Global Advanced Research Journal of Engineering, Technology and Innovation (ISSN: 2315-5124) Vol. 4(2) pp. 016-023, February, 2015
Available online http://garj.org/garjeti/index.htm

Full Length Research Paper

Remaining Useful Life Prediction of Lithium-ion Battery Degradation for a Hybrid Electric Vehicle

Nabil Laayouj* and Hicham Jamouli

Laboratory of Industrial Engineering and Computer Science (LGII), National School of Applied Sciences Ibn Zohr University Agadir, Morocco
** Corresponding author:* nabil.laayouj@gmail.com, tel: +212662267208

Accepted 16 February 2015

Prognostic activity deals with prediction of the remaining useful life (RUL) of physical systems based on their actual health state and their usage conditions. RUL estimation gives operators a potent tool in decision making by quantifying how much time is left until functionality is lost. In addition, it can be used to improve the characterization of the material proprieties that govern damage propagation for the structure being monitored. RUL can be estimated by using three main approaches, namely model-based, data-driven and hybrid approaches. The prognostics methods used later in this paper are hybrid and data-driven approaches, which employ the Particle Filter in the first one and the autoregressive integrated moving average in the second. The performance of the suggested approaches is evaluated in a comparative study on data collected from lithium-ion battery of hybrid electric vehicle.

Keywords: Remaining useful life; prognosis; Particle Filter; ARIMA

INTRODUCTION

Prognosis and health management (PHM) will have significant impact on increasing safety as well as reducing operating and maintenance costs by providing an accurate quantification of degradation and damage at an early stage to reduce or eliminate malfunctions (Medjaher *et al.*, 2012). Furthermore, PHM consists of three main routines: fault detection, diagnostics and prognosis. A prognosis has recently attracted a lot of research interest due to the need of models for accurate RUL prediction (Mosallam *et al.*, 2013).

Numerous methods and tools can be employed to evaluate size of damage by predicting the RUL value. Prognosis techniques can be categorized under three approaches: model-based, data-driven and hybrid approaches. The model based approach (Heng *et al.*, 2009), assumes that a model of system behavior is available and uses this model to predict future of system behavior. Some recent developments in model-based have been reported in literature. Lumped parameter model (Li *et al.*, 2005), functional models (Berruet *et al.*, 1999) and first principal models (Jaw, 1999).

The data-driven approach (Dong *et al.*, 2007) aims at transforming the data provided by sensors into relevant models. In the literature, there is the following works, Relevance vector machine (Tipping, 2000) and neural network (Srivastava *et al.*, 2009). The Hybrid approach (Yan *et al.*, 2007) combines the two approaches cited earlier , and includes Bayesian techniques (Saha *et al.*, 2008; Sheppard *et al.*, 2005).

In this work, we will study two main approaches to predict RUL. The first approach is a hybrid prognosis by using a Particle Filter method, which employs both state dynamic model and a measurement data, the second approach, is a data-driven prognosis based on data collected routinely from condition monitoring devices by using autoregressive integrated moving average model to estimate the system degradation.

This paper is organized as follows. Section 2 contains the descriptions of the approaches at the basis of RUL estimation. In section 3, the results of the application of the methods are presented, and an evaluation of their performance is given. Finally some conclusions on the advantages and limitations of the approaches are given in section 4.

Suggested Predictive Models Based On The Rul Estimation

Prognosis of degradation and remaining useful life

The term prognosis is originally used in medicine for the prediction of a course of an illness. But, later on it has been introduced to industry to predict the future state of operation of the equipment concerned and to set an efficient treatment.

The practitioner uses the results of the forecast models to determine the most appropriate treatment. These forecast models based on simple mathematical tools (e.g. decision tree, conditional probability) (Yang *et al.*, 2008) or more sophisticated (e.g. Markov processes, neural networks, genetic algorithms) (Lucas *et al.*, 1999).

As mentioned earlier, the main metric prognosis seeks for the time before failure. Note that the data prognosis are important information that may be used in decision process. For example, they can be used to delay the maintenance interventions, or stop a machine before its future maintenance due to earlier default. We are interested in our study in assessing RUL to have a clear idea about the evolution of the system degradation.

Methods of prognosis

Particle filter for prognosis

The particle filter method (Arulampalam *et al.*, 2002) is a Monte Carlo technique for the solution of the state estimation problem. The key idea is to represent the required posterior density function by a set of random samples (particles) with associated weights, and to compute the estimates based on these samples and weights. As the number of samples becomes very large, this Monte Carlo characterization becomes an equivalent representation of the posterior probability function, and the solution approaches the optimal Bayesian estimate.

The application of particle filters to prognosis have been reported in the literature, for example, prediction of lithium-ion battery capacity depletion (Saha *et al.*, 2009b), degradation prediction of a thermal processing unit in semiconductor manufacturing (Butler *et al.*, 2010), remaining useful life prediction of a mechanical component subject to fatigue crack growth (Zio *et al.*, 2011), The reported application results have shown that particle filters represent a potentially powerful prognosis tool due to its capability in handling non-linear dynamic systems and non-Gaussian noises using efficient sequential importance sampling (Kong *et al.*, 1994; Ristic *et al.,* 2004) to approximate the future state probability distributions.

Particle filter model

Consider the dynamic system described by the following discrete time model (Zio *et al.*, 2011):

$$x_k = f_k(x_{k-1}, v_k) \qquad (1)$$

$$z_k = h_k(x_k, \omega_k) \qquad (2)$$

Where:

f_k : is the state transition function (damage model)

v_k : is state noise vector of known distribution

h_k : is the measurement function

ω_k : is the measurement noise vector

The goal of tracking is to recursively estimate x_k by using the set of all available measurements $z_{1:k} = (z_1, ..., z_k)$ up to time k, and to create a conditional state PDF (probability density function).like any Bayesian estimation two steps are employed: prediction and update.

In the prediction step, we consider that the PDF $p\langle x_{k-1} | z_{1:k-1} \rangle$ previous state estimate at time $k-1$ and the process model (1) both are used to obtain the prior PDF of the state at time k as shown in Chapman-Kolmogorov equation.

$$p\langle x_k | z_{1:k-1} \rangle = \int p\langle x_k | x_{k-1} \rangle p\langle x_{k-1} | z_{1:k-1} \rangle dx_{k-1} \quad (3)$$

In the update step, at time k, a measurement z_k becomes available from the likelihood defined by the measurement model (2) is used to update the prior distribution to generate the posterior state PDF via Bayes rule (4).

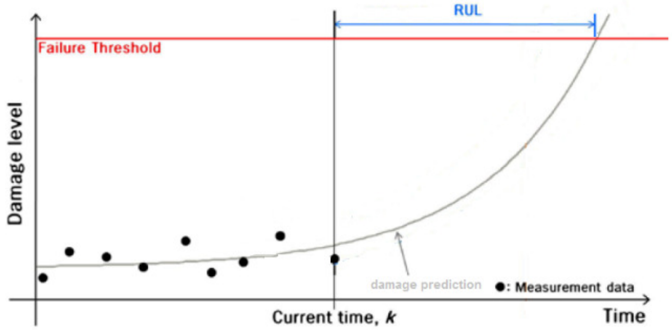

Figure 1. illustration of RUL calculation

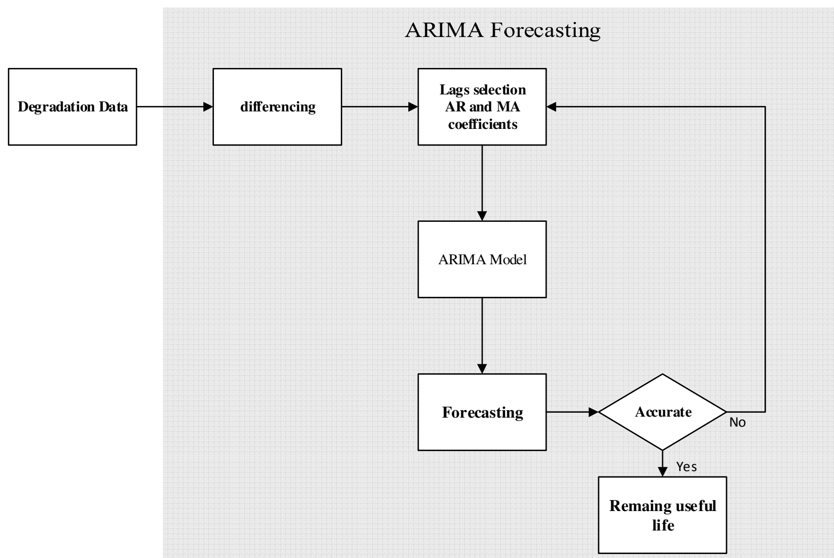

Figure 2. ARIMA prediction Algorithm

$$p\langle x_k \mid z_{1:k} \rangle = \frac{p\langle z_k \mid x_k \rangle p\langle x_k \mid z_{1:k-1} \rangle}{p\langle z_k \mid z_{1:k-1} \rangle} \quad (4)$$

In order to obtaining exact state estimation solutions for Equations (3) and (4) the actual distribution are approximated by a set of samples and their normalized weights. Consider $\{x_{0:k}^i, w_k^i\}_{i=1}^{N_S}$ a random measure that characterizes the posterior PDF $p\langle x_k \mid z_{1:k} \rangle$, where $x_{0:k}^i$ and w_k^i are, respectively a set of support points and associated weights. The weights are normalized such that $\sum_i w_k^i = 1$. Then, the posterior density at time k is approximated (Arulampalam *et al*., 2002) as

$$p\langle x_k \mid z_{1:k} \rangle \approx \sum_{i=1}^{N_S} w_k^i \delta(x_{0:k} - x_{0:k}^i) \qquad (5)$$

The weight process based on importance sampling (Arulampalam *et al*., 2002), such that the weight update equation is given by

$$w_k^i \propto w_{k-1}^i \frac{p\langle z_k \mid x_k^i \rangle p\langle x_k^i \mid x_{k-1}^i \rangle}{\pi\langle x_k^i \mid x_{0:k-1}^i z_{1:k} \rangle} \quad (6)$$

When $N_S \to \infty$ the importance density function $\pi\langle x_k \mid x_{0:k-1} z_{1:k} \rangle$ can be approximated by the prior PDF $p\langle x_k \mid x_{k-1} \rangle$, and weight becomes (Ristic et al., 2004)

$$w_k^i \propto w_{k-1}^i p\langle z_k \mid x_k^i \rangle \quad (7)$$

Another problem arises is the Degeneracy phenomenon, where after a few iterations, all but one particle will have negligible weight. This degeneracy explains that a large number of updating particles is around zero. To overcome

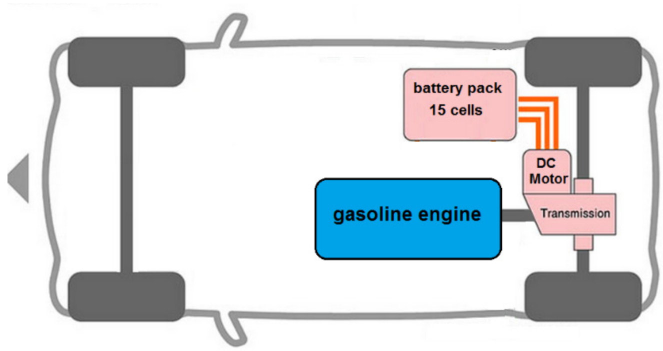

Figure 3. Plan of Hybrid Electric vehicle

Table 1. Data of degradation

Time (T)	Intial,1	2	3	4	5
C/1 (Ah)	1,000	0.981	0.859	0.811	0.788
Time(T)	6	7	8	9	10
C/1 (Ah)	0.714	0.680	0.612	0.56	0.568

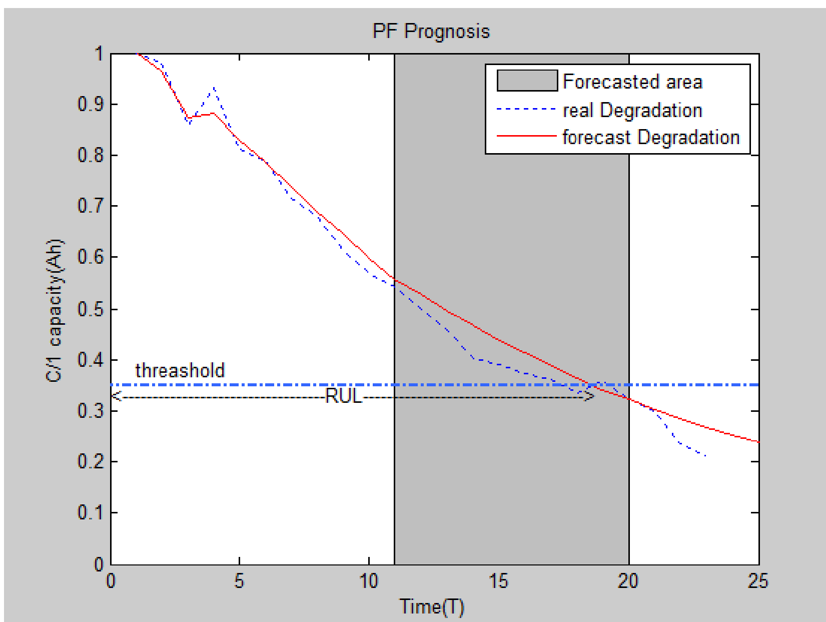

Figure 4. Trajectory of degradation for the cell of battery pack using Particle Filter

this problem, considering resampling procedure (Gordon *et al*., 1993) at each step, we assign $w_{k-1} = \frac{1}{N_S}$ for all the particle weights so we have

$w_k^i \propto p\left\langle z_k \middle| x_k^i \right\rangle$ (8)

To implement SIR (sequential importance resampling) filter as in (7) and (8) we need to know process model, measurements and noise model and likelihood function $p\left\langle z_k \middle| x_k \right\rangle$

RUL Prediction using Particle Filter

Once the estimated parameter is obtained, the future damage state and RUL can be predicted by progressing

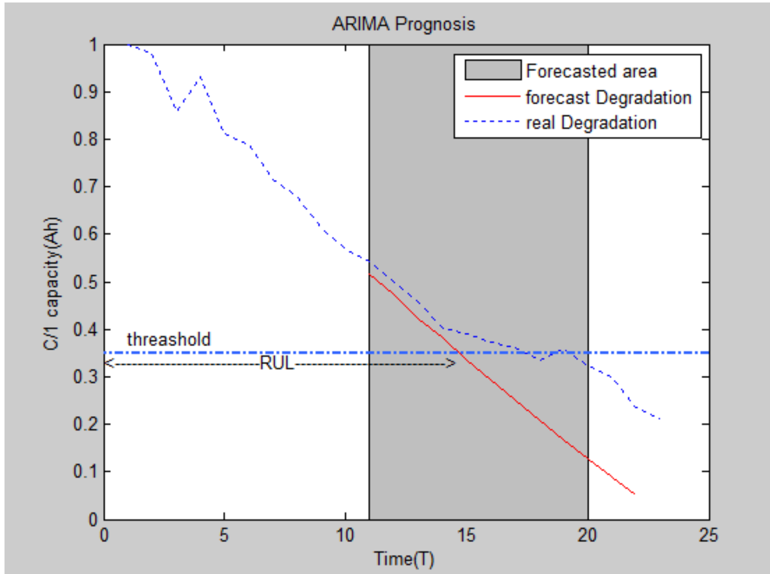

Figure 5. Trajectory of degradation for the cell of battery pack using ARIMA model

Table 2. MASE and RMSE measurement of the cell prognosis

predictive approach	**Particle Filter**	**ARIMA model**
MASE	0,7345	2,6163
RMSE	0,0253	0,0719

the damage state until it reaches the threshold (figure (1)). The PDF curve represent the progress of damage state until it reaches the threshold. The distribution of RUL can be obtained by subtracting this PDF from the threshold

ARIMA model for prognosis

One of the important and widely used time series model is the autoregressive integrated moving average (ARIMA) model, which is a generalization of ARMA model. These models are fitted to time series data to predict future points in the series (forecasting). Many works around ARIMA model have been developed. Among these mechanical deterioration prognosis (Guclu *et al.*, 2010; Kosasih *et al.*, 2014) and economic forecasts (Andreica *et al.*, 2009; Zhang, 2003). In our study, we will use the ARIMA model to predict degradation by computing RUL.

ARIMA forecasting method

ARIMA is a forecasting technique, noted as ARIMA (p,d,q), the general model was introduced by Box and Jenkins (George, 1994) and is a method which allows both autoregressive (AR) and moving average (MA) also, it explicitly includes differencing in the formulation of the model. Where, p and q are, respectively autoregressive parameter and moving average parameter, while d is the number of non-seasonal differences. The autoregressive part of the model of order p is written:

$$x_t = c + \sum_{i=1}^{p} \phi_i x_{t-i} + \varepsilon_t \quad (9)$$

Where x_t is a stationary series, x_{t-i} represents lag i of x_t, the ϕ_i, $i = 1,...,$ p are the parameters of the model, c is a constant and ε_t is a white noise. The moving average part of the model of order q is written:

$$x_t = \mu + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \quad (10)$$

Where the θ_i, $i = 1,...,q$ are the parameters of the model, μ is the expectation of x_t. It is often assumed to equal zero. And the $\varepsilon_t, \varepsilon_{t-1},..., \varepsilon_{t-q}$ are white noise error terms. After an initial differencing step (corresponding to the integrated part of the model) we can present the ARIMA (p,d,q) as ARMA (p,q) process:

$$x_t = c + \varepsilon_t + \sum_{i=1}^{p} \phi_i x_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \quad (11)$$

The estimation of the ARIMA model corresponding to some learning data is done through the Box and Jenkins methods (George, 1994). A procedure of the forecasting can be summarized as:

1) Check stationary: If the data is not stationary, it needs to be transformed into stationary data using the differencing technique.
2) Identification: specify the appropriate number of autoregressive terms, p, and moving average terms, q from the autocorrelation function (acf) and partial autocorrelation function (pacf) correlograms.
3) Forecasting: Based on the forecasting model, multi-step-ahead prediction is then conducted to forecast the final failure time.
4) Verification: If the predictions result in an unexpected trend, repeat step 2 and step 3 until the model fits the historical data well enough.

RUL estimation using ARIMA

Prediction of lifetime using ARIMA can be expressed in two parts: construction of model and prediction of state. In the first step, we construct the corresponding coefficients (differencing, autoregressive and moving average terms) and we obtain an ARIMA model. Next step, when the model is built, a sample is selected to be estimated. Remaining Useful Life (RUL) is defined as the number of predictions from current state until the failure states reached the threshold. The following figure (2) shows the forecasting method for RUL estimation.

RESULTS AND DISCUSSION

Illustrative example

An electric car is powered by an electric motor instead of a gasoline or diesel engine. The electric car (also known as electric vehicle EV) uses energy stored in its battery (or series of batteries), which are recharged by different sources. There are a variety of electric vehicles available in the world, among these HEV (hybrid electric vehicle), the PHEV (plug-in hybrid electric vehicle) and BEV (battery electric vehicle).

We have oriented our work towards the HEV, where a small battery is placed on board, when the vehicle brakes, the energy is stored in the battery and that energy can, later; be used to power the electric motor which assists the gasoline engine. HEV typically provides better fuel economy than similar conventional vehicles; this is why it is necessary to develop a prognosis of battery degradation, in order to ensure a proper functionality.

The cell (or battery) studied in this work (Smith *et al.*, 2012) is a lithium-ion with 1Ah capacity and 3.75 V. the cell is part of a battery pack (Battery pack= 15 cells), which is used to collect and distribute electric power (direct current power), mainly to the electrical drive. We use the 25°C as the baseline for measurement. A simple form of the empirical degradation model is expressed by an exponential growth model as follows (Saha *et al.*, 2009a).

$$\lambda = a \exp(-bt) \quad (12)$$

Where a, b are model parameters, t is the time, and λ is internal cell performance, such as electrolyte resistance R_E or transfer resistance R_{CT}. The internal cell performance is observed instead of capacity. Additionally there is a relationship between $R_E + R_{CT}$ and $C/1$ capacity; $R_E + R_{CT}$ is inversely proportional to the $C/1$. Also the observed data are assumed to be given as a $C/1$ capacity. The threshold for fault declaration is chosen to be 0,35.

RUL estimation

The particle filter uses the exponential growth model (12) to obtain the prior PDF (1). The measurement and process noise variance ω_k and v_k respectively were modeled as Gaussian densities. In Particle Filter a and b are incorporated as internal cell parameters R_E and R_{CT}. The values of a and b in the actual state are used as initial estimates. Then, the resampling of particles is applied in each iteration to solve the degeneracy problem. The predictions are progressed until it reaches the threshold to get the RUL.

ARIMA (p,d,q) model use simply the measurement data of capacity to predict the future degradation. In our case, the data are roughly exponential in nature; d is chosen to be 2 in order to remove the non-stationarity, both p and q are chosen to be 1. The capacity data measurement at every 100 charge/discharge cycles are given in Table 1, where 1T=100 charge/discharge cycles.

The figure (4) show the real and the estimated values of the cell degradation using Particle Filter. Although the predicted results are close to the real values throughout the prediction area. In figure (5) the estimated data of the cell degradation obtained by ARIMA model are far off the real values after T=15.

The performance of the both methods have been evaluated by the mean absolute scaled error (MASE) (Hyndman *et al.*, 2006) and Root Mean Square Error (RMSE).

Definition of MASE:

A scaled error is defined as

$$q_k = \frac{Y_k - \hat{Y}_k}{\frac{1}{N-1}\sum_{i=2}^{N}|Y_i - Y_{i-1}|} \quad (13)$$

Where Y is the real value of testing cell, $\hat{Y}$ is the prediction value and N is the number of prediction data set. The mean absolute scaled error is simply

$$MASE = mean(|q_k|) \quad (14)$$

Definition of RMSE:

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}[Y - \hat{Y}]^2} \quad (15)$$

The detail results is shown in Table 2.

From the Table 2, we can find that, the calculation of MASE and RMSE for ARIMA model is superior than the Particle Filter. Consequently, the particle filter is more accuracy than the ARIMA model.

CONCLUSION

We were interested here in two approaches for health prognostics using particle filter and ARIMA model. The goal in applying these methods is to calculate RUL. In addition, the RUL give us the best idea about the degradation of each system. The results showed that the particle filter was more faithful to the simulated data. We considered different frequencies of inspection for the measurement. This study highlights the value of having a physical failure model to improve the accuracy of results. In contrast, the ARIMA need great possible historical data in order to give proper results without need to physical model. The disadvantage of the particulate filter compared to ARIMA model is the degradation model requirement, which is not always easy in the case of large-scale system, remember that both approaches require a knowledge of a threshold corresponding to the physical system failure to plan the actions of preventive maintenance and expect to benefit from the opportunistic Maintenance. Finally, the obtained result in this paper show that the Particle Filter is more efficient than the ARIMA model.

REFERENCES

Andreica ME, Cataniciu N, Andreica MI (2009). Econometric and neural network analysis of the labor productivity and average gross earnings indices in the Romanian industry. *Proceedings of the 10th WSEAS International Conference on Mathematics and Computers in Business and Economics (MCBE)(ISBN: 978-960-474-063-5/ISSN: 1790-5109).* 106-111.

Arulampalam MS, Maskell S, Gordon N, Clapp T (2002). A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking. *Signal Processing, IEEE Transactions on*. 50(2): 174-188.

Berruet P, Toguyeni A, Craye E (1999). Structural and functional approach for dependability in FMS. *Systems, Man, and Cybernetics, 1999. IEEE SMC'99 Conference Proceedings. 1999 IEEE International Conference on*. 4: 486-491.

Butler S, Ringwood J (2010). Particle filters for remaining useful life estimation of abatement equipment used in semiconductor manufacturing. *Control and Fault-Tolerant Systems (SysTol), 2010 Conference on*. 436-441.

Dong M, He D (2007). A segmental hidden semi-Markov model (HSMM)-based diagnostics and prognostics framework and methodology. *Mechanical Systems and Signal Processing*. 21(5): 2248-2266.

George B (1994). *Time Series Analysis: Forecasting & Control, 3/e*. edn. Pearson Education India.

Gordon NJ, Salmond DJ, Smith AF (1993). Novel approach to nonlinear/non-Gaussian Bayesian state estimation. *IEE Proceedings F (Radar and Signal Processing)*. 140(2): 107-113.

Guclu A, Yılboga H, Eker OF, Camci F, Jennions I (2010). Prognostics with Autoregressive Moving Average for Railway Turnouts. *Annual Conference of Prognostics*.

Heng A, Tan AC, Mathew J, Montgomery N, Banjevic D, Jardine AK (2009). Intelligent condition-based prediction of machinery reliability. *Mechanical Systems and Signal Processing*. 23(5): 1600-1614.

Hyndman RJ, Koehler AB (2006). Another look at measures of forecast accuracy. *International journal of forecasting*. 22(4): 679-688.

Jaw LC (1999). Neural networks for model-based prognostics. *Aerospace Conference, 1999. Proceedings. 1999 IEEE*. 3: 21-28.

Kong A, Liu JS, Wong WH (1994). Sequential imputations and Bayesian missing data problems. *Journal of the American statistical association*. 89(425): 278-288.

Kosasih B, Caesarendra W, Tieu K, Widodo A, Moodie CA, Tieu AK (2014). Degradation trend estimation and prognosis of large low speed slewing bearing lifetime. *Applied Mechanics and Materials*. 493: 343-348.

Li CJ, Lee H (2005). Gear fatigue crack prognosis using embedded model, gear dynamic model and fracture mechanics. *Mechanical systems and signal processing*. 19(4): 836-846.

Lucas PJ, Abu-Hanna A (1999). Prognostic methods in medicine. *Artificial Intelligence in Medicine*. 15(2): 105-119.

Medjaher K, Tobon-Mejia, Zerhouni N (2012). Remaining useful life estimation of critical components with application to bearings. *Reliability, IEEE Transactions on*. 61(2): 292-302.

Mosallam A, Medjaher K, Zerhouni N (2013). Bayesian approach for remaining useful life prediction. *Chemical Engineering Transactions*. 33: 139-144.

Ristic B, Arulampalam S, and Gordon N (2004). Beyond the Kalman Filter: Particle Filters for Tracking Applications. Artech House.

Saha B, Goebel K (2008). Uncertainty management for diagnostics and prognostics of batteries using Bayesian techniques. *Aerospace Conference, 2008 IEEE*. 1-8.

Saha B, Goebel K, Christophersen J (2009a). Comparison of prognostic algorithms for estimating remaining useful life of batteries. *Transactions of the Institute of Measurement and Control*.

Saha B, Goebel K, Poll S, Christophersen J (2009b). Prognostics methods for battery health monitoring using a Bayesian framework. *Instrumentation and Measurement, IEEE Transactions on*. 58(2): 291-296.

Sheppard JW, Kaufman MA (2005). Bayesian diagnosis and prognosis using instrument uncertainty. *Autotestcon, 2005. IEEE*. 417-423.

Smith K, Earleywine M, Wood E, Neubauer J, Pesaran A (2012). *Comparison of plug-in hybrid electric vehicle battery life across geographies and drive cycles*. SAE Technical Paper.

Srivastava AN, Das S (2009). Detection and prognostics on low-dimensional systems. *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*. 39(1): 44-54.

Tipping ME (2000). The Relevance Vector Machine. In S. A. Solla, T K Leen, and Müller KR. (Eds.), Advances in Neural Information

Processing Systems. MIT Press 12, pp. 652–658.
Yan J, Lee J (2007). A hybrid method for on-line performance assessment and life prediction in drilling operations. *Automation and Logistics, 2007 IEEE International Conference on*. 2500-2505.
Yang B-S, Oh M-S, Tan ACC (2008). Machine condition prognosis based on regression trees and one-step-ahead prediction. *Mechanical Systems and Signal Processing*. 22(5): 1179-1193.
Zhang GP (2003). Time series forecasting using a hybrid ARIMA and neural network model. *Neurocomputing*. 50: 159-175.
Zio E, Peloni G (2011). Particle filtering prognostic estimation of the remaining useful life of nonlinear components. *Reliability Engineering & System Safety*. 96(3): 403-409.