Remaining Useful Life Prediction for Aircraft Engines Based on Grey Model

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***Abstract*—Assessing the health status and predicting the remaining useful life (RUL) of system can be carried out effectively by prognostics and health management (PHM). It is a significant guarantee to enhance the security and economy of complex systems such as aircraft engines. A new approach for aircraft engines RUL prediction is proposed to fully assess the health status of the engines. Firstly, the health indicator model is constructed by liner regression. Secondly, the improved grey model GM(1,1) is constructed based on the health indicator (HI). Finally, the system RUL is obtained by the improved GM(1,1) model. A case study is performed on C-MAPSS aircraft engine datasets examining the validity of approach proposed by us. According to the experimental results, a better prediction accuracy is given by the proposed method compared to traditional method.**

Keywords-component; liner regression; health indicator; grey model; RUL prediction

I. Introduction

Prognostics and health management (PHM) is a method that assess security of an actual life cycle of a system, reducing system risk by predicting the occurrence of failures [1]. PHM technology can effectively improve the security and reliability of complex systems, and equipment maintenance are especially important in national defense, aerospace, manufacturing etc. Aircraft engine is one of the typical complex systems. A core technology in PHM is remaining useful life (RUL) prediction. Predicting the RUL of engines enables effective system-level maintenance and provides important information for maintenance decisions. How to build a Health indicator (HI) is a key issue which reflecting degradation trend of the system. This is because the accuracy of RUL prediction can be enhanced and the model of prediction can be simplified by reasonable health indicators.

The current RUL prediction methods are mainly divided into three types: mechanism-based methods, data-driven methods, and a combination of the two [2]. Mechanism-based methods can more accurately give the system degradation process, Haile et al [3] used the most commonly used Paris-Erdogan (PE) model in the RUL prediction of mechanical equipment to model the crack degradation trend of the main components on the rotorcraft. Zhao et al [4] proposed a prediction frame which can be used on gear transmission system, using gear finite element model and damage propagation model to model the gear degradation and RUL prediction. However, the mechanism modeling in the actual industrial process is very difficult, and many complex equipment can not accurately establish the mechanism model. Data-driven method can model the degradation process only by using the observed data of equipment operation, and it has gradually become the mainstream research method. Zhang et al [6] used a blast furnace temperature monitoring data combined with two stochastic processes for describing degradation process of a system in a jumping diffusion process of a non-homogeneous composite Poisson process, and the degeneration model and RUL prediction of blast furnace are carried out. Wen et al [7] proposed a multiphase modeling method for degenerate signals under Bayesian framework, and used improved particle filter algorithm to predict RUL. Zhang et al [8] proposed an iterative estimation method to identify the degradation state using Kalman filtering and expectation maximization algorithm, and studied the RUL prediction of nonlinear multi-degenerate systems under common noise. Wang et al [9] selected different kernel parameters for correlation vector machine regression to get the model of the bearing degradation process, and combined with the exponential model to enhance the RUL prediction accuracy. Yu Yong et al [10] analyzed the progress of data-driven RUL prediction based on the covariate method, and summarized the existing problems and challenges. Liu et al [11] proposed the method of device life assessment basing on evidence reasoning and confidence rule base, and more reliable life assessment results can be obtained by the effective reduction of limited data. Chen et al [12] used GM(1,1) models combined with autoregressive integrated moving average (ARIMA) for online RUL prediction for lithium ion batteries. Peng and Dong [13] presented a hybrid prediction method which combined two methods, one of them is age-dependent hidden Markov model (HMM) and the other is grey model (GM) to predict the health of engineering assets.

According to the object system degradation behavior reflected by the data, namely HI partitioning, there are two types of data-driven RUL prediction methods: direct prediction method and indirect prediction method [14]. The direct prediction method is to use the original data directly as the HI of the system. Usually, the HI curve obtained by such methods has poor performance, which is not conducive to the

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subsequent prediction of RUL. Extracting features of raw data is the normal operation of the indirect prediction method, performing features fusion if necessary and obtaining the system HI through a combination of various features. The indirect HI construction method can more effectively reflect the system degradation process and facilitate the prediction of RUL, so extensive research on it has been done in recent years. Traditional indirect HI construction methods mainly have two categories, basing on signal processing methods, for instance, calculating the rms value [15], wavelet analysis [16], and machine learning based methods, for instance, the principal component analysis (PCA) [17], support vector machine (SVM) [18], neural network [19]. Recently, the theory of deep learning has rapidly emerged on many fields, such as speech recognition [20], fault diagnosis [21] with its powerful modeling and characterization capabilities. And gradually applied in the field of forecasting and health management [22]. Hu et al [23] used a limit learning machine and a self-encoder to form a deep network, and obtained a bearing HI curve with better noise immunity, but did not predict RUL. Liao et al [24] using a restricted Boltzmann machine combined with a self-organizing mapping network for constructing HI, and the prediction accuracy of bearing RUL is effectively enhanced.

We propose an approach which predicting RUL from the perspective of constructing HI based on the above research. In this proposed approach, HI is constructed by liner regression for it has the advantages of easy operation, linearity and good robustness. After constructing the HI, the trend of HI is predicted by improved GM(1,1) model, then RUL could be obtained. By taking logarithmic operations and sliding window prediction, the RUL prediction accuracy can be effectively improved. Verifying validity of the approach proposed by us, a case study is performed on C-MAPSS aircraft engine datasets.

II. THE ENGINE SYSTEM AND DATASET

A. Engine Model Description

An aircraft engine is an important component of aircraft that is used to generate mechanical power. The main elements of our studied engine model are Turbine Shaft (N1), Turbine Axis (N2), Fan, Combustor, Low Pressure Compressor (LPC), High Pressure Compressor (HPC), Low Pressure Turbine (LPT) and High Pressure Turbine (HPT). The aircraft engine model is simulated on the Commercial Modular Aero-Propulsion System Simulation (C-MAPSS), a simulation tool made by NASA. The availability of the system model can be ensured by setting simulating operations including mach numbers whose variation range is 0 to 0.90, altitudes whose variation range is sea level to 40,000 ft, and sea-level temperatures whose variation range is –60 to 103 °F. The engine model whose thrust class is 90,000 lb can be used to model process of degradation for output data that observed on C-MAPSS.

B. Dataset Description

In this paper, the first dataset which contains training units, testing units and the actual remaining lifetime of testing units is used to demonstrate this proposed approach, and the number of the training units, testing units and the actual remaining lifetime of testing units is 100 each. A total of 26 variables are contained, the first two of them are engines ID and number of time cycles, the next three are the operational settings and 21 others are the sensor output data with noise. In the dataset, each training union is run to a failed state and each union starts with a different status, so the length of each union data is different. The stop time of each testing unit is random meanwhile the cycles are recorded. A more detailed description can be seen in [25].

III. METHODOLOGY

Two essential models are consisted in this approach: HI degradation model and GM model. HI degradation model is constructed for identifying degradation process of system by constructing the HI. GM model basing on constructed HI model is constructed for predicting RUL of system.

A. HI Degradation Model

Sufficient training and testing data have been provided to us in the dataset. The HI degradation model can be constructed with the recorded sensor signals. A linear regression model is used to build the HI degradation model due to its good performance.

$$y = b_0 + B^T X = b_0 + \sum_{i=1}^{K} b_i x_i \qquad (1)$$

where $X = (x_1, x_2, \cdots, x_K)$ is the sensor data vector, $(b_0, B) = (b_0, b_1, \cdots, b_K)$ are the model coefficients and y is the health indicator.

A training set, $\Psi = \{(X_1, y_1), (X_2, y_2), \cdots, (X_K, y_K)\}$, is constructed to obtain the coefficients of the linear regression model. Two parts are made up of the training set, one part is the data near the end of engine life which label is 0 and another is the data in the initial state which label is 1. The HI degradation model can be constructed using the training set. The range of the HI can not be guaranteed within 0 to 1 by liner regression while this will not affect the accuracy of RUL prediction.

B. Improved GM Model

A general method of RUL prediction is to fit the curve of the HI and predict the trend of it. The GM(1,1) model has a better prediction effect when there are less sensor data. The law of its change can be found out using GM(1,1) model by sorting out raw data. Weakening its randomness and showing its regularity of the data are the main idea of GM(1,1) model.

The HI degradation model have been constructed using a liner regression model. RUL can be calculated by substituting the HI into GM(1,1) model. A more effective result on the RUL prediction can be given by the improved GM(1,1) model. For the degradation process of HI obeying exponential distribution, a better prediction effect can be given by GM(1,1) model with logarithmic operation on the HI.

The following are the major steps of our improved GM(1,1) model.

1) Input of raw data: The raw data sequence could be defined as

$$\beta_{(0)} = \{\beta_{(0)}(1), \beta_{(0)}(2), \cdots, \beta_{(0)}(L)\} \tag{2}$$

2) Logarithmic operation of the input: The data after logarithmic operation could be defined as

$$\alpha_{(0)} = \{\alpha_{(0)}(1), \alpha_{(0)}(2), \cdots, \alpha_{(0)}(L)\} \tag{3}$$

where $\alpha_{(0)}(1) = \ln(\beta_{(0)}(1))$.

3) Construction of the 1-AGO: The 1-AGO is a new sequence built by the accumulated generating operation (AGO) algorithm, which could be defined as

$$\alpha_{(1)} = \{\alpha_{(1)}(1), \alpha_{(1)}(2), \cdots, \alpha_{(1)}(L)\} \tag{4}$$

where $\alpha^{(1)}(\varepsilon) = \begin{cases} \alpha^{(1)}(0), \varepsilon = 1 \\ \alpha^{(1)}(\varepsilon) = \sum_{i=1}^{\varepsilon} \alpha^{(0)}(i), 1 < \varepsilon \le L \end{cases}$, ε is the time.

Define the consecutive neighbor sequence as

$$\gamma_{(1)}(\varepsilon) = \frac{1}{2}\left(\alpha_{(1)}(\varepsilon) + \alpha_{(1)}(\varepsilon - 1)\right) \tag{5}$$

4) Construction of the first-order different equation: The initial data sequence could be transformed into a first-order different equation, which could be defined as

$$\frac{\mathrm{d}\alpha_{(1)}(\varepsilon)}{\mathrm{d}t} + p\alpha_{(1)}(\varepsilon) = q \tag{6}$$

where coefficients p and q could be obtained using the Least Squares Method. The parameter u could be defined as

$$u = [p, q]^T = (B^T B)^{-1} B^T Y \tag{7}$$

where

$$B = \begin{bmatrix} -\gamma_{(1)}(2) & 1 \\ -\gamma_{(1)}(3) & 1 \\ \cdots & \cdots \\ -\gamma_{(1)}(L) & 1 \end{bmatrix} \text{ and } Y = \begin{bmatrix} \alpha_{(0)}(2) \\ \alpha_{(0)}(3) \\ \cdots \\ \alpha_{(0)}(L) \end{bmatrix}.$$

5) Computation of the grey forecasting predictor: After getting p and q, $\alpha_{(1)}(\varepsilon+1)$ could be obtained by

$$\alpha_{(1)}(\varepsilon+1) = \left(\alpha_{(0)}(1) - \frac{q}{p}\right) e^{-p\varepsilon} + \frac{q}{p} \tag{8}$$

The solution of $\alpha_{(0)}(\varepsilon+1)$ could be obtained by

$$\alpha_{(0)}(\varepsilon+1) = \alpha_{(1)}(\varepsilon+1) - \alpha_{(1)}(\varepsilon) \tag{9}$$

6) Computation of the predicted data: The final predicted data $\alpha_{(1)}(\varepsilon+1)$ could be obtained by

$$\alpha_{(0)}(\varepsilon+1) = \left(\alpha_{(0)}(1) - \frac{q}{p}\right) e^{-p\varepsilon}(1 - e^{p}) \tag{10}$$

C. On-Line RUL Prediction

The novel approach for RUL prediction can be obtained by using the above HI degradation model and improved GM(1,1) model. Then the RUL of system can be calculated. The core procedures of this novel approach based on the hybrid method of liner regression and GM(1,1) model are introduced as below.

1) Data cleaning: The processed training set and testing sset data can be obtained by performing least squares filtering on the original data. The influence of noise can be removed by data cleaning.

2) Construction of the HI degradation model: The data of failure status and data of health status in the extracted training set data are substituted into the linear regression model, and the coefficients are obtained to construct the HI degradation model of testing data.

3) Construction of the improved GM(1,1) model: Performing logarithmic operation with the HI degradation curve and get the cofficient of improved GM(1,1) model.

4) Prediction of RUL: The HI can be constructed with known data and the trend of HI can be predicted by the improved GM(1,1) model. The sliding window is introduced to our improved GM(1,1) model to enhance performance by using the nearest data to predict new data.

The RUL can be calculated by (11).

$$RUL = t_N - t_F \tag{11}$$

where t_N is the current moment, t_F is failure moment and RUL is the remaining useful life.

The whole procedure is displayed in Fig.1.

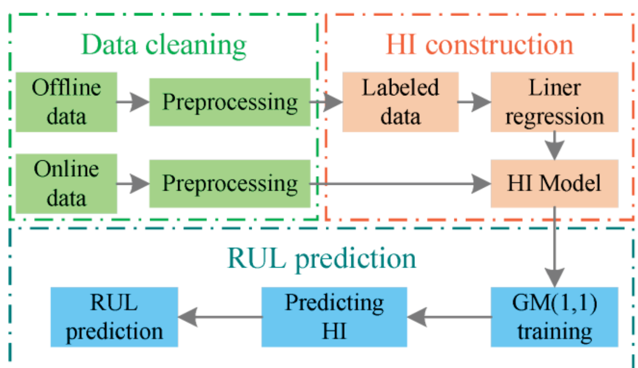

Figure 1. The whole procedure of proposed approach.

IV. CASE STUDY

In the case study, the effectiveness of our novel approach was investigated using aircraft engine degradation dataset. The parameter selection and setting, RUL prediction result and the result analysis are described in detail below.

A. Parameter Selection and Setting

A total of 21 sensor variables are provided while not all variables are necessary. Removing the unchangeable redundant variables is very necessary so the remaining 14 variables of change are selected. Then the training set and testing set data are cleaned by least squares filtering.

The HI degradation model is constructed first to get the health state of an aircraft engine. Part of the engine data are labeled. The first 2% times cycle are labeled 1 representing healthy status and the last 5% times cycle are labeled 0 representing failed status. The initial status of each engine is very different while final status is the same, so the healthy labels are less than failed labels. The parameters of HI degradation model can be obtained using labeled data. Then the HI degradation model can be constructed. The HI curve of 100 training engines can be seen in Fig.2.

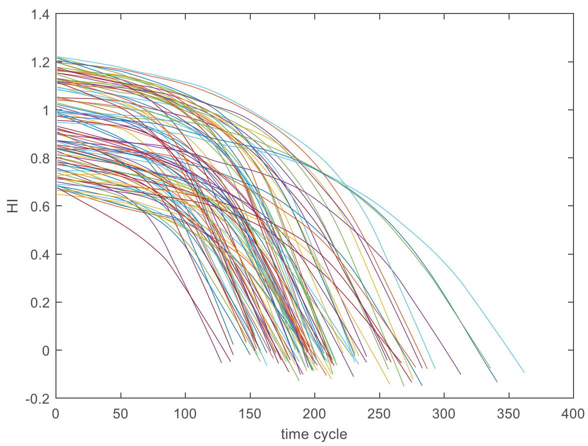

Figure 2. HI curve of 100 units.

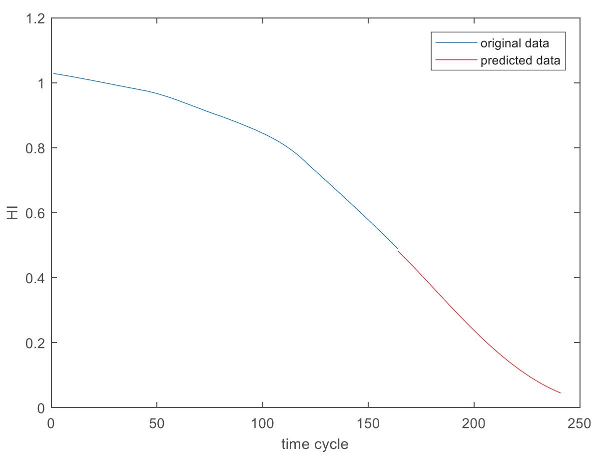

Figure 3. Example of a test unit.

The HI curve after constructing HI degradation model can be obtained. The HI data are substituted to GM(1,1) model using logarithmic operation. The size of the sliding window is 3 which means that 3 new data are predicted each time. The new data are used for the next prediction repeatedly. The result of one engine could be exhibited in Fig.3. Original data is marked as blue line and the predicted data is marked as red line.

B. RUL Prediction Result

The approach performance can be easily compared using evaluation metrics. In this paper, several metrics are used to evaluate the performance such as False Positive Rate (FPR), False Negative Rate (FNR), Accuracy (A), Mean Absolute Error (MAE), Score (S) and Root Mean Square Error (RMSE) [26]. The error of engine i between the prediction RUL($\hat{RUL}$) and true RUL(RUL) are defined as $error_i = \hat{RUL} - RUL$.

$$FPR = \frac{Num_p}{100} \times 100\% \tag{12}$$

where Num_p is the number of $error_i < -10$.

$$FNR = \frac{Num_n}{100} \times 100\% \tag{13}$$

where Num_n is the number of $error_i > 13$.

$$A = \frac{100}{N}\sum_{i=1}^{N} I(error_i) \tag{14}$$

where $I(error_i) = \begin{cases} 1, -10 \le error_i \le 13 \\ 0, error_i < -10, error_i > 13 \end{cases}$.

$$S = \sum_{i=1}^{N} s_n, s_n = \begin{cases} \exp(-\dfrac{error_i}{10}), error_i \le 0 \\ \exp(\dfrac{error_i}{13}), error_i > 0 \end{cases} \tag{15}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |error_i| \tag{16}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} error_i^2} \tag{17}$$

The longer the data length, the more information we know. It is difficult to predict the correct degradation trend when there is little known data. Here we choose testing data with a data length greater than 160. A total of 28 units are selected to predict RUL. The RUL prediction results of Multi-layer Perceptron (MLP), Deep Convolutional Neural Network (Deep CNN), Long Short Term Memory (LSTM) and traditional GM(1,1) are compared in table I. NR in the table means not reported.

The following analysis can be obtained from the comparison results in the table. In the accuracy indicators such as FPR, FNR and A, our proposed approach has better prediction effect. The proposed approach also has better prediction effect on Score and MAE indicator. In the RMSE indictor, Deep CNN is the best. In general, the RUL prediction effect of the proposed method is better.

TABLE I. COMPARISON OF RUL PREDICTION RESULTS

Approach	**FPR**	**FNR**	**A**	**Score**	**MAE**	**RMSE**
MLP[27]	NR	NR	NR	17972	NR	37.56
DeepCNN[27]	NR	NR	NR	1286.7	NR	**18.45**
LSTM[26]	34%	30%	36%	1263	18	NR
GM(1,1)	**3.5%**	53.6%	42.9%	248331	17.13	105.5
Proposed approach	42.9%	**0%**	**57.1%**	**1193**	**4.35**	23.02

V. CONCLUSION

In this paper, a HI is constructed by linear regression, and a new approach of engine RUL prediction is proposed basing on our improved GM(1,1) model. And the application results performing on the C-MAPSS aircraft engine dataset reflect that the system degradation process can be fully modeled by the proposed method and the prediction accuracy of RUL could be enhanced effectively. In the near future, improving the prediction accuracy with less known data is our next plan.

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REFERENCES

[1] Vichare N M, Pecht M G. “Prognostics and health management of electronics,” IEEE Transactions on Components and Packaging Technologies, vol. 29, no. 1, pp. 222–229, 2006.

[2] Pecht M G. Prognostics and Health Management of Electronics, Encyclopedia of Structural Health Monitoring. Hoboken, New Jersey: John Wiley & Sons, Ltd, 2009.

[3] Haile M A, Riddick J C, Assefa A H. “Robust particle filters for fatigue crack growth estimation in rotorcraft structures,” IEEE Transactions on Reliability, vol. 65, no. 3, pp. 1438–1448, 2016.

[4] Zhao F Q, Tian Z G, Zeng Y. “Uncertainty quantification in gear remaining useful life prediction through an integrated prognostics method,” IEEE Transactions on Reliability, vol. 62, no. 1, pp. 146 –159, 2013.

[5] Si X S, Hu C H. Data-driven Remaining Useful Life Prediction Theory and Applications for Equipment. Beijing: Defense Industrial Press, 2016.

[6] Zhang J X, Hu C H, He X, Si X S, Liu Y, Zhou D H. “Lifetime prognostics for deteriorating systems with time-varying random jumps,” Reliability Engineering &System Safety, vol. 167, pp. 338–350, 2017.

[7] Wen Y X, Wu J G, Yuan Y. “Multiple-phase modeling of degradation signal for condition monitoring and remaining useful life prediction,” IEEE Transactions on Reliability, vol.66, no. 3, pp. 924–938, 2017.

[8] Zhang H W, Chen M Y, Zhou D H. “Remaining useful life prediction for a nonlinear multi-degradation system with public noise,” Journal of Systems Engineering and Electronics, vol. 29, no. 2, pp. 429–435, 2018.

[9] Wang B, Lei Y G, Li N P, Lin J. “An improved fusion prognostics method for remaining useful life prediction of bearings,” International Conference on Prognostics and Health Management. Dallas, TX: IEEE, pp. 18–24, 2017.

[10] Yu Y, Si X S, Hu C H, Cui Z M, Li H P. “Data driven reliability assessment and life-time prognostics: a review on covariate models,” Acta Automatica Sinica, vol. 44, no. 2, pp. 216–227, 2018.

[11] Liu J J, Hu C H, Zhou Z J, Zhang X, Wang P. “Life assessment approachof equipment based on belief-rule-base and evidential reasoning,” Control Theory & Applications, vol. 32, no. 2, pp. 231–238, 2015.

[12] Chen L, Xu L, Zhou Y. “Novel approach for lithium-ion battery on-line remaining useful life prediction based on permutation entropy,” Energies, vol. 11, no. 4, pp. 820, 2018.

[13] Peng Y , Dong M. “A hybrid approach of HMM and grey model for age-dependent health prediction of engineering assets,” Expert Systems with Applications, vol. 38, no. 10, pp. 12946–12953, 2011.

[14] Peng Y, Liu D T. “Data-driven prognostics and health management: a review of recent advances,” Chinese Journal of Scientific Instrument, vol. 35, no. 3, pp. 481–495, 2014.

[15] Shen Z J, Chen X F, He Z J, Sun C, Zhang X L, Liu Z W. “Remaining life predictions of rolling bearing based on relative features and multivariable support vector machine,” Journal of Mechanical Engineering, vol. 49, no. 2, pp. 183–189, 2013.

[16] Abbas R B, Aref A, Addin A H. “Estimation of remaining useful Life of rolling element bearings using wavelet packet decomposition and artificial neural network,” Iranian Journal of Science and Technology Transactions of Electrical Engineering, pp. 1–13, 2018.

[17] Lasheras F S, Nieto P J G, De Cos Juez F J, Bayon R M, Suarez V M G. “A hybrid PCA-CART-MARS-based prognostic approach of the remaining useful life for aircraft engines,” Sensors, vol. 15, no. 3, pp. 7062–7083, 2015.

[18] Huang H Z,Wang H K, Li Y F, Zhang L L, Liu Z L. “Support vector machine based estimation of remaining useful life: current research status and future trends,” Journal of Mechanical Science and Technology, vol. 29, no. 1, pp. 151–163, 2015.

[19] Guo L, Li N P, Jia F, Lei Y G, Lin J. “A recurrent neural network based health indicator for remaining useful life prediction of bearings,” Neurocomputing, vol. 240, pp. 98–109, 2017.

[20] Zhang Z X, Geiger J, Pohjalainen J, Mousa A E, Jin W Y, Schuller B. “Deep learning for environmentally robust speech recognition,” ACM Transactions on Intelligent Systems and Technology, vol. 9, no. 5, pp. 1–28, 2018.

[21] He M, He D. “Deep learning based approach for bearing fault diagnosis,” IEEE Transactions on Industry Applications, vol. 53, no. 3, pp. 3057–3065, 2017.

[22] Khan S, Yairi T. “A review on the application of deep learning in system health management,” Mechanical Systems and Signal Processing, vol. 107, pp. 241–265, 2018.

[23] Hu Y, Palme T, Fink O. “Deep health indicator extraction: a method based on auto-encoders and extreme learning machines,” Annual Conference of the Prognostics and Health ManagementSociety. Denver, CO: PHM Society Conference, pp. 1–7, 2016.

[24] Liao L X, Jin W J, Pavel R. “Enhanced restricted boltzmann machine with prognosability regularization for prognostics and health assessment,” IEEE Transactions on Industrial Electronics, vol. 63, no. 11, pp. 7076–7083, 2016.

[25] Saxena A, Kai G, Simon D, Eklund, N. “Damage propagation modeling for aircraft engine run-to-failure simulation,” 2008 Proceedings of the IEEE International Conference on Prognostics and Health Management, Denver, CO, USA, pp. 1–9, 2008.

[26] Malhotra P, TV V, Ramakrishnan A, Anand G, Vig L, Agarwal P, et al. “Multi-Sensor prognostics using an unsupervised health index based on LSTM encoder-decoder,” arXiv: 1608.06154, 2016.

[27] Babu G S, Zhao P, Li X L. “Deep convolutional neural network based regression approach for estimation of remaining useful life,” 21th International Conference on Database Systems for Advanced Applications (DASFAA). Dallas, USA: Spinger, pp. 214–228, 2016.