Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 16 (2014) 158 – 163

www.elsevier.com/locate/procedia

Product Services Systems and Value Creation. Proceedings of the 6th CIRP Conference on Industrial Product-Service Systems

Overview of Remaining Useful Life Prediction Techniques in Through-Life Engineering Services

C. Okoh, R. Roy, J. Mehnen, L. Redding

EPSRC Centre for Innovative Manufacturing in Through-Life Engineering Services
Department of Manufacturing and Materials, Cranfield University, MK43 0AL, Cranfield, United Kingdom

Corresponding author. Tel.: +44-1234-750111. *E-mail address:* c.okoh@cranfield.ac.uk

Abstract

Through-life Engineering Services (TES) are essential in the manufacture and servicing of complex engineering products. TES improves support services by providing prognosis of run-to-failure and time-to-failure on-demand data for better decision making. The concept of Remaining Useful Life (RUL) is utilised to predict life-span of components (of a service system) with the purpose of minimising catastrophic failure events in both manufacturing and service sectors. The purpose of this paper is to identify failure mechanisms and emphasise the failure events prediction approaches that can effectively reduce uncertainties. It will demonstrate the classification of techniques used in RUL prediction for optimisation of products' future use based on current products in-service with regards to predictability, availability and reliability. It presents a mapping of degradation mechanisms against techniques for knowledge acquisition with the objective of presenting to designers and manufacturers ways to improve the life-span of components.

Keywords: Through-life engineering services; Remaining Useful Life; Prediction techniques; Prediction methodologies; Degradation mechanisms

1. Introduction

Through-life engineering services (TES) are essential to the support of manufactured complex engineering products. As organisations adopt Industrial Product Service Systems (IPSS) there is the need to maximise the product availability for use.

Through-life engineering services are technical services that are necessary to guarantee the required and predictable performance of a complex engineering system throughout its expected operational life with optimum whole life cost [1]. This is driven by timely maintenance, repair and overhaul (MRO) [1] of the decision making process with the aim to restore assets to a state to continually perform its design specifications; these maintenance decisions are the combination of managerial, supervisory, technical and corresponding administrative activities facilitated by the ability to predict Remaining Useful Life (RUL) [2]. Such predictions are typically undertaken either by model-based, analytical-based, knowledge-based, and hybrid-based simulation algorithms and tools, the application of which aims to manage product support systems, structures, and infrastructures more efficiently.

Prognostic is defined as the estimation of RUL (or time-to-failure) of a component or system which can be filtered by existing or future failure modes [3].

This paper reports the findings of a recent review of the literature relative to the use of prognostics in support of TES enabled IPSS. The techniques applied to determine the RUL of gas turbine components are also discussed. The research uses data from semi-structured interviews with academics and practitioners to identify types of degradation mechanisms for aero-engine components as part of an ongoing case study, the

doi:10.1016/j.procir.2014.02.006

aim of which is to categorise such failures and identify the root causes. This paper appraised various degradation mechanisms for the chosen component (section 2), and then maps the degradation mechanisms against RUL prediction techniques to ease the identification of appropriate prediction methods for engine parts (section 3). The importance of TES is then discussed in section 4.

2. Degradation Mechanisms

This research relates the characterisation of service acquired knowledge and its feedback to design, identifies the following degradation mechanisms as being predominant in metallic components: corrosion, deformation, fracture and wear. There is a need to curtail component's failure and a timely awareness of failure mechanism is essential for maintenance decisions based on threshold levels, confidence interval and RUL estimate with regards to through-life engineering services in the field of industrial products systems.

Current research activities include complexity based failure modeling for planned maintenance proposed by Meselhy et al, [4], who explained that failure results from a machine operating condition and structure breakdown of components. The complexity based failure modeling would enhance preventive maintenance. ElMaraghy et al, [5] demonstrated a novel complexity coding system to capture manufacturing system information; failure threshold with regards to functional requirements is dependent upon usage complexity. Karandikar et al, [6] focused on wear failure mode predictions using Bayesian inference. Corran and Williams, [7] proposed lifing methods and safety criteria in aero gas turbines. Fashandi and Umberg, [8] discussed the essential requirements for establishing concise and effective reliability specifications. ElMaraghy and Urbanic [9] focused on operational complexity by considering human characteristics relative to system performance and sensitivities.

Future potential research includes predictive maintenance strategies required to reduce the failure of industrial manufactured products, increase and improve productivity, enhance reliability and availability of engineering services, reduce costs and downtime on production by estimating the remaining useful life of the asset or equipment in-service [10]. ElMaraghy [5] iterated that man, machine and software interaction is crucial in manufacturing systems with operational level complexity; various components should be designed within the system; further detailing needed as connectivity affects the degree of complicatedness; complicated manufacturing systems cost more to implement, operate, support and maintain. Also, software tools should adapt computational intelligence techniques to deliver quick, accurate and precise estimate for maintenance decision making. According to Ajai [11], the healthcare should explore point-of-care devices for use in remote environments in order to deliver services which would assist users to know when to take medications. The adaptation and implementation of RUL would aid the healthcare point-of-care devices to provide estimates of time for medication

2.1. Types of Degradation Mechanisms

- **Wear** is the loss of material over a period of time resulting from component use. The estimation of wear (or resistance to wear) can be achieved by implementing the weighting method to fix and measure wear. This is calculated done by weighting the component before and after use. The variables to consider include speed, friction co-efficient, surface finish/texture, surface hardness, load, number of cycles, and time are all critical in estimating adhesion wear of metallic engine components (e.g brass, aluminum, and steel) [12].

- **Corrosion** is a chemical deterioration process (material loss) resulting from electrical or biological reaction, which includes oxidation and sulphidation (Fig. 2). Methods to measure corrosion rate include an electro-chemical technique shows the speed at which reinforcing steels are corroding and identify degraded areas [13].

Fig. 1: Metal discs showing corrosion on the surface

- **Fracture** is separation of material by means of cracking or disintegration which makes a component incapable of performing its designed functions. It can occur as a result of chemical effects, shock, and/or stress. This failure mechanism occurs via loading which is independent of time [14]. A slow change (creep) in structure can lead to fracture whereby the presence of crack can grow rapidly in steels or aluminum alloys (Fig. 2). Thus, [15] indicated that fracture increases slightly as strain rate increases in copper, iron and steel using a fracture model, pressure - strain ratio is critical as well as temperature and stress rate.

(a) (b)

Fig. 2: Bearing (a) external ring failure, and (b) inner ring failure with fracture (Source: [3])

- **Deformation** is a change in the geometry or shape of a component such as shrinking, stretching, bending, and twisting have cumulative effects upon strain in a component due to an applied force [14]. Deformation is categorized into a time dependent and time independent mechanisms (Fig. 3).

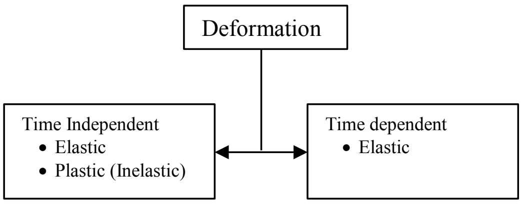

Fig. 3: Types of Deformation (Adapted source: [14])

In Creep deformation the component gradually accumulates over time with the presence of high temperature and thermal cycles stress until the product fails. Elastic deformation results from applied loads and when the load is removed, the assets returns to its original condition. Plastic deformation occurs when the material exceeds its elastic limit and results in a permanent change to the physical structure of the material even when the load is removed [14]. Typically Monte Carlo-based uncertainty technique, optical measurement systems, digital image correlation, the intensity method, or phase shift method are often used for deformation measure. [16].

This research submits that deformation, fracture, wear and corrosion can be measured to ascertain through-life perspectives of the product or component using a variety of methods relative to RUL.

3. Remaining Useful Life (RUL)

Remaining Useful Life (RUL) is the time remaining for a component to perform its functional capabilities before failure. Xiongzi et al, [2] defined RUL as the duration from current time to end of useful life for a component (Fig. 4).

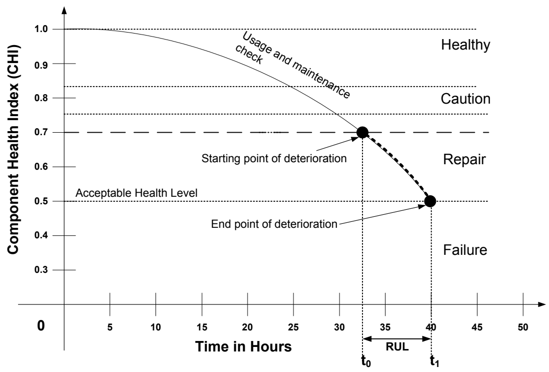

Fig. 4: CHI against Time (hours) (Adapted source: [2])

3.1. Classification of Techniques for RUL Prediction

There are several prognostics prediction methods used for determining the RUL of subsystems or components. These are categorised as *methodologies* and *techniques*. The techniques for RUL prediction are presented in Fig. 5.

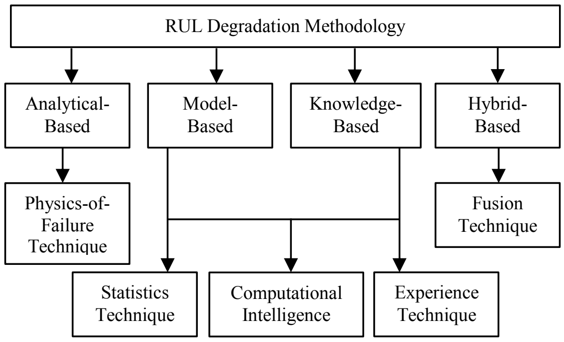

Fig. 5: Classification of techniques for RUL predictions

3.2. Types of Prediction Methodology

- **Model-Based:** RUL prediction is applicable to Statistics and Computational Intelligence (CI) approaches. These models are derived from configuration, usage, and historical 'run-to-failure' data and applicable to maintenance decision making. Such components that are analysed and documented in literature include bearings and gear plates from manufacturing industries. Model-based methodology is often used to estimate RUL thereby informing the maintenance decision based upon failure threshold.

  In using model-based predictions, it is proposed that a '*wavelet packet*' decomposition approach and/or Hidden Markov Models (HMMs) is used to predict RUL where the time frequency features allow more precise results than using only time features [16]. Similarly Xiongzi [2] noted that methods derived from failure and historical data can be used to predict functioning asset RUL without foreknowledge of the physics of formation of a component.

- **Analytical-Based:** Analytical-based RUL prediction approach represents the physical failure technique. The analytical-based model refers to an understanding of techniques which aid reliability estimates of the physics-based model [17] attributed to Physics-of-Failure (PoF), physical science of components and generated experimental equations. Coppe et al, [18] proposed using a simple crack growth model to predict the RUL of a system experiencing fatigue. Failure events such as crack by fatigue, wear, and corrosion of components are based on mathematical laws used to estimate RUL [3]. Analytical-based model requires the combination of experiment, observation, geometry, and condition monitoring of data to estimate any damage in a specific failure mechanism. It also requires the identification of specific parameters to monitor, and the tools to identify and extract features by using failure modes, mechanism and effects analysis.

- **Knowledge-Based:** This model is a combination of CI and experience. The knowledge-based approach relates to the collection of stored information from subject matter experts and interpretation of rules set [19]. It can be seen as a service performance system for service delivery based upon the principles of service feedback for analysis. Parameters of reliability are estimated using an experience based approach to information gathered from understanding the asset [3].

- **Hybrid:** A hybrid model is a collection methodology and technique. Hybrid model uses several techniques for RUL estimation to improve accuracy. Hybrid model uses parametric and non-parametric data to perform RUL estimations and to improve accuracy. It predicts RUL individually and through methods based on probability theory facilitates the fusion two or more RUL prediction results to achieve a new RUL [3].

3.3. Types of Prediction Techniques

- **Statistics:** This technique relates past and present data duly observed and analysed with methods such as auto regressive moving average (ARMA), and exponential smoothing for effective prediction of result. This model applies random variables to new data which improves distribution of unknown parameters [18].

  Cheng and Pecht [20] argued that regression identified the relation between variables and parameter values to predict RUL. In normal operating conditions, ARMA is used to recognize the dynamic behavior of components [21]. Another statistical approach used in the medical and biomedical field is Proportional Hazard Model (PHM) which, when applied to lifecycle issues, can deliver predictions which are more accurate and reliable RUL [22].

- **Experience:** This approach is specific to expert judgment. Knowledge is either explicit or tacit, and gained from subject matter experts. It aids degradation maintenance decision making whereby processes and objects are under consistent observation. Such understanding is obtained from data gathered from failure events and developmental test events. An analysis of the data enables the extraction of feature based on degradation mechanisms which facilitate the construction of datasets. Also, it facilitates the introduction of ‘rules’ for classification of the information in order to determine the RUL of an asset directly by predefining threshold level [23].

- **Computational Intelligence (CI)**: This method – also known as Soft Computing includes fuzzy logic and neural networks which are dependent upon parameters and input data to create the desired output. Artificial Neural Networks (ANN) uses data from continuous monitoring systems and requires training samples. The ANN usually called ‘black-boxes’, provides only little insight into the internal structures [2]. The study so far confirms that data collected from sensors can be translated through ANN to predict RUL of an asset. Other alternative approaches are Bayesian prediction method and Support Vector Machines (SVM) which makes use statistical estimates of condition for limited samples to define predictive learning base [24].

- **Physics-of-Failure (PoF)**: This technique requires parametric data and cover techniques such as Continuum Damage Mechanics, Linear Damage Rules, Non-Linear Damage Curves and Two Stage Linearization. In addition, Life Curve Modification Method of Stress and Load Interaction, Crack Growth Concept, and Energy-Based Damage Models are also available [25].

- **Fusion**: This is the merging of multiple data into a refined state. This approach extracts, pre-process and fuse data for accurate and fast forecast of the RUL of an asset as illustrated in Fig. 6. A better way to incorporate fusion is to classify data with the aid of fuzzy method to improve accuracy of the RUL estimate [26]. In the context of uncertainty in RUL estimation, on-demand information collected from different sensors are fused by either centralized or decentralized means to accurately predict useful life by incorporating Principal Component Analysis (PCA) [27; 28].

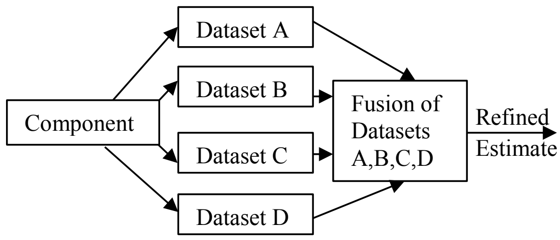

Fig. 6: Sample Fusion Estimate (Adapted source: [28])

3.4. Mapping Degradation Mechanism and Techniques

Having identified the relevant mechanisms, this paper presents the most prominent algorithms for prediction. Table 1 shows the techniques mapped against mechanisms to aid the selection of the correct prediction algorithm for major degradation mechanisms.

When data are mapped against techniques, a decision can be reached on which technique to use for a degradation mechanism. Where planned maintenance of six months interval is required to service the component, the decision can be dependent on past information to predict the life span of the asset.

Employing TES strategies on MRO, once a fracture or crack is identified, a computational intelligence technique such as fuzzy logic is employed. For example, threshold level should NOT be more than a specified crack length otherwise, the asset is scrapped and replaced. Where fracture is within the tolerance margin of a specified crack length, component is repaired and reused.

Table 1: Mapping of Degradation mechanisms versus Prediction techniques

Degradation Mechanism	Statistics	PoF	CI	Experience	Fusion
Fracture	X	X	X	-	X
Wear	X	X	X	-	X
Deformation	-	X	-	X	-
Corrosion	X	X	X	-	X

A mapping of datasets against techniques is presented in Table 2. The architecture of a model for predicting RUL follows the structure of pre-processing, fusion and post-processing. The confidence interval used to justify the maintenance decision is very important when implementing a statistical method of prediction.

PoF requires large amounts of parametric datasets for better prediction with confidence. A regular update of the data is required to successfully use TES strategies for better decision making for MRO. With regards to ordinal datasets for instance, a classification of (low (1-3), medium (4-6), high (7-10)), can be used in fusion, CI and experience techniques to estimate RUL during MRO. These techniques can be embedded in information system application for product service systems such as product lifecycle management (PLM).

Table 2: Techniques versus types of data

Techniques	Large Dataset	Few Dataset	Numerical Dataset	Categorical Dataset	Ordinal Dataset
Fusion	X	-	X	X	X
Statistics	-	X	X	X	-
CI	X	-	X	X	X
Experience	X	X	-	-	X
PoF	X	-	X	-	-

4. Through-Life Engineering Services in relation to degradation mechanisms and techniques to predict RUL

Elements relating to the scope of Through-life engineering services are presented (Fig. 7). It is important that the MRO function aligns with the operations strategy of the organisation. This is facilitated by the correct application of technology supported by efficient use of service knowledge. The benefits obtained from accurate life prediction and improved MRO decision making is significant.

The use of simulation tools, adaptability procedures, modular maintenance systems, and informed disposal decision facilitate the prediction of reliable life expectancy. Also, the increased application of advanced information technology such as PLM for distribution and collaboration, condition monitoring, and prognosis will reduce downtime and provide improved availability of products.

While the issue of Degradation management is a key aspect in TES, the maintenance of autonomous systems and development of capabilities in a collaborative environment can enhance the life-span of components.

The concept of cost engineering provides a performance-based service approach, and whole-life cost model, which is applicable to the whole system maintenance and service delivery systems in order to deliver effective business solutions.

The uncertainty modelling and simulation techniques based on technological and business uncertainties are used to improve component/product designs.

The aforementioned tools and methodologies when supported by obsolescence management, service network for capability assessment, and cost estimation, have the potential to greatly improve the design function. As a result, there will be an improvement in quality, reliability, availability and safety whilst yielding feedback to manufacturers [1].

In view of the above, the mechanisms which can cause component failure are monitored. The techniques for measuring and estimating time-to-failure are also identified together with the input variables and the datasets that would be essential in predicting the remaining useful life of a component.

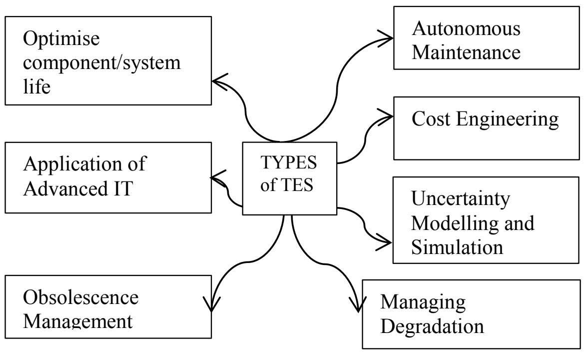

Fig. 7: Types of Through-Life Engineering Services (Adapted source: [1])

5. Conclusion

The effective prediction of RUL for manufactured products within the Industrial Product Service System is a key factor I the sustainable service delivery. Thus, the advantages are: encourages swift MRO decision making and enhances availability of reliable components for use. It reduces regular maintenance cost. It improves operational efficiency.

This paper identifies the main degradation mechanisms (not exclusively) which can affect engine components. The Remaining Useful Life simulation and modelling tools and methods, the mapping of degradation mechanisms versus the prediction techniques have been highlighted. This is coupled with mapping the technique against data type to enable the selection of the relevant modelling methodology.

In the final analysis, it is however seen that TES is a strategic approach within a service delivery system which enables, facilitates and supports IPSS solutions. These toolsets can be embedded within the TES architecture to assist or guide policymakers to make swift and better maintenance decisions.

Acknowledgements

This work is funded by the EPSRC (Engineering and Physical Sciences Research Council, UK), grant number EP/I033246/1 delivered by EPSRC Centre for Innovative Manufacturing in Through-life Engineering Services. The authors also acknowledge Rolls-Royce Plc for their support in this research.

References

[1] Roy, R, Shaw A, Erkoyuncu JA, Redding L. Through-Life Engineering Services. J Measu & Control 2013;46(6):172-175.

[2] Xiongzi, C., Jinsong, Y., Diyin, T. and Yingxun, W. Remaining useful life prognostic estimation for aircraft subsystems or components: A review. 10th IEEE International Conference on Electronic Measurement & Instruments (ICEMI) 2011;2:94.

[3] Medjaher, K., Tobon-Mejia, D. A. and Zerhouni, N. Remaining Useful Life Estimation of Critical Components with Application to Bearings. IEEE Journal of Transactions on Reliability 2012;61(2):292-302.

[4] Meselhy, K. T., ElMaraghy, H. A. and ElMaraghy, W. H. Comprehensive Complexity-Based Failure Modelling for Maintainability and Serviceability. Industrial Product Service Systems IPS2; 89-93; 01-02 April; Cranfield University; 2009.

[5] ElMaraghy, H. A., Kuzgunkaya, O. and Urbanic, R. J. Manufacturing Systems Configuration Complexity. CIRP Ann Manuf Technol 2005;54(1):445-450.

[6] Karandikar, J. M., Abbas, A. and Schmitz, T. L. Remaining useful tool life predictions in turning using Bayesian inference. International Journal of Prognostics and Health Management 2013;4(2):025.

[7] Corran, R. S. J. and Williams, S. J. Lifing methods and safety criteria in aero gas turbines. Eng Failure Anal 2007 4;14(3):518-528.

[8] Fashandi, A. and Umberg, T. Equipment failure definition: a prerequisite for reliability test and validation. Electronics Manufacturing Technology Symposium, IEMT. IEEE/CPMT/SEMI 28th International; 2003.

[9] EIMaraghy, W. H. and Urbanic, R. J. Assessment of Manufacturing Operational Complexity. CIRP Ann Manuf Technol 2004;53(1):401-406.

[10] Gouriveau, R. and Ramasso, E. From real data to remaining useful life estimation: an approach combining neuro-fuzzy predictions and evidential Markovian classifications. 38th ESReDA Seminar Advanced Maintenance Modelling.; 2010.

[11] Ajai, O., Tiwari, A. and Alcock, J. R. Informatics-Based Product-Service-Systems for Point-of-Care Devices *Proceedings of the First CIRP Conference on Industrial Product-Service Systems*; 2009.

[12] Ameen, H. A., Hassan, K. S. and Mubarak, E. M. M. Ameen HA, Hassan KS, Mubarak EMM. Effect of loads, sliding speeds and times on the wear rate for different materials. American journal of scientific and industrial research 2011;2:99-106.

[13] Soleymani, H. R. and Ismail, M. E. Comparing corrosion measurement methods to assess the corrosion activity of laboratory OPC and HPC concrete specimens. Cem Concr Res 2004 11;34(11):2037-2044.

[14] Norman, E. D. Mechanical Behavior of Materials. 4th ed. England: Pearson; 2013.

[15] Johnson, G. R. and Cook, W. H. Fracture characteristics of three metals subjected to various strains, strain rates, temperatures and pressures. Eng Fract Mech 1985;21(1):31-48.

[16] Gåsvik, K. J., Robbersmyr, K. G., Vadseth, T. and Karimi, H. R. Deformation measurement of circular steel plates using projected fringes. The International Journal of Advanced Manufacturing Technology 2014;70(1):321-326.

[17] Bolander, N., Qiu, H., Eklund, N., Hindle, E. and Rosenfeld, T. Physics-based remaining useful life prediction for aircraft engine bearing prognosis. Proceedings of the annual conference of the prognostics and health management society; 2010.

[18] Coppe, A., Pais, M. J., Haftka, R. T. and Kim, N. H. Using a Simple Crack Growth Model in Predicting Remaining Useful Life. J Aircr 2012;49(6):1965-1973.

[19] Chen, C., Vachtsevanos, G. and Orchard, M. E. Machine remaining useful life prediction: An integrated adaptive neuro-fuzzy and high-order particle filtering approach. Mechanical Systems and Signal Processing 2012 4;28(0):597-607.

[20] Cheng, S. and Pecht, M. Multivariate state estimation technique for remaining useful life prediction of electronic products. *AAAI Fall Symposium Artificial Intelligence. Prognostics, Arlington, VA.*; 2007.

[21] Tran, V. T., Thom Pham, H., Yang, B. and Tien Nguyen, T. Machine performance degradation assessment and remaining useful life prediction using proportional hazard model and support vector machine. Mechanical Systems and Signal Processing 2012;32:320-330.

[22] You, M. Y., Lin, L., Guang, M. and Jun, N. Two-zone proportional hazard model for equipment remaining useful life prediction. Journal of manufacturing science and engineering 2010;132(4).

[23] Si, X., Wang, W., Hu, C. and Zhou, D. Remaining useful life estimation – A review on the statistical data driven approaches. Eur J Oper Res 2011 8/16;213(1):1-14.

[24] Yang, S., Liu, C., Zhou, X., Liang, W. and Miao, Q. Investigation on data-driven life prediction methods. International Conference on Quality, Reliability, Risk, Maintenance, and Safety Engineering (ICQR2MSE),: IEEE; 2012.

[25] Fatemi, A. and Yang, L. Cumulative fatigue damage and life prediction theories: a survey of the state of the art for homogeneous materials. Int J Fatigue 1998 1;20(1):9-34.

[26] Di Maio, F., Ng, S. S., Tsui, K. and Zio, E. Naïve Bayesian Classifier for On-line Remaining Useful Life Prediction of Degrading Bearings. Proceedings of the Seventh International Conference on Mathematical Methods in Reliability; 2011.

[27] Cheng, S. and Pecht, M. A fusion prognostics method for remaining useful life prediction of electronic products. IEEE International Conference on Automation Science and Engineering; 2009.

[28] Wei, M., Chen, M., Zhou, D. and Wang, W. Remaining useful life prediction using a stochastic filtering model with multi-sensor information fusion. Prognostics and System Health Management Conference (PHM-Shenzhen); 2011.