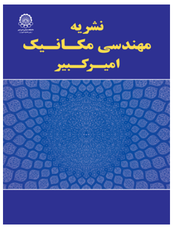

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Prognostics of rolling element bearings using shock pulse method and vibration method records and employing feedforward neural-network

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ABSTRACT: Early fault detection of the rolling element bearings has a very important role in increasing the reliability of rotating machines. It leads to better decision-making for maintenance activities. In recent decades, the shock pulse method has been developed to detect faults in the early stage of rolling element bearings degradation. In this paper, the accuracy of the remaining useful life estimation using extracted features from vibration signals and that from the shock pulse method are compared. In this regard, a set of accelerated life tests on rolling element bearings were designed and performed. Both shock pulse signals and vibration signals of the under-test rolling element bearings were recorded. Then two models based on feed-forward neural-network are developed to predict the remaining useful life of rolling element bearings. In the first model, only extracted features from vibration signals are fed for remaining useful life prediction. In the second model, the extracted features from shock pulse method are fed too. The results show that using shock pulse method-based features improves the accuracy of remaining useful life estimation. Also, using the health indicators extracted from vibration analysis and shock pulse method leads to a better estimating of the degradation behavior.

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1- Introduction

Accurate failure time estimation of mechanical components plays a significant role in enhancing the reliability and maintenance schedule of the machines. Rolling Element Bearings (REBs) failures are the most probable failure mode of the industrial rotating machinery [1]. Therefore, many researchers have studied the prognostics methods for the REB. The majority of the researches are used vibration data for prognostics. One of the main categories of prognostic approaches is known as data-driven methods. These methods have been developed extensively in the last two decades [2, 3]. Generally, data-driven methods are categorized into statistical methods and Artificial Intelligence (AI) methods. All AI methods include two stages. In the first stage, Condition Monitoring (CM) data of some run-to-failure tests are used for training and developing an AI model. Then, in the second stage, the trained model is employed for predicting the Remaining Useful Life (RUL) of the other similar components by using their CM data history. In recent decades, Shock Pulse Method (SPM) has been developed to detect faults in the early stage of REBs degradation. Some papers have compared the capabilities of vibration analysis and SPM in REBs early fault detection [4-7]. However, reviewing the literature, the feathers extracted from the SPM have not been used for prognostics of REBs.

In this study, a set of accelerated life tests have been planned and conducted and vibration data, as well as shock pulse data, have been recorded regularly during the whole life of each REB. Two models based on the Feedforward Neural Network (FFNN) have been developed to predict the RUL of REBs for studying the effect of input features. Comparing the prediction results of the two models show that the accuracy increases as the SPM feature are employed for RUL prediction.

2- Methodology

In this research, the FFNN method is employed for the RUL prediction of the REBs. The proposed algorithm is summarized in a flowchart shown in Fig. 1. Also, Figs. 2 and 3 show the structures of two proposed FFNN models. These two models include two layers. The Levenberg–Marquardt (LM) backpropagation algorithm is used for training the model. The output of both models are the estimated normal RUL (estimated RUL per useful life). The inputs of model 1 are the current life (time), the Root Mean Square (RMS) of the last acceleration signal and its derivative (*dRMS*), and the introduced vibration health indicator (*Tv*) which is defined as the elapsed time from the first detection of the defect by vibration signal analysis. The inputs of model 2 are those of model 1 as well as the extracted feature from SPM (*HDm*) and its derivative (*dHDm*), and the SPM health indicator (*Ts*) which is defined as the elapsed time from the first detection of the defect by SPM.

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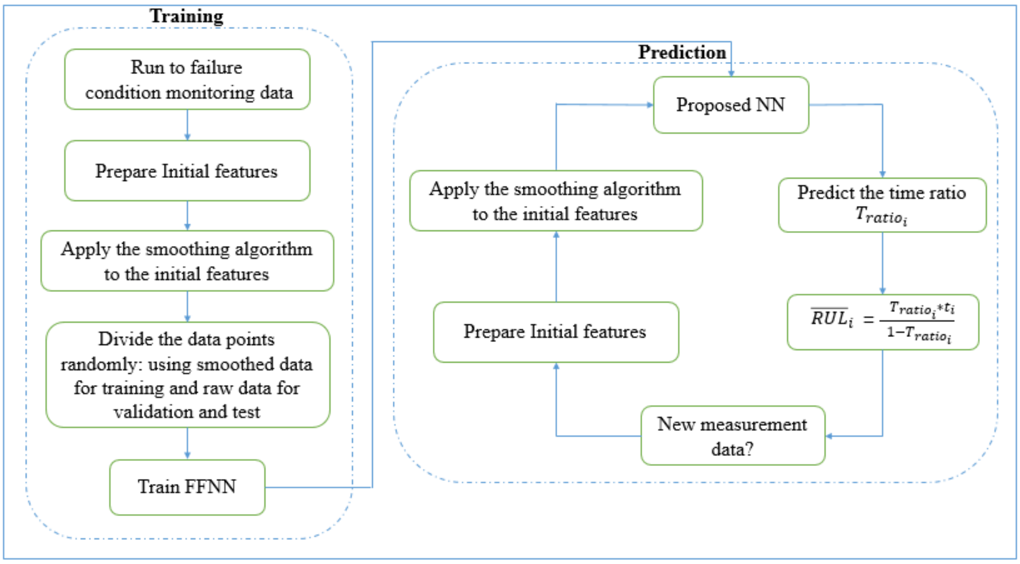

Fig. 1. The proposed algorithm for RUL prediction of REBs

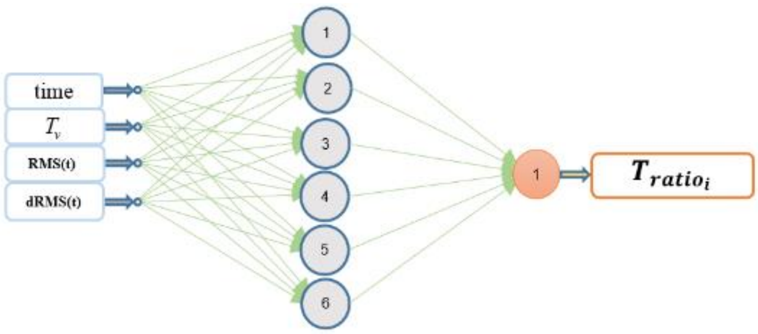

Fig. 2. The structure of the first proposed model

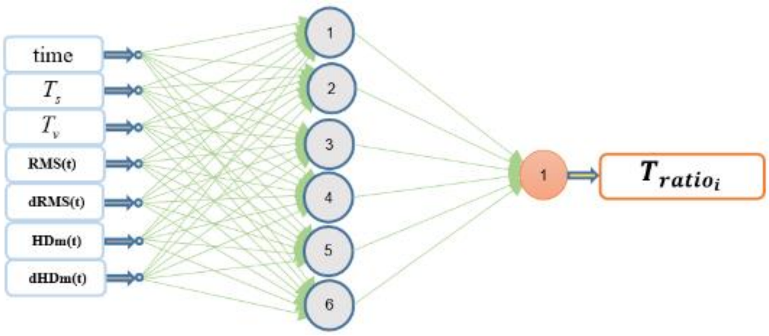

Fig. 3. The structure of the second proposed model

3- Experimental Setup

To compare SPM and vibration analysis, a set of accelerated life tests on REBs were designed and conducted. The test rig is shown in Fig. 4. It hosts a test REB at one end of the shaft. Two larger REBs also support the shaft. The shaft is coupled to an AC electromotor (as a driver of the system) through a pulley and belt mechanism. Experiments were performed in constant operating conditions including 2000 rpm rotational speed and 9000 N radial load. Both shock pulse and vibration of test REB were recorded during the test through a shock pulse sensor and an accelerometer, respectively. Totally, six run-to-failure tests were conducted and their results will be analyzed in the next section.

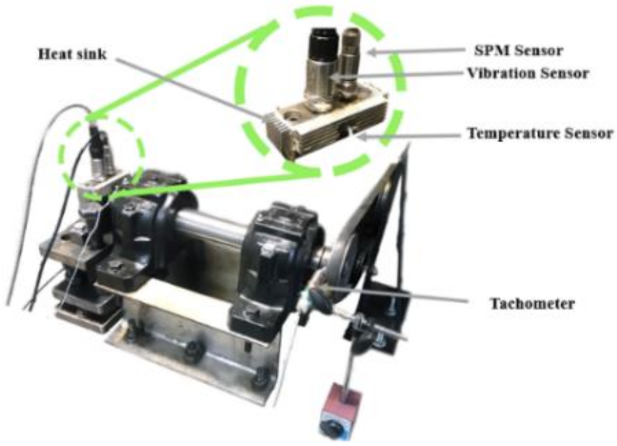

Fig. 4. The test-rig for the REB accelerated-life test

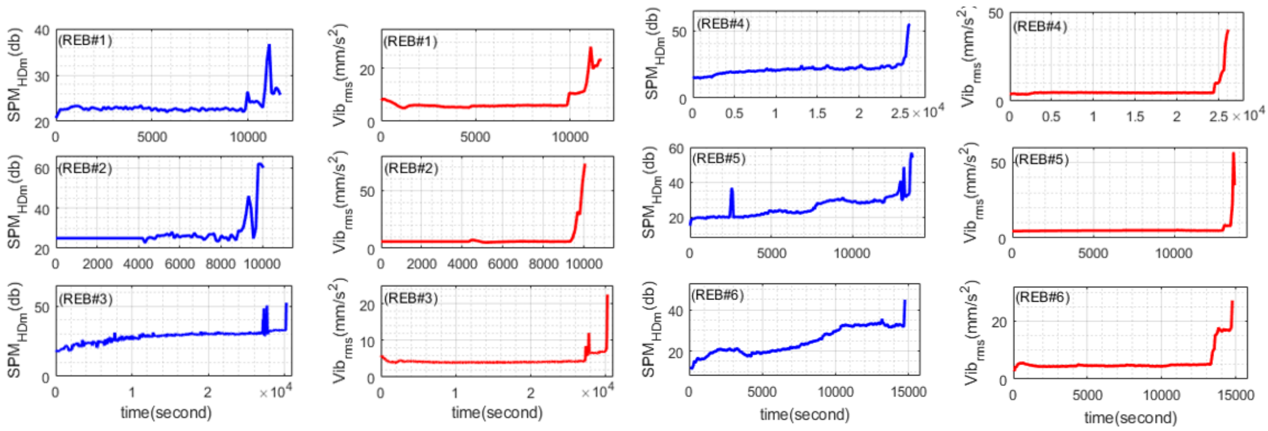

Fig. 5. The comparison between the trend of SPM_{HDm} and V_{rms} for all six accelerated-life experiments

Table 1. The average of two introduced errors for all 15 cases of two proposed models

	$err_{30\text{-}90}$	$Err_{30\text{-}90}$	$err_{30\text{-}90}$	$Err_{30\text{-}90}$
Average error (%)	33.7	58.2	22.1	40.4

4- Results and Discussion

The trend of *RMS* extracted from the vibration acceleration signals (Vib_{rms}), and the trend of *HDm*, extracted from the shock pulse signals (SPM_{HDm}) for all accelerated-life tests of REBs are plotted in Fig. 5. All possible cases of selecting four tests out of six tests (15 cases) are considered for training the two models. Then, each trained model is employed for predicting the RUL of the two other remaining tests in each case. The parameter $Err_{30\text{-}90}$ is introduced to investigate and compare the error of two proposed models. This parameter is defined as the maximum error of predicted time ratio T_{ratio}, between 0.3 and 0.9 of the whole life of test REB. In the same way, $err_{30\text{-}90}$ is introduced the average value of error between 0.3 and 0.9 of the whole life. Table 1 reports the average of two introduced errors for all 15 cases for each model.

The reported results correspond to the thirty predictions in 15 cases. Because of the space limitation, only two predictions (out of thirty) are presented here. To this aim, the results of training the two models with data of REBs 3, 4, 5, and 6 and applying them fore predicting REB 1 are depicted in Figs. 6 and 7.

5- Conclusions

In this paper, two data-driven models based on the use of FFNN were developed to predict the *RUL* of REBs. In the first model, only extracted features from vibration signals were used for *RUL* prediction. In the second model, the extracted features from SPM were used too. The results showed that the performance of the second model in which the features extracted from SPM were considered as input, led to results with less error. Meanwhile, using the health indicators extracted from vibration analysis and SPM leads to a better estimating of the degradation behavior.

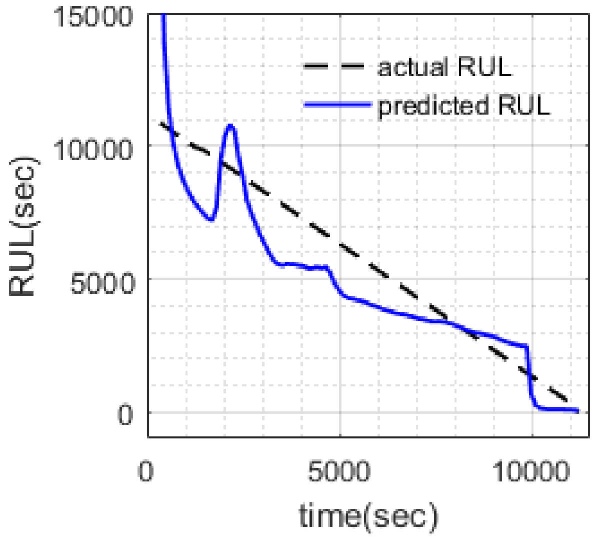

Fig. 6. Predicting RUL of REB 1 with Model 1 (with training datasets including REBs 3, 4, 5, and 6)

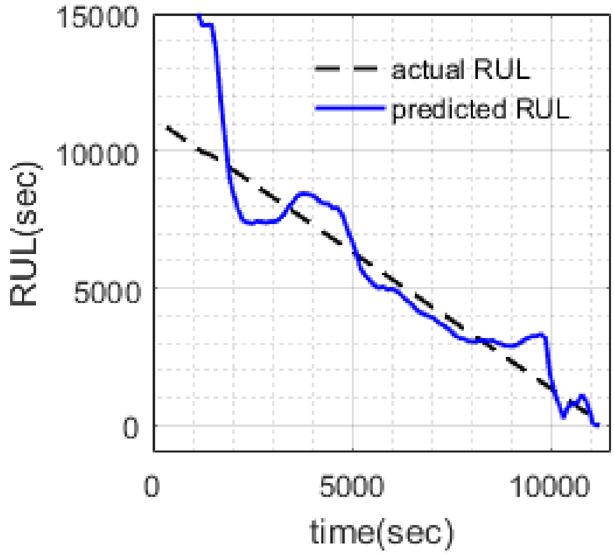

Fig. 7. Predicting *RUL* of REB 1 with Model 2 (with training datasets including REBs 3, 4, 5, and 6)

References

[1] P. Albrecht, J. Appiarius, E. Cornell, D. Houghtaling, R. McCoy, E. Owen, D.J.I.t.o.e.c. Sharma, Assessment of the reliability of motors in utility applications, (3) (1987) 396-406.

[2] Y. Lei, N. Li, L. Guo, N. Li, T. Yan, J.J.M.S. Lin, S. Processing, Machinery health prognostics: A systematic review from data acquisition to RUL prediction, 104 (2018) 799-834.

[3] M. Behzad, H.A. Arghand, A.J.P.o.t.I.o.M.E. Rohani Bastami, Part C: Journal of Mechanical Engineering Science, Remaining useful life prediction of ball-bearings based on high-frequency vibration features, 232(18) (2018) 3224-3234.

[4] N. Tandon, K.J.N. Kumar, V. Worldwide, Detection of defects at different locations in ball bearings by vibration and shock pulse monitoring, 34(3) (2003) 9-16.

[5] N. Tandon, G. Yadava, a.K.J.M.s. Ramakrishna, s. processing, A comparison of some condition monitoring techniques for the detection of defect in induction motor ball bearings, 21(1) (2007) 244-256.

[6]] A.D. Mehdi Behzad, Hesam Addin Arghand, Using Shock Pulse Method for Early Fault Detection of Rolling Element Bearings and Comparing with Vibration Envelope Technique, Amirkabir J. Mech. Eng., (2019).

[7] T.J.A.S.I.W.P. Sundström, SPM Instruement AB, An introduction to the SPM HD method, (2010).

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