Research progress on AI-based RUL prediction methods of mechanical equipment

Yuefeng Liu, Gong Zhang, Chenrong Zhang, Yuhui Yang, Lina Zhang
School of Information Engineering
Inner Mongolia University of Science and Technology
Baotou, China
liuyuefeng01035@163.com

***Abstract*—With the development of the industry, the performance of large and complex systems is constantly increasing and the complexity is increasing. In the process of using mechanical equipment, there is often a phenomenon of downtime and the most of the reasons is that the related parts are faulty. As one of the foremost tasks of prognostic and health management (PHM) and condition based maintenance (CBM), the prediction of remaining useful life (RUL) for mechanical equipment is receiving more and more attention. By knowing the RUL of the equipment, it can play an important role in maintaining related equipment in advance. It is more effective than the traditional regular maintenance and post-repair maintenance, thus avoiding the occurrence of malfunctions and the reduction of property loss. This paper focuses on the AI-based RUL prediction methods and explains the strengths and weaknesses of each of these methods and summarizes the latest literature on various methods in the last few years. Finally, the present methods and future trends are discussed and hot spots for the future are given.**

Keywords-mechanical equipment; condition based maintenance; prognostic and health management; remaining useful life;

I. INTRODUCTION

With the progress of industry, the application of mechanical equipment is more extensive and the level of production is constantly improving. However, the occurrence of mechanical failures has brought a lot of loss. In recent years, the concept of CBM and PHM has been proposed. The prediction of RUL is one of their most important tasks. It is an engineering discipline designed to predict when a system or component is not performing its intended function properly. The prediction of RUL which is an integrated emerging discipline of machine, electronic, computer, communication, control and material is one more advanced form of maintenance ways than fault diagnosis. As one of Health Management tasks of machinery, it consists of these parts:

- Data acquisition: By installing sensors on mechanical equipment, we generally get temperature data, vibration data etc.
- Data preprocess and features selection: By analyzing vibration signal of original data which is obtained in the first step, time domain features, frequency domain features and time-frequency domain features can be obtained. The final features are compressed and selected to maximize the retention of original data information.
- The constructions of health indicators (HI): Using signal process technology and artificial intelligence technology processes the characteristics of the data and obtains a single feature or fusion of a plurality features as HI.
- Division of the health stage (HS): According to the trend of HI, the degradation process of mechanical equipment is divided into different HSs to make it close to actual situation. The role of HS is to detect initial mechanical degradation and to provide an eligible first predicted time (FPT) to predict RUL, which is critical to the next step.
- RUL prediction: RUL prediction is the most critical task in the whole process. Its purpose is to get the length of time from the start of prediction to the end of machine life.
- The processing of uncertain problem: Determination of the threshold is changed from setting of the constant to setting of the probability interval and result of the RUL prediction has uncertain expressiveness.

In above PHM processes, this paper is concerned with the prediction of RUL.With the development of artificial intelligence, the AI-based approaches have gradually become a rising star in the RUL field. As a embranchment of machine learning, deep learning approaches have ability to process high-dimensional nonlinear data in the big data environment. So we will focus on AI-based methods.

II. AI-BASED METHODS FOR RUL PREDICTION

In recent years, as artificial intelligence technology develops, some approaches based on AI have been gradually used to the field of RUL prediction. Because deep learning models have the characteristics of dealing with nonlinear and high-dimensional data, it has become a research hotspot for researchers.

A. Support Vector Machine (SVM) and Relevance Vector Machine (RVM)

SVM is an artificial intelligence technology based on V.N. Vapnik [1] theory. In 2018, Akhand Rai et al. [2] input the HI newly proposed into SVR model and RUL was used as the output. The best model is adjusted by the parameters. In

This work is supported partly by Inner Mongolia Natural Science Foundation of China under Grant No. 2018MS06019.

978-1-7281-0860-5/19/$31.00 ©2019 IEEE

2018, Y. Peng et al. [3] used the Gaussian Mixture Model (GMM) to identify the anomalous dataset and input the selected features into the least squares support vector machine(LS-SVM) for the prediction of the rolling bearing's RUL. In 2018, Z. Chen et al. [4] used data of entire life cycle of an aircraft engine to predict RUL under the framework of similarity theory and SVM. In 2017, Dong Gao et al. [5] proposed a multi-core SVM (PSO-MSVM) model based on particle swarm optimization (PSO) algorithm to predict the RUL of lithium batteries. Compared with traditional single-core SVM, it has better prediction accuracy and stronger generalization performance under different conditions, and its mean square error (MSE) is less than 3%. In 2015, T. Benkedjouh et al. [6] utilized SVR to form HI to nonlinear regression and then used the regression model for mechanical RUL prediction. In 2015, E. Fumeo et al. [7] put forward an online SVR model to predict bearing's RUL. There are other SVMs that were applied to predict the RUL of mechanical equipment [8-10]. Although SVMs are widely used in RUL prediction, they are only point predictions rather than probabilistic predictions. In order to solve this problem, RVM technology was proposed. In 2018, X. Wang et al. [11] combined RVM with sparse Bayes to develop a RUL online prediction algorithm for high-speed train traction systems. RVM and SVM are very similar, but RVM is a probabilistic prediction. SVM and RVM handle small sample data and the associated performance is strongly related to its chosen kernel function. The amount of data on mechanical equipment is large. SVM and RVM are slowly relegating to the second place.

B. Boltzmann machine (BM) and its variants

We generally refer to BM as a binary BM, which means that the relevant variables are N-dimensional 0-1 variables. The BM was invented by Geoffrey Hinton and Terry Sejnowski in 1985. It is one of the earliest neural networks that can learn internal expressions and solve combinatorial optimization problems over a period of time. The BM is an energy-based model. For the dataset to be trained, knowing distribution of data, such as Gaussian distribution is important. It can quickly learn the relevant parameters through maximum likelihood function. But when the weight W between every two units of the BM is trained, only the data of two units is used, which means that the relevant rules for training are local and effect that can be achieved is locally optimal. In order to solve above shortcomings of BM, relevant researchers have introduced restricted Boltzmann machine (RBM), which has only two layers of structure. RBM can be regarded as a process of encoding and decoding. Adding a hidden layer to RBM can get deep Boltzmann machine (DBM). The basic algorithm is same as RBM, except that the relevant parameters become more and the training becomes more complicated. RBM and its related variants have recently been used as structural units of deep neural networks because they reduce the risk of gradient disappearance and over fitting in neural networks. In 2016, L. Liao et al. [12] proposed an enhanced RBM that automatically generates features suitable for RUL. In 2016, Jason Deutsch and David He [13] used RBM to predict RUL of bearings. In the RUL prediction of mechanical equipment, we generally use a combination of multiple layers of RBM-DBN. The following is a detailed introduction of the theory and application of DBN.

C. Deep Belief Network (DBN)

The DBN is composed of multiple RBMs, but when using the backpropagation algorithm for DBN, there must be a labeled training set and there will be a local optimal solution due to the selection of parameters. Hinton pre-trained the weight of the generated model through an unsupervised greedy layer-by-layer method and called this method as contrast divergence to solve above problems. Training with above DBN model consists two steps: the first step is called Pre-Training. The purpose of unsupervised training of each layer is to retain relevant feature information to the greatest extent. The second step is called Fine-Tuning. On the last layer, a BP network is set up to adjust the relevant parameters. This makes DBN overcome shortcomings of the BP network that training time becomes longer due to random initialization parameters and the local optimal problem. When we are predicting the RUL of mechanical equipment, we can turn the top BP network classifier into a related regression model to get relevant prediction curve. In 2017, G. Zhao et al. [14] used DBN to predict RUL of mechanical bearings. Although DBN is widely used in RUL prediction, there are still some shortcomings. For example, it requires one-dimensional input data. But for mechanical bearings, most of the data is high-dimensional.

D. Auto-encoder (AE) and its variants

Prior to the related multidimensional data processing, DBN-related researches included stacking auto-encoder (SAE), which replaced RBMs in traditional DBNs with SAE. However, it lacks the parameter requirements in each layer of DBN. If SAE is replaced by the denoising auto-encoder (DAE), this problem can be solved perfectly. Next we will introduce the relevant theory of the AE and its application. AE is a kind of feed forward neural network (FFNN), which is usually used for compression and extraction of features under unsupervised learning. The concept of AE was first proposed by Rumelhart [15]. Since it is proposed, AE has been applied to many areas. In the field of RUL prediction, AE and its variants have also been applied, but most of the literature used multiple AE stacks for RUL prediction. In 2018, L. Ren et al. [16] combined depth AE with DNN, experimented with the HI newly proposed and used the PHM2012 dataset to conduct comparative experiments. The proposed approach can improve the prediction accuracy and reduce prediction error. In 2018, Y. Song et al. [17] combined AE with bidirectional long-term and short-term memory (Bi-LSTM). AEs were used for feature extraction and Bi-LSTM was used to solve long-range dependence for RUL prediction of turbine engines. In 2018, J. Ma et al. [18] combined stack sparse auto encoders (SSAE) with logistic regression (LR) to predict the RUL of aircraft engines. SSAE were used to extract and fuse features. LR was used for RUL prediction and the grid search algorithm was used to select hyper parameters in SAE. Although the AE and its variants have been improved on DBN and their performance has been improved, the data they process is one-dimensional. But data of related mechanical equipment is high-dimensional. All of the above, the Convolutional Deep Belief Network (CDBN) has been applied. In the processing of high-dimensional data, CNN has a unique advantage and it is suitable for the related processing of the data of time series of mechanical equipment.

E. Convolutional Neural Network (CNN)

CNN contains three types of neural network layers. Convolutions layer is a characteristic representation of learning data. It consists of many convolution kernels. The function of convolution kernels is to calculate different feature maps. Combined with related activation functions such as Relu to introduce nonlinear factors into neurons in CNN, it can deal with related nonlinear problems. The role of the Pooling layer is to obtain more abstract features of data through maximum pooling or average pooling. The Full connected layer acts as a classification and regression to serve the final RUL curve. In 2019, Xiang Li et al. [19] used CNN for multi-scale feature extraction which is input into the DNN to predict RUL of mechanical bearings. In 2018, L. Ren et al. [20] proposed a new HI (spectrum-principal-energy-vector) and used deep convolutional neural network (DCNN) for RUL prediction of mechanical bearings. In 2016, Giduthuri Babu et al. [21] first used CNN for RUL prediction and compared it with SVR, which improved the accuracy of prediction and made great contributions to the development of RUL prediction. Although CNN has great advantages in processing high-dimensional data, there is no need to manually select related features. It is insensitive to previous data and requires a lot of experimentations on parameters, which takes a lot of time.

F. Recurrent Neural Network (RNN)

In 2018, L. Guo et al. [22] used the new HI (RNN-HI) constructed by RNN to predict RUL by a double exponential model. In 2017, N. Gugulothu et al. [23] processed the multivariate time series data by the sequence-to-sequence model in RNN and input it into the RNN model to predict RUL of turbine engine. In 2014, D. Liu et al. [24] input two HIs into the improved RNN for RUL prediction of lithium batteries. In 2012, Y. Peng et al. [25] predicted the RUL of the turbofan engine by replacing the hidden layer in the RNN with the sparse layer. In 2011, A. Malhi et al. [26] processed the original data by continuous wavelet transform (CWT) and then input it into RNN. The input data was clustered to simulate the degradation state of bearing. This model was applied to the prediction of bearing's RUL and performed well.

Although RNN is able to store the previous information in the memory unit and apply it to current related tasks, gradient disappearance and gradient explosion of the RNN and long-distance dependence problem cannot be solved so that RNN is gradually replaced by LSTM to predict RUL.

G. Long and short term memory network (LSTM)

LSTM is a special form of RNN. All information of LSTM is processed through the structure of the ‘gate’. The LSTM has three types of gates: forgotten gate, input gate, output gate and cell state. Three gates function as follows:

Forgotten Gate: Its function is to decide whether to retain information. The information from previous hidden state and currently input information are simultaneously passed to sigmoid function and retained as close to 1, but discarded if they are close to 0.

Input gate: Its function is to update cell state. The information of previous hidden state and currently input information are simultaneously passed to sigmoid function. Then it is passed to tanh function, which is multiplied and passed to cell state.

Output Gate: Its purpose is to determine numerical value of next hidden state. Hidden state contains the information previously entered. First, we pass previous hidden state and current input to sigmoid function. Then pass newly obtained cell state to tanh function. Finally, output of tanh is multiplied by output of sigmoid to be used as numerical value for next hidden state.

In 2019, B. Zhang et al. [27] constructed LSTM cyclic network model for bearing’s RUL prediction and the newly constructed HI (waveform entropy) (WFE) was used as the model input. In 2018, S. Basak et al. [28] proposed an LSTM’s pre-trained two-layer prediction architecture, it for predicting RUL of hard disks with an average accuracy of 0.8435. In 2018, J. Zhang and R. Yan et al. [29] applied bidirectional LSTM to RUL prediction of engine. The results obtained were better than those of SVR, DCNN and bidirectional RNN (Bi-RNN). In 2018, A. Z. Hinchi et al. [30] proposed an LSTM-based model to predict rolling bearings’ RUL. In 2018, Y. Wu et al. [31] applied vanilla LSTM to RUL prediction and compared the experimental results with RNN and GRU for aircraft turbofan engines. The results demonstrate effectiveness of the proposed method. Although LSTM can solve many problems of RNN, the processing of time series is also perfect, but it requires a lot of calculations. GRU has gradually been favored by relevant researchers because of its simple structure and small amount of calculations.

H. Gated recurrent unit (GRU)

The GRU is a variant of LSTM, The most important change transforms integration of input and forgotten gate to an update gate, transforms output gate into a reset gate. In 2019, J. Chen et al. [32] put forward a two-step solution to the RUL prediction of nonlinear degenerate systems. First, kernel principal component analysis (KPCA) was used to extract the nonlinear features. Second, GRU was used to predict RUL. In 2019, L. Ren et al. [33] applied multi-scale dense GRU (MDGRU) to the RUL prediction of rolling bearings. Because it is an end-to-end network that is suitable for today's industrial big data background and prevents over fitting. The prediction of bearing achieves higher precision.

In the above mentioned methods, deep learning-based methods dominate the RUL field and its prediction accuracy is high. Although there are many advantages, hybrid methods can further improve the prediction accuracy and it is more noticed by researchers.

For a comparison of advantages and disadvantages of the above methods, refered to Table I.

TABLE I. COMPARISON OF THE DEEP LEARNING-BASED APPROACHES

Approach	Compared-items		
	Advantage	***Disadvantage***	***Reference***
SVM and RVM	Simple model, high prediction accuracy, fast model training, Performance related to selected kernel functions.	Cannot process large amounts of data, SVM is point prediction.	Akhand Rai et al.[2-11]
BM	Models can be built from the probability distribution of the input data,All layer parameters can be optimized together.	It is difficult to train, long calculation time, and sensitive to noise.	L. Liao et al.[12-13]
DBN	It is used to process one-dimensional data and to obtain global characteristics of the input data.	Slow training, difficult to process high-dimensional data.	G. Zhao et al.[14]
AE	The dimensionality reduction compression of the data is obvious, and more information can be retained.	The amount of data required to train is large, Self-supervised algorithm.	L. Ren et al.[16-18]
CNN	Suitable for processing high-dimensional data, capable of extracting local features of input data.	Long training time, complex model.	Xiang Li et al.[19-21]
RNN	Ability to process time series data and store past information into memory cells.	Gradient disappearance and gradient explosion problems.	L. Guo et al.[22-26]
LSTM	Processing time series data, solving the problem of gradient disappearance and gradient explosion of RNN.	Complex model and long training time.	B. Zhang et al.[27-31]
GRU	Simple model for processing time series data.	Difficult to achieve, long training time.	J. Chen et al.[32-33]

I. Hybrid methods

The above methods have their limitations and shortcomings in RUL prediction. How to integrate their advantages and minimize the problems caused by related limitations has become a hot issue in current research.

In 2019, André Listou Ellefsen et al. [34] used RBM for unsupervised pre-training. LSTM was used to RUL prediction. Genetic algorithm (GA) was used to parameter optimization and semi-supervised approach was used to RUL prediction of aero engines with insufficient tag data. In 2019, Bo Sun et al. [35] put forward a model based on physical degradation mechanism and particle filter (PF) for RUL prediction of electrical connector. In 2019, Celestino Ordóñez et al. [36] applied the hybrid ARIMA-SVM model to RUL prediction of aircraft engines. First he used ARIMA to estimate value of predictor. Then he used it as an input to SVR to predict RUL.

III. SUMMARY

Next, we will first enumerate the current review articles in the field, then discuss the existing methods and finally look forward to the future research hotspots.

A. Current contribution

In the field of RUL prediction, relevant research groups at domestic and abroad have done in-depth research on RUL prediction. The inspiration of this article also comes from following papers. The detailed summary is shown in Table II.

TABLE II. SUMMARY OF EXISTING(2015-2019) RUL REVIEWS IN THE FIELD

Date	Compared-items		
	Author	***Advantage***	***Institute***
2019	Shujie Liu	Proposed physics model based and data driven based methods and a hybrid method of both and the state space model (SSM).	Dalian University of Technology
2018	Yaguo Lei	A comprehensive discussion of the entire process of RUL prediction, including data sets, HI, HS and RUL predictions.	Xi'an Jiao tong University
2018	Samir Khan	Introduced AE, CNN, RNN in AI-based methods, looking forward to the future.	University of Tokyo
2018	M A Hannan	Sum up SOH and RUL estimation approaches of electric vehicles.	National Energy University of Malaysia
2017	Qiang Miao	Review the construction method of vibration-based bearing and gear health indicators.	Sichuan University
2016	G.Q. Zhao	Give a review of fault diagnosis and prognostic based on deep learning.	Harbin Institute of Technology
2015	Ruqiang Yan	Introduced AE, DBN, CNN, DBM, RNN in AI-based methods, looking forward to the future.	Xi'an Jiao tong University

B. Discussion of existing methods and outlook for future

According to above-mentioned collation of related literature in recent years, it is found that fusion methods and deep learning-based methods occupy a major position in the RUL prediction field. In deep learning-based methods, we can find that there are very few literature used DBN method. On the one hand, the ability to process related sequence data is not as good as LSTM. On the other hand, its structure is relatively simple and the performance of RBM is not very strong. But in the latest literature, the relatively advanced DBN model has received a lot of attention, such as the CDBN which can process related sequence data. It turns the base unit RBM in the

DBN into a variant of the associated AE. It also shows good results. Regarding the application of RNN, it is difficult to deal with gradient disappearance, gradient dependence and long-distance dependence problems. Its own network structure results limited application scope so that relevant researchers pay attention to LSTM.

In the future research, it is suggested to improve the network structure of DBN and RNN, which makes it more in line with actual situation. Prediction of RUL is more accurate and training time of the model becomes shorter. Recently, GRU applied from the NLP field has been applied to RUL prediction field by relevant researchers and related GRU researches are still very limited. It is recommended to do more research on GRU in the future. Future researches should be close to the actual situation of industrial applications, making relevant models more realistic. Some theoretical research results are very different from actual industrial applications so the prediction accuracy of RUL was lower than that obtained by simulation experiments. Since the theory of deep learning has been used in the area of RUL for a long time without the emergence of large-scale new methods, it is recommended that in other fields such as NLP, image processing, etc. would be well-transferred to the RUL field and related improvements suitable for mechanical equipment will be made. Although great results have been achieved in the field of RUL prediction for mechanical equipment, the following hot spots still need to be noticed and solved.

- How to handle related data and maintain the diversity of its features in today's big data environment.
- How to use the data of the whole life cycle of industrial enterprise to be in line with the industry.
- How to use the very limited degradation data in the full life cycle for RUL prediction.
- How to predict the RUL of a system composed of parts with different degradation mechanism.
- How to deal with the uncertain problem of the RUL prediction.
- How to accurately predict RUL of relevant equipment in real time without degraded data available for training.

These problems need to be solved urgently and prospect of RUL prediction is excellent.

IV. Conclusion

Due to large number of applications of mechanical equipment in the industrial 4.0 era, the prediction of mechanical equipment's RUL has become more and more important and traditional Breakdown Maintenance has been eliminated by CBM. Based on the above background, this paper reviews AI-based methods. This paper concentrates on the theory based on AI methods. Shortcomings of above methods in the area of RUL prediction are discussed, as well as the exploration of future developments in the area of RUL prediction.

Acknowledgment

This work was supported by Inner Mongolia Natural Science Foundation (2018MS06019).

References

[1] V. N. Vapnik, "An overview of statistical learning theory," IEEE Trans. neural networks, vol. 10, no. 5, pp. 988–999, 1999.

[2] A. Rai and S. H. Upadhyay, "Intelligent bearing performance degradation assessment and remaining useful life prediction based on self-organising map and support vector regression," Proc. Inst. Mech. Eng. Part C J. Mech. Eng. Sci., vol. 232, no. 6, pp. 1118-1132, 2018.

[3] Y. Peng, J. Cheng, Y. Liu, X. Li, and Z. Peng, "An adaptive data-driven method for accurate prediction of remaining useful life of rolling bearings," Front. Mech. Eng., vol. 13, no. 2, pp. 301–310, 2018.

[4] Z. Chen, S. Cao, and Z. Mao, "Remaining useful life estimation of aircraft engines using a modified similarity and supporting vector machine (SVM) approach," Energies, vol. 11, no. 1, p. 28, 2017.

[5] D. Gao and M. Huang, "Prediction of remaining useful life of lithium-ion battery based on multi-kernel support vector machine with particle swarm optimization," J. Power Electron., vol. 17, no. 5, pp. 1288–1297, 2017.

[6] T. Benkedjouh, K. Medjaher, N. Zerhouni, and S. Rechak, "Health assessment and life prediction of cutting tools based on support vector regression," J. Intell. Manuf., vol. 26, no. 2, pp. 213–223, 2015.

[7] E. Fumeo, L. Oneto, and D. Anguita, "Condition based maintenance in railway transportation systems based on big data streaming analysis," Procedia Comput. Sci., vol. 53, pp. 437–446, 2015.

[8] G. Niu and B.-S. Yang, "Intelligent condition monitoring and prognostics system based on data-fusion strategy," Expert Syst. Appl., vol. 37, no. 12, pp. 8831–8840, 2010.

[9] J. A. Carino, D. Zurita, M. Delgado, J. A. Ortega, and R. J. Romero-Troncoso, "Remaining useful life estimation of ball bearings by means of monotonic score calibration," in 2015 IEEE International Conference on Industrial Technology (ICIT), 2015, pp. 1752–1758.

[10] J. K. Kimotho, C. Sondermann-Woelke, T. Meyer, and W. Sextro, "Machinery prognostic method based on multi-class support vector machines and hybrid differential evolution-particle swarm optimization," Chem. Eng. Trans., vol. 33, pp. 619–624, 2013.

[11] X. Wang, B. Jiang, and N. Lu, "Adaptive relevant vector machine based RUL prediction under uncertain conditions," ISA Trans., vol. 87, pp. 217–224, 2019.

[12] L. Liao, W. Jin, and R. Pavel, "Enhanced restricted Boltzmann machine with prognosability regularization for prognostics and health assessment," IEEE Trans. Ind. Electron., vol. 63, no. 11, pp. 7076–7083, 2016.

[13] J. Deutsch and D. He, "Using deep learning based approaches for bearing remaining useful life prediction," in Annual conference of the prognostics and health management society, 2016.

[14] G. Zhao, X. Liu, B. Zhang, G. Zhang, G. Niu, and C. Hu, "Bearing Health Condition Prediction Using Deep Belief Network," in Proceedings of the Annual Conference of Prognostics and Health Management Society, Orlando, FL, USA, 2017, pp. 2–5.

[15] D. E. Rumelhart, G. E. Hinton, R. J. Williams, and others, "Learning representations by back-propagating errors," Cogn. Model., vol. 5, no. 3, p. 1, 1988.

[16] L. Ren, Y. Sun, J. Cui, and L. Zhang, "Bearing remaining useful life prediction based on deep autoencoder and deep neural networks," J. Manuf. Syst., vol. 48, pp. 71–77, 2018.

[17] Y. Song, G. Shi, L. Chen, X. Huang, and T. Xia, "Remaining Useful Life Prediction of Turbofan Engine Using Hybrid Model Based on Autoencoder and Bidirectional Long Short-Term Memory," J. Shanghai Jiaotong Univ., vol. 23, no. 1, pp. 85–94, 2018.

[18] J. Ma, H. Su, W. Zhao, and B. Liu, "Predicting the remaining useful life of an aircraft engine using a stacked sparse autoencoder with multilayer self-learning," Complexity, vol. 2018, 2018.

[19] X. Li, W. Zhang, and Q. Ding, “Deep learning-based remaining useful life estimation of bearings using multi-scale feature extraction,” Reliab. Eng. Syst. Saf., vol. 182, pp. 208–218, 2019.

[20] L. Ren, Y. Sun, H. Wang, and L. Zhang, “Prediction of bearing remaining useful life with deep convolution neural network,” IEEE Access, vol. 6, pp. 13041–13049, 2018.

[21] G. S. Babu, P. Zhao, and X.-L. Li, “Deep convolutional neural network based regression approach for estimation of remaining useful life,” in International conference on database systems for advanced applications, 2016, pp. 214–228.

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

[23] N. Gugulothu, V. TV, P. Malhotra, L. Vig, P. Agarwal, and G. Shroff, “Predicting remaining useful life using time series embeddings based on recurrent neural networks,” arXiv Prepr. arXiv1709.01073, 2017.

[24] G. Niu and B.-S. Yang, “Intelligent condition monitoring and prognostics system based on data-fusion strategy,” Expert Syst. Appl., vol. 37, no. 12, pp. 8831–8840, 2010.

[25] Y. Peng, H. Wang, J. Wang, D. Liu, and X. Peng, “A modified echo state network based remaining useful life estimation approach,” in 2012 IEEE Conference on Prognostics and Health Management, 2012, pp. 1–7.

[26] A. Malhi, R. Yan, and R. X. Gao, “Prognosis of defect propagation based on recurrent neural networks,” IEEE Trans. Instrum. Meas., vol. 60, no. 3, pp. 703–711, 2011.

[27] B. Zhang, S. Zhang, and W. Li, “Bearing performance degradation assessment using long short-term memory recurrent network,” Comput. Ind., vol. 106, pp. 14–29, 2019.

[28] S. Basak, S. Sengupta, and A. Dubey, “A Data-driven Prognostic Architecture for Online Monitoring of Hard Disks Using Deep LSTM Networks,” arXiv Prepr. arXiv1810.08985, 2018.

[29] J. Zhang, P. Wang, R. Yan, and R. X. Gao, “Long short-term memory for machine remaining life prediction,” J. Manuf. Syst., vol. 48, pp. 78–86, 2018.

[30] A. Z. Hinchi and M. Tkiouat, “Rolling element bearing remaining useful life estimation based on a convolutional long-short-term memory network,” Procedia Comput. Sci., vol. 127, pp. 123–132, 2018.

[31] Y. Wu, M. Yuan, S. Dong, L. Lin, and Y. Liu, “Remaining useful life estimation of engineered systems using vanilla LSTM neural networks,” Neurocomputing, vol. 275, pp. 167–179, 2018.

[32] J. Chen, H. Jing, Y. Chang, and Q. Liu, “Gated recurrent unit based recurrent neural network for remaining useful life prediction of nonlinear deterioration process,” Reliab. Eng. Syst. Saf., vol. 185, pp. 372–382, 2019.

[33] L. Ren, X. Cheng, X. Wang, J. Cui, and L. Zhang, “Multi-scale dense gate recurrent unit networks for bearing remaining useful life prediction,” Futur. Gener. Comput. Syst., vol. 94, pp. 601–609, 2019.

[34] A. L. Ellefsen, E. Bjørlykhaug, V. Æsøy, S. Ushakov, and H. Zhang, “Remaining useful life predictions for turbofan engine degradation using semi-supervised deep architecture,” Reliab. Eng. Syst. Saf., vol. 183, pp. 240–251, 2019.

[35] B. Sun et al., “Remaining useful life prediction of aviation circular electrical connectors using vibration-induced physical model and particle filtering method,” Microelectron. Reliab., vol. 92, pp. 114–122, 2019.

[36] C. Ordóñez, F. S. Lasheras, J. Roca-Pardiñas, and F. J. de Cos Juez, “A hybrid ARIMA--SVM model for the study of the remaining useful life of aircraft engines,” J. Comput. Appl. Math., vol. 346, pp. 184–191, 2019.