A predicting method for the health state of the rolling bearing

Hongyan Jiang a,b,c, Dianjun Fang a,c
a Tongji University, ShangHai 201804, China
b Jiangsu University of Science and Technology, ZhenJiang 212003, China
c Sino-German Institute for Intelligent Technologies and PhD Study, QingDao 266000, China
*E-mail: 1733316@tongji.edu.cn

Abstract. As an important component of rotating machinery, the health of rolling bearings is related to the normal operation of the whole machinery. A Period-Sequential Index (PSI) method was used for forecasting the three working states of the rolling bearing: health, fault, or failure. A sample from the vibration signals of the bearing, running only 2538 min because of a fault of its inner race, were tested by using the PSI algorithm. The results show that, this proposed PSI algorithm showed satisfactory forecasting quality in predicting whether the bearing is working in a healthy state or not. And, the value of the mean absolute percentage error at a fault state or a failure state was higher than that at a health state.

1. Introduction
Bearing failure often occurred in rotating machinery [1,2], which could result in breakdown of facility as well as costly downtime. So bearing monitoring was a big challenge of machine maintenance and automation processes. Especially in a big data era, a large number of time-serie datasets can be continuously generated in the bearing monitoring system [3,4], which has received much interest in predicting the health state of the bearing. Now, growing numbers of new algorithms have been proposed to forecast time series, such as exponential smoothing (ES), moving average (MA), support vector machine (SVM) and auto-regressive integrated moving average (ARIMA) method, and so on [5-9]. However, no traditional methods are suitable for the prediction of the bearing health. In the study, a new Period-Sequential Index (PSI) algorithm with four factors, which are period index, sequential index, small period index and super sequential index, is firstly introduced to predict the health state of the running rolling bearing.

2. Theoretical model
Finding Index-values carrying implicitly structure information usable, a heuristic method, the Period-Sequential Index (PSI) method [10], is used to predict the serial time-series data set. Fig.1 shows the schematic diagram of the PSI algorithm. $H_2$, $H_1$ denote historical periods, i.e. the year before last and last year. $H_0$ represents the forecasting period. $PI(t_i)$, $SI(t_i)$, $pi(t_i)$, $si(t_i)$ describe the period index, sequential index, small period index and super sequential index, respectively.

2.1 Period index $PI(t_i)$
The period index indicates the relationship between the historical data and the reference value. The period index can be explained through equation (1) and (2),

$$PI_{-2}(t_i) = \frac{y_{-2}(t_i)}{K_{-2}}$$ (1)
\[
PL_{-1}(t_i) = \frac{y_{-2}(t_i)}{K_{-1}}
\]

where \(y_{-2}(t_i)\) and \(y_{-1}(t_i)\) describe the historical data at time of \(t_i\) during the period of \(H_2\) and \(H_1\), respectively. \(K_2\) and \(K_1\) are reference functions of period index. A standard period average is originally set to be a reference function of period index, and where it is defined as a constant.

\[
SI_{-2}(t_i) = \frac{y_{-2}(t_{i+1})}{y_{-2}(t_i)}
\]

\[
SI_{-1}(t_i) = \frac{y_{-1}(t_{i+1})}{y_{-1}(t_i)}
\]

2.2 Sequential index \(SI(t_i)\)

The sequential index indicates the relationship between two adjacent historical data with the defined time steps. It is calculated through expression (3) and (4).

\[
pl_{-2}(t_i) = \frac{y_{-2}(t_{i+1})}{K_{-2}}
\]

\[
pl_{-1}(t_i) = \frac{y_{-1}(t_{i+1})}{K_{-1}}
\]

2.3 Small period index \(pi(t_i)\)

The small period index indicates the relationship between the historical data and the reference value, which can be explained through equation (5) and (6),

\[
si_{-2}(t_i) = \frac{y_{-2}(t_{i+2})}{y_{-2}(t_i)}
\]

\[
si_{-1}(t_i) = \frac{y_{-1}(t_{i+2})}{y_{-1}(t_i)}
\]

where \(k_{-2}\) and \(k_{-1}\) are reference functions of small period index. Here a small period (such as three months) average, because of seasonal factors, is originally set to be a reference function of small period index.

2.4 Super sequential index \(si(t_i)\)

The super sequential index indicates the relationship between two interval historical data with the defined steps. It is calculated through expression (7) and (8).

\[
F(t_i) = c \cdot PL(t_i) \cdot K_0 + d \cdot SL(t_{i-1}) \cdot y_0(t_{i-1}) + e \cdot pi(t_i) \cdot k_0 + f \cdot si(t_{i-2}) \cdot y_0(t_{i-2})
\]

where,

\[
PL(t_i) = a \cdot PL_{-2}(t_i) + b \cdot PL_{-1}(t_i)
\]
\[ SL(t_{i-1}) = a \cdot SL_{i-2}(t_{i-1}) + b \cdot SL_{i-1}(t_{i-1}) \]  
\[ p_i(t_i) = a \cdot p_{i-2}(t_i) + b \cdot p_{i-1}(t_i) \]  
\[ s_i(t_{i-2}) = a \cdot s_{i-2}(t_{i-2}) + b \cdot s_{i-1}(t_{i-2}) \]  
\[ K_0 = \gamma_0 \cdot K_{-1}; \quad k_0 = \gamma_0 \cdot k_{-1} \]  
\[ \gamma_0(t_i) = \gamma_0 \cdot y_1(t_i); \quad \gamma_0(t_{i-2}) = \gamma_0 \cdot y_1(t_{i-2}) \]

where, \( c, d, e, f = 0.25 \) are the weighing factors of forecasting equation (9). \( K_0 \) and \( k_0 \) are the correction coefficients for period index and small period index, respectively. \( a, b = 0.5 \) are the weighing factors of period index in \( H_3, H_1 \) or the factors for sequential index. \( \gamma_0 \) is the prediction factor. The mean absolute percentage error (MAPE), given in the below formula (16), is used to evaluate the obtained results.

\[ \text{MAPE} = \frac{1}{N} \sum_{i=0}^{\infty} \left| \frac{y_0(t_i) - F(t_i)}{y_0(t_i)} \right| \times 100\% \]

where \( y_0(t_i) \) is the measured value at time of \( t_i \) during \( H_0 \); \( F(t_i) \) is the forecasting value at time of \( t_i \) during \( H_0 \). \( N \) represents the number of model forecasting samples.

3. Simulation results and discussions

![Figure 2. The mean square root (RMS) values of the bearing horizontal signals.](image)

A sample [11] from the horizontal vibration signals of the rolling bearing were used and trained to forecast the three working states [12]: health (RMS≤2), fault (2<RMS≤5), and failure (RMS>5). In this sample, the rolling bearing with 10 kN load was operated at a speed of 2400 rpm, and run only 2538 min because of a fault of its inner race. The sampling frequency and period were set to 25.6 kHz and 1 min, respectively. Fig.2 showed the mean square root values of the bearing horizontal signals. Then, using the equation (9), simulation results were obtained as follows.

Fig.3, Fig.4 and Fig.5 showed the bearing horizontal signals and prediction in different working states. First, after training the historical datasets from 480 min to 540 min, the RMS values from 540 min to 570 min were predicted by using the PSI algorithm, as shown in Fig.3. It was seen from Fig.3 that, the predicted RMS values were all less than 2 g, and very close to the observed values, and a lower MAPE value of 1.61% was achieved by Eq. (16). The forecasting results also showed that, the bearing worked at a health state now between 540 min and 570 min. Then, the periodic detection results from 2400 to 2460 min and the prediction results between 2460 and 2490 min, were shown in Fig.4. It was seen from Fig.4 that, the real value and the predicted value reached 2.0 g at the running time of 2465 min and 2469 min, respectively. Although a time-lag of 4 minutes, the fault state of the bearing was still quickly predicted by using the PSI method. Finally, the simulation results in the working failure state was further shown in Fig.5. The predicted value was just more than 5.0 g at the running time of 2533 min, which nearly was equivalent to the real failure time of 2532 min. However, the higher MAPE values of 4.42%
and 6.26% were also achieved by Eq. (16) when the bearing worked in a fault state and failure state, respectively. The example showed that, the proposed PSI algorithm achieved a high accuracy in predicting whether the bearing was working in a healthy state or not.

4. Conclusions
(1) A Period-Sequential Index (PSI) method with four factors, which are period index, sequential index, small period index and super sequential index, was applied for forecasting the three working states of the rolling bearing: health, fault, or failure.
(2) During a health state, the predicted RMS values were less than 2 g and close to the observed values. In a failure state, the predicted value was just more than 5.0 g at the running time of 2533 min, which nearly was equivalent to the real failure time of 2532 min. The proposed PSI method showed satisfactory forecasting quality in predicting whether the bearing is working in a healthy state or not.
(3) The lower MAPE value of 1.61% was achieved in the health state; while the higher MAPE values of 4.42% and 6.26% were achieved when the bearing worked in a fault state and failure state, respectively. So the MAPE value at a fault state or a failure state was higher than that at a health state.

Figure 3. The bearing horizontal signals and prediction in health state.

Figure 4. The bearing horizontal signals and prediction in fault state.
The mean square root values of the horizontal vibration signals (g)
The running time of the bearing (min)

Figure 5. The bearing horizontal signals and prediction in failure state.

Nomenclature

\( a, b \): weighing factors of period index or sequential index
\( c, d, e, f \): weighing factors of forecasting equation
\( F(t_i) \): forecasting value at time of \( t_i \) during \( H_0 \) period
\( G() \): measurement equation for forecasting value
\( H_2, H_1, H_0 \): historical period
\( H_0 \): forecasting period
\(-2, -1, 0 \): subscripts, and represent during period of \( H_2, H_1, H_0 \), respectively
\( k_0 \): correction coefficients for small period index
\( k_1, k_2 \): reference function of small period index
\( K_0 \): correction coefficients for period index
\( K_1, K_2 \): reference function of period index
\( MAPE \): mean absolute percentage error
\( N \): number of forecasting samples
\( p_i(t_i) \): small period index at time of \( t_i \)
\( P_i(t_i) \): period index at time of \( t_i \)
\( s_i(t_i) \): super sequential index at time of \( t_i \)
\( S_i(t_i) \): sequential index at time of \( t_i \)
\( t_i \): time point
\( y_0(t_i) \): measured value at time of \( t_i \) during \( H_0 \) period
\( y_1(t_i) \): measured value at time of \( t_i \) during \( H_1 \) period
\( y_2(t_i) \): measured value at time of \( t_i \) during \( H_2 \) period
\( \gamma_0 \): planning factor

Acknowledgment
The authors gratefully acknowledge the support of key projects for international cooperation in scientific and technological innovation between governments, through grant No. 2017YFE0101600.

References
[1] Huang R.; Xi L.; Li X., Liu C., Qiu H., Lee J. Residual life predictions for ball bearings based on self-organizing map and back propagation neural network methods. Mechanical Systems and Signal Processing 2007, 21: 193–207.
[2] Narendiranath Babu T.; Devendiran, S; Aravind Arun; Rakesh A.; Jahzan M. Fault Diagnosis on Journal Bearing Using Empirical Mode Decomposition. Materials Today: Proceedings, 2018, 5:12993–13002.
[3] Wang Z.; Du W.; Wang J. Research and Application of Improved Adaptive MOMEDA Fault Diagnosis Method, Measurement. 2019, 140: 63-75.
[4] Wang Z.; He G; Du W.; Zhou J.; Han X.; Wang J.; He H.; Guo Xi.; Wang J.; Kou Y. Application of Parameter Optimized Variational Mode Decomposition Method in Fault Diagnosis of Gearbox.
IEEE Access. 2019, 7:44871-44882.

[5] Billah, B.; King, M.L.; Snyder, R.D.; Koehler, A.B. Exponential smoothing model selection for forecasting. International Journal of Forecasting, 2006, 22: 239-247.

[6] Barrow, D.K. Forecasting intraday call arrivals using the seasonal moving average method. Journal of Business Research, 2016, 69: 6088-6096.

[7] Stul, M.; Stul, K.; Leenders, R.; Butaye, L. Development of a SVM Prediction Model to Optimize the Energy Consumption of Industrial Installations by Detecting and Classifying Errors at an Early S. International Journal of Mechanical Engineering and Robotics Research, 2017, 6: 108-113.

[8] Eltayb, N. S. M.; Hamdy, A. LS-SVM Approach for Predicting Frictional Performance of Industrial Brake Pad Materials. International Journal of Mechanical Engineering and Robotics Research, 2018, 7: 105-112.

[9] Büyüksahin, U.C.; Ertekin S. Improving forecasting accuracy of time series data using a new ARIMA-ANN hybrid method and empirical mode decomposition. Neurocomputing, 2019, 361:151-163.

[10] Jiang H.; Fang D.; Spicher K.; Cheng F; Li B. A new period-sequential index forecasting algorithm for time series data. Applied sciences, 2019, 9: 4386: 1-12.

[11] Xi’an Jiaotong University-Sun Rising Science and Technology Joint Laboratory-the experimental data of accelerated life of bearings, 2020, https://www.sumyoungtech.com.cn/news/xianjiaoda-yangkejilianheshiyanshiabuzhouchengjiasushoumingshiyanshujuzhulindephmyanju.html.

[12] Li Y.; Ma X.; Zhao Y. A condition-based maintenance model for a three-state system subject to degradation and environmental shocks. Computers & Industrial Engineering, 2017, 105: 210-222.