A Feature Fusion-Based Prognostics Approach for Rolling Element Bearings

Ugochukwu Ejike Akpudo[1*] and Jang-Wook Hur[2]

Department of Mechanical Systems Engineering
Kumoh National Institute of Technology
Gumi, Republic of Korea

*ugoakpudo@kumoh.ac.kr, hhjw88@kumoh.ac.kr

1. Introduction

A Rolling element bearing (REB) is the heart of rotating components; however, its failure can have daunting effects; hence the need for accurate condition monitoring and prognostics. In view of achieving a more comprehensive condition assessment and prognostics of rolling element bearings, this study proposes a kernel principal component analysis (KPCA) feature fusion technique for degradation assessment, and a deep learning model for prognostics.

2. Body of abstract

The emerging concept of reliability has shown evident exponential growth against traditional preventive maintenance approaches and is showing strong dependence on the more robust Big data-driven Prognostics and health management (PHM) approaches which are deeply rooted in big data analytics, statistical model-based, and data-driven prognostics methods [1].

In view of achieving a more comprehensive condition assessment and prognostics of REBs, this study proposes a KPCA feature fusion technique for degradation assessment, and a deep learning model for prognostics. As verified in [2-3], the KPCA as a feature fusion and dimensionality reduction technique better reflect degradation behavior of systems.

Deep Long short-term memory (DLSTM) for time-series forecasting have recently shown remarkable advantages over standard recurrent neural networks in weather forecasting [4], speech recognition [5], etc., and subsequently employed for the proposed study.

The KPCA-LSTM model performance was validated with a run-to-failure experiment of a rolling element bearing and measured for accuracy against a single LSTM model, a back propagation neural network (BP) model, and a support vector regression (SVR) model [6]. The results show that the proposed model not only reflects a more monotonic bearing degradation trend; it also yields better prognostics results.

3. Principle of Principal Component Analysis

By mapping several time-based n-dimensional features (root mean square, kurtosis, crest factor, etc.). to new reconstructed k-dimensional features (k < n), a more comprehensive degradation index which better reflect bearing degradation trend can be constructed as input feature vector for a designed prognostics model.

Given a sample set X = $\{x_1, x_2, \dots, x_m\}$ and a new coordinate system after transformation is $\{w_1, w_2, \dots, w_d\}$ where w_i is the standard orthogonal basis vector, the projection of x_i, in the new space is $W^T x^i$ and the variance of the projected sample points x^i can be expressed in (1) as:

$$\sum_i^n (W^T x^i x_i^T W) \tag{1}$$

Applying the Lagrange multiplier method:

$$XX^T W = \lambda W \tag{2}$$

performing eigenvalue decomposition on the covariance matrix XX^T yields eigenvalues: eigenvalues: $\lambda_1 \geq \lambda_1 \geq \cdots \lambda_m$. The number of principal components selected depends on the variance contribution rate and cumulative variance contribution rate which are expressed mathematically in (3) and (4) respectively:

$$\eta_i = \frac{100\%\lambda_i}{\sum m \lambda_i} \tag{3}$$

$$\eta\Sigma(\mathrm{p}) = \sum_i^p \eta_i \tag{4}$$

The resultant PCA is to form W = $\{w_1, w_2, \dots, w_p\}$ where w_p principal component contains most of the information that can be provided by the original variables.

4. Long Short-Term Memory (LSTM)

A network of LSTM cells forms a larger deep neural network, which can reflect the long-term memory effect. A typical LSTM cell as shown in Fig. 1 comprises of the input gate I_t, forget gate f_t, and output gate O_t.

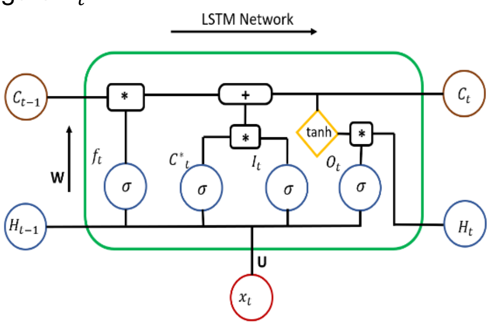

Fig.1 A single LSTM cell

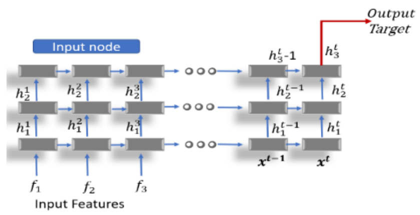

Fig.2 LSTM network at different time steps

$$f_t = \sigma\left(u_f x_t + w_f H_{t-1} + b_f\right) \quad (5)$$
$$i_t = \sigma(u_i x_t + w_i H_{t-1} + b_i) \quad (6)$$
$$O_t = \sigma(u_o x_t + w_o H_{t-1}) + b_0) \quad (7)$$

The singled layered I_t, O_t and f_t contain sigmoid activation functions while the candidate layer $C^*{}_t$ (8) contains the *tanh* activation function. The current cell memory C_t emanates from $C^*{}_t$, and an element-wise multiplication of the previous memoryC_{t-1} and f_t as shown in (9).

$$C^*{}_t = tanh(w_c \cdot H_{t-1} + u_c x_t + b_c) \quad (8)$$
$$C_t = f_t \cdot C_{t-1} + i_t \cdot C^*{}_t \quad (9)$$

Each LSTM cell output H_t is a function of the last output layer O_t and the tanh activated function of C_t as shown in (10). The averaged sum over time is represented in (11) and shown in Fig. 2.

$$H_t = O_t \cdot \tanh(C_t) \quad (10)$$
$$H = \sum_{i=1}^{n} H_j/n \quad (11)$$

5. Proposed KPCA-DLSTM model

Fig. 3 shows a pictorial view of the proposed KPCA-DLSTM for degradation assessment and RUL prediction of the test bearing.

6. Experimental setup and results

The run-to-failure experiment on four Rexnord ZA-2115 double row bearings was conducted by the NASA and the results reported in [7].

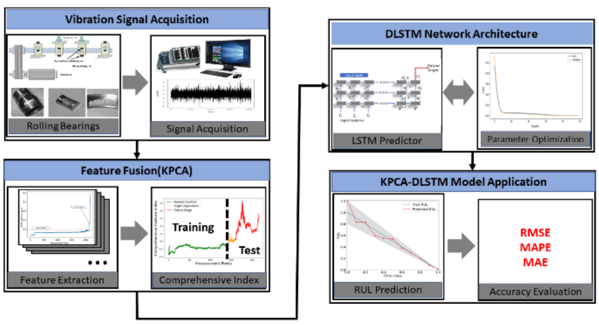

Fig.3 Framework of proposed prognostics model

7. RUL prediction results

Fig. 4 shows the RUL prediction result of the proposed model on Bearing3.

8. Performance Evaluation

Table 1 presents the performance evaluation results of the proposed model on bearing3.

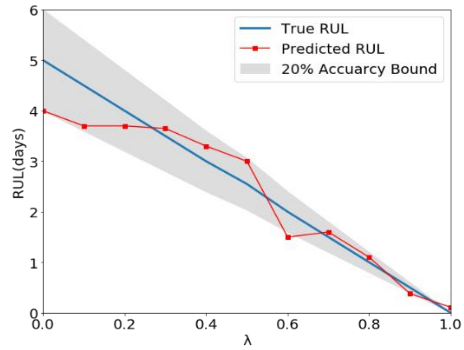

Fig.4 RUL prediction Result on bearing3

Table 1 performance evaluation results

Metric	Basic LSTM	BP	SVR	DLSTM
RMSE	0.03	0.0287	0.016	0.010
MAPE	1.9216	1.5832	1.0323	0.7137
MAE	0.027	0.0169	0.0108	0.0097

References

[1] K. L. Tsui, N. Chen, Q. Zhou, Y. Hai, and W. Wang, Prognostics and Health Management: A Review on Data Driven Approaches, *Mathematical Problems in Engineering, vol. 2015,* Article ID 793161, (2015).

[2] L. Duan, F. Zhao, J. Wang, N. Wang, and J. Zhang, An Integrated Cumulative Transformation and Feature Fusion Approach for Bearing Degradation Prognostics, *Shock and Vibration, vol. 2018,* Article ID 9067184, (2018).

[3] X. Zhang, R. Xu, C. Kwan, S. Y. Liang, Q. Xie and L. Haynes, An integrated approach to bearing fault diagnostics and prognostics, *Proceedings of the 2005, American Control Conference, 2005., Portland, OR, USA,* (2005) 2750-2755.

[4] A. G. Salman, Y. Heryadi, E. Abdurahman and W. S. Uyili, Weather Forecasting Using Merged Long Short-Term Memory Model (LSTM) and Autoregressive Integrated Moving Average (ARIMA) Model, *Journal of Computer Science,* 14 (7) (2018) 930 – 938.

[5] I. Medennikov and B. Anna, LSTM-Based Language Models for Spontaneous Speech Recognition, *International Conference on Speech and Computer*, (2016) 469-475

[6] H. Shao, H. Jiang, X. Li, T. Liang, Rolling bearing fault detection using continuous deep belief network with locally linear embedding, *Computers in Industry Volume 96*, (2018) 27-39

[7] H. Qiua, J. Lee, J. Lin, G. Yu, Wavelet filter-based weak signature detection method and its application on rolling element bearing prognostics, *Journal of Sound and Vibration,* 289 (2006) 1066–1090.