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RESIDUAL LIFE PREDICTION OF ROTATING MACHINERY GUIDED BY QUANTUM DEEP NEURAL NETWORK

GANGHONG YE *AND NINGXUAN SHI†

Abstract. In order to avoid the low prediction rate and high evaluation rate in estimating the service balance life of rotating machinery, this paper presents a quantum gene chain encoded bidirectional neural network (QGCCBNN) for estimating the service balance life of rotating machinery. In QGCCBNN, quantum bidirectional transmission mechanism has been developed. In order to improve the global optimization ability and convergence speed, we have developed a quantum gene chain encoding method to transform the gradient descent into the data transmission and updating. Because of the advantages of QGCCBNN in nonlinear estimation ability and convergence speed, the proposed QGCCBNN for predicting the remaining service life of rotating machinery can achieve higher prediction precision and optimization.The predicted value of the proposed method for the remaining service life of double row roller bearings is 6.33h (actual value is 7.17h), with a prediction error of only 0.84h and a relative prediction error of only 11.72%. The experimental results demonstrate the effectiveness of the proposed method.

Key words: Quantum bidirectional transmission mechanism; Quantum gene chain encoding; Prediction of remaining service life; Rotating machinery

1. Introduction. In the current era, China's industrial production is rapidly developing. With the proposal of "Made in China 2025", various types of mechanical equipment are experiencing rapid development [1]. There are various types of rotating machinery in various industrial fields, such as aviation engines in the aerospace field, gas turbines and wind turbines in the energy field, and automotive transmissions in the transportation field.

Although there are various types of rotating machinery, they generally include some common basic rotating components, such as rotors, rolling bearings, and gearboxes. This type of precision rotating mechanical equipment has the characteristic of complex operation and difficult maintenance. In the production process, many factors, such as decreased performance of components, inaccurate measurement of important components, and wear and tear of easily worn components, can lead to damage or shutdown of the entire equipment, causing economic losses, major accidents, and even casualties. Prognostics and Health Management (PHM) is an effective means to improve the availability, reliability, and safety of rotating machinery, and has a wide range of applications in practical industrial production environments [2, 3].

Researchers in the field of fault diagnosis are committed to developing an effective method that can detect faults that occur in the early stages of a fault and determine the severity of the fault. Ensure that production can be stopped and corresponding components can be replaced in a timely manner to avoid causing greater losses and better ensure the safety of people around.

The condition monitoring and fault diagnosis of rotating machinery play a crucial role in ensuring safe operation, reducing maintenance costs, and avoiding industrial accidents. In recent years, data-driven methods have gradually been developed and applied, and this technology has been reflected in many fields. It aims to learn the operational status of the system from data, achieve decision-making and control of equipment and production processes, and is currently the most common fault diagnosis technology.

This method can explore the internal information of various collected data through methods such as machine learning and statistical analysis, thereby establishing a fault diagnosis model. In response to this research issue, Xiao, W. et al. A network monitoring system which has three specifications is proposed to predict the

*School of Mechanical & Electrical Engineering,Zhangjiakou Vocational and Technical College, Zhangjiakou, Hebei, 075000, China

†College of Mathematics and Information Science, Zhangjiakou University, Zhangjiakou, Hebei, 075000, China (Corresponding author)

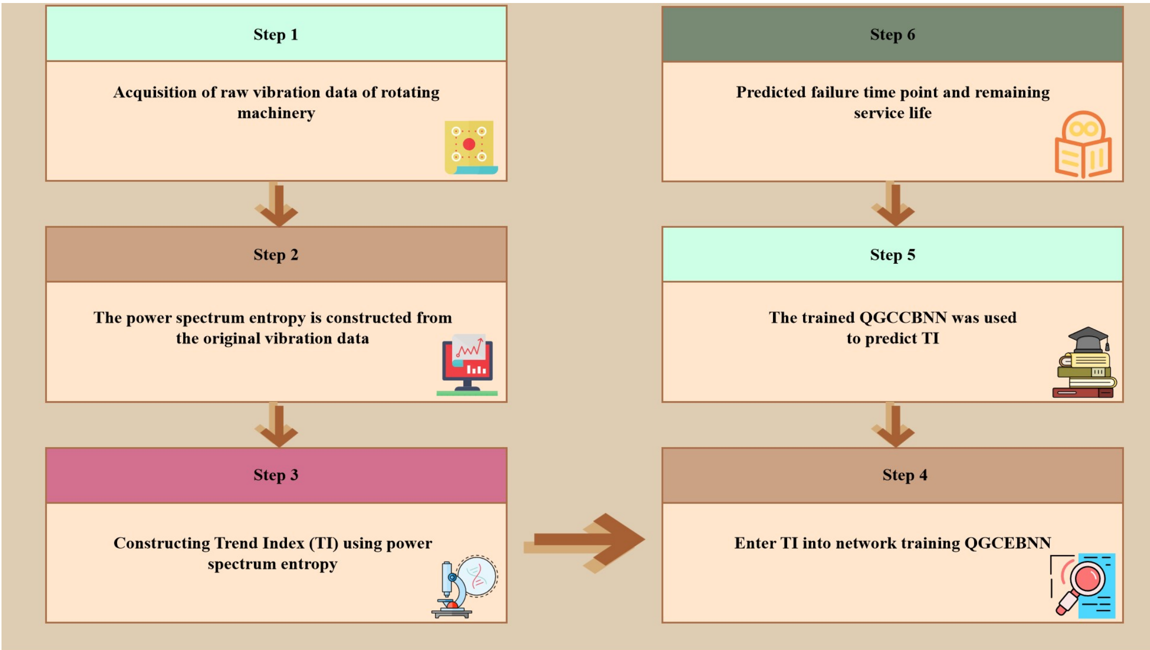

Fig. 2.1: Implementation process of residual service life prediction method for rotating machinery based on QGCCBNN

remaining service life of the bearing.First, connect channel listeners and broadband with a series of additional neural networks to get new attention in the network, making new deep learning more suitable for dynamic state feedback systems. Secondly, using the concept of ”three characteristics” as the color in the network enables in- depth study of the network to better understand the changes in the carrying capacity and achieve better prediction of carrying RUL. Finally, the effectiveness of this method is verified by the establishment of experimental data. The results show that this method is simple, effective, has high prediction precision, and reduces manual interference [4].

In the prediction of time series, there is a cumulative effect of historical information, and it has shown certain application prospects in the prediction of remaining service life [5]. However, due to the lack of a reverse feedback mechanism from output to input in the network structure of recurrent neural networks, the bidirectional transmission mechanism can compensate for the aforementioned shortcomings.Which has good global convergence ability and convergence speed. Based on the above mentioned results, the author proposes a method to estimate the service remaining life of rotating machinery based on QGCCBNN. Firstly, the indicator model (TI) was established using the vibration data of rotating machinery as the feature of dynamic parameters. Then, TI was introduced into QGCCBNN to predict the damage of rotating mechanism. Finally, the failure probability model is established by estimating the transient dynamic curve (i.e. TI curve) to predict the remaining service life of the rotating machinery. This method has high prediction accuracy and efficiency [6, 7].

2. Prediction Method for Remaining Service Life of Rotating Machinery Based on QGCCBNN.

2.1. Implementation process of QGCCBNN based prediction method. The implementation process of the residual service life prediction method for rotating machinery based on QGCCBNN is shown in Figure 2.1 [8, 9].

Collect raw vibration data of rotating machinery; Constructing power spectral entropy using raw vibration data [10]; Extract trend features from power spectral entropy to obtain trend index (TI), and use TI as a performance degradation feature; Using well trained QGCEBNN to predict TI.

2.2. Prediction process of QGCCBNN. Use the trained QGCCBNN to predict degradation trends. The author used a multi-step prediction method for prediction, with specific instructions as follows: Input the test sample $(x_{b-n+1}, x_{b-n+2}, ..., x_b)$ into the trained QGCCBNN to calculate the output value $\tilde{x}_{b+1}$ at time b+1 [11, 12]. Input the latest test sample $(x_{b-n+2}, x_{b-n+3}, ..., x_{b+1})$ into the trained QGCCBNN to calculate the output value $\tilde{x}_{b+2}$ at time b+2. Input the latest test sample $(x_{b-n+3}, x_{b-n+4}, ..., x_{b+2})$ into the trained QGCCBNN to calculate the output value $\tilde{x}_{b+3}$ at time b+3 [13].

2.3. Prediction of remaining service life. Based on TI prediction results of QGCCBNN, a failure probability model for predicting the remaining service life of rotating machinery was established. Specific procedures are as follows: First, the regular operation of the process of rotating machinery can be expressed as:

$$x_t = x_0 + \lambda t + \sigma B_t \tag{2.1}$$

where x_0 and x_t are the initial and cumulative values of performance degradation characteristics (i.e. TI), respectively; λ is the degradation rate [14]; Because $B(t) \sim N(0, t)$, then x follows the following probability distribution:

$$x_t \sim N(x_0 + \lambda t, \sigma^2 t) \tag{2.2}$$

In order to find out λ and σ^2, using the maximum likelihood estimation method, represent the likelihood function $\Psi(\lambda, \sigma)$ as:

$$\Psi(\lambda, \sigma) = \prod_{k=1} \Phi_k(x_{t_k} - x_{t_{k-1}}) \tag{2.3}$$

Among them, $\Phi(\cdot)$ is the probability density function of the standard normal distribution [15, 16].

According to the maximum likelihood estimation method, take the derivative of $l(\lambda, \sigma)$:

$$\begin{aligned} \frac{\partial ln\psi(\lambda,\sigma)}{\partial\sigma} &= \sum_{k=1}^{n} \frac{x_{t_k} - x_{t_{k-1}} - \lambda(t_k - t_{k-1})}{\sigma^2} = 0 \\ \frac{\partial ln\psi(\lambda,\sigma)}{\partial\sigma} &= \frac{1}{\sigma}(-n + \sum_{k=1}^{n} \frac{(x_{t_k} - x_{t_{k-1}} - \lambda(t_k - t_{k-1}))^2}{\sigma^2(t_k - t_{k-1})}) = 0 \end{aligned} \tag{2.4}$$

According to equation (2.4), λ and σ^2 can be obtained as follows:

$$\begin{aligned} \lambda &= \frac{\sum\limits_{k=1}^{n}(x_{t_k} - x_{t_{k-1}})}{\sum\limits_{k=1}^{n}(t_k - t_{k-1})} \\ \sigma^2 &= \frac{1}{n}\sum_{k=1}^{n} \frac{(x_{t_k} - x_{t_{k-1}} - \lambda(t_k - t_{k-1}))^2}{(t_k - t_{k-1})} \end{aligned} \tag{2.5}$$

After obtaining λ and σ^2, the probability of failure can be expressed as follows:

$$F(t) = 1 - P(x_t < w) \tag{2.6}$$

where w is the TI value of the failure point. At this point, the failure probability model was established [17]. The predicted remaining service life of the rotating machinery is calculated as follows:

$$RUT_{predicted} = (NT_{QGCCBNN} - NT_1 + 1) \times \Delta NT \tag{2.7}$$

$NT_{QGCCBNN}$ is the predicted failure probability threshold point in the power spectral entropy curve, and s is the number of rows in the reconstruction matrix P.

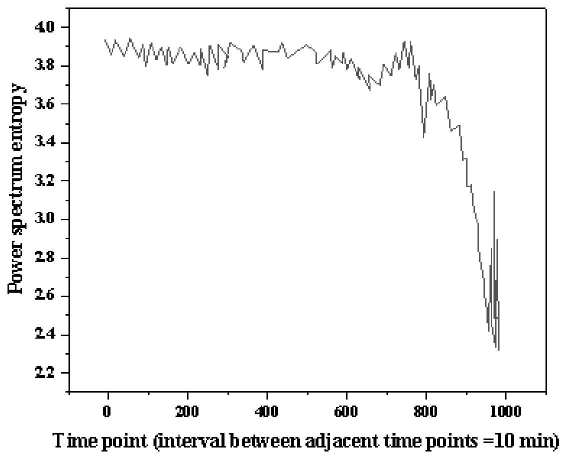

Fig. 3.1: Power spectral entropy of bearing 1

3. Example analysis.

3.1. Experimental Platform. The residual service life prediction method for rotating machinery based on QGCCBNN has been validated using rolling bearing quality data measured by the University of Cincinnati [18]. Install four ZA-2115 double row roller bearings produced by Linuo Company on rotary bearing test bench, use 2000r/min motor to drive the shaft through belt, and apply radial load of 6000 pounds to rotating shaft and bearing by spring mechanism. Install pressure sensitive ICP accelerometer on bearing seat and collect vibration data every 10 minutes.

3.2. Prediction Results of Bearing 1 Based on QGCCBNN Method.

3.2.1. Prediction process and results. Bearing 1 ran continuously for 9840 minutes (about 7 days) and began to experience outer ring failure at a later point in operation. A total of 984 sets of vibration data were collected, each with a length of 20480 points. The power spectral entropy of each set of data was calculated to obtain the power spectral entropy curve for the full life interval as shown in Figure 3.1 [19].

From the beginning to point 805, the power spectral entropy is still stable,which is the early fault; From NT2=948 to the end point,the power spectral entropy curve becomes irregular,indicating that the outer ring defects of the bearing expand rapidly and eventually become incomplete.

Next, 729 TI values are constructed from the power spectral entropy. As shown in Figure 3.2, the TI changes slowly from the starting point to point 550. After point 693 (for example, the actual TI value shown in figure 3.2 is input into the failure probability model in section 2.5, and the actual failure probability is calculated as the failure probability F(t)=90 of NT2=948), the TI is increased, indicated that the bearing was in a high speed stage and finally met the outer ring failure.

Use TI values from point 551 to point 650 as training samples, and use point 651 and its data extension (i.e. section 79 TI values) as test samples. The number of chromosomes τ=50, the update step of quantum bit phase Δw_0=0.07 π, the maximum number of chromosome iterations g_{max}=50, and the predicted mean square error threshold $E^t_{mse-min} = 5 \times 10^{-6}$ are shown in Figure 3.3. It is not difficult to find that within the interval [651729], the predicted TI value of QGCCBNN is very close to the actual value, and the trend of change between the two is highly consistent.

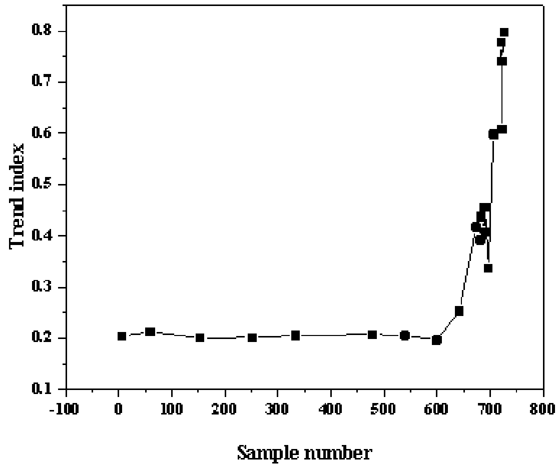

Fig. 3.2: Trend index of bearing 1

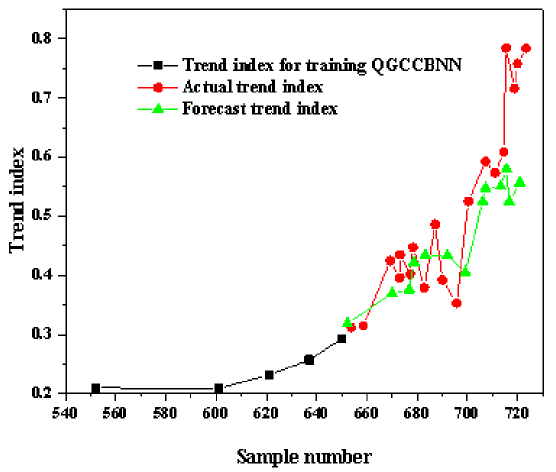

Fig. 3.3: Trend index predicted by QGCCBNN

Based on the incomplete probability model, in terms of parameters λ and σ During the calculation process, the approximate value of TI value is proposed, and then the approximate incomplete probability F(t) is calculated, as shown in Figure 3.4.

Then, predict the program's remaining lifecycle behavior 1. Because the remaining service life can often be represented by a time interval $[SN_{\text{forecast}}, SN_{\text{Lose effectiveness}}]$ between the initial prediction point SN_{forecast} and point $SN_{\text{Lose effectiveness}}$ failure, this interval corresponds to the interval $[NT_1, NT_{QGCCBNN}]$ shown in Figure 3.4, which is the predicted remaining service life of bearing 1. According to equation (2.7), $NT_1 = SN_{\text{Lose effectiveness}} + s - 1$, where s=256 is the number of rows in the reconstruction matrix P. Therefore, the predicted remaining service life is $RUL_{\text{forecast}} = (NT_{QGCCBNN} - NT_1 + 1) \times \Delta NT = 6.33h$; Meanwhile, the actual remaining life is $RUL_{\text{actual}} = (NT_2 - NT_1 + 1) \times \Delta NT = 7.17h$[20].

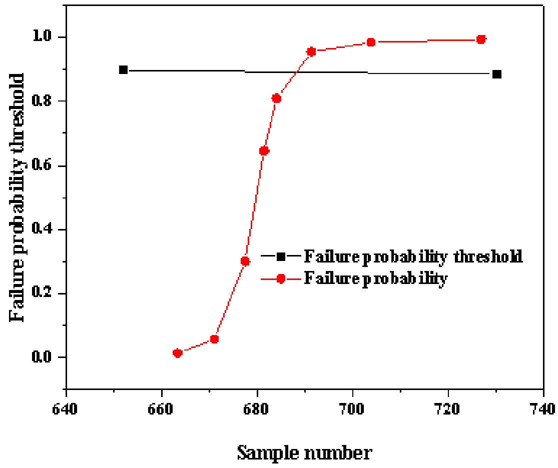

Fig. 3.4: Failure Probability Predicted by QGCCBNN

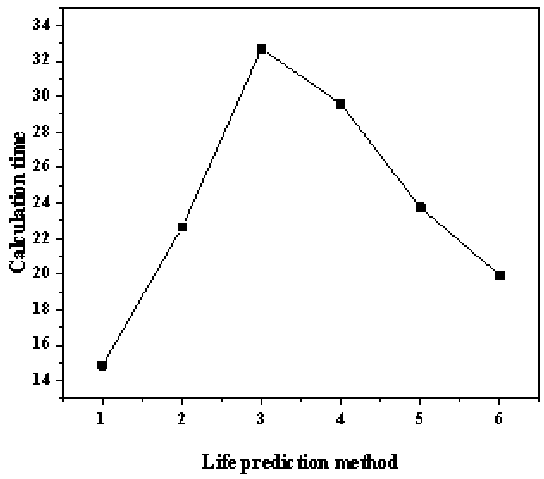

Fig. 3.5: Comparison of calculation time for remaining service life prediction methods

3.2.2. Comparative analysis with other methods. In order to ascertain the quality of QGCCBNN as a service life prediction tool for rotating machinery, the calculation time (training/training time, TI prediction time, total service life prediction time) was compared with QGCCBNN as the service life prediction method and RNN, DADNN, GRUNN, FCRBFNN, LS-SVM based methods. The results are shown in Figure 3.5. Obviously, the calculation time of the QGCCBNN based prediction method is shorter than that of the RNN, DA DNN, GRUNN, FCRBFNN, and LS SVM based methods, indicating that using QGCCBNN for predicting the remaining service life of double row roller bearings has faster convergence speed and higher computational efficiency compared to the compared methods.

4. Conclusion. When applying QGCCBNN, quantum bidirectional transmission mechanism was designed to establish the relationship between time and weight based on feedback from output network, thus improving the consistency between input data and the whole network memory, and having better nonlinear estimation ability. During the training of QGCCBNN, quantum gene chain encoding was designed to transmit and transfer information, avoiding the problems of slow convergence and high time value caused by gradient loss and gradient dispersion in the traditional value system.Therefore, QGCCBNN has better global convergence ability and faster convergence. Because of the advantages of QGCCBNN such as poor prediction ability, global convergence ability, and fast convergence, the service life prediction of rotating machinery based on QGCCBNN can achieve high prediction precision and reduce computation cost.

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