibration-based degradation signals: a neural network approach. IEEE Transactions on Industrial Electronics, 51: 694-700.
[3] Tian, Z. (2012) An artificial neural network method for remaining useful life prediction of equipment subject to condition monitoring. Journal of Intelligent Manufacturing, 2: 227-237.
[4] Shao Wu, D., Qiang Qiang, C., Yu, D. (2019) Rolling bearing life prediction based on time domain characteristics. Computer Measurement and Control, 10: 60-63.
[5] Gao Yan, H., Yong, L., Han, X., & Tuo, Q. (2014) Application of EEMD adaptive morphology in gear fault diagnosis. Journal of Vibration and Shock, 18:145-148.
[6] Liang, X., Rui Dong, W. (2021) Neural network structure optimization algorithm based on adaptive genetic algorithm. Journal of Harbin University of Science and Technology, 01:39-44.
[7] Wang, B., Lei, Y., Li, N., & Li, N. (2018) A hybrid prognostics approach for estimating remaining useful life of rolling element bearings. IEEE Transactions on Reliability, 1-12.
[8] Ya Guo, L., Tian Yu, H., Biao, W., Nai Peng, L., Tao, Y., & Jun, Y. (2019) Interpretation of XJTU-SY rolling bearing accelerated life test data set. Journal of Mechanical Engineering, 16:1-6.
[9] Jian Jun, M., Wern Tao, M. (2020) Remaining life prediction of rolling bearings based on mutual information and SVR. Machine Design and Research, 06:92-95.