A Summary of Health Prognostics Methods for Industrial Robots

Qiaoqian Zhou, Yuanchao Wang, Jianming Xu
College of Information Engineering
Zhejiang University of Technology
Hangzhou, China
zhouqq@zjut.edu.cn

***Abstract*—With the rise of intelligent manufacturing, the requirements for precision and reliability of industrial robots are increasing. Through the industrial robot system status monitoring and health prognostics, when maintenance is needed, this strategy of condition-based maintenance (CBM) can reduce unnecessary maintenance operations effectively, and reduce the overall maintenance cost. The health prognostics usually consists of data acquisition and processing, health indicator (HI) construction and remaining useful life (RUL) prediction. Industrial robots are complex systems composed of sensors, reducers, motors, servo drivers and controllers. In this paper, the methods of health prognostics are summarized from two aspects: component level and system level. Finally, the health prognostics methods for industrial robots are prospected and summarized combined with literature.**

Keywords-robot; remaining useful life; prognostics and health management; industrial robot

I. INTRODUCTION

With the deep integration of industrialization and informatization, engineering systems in various fields such as industry, aerospace and communications are becoming more and more complex. Considering the reliability, safety, and economy of complex systems, prognostics and health management (PHM) has become an important foundation and technical support for equipment and system security. According to specific needs, PHM can maintain equipment before failures so that it can reduce maintenance cost and keep machine uptime as much as possible. The estimated remaining useful life (RUL) of each monitored component can be used to plan the repair of the unit in advance of the failure [1], thereby having a significant impact on subsequent operations.

In industrial automation manufacturing, industrial robots have become a core factor in improving productivity, availability and safety; in the process of using industrial robots, unexpected robot downtime or failure may not only affect daily production tasks, but also cause unpredictable additional production losses and economic losses. Condition monitoring and health prediction for industrial robot systems, this state-based maintenance (CBM) strategy can enhance mechanical reliability and reduce overall maintenance costs effectively when maintenance is required. Therefore, it has become increasingly popular in recent years. National Institute of Standards and Technology (NIST) is conducting a health management and control project for robots research which aims to develop measurement science in the field of industrial robots to promote advances in monitoring, diagnostics, predictive, and maintenance strategies, which support the test of the decline in the robot accuracy [2, 3].

PHM usually consists of three technical processes, including data sets, construction of health indicators (HI), and prediction of RUL. In the acquisition of data sets, the databases provided by NIST are widely used, such as: turbofan engine degradation simulation data set [4], intermediate shaft bearing data set [5], battery data set [6].

In the construction of HI, the root mean square (RMS) [7], peak [8], frequency [9] and other statistical properties of the signal are often used as the physical health indicators (PHIs) in the machine RUL prediction. A. Mosallam [10] captured the difference between the correlation coefficient of degraded bearings' vibration signals and a nominal bearing's vibration signals as a PHI.

Several conventional rotating machinery PHIs are summarized in [11]. Principal component analysis (PCA) [12], and neural network [13] are commonly used to construct virtual health indicators (VHIs) with the fusion of multiple sensor signals. T. Benkedjouh [14] used the energy coefficient of the wavelet packet decomposition as the tool's VHI, and then used the nonlinear feature extraction techniques to extract the feature.

In the RUL prediction, there are some physical model-based methods, such as Pari-Erdogan crack extension law [15], Forman crack extension law [16], Norton's law for describing creep evolution of turbines [17]; some statistical model methods such as Autoregressive model [18, 19], random coefficient model [20], Markov model [21]; artificial intelligence based methods such as artificial neural network[22], neural fuzzy [23], support vector machine [24], Gaussian process regression [25], and some mixed models, as in [26].

Not only can PHM determine the current system status through diagnostic analysis, but also it can predict the future trends through prediction methods. It has been applied in related fields, such as aerospace [27], nuclear energy [24], wind power generation machine [28], railway and transportation [29], intelligent manufacturing [2, 30-32]. A robotic failure can

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

cause the production line to shut down, and may damage the product being processed [33].

PHM can be applied to component levels such as bearings [22], gearbox [34], motor [35],as well as turbine [36]. And PHM can also be used in system levels. For the aircraft environmental control system, J. P. Gomes [1] assumed the RUL probability density function of each component is known, then combined the single component RUL estimation as well as fault tree for predicting the system RUL. This method can also be used to predict aircraft failures and prevent airplanes on the ground events from occurring successfully. Different from the RUL that only considering key components in the system RUL prediction [37], the influence of multiple components in the system is considered in this method. However, the shortcoming is that the interaction of faults between components is not taken into account. Enrico, D. I. Maio [38] predicted the RUL of nuclear systems' lead-bismuth eutectic accelerator drive system based on the similarity method. Before detecting the fault, the RUL in the reference trajectory is averaged as the RUL of the test trajectory; after the fault is detected, then the RUL of the reference trajectory is weighted averaged as the RUL of the test trajectory. And the fuzzy similarity analysis is used to determine the similarity, the higher similarity, the higher weight. A. Cordoba-Arenas [39] proposed a method for handling interconnected battery systems, in which the effects of different topologies, the effect of battery levels on the system, and the interaction between different battery levels are taken into account. E. Fumeo [40] proposed a CBM algorithm based on streaming data analysis for railway transportation systems, which uses online support vector regression to predict RUL.

In the field of robotics, the acceleration signals [41, 42], vibration signals [43], acoustic emission (AE) signals [44], motor current signals and voltage signals [45, 46] of the robot are generally acquired; and wavelet transform [47] is often used for signal processing.

At present, there are many good reviews to sort out these tasks. For example, Z. X. Zhang [48] reviewed the latest modeling developments of RUL estimation methods Wiener processes and the applications in prediction and health management. G. W. Vogl [49] reviewed the challenges, requirements, methods, and the best practices of PHM in the manufacturing systems. N. C. K. L. Tsui [50] briefly reviewed the mainstream methodological framework for PHM, especially focused on the data-driven approaches; and provided some real-world examples of PHM. Y. Lei [51] conducted a systematic evaluation of the whole process. Although there are many reviews, the current PHM review for robots has not been found yet.

In the PHM of industrial robot systems, this paper describes the health prognostics methods from the component level as well as the system level. According to the physical structure analysis of the industrial robot, the position of the fault mainly lies in the moving joint part, and the moving joint includes a gearbox (reducer) and a servo motor. The paper analyzes the papers related to the diagnosis and prediction of the industrial robot's gearbox (reducer) and servo motor, including data acquisition and processing, HI construction and RUL prediction during the diagnosis and prediction process. Finally, some prospects and conclusions have been made in the field of industrial robots. The rest of this article is organized as follows. Section II presents the PHM of the robot's components. Section III presents the PHM of robot from the system level. Finally, prospects are presented in Section IV.

II. COMPONENT LEVEL

When industrial robots operating under long working loads, the most common causes of failure are the gearbox (reducer) [41] and the servo motor [52] in the joint. Therefore, it is significant to perform fault prediction and health management assessment on them.

A. Gearbox (reducer)

The gearbox (reducer) is a transmission device used in robot joint, which is the core part of the robot. Transmission error is a key index to measure transmission precision. The main reasons of transmission error are the friction and wear caused by the movement of the components during the long-term work. When the robot is working, the small transmission error of the gearbox (reducer) will affect the trajectory accuracy of the robot, or even cause industrial accidents, so it is necessary to diagnose and estimate it.

1) Data acquisition and processing

In the data collection of the gearbox (reducer), vibration signals acquisition is a preferred method. A. C. Bittencourt [43] extracted the vibration signals of the gearbox from the accelerometer and used it to diagnose the wear of gearbox of industrial robots. A. A. Jaber [41] collected wrist vibration signals through an accelerometer, and used discrete wavelet transform (DWT) analysis to extract signal-decomposed coefficients as features to diagnose gear faults of industrial robots.

Z. Chen [53] chose the vibration signal as the experimental data source because the transmission was sensitive to the existence of faults. M. Khazaee [54] proposed a fault diagnosis method that combines the analysis of two kinds of signals (vibration signals and AE signals) and successfully completed the experiment on the planetary gearbox. X. Q. Liu [44] used vibration signal and AE signal to monitor and diagnose industrial robot reducer. H. D. Ardakani [45] collected the current signal and speed signal, and used motor current signature analysis to diagnose the transmission fault under instantaneous speed.

2) HI construction

A. C. Bittencourt [43] used kernel density estimation and Kullback-Leibler distance as the indicators of industrial robot gearbox fault diagnosis. A. A. Jaber[41] discovered that the standard deviation of vibration signals is the best fault sensitive feature, which can be used to judge the health status of the robot gear. X. Q. Liu [44] selected the vibration signal's rate ratio and the amplitude of AE signal as indicators to determine the fault. M. Khazaee [54] selected 30 particulars of wavelet coefficients after processing of vibration signal and AE signal as important characteristics, and applied them to train ANN classifier.

3) RUL prediction

B. Ayhan [34] mentioned four methods to predict the RUL of gearbox. The first is the rule-based method, and the second is the combination of damage curve method and rule-based method. The third is the quadratic discriminant analysis method. The last one is a combination of the first three methods. M.

Gašperin [55] proposed a data-driven prediction framework based on online model estimation RUL, constructs a nonlinear model by using Kalman filter or PF, and the experiment was successfully verified on the single-stage gearbox.

B. Motor

The servo motor is the power system of industrial robots and the "heart" of robot movement. In order to keep the robot in good working performance, the servo motor must have high reliability and stability. However, since the motor is under high load for a long time, it is easy to cause wear and tear of internal parts and mechanical vibration, which will damage the robot and affect its normal operation. Therefore, it is very important to evaluate the working condition and fault diagnosis of the motor.

1) Data acquisition and processing

In the diagnosis and prediction of motor, it is common to collect vibration signals and current and voltage signals of motor. R. Razavi-Far [56] diagnosed faulty motor faults by acquiring and processing vibration signals. Q. Wu [46] selected the current signal and voltage signal of the motor as the experimental signals for motor fault diagnosis. Y. Feng [35] selected the motor's current signal and voltage signal as the main reference signals for the motor RUL prediction experiment. S. S. H. Zaidi [57] only collected motor current signal to predict the future state of motor fault. M. Seera [58] processed current signals for experiments and classified motor faults. A. Glowacz [59] proposed a motor fault diagnosis method based on sound signal.

2) HI construction

R. Razavi-Far [56] carried out preliminary processing on the vibration signals, and extracted root mean square, variance, skewness, kurtosis, etc. as the time domain characteristic index for analysis. Q. Wu [46] proposed 11 characteristics (partial value, peak value, peak factor, etc.) as HIs for the experiment in his research. M. Seera [58] used fuzzy min-max - classification and regression tree to extract power spectral density as the input feature of feature recognition. B. Park [60] introduced the observer-based residual error as an index to predict the servo motor RUL.

3) RUL prediction

Y. Feng [35] proposed a data-driven prediction method of motor RUL with linear degradation health index. The model from the input signal characteristic data to the predicted health index is established firstly, and then the mapping from the health index to the remaining service life is constructed. S. S. H. Zaidi [57] extracted the time-frequency characteristics from the motor current and used hidden Markov model to judge the future state of fault severity, where RUL is obtained from the probability estimation of the fault state. Q. Yuan [61] built a nonlinear model referred to wiener process, and calculated the life distribution at different times by using the multi-stage model, and obtained the predicted value of motor life.

C. Joint

The joint part of the industrial robot can be considered as a "small system" of reducer and servo motor, multiple error fusion within the joint is considered as a whole to be studied. In this part, the data acquisition and processing content are introduced related to industrial robot joints and the construction of health indicators. The data acquisition and processing scheme of the industrial robot system level will be elaborated in the following part.

1) Data acquisition and processing

A. Datta [33] proposed to use joint motion signals of industrial robots, and then applied wavelet multi-resolution analysis to modulate signals into multiple resolution levels, finally trained the neural network and diagnosed joint faults. I. Trendafilova [42] proposed a method to detect the joint gap fault of the robot by using the acceleration signals measured at the end of the robot. H. Liu [62] collected and processed the acceleration signals of the end-effector of the robot, and analyzed the fault diagnosis of the robot joint.

2) HI construction

I. Trendafilova [42] pointed out that the amplitude, variance and skewness of the signals can be used as the detection indexes of robot joints. H. Liu [62] proposed a de-trending algorithm to separate the program related acceleration and transmission related acceleration signals from the signals measured by the joint accelerometer, and took the difference between the measured signals and the theoretical signals as the reference value for fault analysis.

III. System level

In robot fault diagnosis and health prognostics, many researchers will consider robot system level for robot diagnosis. The following is a summary of relevant research work in the field of robots from data acquisition and processing and HI construction.

1) Data acquisition and processing

At the level of robot systems, generally by taking the robot's historical event log [63], the robot's joint signal [33], the acceleration signal measured by the joint [42], the terminal acceleration signal [47, 62] and robot's position signal [30]. Lee Y. H [64] proposed to use the data on joint currents and angles which could be measured by the robot itself to prognostic the state of the robot.

2) HI construction

At the system level, the tool center position (TCP) of robot system accuracy degradation analysis is a key factor to evaluate the condition of industrial robots in the manufacturing industry. TCP precision is generally defined by considering such aspects as velocity, force, torque, acceleration, and position. Precision can also represent the deviation between the command and actual speed, acceleration, force as well as torque [30].

IV. Research prospect

Although many achievements have been made in the PHM field, further research is needed in the field of robotics. There are still many obstacles in the research process for forming a mature and perfect robot PHM system. Y. Lei et al. [51] proposed several challenges and suggestions for PHM in the literature to help researchers point out the direction. J. Lee et al. [65] identified a new trend for PHM development in the future. NIST researchers mentioned the development direction of industrial robot PHM in the literature[66].

1) Effective data utilization

In general, there is little historical data available for new equipment, and data collection is a major challenge [67]. In this case, it is needed to make the most of the available information, such as the physical information of similar devices, the subjective expertise of engineers and manufacturers [51]. Through transfer learning methods [68], applying laboratory data migration to the prognostic and health management of industrial robots can enhance the precision of RUL prediction [51]. Data sharing of industrial robots of the same type based on cloud framework can enrich data sets and help to build models [69]. It is of great significance to develop new or more advanced multi-source sensor information fusion methods [51, 70].

2) Robot system RUL prediction

Without special design experiment and advanced micro measurement technology, it is difficult to measure the damage degree of equipment directly. It is tough to reveal the relationship between damage degree and residual service life. The faults between different parts make the robot system more complex. The uncertainty makes it hard to accurately predict the robot system RUL [51]. Effective estimation and processing of uncertainty is the basis of accurate prediction of RUL [8]. HI construction plays an important role in mechanical prediction. And finding an appropriate HI can simplify the prediction model and produce accurate prediction results [51]. This field needs to develop a more perfect fault diagnosis scheme of the industrial robot system and more accurate RUL prediction system [50].

References

[1] J. P. Gomes, L. Rodrigues, R. K. H. Galvão, and T. Yoneyama, "System level RUL estimation for multiple-component systems," in *Proceedings of Annual conference of the Prognostics and Health Management Society*, 2013, pp. 74-82.

[2] G. Qiao and B. A. Weiss, "Advancing measurement science to assess monitoring, diagnostics, and prognostics for manufacturing robotics," *International journal of prognostics and health management,* vol. 13, 2016.

[3] B. A. Weiss *et al.*, "Measurement science for prognostics and health management for smart manufacturing systems: key findings from a roadmapping workshop," in *Proceedings of the Annual Conference of the Prognostics and Health Management Society*, 2015.

[4] R. Moghaddass and M. J. Zuo, "An integrated framework for online diagnostic and prognostic health monitoring using a multistate deterioration process," *Reliability Engineering & System Safety,* vol. 124, pp. 92-104, Apr 2014.

[5] D. A. Tobon-Mejia, K. Medjaher, N. Zerhouni, and G. Tripot, "A data-driven failure prognostics method based on mixture of gaussians hidden markov models," *IEEE Transactions on Reliability,* vol. 61, no. 2, pp. 491-503, Jun 2012.

[6] E. F. Hogge *et al.*, "Verification of a remaining flying time prediction system for small electric aircraft," 2015.

[7] A. Malhi, R. Yan, and R. X. Gao, "Prognosis of defect propagation based on recurrent neural networks," *IEEE Transactions on Instrumentation and Measurement,* vol. 60, no. 3, pp. 703-711, Mar 2011.

[8] Y. Lei, N. Li, and J. Lin, "A new method based on stochastic process models for machine remaining useful life prediction," *IEEE Transactions on Instrumentation and Measurement,* vol. 65, no. 12, pp. 2671-2684, Dec 2016.

[9] J. Hu and P. W. Tse, "A relevance vector machine-based approach with application to oil sand pump prognostics," *Sensors,* vol. 13, no. 9, pp. 12663-12686, Sep 2013.

[10] K. Medjaher, N. Zerhouni, and J. Baklouti, "Data-driven prognostics based on health indicator construction : application to PRONOSTIA's data," in *European Control Conference (ECC)*, 2013, pp. 1451-1456.

[11] P. Večeř, M. Kreidl, and R. Šmíd, "Condition indicators for gearbox condition monitoring systems," *Acta Polytechnica,* vol. 45, no. 6, 2005.

[12] M. Zhao, B. Tang, and Q. Tan, "Bearing remaining useful life estimation based on time-frequency representation and supervised dimensionality reduction," *Measurement,* vol. 86, pp. 41-55, May 2016.

[13] 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, May 2017.

[14] T. Benkedjouh, K. Medjaher, N. Zerhouni, and S. J. J. o. I. M. Rechak, "Health assessment and life prediction of cutting tools based on support vector regression," *Journal of Intelligent Manufacturing,* vol. 26, no. 2, pp. 213-223, Apr 2015.

[15] F. E. P.C. Paris, " A critical analysis of crack propagation laws," *Journal of basic engineering,* vol. 85, no. 4, pp. 528–533, Dec 1963.

[16] W. Ostachowicz and M. Krawczuk, "Coupled torsional and bending vibrations of a rotor with an open crack," *Archive of applied mechanics,* vol. 62, no. 3, pp. 191-201, 1992.

[17] Y. Hu, P. Baraldi, F. Di Maio, and E. Zio, "Online performance assessment method for a model-based prognostic approach," *IEEE Transactions on Reliability,* vol. 65, no. 2, pp. 718-735, Jun 2016.

[18] D. Barraza-Barraza, V. G. Tercero-Gomez, M. G. Beruvides, and J. Limon-Robles, "An adaptive ARX model to estimate the RUL of aluminum plates based on its crack growth," *Mechanical Systems and Signal Processing,* vol. 82, pp. 519-536, Jan 2017.

[19] Y. Qian and R. Yan, "Remaining useful life prediction of rolling bearings using an enhanced particle filter," *IEEE Transactions on Instrumentation and Measurement,* vol. 64, no. 10, pp. 2696-2707, Oct 2015.

[20] R. Zhou, N. Gebraeel, and N. Serban, "Degradation modeling and monitoring of truncated degradation signals," *IIE Transactions,* vol. 44, no. 9, pp. 793-803, Jun 2012.

[21] Y. Liu, M. J. Zuo, Y.-F. Li, and H.-Z. Huang, "Dynamic reliability assessment for multi-state systems utilizing system-level inspection data," *IEEE Transactions on Reliability,* vol. 64, no. 4, pp. 1287-1299, Dec 2015.

[22] M. Elforjani, "Estimation of remaining useful life of slow speed bearings using acoustic emission signals," *Journal of Nondestructive Evaluation,* vol. 35, no. 4, pp. 1-16, Dec 2016.

[23] F. Zhao, J. Chen, L. Guo, and X. Li, "Neuro-fuzzy based condition prediction of bearing health," *Journal of Vibration and Control,* vol. 15, no. 7, pp. 1079-1091, Jul 2009.

[24] J. Liu, V. Vitelli, E. Zio, and R. Seraoui, "A novel dynamic-weighted probabilistic support vector regression-based ensemble for prognostics of time series data," *IEEE Transactions on Reliability,* vol. 64, no. 4, pp. 1203-1213, Dec 2015.

[25] S. Saha, B. Saha, A. Saxena, and K. Goebel, "Distributed prognostic health management with gaussian process regression," in *IEEE Aerospace Conference*, 2010, pp. 1-8.

[26] G. Bai and P. Wang, "Prognostics using an adaptive self-cognizant dynamic system approach," *IEEE Transactions on Reliability,* vol. 65, no. 3, pp. 1427-1437, Sep 2016.

[27] J. Xu, Y. Wang, and L. Xu, "PHM-oriented integrated fusion prognostics for aircraft engines based on sensor data," *IEEE Sensors Journal,* vol. 14, no. 4, pp. 1124-1132, Apr 2014.

[28] R. K. Pandit and D. Infield, "Performance assessment of a wind turbine using SCADA based Gaussian process model," *International Journal of Prognostics and Health Management,* vol. 9, no. 1, Jun 2018.

[29] A. De Martin, A. Dellacasa, G. Jacazio, and M. Sorli, "Integrated health monitoring for the actuation system of high-speed tilting trains," 2019.

[30] G. Qiao, and Weiss, B. A, "Accuracy degradation analysis for industrial robot systems," in *ASME International Manufacturing Science and Engineering Conference*, 2017, p. 9.

[31] B. Y. Choo, B. A. Weiss, J. A. Marvel, S. C. Adams, and P. A. Beling, "Adaptive multi-scale prognostics and health management for smart manufacturing systems," *International Journal of Prognostics and Health Management,* vol. 7, pp. 014-014, 2016.

[32] P. O'Donovan, K. Bruton, and D. T. J. O'Sullivan, "Case study: the implementation of a data-driven industrial analytics methodology and platform for smart manufacturing," *International Journal of Prognostics and Health Management,* vol. 7, 2016.

[33] A. Datta, C. Mavroidis, J. Krishnasamy, and M. Hosek, "Neural netowrk based fault diagnostics of industrial robots using wavelt multi-resolution analysis," in *American Control Conference*, 2007, pp. 1858-1863.

[34] B. Ayhan, C. Kwan, and S. Y. Liang, "High performance remaining useful life prediction for gearbox," in *IEEE International Conference on Prognostics and Health Management*, 2018, pp. 1-8.

[35] Y. Feng, M. Salahuddin, T. Zhang, X. Zhao, and S. Nadarajan, "Health index-based prognostics for remaining useful life predictions in electrical machines," *IEEE Transactions on Industrial Electronics,* vol. 63, no. 4, pp. 2633-2644, 2016.

[36] S. Yin, G. Wang, and H. R. Karimi, "Data-driven design of robust fault detection system for wind turbines," *Mechatronics,* vol. 24, no. 4, pp. 298-306, Jun 2014.

[37] G. R. Jouin M, Hissel D, Péra M-C, Zerhouni N, "Degradations analysis and aging modeling for health assessment and prognostics of pemfc," *Reliability Engineering & System Safety,* vol. 148, pp. 78–95, Apr 2016.

[38] Enrico, D. I. Maio, F. J. R. Engineering, and S. Safety, "A data-driven fuzzy approach for predicting the remaining useful life in dynamic failure scenarios of a nuclear system," *Reliability Engineering & System Safety,* vol. 95, no. 1, pp. 49-57, 2010.

[39] A. Cordoba-Arenas, S. Onori, G. Rizzoni, and G. Fan, "Aging propagation in advanced battery systems: preliminary results," *IFAC Proceedings Volumes,* vol. 46, no. 21, pp. 313-318, 2013.

[40] E. Fumeo, L. Oneto, and D. Anguita, "Condition based maintenance in railway transportation systems based on big data streaming analysis," *Procedia Computer Science,* vol. 53, pp. 437-446, 2015.

[41] A. A. Jaber and R. Bicker, "Fault diagnosis of industrial robot gears based on discrete wavelet transform and artificial neural network," (in English), *Insight,* Article vol. 58, no. 4, pp. 179-186, Apr 2016.

[42] I. Trendafilova and H. V. J. M. Brussel, "Condition monitoring of robot joints using statistical and nonlinear dynamics tools," *Meccanica,* vol. 38, no. 2, pp. 283-295, 2003.

[43] A. C. Bittencourt, K. Saarinen, S. Sander-Tavallaey, S. Gunnarsson, and M. J. M. Norrlöf, "A data-driven approach to diagnostics of repetitive processes in the distribution domain–applications to gearbox diagnostics in industrial robots and rotating machines," *Mechatronics,* vol. 24, no. 8, pp. 1032-1041, 2014.

[44] X. Liu, X. Wu, C. Liu, and T. J. T. o. t. C. S. f. M. E. Liu, "Research on condition monitoring of speed reducer of industrial robot with acoustic emission," *Transactions of the Canadian Society for Mechanical Engineering,* vol. 40, no. 5, pp. 1041-1049, 2016.

[45] H. D. Ardakani, Z. Liu, J. Lee, I. Bravo-Imaz, and A. Arnaiz, "Motor current signature analysis for gearbox fault diagnosis in transient speed regimes," in *IEEE Conference on Prognostics and Health Management* 2015, pp. 1-6.

[46] Q. Wu, X. Yang, Q. J. J. o. I. Zhou, and C. Science, "Pattern recognition and its application in fault diagnosis of electromechanical system," *Journal of Information &Computational Scienc,* vol. 9, no. 8, pp. 2221-2228, 2012.

[47] A. Jaber and R. Bicker, "Industrial robot fault detection based on wavelet transform and LabVIEW," in *International Conference on Systems Informatics*, 2014, pp. 118-123.

[48] Z. X. Zhang, X. S. Si, C. H. Hu, and Y. G. Lei, "Degradation data analysis and remaining useful life estimation: a review on wiener-process-based methods," *European Journal of Operational Research,* vol. 271, no. 3, pp. 775-796, Dec 2018.

[49] G. W. Vogl, B. A. Weiss, and M. Helu, "A review of diagnostic and prognostic capabilities and best practices for manufacturing," *Journal of Intelligent Manufacturing,* vol. 30, no. 1, pp. 79-95, Jan 2019.

[50] T. Kwok L, 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, pp. 1-17, Jan 2015.

[51] Y. Lei, N. Li, L. Guo, N. Li, T. Yan, and J. Lin, "Machinery health prognostics: a systematic review from data acquisition to RUL prediction," *Mechanical Systems and Signal Processing,* vol. 104, pp. 799-834, May 2018.

[52] R. Konowrocki, T. Szolc, A. Pochanke, A. Pręgowska, and S. Processing, "An influence of the stepping motor control and friction models on precise positioning of the complex mechanical system," *Mechanical Systems and Signal Processing,* vol. 70, pp. 397-413, 2016.

[53] Z. Chen, C. Li, R.-V. J. S. Sanchez, and Vibration, "Gearbox fault identification and classification with convolutional neural networks," *Shock and Vibration,* vol. 2015, pp. 1-10, 2015.

[54] M. Khazaee, H. Ahmadi, M. Omid, A. Moosavian, and M. Khazaee, "Classifier fusion of vibration and acoustic signals for fault diagnosis and classification of planetary gears based on dempster–shafer evidence theory," in *Proceedings of the Institution of Mechanical Engineers*, 2014, pp. 21-32.

[55] M. Gašperin, Đ. Juričić, and P. Boškoski, "Prediction of the remaining useful life: an integrated framework for model estimation and failure prognostics," in *IEEE Conference on Prognostics and Health Management*, 2012, pp. 1-8.

[56] R. Razavi-Far, M. Saif, V. Palade, and E. Zio, "Adaptive incremental ensemble of extreme learning machines for fault diagnosis in induction motors," in *International Joint Conference on Neural Networks* 2017, pp. 1615-1622.

[57] S. S. H. Zaidi, S. Aviyente, M. Salman, K.-K. Shin, and E. G. Strangas, "Prognosis of gear failures in dc starter motors using hidden markov models," *IEEE Transactions on industrial Electronics,* vol. 58, no. 5, pp. 1695-1706, 2011.

[58] M. Seera, C. P. Lim, D. Ishak, H. J. I. t. o. n. n. Singh, and l. systems, "Fault detection and diagnosis of induction motors using motor current signature analysis and a hybrid FMM–CART model," *IEEE Transactions on Neural Networks and Learning Systems,* vol. 23, no. 1, pp. 97-108, 2012.

[59] A. Glowacz and S. Processing, "Fault diagnosis of single-phase induction motor based on acoustic signals," *Mechanical Systems and Signal Processing,* vol. 117, pp. 65-80, 2019.

[60] B. Park, H. Jeong, H. Huh, M. Kim, and S. Lee, "Experimental study on the life prediction of servo motors through model-based system degradation assessment and accelerated degradation testing," *Journal of Mechanical Science and Technology,* vol. 32, no. 11, pp. 5105-5110, Nov 2018.

[61] Q. Yuan, X. Li, and Y. Gao, "Multistage degradation modeling for BLDC motor based on wiener process," in *IOP Conference Series: Materials Science and Engineering*, 2018, vol. 351, no. 1, p. 012009: IOP Publishing.

[62] H. Liu, W. Tao, and X. Wang, "Signal decomposition and fault diagnosis of a SCARA robot based only on tip acceleration measurement," in *International Conference on Mechatronics & Automation*, 2009, pp. 4811-4816.

[63] V. Sathish, S. D. Sudarsan, and S. Ramaswamy, "Event based robot prognostics using principal component analysis," in *IEEE International Symposium on Software Reliability Engineering Workshops*, 2014, pp. 14-17.

[64] Y. H. Lee, K. J. Kim, S. I. Lee, and D. J. Kim, "Seq2Seq model-based Prognostics and Health Management of Robot Arm," *The Journal of Korea Institute of Information, Electronics, and Communication Technology,* vol. 12, no. 3, pp. 242-250 2019.

[65] J. Lee *et al.*, "Prognostics and health management design for rotary machinery systems—reviews, methodology and applications," *Mechanical systems and signal processing,* vol. 42, no. 1-2, pp. 314-334, 2014.

[66] Z. Huang, Z. Xu, X. Ke, W. Wang, and Y. Sun, "Remaining useful life prediction for an adaptive skew-wiener process model," *Mechanical Systems and Signal Processing,* vol. 87, pp. 294-306, Mar 15 2017.

[67] R. Gao *et al.*, "Cloud-enabled prognosis for manufacturing," *CIRP Annals,* vol. 64, no. 2, pp. 749-772, 2015.

[68] S. J. Pan, Q. J. I. T. o. k. Yang, and d. engineering, "A survey on transfer learning," *IEEE Transactions on Knowledge and Data Engineering,* vol. 22, no. 10, pp. 1345-1359, 2010.

[69] X. V. Wang, L. Wang, A. Mohammed, M. J. R. Givehchi, and C.-I. Manufacturing, "Ubiquitous manufacturing system based on cloud: a robotics application," *Robotics and Computer-Integrated Manufacturing,* vol. 45, pp. 116-125, 2017.

[70] J. Pellegrino, M. Justiniano, A. Raghunathan, and B. A. Weiss, "Measurement science roadmap for prognostics and health management for smart manufacturing systems," No. Advanced Manufacturing Series (NIST AMS)-100-22016.