Development of Integrated Prognostics: Application to Bearing and Bevel Gear Life Prediction

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THESIS

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Dedicated to my parents, Guodong Ma and Shuling Sun, and my husband, Zhanjun Feng.

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TABLE OF CONTENTS

CHAPTER PAGE

TABLE OF CONTENTS (continued)

TABLE OF CONTENTS (continued)

TABLE OF CONTENTS (continued)

LIST OF FIGURES

LIST OF FIGURES (continued)

FIGURE PAGE

LIST OF FIGURES (continued)

FIGURE PAGE

LIST OF FIGURES (continued)

<u>FIGURE</u> <u>PAGE</u>

LIST OF TABLES

LIST OF ABBREVIATIONS

ARIMA	Autoregressive Integrated Moving Average
CBM	Condition- based on Maintenance
CM	Condition Monitoring
CI	Condition Indicator
EMD	Empirical Mode Decomposition
HI	Health Indicator
PHM	Prognostics and Health Management
FDI	Fault Detection and Identification
RUL	Remaining Useful Life
RMS	Root Mean Square
IID	Independent and Identical
PFA	Predictive Failure Alarm
SPL	Spall Length
ODM	Oil Debris Mass

SUMMARY

Effective maintenance of complex systems has become a key issue in fields in which the economic impact of reliability related issues and the cost effective operation of critical assets is steadily increasing. Current maintenance strategies have progressed from periodical maintenance and break down maintenance, to preventive maintenance, then to condition-based maintenance (CBM). CBM is based on using real-time data to prioritize and optimize maintenance resources. Prognosis as the most important part of CBM is becoming more and more important in these fields such as aeronautics and astronautics.

In this dissertation, an integrated machinery prognostic methodology based on particle filtering has been developed. In particular, three fundamental issues in developing particle filtering based prognostic tools have been addressed in this research: (1) how to define the state transition function used in particle filtering to estimate the fault progression; (2) how to define the measurement function using a one-dimensional health index (HI) in particle filtering to estimate the fault progression parameters; (3) how to define an error guided l-step ahead remaining useful life (RUL) estimator. In the development of the proposed prognostic methodology in this research, these three fundamental issues have been addressed by: (1) defining the state transition function using a data mining approach; (2) integrating a one-dimensional health index (HI) into particle filtering to define the measurement function; (3) developing an l-step ahead RUL estimator incorporating with a measure of the associated error. The developed prognostic methodology has been validated using three industrial case studies. The first case study concerns steel bearing prognosis and remaining useful life prediction. The bearing fault data used in this research are the spalled bearing run to failure test data with intermediate inspection. The second case study concerns spiral bevel gear prognosis and RUL prediction. The spiral bevel gear case study data were collected in the NASA Glenn Spiral Bevel Gear Test Facility. In the last case study, the ground truth data of hybrid ceramic bearings gathered experimentally by our group are used to validate the methodology.

The specifically contributions of the dissertation are summarized as follows:

(1) An integrated particle filtering algorithm was developed in which a one-dimensional HI was integrated into particle filtering to define the observation parameters. The results show that using the one-dimensional HI gives better prognostic results than those obtained without combining different condition indicators into one HI.
(2) Instead of using Paris' Law, data mining algorithm was used to build the state function. The results have shown that the state function models built using the data mining algorithm work effectively for describing the fault propagation.
(3) Data mining based approaches were used to build the observation function. The data mining based approaches use both the prediction information from the last step and observation data. The results show that the data mining based methods work better than existing methods reported in the literature.

(4) An *l*-step ahead state parameter prediction and RUL estimator was developed. Most of the publications in the current literature use only one-step prediction.

(5) The presented prognostics method has been validated using data from steel bearing, hybrid ceramic bearing and spiral bevel gear case studies. To date, no results on spiral bevel gear or ceramic bearing prognosis and remaining useful life prediction using particle filtering based approaches have been reported in the literature. And the results on steel bearing prognostics using particle filtering algorithm are limited.

1. INTRODUCTION

Prognosis and health management (PHM) for complex systems have become more and more important when the economic impact of reliability related issues and the cost effective operation of critical assets is rapidly increasing. Current maintenance strategies have changed from break down maintenance, periodical maintenance to preventive maintenance, then to condition based maintenance (CBM) (Heng, *et al.*, 2009). For some cheap and non-critical systems, the regular condition checking and on-line monitoring are not necessary, such as personal computers, cell phones. For some other systems like vehicles, the periodical maintenance should be combined with the break down maintenance. For example, we have to do the regular maintain and change oil every three months. Preventative maintenance also needs information such like historical operation data, working conditions or loading information. But preventative maintenance usually doesn't do the online in time monitoring like CBM does. Condition-based maintenance is maintenance when it is needed. CBM is becoming more and more important in recent years. For the old traditional air fighters like F15 or F16, they are still using the maintenance strategies by combing break down maintenance, periodical maintenance and preventative maintenance. However, for the new generation of air fighters like F22 and F35, also some commercial aircrafts like A380 and Boeing 787 are all equipped with CBM systems. Condition-based maintenance is maintenance when it is needed. When one or more indicators show that equipment performance is deteriorating or that equipment is going to fail, then the maintenance strategy is performed. Condition-based maintenance was introduced to try to check, replace or repair the correct components at the right time (Renewables, 2007). CBM uses real-time data to prioritize and optimize maintenance resources. It was reported that 99% of mechanical failures are preceded by noticeable indicators (Bloch and Geitner, 1997). Prognostics as an important part of CBM is increasing in importance (Westwick-Farrow, 2006).

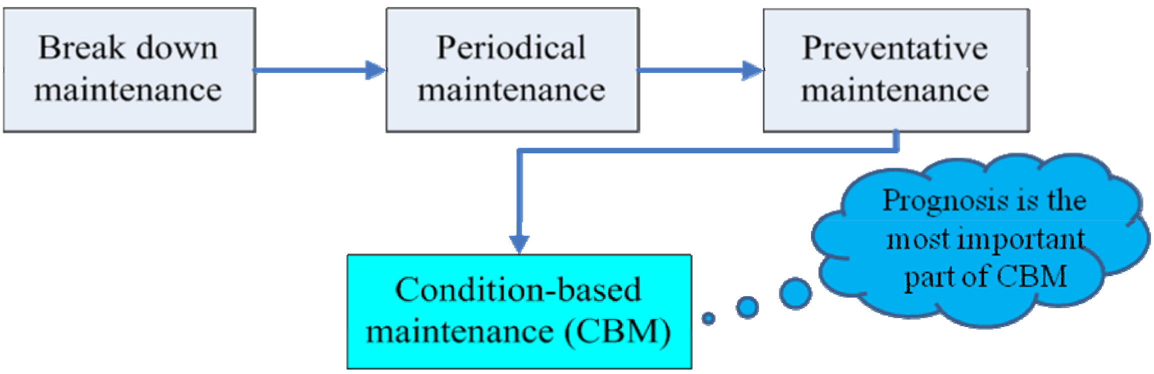


Figure 1. Develop of the different maintenance strategies

FIGURE 2 shows the three stages of CBM system (Sun and Ma, 2006).

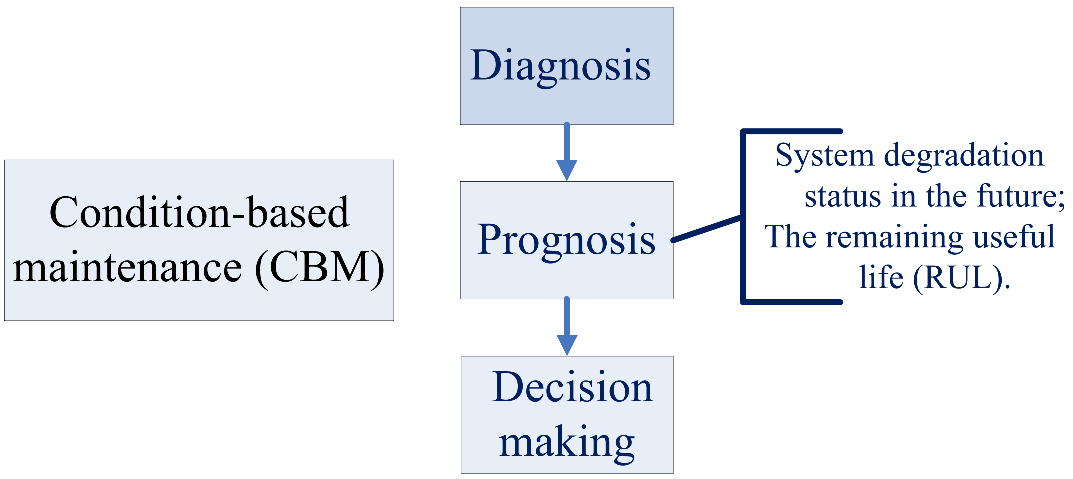


Figure 2. Condition-based maintenance stages

So the objective of this dissertation is to develop an integrated machinery prognostic methodology based on particle filtering and validate the developed prognostic methodology using real industrial case studies.

As a natural extension to the fault detection and identification (FDI) issue, prognosis intends to describe and reflect the evolution in time of the detected failure condition. So the estimation of the remaining useful life (RUL) for affected subsystems or components is allowed (Orchard, 2005). In this research, a particle filtering based prognostics method using one-dimensional health index method is presented. In particular, in developing the method, the three particle filtering prognostics implementation related issues will be addressed: (1) define the state transition function using data mining approach; (2) use an one-dimensional health index (HI) obtained by a whitening transform to define the measurement function; (3) an *l*-step ahead RUL estimator incorporated with a measure of the associated error. The developed prognostics will enhance the machine condition monitoring performance and make remaining useful life predictions more reliable. The presented prognostics method is validated using data from steel bearings, hybrid ceramic bearings and spiral bevel gears case studies.

1.1 The Needs for Prognostics

From a systematic point of view, fault detection, fault diagnostics and fault prognostics are three levels in failure prevention. Fault detection means the detection of the status of the machine, healthy or faulty. Fault diagnostics is the determination of the type or location of the fault. And the forecast of the remaining operational life, future condition, or probability of reliable operation of equipment based on the acquired condition monitoring data is machinery prognosis. This approach to modern maintenance practice promises to reduce downtime, spares inventory, maintenance costs, and safety hazards (Heng *et al.*, 2009).

The three levels of fault prevention technologies are not necessary in all CBM systems. For some end users, inexpensive fault detection systems are sufficient. When damage is found in such a system, damaged components are simply replaced with new ones. However, fault detection is not enough for some critical and expensive systems such as in helicopter transmission systems, and many other geared transmission systems. Fault diagnostics and fault prognostics are necessary in such a system.

As reported by Ferret *et al*. (2006) and Heng *et al*. (2009), traditional maintenance costs (i.e. labor and material) in the U. S. have escalated at a tremendous rate over the past 10 years. In 1981, domestic plants spent more than $600 Billion to maintain their critical plant systems. The costs had increased to more than $800 Billion by 1991 and topped $1.2 Trillion in 2000. We can see that through ineffective maintenance management methods between one third and one half of these maintenance dollars are wasted. The combination of lack of timely, factual knowledge of asset condition and the ineffective management methods cause a lot of problems and artificially high maintenance costs. However, this kind of situation also represents a substantial opportunity for implementing CBM on almost every manufacturing and production facility.

Effective use of the preventive/predictive technologies provides ways to take advantage of this opportunity. Used correctly, the 33 % to 50 % of wasted maintenance expenditures can be eliminated and effective use of plant resources; both production and maintenance can be achieved and sustained (Ferret, 2006).

As mentioned before, prognostics represents the process of predicting the reliability in the future, probability of failure of an equipment, and the prediction of the remaining useful life based on the acquired condition monitoring data by assessing the extent of deviation or degradation of a product from its expected normal operating conditions (Pecht *et al.*, 2008; Heng, *et al.,* 2009; Niu *et al.*, 2011;). The analysis of failure modes, detection of early signs of wear and aging, and fault conditions are needed in the science of prognostics (Gilmartin, 2000). A damage propagation model will be correlated with these signs to get the prognosis results. Prognostics plays a very important role in condition-based maintenance. Down time, spares inventory, maintenance labor costs and hazardous conditions can be significantly reduced by prognostics. However, compared to the other areas of CBM, prognostics as a relatively new research area has yet to gain prominence.

1.2 Development of the Integrated Prognostics Using Particle Filtering

In this research, the development of integrated prognostics is based on an effective state estimation technique called particle filtering. Particle filtering is a sequential Monte Carlo method for state tracking and prediction. Particle filtering has caught the attention of many researchers in various fields, including signal processing, statistics, and econometrics. The method has been proved effective to model systems including elements of nonlinearity and non-Gaussianity (Arulampalam and Ristic, 2000). The information obtained from both the system measurements and the system models are used to describe system behaviors.

In the case when the system is nonlinear or in the presence of non-Gaussian process/observation noise, such as bearings, gas turbines, gearboxes and engines in which the nonlinear nature and ambiguity of the rotating machinery world is significant when operating under fault conditions, particle filtering is very suitable because it is founded on the concept of sequential importance sampling (SIS) and the use of Bayesian theory (Wren, *et al.*, 1997). Furthermore, particle filtering allows information from multiple measurement sources to be fused in a principled manner, which is an attribute of decisive significance for fault detection/diagnostic purposes:

(1) Particle filtering is effective to model systems including elements of nonlinearity and non-Gaussianity;

(2) Also good for the information from different measurement sources to be fused in one prognosis model;

(3) Multiple fault modes prognosis can be built in this framework.

As we know, there is no single CI which is sensitive to every failure mode of a bearing or gear. This suggests that some form of sensor fusion is needed in the condition based maintenance system. Three statistical models were developed to define a health indicator (HI) as a function of CI: order statistics (max of *n* CIs), sum of CIs and normalized energy. Since CIs tend to be correlated, a whitening process was developed to ensure the HI threshold is consistent with a defined probability of false alarm (Bechhoefer *et al.*, 2011). These models were developed for CIs with Gaussian or Rayleigh (skewed) distributions. In our previous research, the results show the HIs performed well detecting pitting damage to gears (Bechhoefer *et al.*, 2011). The functions, used to generate HIs, were tested on gear and bearing test stand data and their performance evaluated as compared to the end state of the gear or bearing.

One of the motivations for the research is because there is still no research that involves combining HI into particle filtering algorithm.

One of the research objectives focuses on the use of a particle-filtering based framework for on-line failure prognosis in nonlinear, non-Gaussian systems. The implementation will statistically characterize the remaining useful life (RUL) of a subsystem or component affected by a fault condition, that is, estimate the probability density function of the subsystem RUL. A set of measurements will be used to improve current estimates, and nonlinear state-space models define the evolution in time of the fault indicator. The outcome of the prognosis module, namely the RUL Probability Density Function (PDF), will be available and updated in real time, providing information about statistical confidence intervals and expectations.

Most authors have used Particle filtering (and other nonlinear filtering approaches) as a tool for detection (that is, one step prediction), but not for prognosis (*l*-step prediction). While the assumptions about model nonlinearities and non-Gaussian noise structures are kept, one step prediction is used mainly because there are no clear indications about how to project the particle population in time. In specific applications, it has been suggested to assume absence of both process and measurement noise for prediction purposes (Orchard, 2005), thus obtaining a long-term prediction with minimum variance, such as chaos prediction (Zhang, 2007, 2008). Initial conditions for deterministic models are defined as the particle population in order for them to be used for decision theory, risk calculations and other statistical approaches (Orchard, 2005). The implications of these assumptions, though, could be significant in real processes, especially in presence of vibration signals and therefore they must be evaluated with care.

1.3 The Motivation of the Cases Studies

Rotating machinery is widely used in various industrial, military, and commercial processes. Bearings and gears are essential components in such applications and their failures often result in a critical damage, downtime, and costly repair (Zakrajsek, 1993; Zaretsky, 1997; Howe and Muir, 1998; Ho, 2000; Zhang, 2005; Abbas, *et al*, 2007; Vachtsevanos, 2006). Therefore, fault diagnosis and failure prognosis, which provide a condition based maintenance strategy to either machinery or components, such as bearings, is important to the safety of the system and results in substantial economic benefits (Sunnersjo, 1985; McFadden and Smith, 1984, 1985; Howard, 1994; Goode and Chow, 1995; Ho and Randall, 2000; Li, 2000; Tse, 1999, 2001).

The implementation and testing of the proposed particle-filtering-based methodology for fault prognosis on real process data, and the subsequent assessment of the obtained results, will be presented in the research work. The first case study is about steel bearing prognosis and remaining useful life predictions. The bearing fault data used in this research project are the spalled bearings run to failure test data with intermediate inspections. Then, a second case study about spiral bevel gear prognosis and RUL prediction will be illustrated. The spiral bevel gear case study was performed in the NASA Glenn Spiral Bevel Gear Test

Facility. In the last case study, the ground true data of hybrid ceramic bearings tested by our group at UIC will be used to validate the methodology.

The reason why I chose these three cases in the research is because there is currently no research published on particle filtering applied to spiral bevel gears and ceramic bearings prognosis and remaining useful life predictions. Also, few papers have been published about steel bearings prognostics by particle filtering algorithm.

For the first case study, Sentient Corporation has accrued a large database of seeded spall propagation tests on angular contact ball bearings. This testing was part of Phase I of the DARPA Prognosis Program. The test bearings were a 106 size angular contact bearing, primarily of SAE 52100 steel, although some M50 Nil and hybrid bearings were also tested. A Rockwell C indent was used as the seeded fault. Each bearing was removed for inspection at least 10 to 15 times during the spall propagation, with some bearings being inspected as many as 30 times. Each inspection included both measurements and photographs of the bearing races and specifically the spalls (Lybeck, *et. at,* 2007).

The second case study was applied to spiral bevel gears. The main application of spiral bevel gears are in a vehicle differential, where the direction of drive from the drive shaft must be turned 90 degrees to drive the wheels (Dempsey *et al.*, 2002). Less vibration and noise is produced by using the helical design than using the conventional straight-cut or spur-cut gear with straight teeth. Because helicopters depend on the power train for propulsion, lift, and flight maneuvering, helicopter transmission integrity becomes very important to the safety of helicopter (Handschuh，1995, 2001；Ebersbacha, 2006). The ideal diagnostic tools used in the health monitoring system would provide real time health monitoring of the transmission and would demonstrate a high level of reliable detection to minimize false alarms in order to detect impending transmission failures (Dempsey *et al.*, 2002). Spiral bevel gears are used in helicopter transmissions to transfer power between nonparallel intersecting shafts. In the case study, the experimental data was recorded from tests performed in the Spiral Bevel Gear Test facility at NASA Glenn Research Center. In the references (Handschuh, 1995; 2001), a detailed analysis of this test facility can be found.

The final case study was on ceramic hybrid bearings. Ceramic bearings exhibit a service life three times longer than that of steel bearings. Conventional steel ball bearings are quickly replaced by ceramic bearings in many different fields and applications (Ebert, 1990). There are two types of ceramic bearings: hybrid ceramic bearings and full ceramic bearings. Hybrid ceramic bearings have steel races and ceramic balls and full ceramic bearings have both ceramic balls and races. The data from hybrid ceramic bearing experiments were used in one of the case studies. Under many extreme operating conditions, hybrid bearings perform well and offer high-speed operation with low friction. Rapid accelerations and decelerations can be provided because of the lower weight of hybrid balls. Ceramic bearings are less sensitive to heat differences between races since the thermal expansion of hybrid ceramic bearings is about 30% lesser than that of steel ones (Zaretsky, 1997). Ceramic bearings are less sensitive to fluctuations in lubrication conditions.

Ceramic balls can operate under the same lubrication conditions at speeds up to 20% higher compared to steel bearings. The hybrid bearings eliminate the chance for oil leakage into the environment because of the desired operability in greased-for-life applications and their lesser to no requirement for oil lubrication. Due to the coefficient of friction in hybrid bearings is approximately 20% of similar steel balls, hybrid bearings also generate less vibration than all-steel bearings and noise levels can be reduced during operation because of the smoothness. In comparison with other bearings, hybrid bearings often last longer than other bearing types and have a lower life cycle cost, reduced operating and maintenance costs, increased production quality and simple handling and mounting (Stoneburner, 2005).

1.4 Research Objective

The aim of this research is to develop an integrated prognostics methodology with an application to bearing and gear life prediction. In particular, the following research issues in developing integrated prognostics using particle filtering will be addressed:

(1) How to define the state transition function?

(2) How to define the observation function?

(3) How to build up an *l*-step ahead remaining useful life (RUL)?

(4) How to validate the developed methodology?

In this dissertation, the research issues in developing integrated prognostics using particle filtering will be addressed by using:

(1) Define the state transition function using data mining approach;

(2) Integration of one-dimensional health index into particle filtering methodology;

(3) Develop an *l*-step ahead RUL estimator incorporated with a measure of the associated error;

(4) Validate the integrated methodology using real case study data.

1.5 Outline

This research presents a methodology for gear and bearing prognostics using particle filtering. Data collected from real-time run to failure tests are used to validate the presented prognostic methodology. The remainder of the dissertation is organized as follows. Chapter 2 is the literature review part. Chapter 3 presents the methodology of particle filtering for prognostics. Chapter 4 integrates a one-dimensional health index into particle filtering methodology. Chapter 5 is about the one of the case studies: steel bearing prognostics. Chapter 6 is about bevel gear prognostics. Chapter 7 presents the results of hybrid ceramic bearing prognosis. The conclusions of the research are provided in Chapter 8.

2. LITERATURE REVIEW

In the past few years, an increasing number of published papers on rotating machinery prognostics, such as bearings, gears and shafts have been published because of the significance of prognostics capabilities and the development of condition monitoring technology. A wide spectrum of prognostics techniques was covered in these publications. The current research status of the prognostics and particle filtering algorithm used in the research are summarized. Also, the merits and weaknesses of these methods have been identified in this chapter.

2.1 The Prognostics Types and Remaining Useful Life Prediction

In machine prognostics, two main prediction types have been developed. The most obvious and widely used prognostics is to predict how much time is left before a failure occurs (or, one or more faults) given the current machine condition and past operation profile. Remaining useful life (RUL) is the time left before a failure is observed. In some situations, especially when a fault or a failure is catastrophic, such as, in the fields of military, aeronautics, astronautics, and nuclear power plant, prognosis and remaining useful life prediction would be more desirable. The prognosis actually is using the information like current machine condition and past operation profile to predict the chance that a machine will run without a fault or a failure up to some future time (e.g., next inspection interval). The probability that how long a machine can operate without a fault is a good reference for experts in related fields to determine whether the maintenance schedules determined are appropriate or not. Most of the papers in the literature of machine prognostics discuss only the first type of prognostics, namely RUL estimation. Only few papers addressed the second type of prognostics (Farrar *et al.*, 2003; Lin and Makis, 2003).

Remaining useful life refers to the time left before observing a failure given the current machine age and condition, and the past operation profile (Kacprzynski, *et al.*, 2004). In some cases, it means finding the distribution of RUL. In some other cases, however, it just means the expectation of RUL (Jardine *et al.*, 2006).

The outcome of a prognosis system built based on any prognosis algorithm is actually an estimate for the system RUL probability density function (PDF), which is the probability of failure at future time instants. This probability can be obtained from long-term predictions, when the empirical knowledge about critical conditions for the system is included in the form of thresholds for main fault indicators, also referred to as the hazard zones (Orchard, 2005). Usually a pre-specified threshold has to be decided to describe the critical system degradation status. Sometimes this threshold is a fixed number and sometimes it can be described by a probability density function. This threshold can be statistically determined on the basis of historical failure data, defining a critical PDF with lower and upper bounds for the fault indicator (H_{lb} and H_{up}, respectively).

2.2 Current Research Status of Prognostics

In this section, current methodologies for prognostics are summarized and classified as data driven based methods, physics model based prognostics models and hybrid methodologies reliability and prognostics.

In the past few years, methodologies and technologies in machine condition monitoring (CM) and fault diagnostics have been developed. Data such as vibration signal, acoustic emissions and oil debris mass can be collected, processed and analyzed through sensors, data base software and parallel computation technologies (Heng, 2008).

The current Research Status in Related Fields can be summarized as following:

(1) Current particle filtering based prognostics methods in mechanical system use Paris' Law to build the state transition function;

(2) There is still no research on how to integrate HI into particle filtering algorithm to do the prognosis;

(3) Current particle filtering based prognostics methods mostly use linear regression to build the observation function;

(4) Most of the research on particle filtering based applications are for diagnosis (that is, one step prediction), but not for prognosis (*l*-step prediction);

(5) No research results on spiral bevel gears and ceramic bearings prognosis and remaining useful life prediction using particle filtering based prognostics methods have been reported;

(6) There are just a few papers have been published about steel bearings prognostics by particle filtering algorithm.

Pusey and Roemer (1999) provided a broad overview of the development in diagnostics and prognostics technologies applicable to high-performance turbo-machines. Jardine *et al.* (2006) provided an overview and a catalogue of publications on data acquisition, data processing, diagnostics and prognostics of various machines. Vachtsevanos *et al.* (2006) defined and described intelligent fault diagnostics and prognostics approaches for engineering systems through examples.

The current methodologies for failure prediction can be grouped into three types like TABLE I shows:

TABLE I

PROGNOSTICS TYPES AND THEIR DESCRIPTIONS

	Types of Prognostics	Description
1.	Traditional reliability approaches	Event data based prediction
2.	Prognostics approaches	Condition data based prediction
3.	Integrated approaches	Prediction based on both event and condition data

Under these three approaches, there are some existing models to do the failure prediction. These models are listed in the following.

The first approach: Traditional reliability—use event data, e.g. replacement/failure times of historical units (Kapur and Lamberson, 1977; Keller, *et al*., 1982; Crowder, 1994; Elsayed, 1996; Groer, 2000; Lawless, 2002; Farrar, 2003, 2006). Traditional reliability approaches include some distribution models such as Weibull, Poisson, Exponential, and Log-Normal distribution. In these kinds of approaches, population characteristics information enable longer-range forecast and they do not require condition monitoring. However, traditional reliability approaches only provide general and overall estimates for the entire population of identical units, and these approaches are not necessarily accurate for individual operating units (Batko W., 1984).

Condition data based prediction is a prognosis approach use CM data, e.g., vibration measurements of operating units. It can be divided into three models: physics-based prognostics models, data-driven prognostics models and hybrid models. These kinds of approaches become more and more important than the traditional reliability approaches.
The following parts are about the research status of condition data based prediction (Yan, *et al*., 2004).

2.2.1 **Physics-based Prognostics Models**

Physics-based models based prognostics needs to build comprehensive mathematical models to describe the physics of the system and failure modes, such as crack propagation and spall growth.

The failure natural frequency and the acceleration amplitude were related to the running time and failure time established from damage mechanics. As physics-based models, these techniques require the estimation of various physics parameters (Deb, 2003).

The main physics-based prognostics models are listed in TABLE II:

TABLE II

MAIN PHYSICS-BASED PROGNOSTICS MODELS

Approach	Merits	Limitations
Paris law crack growth modeling (Paris, 1963; Li *et al.*, 1999; Warrier *et al.*,, 2000; Li *et al.*, 2000, 2005; Wemhoff, *et al.*, 2007)	Least-square scheme enables adaptation of model parameters to changes in condition.	Defect area size is assumed to be linearly correlated to vibration RMS level; Least-square scheme similar to single-step adaptation in time series prediction; Material constants to be determined empirically.
Paris law modeling with FEA (Li and Choi, 2002; Li and Lee, 2005)	FEA enables material stress calculation based on bearing geometry, defect size, load and speed.	Performance relies on the accuracy of crack size estimation based on vibration data; Computationally expensive.
Forman law crack growth modeling (Wereszczak, *et al.*, 2007; Oppenheimer and Loparo, 2002)	Relates CM data and crack growth physics to life models.	Simplifying assumptions need to be examined; Model parameters yet to be determined for complex conditions e.g. in shaft loading zone and plastic zones).
Fatigue spall initiation and progression model (Orsagh *et al.*, 2003; Orsagh *et al.*, 2004; Kacprzynski *et al.*, 2004)	Calculates the time to spall initiation and the time from spall initiation to failure; Cumulative damage since installation is estimated with consideration of operating conditions.	Various physics parameters need to be determined.
Contact analysis for bearing prognostics (Marble and Morton, 2006)	FEA enables material stress calculation based on bearing geometry, defect size, load and speed.	Various physics parameters need to be determined; Computationally expensive.
Stiffness-based damage rule model (Qiu *et al.*, 2002, 2003)	Relates bearing component natural frequency and acceleration amplitude to the running time and failure time.	Least-square scheme similar to single-step adaptation in time series prediction; Various material constants need to be determined.

Physics-based models might not be the most practical solution since the fault type in question is often unique from component to component and is hard to be identified without interrupting operation. However, a physics-based model is very complicated to be applied because a lot of related information and knowledge such as material properties, working loading, stress factors and historical operation. They also generally require less data than data-driven models (Heng, 2009).

2.2.2 **Data-driven Prognostics Models**

Another prognostics method is data driven based methodology. Data-driven based method primarily use data obtained from the system historical operation for predicting future faults. AE, vibration and oil debris are three typical condition indicators - CIs which can be monitored continuously in order to get the diagnostic and prognostic information (Crowder, 1994).

The simplest methods of data driven based methods are autoregressive such as linear regression (Ross, 1989).

The main data driven- based prognostics models are listed in TABLE III:

TABLE III

DATA DRIVEN-BASED PROGNOSTICS MODELS

Approach	Merits	Limitations
Time series prediction using ANNs (Caldwell, 1971 and 2007; Kazmierczak , 1983; Friedman, 1991; Tse and Atherton, 1999; Yam, *et al*. 2001; Wang and Vachtsevanos, 2001; Wang *et al*., 2004; Wang, 2007; Shao and Nezu, 2000; Lawless, 2002; Schomig and Rose, 2003; Tong and Lim, 1980);	Fast in handling multivariate analysis; Provide non-linear projection; Do not require a priori knowledge.	Assume that condition indices deterministically Represent actual asset health; Assume that failure occurs once the condition index exceeds a presumed threshold; Short prediction horizon.
Exponential projection using ANN (Samanta *et al*., 2006;Gebraeel *et al*., 2004; Gao, 2006)	Estimates actual failure time instead of condition index at future time steps; Longer prediction horizon.	Assumes that all bearing degradation follow an exponential pattern; Requires training one ANN for each historical data set.
Data interpolation using ANN (Li , *et al*., 2000; Huang *et al*., 2007)	Longer prediction horizon	Requires training one ANN for each historical dataset
Regression analysis and fuzzy logic (Rao, 1981; Lennart, 1987; Fukunaga , 1990; Jantunen, 2004; Shin, et al., 2005; Wang and Vachtsevanos, 2001; Wang, *et al*., 2004)	Emphasizes the most recent condition information; Fuzzy logic enables condition classification based on histories.	Does not provide indication of time to failure or probability of failure
Recursive Bayesian technique (Zhang *et al*., 2007; Hastie, 2009)	Estimates reliability using CM data of individual assets, rather than event data	Accuracy relies strongly on the correct determination of thresholds for various trending features
Hidden Markov Model and Hidden Semi-Markov Model (Zhang *et al*., 2005; Dong and He, 2007)	Can be trained to recognize different bearing fault types and states	Lack of relation of the defined health-state change point to the actual defect progression since it is often impractical to physically observe a defect in an operating unit; Prognosis projection relies on a failure threshold.
Bearing dynamics model using system identification (Li and Shin, 2004)	Tracks defect severity based on features that are not affected by operating condition and nearby equipments	Reasonably accurate only when the signal-to-noise ratio is high, e.g. damage is severe and running speed is relatively high.

2.2.3 **Hybrid Approaches**

Physics model based approach utilizes knowledge of a product's life-cycle loading and failure mechanisms as well as knowledge about the components and systems. Data-driven approaches can include parameters that are monitored at system level and utilize machine learning and pattern recognition techniques for diagnostic and prognostics. One can utilize the advantages of one technique to overcome the limitations associated with others. The incorporation of physics based models with data-driven approaches improves prognostic capabilities and provides more accurate diagnostics (Kumar *et al.*, 2008). We can combine theses two method to do the prognosis. Hybrid approaches attempt to leverage the strength from both data-driven approaches as well as model-based approaches. In reality, it is rare that the fielded approaches are completely either purely data-driven or purely model-based. More often than not, model-based approaches include some aspects of data-driven approaches and data-driven approaches glean available information from models. An example for the former would be where model parameters are tuned using field data. An example for the latter is when the set-point, bias, or normalization factor for a data-driven approach is given by models. Hybrid approaches use knowledge about the physical process and information from observed data together, such as, Particle filtering, Kalman filtering, etc. Particle filtering provides non-linear projection (Orchard, 2005).

The advantages of these methods are:

(1) Does not necessarily require high fidelity models or large volumes of data –works in a complementary fashion;

(2) Retains intuitiveness of a model but explains observed data;

(3) Helps in uncertainty management;

(4) Flexibility.

2.3 <u>Vibration Based Prognostics for Bearings and Gears</u>

By measuring and analyzing the vibration signal from the objective system, determining both the locations and severity of the faults, and hence predicting the machine's useful life or failure point will become possible (Lewicki *et al.*, 2010). The main advances in vibration analysis in recent years are the development in signal processing techniques, for vibration diagnostics of gearing systems (Cempel, 1987; Wang and McFadden, 1996; McCormick, 1998; Andrade *et al.*, 2001; Baydar and Ball, 2001; Liu, 2003; Rao *et. al*, 2003). A lot of vibration analysis software packages are available for automated analyses of common machinery faults such as bearings, gears, motors, etc. (Sohn *et al,* 2004).

Byington *et al*. (2002; 2003; 2006) presented a feature extraction and analysis driven system: ImpactEnergy. This system recorded high frequency vibration/acoustic emission data and combines advanced diagnostic features derived from waveform analysis, high-frequency enveloping, and more traditional time domain processing like root mean square (RMS) and kurtosis with classification techniques to provide bearing health information. Also, the effect and feasibility of ImpactEnergy as a bearing diagnostics system was proved by a case study on aircraft engine ceramic bearing data. The object includes two identical hybrid bearings. The test speed and load simulated the test conditions of the military accelerated mission tests (AMT's). The focus of this paper is the fault detection and diagnostic algorithms. Vibration data were collected as indictor to detect incipient ball spall defects and capture the degradation trend of hybrid ceramic bearings. The prediction algorithm of remaining useful life of hybrid ceramic bearings was not reported and verified in this paper. Takebayashi (2001) used vibration data as the diagnostic tool to indicate bearing fatigue damage and compared the rolling fatigue life of steel, hybrid, and all ceramic bearings.

Two different diagnostic methods can be used to indicate bearing failures: oil debris based diagnostics and vibration based diagnostics (Dempsey *et al.*, 2005). Dempsey *et al.* (2004) summarized the currently known failure modes of the hybrid bearing and used both the magnetic and non- magnetic sensors instead of using the magnetic oil debris sensor only to detect the silicon nitride debris. A hybrid bearing test rig has been developed by National Aeronautics and Space Administration (NASA) at Glenn Research Center in order to evaluate the performance of sensors and algorithms developed in predicting failures of rolling element bearings for aeronautic and space applications (Dempsey *et al.*, 2005). The failure progression of both conventional and hybrid (ceramic rolling elements, metal races) bearings can be tested from fault initiation to total failure. The effects of different lubricants on bearing life can also be evaluated. Different diagnostic tools, both oil based and vibration based systems, were used to indicate bearing failures. The vibration data were recorded and analyzed in time domain, frequency domain, and envelope analysis techniques to indicate the health condition of bearings in real-time. In the meanwhile, several different oil debris sensors were installed to get the information of both metallic and non-metallic debris particles. Using the magnetic properties of the oil debris to detect damage is not enough since the ceramic rolling elements of hybrid bearings have no metallic properties (Dempsey *et al.*, 2004). Oil debris sensor measures the change in a magnetic field caused by passage of a metal particle, and electric chip detectors measures magnetic debris generated during bearing tests. On the other hand, ultrasonic sensor uses a high-frequency acoustic impulse that is reflected by both metallic and non-metallic debris particles to yield particle counts (Howe and Muir, 1998). The video image based diagnostic sensor also can measure both metallic and nonmetallic debris (Dempsey *et al.*, 2005). All the data captured by the sensors indicate the process of failures and different types of failures.

2.4 Current Development of Particle Filtering Method

Recently, applications of particle filtering to prognostics have been reported in the literature, for example, remaining useful life (RUL) predication of a mechanical component subject to fatigue crack growth (Zio and Peloni, 2011), on-line failure prognosis of UH-60 planetary carrier plate subject to axial crack growth (Orchard and Vachtsevanos, 2011), degradation prediction of thermal processing unit in semiconductor manufacturing (Butler and Ringwood, 2010), and prediction of lithium-ion battery capacity depletion (Saba *et al.*, 2009). The reported application results have shown that particle filtering represents a potentially powerful prognostics tool due to its capability in handling non-linear dynamic systems and non-Gaussian noises using efficient sequential importance sampling to approximate the future state probability distributions (Ng Ka Ki and Edward Delp, 2009).

Particle filtering was developed as an effective on-line state estimation tool (Doucet *et al*., 2000; Arulampalam *et al*., 2000; Arulampalam *et al*., 2002). In order to apply particle filtering to RUL prediction of a mechanical component such as gears, a few practical implementation problems have to be solved: (1) define a state transition function that represents the degradation evolution in time of the component; (2) select the most sensitive health monitoring measures or condition indicators (CIs) and define a measurement function that represents the relationship between the degradation state of the component and the CIs; (3) define an effective *l*-step ahead RUL estimator. In solving the first problem, research on using particle filtering for mechanical component RUL prognostics has used Paris' law to define the state transition function (Zio and Peloni, 2011; Orchard and Vachtsevanos, 2011). As an empirical model, Paris' law can be effective for defining a state transition function that represents a degradation state subject to fatigue crack growth. For other type of failure modes such as pitting and corrosion, effective alternatives for defining the state transition function should be explored. Regarding the second problem, on the surface, it doesn't seem to be a problem to use multiple CIs to define a measurement function for particle filtering as it allows information from multiple measurement sources to be fused in a logical manner (Zio and Peloni, 2011). In particle filtering, measurements are collected and used to update the prior state distribution via Bayes rule so as to obtain the required posterior state distribution (Patrick *et al*., 2007). Subsequently, various kinds of uncertainties arise from different sources that are correlated. In most real applications, no single CI is sensitive to every failure mode of a component. This suggests that defining the measurement function will have some form of de-correlated sensor fusion. In order to apply particle filtering to estimate the RUL, an *l*-step ahead estimator has to be defined. Both biased and unbiased *l*-step ahead estimators have been reported by Zio and Peloni (2011), and Orchard and Vachtsevanos (2011). However, as pointed out by Zio and Peloni (2011), one issue related to these estimators is that state estimation and prediction must be accompanied by a measure of the associated error. However, almost all these researches in PHM field use only one cue as the observation parameter.

Saha and Goebel (2009) utilized PF to predict the life of the Li-ion battery. Cadini *et al*. (2009) use PF based algorithm for modeling fatigue crack growth. Also in (Zhang *et al*., 2009), a PF based multiple faults model enhanced by a simple on-line parameter adaptation algorithm for the rolling element bearing was proposed to estimate the fault size and the remaining useful life of the bearing. In the practical sense, to determine the value of the parameters for the state model of the system is critical important. For example, in (Orchard and Vachtsevanos, 2009), the authors used finite element analysis method to determine the parameter describing the relationship of fatigue crack growth under a stress intensity regime. Also, in (Zhang *et al*., 2009), an adaptive recursive algorithm is applied to determine the parameter for the state model of the bearing fault growth model.

3. THE METHODOLOGY OF PARTICLE FILTERING

3.1 Scheme of the Presented Prognosis Methodology

For any diagnosis and prognostic system, the first step is to build a Scheme of the Presented Methodology. The real-time diagnosis and prognosis system can be divided into two parts: hardware and software. For hardware, we need to select appropriate sensors, a feature collection system, and a data transmission, integration and analysis system. On the other hand, for software, first we need to define the technique framework, flow path and methods used. Then we can select data processing and feature analysis software. Next, prognosis and RUL prediction algorithms can be applied to get the failure rate and RUL distribution. Finally, we can schedule the maintenance.

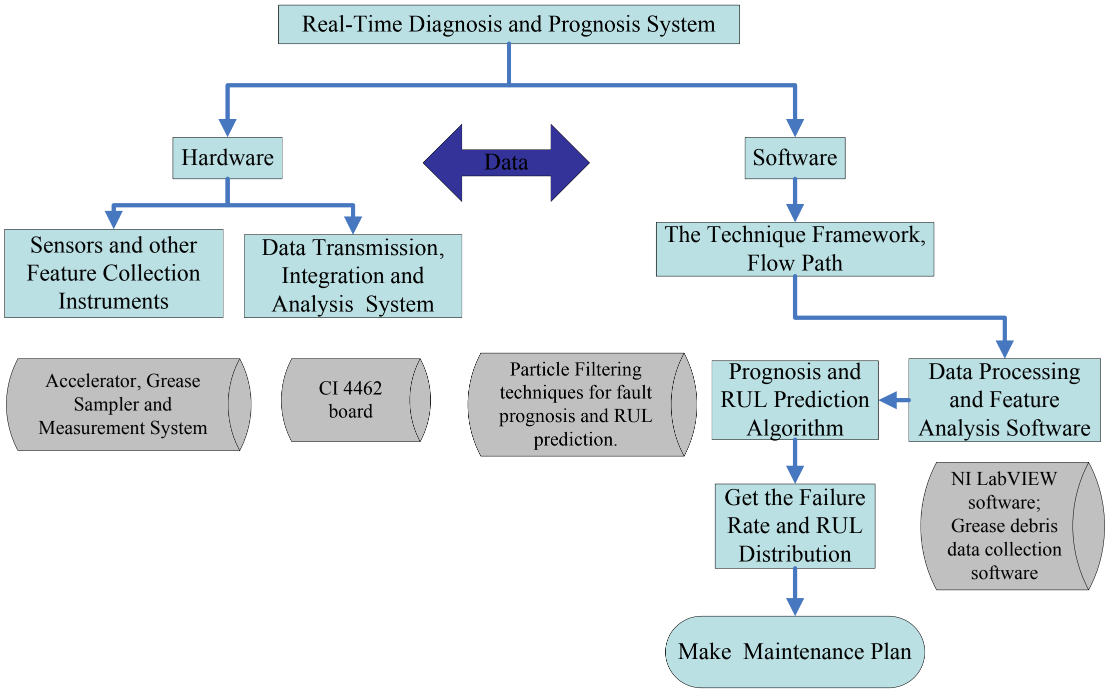


Figure 3. Scheme of the presented methodology

3.2 <u>The Scheme of the Particle Filtering Based Bearing Fault Prognostics</u>

The scheme of the methodology presented in this dissertation is shown in FIGURE 4. The vibration signal is first processed to generate the fault features, such as root mean square (RMS), kurtosis and so on. And then the particle filtering based prognostics algorithm is applied to predict the remaining useful life (RUL) of the bearing (Chen, 2010; 2011).

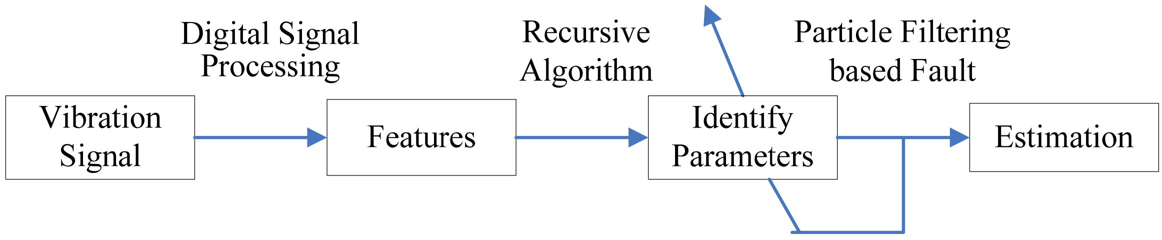


Figure 4. The particle filtering based prognostics algorithm

3.3 Conceptual Illustration of Model Updating

In particle filtering framework, the weighted particles actually represent the possible status of system degradation. The weight for each particle is also called importance and it represents how good or bad for a particle value to describe the true system status (Zio and Peloni, 2011). If a particle has a small weight that means that particle value is far away from the true system status. And if another particle has a bigger weight that means this particle can describe the system status very well. By using the developed methodology, the dynamic system degradation evolution can be estimated in terms of probability density function. And PDF is described by a swarm of weighted particles (Koller-Meier and Ade, 2001).

Figure 5 describes the two steps diagnosis result based on current measurements using the developed diagnosis procedure.

In this figure the vertical axis is the system degradation evolution and the horizontal axis is time horizon. Usually, a pre-specified threshold can be defined for the system degradation status. Sometimes this threshold can be a fixed value and sometimes it can be represented by a probability density function. In FIGURE 5, the upper part is the estimation result based on current measurement y_{k-2}, and the lower part shows the updated prediction result based on the updated measurement information y_{k1} (Xie, 2004; Ma,*et al*, 2006, 2010).

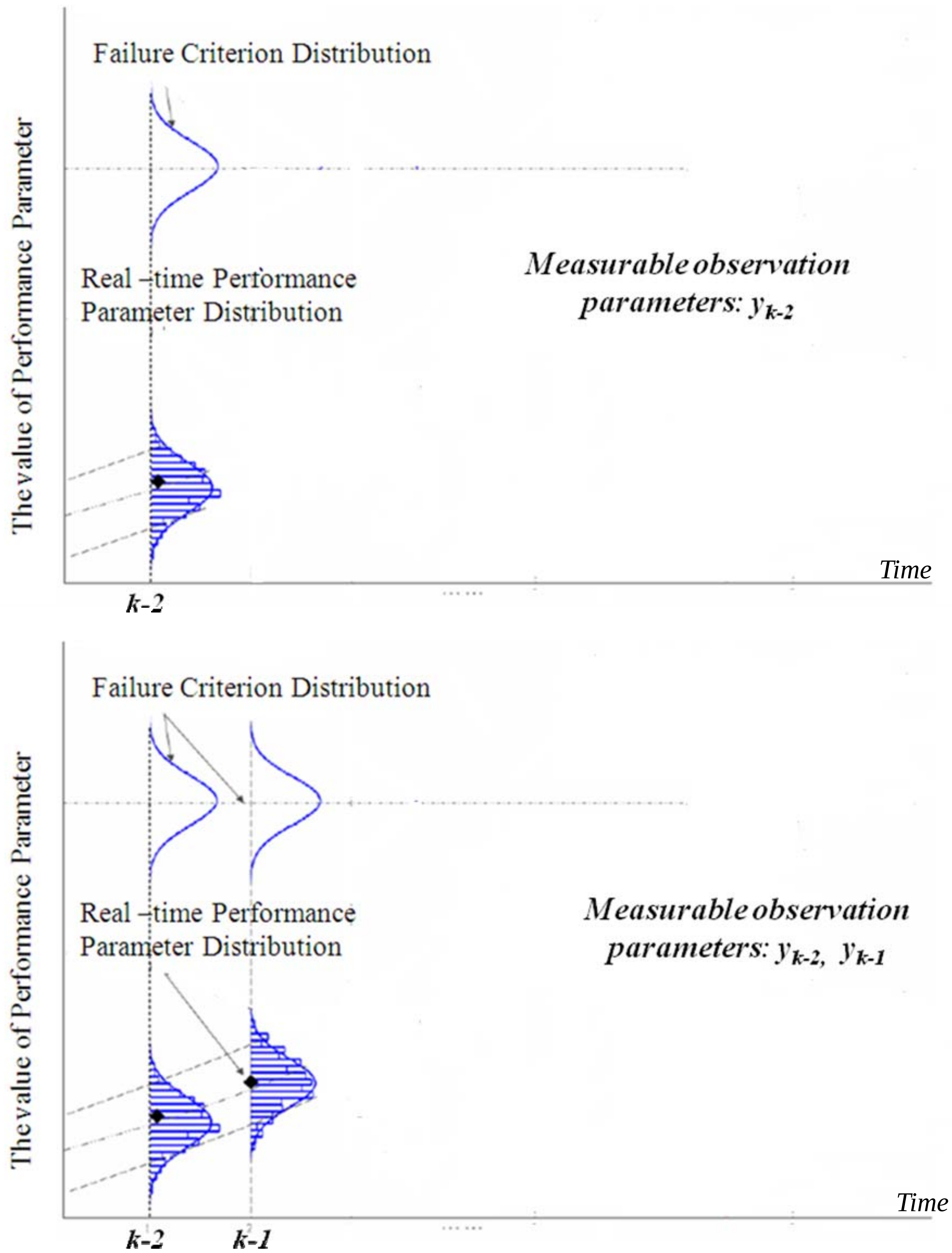


Figure 5. Two steps diagnosis based on the developed diagnosis procedure

FIGURE 5 shows the estimation result based on current measurement information y_k and the prediction result based on the current measurement information y_k.

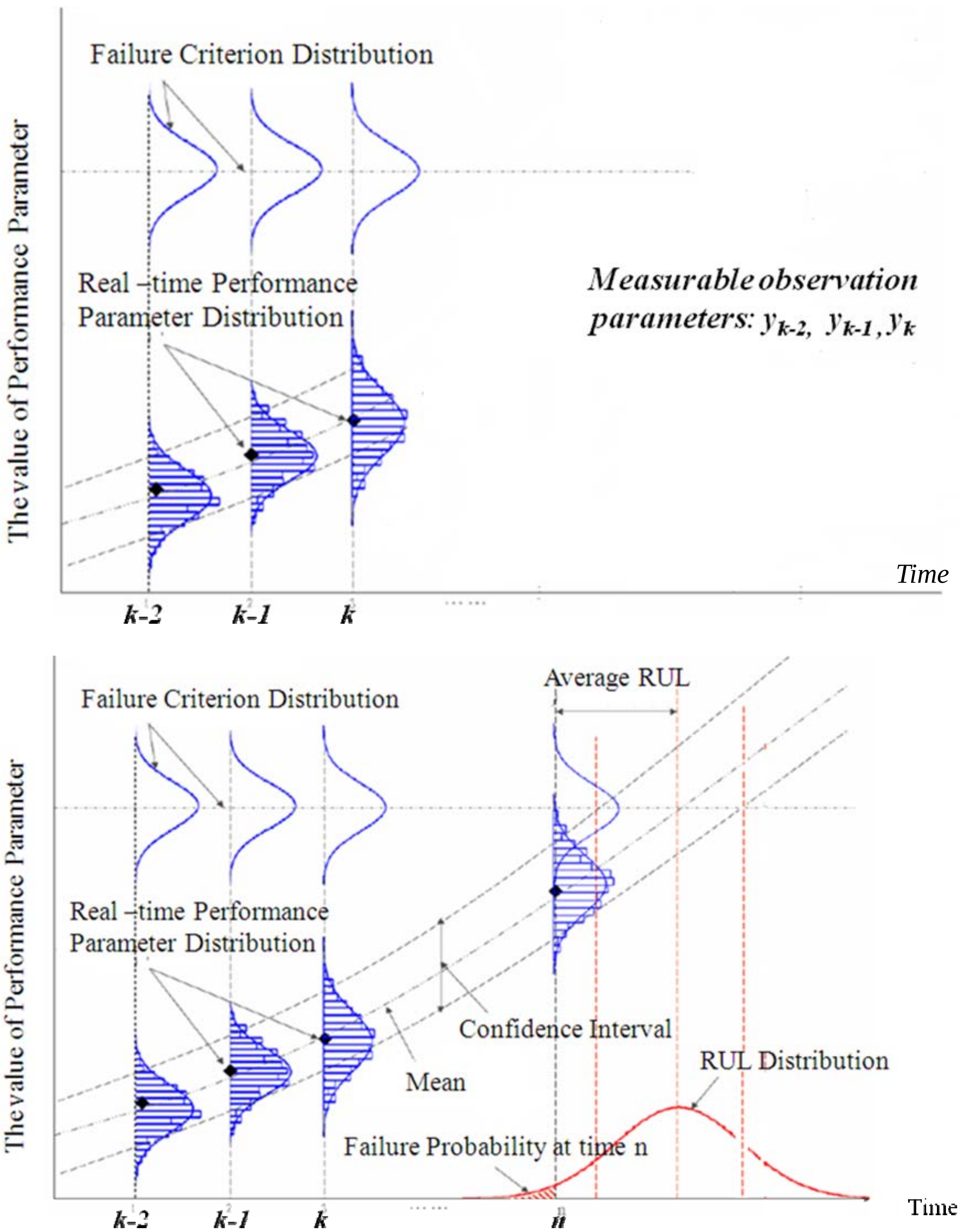


Figure 6. Conceptual illustration of model updating and *l*-step ahead prediction

By comparing the predicted system degradation and the pre-specified threshold, the probability of the system is going to fail can be obtained based on the current measurements. Also, the probability of system remaining useful life less than (n-k) can be obtained by using the developed remaining useful life estimator.

In the following sections, the developed methodology will be explained with details about how to get the results mentioned above.

3.4 <u>The Introduction of Particle Filtering</u>

Particle filtering is sequential Monte Carlo methods for state tracking and prediction. The method has been proved effective to model systems including elements of nonlinearity and non-Gaussianity (Arulampalam and Ristic, 2000). The information available from both the system measurements and the models are used for describing system behaviors. Recently, many successful applications on using PF have been reported (Pérez *et al.*, 2004). Representing the posterior probability density function by a set of discrete particles (samples) is the key of particle filtering (Spengler and Schiele, 2001). The reason why a sample is also called as a particle is because the probability density function describes its discrete nature and its discrete representation. Each particle represents a hypothesis of the state and it is randomly drawn from the prior density (Sanjeev, 2002). In (Li *et al.*, 2010), an online adaptive recursive algorithm is utilized to identify the parameter of the state model of the crack growth model of the bearing.

The fault prognostics can be classified into two categories according to the way the data is used to describe the behavior of the system. The first one is data-driven techniques (He and Bechhoefer, 2008) and the second one is model-based approaches (Li *et al.*, 1999). Based on nonlinear dynamic state model, particle filtering methodology combines these two techniques by using Eq. (3.1) and Eq. (3.2). The filtering problem can be described as:

$$x_t = f_t(x_{t-1}, v_{t-1}) \qquad (3.1)$$

$$y_t = h_t(x_t, u_t) \qquad (3.2)$$

where f_t is the system state evolution function and h_t is the observation function. x_t represents the states of the system at time t, y_t denotes the observation parameter, v_t the process noise, and u_t the observation noise. $p(x_0)$ represents the prior distribution at $t=0$.

This section focuses on the implementation of the particle filtering framework for analyzing the spall size of hybrid ceramic bearing. The scheme of the methodology is shown in FIGURE 7 (Li, 2010).

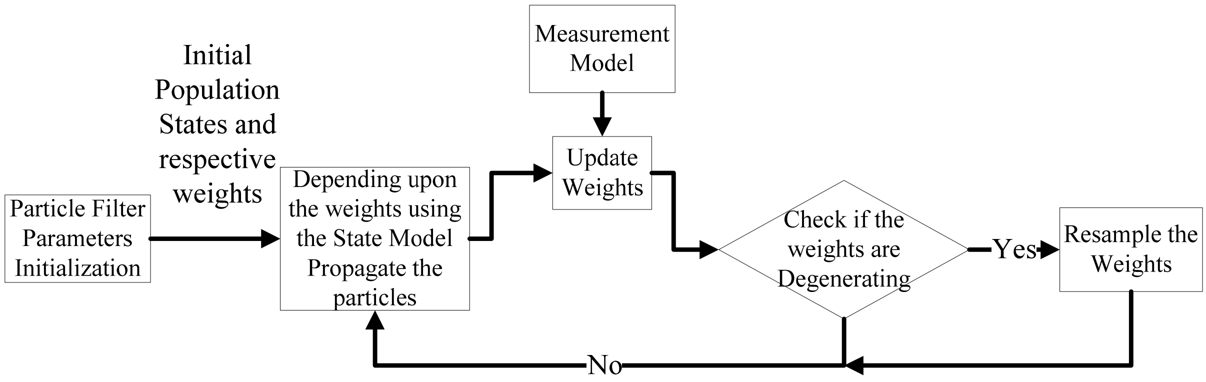


Figure 7. Particle filtering scheme of presented methodology

There are two stages in particle filtering process: prediction and update. The particles are modified according to the state function in the prediction process (Musso, 2001). Otherwise, in the update process, the particles' weights are re-evaluated based on the difference between the particle values got by observation function and the values from the prediction process.

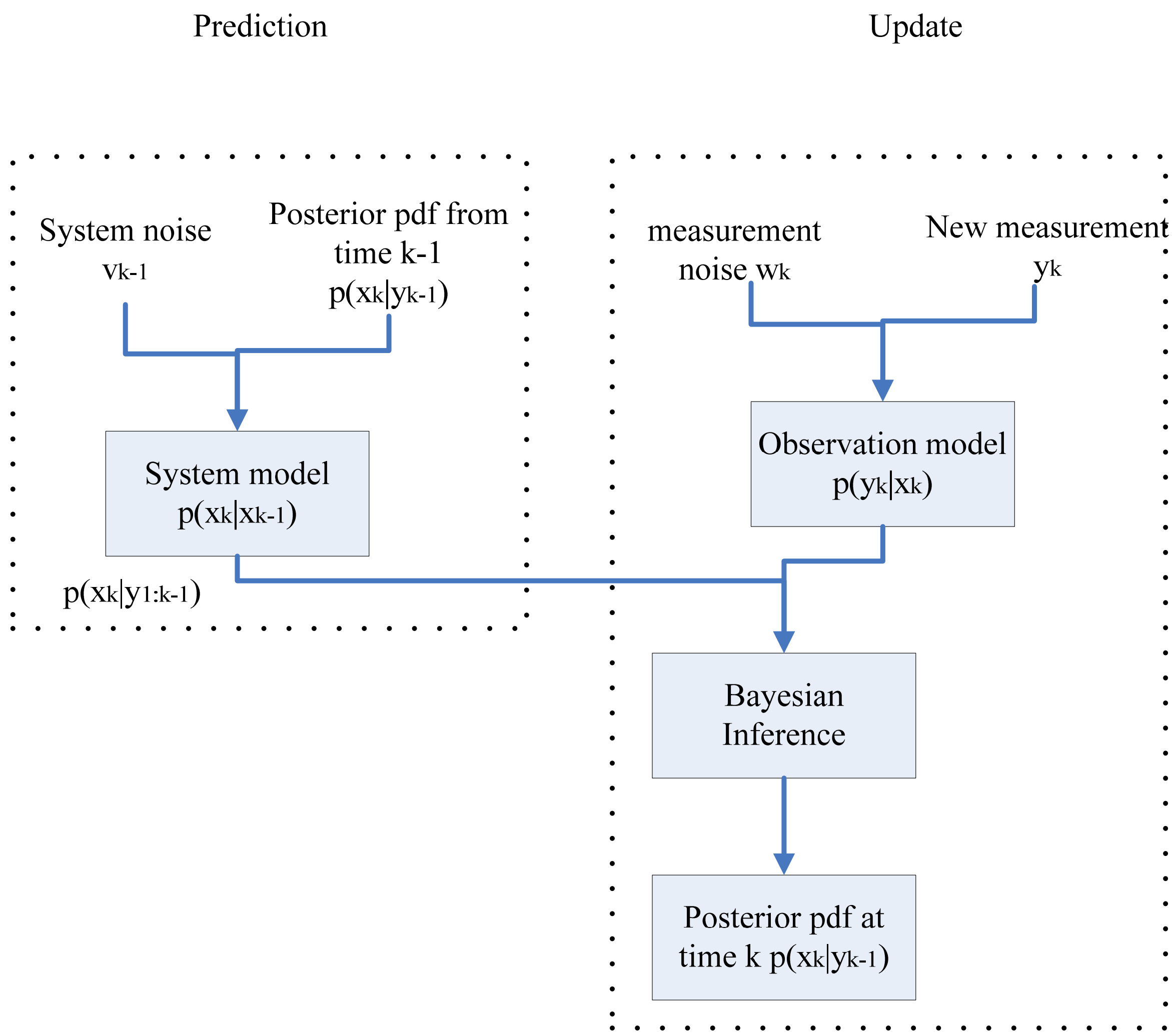


Figure 8. One iteration of the prediction and update

Figure 8 shows the one iteration of the prediction and update of filtering. The goal is to find the posterior probability density function at time k (Ki and Delp, 2009). The posterior probability density function is constructed recursively by the set of weighted random samples $\{x_t^{(i)},\ \omega_t^{(i)}; i = 1, \ldots, N\}$ where N is the total number of particles. At each time t, the particle filtering algorithm repeats a two-stage procedure: prediction and update

(Ki and Delp, 2009):

(1) Prediction stage: Every particle $x_t^{(i)}$ evolves independently and a new state value being obtained according to the state function (4.1). In order to simulate the unknown disturbance, the random noise is applied in this stage. An approximation of the prior probability density function is generated and represented by a batch of the particles in this step. Approximating the filtering probability density function by using a set of particles $x_t^{(i)}$, $i = 1, \ldots, N$ is the main idea of the particle filtering:

$$p(x_t) = \frac{1}{N} \sum_{i=1}^{N} \delta[x_t - x_t^{(i)}]$$

(2) Update stage: The weights of the particles are calculated based on the latest measurement according to the measurement function (likelihood function) (3.2). In the form of a discrete approximation, the posterior probability density function at time *t* can be written as:

$$p(x_t | y_{1:t}) = \sum_{i=1}^{N} \omega_t^i \delta[x_t - x_t^{(i)}] \qquad (3.3)$$

In Eq. (3.3), an important weight $\omega_t^{(i)}$ is assigned to each particle $x_t^{(i)}$. This weight implies the importance of the particle in constituting the formulation of filtering probability density function (PDF). After a particle is generated, it then propagates according to the state function. Each propagated particle is verified by a weight assignment by the measurement function. The quality of a specific particle is characterized by the weight. A good particle will be assigned with a large weight and a small weight will be given to a bad particle (Ki and Delp, 2009). $\delta[x_t - x_t^{(i)}]$ represents the delta-Dirac function located at $x_t^{(i)}$.

A finite sum approximates the general integral representation of the filtering PDF by using Eq. (3.3).

Corresponding weight for each particle is computed by (3.4):

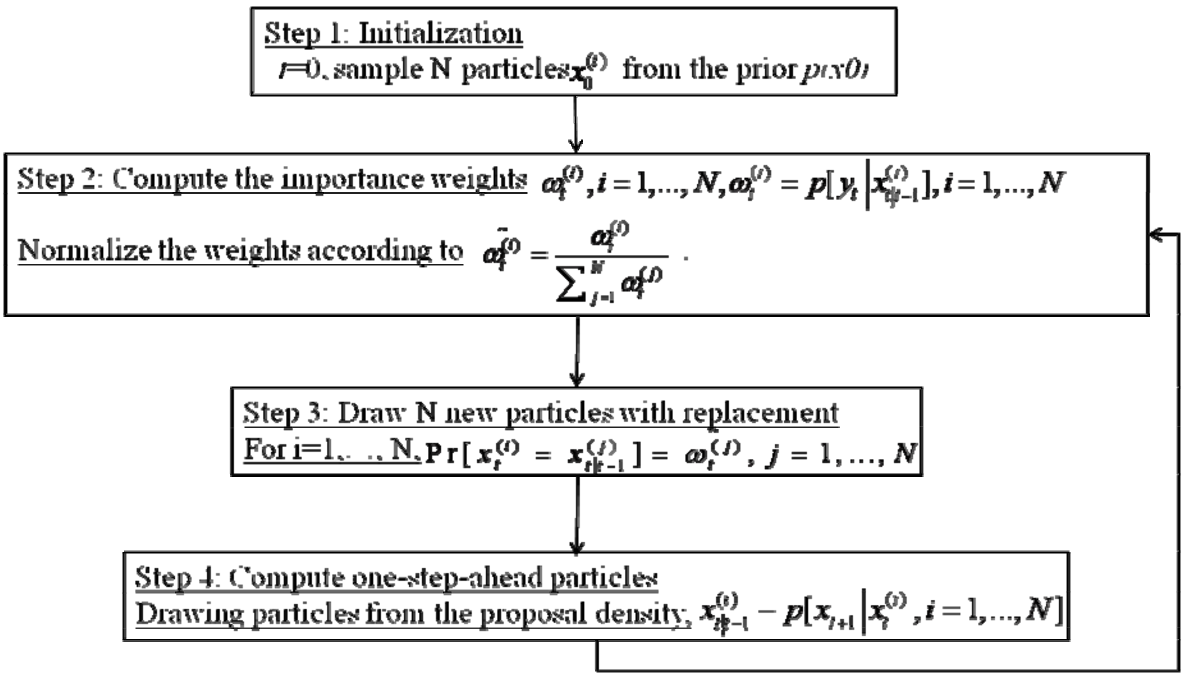
$$\omega_t^i = \omega_{t-1}^i \frac{p[y_t | x_t^{(i)}] p[x_t^{(i)} | x_{t-1}^{(i)}]}{q[x_t^{(i)} | x_t^{(i)}, y_t]} \tag{3.4}$$

In Eq. (3.4), $q[x_t^{(i)} | x_t^{(i)}, y_t]$ is the proposal density function, and $p[y_t | x_t^{(i)}]$ is the likelihood function of the measurements y_t.

The particle filtering method tracks multiple possibilities at the same time and each possibility is defined by a particle. According to the observation function, a particle is assigned with a weight. If the value of a particle is close to the value of the target, the distance of this particle is smaller from the object model, and then this particle will be assigned with a larger weight according to the observation function.

The observation likelihood function is very important in tracking performance using particle filtering. The first reason is because that this function determines the weights of the particles and the weights determine how the particles are re-sampled. The second one is that the predicted state value is the weighted mean of all particles and it affects the estimations directly (Ki and Delp, 2009).

The algorithm of a standard particle filtering includes the following four steps (Sanjeev *et al.*, 2002):



After step 4, go to Step 2 or end the algorithm according to the conditions.

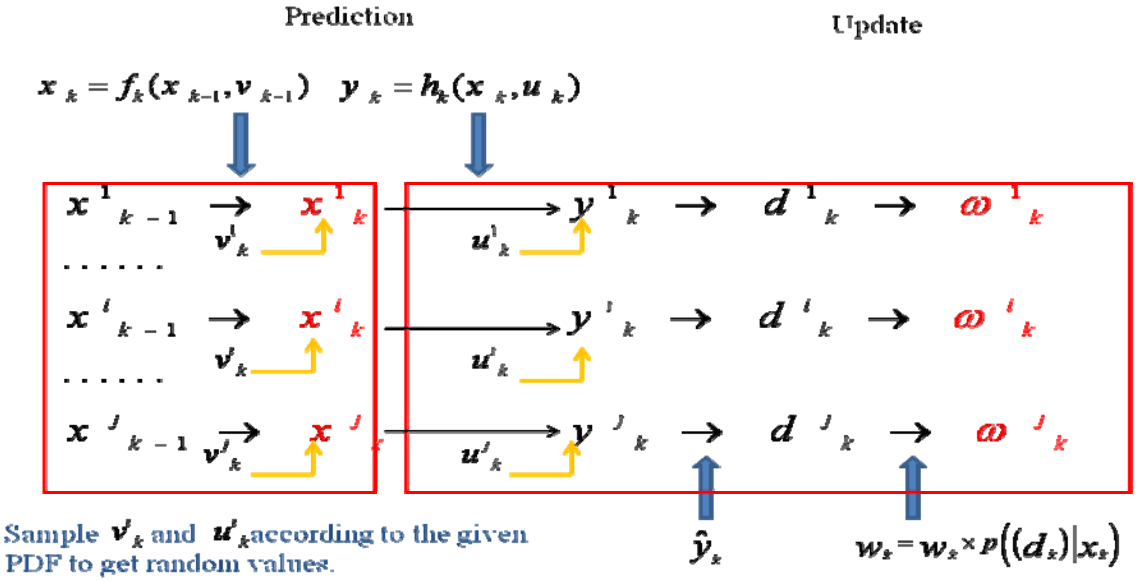
The nonlinear mapping between the observation parameter and state parameter can be assumed as one-to-one. Following the representation of the state and observation functions defined in (Zhang *et al.*, 2009), the particle filtering model for bearing prognostics can be written as follows:

$$x_c(t+1) = [kx_c(t)] + \omega(t) \tag{3.5}$$

$$y(t) = x_c(t) + v(t) \tag{3.6}$$

In this model, $x_c(t)$ represent the operation status – let's say the size of the crack area, $y(t)$ is the fault feature contaminating noise, and *k* is a time-varying model parameter that describes the progression of the fault dimension under a fatigue stress. Parameter *k* can be determined by using finite element analysis model (Orchard and Vachtsevanos, 2009) or online identified by the experimental data (Zhang *et al.*, 2009). In (Li, *et al.*, 2010), to simplify the way to calculate *k*, an online identification algorithm can be used to find the value of *k*.

The following framework shows the calculation steps with details:



The following figures show the all possible evolution paths by using 5 particles as an example, like FIGURE 9 - FIGURE 15 show.

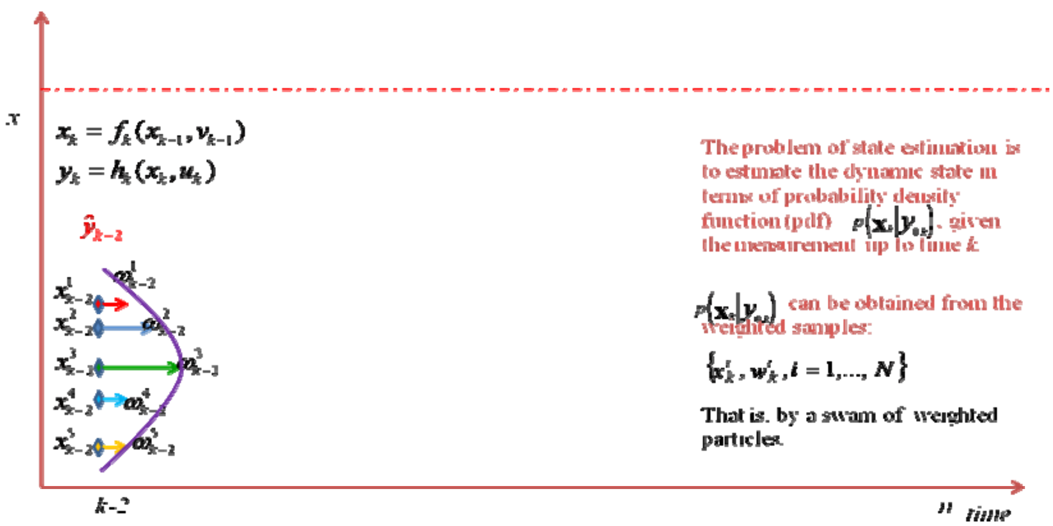


Figure 9. The current particles at current time point *k*-2

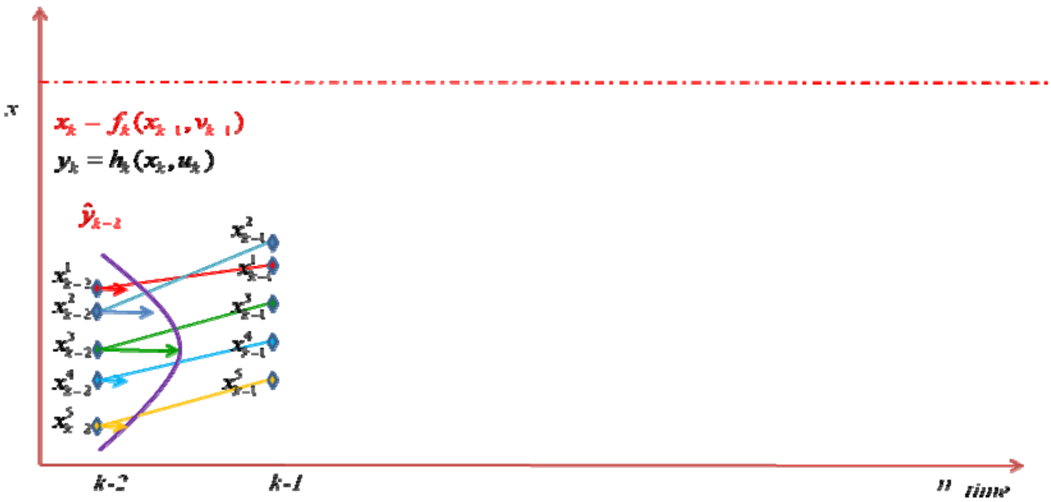


Figure 10. The updated particle values by using state function

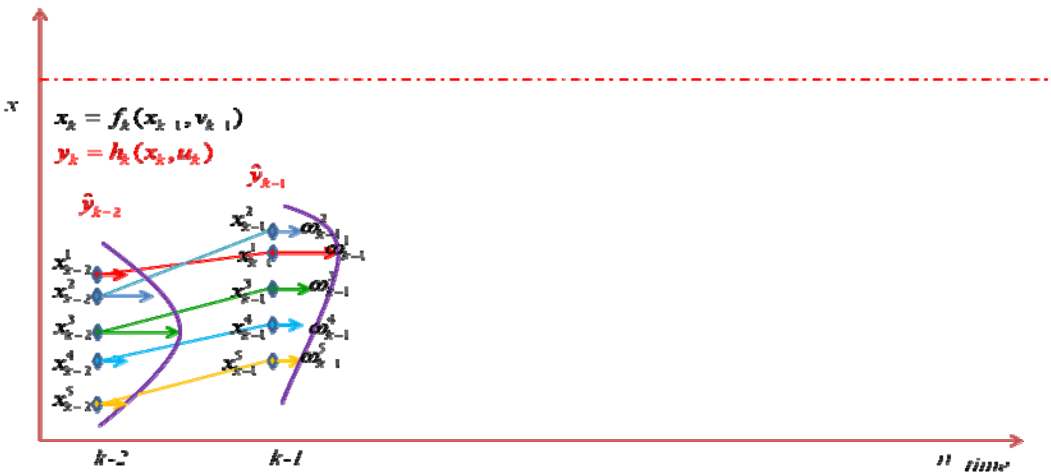


Figure 11. The updated weights for each updated particle by using observation function

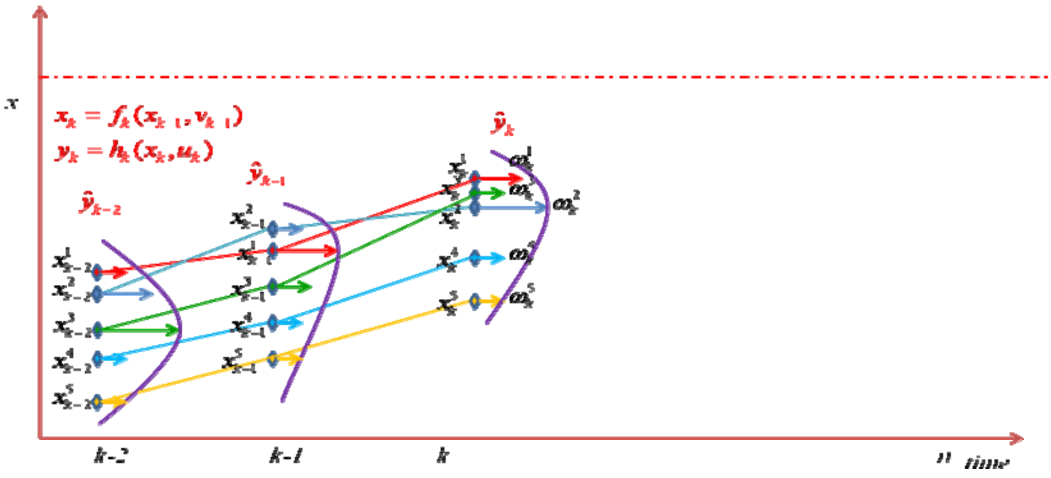


Figure 12. Updated particle and their weights based on current measurement

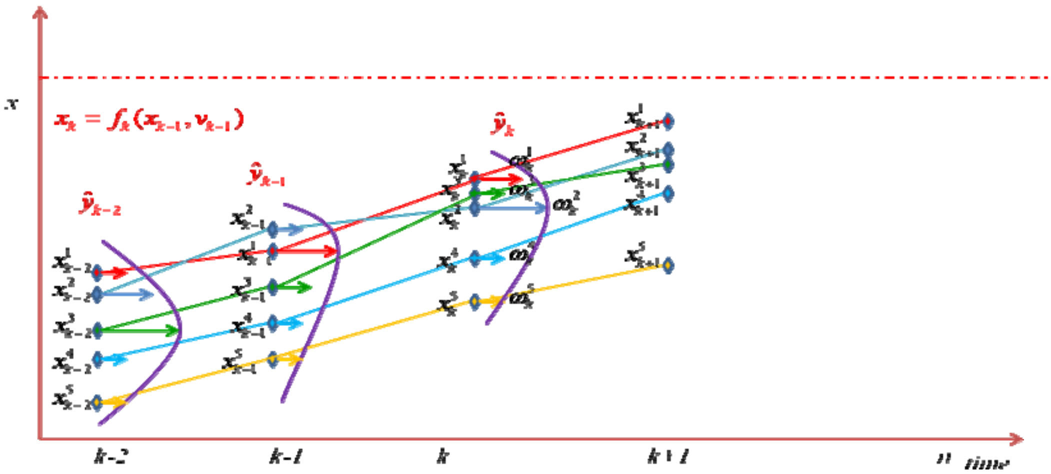


Figure 13. The one step ahead predicted particle values based on the current measurement

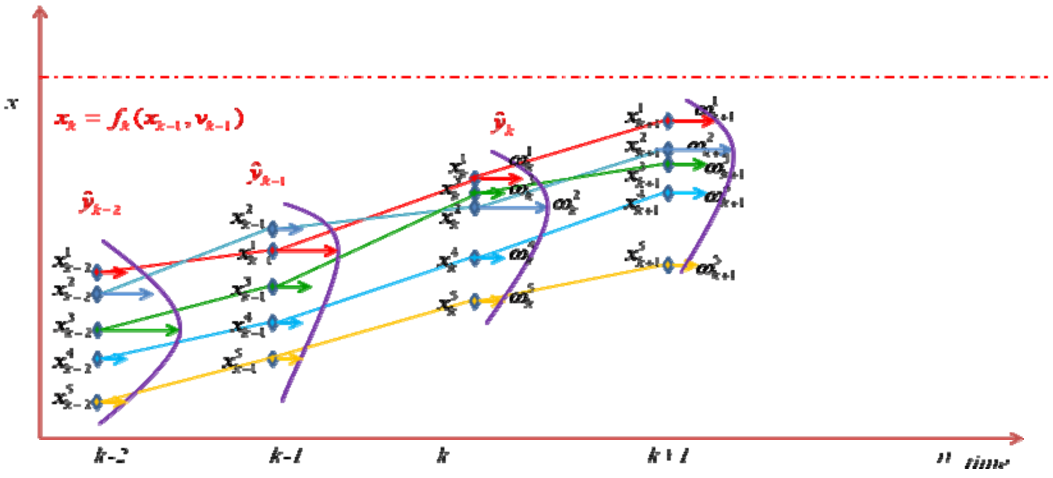


Figure 14. One step ahead prediction result for system degradation

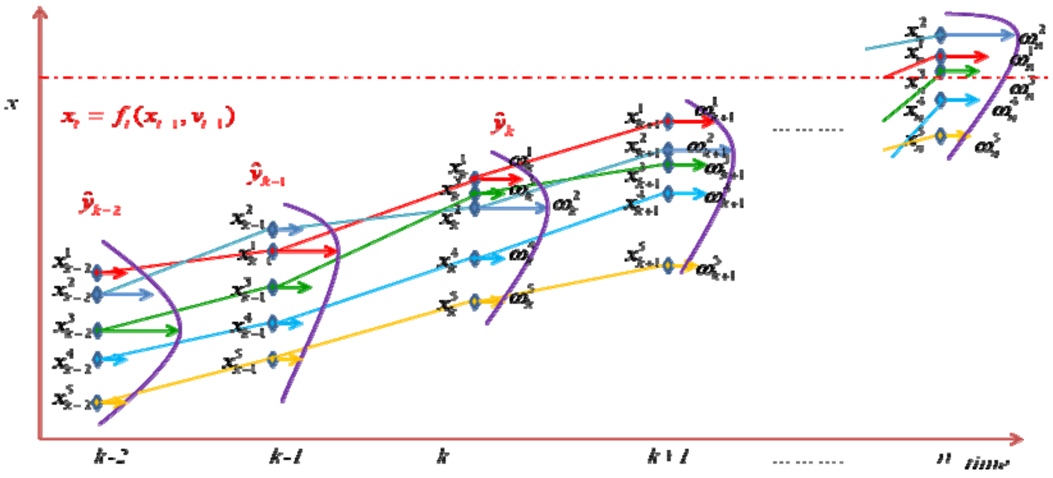


Figure 15. The *l*-step ahead prediction for system degradation status by using 5 particles

The task of tracking a state variable and predicting the future values is usually solved as a filtering problem (Saha and Goebel, 2009). Particle filtering can easily deal with uncertainties when they occur. The detailed implementation of the particle filtering is shown in FIGURE 16.

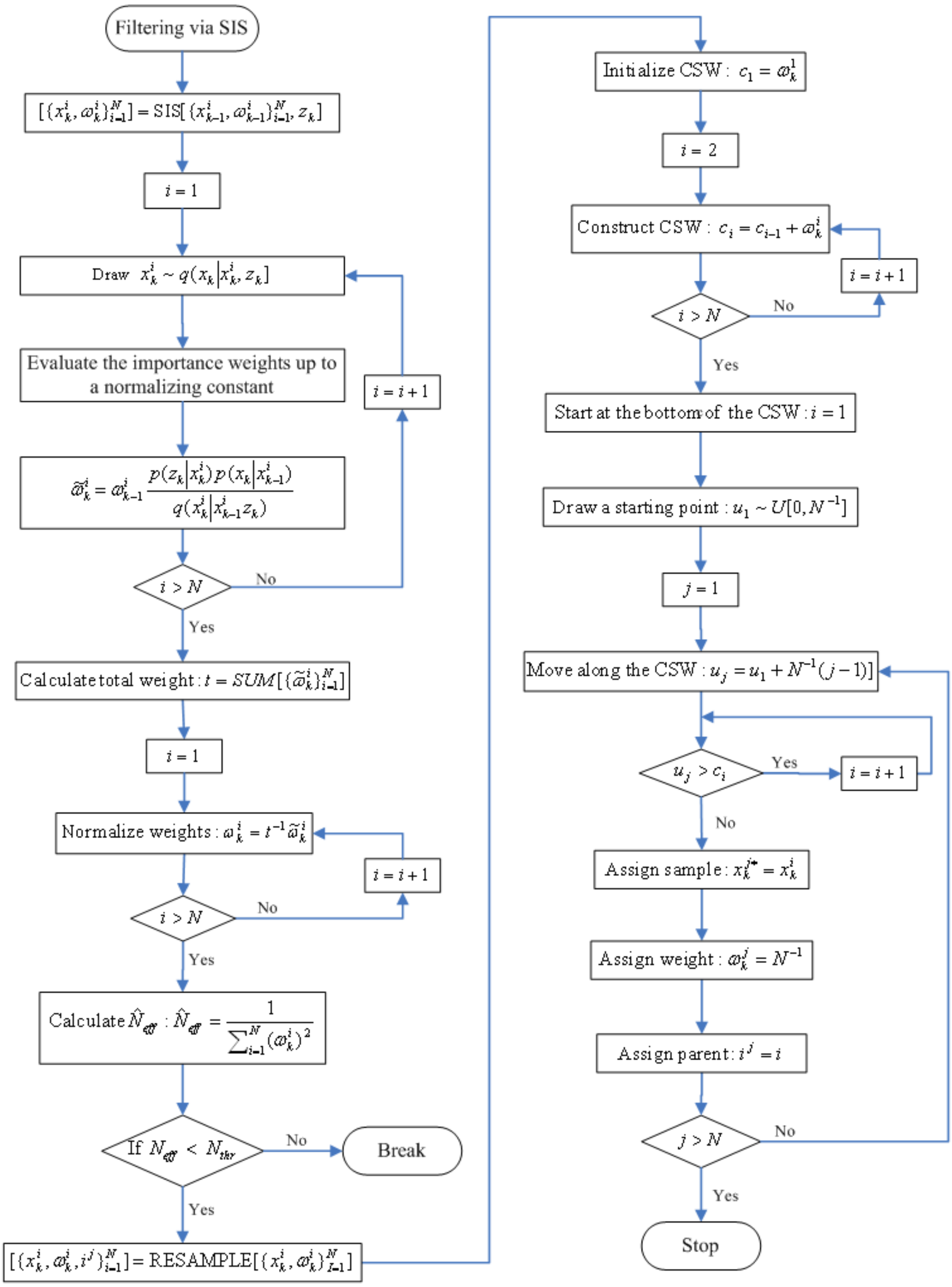


Figure 16. Particle filtering flowchart

3.5 RUL Prediction using Particle Filtering

3.5.1 Particle Filtering for Fault Status Prediction

Assume the following discrete time state space model can describe a system:

$$x_k = f_k(x_{k-1}, \omega_{k-1}) \tag{3.7}$$

$$y_k = h_k(x_k, v_k) \tag{3.8}$$

where:

$f_k : R^n{}_x \times R^n{}_\omega \to R^n{}_x$ is the state function

ω_k : the independently and identically distributed (*iid*) state noise vector

h_k : $R^n{}_x \times R^n{}_v \to R^n{}_y$: the measurement function

v_k : the independently and identically distributed(*iid*) measurement noise vector

State transit estimation is a problem which estimate the dynamic state x_k according to probability density function (PDF) $p(x_k | y_{0:k})$, given the measurement at time *k*. Assume that the initial distribution of the state $p(x_0)$ is known.

Normally, prediction and update is the two steps of the Bayesian solution to the state estimation problem. In the prediction step, the prior probability distribution of the state x_k at time *k*, starting from the probability distribution $p(x_{k-1} | z_{0:k-1})$ at time *k*-1, is obtained as:

$$\begin{aligned} p(x_k | y_{0:k-1}) &= \int p(x_k | x_{k-1}, y_{0:k-1}) p(x_{k-1} | y_{0:k-1}) dx_{k-1} \\ &= \int p(x_k | x_{k-1}) p(x_k | y_{0:k-1}) dx_{k-1} \end{aligned} \tag{3.9}$$

In the update step, at time *k*, a new measurement y_k is got and applied to update the prior distribution to obtain the posterior distribution of the current system state x_k as:

$$p(x_k | y_{0:k}) = \frac{p(x_k | y_{0:k-1}) p(y_k | x_k)}{p(y_k | y_{0:k-1})} \tag{3.10}$$

The normalizing constant is formulated as:

$$p(y_k | y_{0:k-1}) = \int p(x_k | y_{0:k-1}) p(y_k | x_k) dx_k \tag{3.11}$$

In most of cases, solving Eq. (3.9) and Eq. (3.10) is very hard and not realistic. Therefore, particle filtering is applied to solve the equations. The following two steps can be performed to get the prediction at time *k*:

(1) Drawing N random samples (particles) $x_{k-1}^i, i=1,...,N$ from the probability distribution of the state noise ω_{k-1};

(2) Using Eq. (3.7) to Generate N new set of samples $x_{k-1}^i, i=1,...,N$. In the update step, each new sampled particle x_k^i is assigned a weight ω_k^i based on the likelihood of the new measurement y_k at time k as:

$$\omega_k^i = \frac{p(y_k \left| x_k^i \right.)}{\sum_{i=1}^{N} p(y_k \left| x_k^i \right.)} \qquad (3.12)$$

The approximation of the posterior distribution $p(x_k \left| y_{0:k} \right.)$ can be obtained from the weighted particles $x_k^i, \omega_k^i, i=1,...,N$ (Doucet *et al*., 2000).

3.5.2 <u>**Particle Filtering for RUL Prediction**</u>

An *l*-step ahead estimator has to be developed to estimate the remaining useful life by using particle filtering. A long term prediction of the state PDF $p(x_{k+l} \left| y_{0:k} \right.)$ can be obtained by using the *l*-step ahead estimator, where, $l=1,...,T-k$, T is the time horizon. It is assumed that no measurement data are available for estimating the likelihood of the state following the future *l*-step path $x_{k+1:k+l}$. So, one can only project the initial condition $p(x_k \left| y_{0:k} \right.)$ using state transition PDF $p(x_j \left| x_{j-1} \right.), j=k+1,...,k+l$ along all possible future paths weighted by their probability $\prod_{j=k+1}^{k+l} p(x_j \left| x_{j-1} \right.) dx_{j-1}$. By combining Eq. (3.7) and Eq.

(3.10), an unbiased *l*-step ahead estimator can be obtained (Zio and Peloni, 2011; Orchard and Vachtsevanos, 2011):

$$p\left(x_{k+l}\middle|z_{0:k}\right)=\int\cdots\int\prod_{j=k+1}^{k+l}p\left(x_j\middle|x_{j-1}\right)p\left(x_k\middle|z_{0:k}\right)\prod_{j=k}^{k+l-1}dx_j \qquad (3.13)$$

However, solving Eq. (3.13) is very difficult and computationally expensive. A particle filtering approximation procedure of the *l*-step ahead estimator is provided in (Zio and Peloni, 2011).

Assume that the state x_k represents the fault status indicator and RUL is the remaining useful time before the fault indicator arriving at the pre-specified threshold λ. Estimating $\hat{p}(RUL \le y_{0:r})$ is equivalent to estimating $\hat{p}(x_{k+l} \ge \lambda | y_{0:r})$ at each time $k+l$.

Note that in computing the *l*-step ahead RUL estimator using particle filtering, at each updating step, a weight is computed according to Eq. (3.12) without considering any measurement of the associated errors. $\hat{y}_k$ the measurement parameter at time *k* computed by using Eq. (3.8). y_k is the true measurement parameter collected by sensors. Then a weighting process in particle filtering that takes into account the measurement errors can be defined as:

$$\omega_k^i = \frac{p((y_k - \hat{y})|x_k^i)}{\sum_{i=1}^{N} p((y_k - \hat{y})|x_k^i)} \qquad (3.14)$$

In the particle filtering based case studies in this dissertation, Eq. (3.14) is used to calculate the weights of particles for the *l*-step ahead fault parameters.

3.6 <u>Particle Filtering *l*-step Prognosis</u>

Prognosis is a problem about how to generate the long-term predictions which describe the evolution of the system operation status or fault indicator. After that, the remaining useful life (RUL) of a failing component/subsystem can be estimated based on the current information. In order to apply particle filtering to estimate the RUL, an *l*-step ahead estimator has to be developed. An *l*-step ahead estimator will provide a long term prediction of the state pdf $p(\mathbf{x}_{k+l}|\mathbf{z}_{0:k})$ for $l = 1,...,T-k$, where *T* is the time horizon of interest. In making an *l*-step ahead prediction, it is necessary to assume that no information is available for estimating the likelihood of the state following the future *l*-step path $\mathbf{x}_{k+1:k+l}$, that is, future measurements $\mathbf{z}_{k+l}, l = 1,...,T-k$ cannot be used for making the prediction. Therefore, one can only project the initial condition $p(\mathbf{x}_k|\mathbf{z}_{0:k})$ using state transition pdf $p(\mathbf{x}_j|\mathbf{x}_{j-1}), j = k+1,...,k+l$ along all possible future paths weighted by their probability $\prod_{j=k+1}^{k+l} p(\mathbf{x}_j|\mathbf{x}_{j-1})d\,\mathbf{x}_{j-1}$.

The most important issue is projecting the current particle population when new observations are absent. If necessary, weights may have to be adjusted (Orchard, Ph. D thesis, 2007).

The errors which are generated by considering the changes of particle weights in the future time instants is negligible considering other sources of error, such as model inaccuracies or even in the assumptions made for process and measurement noise parameters (Doucet *et al.*, 2000).

Based on this standpoint, equation (3.8) is considered sufficient enough to extend the projection of $\hat{x}^{(i)}_{0:t+k}$, and the current particle weights are propagated in time without changes. The results from the case studies in this dissertation prove that the method still provides a satisfactory result when predicting how the system behaves.

4. INTEGRATION OF ONE-DIMENSIONAL HEALTH INDEX INTO PARTICLE FILTERING METHODOLOGY FOR PROGNOSTICS

4.1 Introduction

There is no single CI that is sensitive to every failure mode of a gear or bearing (Bechhoefer *et al*., 2011). Some form of sensor fusion is required for the condition based maintenance system of gears or bearings. In this chapter, a one-dimensional health index calculation method will be introduced and the integration of one-dimensional health index into particle filtering methodology will be developed. The steel bearing test data will be used as an example to illustrate the methodology.

There are three statistical models which can define a gear HI as a function of a CI (Bechhoefer *et al*., 2011):

(1) HI1: order statistics (max of *n* CIs);

(2) HI2: sum of CIs;

(3) HI3: normalized energy.

The condition indicators are regarded as statistics. They have to be independent in order to calculate the three HIs by using the related formulas. Usually, CIs tend to be correlated, so a whitening process was developed to ensure the use of the calculation models can be correctly applied. Rayleigh and Gaussian distributions were used to develop the models for these CIs. These models, which were used to calculate HIs, were tested on gear and bearing test stand data and their performance evaluated as compared to the end state of the gear and bearing (Bechhoefer *et al*., 2011). The results show the HIs worked well in detecting surface fatigue pitting faults on bearing races and gear teeth.

All CIs have a probability distribution (PDF). Any operation on the CI to form a health index (HI), is then a function of distributions (Wackerly, 1996). For example, the following three functions can be used to get HI:

(1) The maximum of n condition indicators (the order statistics);

(2) The sum of n condition indicators;

(3) The norm of n condition indicators (energy).

These three functions are valid if and only if the distributions of CIs are independent and identical (*IID*) (Wackerly, 1996). The correlation between CIs implies that for a given function of distributions, the CIs must be whitened (e.g. de-correlated). A whitening transform using the Eigenvector matrix multiplied by the square root for the Eigenvalues (diagonal matrix) of the covariance of the CIs was developed (Fukinaga, 1990; Bechhoefer *et al*., 2011).

$$\mathbf{A} = \Lambda^{1/2}\Phi^{T} \tag{4.1}$$

where Φ^T is the transpose of the eigenvector matrix, and Λ is the eigen value matrix.

If the CIs represented a metric such as shaft order acceleration, then one can construct an HI which is the square of the normalized power (e.g. square root of the acceleration squared) (Bechhoefer *et al.*, 2011). This can be defined as normalized energy, where the health index is:

$$HI = \sqrt{CI \times \mathrm{cov}(CI)^{-1} \times CI^T} \qquad (4.2)$$

Bechhoefer *et al.* (2007) whitened the condition indicators CIs.

The diagnostic capability for gear and bearing health index can be improved by generalizing a method to develop HI based on CIs with related functions and statistical distributions.

4.2 Generalized Function of Distributions

The following equations show the desired linear transformation operation for the vector CI:

$$\begin{aligned} &\mathbf{Y} = \mathbf{L} \times CI^T, \\ &0 = \rho = correlation(\mathbf{Y}) \end{aligned} \qquad (4.3)$$

where Y kept the original distribution of the CIs. And the vectors of Y are *IID*.

The Cholesky Decomposition of Hermitian, positive definite matrix results in $A = LL^*$, where L is a lower triangular, and L^* is its conjugate transpose. We know that the inverse covariance is positive definite Hermitian by the definition. L follows that:

$$\mathbf{LL}^{*} = \Sigma^{-1} \tag{4.4}$$

and using Eq. (4.3), get:

$$\mathbf{Y} = \mathbf{L} \times CI^{T} \tag{4.5}$$

Where, Y is n number of independent CI with unit variance.

The Cholesky Decomposition generates the square root of the inverse covariance. This in turn is analogous to dividing the CI by its standard deviation (the trivial case of one CI). In turn, Eq. (4.5) creates the necessary independent and identical distributions required to calculate the critical values for a function of distributions (Bechhoefer *et al*., 2011).

4.3 HI Based on Gaussian PDFs

If it is found that the distribution of the CI data follows a Gaussian distribution a comparable mathematical process can be applied. The probability density function of the Gaussian distribution is:

$$f(x) = \frac{x}{\sigma\sqrt{2\pi}\exp\left(\frac{-(x-\mu)^2}{2\sigma^2}\right)} \tag{4.6}$$

The cumulative distribution function, the integral of probability density function Eq. (4.6) is

$$F(x) = \frac{x}{\sigma\sqrt{2\pi}\int_{-\infty}^{x}\exp[-\frac{(t-u)^2}{2\sigma^2}]dt} \tag{4.7}$$

4.3.1 The First Calculation Method of HI: the Gaussian Order Statistic

The order statistic PDF of a Gaussian HI function:

$$f(x) = 3\{\frac{x}{\sigma\sqrt{2\pi}\int_{-\infty}^{x}\exp[\frac{-(t-\mu)^2}{2\sigma^2}]dt}\}^2 \times \frac{x}{\sigma\sqrt{2\pi}\exp[\frac{-(x-\mu)^2}{2\sigma^2}]} \tag{4.8}$$

By solving the inverse CDF the threshold can be determined Assume there are three CIs, that is, $n = 3$, and PFA of 0.95, we can get that the lower threshold t equals to -0.335, and upper threshold for a PFA of 10^{-3}, the threshold t is 3.41 (for HI of 0.5). The CIs become z distribution (Gaussian distribution normalized with zero mean and unit variance). The HI algorithm is (Bechhoefer *et al*., 2011):

$$HI = \frac{[\max\{\mathbf{L}\times(\mathbf{CI}^T - \mathbf{m})\} + 0.34]\times 0.5}{(3.41 + 0.34)} \tag{4.9}$$

where m is the mean value of all used CIs. The CIs into n Z distributions (zero mean, *IID* Gaussian distributions) by subtracting the mean and multiplying by L transforms.

4.3.2 <u>The Second Calculation Method of HI: the Sum of *n* Gaussian</u>

Consider a HI function that takes the sum of n Gaussian CIs. Then the mean and variance of the sum of the CI are (Bechhoefer *et al*., 2011):

$$\mu = \sum_{i=1}^{3} E[\mathbf{L}_i], \quad \sigma^2 = n \tag{4.10}$$

Same the inverse normal cumulative distribution function is used to calculate the parameter. For $n = 3$ CIs, the mean μ is 3 and variance σ^2 equals 3. Using the inverse normal cumulative distribution function, the lower threshold (PFA of .95) is -0.15 and the upper threshold (PFA 10^{-3}), is 8.352, then the HI algorithm is then (Bechhoefer *et al.*, 2011):

$$HI = \frac{0.5}{(8.352 - 0.15)}[-0.15 + \sum\nolimits_{i=1}^{3} (\mathrm{L} \times \mathrm{CI}^{T})] \qquad (4.11)$$

4.3.3 <u>**The Third Calculation Method of HI: Total Energy**</u>

In this case we consider a HI function which uses the norm of *n* Gaussian CIs. For *n* = 3 CIs and a PFA of 10^{-3}, the threshold equals 3.368. The HI algorithm is then (Bechhoefer *et al.*, 2011):

$$\begin{aligned} &\mathbf{Y} = \mathbf{L} \times CI^{T} \\ &HI = {}^{0.5}\!/_{3.368} \sqrt{\sum\nolimits_{i=1}^{3} \mathbf{Y}_i^2} \end{aligned} \qquad (4.12)$$

4.4 <u>Steel Bearing Case Study</u>

In this section, a case study about steel bearing data was applied. The two different methods were used to obtain the fault status prediction and remaining useful life estimation. The first method is combines multiple condition indicators into particle filtering model directly to get the system status update. The second method uses the HI, the integrated indicator, as the observation parameter needed in the particle filtering model.

4.4.1 **Combing Multiple Condition Indicators into Particle Filtering Model Directly**

FIGURE 17 shows the predicted spall size and true spall size, the prediction result can track the trend of the true value. The vertical axis represents the spall size and the horizontal axis is time horizon.

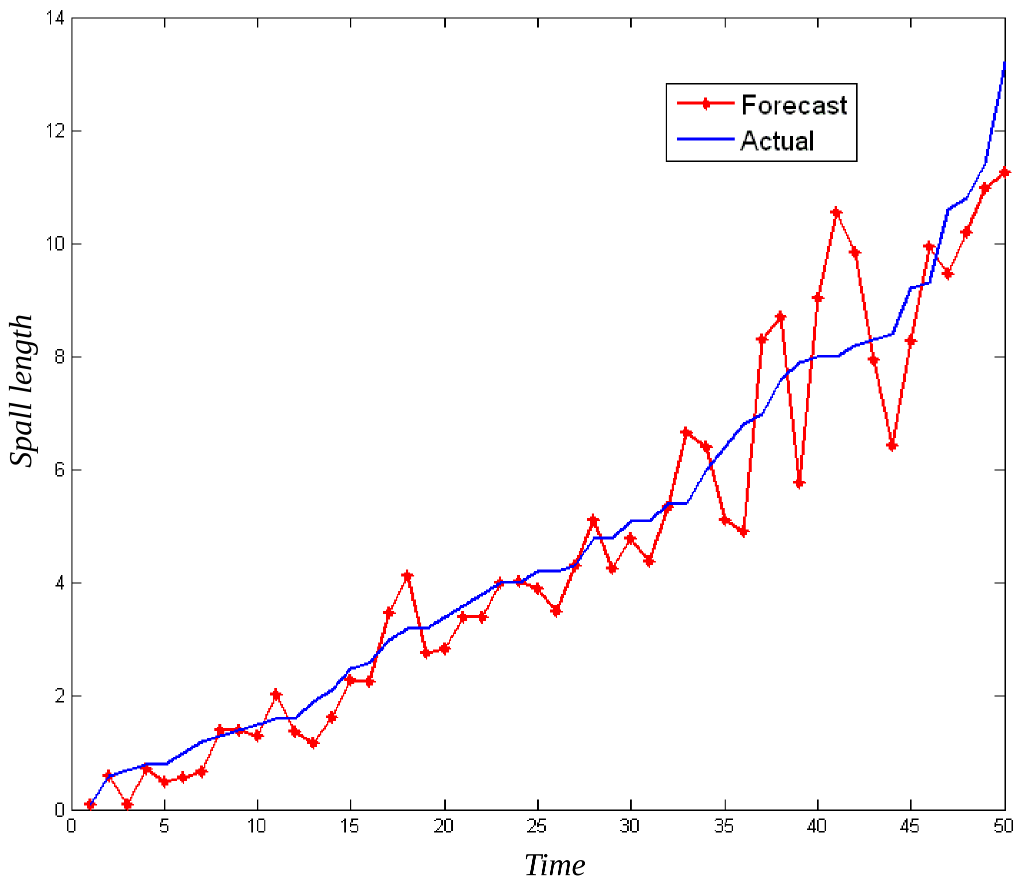


Figure 17. The actual spall size vs. the predicted spall size by combing multiple condition indicators into particle filtering model

To compute the RUL, the critical value λ was set to be the level of *SPL* = 12.5mm. The estimated mean RUL and corresponding 90% confidence intervals are shown in FIGURE 18.

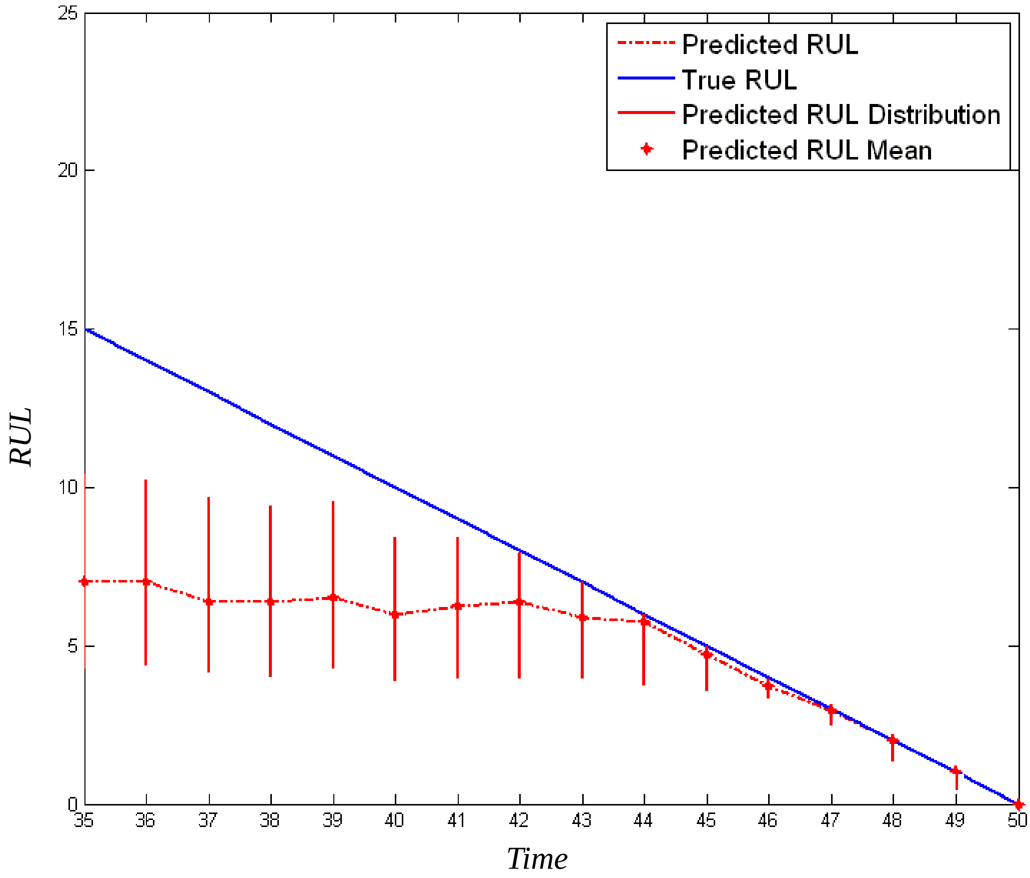


Figure 18. The predicted RUL mean and corresponding 90% confidence intervals

4.4.2 Using One Dimension HI as Observation Parameter in Particle Filtering Model

Using the station transition function f_k and the measurement function h_k defined by the spall length and HI data from the experiment, the particle filtering based *l*-step ahead RUL estimator was run on the data from steel bearing experiment using $N = 1000$ particles. FIGURE 19 shows the predicted spall size and true spall size, the prediction result match pretty well with the true value.

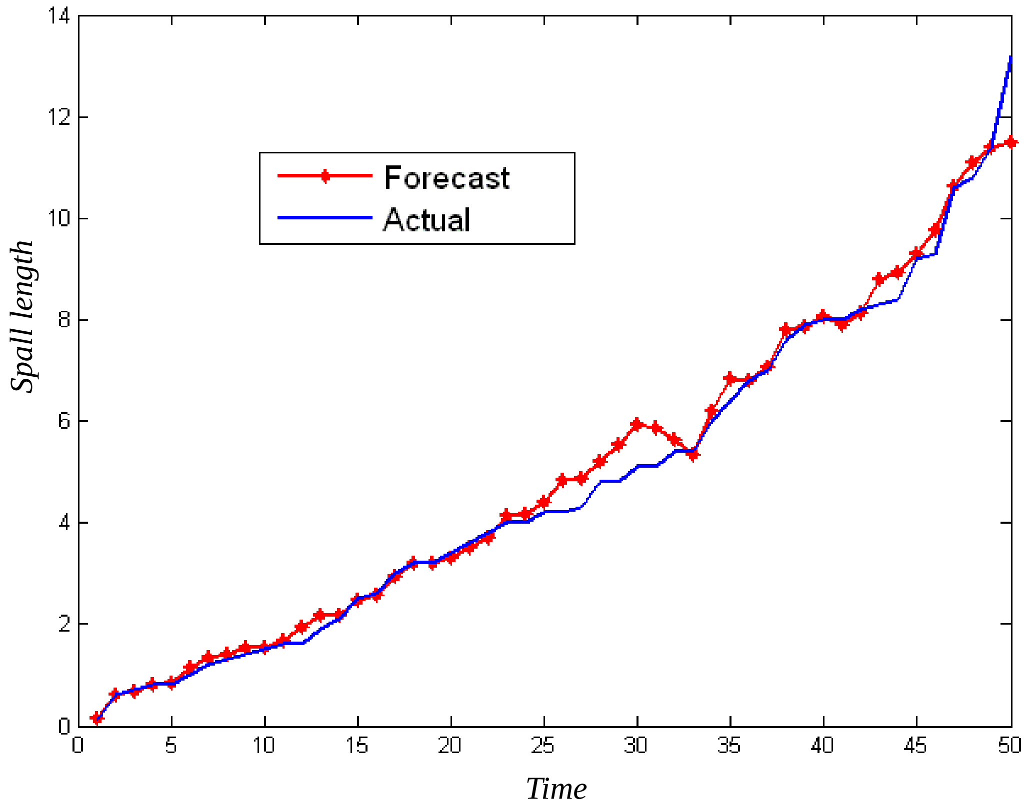


Figure 19. True spall length and predicted spall length using HI and particle filter model

To compute the RUL, the critical value λ was set to be the level of SPL = 12.5mm. The estimated mean RUL and corresponding 90% confidence intervals are shown in FIGURE 20.

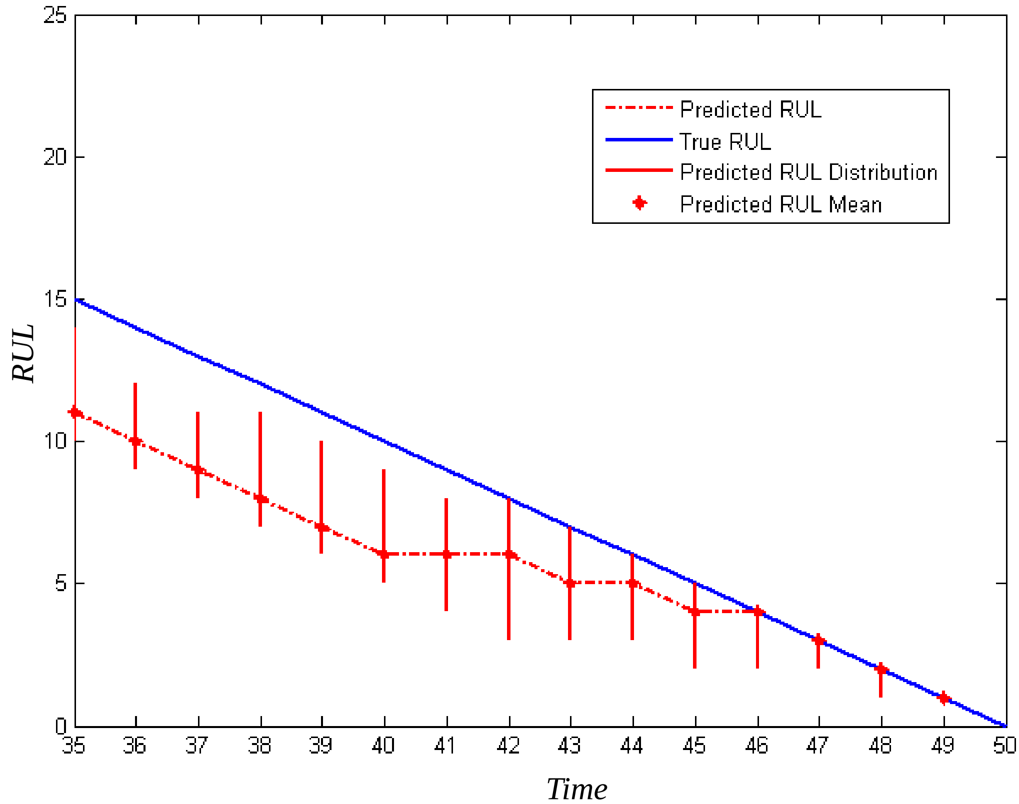


Figure 20. The predicted mean RUL and corresponding 90% confidence intervals using estimator updated with error measurement

By comparing FIGURE 17 and FIGURE 19, we can see that the predicted spall size using one dimension HI matches much better than the predicted result by combining multiple condition indicators directly. Also, by comparing FIGURE 18 and FIGURE 20, the RUL prediction using one-dimensional HI approaches the true RUL faster and provides better long-term RUL prediction than that without using one-dimensional HI.

4.5 <u>Summary</u>

Because the condition indicators (CI) are correlated, a method was presented whitening the CIs used in gear fault detection. The whitening was achieved by a linear transformation of the CI using the Cholesky decomposition of the inverse of the CIs covariance.

With this transformed, using whitened CI data, a health index based on a specified PFA was demonstrated. Three candidate HI algorithms (order statistics, normalized energy and sum of CI) for two different CI probability distribution functions (Gaussian, were presented and tested on three data sets of pitted bearings from a test stand.

It was observed that the predicted spall size using one dimension HI matches much better than the predicted result by combining multiple condition indicators directly. Also, the estimated remaining useful life by the HI is closer to the actual than the result by multiple CIs. The HI trends were low in noise. This can improve the prognostics process

The results have shown that using the one-dimensional HI gives better prognostic results than without combining different condition indicators into one HI.

5. CASE STUDY 1: STEEL BEARING PROGNOSTICS

5.1 Diagnostics, and Prognostics for Sentient Bearing

The bearing fault test data used in this research are spalled bearings run to failure with intermediate inspections. This testing was part of Phase I of the DARPA Prognosis Program. The test bearings were a 106 size angular contact bearing, primarily of SAE 52100 steel, although some M50 Nil and hybrid bearings were also tested. A Rockwell C indent was used to seed the seeded fault. Each bearing was removed for inspection at least 10 to 15 times during the spall propagation, with some bearings being inspected as many as 30 times. Each inspection included both measurements and photographs of the bearing races and specifically the spalls (Lybeck *et. at,* 2007).

5.2 The One-Dimensional Health Index for Sentient Bearing

A total of 15 condition indicators were calculated (Bechhoefer, 2011):

(1) ce1;

(2) bse1;

(3) ie1;

(4) oe1;

(5) rms1;

(6) ce20;

(7) bse20;

(8) ie20;

(9) oe20;

(10) rms20;

(11) ce25;

(12) bse25;

(13) ie25;

(14) oe25;

(15) rms25;

The method used to choose effective condition indicators was calculating the correlation values between these condition indicators and damage progression over time. The CIs were selected with high correlation values with time.

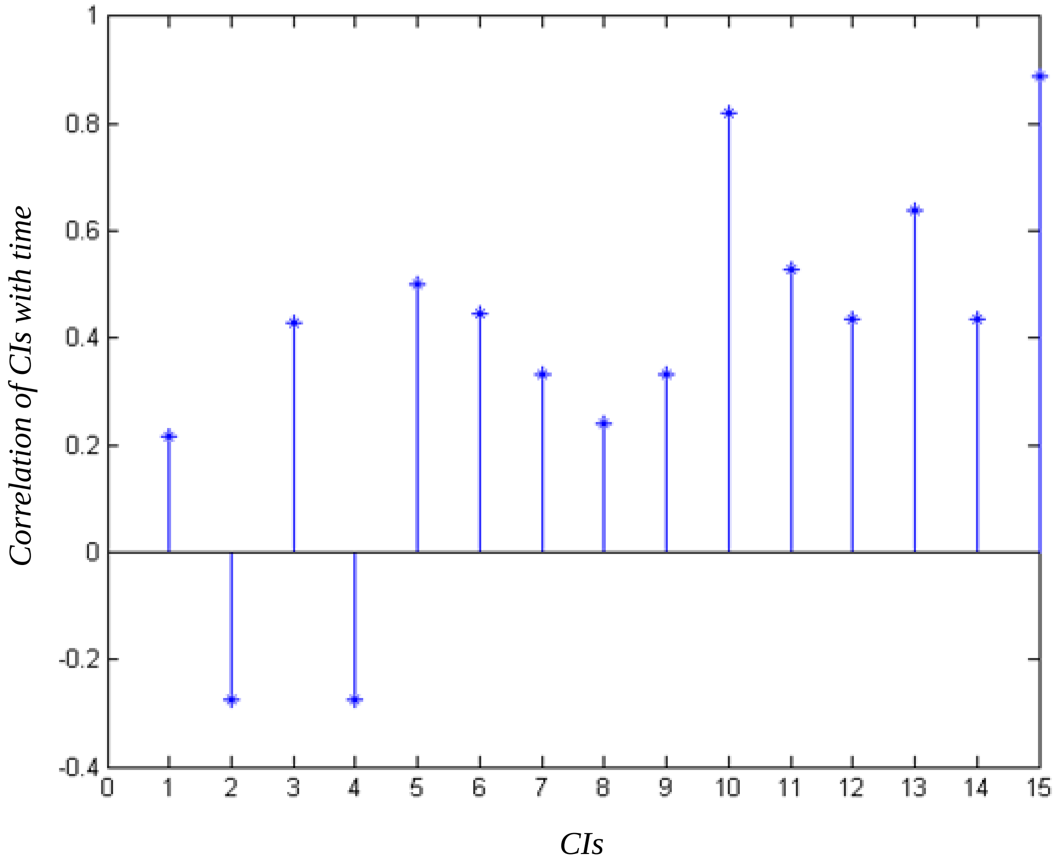


Figure 21. The correlation values between the condition indicators and time

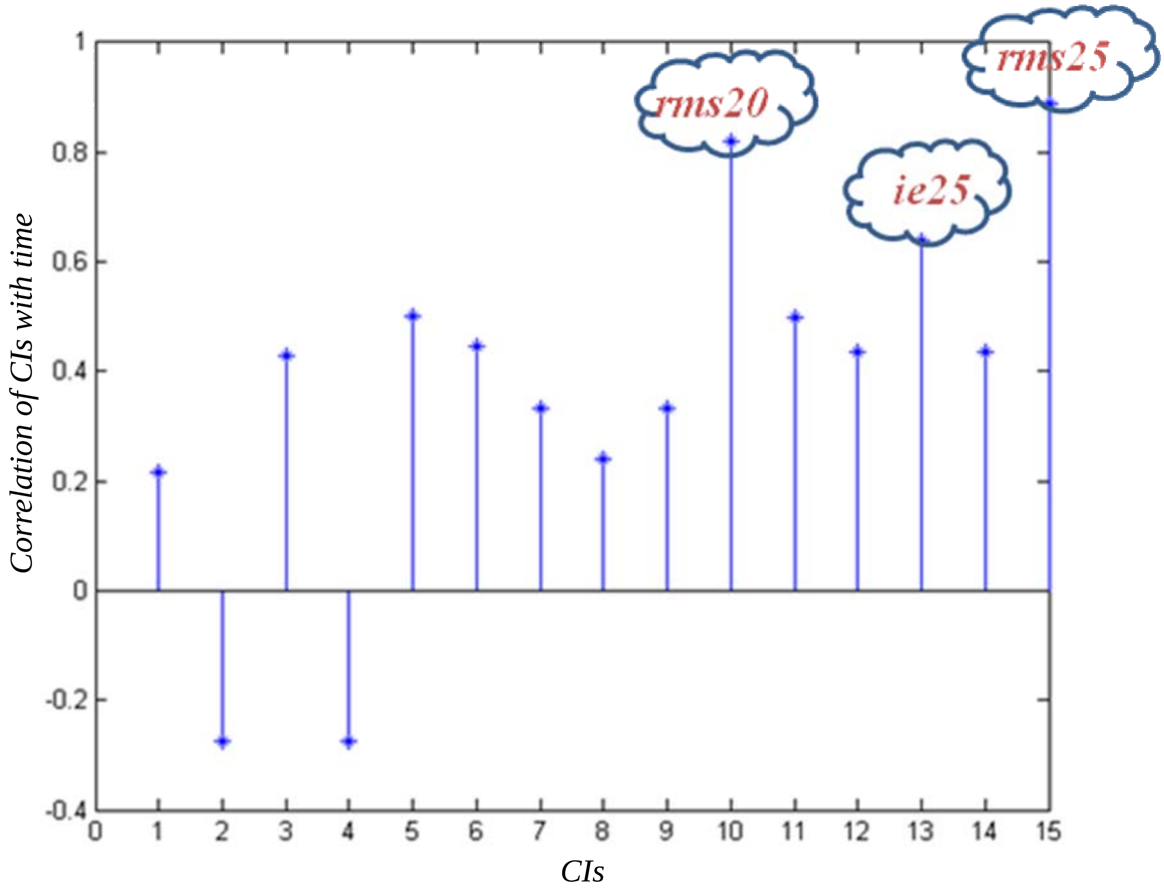


Figure 22. The chosen condition indicators to compose HI

Then three condition indicators:

(1) rms20;

(2) ie25;

(3) rms25

were chosen to define the HI as the observation parameter. The one-dimension HI calculation method in Chapter 4 was used.

HI1, HI2 and HI3 were calculated and HI1 (the Gaussian order statistic) was chosen for this case study because it trends very well with the spall size propagation

5.3 Sentient Bearing Case Study Experimental Setup and Data Collection

Ground truth data is crucial for validation of both diagnostics and prognostics, but availability is currently very limited. Often one or a few seeded fault tests are all the data that exists for a newly deployed platform. Existing platforms may have historical data that could be leveraged, but it is often stored in multiple locations and disparate formats, making access to that data in a format suitable for validation a challenge.

Sentient has accrued a large database of seeded spall propagation tests on angular contact ball bearings. This data was specifically acquired to aid in the understanding of how spalls propagate and to provide data for diagnostic and prognostic algorithms.

The quality of a prognosis is directly impacted by the quality of the diagnostic values. Because vibration is the most commonly used monitoring parameter for mechanical equipment, diagnostics are frequently based on these signals. There are many standard vibration-based metrics that are traditionally used for machinery diagnostics, including root mean square, kurtosis, variance, and signal amplitude, as well as higher order statistics.

The data purchased from Sentient for this project consists of 12 different bearing datasets, 10 spalled bearing datasets and 2 normal bearing datasets. For each of the spalled datasets, an indent was placed on the inner raceway of the bearing from which a spall formed and grew in size as the test proceeded. There were five inspection points for each dataset to document the fault progression. Collection of vibration signals occurred at each inspection point. Each vibration signal was taken just before its respective inspection point. Five of the faulted bearings and one normal bearing were run with a 515 lbs load, while the other 5 faulted bearings and one normal bearing were run under a load of 800 lbs. Pictures of the bearing spalls at each of the five inspection points were taken for each bearing. A scale (1 mm per division) is present in each picture (See FIGURE 23).

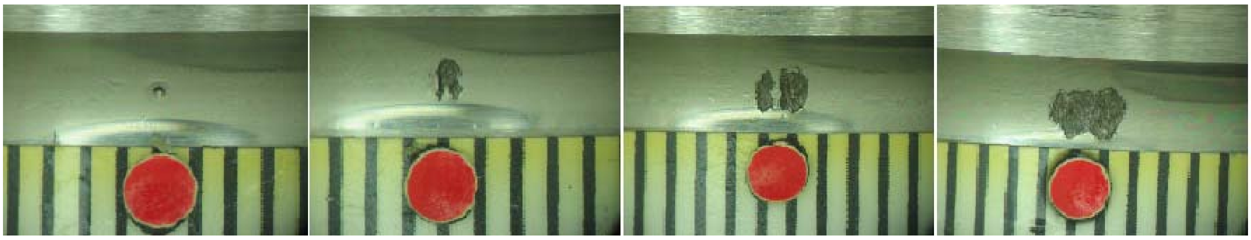


Figure 23. Propagation of inner race fault from left to right: initiation, 0.7, 1.6, and 2.96 mm spall length

All vibration signals were collected with the same type of accelerometer and analog filtering.

The accelerometer was the Endevco Model 7259B-100. This is a miniature, light weight piezoelectric accelerometer with integral electronics, designed specifically for high frequency vibration measurement on structures and objects. The accelerometer has a wide bandwidth, flat to 50 KHz.

The filtering was a Frequency Devices 5BAF series differential fixed frequency filtering. The filtering is an 8-pole Butterworth with a pass band at 40KHz.

The bearing fault data were processed to generate bearing damage condition indictors. The methods used for generating these condition indictors included (Lybeck *et. at,* 2007):

(1) Bearing passing frequencies at the base frequency. This consisted of measuring the PSD (power spectral density) at the bearing defect frequencies of the BPFO, BPFI, BFF and FTF (Lybeck *et. at,* 2007).

(2) RMS of the vibration signal between 0 and 1000 Hz.

(3) Envelope analysis of the bearing passing frequencies at 2 and 5 KHz windows.

(4) RMS of the envelope analysis.

(5) Cepstrum analysis of the bearing passing frequencies.

5.4 Building the State Function by Data Mining Method

Other research has been published using Paris' Law to build the state function to describe the spall or crack size propagations (Orchard, 2005; Jardine *et al.*, 2006; Heng, 2009). However, Paris' Law, as a physics model based methodology, is difficult to build because a lot of related system design knowledge is needed, such as, materialogy, mechanics and structural mechanics. The simulation results based on finite-element analysis (FEA) usually have some significant differences with the true design. Also, some parameters have to be changed when operating conditions or components size or shapes change. All these make Paris' Law harder to be applied than data mining methods. Also, from simulation results, we observed the state function by data mining methods can adequately describe the spall or crack propagation. That makes the use of Paris' Law lose some of its advantages.

5.4.1 **The ARIMA Model**

ARIMA methodology, popularized by Box and Jenkins (Box and Jenkins, 1970; Caldwell, 1971; Caldwell, 2007), is based on the idea that a stationary series *Yt* can be approximated to any desired degree of accuracy by an ARMA (Autoregressive-Moving Average) process. We can write the ARMA (p, q) model as:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots \phi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \dots - \theta_q e_{t-q}$$

where p is the order of the autoregressive (AR) component, and q is the order of the moving average (MA) component. Using the "backshift" or "lag" operator B this becomes:

$$Y_t = c + \phi_1 B Y_t + \dots \phi_p B^p Y_t + e_t - \theta_1 B e_t - \dots - \theta_q B^q e_t$$

or $$\left(1 - \phi_1 B - \dots - \phi_p B^p\right) Y_t = c + \left(1 - \theta_1 B - \dots - \theta_q B^q\right) e_t$$

If Y has been differenced d times to achieve stationary then the model is Autoregressive Integrated Moving Average: ARIMA (p, d, q):

$$\left(1-\phi_1 B-\ldots-\phi_p B^p\right)(1-B)^d Y_t = c+\left(1-\theta_1 B-\ldots-\theta_q B^q\right)e_t$$

Note that e_t is defined as $Y_t-\hat{Y}_t$, where $\hat{Y}_t$ is defined as the predicted (estimated) value of Y_t.

The state parameter used in the case study is spall length. A two order ARIMA model was used to build the state function. The spall length values at t-1 and t-2 were used to predict the spall size value at time t. Autoregressive Integrated Moving Average (ARIMA (p, d, q)) model was used to build the state function. p, d, and q are non-negative integers that refer to the order of the autoregressive, integrated, and moving average parts of the model respectively. ARIMA modeling technique is a generalization of autoregressive moving average. ARIMA model can handle non-stationary time series problems. 2 order ARIMA (2, 0, 0) model was used to build the state function.

The state parameter values at t-1 and t-2 were used to predict the state parameter value at time t:

$$x(t) = C + AR(2)\times x(t-2) + AR(1)\times x(t-1) + v(t-1)$$

The state function used in the case study is:

$$x(t) = 0.01922955 - 0.64840275 \times x(t-2) + 1.6446352 \times x(t-1) + \omega(t)$$

5.5 Building the Observation Function by Data Mining Method

Double exponential smoothing was used to build the relationship between state parameter spall size and observation parameter HI. The relationship between state parameter and observation parameter was defined as a linear function. The model parameters of this linear function can be obtained by using this method. By using this method, the model parameter can be updated step-by-step using the information of the previous step. This makes the prognosis more accurate and effective. There is no single condition indicator (CI) which is sensitive to every failure mode of a bearing or gear. The solution is composing a one-dimensional health index (HI) and integrating this HI into particle filtering.

Double exponential smoothing was chosen to build the relationship between the state parameter and observation parameter.

The advantages to use double exponential smoothing:

(1) Double exponential smoothing works well for time series without an overall trend.;

(2) It does not require maintaining a history of previous data.

(3) It can be helpful in predicting future observations.

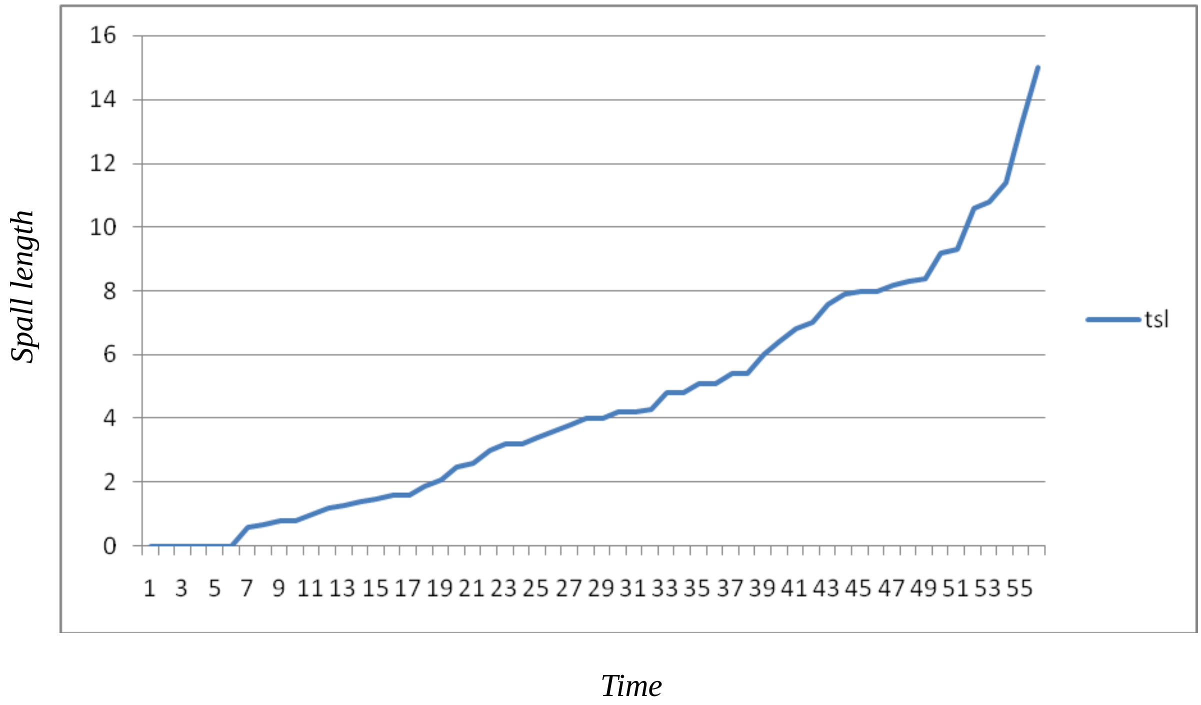
The observation function used in the case study is:

$$y(t) = k(t) \times x(t) + v(t)$$

k(t) is a time variable obtained by double exponential smoothing.

5.6 Prognostics Results

The spall length and HI data from the experiment are shown in FIGURE 24.



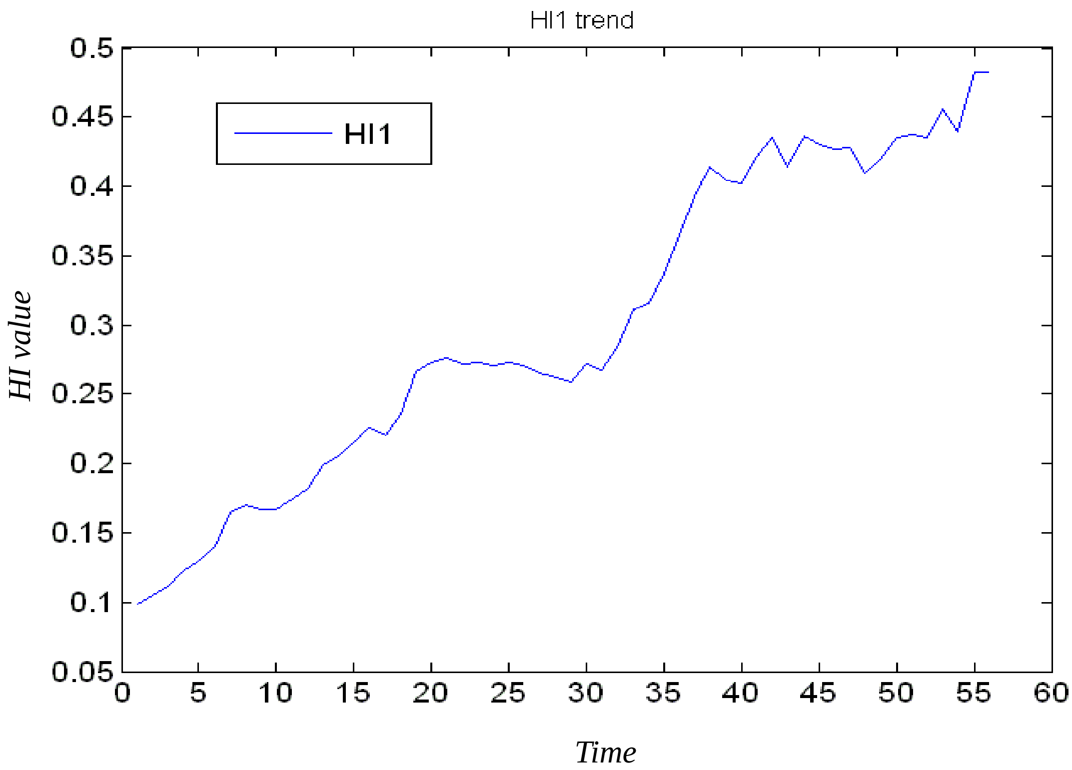


Figure 24. Spall length and HI of steel bearing experiment

The measurement function $\mathbf{h}_k$ was defined using a double exponential smoothing model with α = 0.05 to fit the relation between HI and spall length. FIGURE 25 shows the plot of HI against spall length for the steel bearing experiment.

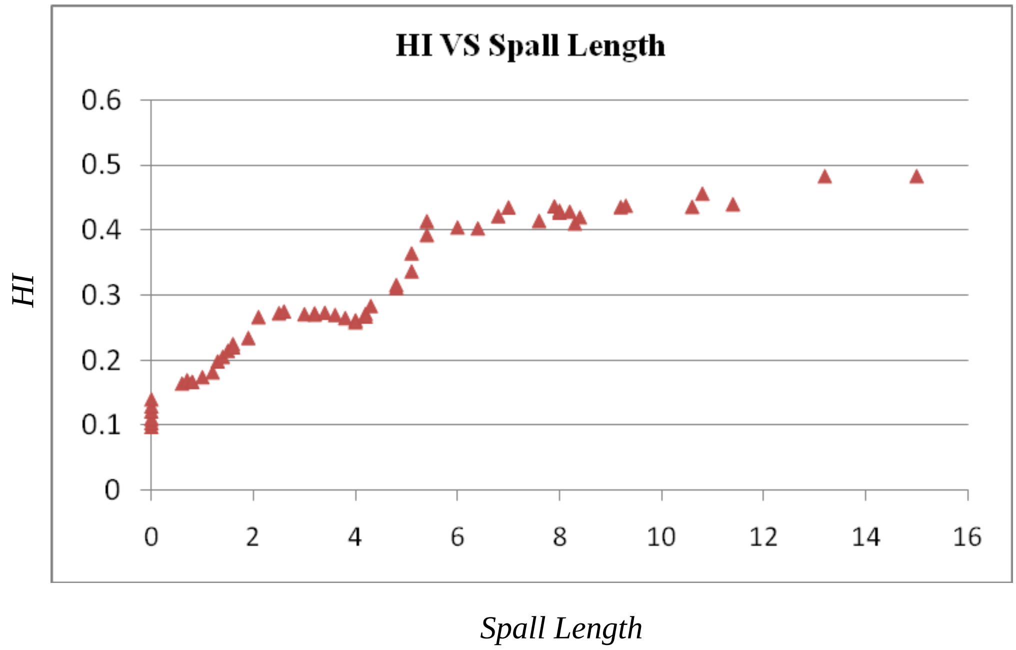


Figure 25. Plot of HI against spall length for steel bearing experiment

Using the station transition function f_k and the measurement function h_k defined by the spall length and HI data from the experiment, the particle filtering based l-step ahead RUL estimator was run on the data from steel bearing experiment using N = 1000 particles. To compute the RUL, the critical value λ was set to be the level of total spall length SPL = 12.5mm. The estimated mean RUL and corresponding 90% confidence intervals are shown in FIGURE 26.

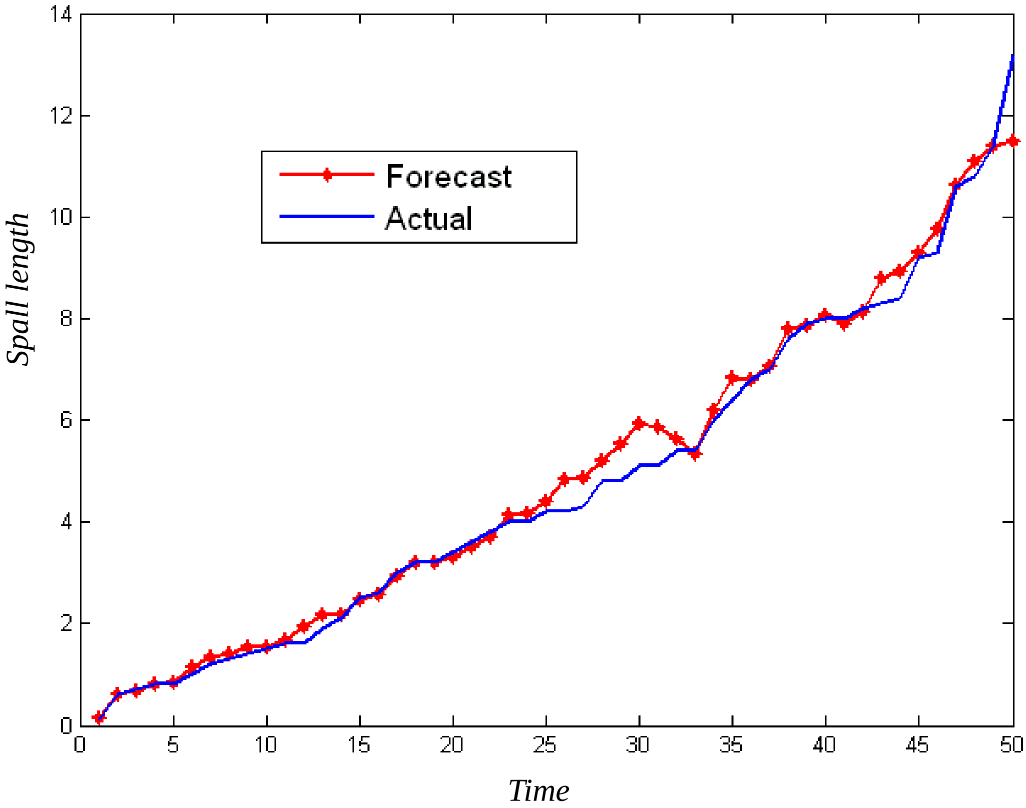


Figure 26. True spall length and predicted spall length

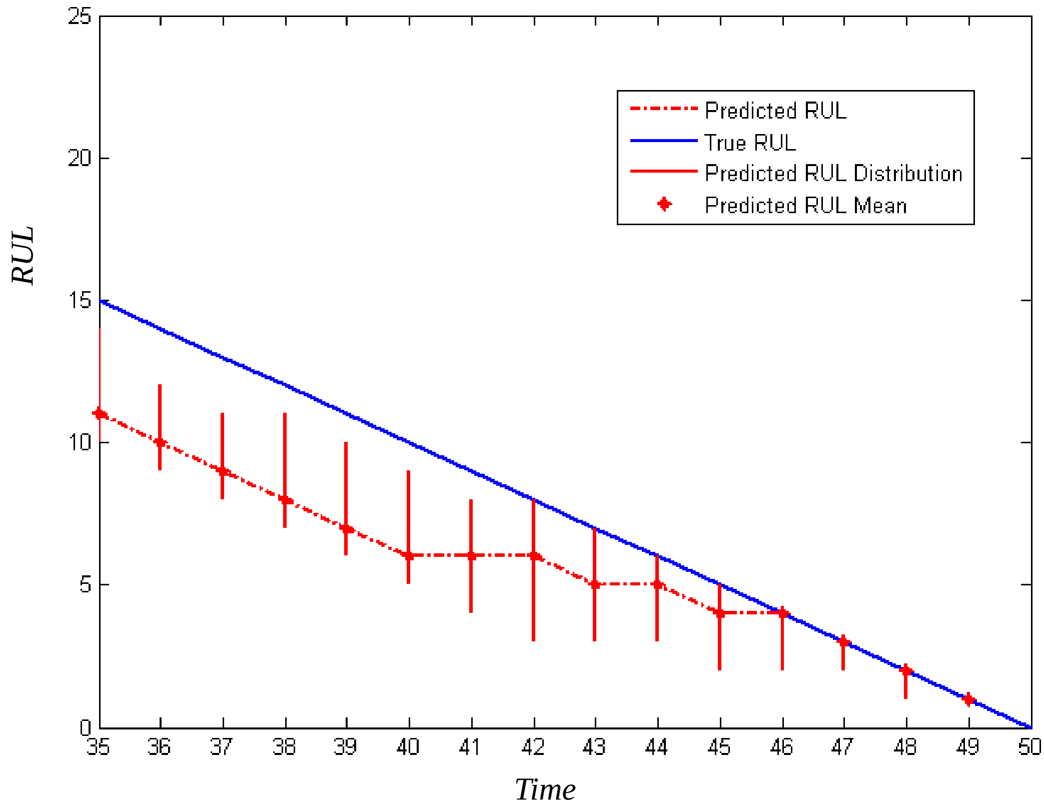


Figure 27. The predicted mean RUL and corresponding 90% confidence intervals using estimator updated with error measurement

5.7 <u>Summary</u>

A particle filtering based steel bearing prognostics method using a one-dimensional health index was presented in this chapter. The presented method effectively addresses the issues in applying particle filtering to mechanical component remaining useful life (RUL) prognostics by integrating several new components into particle filtering. Data mining based techniques were effectively used to define the degradation state transition and measurement functions using a one-dimensional health index obtained by a whitening transform. An *l*-step ahead steel bearing fault progression and remaining useful life prediction were performed. The results show the integrated methodology performs well in predicting RUL.

The presented prognostics method was validated using data from a steel bearing case study. The validation results have shown the effectiveness of the presented method.

6. CASE STUDY 2: SPIRAL BEVEL GEAR PROGNOSTICS

6.1 Diagnostics, and Prognostics for Spiral Bevel Gear

In this section, a particle filtering based gear prognostics method using a one-dimensional health index for spiral bevel gears subject to surface fatigue pitting failure mode is presented. The spiral bevel gear case study was performed in the NASA Glenn Spiral Bevel Gear Test Facility. The presented method effectively addresses the issues in applying particle filtering to mechanical component remaining useful life (RUL) prognostics by integrating a couple of new components into particle filtering: (1) data mining based techniques to effectively define the degradation state transition and measurement functions using a one-dimensional health index obtained by a whitening transform; (2) an unbiased l-step ahead RUL estimator updated with measurement errors. The presented method is validated using fatigue testing data from a spiral bevel gear case study performed in the NASA Glenn Spiral Bevel Gear Test Facility.

6.2 The Prognostics Method and Flowchart for Spiral Bevel Gear

The general framework of the particle filtering based gear prognostics method for spiral bevel gear subject to pitting failure mode is shown in FIGURE 28.

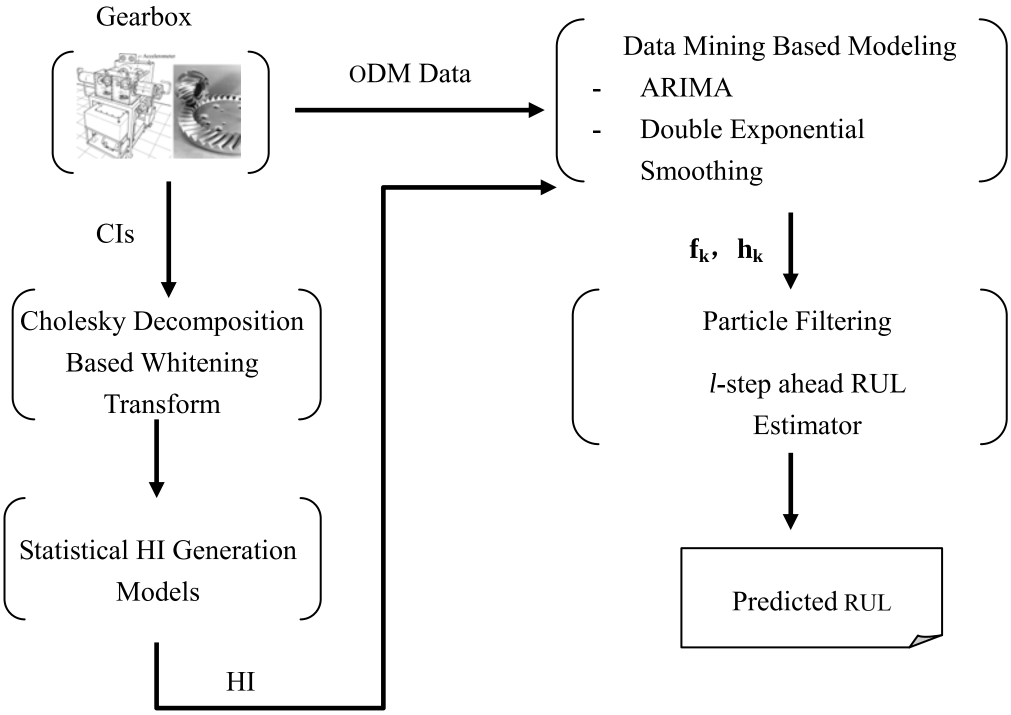


Figure 28. Particle filtering based gear prognostics framework

As shown in FIGURE 28, to predict the RUL of the spiral bevel gear subject to pitting failure mode, the oil debris mass (ODM) is used to represent the degradation state of the gear. Therefore, the state transition function $\mathbf{f}_k$ is defined by an ODM ARIMA model established using a data mining based approach. The one-dimensional HI obtained by applying Cholesky decomposition based whitening transform and statistical generation models are used to define the measurement function $\mathbf{h}_k$ by double exponential smoothing. Based on the defined functions $\mathbf{f}_k$ and $\mathbf{h}_k$, an l-step ahead RUL estimator incorporated with measurement error is used in particle filtering to provide an accurate prediction of RUL. The generation of the one-dimensional HI and the l-step ahead RUL estimator used in particle filtering are explained in the next two sections.

6.3 Spiral Bevel Gear Case Study Experimental Setup and Data Collection

In this chapter, data from a spiral bevel gear case study conducted in the NASA Glenn Spiral Bevel Gear Test Facility at are used to validate the presented method.

Vibration data from experiments performed in the Spiral Bevel Gear Test facility at NASA Glenn was reprocessed for this analysis. A description of the test rig and test procedure is given in Dempsey *et al*. (2002). The rig is used to quantify the performance of gear material, gear tooth design and lubrication additives on the fatigue strength of gears. During this testing, CIs and oil debris monitoring were used to detect pitting damage on spiral bevel gears.

The tests consisted of running the gears under load through a "back to back" configuration, with acquisitions made at 1 minute intervals, generating time synchronous averages (TSA) on the gear shaft (36 teeth), using an optical once per revolution sensor on the gear shaft. The pinion, on which the damage occurred, has 12 teeth, Figure 29. Test rig and gears (Dempsey *et al., 2002*).

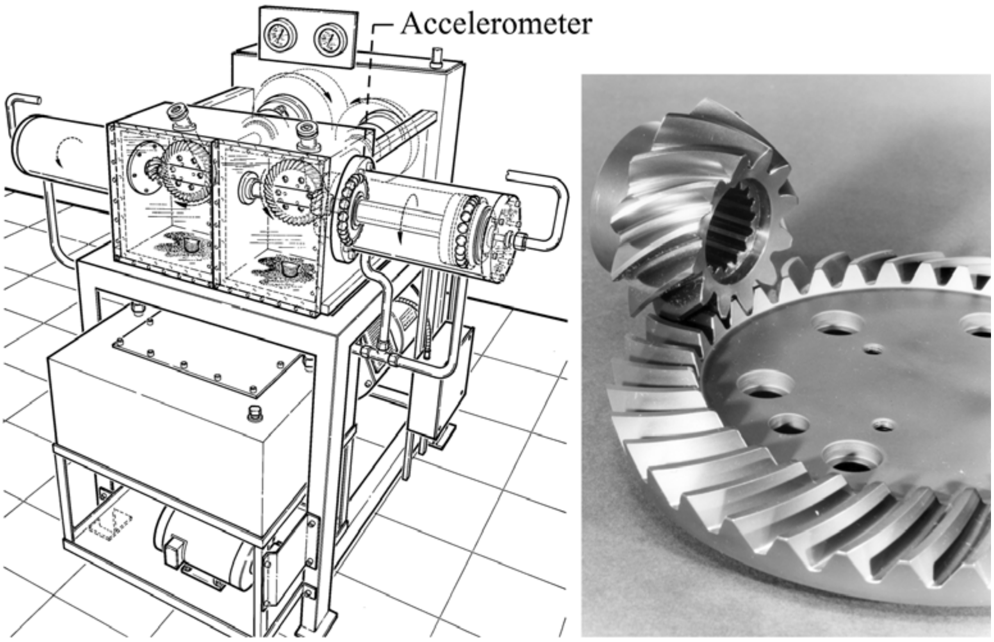


Figure 29. Test rig and gears (Dempsey *et al.*, 2002)

TSA data was re-processed with gear CI algorithms presented in Zakrajsek (1993) and Wemhoff (2007), to include:

(1) TSA: RMS, Kurtosis (KT), Peak-to-Peak (P2P), Crest Factor (CF)

(2) Residual RMS, KT, P2P, CF

(3) Energy Operator RMS, KT

(4) Energy Ratio

(5) FM0

(6) Sideband Level factor

(7) Narrowband (NB) RMS, KT, CF

(8) Amplitude Modulation (AM) RMS, KT

(9) Derivative AM KT

(10) Frequency Modulation (FM) RMS, KT

From these CIs, a total of six CIs were used for the HI calculation:

(1) Residual RMS;

(2) Energy Operator RMS;

(3) FM0;

(4) NB KT;

(5) AM KT;

(6) FM RMS.

Covariance and mean values for the six CIs were calculated by sampling four gears' data prior to the fault propagating. This was done by randomly selecting 100 data points from each gear, and calculating the covariance and means over the resulting 400 data points.

The selected CI's PDF were not Gaussian, but exhibited a high degree of skewness. Because of this, the PDFs were "left shifted" by subtracting an offset such that the PDFs exhibited Rayleigh like distributions. Then, the threshold setting algorithms were tested for:

(1) Rayleigh order statistic (OS): threshold 8.37 for n = 6 and a PFA of 10-6,

(2) Rayleigh normalized energy (NE): threshold 10.88 for n = 6 and a PFA of 10-6,

(3) Sum of Rayleigh (SR): threshold 24.96 for n = 6 and a PFA of 10-6.

FIGURE 30, FIGURE 32 and FIGURE 34 are HI plots that compare the OS, NE and SR algorithms during three experiments in the test rig. The HI trend (in black) is plotted on top of the raw HI values (in blue). FIGURE 31, FIGURE 33 and FIGURE 35 show the amount of pitting damage on the pinion teeth at each test completion.

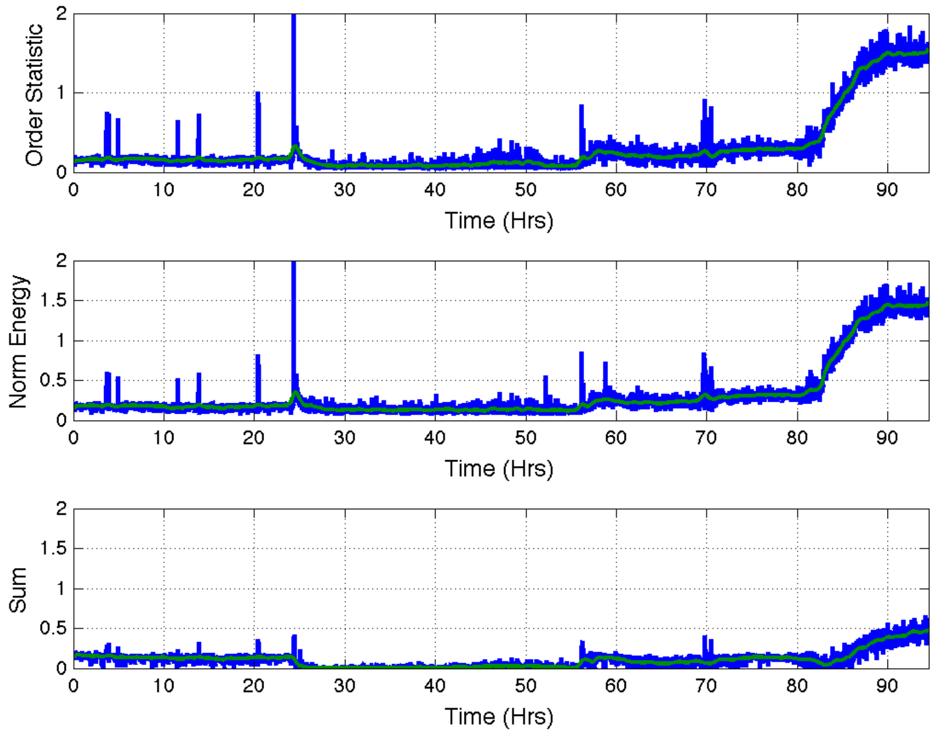


Figure 30. Experiment 4

Note that the spikes corresponded to changes in torque on the rig. All the HI algorithms where sensitive to damage, although in general, the best system response was from both the OS and NE.

Figure 31. Damage on gear from experiment 4

Note that the decrease in the HI rate of change corresponds to a decrease in torque load towards the end of the test.

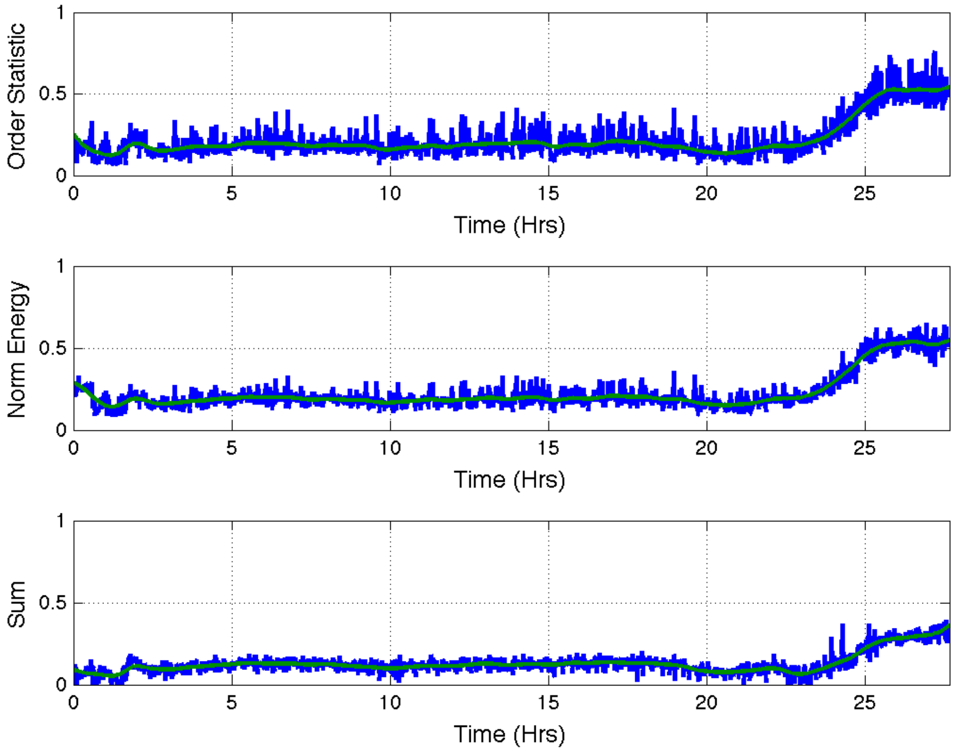


Figure 32. Experiment 5

For the data plotted in FIGURE 30, this test appears to have been halted prior to heavy pitting damage, as the gear HI is reach only 0.5. However, the photo of gear EX5 (FIGURE 31) shows extensive pitting damage.

Figure 33. Damage on experiment 5 gear

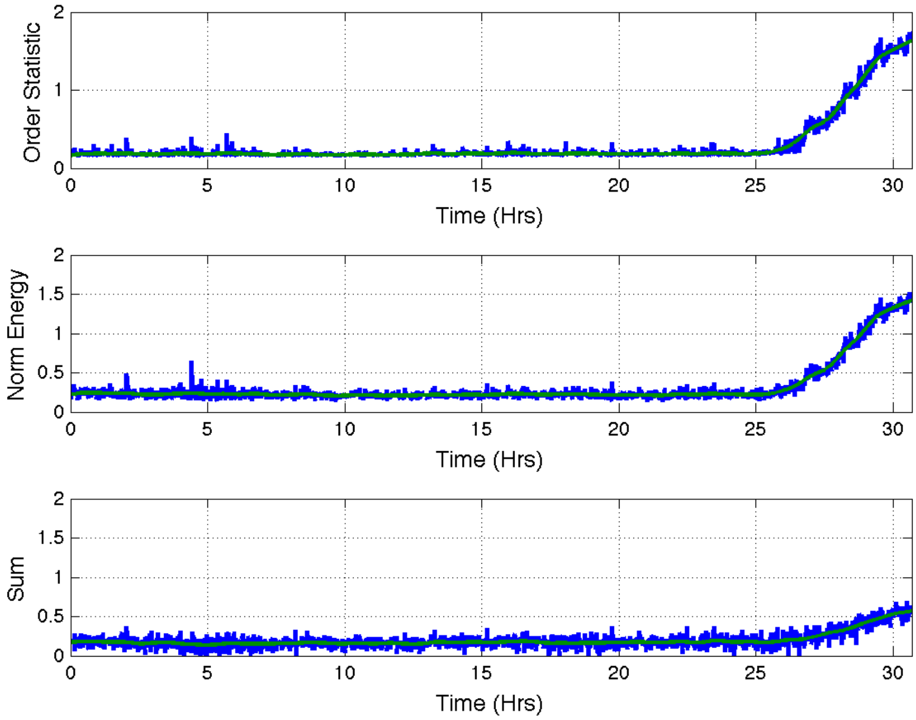


Figure 34. Experiment 6

Figure 35. Damage on experiment 6 gear

TSA data was re-processed with gear CI algorithms presented in (Zakrajsek *et al*., 1993) and (Wemhoff *et al*., 2007). A total of 6 CIs were used for the HI calculation: residual RMS, energy operator RMS, FM0, narrowband kurtosis, amplitude modulation kurtosis, and frequency modulation RMS.

6.4 Building the State Function by Data Mining Method

The state parameter used in the case study is oil debris mass (ODM). This value is directly related to the spall size. 2 order ARIMA model was used to build the state function.

The ODM values at *t*-1 and *t*-2 were used to predict the ODM value at time *t*.

In order to define the state transition function using the ODM data, various ARIMA models were fitted into the ODM data of experiment 6. The best fitted ARIMA model was: ARIMA (1, 1, 1).

Let:

x_k = true ODM value at time *k*;

$\hat{x}_k$ = predicted ODM value at time *k*.

The state transition function $\mathbf{f}_k$ was defined as:

$$x_k = 0.0165 + 1.1415 x_{k-1} - 0.415 x_{k-2} - 0.1032\left(x_{k-1} - \hat{x}_{k-1}\right) + \omega_k$$

6.5 <u>Building the Observation Function by Data Mining Method</u>

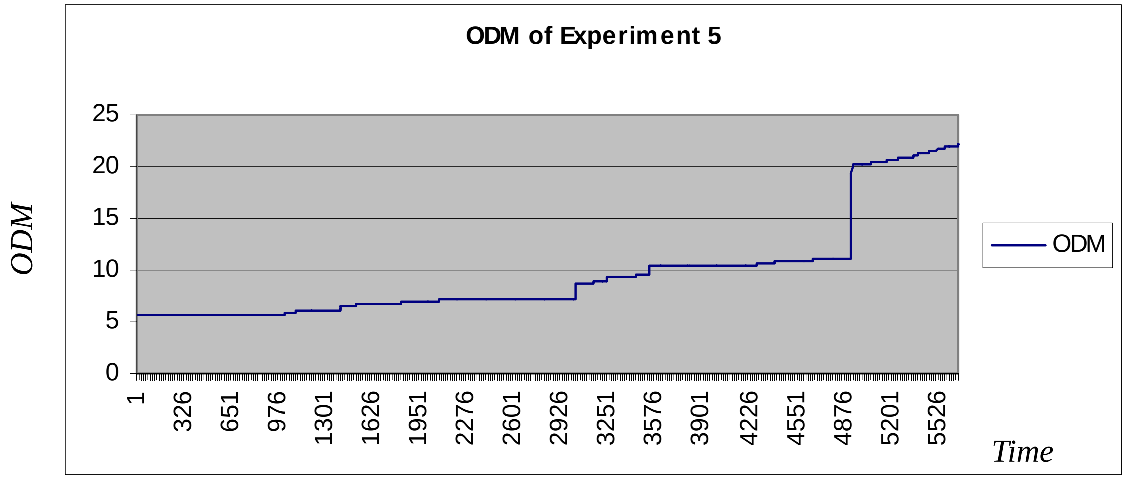
Double exponential Smoothing was used to build the relationship between state parameter ODM and observation parameter HI. The relationship between state parameter and observation parameter was defined as a linear function. The model parameters of this linear function can be obtained by using this method. Using this method, the model parameter can be updated step-by-step by using the information of the former step. This makes the prognosis more accurate and effective. The observation function is defined just like the observation function in chapter 4:

$$y(t) = k(t) \times x(t) + v(t)$$

k(t) is a time variable obtained by double exponential smoothing.

6.6 Prognostics Results of First Case Study

The ODM and HI data from experiments are shown in FIGURE 36 and FIGURE 37, respectively.



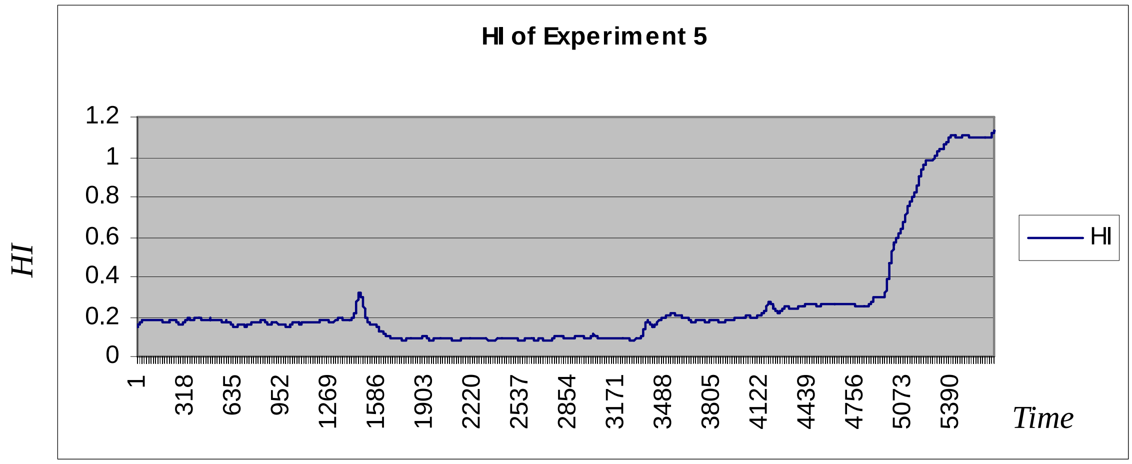
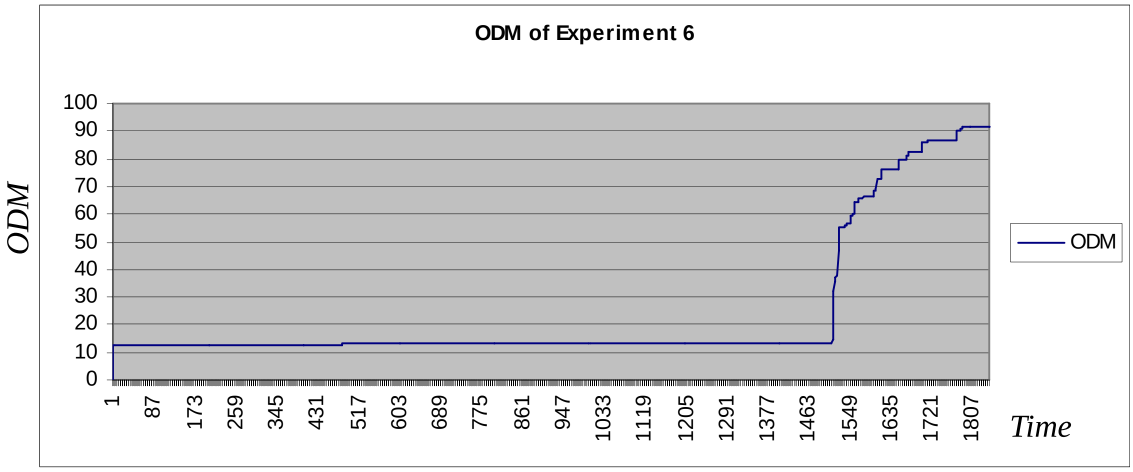


Figure 36. ODM and HI of experiment 5



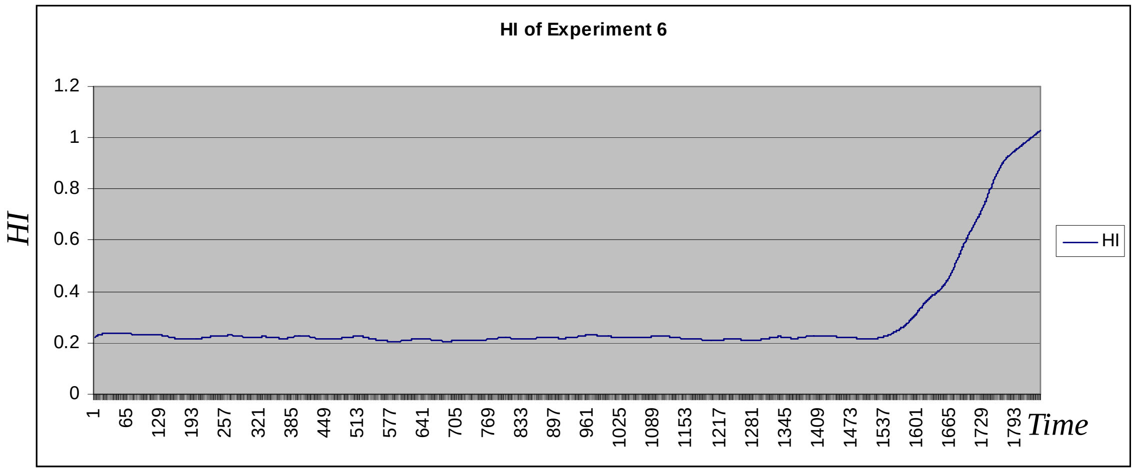


Figure 37. ODM and HI of experiment 6

The plot of actual ODM values against the predicted ODM values is shown in FIGURE 38. From FIGURE 38, it is obvious that the ARIMA (1, 1, 1) model is almost a perfect fit to the ODM data.

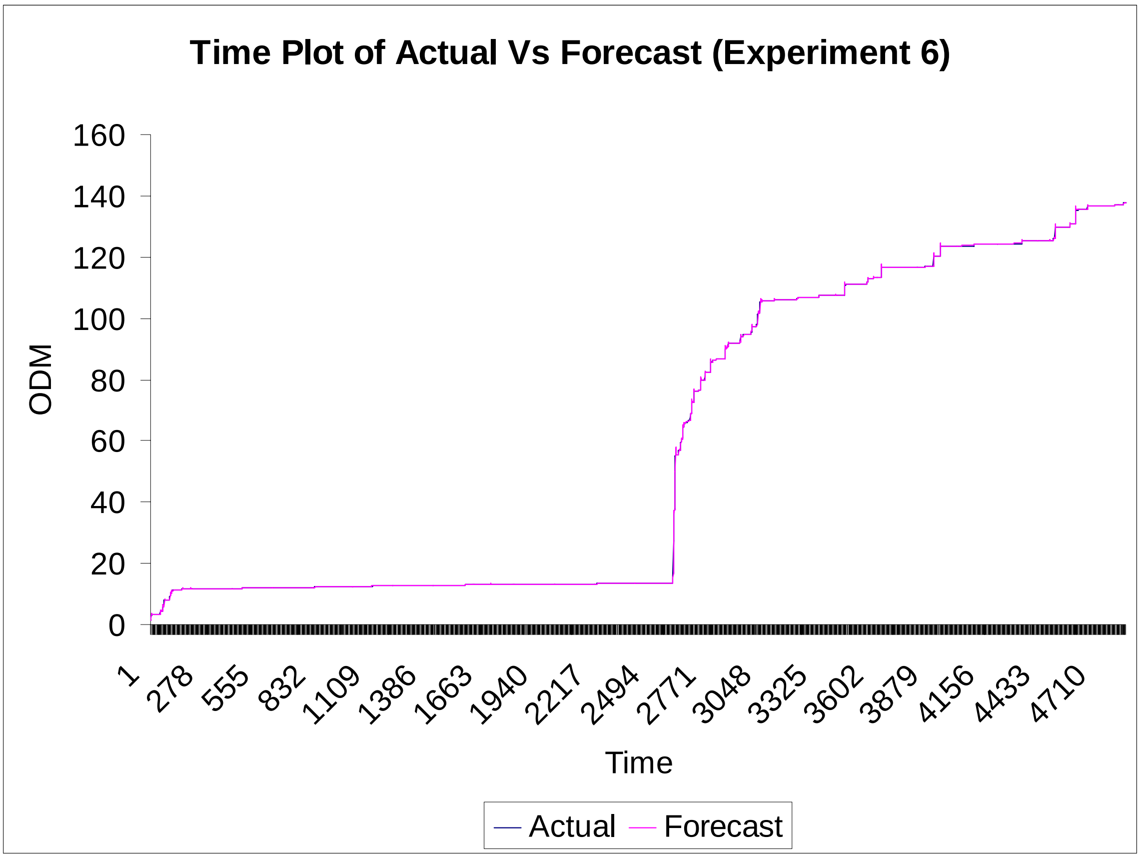


Figure 38. The actual ODM vs. the predicted ODM using ARIMA (1, 1, 1) model

The measurement function h_k was defined using a double exponential smoothing model with α = 0.05 to fit the relation between HI and ODM. FIGURE 39 shows the plot of HI against ODM for experiment 6.

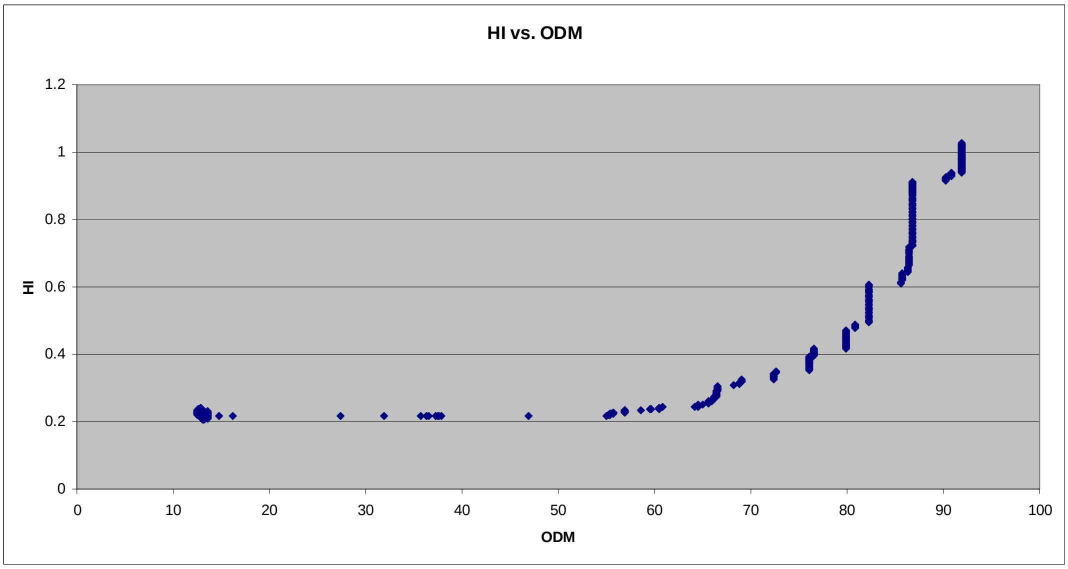


Figure 39. Plot of HI against ODM for experiment 6

FIGURE 40 shows the predicted HI values using the double exponential smoothing model against the actual HI values.

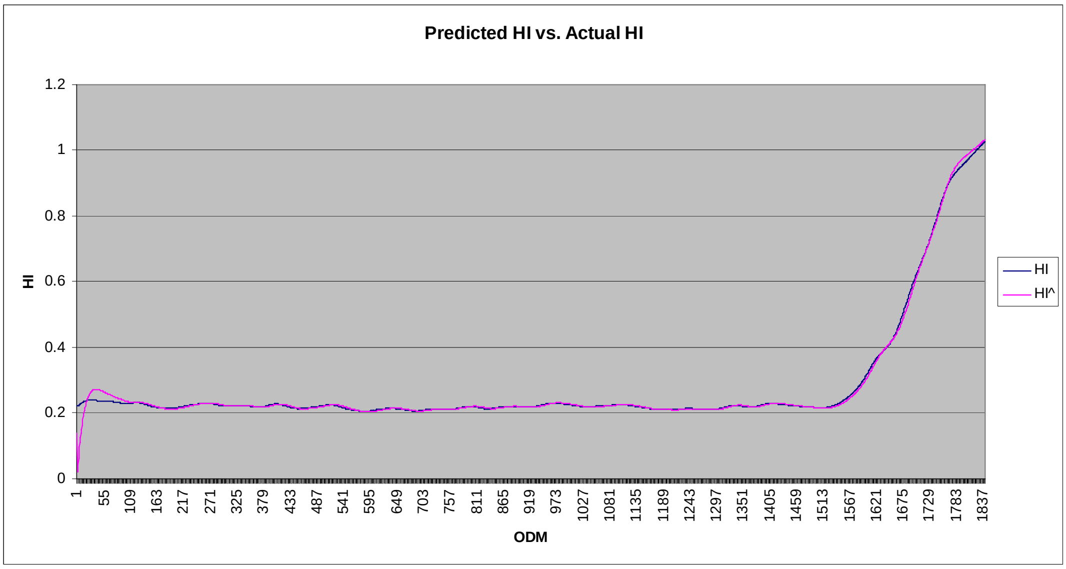


Figure 40. Predicted HI values using double exponential model vs. the actual HI values

Using the station transition function f_k and the measurement function h_k defined by the ODM and HI data from experiment 6, the particle filtering based *l*-step ahead RUL estimator was run on the data from experiment 5 using N = 2000 particles. The predicted ODM values are shown in

FIGURE 42. To compute the RUL, the critical value λ was set to be the level of ODM = 22 mg. Updating the estimated PDF on the basis of the measurements collected very 100 temporal steps, the estimated mean RUL and corresponding 90% confidence intervals are shown in FIGURE 44.

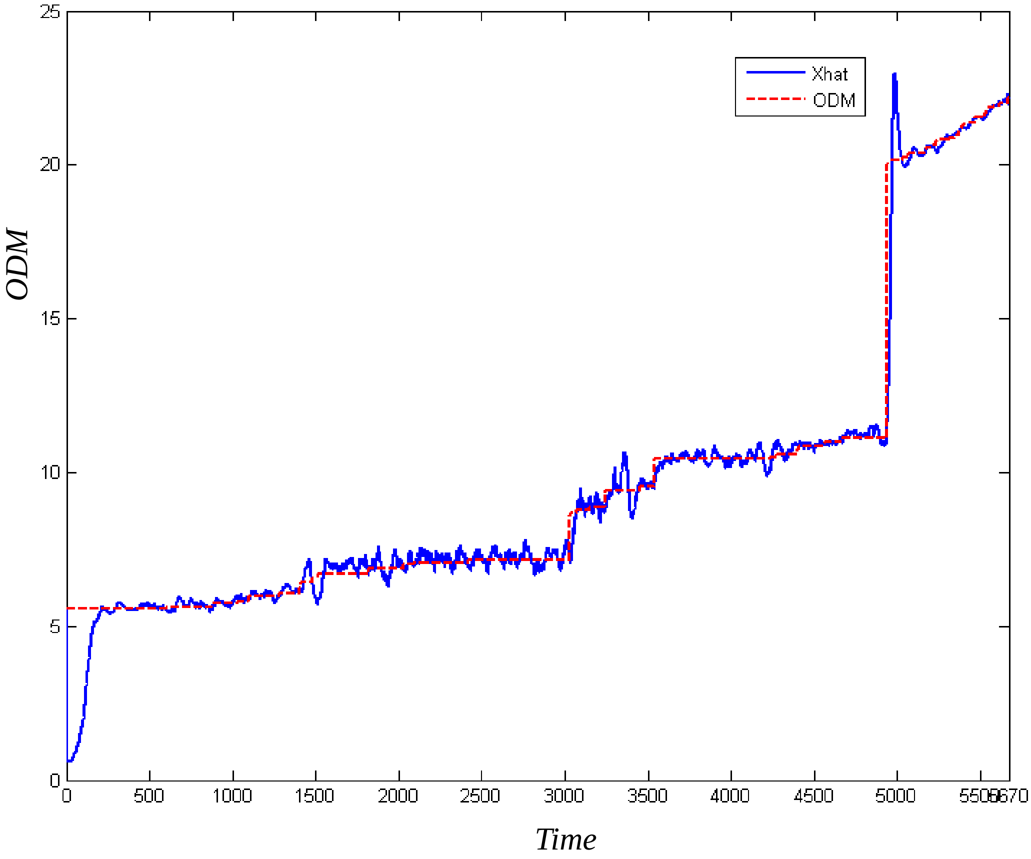


Figure 41. The predicted ODM and the true ODM

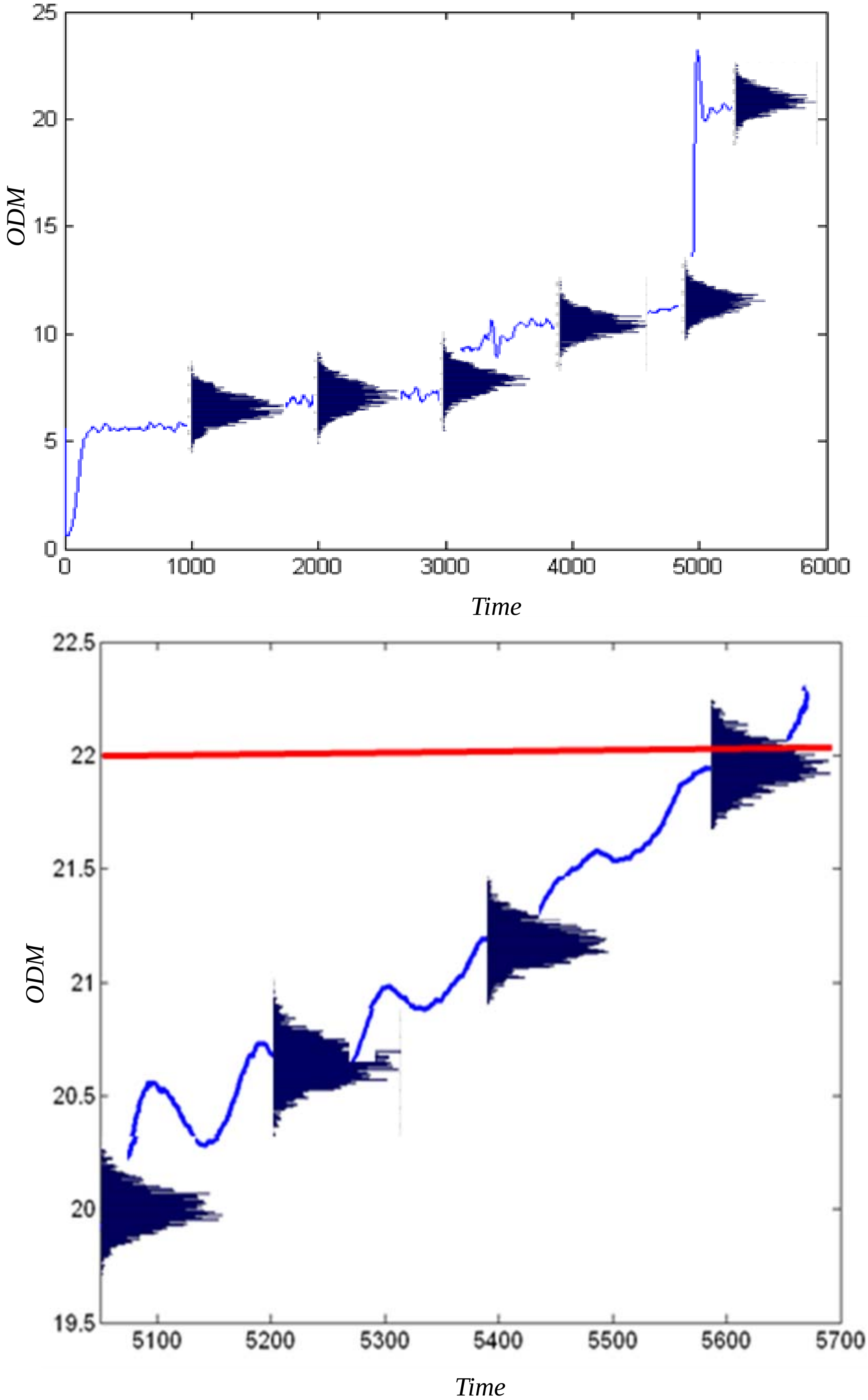


Figure 42. The distribution of predicted ODM at different test points

The probability of the system is going to fail at future time point 5600 based on current measurement at time point 5050. And the probability of remaining useful life less than 550 is equal to this value. The red line is the pre-specified threshold.

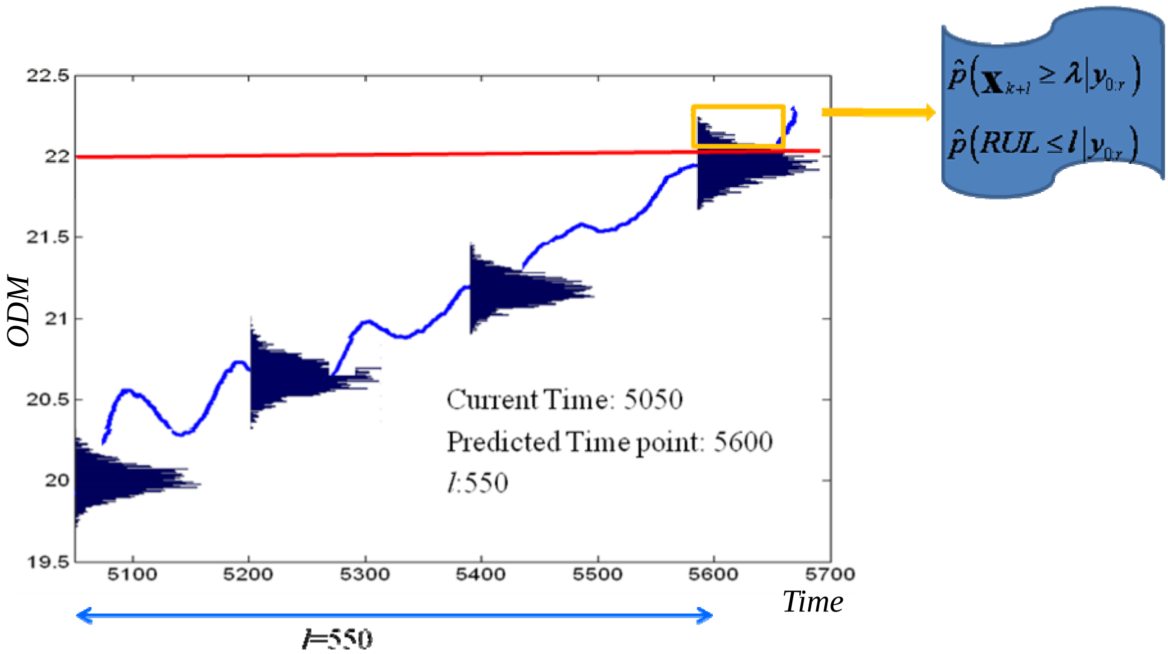


Figure 43. Failure rate and remaining useful life distribution based on the predicted system degradation result

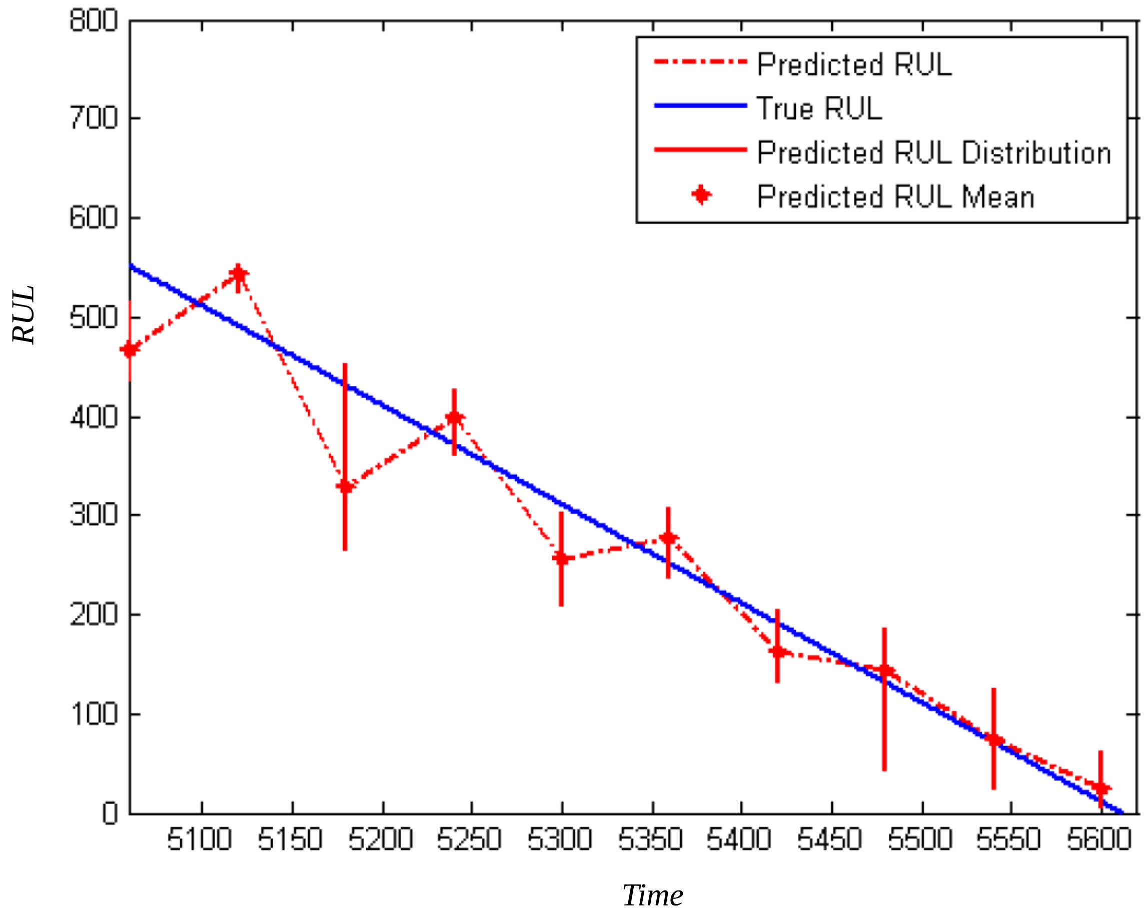


Figure 44. The predicted mean RUL and corresponding 90% confidence intervals using estimator updated with error measurement

Actually, the prediction results can be expressed by FIGURE 45.

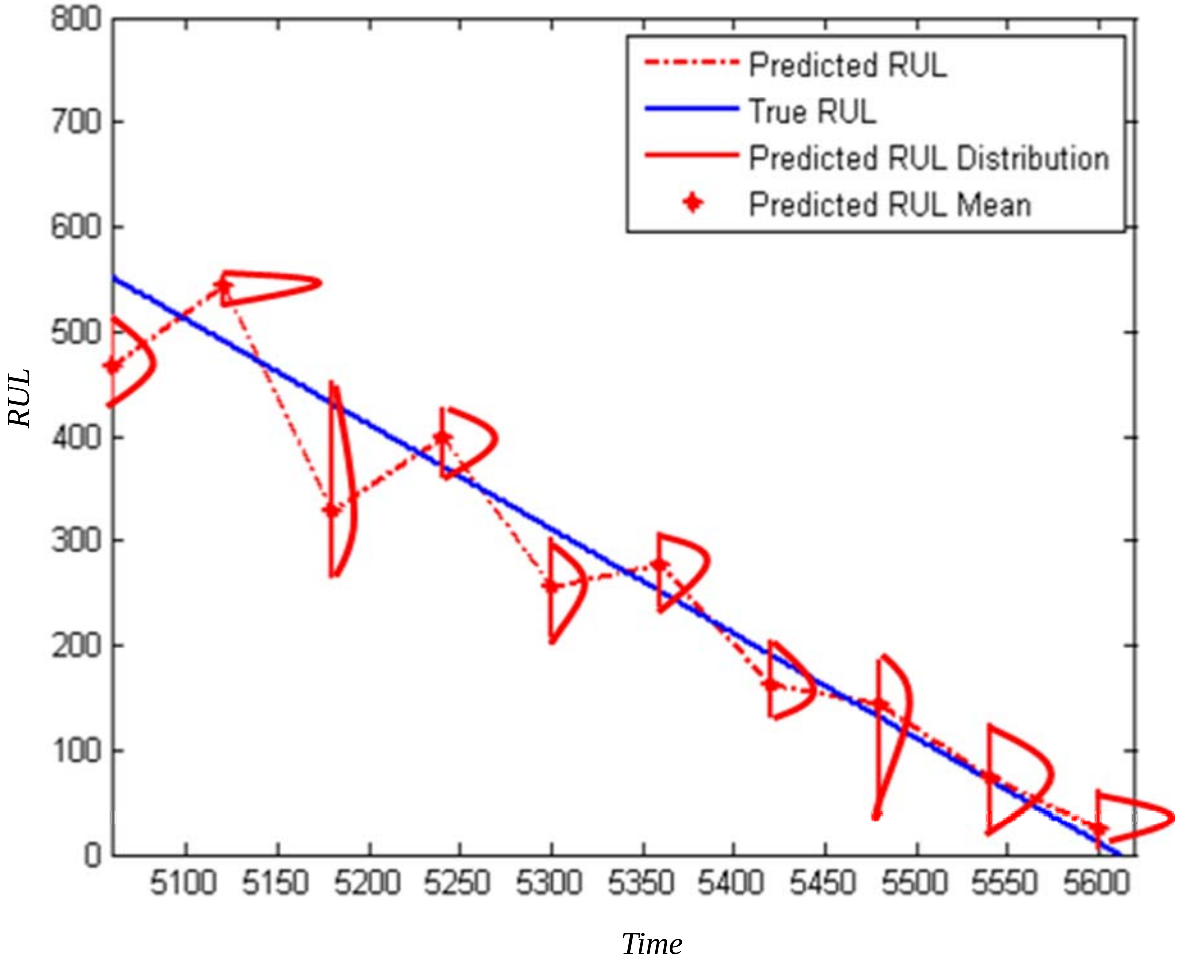


Figure 45. The PDF of RUL using estimator updated with error measurement

Then make a comparison, the estimated mean RUL and corresponding 90% confidence intervals using the estimator without error measurement update are shown in FIGURE 46.

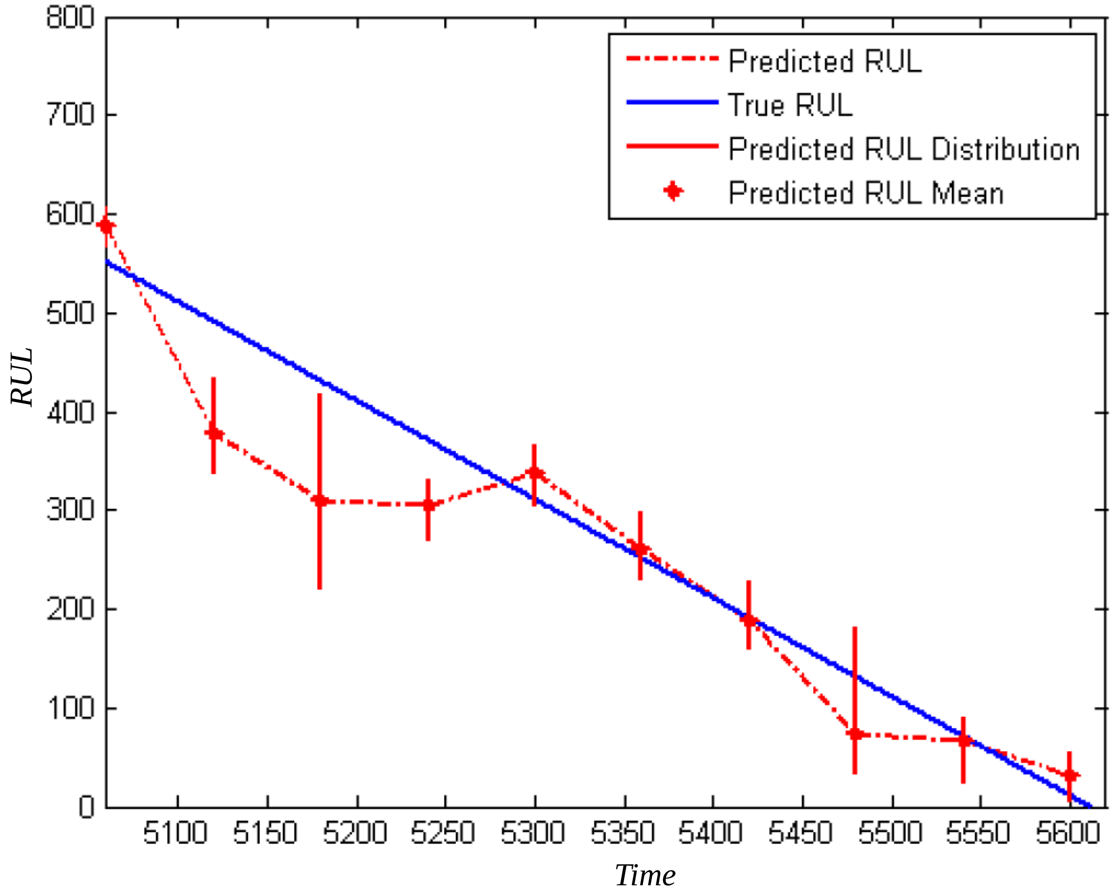


Figure 46. The predicted mean RUL and corresponding 90% confidence intervals using estimator updated without error measurement

From FIGURE 44 and FIGURE 46, one can see that the *l*-step ahead RUL estimator updated with the error measurement gives a better performance.

6.7 <u>Prognostics Results of the Second Case Study</u>

In this case study, the data are also form the same test rig. The difference between this case study and the former one is the Empirical Mode Decomposition (EMD) was applied for the original vibration signal before HI was calculated.

RMS was used as an example to show the improvement after EMD. FIGURE 47 is the RMS feature with EMD. After EMD, difference between normal status and fault status is more obvious and the fault feature can be identified easier.

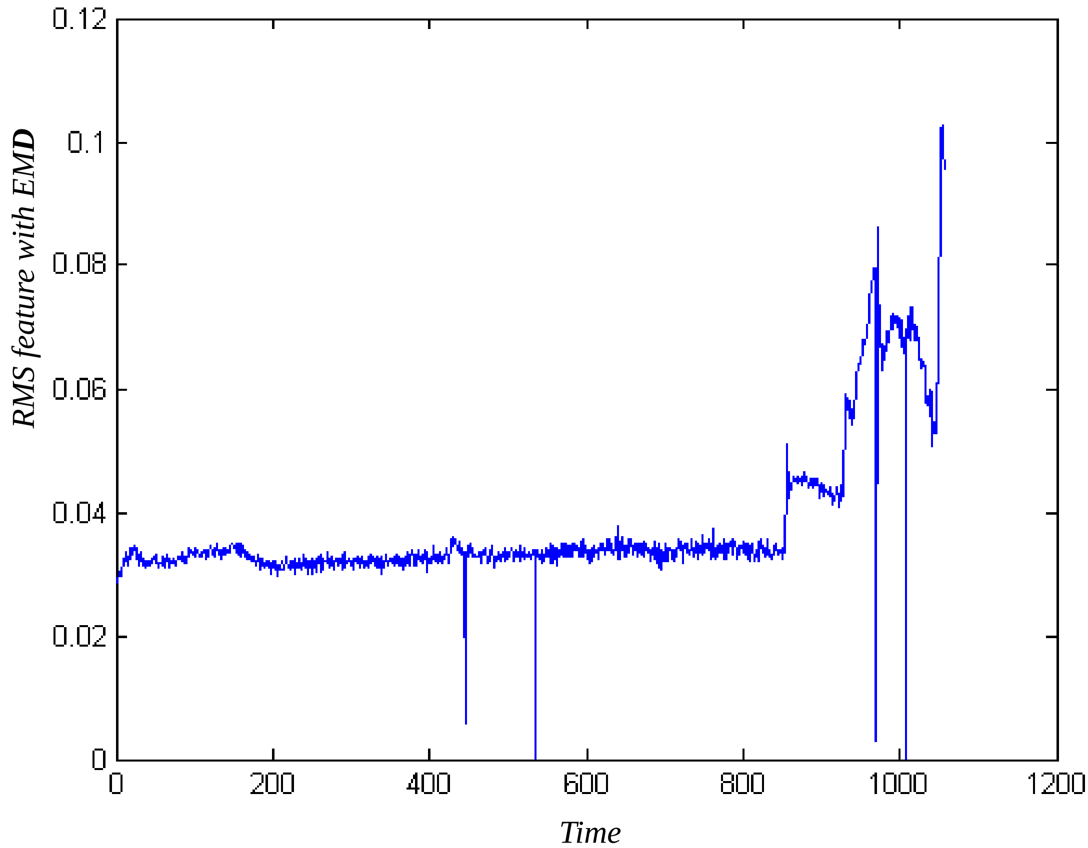


Figure 47. RMS feature with EMD

Also, Crest Factor and Kurtosis were also processed using EMD, FIGURE 48 and FIGURE 49 show the results.

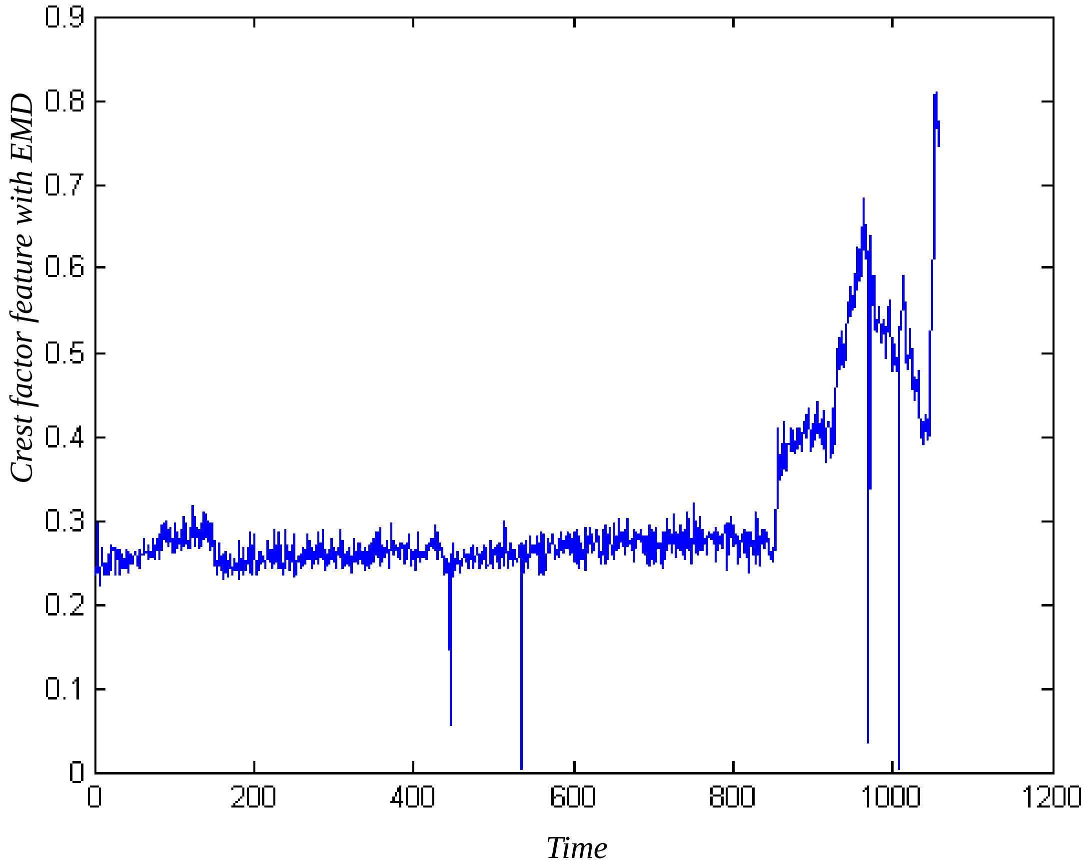


Figure 48. Crest factor feature with EMD

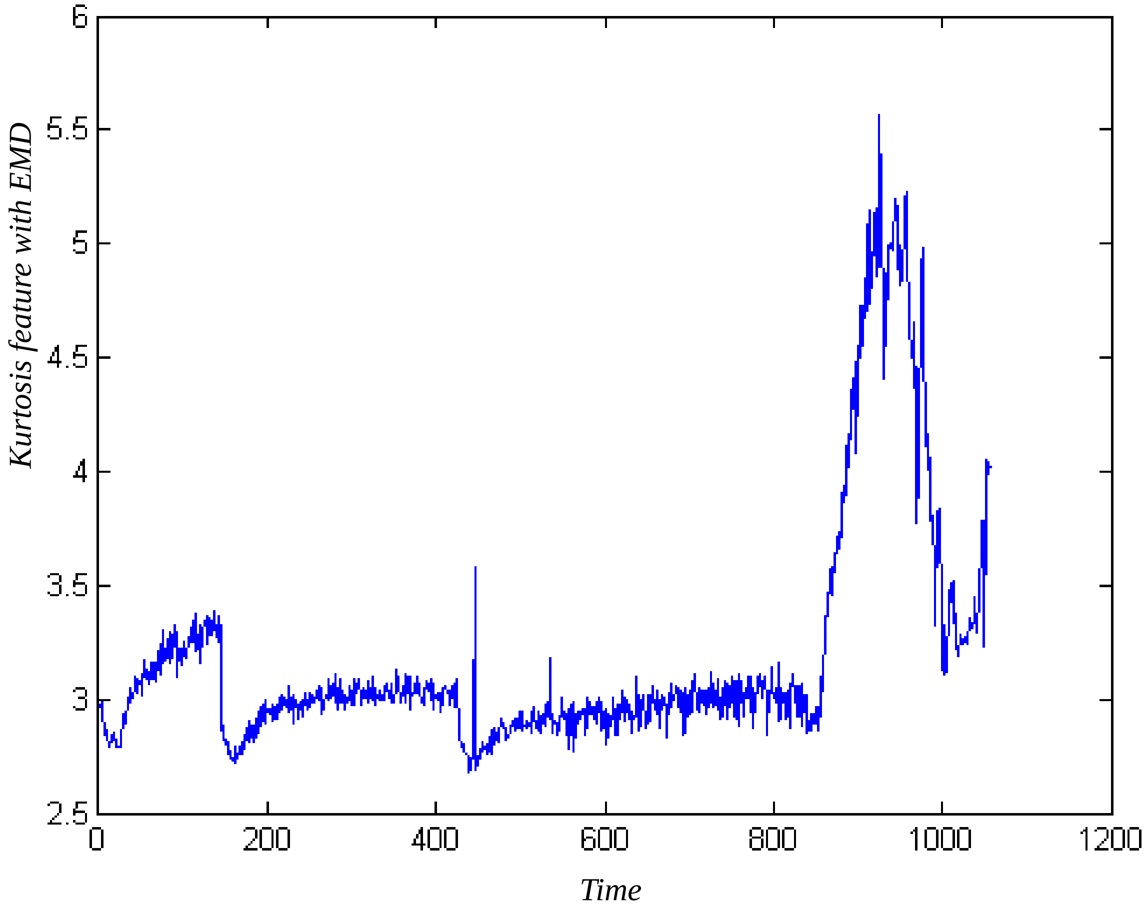


Figure 49. Kurtosis feature with EMD

These three features were used to calculate a HI and the HI was used as the observation parameter in the prognosis. FIGURE 50 shows the HI.

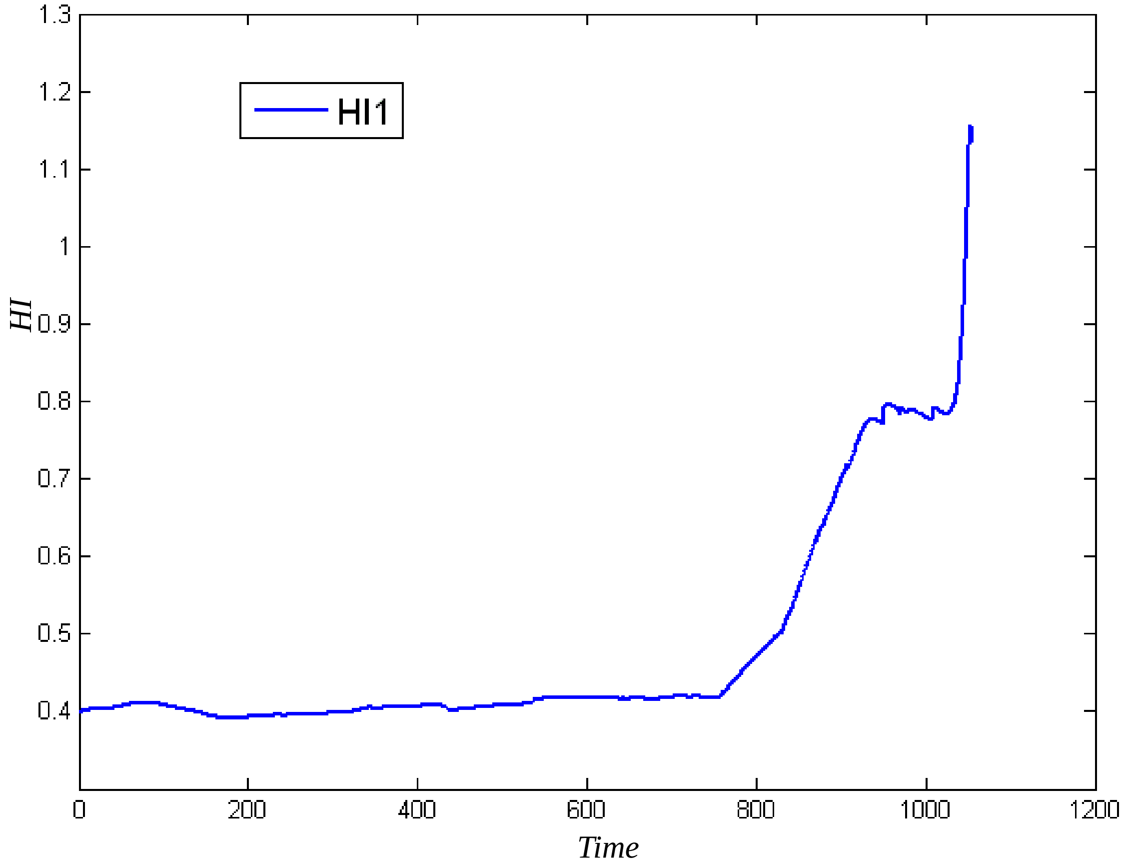


Figure 50. Health indicator

The plot of actual ODM values against the predicted ODM values is shown in FIGURE 51.

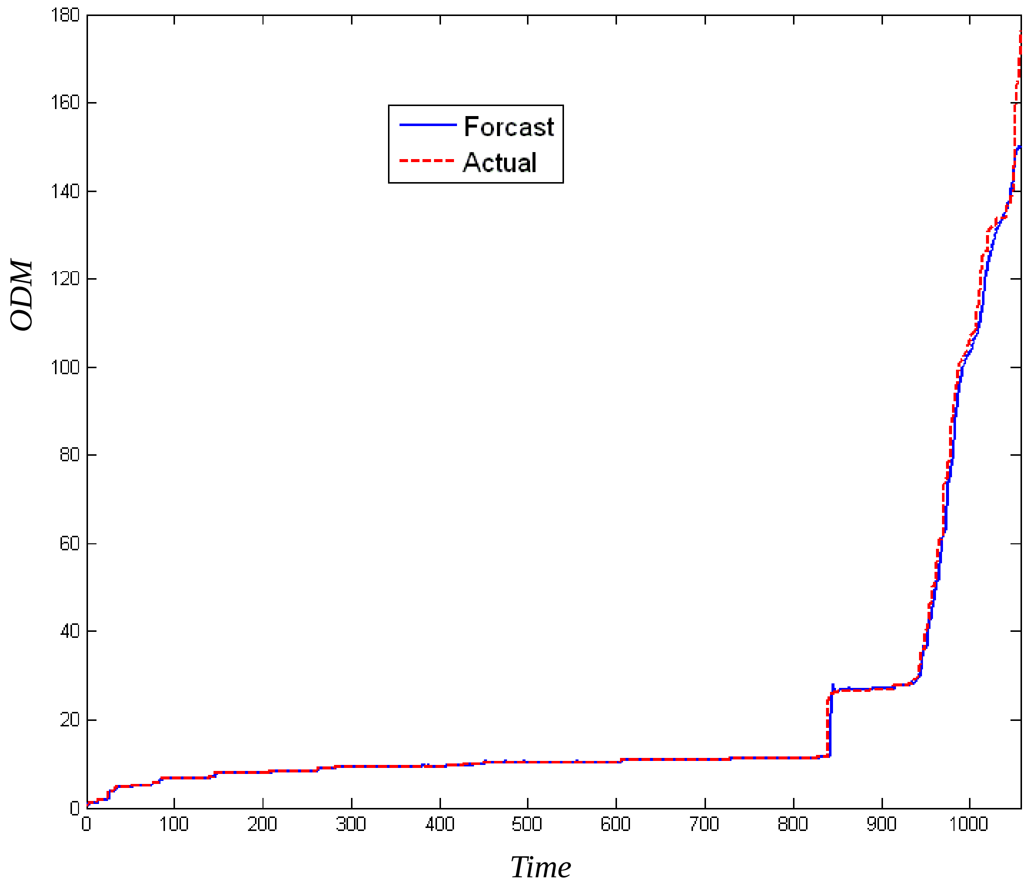


Figure 51. Actual ODM values against the predicted ODM

Using the station transition function f_k and the measurement function h_k defined by the ODM and HI data from experiment 6, the particle filtering based *l*-step ahead RUL estimator was run on the data from experiment 5 using $N = 2000$ particles. To compute the RUL, the critical value λ was set to be the level of ODM = 130 mg. The estimated mean RUL and corresponding 90% confidence intervals are shown in FIGURE 52.

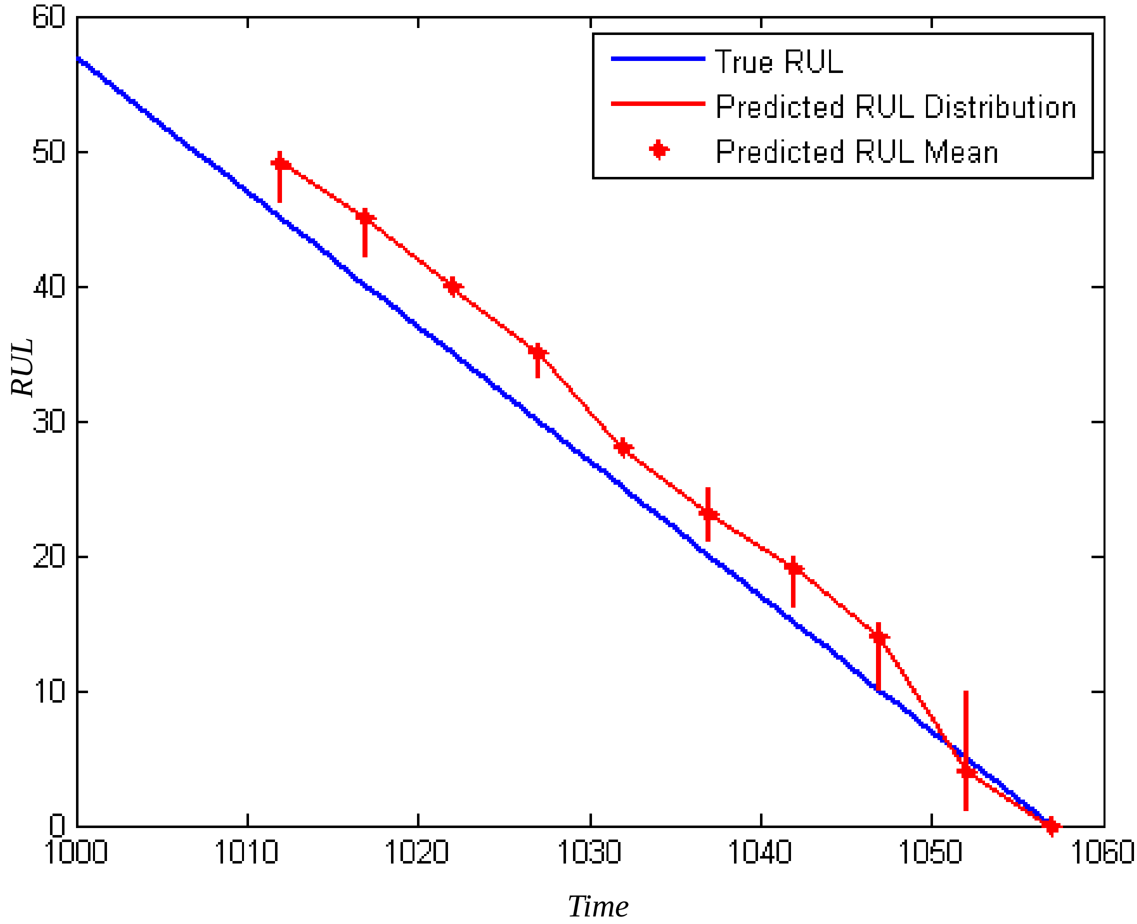


Figure 52. The predicted mean RUL and corresponding 90% confidence intervals using estimator updated with error measurement

6.8 Summary

A particle filtering based gear prognostics method using a one-dimensional health index for spiral bevel gear subject to pitting failure mode was presented in this chapter. The presented method effectively addresses the issues in applying particle filtering to mechanical component remaining useful life (RUL) prognostics by integrating several new components into particle filtering: (1) data mining based techniques to effectively define the degradation state transition and measurement functions using a one-dimensional health index obtained by a whitening transform; (2) an unbiased *l*-step ahead RUL estimator updated with measurement errors.

In addition, in the second spiral bevel gear case study, Empirical Mode Decomposition (EMD) was applied for processing original vibration signal. The RMS feature with EMD and the RMS feature without EMD were compared and the result shows that using EMD makes fault feature easier to be detected. After EMD processing, the feature during machine health status is stable and smooth and is sensitive to fault initiation. .

The presented prognostics method was validated using data from a spiral bevel gear case study. The validation results have shown the effectiveness of the presented method.

7. CASE STUDY 3: HYBRID CERAMIC BEARING PROGNOSTICS

7.1 Diagnostics, and Prognostics for Hybrid Ceramic Bearing

Ceramic bearings are quickly replacing conventional steel ball bearings in various fields and applications because they exhibit a service life three times longer than that of steel bearings (Wang, *et al.*, 2000; Ohta and Kobayashi, 1995). There are two types of ceramic bearings: hybrid ceramic bearings and full ceramic bearings. Hybrid ceramic bearings have steel races and ceramic balls while full ceramic bearings have both ceramic balls and races. Different types of ceramics are used in ceramic bearings. Silicon nitride Si3N4 and Zirconia ZrO2, are perhaps the most common ceramics used in ceramic bearings. However there are many other ceramics that would work well in bearing applications (Rhoads and Bashyam, 1994; Chao, *et al.*, 1995; Niizeki, 2000).

This chapter presents a methodology for hybrid ceramic bearing prognostics using particle filtering. Data collected from real hybrid ceramic bearing run to failure are used to validate the presented prognostic methodology.

7.2 Hybrid Ceramic Bearing Case Study Experimental Setup and Data Collection

7.2.1 The Information of Hybrid Ceramic Bearing

The hybrid ceramic bearings used in the test, RTF13 and RTF14. RTF13 and RTF14, were ball bearings with stainless steel inner and outer races and ceramic balls. The bearings were mounted on our test rig. Two accelerometers were stunt mounted on the bearing housing in the direction perpendicular to the shaft. The test bearing was mounted on our test rig and the rig was run at a speed of 1800 rpm (30 Hz) and was subjected to a radial load of 600 psi. A sampling rate of 102.4 kHz was used for 2 seconds of data collection at each sampling point. The data was collected every 5 minutes during the test. For the first case, there were a total of 173 files with the length of 14.42 hours used for analysis. For another case, there were a total of 804 files with the length of 67 hours used for analysis. TABLE IV shows the tested bearings and their loading information.

TABLE IV

BRIEF OVERVIEW OF EXPERIMENTAL SETTING

Name	**Type**	**Pressure (psi)**	**Speed (Hz)**
RTF13	Hybrid Ceramic Bearing	600	30
RTF14	Hybrid Ceramic Bearing	600	31

TABLE V shows the hybrid bearings specification.

TABLE V

HYBRID BEARINGS SPECIFICATION

Parameter	Specification	Parameter	Specification
Bearing Material	Stainless Steel 440c	ABEC/ISO Rating	ABEC #3 / ISOP6
Ball Material	Ceramic SI3N4	Radial Play	C3
Inner Diameter (d)	25 m	Lube	Klubber L55 Grease
Outer Diameter (D)	52 m	RPM Grease (x 1000 rpm)	19
Width (B1)	15 m	RPM Oil (x 1000):	22
Enclosure	Two Shields	Dynamic Load (Kgf)	1429
Enclosure Material	Stainless Steel	Basic Load (Kgf)	804
Enclosure type	Removable (S)	Working Temperature Deg (c)	121
Retainer Material	Stainless Steel	Weight (g)	110.32

7.2.2 <u>**The Run to Failure Test Rig**</u>

The bearing run to failure test was conducted in a customized bearing prognostics test rig as shown in FIGURE 53.

The key features of the test rig include:

(1) It is driven by a 3-HP AC motor with a maximum speed up to 3600 rpm and variable speed controller,

(2) It is equipped with a hydraulic dynamic loading system with a maximum radial load up to 4400 lbs or 19.64 kN,

(3) An integrated loading and bearing housing that can be used for testing both ball and tapered roller bearings,

(4) A support shaft with 2” main diameter balanced with 2 pillow blocks.

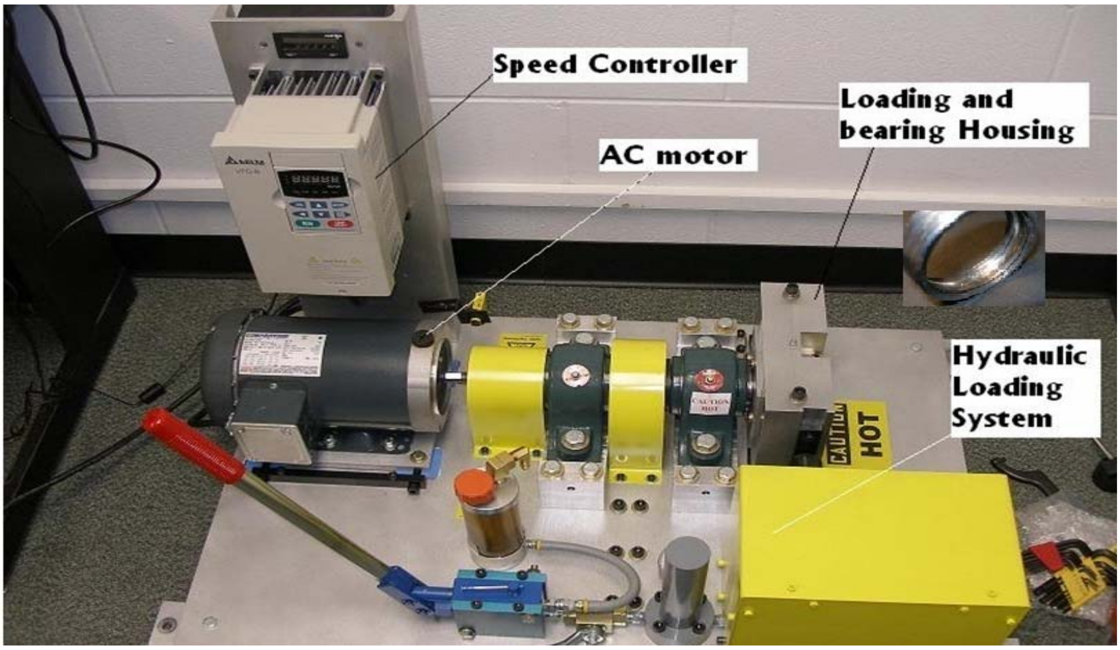


Figure 53. Bearing prognostic test rig

An automatic data acquisition system based on National Instruments’ CI 4462 board and NI LabVIEW software was constructed for data collection purpose. The automatic data acquisition system has the following features:

(1) Maximum sampling rate up to 102.4 kHz,

(2) Input simultaneous anti-aliasing filters,

(3) Software-configurable AC/DC coupling and IEPE (Integrated Circuit Piezoelectric) conditioning,

(4) Vibration analysis functions such as envelope analysis, cepstrum analysis, and so on for computing necessary condition indicators.

The hybrid ceramic bearings used in the test were RTF13 and RTF14. RTF13 and RTF14 were ball bearings with stainless steel inner and outer races and ceramic balls.

7.3 <u>The One-Dimensional Health Index for Hybrid Ceramic Bearing</u>

The condition indicators we extracted are (Li *et al*. 2010):

(1) RMS;

(2) Kurtosis;

(3) Crest Factor;

(4) Shape Value;

(5) Impulse Value;

(6) PeakValue;

(7) Kurtosis_H;

(8) Kurtosis_L;

(9) Skewness_H;

(10) Skewness_L;

(11) Skewness;

(12) AR_Energe.

The rule applied to select the appropriate condition indicators to compose the HI to calculate the correlation values between these condition indicators and time. There are three CIs:

(1) RMS,

(2) Peak Value,

(3) Skewness

chosen by using this method. Then, the one-dimension HI method mentioned in Chapter 4 was used to calculate the HI. FIGURE 54 shows all calculated correlation values between the condition indicators with time horizon. And FIGURE 55 shows the chosen condition indicators.

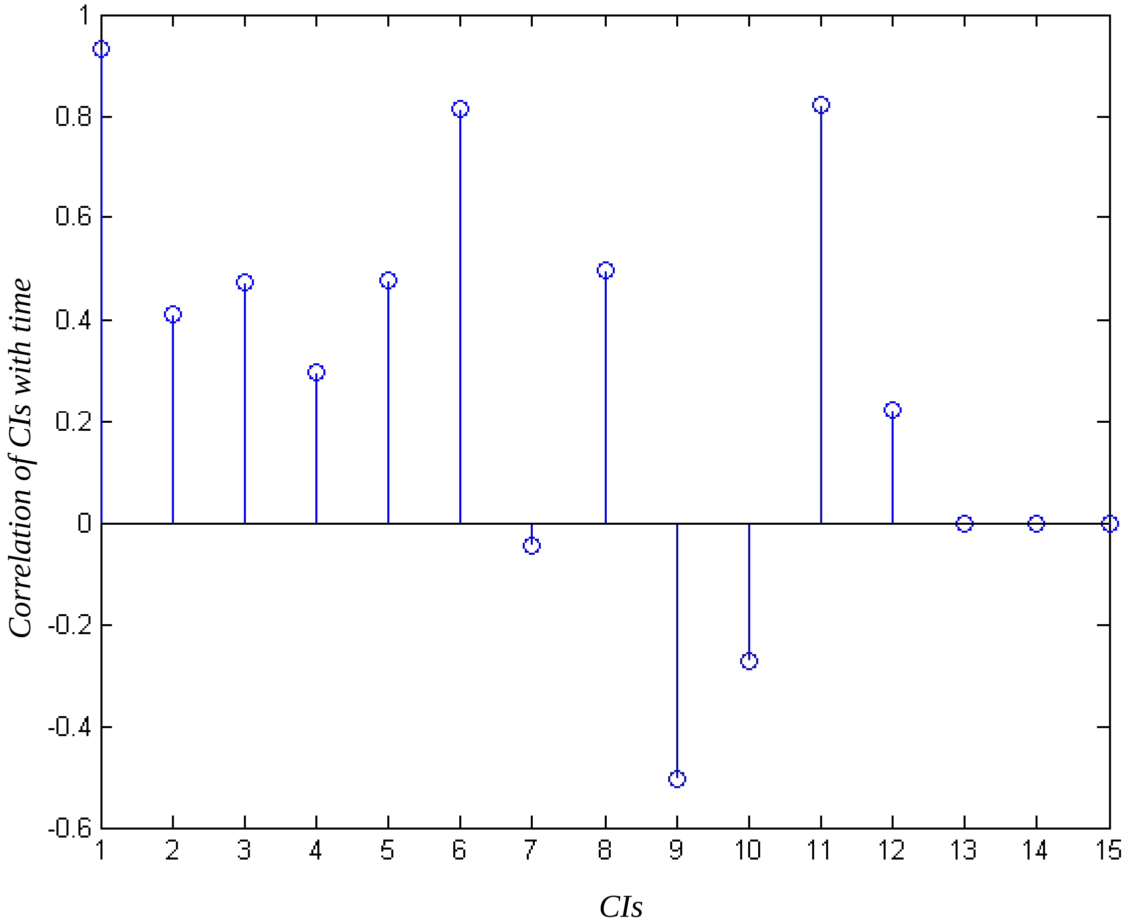


Figure 54. The correlation values between these condition indicators and time

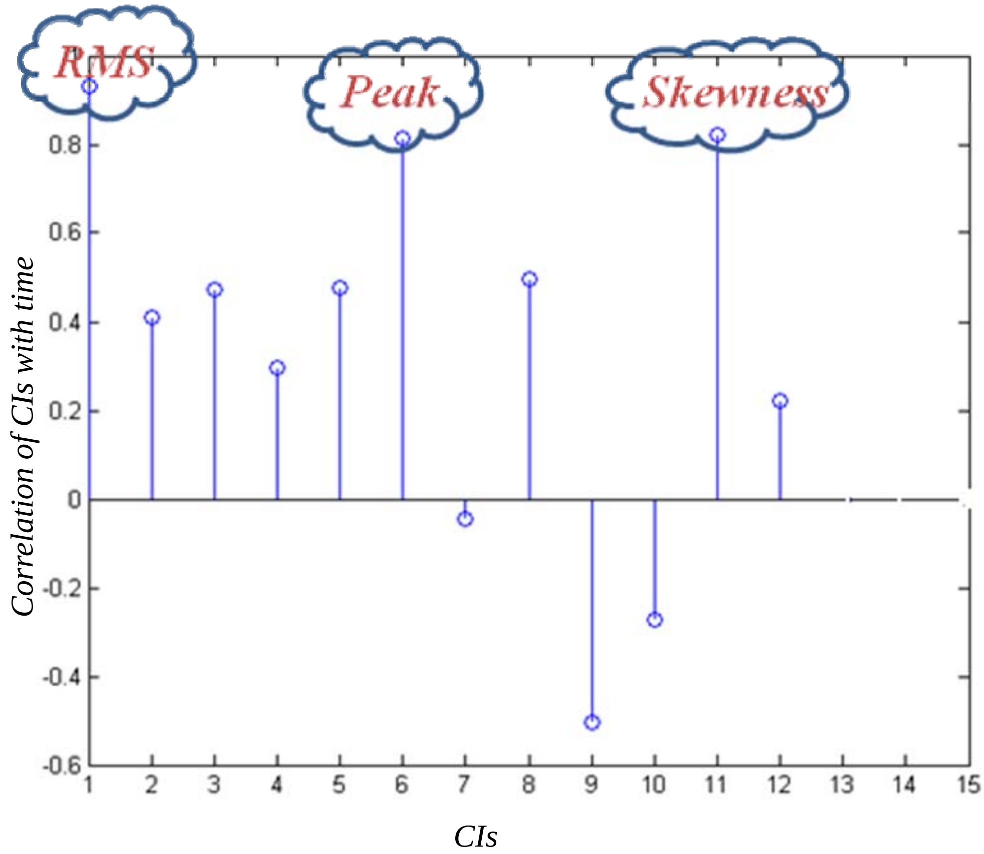


Figure 55. The chosen condition indicators to compose HI

FIGURE 56 shows the generated HI.

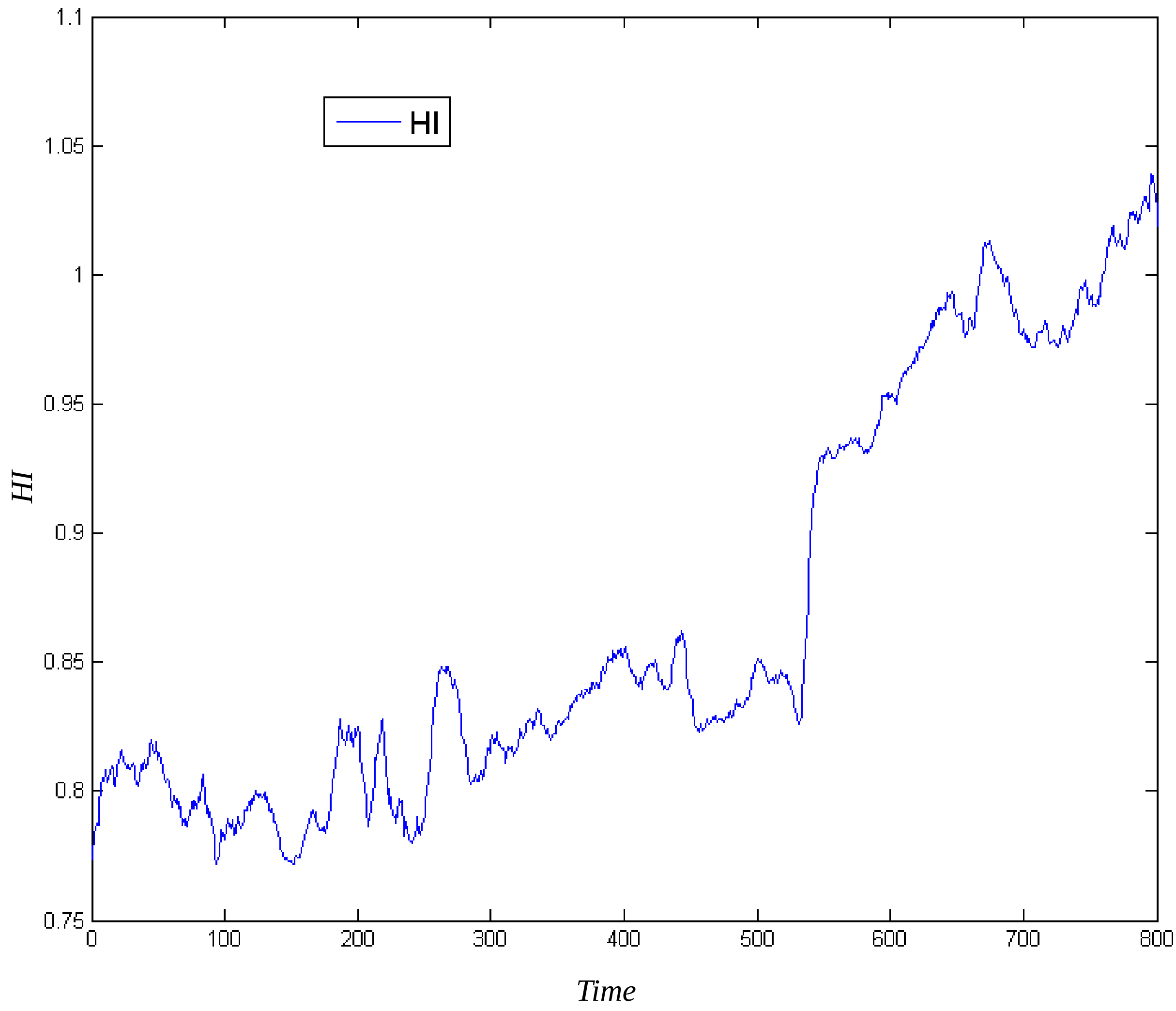


Figure 56. HI of hybrid ceramic bearing

7.4 Prognostics Results

Using the station transition function f_k and the measurement function h_k defined by the spall size and HI data from experiment 6, the particle filtering based *l*-step ahead RUL estimator was run on the data from experiment 5 using $N = 2000$ particles. To compute the RUL, the critical value λ was set to be the level of spall mass = 220 mg.

The plot of actual spall size values against the predicted spall size values is shown in Figure 57.

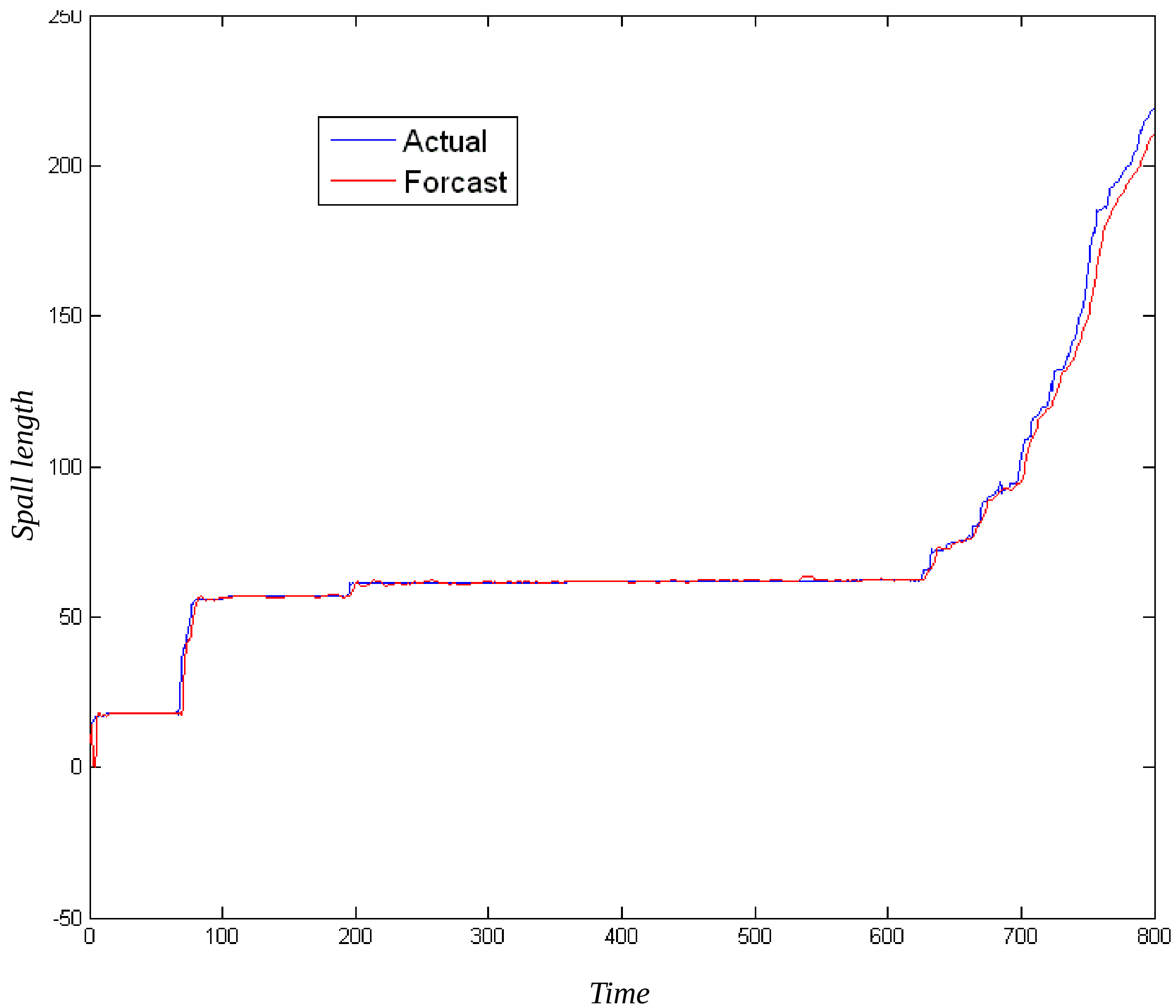


Figure 57. Actual spall size values against the predicted spall size

The estimated mean RUL and corresponding 90% confidence intervals are shown in Figure 58.

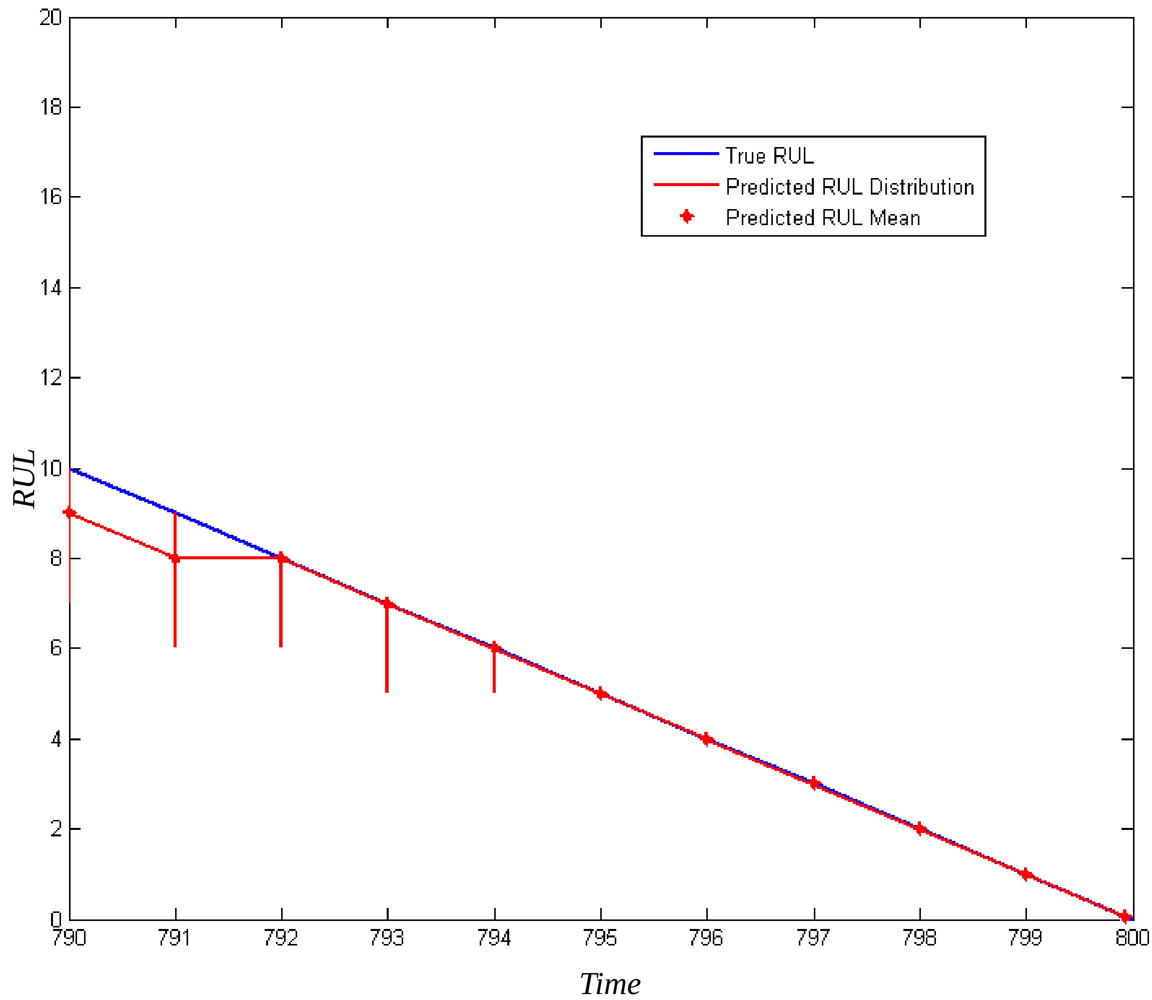


Figure 58. The estimated mean RUL and corresponding 90% confidence intervals

7.5 Summary

A particle filtering based hybrid ceramic bearing prognostics method using a one-dimensional health index was presented in this chapter. Data collected from real hybrid ceramic bearing run to failure are used to validate the presented prognostic methodology. Data mining based techniques were used to define the degradation state transition and measurement functions using a one-dimensional health index which is taken as the observation parameter. An *l*-step ahead steel bearing fault progression and remaining useful life prediction were performed. The 90% confidence interval became narrower as more information was obtained, providing a more accurate prediction. The validation results have shown the effectiveness of the presented method.

8. CONCLUSIONS

In this dissertation, an integrated machinery prognostic methodology based on particle filtering has been developed. In the development of the proposed prognostic methodology in this research, three fundamental issues have been addressed by: 1) defining the state transition function using a data mining approach; (2) integrating an one-dimensional HI into particle filtering to define the measurement function; (3) developing an *l*-step ahead RUL estimator incorporated with a measure of the associated error. The developed prognostic methodology has been validated using three sets of industrial case studies. The first case study was about steel bearing prognosis and remaining useful life prediction. The bearing fault data used in this research were spalled bearings run to failure test data with intermediate inspections. The second case study was about spiral bevel gear prognosis and RUL prediction. The spiral bevel gear case study data were collected in the NASA Glenn Spiral Bevel Gear Test Facility. In the last case study, the ground truth data of hybrid ceramic bearings test by our group at UIC were used to validate the methodology.

The results from the three case studies have shown the effectiveness of the developed integrated methodology.

(1) An integrated prognostics methodology has been developed and illustrated by real engineering case studies;

(2) The presented method effectively addresses the issues in applying particle filtering

to mechanical component remaining useful life (RUL) prognostics by integrating several new components into particle filtering；

(3) The state transition function defined by applying a data mining approach can track the spall size propagation well. It was also found that a data mining approach is much more efficient than applying Paris' Law, which is widely used as the state transit function in other published research;

(4) The predicted spall size propagation by integrating HI into particle filtering to define the measurement function matches much better than the predicted result by directly combining multiple condition indicators. Also, by comparing the RUL predictions, the RUL prediction using one-dimensional HI approaches the true RUL faster and provides better long-term RUL prediction than that without using one-dimensional HI;

(5) An *l*-step ahead state parameter prediction and RUL estimator by extending the projection of particles without changing their weights prove that the method still provides a satisfactory result in predicting how the system behaves.

Specifically, the contributions of the dissertation are summarized as follows:

(1) An integrated particle filtering algorithm was developed in which a one-dimensional HI was integrated into particle filtering to define the observation function. The results have shown that using the one-dimensional HI gives better prognostic results than combining different condition indicators into one HI.

(2) Instead of using Paris' Law, a data mining algorithm was used to build the state

function. The results have shown that the state function models built by the data mining algorithm work effectively for describing the fault propagation.

(3) Data mining based approaches were used to build the observation function. The data mining based approaches use both the prediction information from the last step and observation data to determine the model parameters. The results have shown that the data mining based methods work better than existing methods reported in the literature.

(4) An *l*-step ahead state parameter prediction and RUL estimator was developed. Most of papers published just show one-step prediction.

(5) The presented prognostics method has been validated using data from steel bearings, hybrid ceramic bearings and spiral bevel gears case studies. Up to date, no results on spiral bevel gears and ceramic bearings prognosis and remaining useful life prediction using particle filtering based approaches have been reported in the literature. In addition, the results on steel bearings prognostics using particle filtering algorithm are limited. The results from the three case studies show that the developed integrated methodology works well in performing the system state tracking and remaining useful life prediction.

9. CITED LITERATURE

1. Abbas, M., Ferri, A., Orchard, M., and Vachtsevanos, G.: An intelligent diagnostic/prognostic framework for automotive electrical system. IEEE Intelligent Vehicles Symposium-IV'07, Istanbul, Turkey, June 13-15, 2007.

2. Andrade F.A., Esat I. and Badi M.N.M.: A new approach to time-domain vibration condition monitoring: gear tooth fatigue crack detection and identification by the kolmogorov-smirnov test, Journal of Sound and Vibration, Vol. 240, pp. 909 - 919, 2001.

3. Arulampalam S. and Ristic B.: Comparison of the particle filtering with range parameterized and modified polar ekfs for angle-only tracking, Proceedings of SPIE conference Signal and Data Processing of Small Targets, Vol. 4048, pp. 288 – 299, Orlando, FL, April 24, 2000.

4. Arulampalam, S. M., Maskell, S., Gordon, N., & Clapp, T.: A tutorial on particle filterings for online nonlinear/non-Gaussian Bayesian tracking, IEEE Transactions on Signal Processing, Vol. 50, No. 2, pp. 174 - 188, 2002.

5. Batko W.: Prediction method in technical diagnostics, Doctoral Thesis, Cracov Mining Acadethe, Polish, 1984.

6. Baydar N. and Ball A.: A comparative study of acoustic and vibration signals in detection of gear failures using Wigner-Ville distribution, Mechanical Systems and Signal Processing, Vol. 15, No. 6, pp. 1091 - 1107, 2001.

7. Bechhoefer, E. and Bernhard, A.: Use of non-Gaussian distribution for analysis of shaft components, IEEE Aerospace Conference, Big Sky, MT, March, 2006.

8. Bechhoefer, E., and Bernhard, A.: A generalized process for optimal threshold setting in HUMS, IEEE Aerospace Conference, Big Sky, MT, March, 2007.

9. Bechhoefer, E., He, D., and Dempsey, P.: Gear health threshold setting based on a probability of false alarm, Working Paper#5, Intelligent Systems Modeling & Development Lab, Department of Mechanical and Industrial Engineering, University of Illinois-Chicago, IL 60607, 2011.

10. Bloch H. P., Geitner F. K.: Machinery Failure Analysis and Trouble Shooting, Houston, Texas, Gulf Professional Publishing, 1997.

11. Box G. and Gwilym J.: Time Series Analysis: Forecasting and Control, New York, NY, John Wiley & Sons Inc, 1970.

12. Butler, S. & Ringwood, J.: Particle filtering for remaining useful life estimation of abatement equipment used in semiconductor manufacturing,

Proceedings of the First Conference on Control and Fault-Tolerant Systems, pp. 436 – 441, Nice, France, October 6-8, 2010.

13. Byington C.: Prognostic enhancements to diagnostic systems for improved condition-based maintenance systems, IEEE Aerospace Conference, Vol. 6, pp. 2815 – 2824, Big Sky, MT, March, 2002.

14. Byington C.S., Orsagh R., Pattada K., Sheldon J., DeChristopher M., Amin S. and Hines J.: Recent case studies in bearing fault detection and prognosis, IEEE Aerospace Conference, Big Sky, MT, March, 2006.

15. Byington, C.: Metrics evaluation and tool development for health and usage monitoring system technology, Third International Conference on Health and Usage Monitoring, DSTO-GD-0348, Melbourne, Canada, February 17 - 18, 2003.

16. Cadini F., Zio E., and Avram D.: Monte Carlo-based filtering for fatigue crack growth estimation, Probabilistic Engineering Mechanics, Vol. 24, No. 3, pp. 367 - 373, 2009.

17. Caldwell J. G.,: The Box-Jenkins Forecasting Technique, http://www.foundationwebsite.org/BoxJenkins.htm 1971.

18. Caldwell J. G.: Mathematical Forecasting Using The Box-Jenkins Methodology, http://www.foundationwebsite.org/MathematicalForecasting_Box-Jenkins.pdf, 2007.

19. Cempel C.: Simple condition forecasting techniques in vibro-acoustical diagnostics, Mechanical Systems and Signal Processing, Vol. 1, No.1, pp. 75 - 82, 1987.

20. Chao L.Y., Shetty D.K., Adair J.H. and Mecholsky Jr. J.J.: Development of silicon nitride for rolling contact bearing applications: a review, Journal of Materials Education, Vol. 17, No. 5-6, pp. 245 - 303, 1995.

21. Chen C., Zhang B., Vachtsevanos G., and Orchard M.: Machine condition prediction based on adaptive neuro-fuzzy and high-order particle filtering, IEEE Transactions on Industrial Electronics, Vol.58, No.9, pp. 4353-4363, 2011.

22. Chen C., Brown D., Sconyers C., Vachtsevanos G., Zhang B., and Orchard M: A . NET framework for integrated fault diagnosis and failure prognosis architecture, Proceedings of IEEE AUTOTESTCON, pp.36 - 41, Orlando, FL, September 13-16, 2010.

23. Chen C., Vachtsevanos G., and Orchard M.: Machine remaining useful life prediction based on adaptive neuro-fuzzy and high-order particle filtering, Annual Conference of the Prognostics and Health Management Society, Portland, OR, October 10-16, 2010.

24. Chen C., Zhang B., Vachtsevanos G.: Prediction of machine health condition using neuro-fuzzy and bayesian algorithms, http://icsl.gatech.edu/aa/uploads/b/b1/TIM.pdf, 2011

25. Crowder M.J., Kimber A., Sweeting T., and Smith R.: Statistical Analysis of Reliability Data, Chapman & Hall/CRC, London, UK, 1994.

26. Deb S., Pattipati K. R., Raghavan V., Shakeri M., and Shrestha R.: Intelligent model-based diagnostics for vehicle health management, SPIE Conference Proceedings,

Vol. 5107, pp. 13–26., Orlando, FL, April, 2003.

27. Dempsey P.J., Certo J.M. and Morales W.: Current status of hybrid bearing damage detection, NASA/TM - 2004-212882, NASA, Cleveland, OH, 2004.

28. Dempsey P.J., Joseph M.C., Robert F.H., and Florin D.: Hybrid bearing prognostic test rig, NASA/TM—2005-213597, NASA, Cleveland, OH, 2005.

29. Dempsey, P., Handschuh, R., & Afjeh, A.: Spiral bevel gear damage detection using decision fusion analysis, NASA/TM-2002-211814, NASA, Cleveland, OH, 2002.

30. Dong M., and He D.: A segmental Hidden Semi-Markov model (HSMM) - based diagnostics and prognostics framework and methodology, Mechanical Systems and Signal Processing, Vol. 21, No. 5, pp. 2248 - 2266, 2007.

31. Doucet, A., Godsill, S., & Andrieu, C.: On sequential Monte Carlo sampling methods for Bayesian filtering, Statistics and Computing, Vol. 10, pp. 197 - 208, 2000.

32. Ebersbacha S., Penga Z. and Kessissoglou N.J.: The investigation of the condition and faults of a spiral gearbox using vibration and wear debris analysis techniques, Wear, Vol. 260, No. 1-2, pp. 16 - 24, 2006.

33. Ebert F.J.: Performance of silicon nitride components in aerospace bearing applications, The American Society of Mechanical Engineers, ASME publication, No. 90-GT-166, 1990.

34. Elsayed E.A.: Reliability Engineering, Englewood Cliffs, NJ,Prentice-Hall, 1996.

35. Farrar C.R., Hemez F., Park G., Robertson A.N., Sohn H., and Williams T.O.: A coupled approach to developing damage prognosis solutions, Damage Assessment of Structures—The Fifth International Conference on Damage Assessment of Structures (DAMAS 2003), Southampton, UK, 2003.

36. Ferret: The basics predictive/preventive maintenance, http://www.homeinspex.com/pdfs/thermography.pdf, 2006

37. Friedman J.: Multivariate adaptive regression splines, The Annals of Statistics, Vol. 19, No. 1, pp. 1 - 67, 1991.

38. Fukunaga, K.: Introduction to Statistical Pattern Recognition, London, UK, Academic Press, 1990.

39. Gao R.X., Changting W., Ruqiang Y., and Malhi A.: A neural network approach to bearing health assessment, International Joint Conference on Neural Networks, pp. 899 – 906, Vancouver, Canada, July 16-21, 2006.

40. Gilmartin S.J., Bongort, K. and Hess A.: Prognostics, the real issues involved with predicting life remaining engel, Proceedings of IEEE Aerospace Conference, Vol. 6, pp.457 – 469, Big Sky, MT, March, 2000.

41. GL Renewables: Guidelines for the Certification of Condition Monitoring Systems for Wind Turbines, http://www.gl-group.com/en/certification/renewables/CertificationGuidelines.php, 2007.

42. Goode P. and Chow M.-Y.: Using a neural/fuzzy system to extract heuristic knowledge of incipient faults in induction motors, Part I-Methodology, IEEE Transactions on Industrial Electronics, Vol. 42, No. 2, pp 131 - 138, 1995.

43. Groer P.G.: Analysis of time-to-failure with a Weibull model, Proceedings of the Maintenance and Reliability Conference, pp. 59.01 - 59.04, Knoxville, TN, May 7-10, 2000.

44. Handschuh, R. F.: Thermal Behavior of Spiral Bevel Gears, NASA TM − 106518, 1995.

45. Handschuh, R. F.: Testing of Face - Milled Spiral Bevel Gears at High - Speed and Load, NASA/TM—2001-210743, 2001.

46. Hastie T., Tibshirani R. and Friedman J.: The Elements of Statistical Learning, New York, NY, Springer, 2009.

47. He D. and Bechhoefer E.: Bearing prognostics using HUMS condition indicators, American Helicopter Society 64th Annual Forum, Montreal, Canada, April 29 - May 1, 2008.

48. He D., Bechhoefer E., Al-Kateb M., Ma Ji., Joshi P. and Imadabathuni M.: A Novel Configuration-Driven Data Mining Framework for Health and Usage Monitoring System, ISBN: 978-953-307-547-1, Publisher: InTech, 2011.

49. He D., Bechhoefer E., Ma J., and Li R.: Particle filtering based gear prognostics using one-dimensional health index, Annual Conference of the Prognostics and Health Management Society, Vancouver, Canada, September 25-29, 2011.

50. He D., Panyala A., Li R., and Ma J.: The use of vibration signals for ceramic bearing prognostics, Proceedings of the 2010 Industrial Engineering Research Conference, Cancun, Mexico, June 5-9, 2010.

51. Heng A., Zhang S., Tan A. C. C., and Mathew J.: Rotating machinery prognostics: state of the art, challenges and opportunities, Mechanical Systems and Signal Processing, Vol, 23, No., pp. 724 - 739, 2009.

52. Ho D., Randall B.: Optimization of bearing diagnostic techniques using simulated and actual bearing fault signals, Mechanical System and Signal Processing, Vol. 14, No. 5, pp. 765 - 788, 2000.

53. Howard I.: A Review of Rolling Element Bearing Vibration: Detection, Diagnosis And Prognosis, DSTO-RR-0013, Airframes and Engines Division, 1994.

54. Howe B. and Muir D.: In-Line Oil Debris Monitor (ODM) for Helicopter Gearbox Condition Assessment, AD−a347 503, BF Goodrich Corporation, 1998.

55. Huang R. Q., Xi L. F., Li X. L., Liu C.R., Qiu H. and Lee J.: Residual life predictions for ball bearings based on self-organizing map and back propagation neural network methods, Mechanical Systems and Signal Processing, Vol. 21, No. 1, pp. 193 - 207, 2007.

56. Jantunen E.: Prognosis of rolling bearing failure based on regression analysis and fuzzy logic, Proceedings of the VETOMAC-3 and ACSIM-2004, New Delhi, India, pp. 836 - 846, 2004.

57. Jardine A. K.S., Lin D and Banjevic D.: A review on machinery diagnostics and prognostics implementing condition-based maintenance, Mechanical Systems and Signal Processing, Vol. 20, No.7, pp.1483 - 1510, 2006.

58. Kacprzynski G.J., Sarlashkar A., Roemer M.J., Hess A. and Hardman B.: Predicting remaining life by fusing the physics of failure modeling with diagnostic, Journal of the Minerals, Metals and Materials Society, Vol.56, No.3, pp.29 - 35, 2004.

59. Kapur K. C. and Lamberson L.R.: Reliability in Engineering Design, New York, Wiley, 1977.

60. Kazmierczak K.: Application of autoregressive prognostic techniques in diagnostics, Proceedings of the Vehicle Diagnostics Conference，Tuczno, Poland, March, 1983.

61. Keller A.Z., Perera U.D., and Kamath A.R.R.: Reliability analysis of CNC machine tools, Reliability Engineering, Vol.3, No.6, pp. 449 - 473, 1982.

62. Ki N. K. and Delp E. J.: New models for real-time tracking using particle filtering, Visual Communications and Image Processing, Vol. 7257, No. 1. 72570B, 2009.

63. Koller-Meier E. and Ade F.: Tracking multiple objects using the condensation algorithm, Journal of Robotics and Autonomous Systems, Vol. 34, No. 2–3, pp. 93 - 105, 2001.

64. Kumar S., Torres M., Chan Y. C., and Pecht M.: A hybrid prognostics methodology for electronic products, Proceedings of the IEEE International Joint Conference on Neural Networks, pp. 3479 – 3485, Hong Kong, October 26-30, 2008.

65. Lawless. F.: Statistical Models and Methods for Life time Data, New York, NY, Wiley-Inter science, 2002.

66. Lennart L.: System Identification: Theory for the User, Upper Saddle River, NJ, Prentice Hall, 1987.

67. Lewicki, D., Dempsey, P., Heath, G., and Shanthakumaran P.: Gear Fault Detection Effectiveness as Applied to Tooth Surface Pitting Fatigue Damage, NASA/TM—2009-215667, 2010

68. Li B., Chow M.-Y., Tipsuwan Y. and Hung J.: Neural networks based motor rolling bearing fault diagnosis, IEEE Transactions on Industrial Electronics, Vol. 47, No. 5, pp. 1060 - 1069, 2000.

69. Li C.J. and Lee H.: Gear fatigue crack prognosis using embedded model, gear dynamic model and fracture mechanics, Mechanical Systems and Signal Processing, Vol. 19, No.4, pp. 836 - 846, 2005.

70. Li C.J. and Shin H.: Tracking bearing spall severity through inverse modeling, Proceedings of the ASME International Mechanical Engineering Congress, pp.1 - 6, Anaheim, CA, 2004.

71. Li C.J. and Choi S.: Spiral gear root fatigue crack prognosis via crack diagnosis and fracture mechanics, Proceedings of the 56th Meeting of the Society of Mechanical Failures Prevention Technology, pp. 311 - 320, Virginia Beach, VA, 2002.

72. Li R., Ma J., Panyala A. and He D.: Hybrid ceramic bearing prognostics using particle filtering, Conference of The Society For Machinery Failure Prevention Technology, Huntsville, AL, April 13-15, 2010.

73. Li Y., Billington S., Zhang C., Kurfess T., Danyluk S., and Liang S.: Adaptive prognostics for rolling element bearing condition, Mechanical Systems and Signal Processing, Vol. 13, No.1, pp. 103 - 113, 1999.

74. Li Y., Kurfess T.R., Liang S.Y.: Stochastic prognostics for rolling element bearings, Mechanical Systems and Signal Processing, Vol. 14, No.5, pp. 747 - 762, 2000.

75. Lin D. and Makis V.: Recursive filters for a partially observable system subject to random failure, Advances in Applied Probability, Vol. 35, No.1, pp. 207 - 227, 2003.

76. Liu B.: Adaptive harmonic wavelet transform with applications in vibration analysis, Journal of Sound and Vibration, Vol. 262, No.1, pp. 45 - 64, 2003.

77. Lybeck N., Marble S. and Morton B.: Validating prognostic algorithms: a case study using comprehensive bearing fault data, IEEE Aerospace Conference, pp. 1 – 9, Big Sky, MT, March, 2007.

78. Ma J.: Methodology for health monitoring and prognostic for electronic products, the Annual Reliability of China Aeronautics Association, pp. 325 – 333, Kunming, China, July, 2006.

79. Ma, J. and He, D.: Development of integrated prognostics: an application to hybrid ceramic bearing life prediction, Proceedings of the 2010 Second IITA International Joint Conference on Artificial Intelligence, Shanghai, China, December 25 – 26, 2010.

80. Marble S., and Morton B.P.: Predicting the remaining life of propulsion system bearings, Proceedings of the IEEE Aerospace Conference, pp.1 - 8, Big Sky, MT, March, 2006.

81. McCormick A.C., Nandi A.K. and Jack L.B.: Application of periodic time-varying autoregressive models to the detection of bearing faults, Proceedings of Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science, Vol. 212, No.6, pp. 417 - 428, 1998.

82. McFadden P. and Smith J.: Model for the vibration produced by a single point defect in a rolling element bearing, Journal of Sound and Vibration, Vol. 96, pp. 69 - 82, 1984.

83. McFadden P. D. and Smith J. D.: Vibration monitoring of rolling element bearings by the high-frequency resonance technique—a review, Tribology International, Vol. 17, No. 1, pp. 3 - 10, 1984.

84. McFadden, P. and Smith, J.: A signal processing technique for detecting local defects in a gear from a signal average of the vibration, Proceedings of Institution of Mechanical Engineers, Vol. 199, No. C4, pp. 287-292, 1985.

85. Musso, C., Oudjane, N., and Le Gland, F.: Improving Regularised Particle Filters, in Sequential Monte Carlo Methods in Practice, New York, NY, Springer-Verlag, 2001.

86. Ng K. and Edward J.: New models for real-time tracking using particle filtering, Proceedings of SPIE Electronic Imaging, San Jose, CA, 2009.

87. Niizeki S.: Ceramic bearing for special environments, NSK Journal of Motion and Control, No. 8, pp. 17 - 22, 2000.

88. Niu G., Singh S., Holland S. W. and Pecht M.: Health monitoring of electronic products based on mahalanobis distance and Weibull decision metrics, Microelectronics Reliability, Vol.51, No. 2, pp. 279 - 284, 2011.

89. Ocak H., Loparo K.A. and Discenzo F.M.: Online tracking of bearing wear using wavelet packet decomposition and probabilistic modeling: a method for bearing prognostics, Journal of Sound and Vibration, Vol. 302, No. 4-5, pp. 951 - 961, 2007.

90. Ohta H. and Kobayashi K.: Vibrations of hybrid ceramic ball bearings, the Japan Society of Mechanical Engineers, Vol. 61, No. 589, pp. 4736 - 4743, 1995.

91. Oppenheimer C.H., Loparo K.A.: Physically based diagnosis and prognosis of cracked rotor shafts, Proceedings of SPIE Component and Systems Diagnostics, Prognostics, and Health Management II, pp.122 - 132, Bellingham, WA, 2002.

92. Orchard, M. E. & Vachtsevanos, G. J.: A particle-filtering approach for on-line fault diagnosis and failure prognosis, Transactions of the Institute of Measurement and Control, Vol. 31, No.3, pp. 221 - 246, 2011.

93. Orchard, M.: On-line Fault Diagnosis and Failure Prognosis Using Particle Filters. Theoretical Framework and Case Studies, VDM Verlag Dr. Müller Aktiengesellschaft and Co. KG, Saarbrücken, Germany, 2009.

94. Orchard, M., and Vachtsevanos, G.: A particle filtering-based framework for real-time fault diagnosis and failure prognosis in a turbine engine, 15th Mediterranean Conference on Control and Automation – MED'07, Athens, Greece, 2007.

95. Orchard, M., Kacprzynski, G., Goebel, K., Saha, B., and Vachtsevanos, G.: Applications of Intelligent Control to Engineering Systems, Dordrecht, Netherlands, Springer, 2009.

96. Orchard, M., Tobar, F., and Vachtsevanos, G.: Outer feedback correction loops in particle filtering-based prognostic algorithms: statistical performance comparison, Studies in Informatics and Control, Vol. 18, No. 4, pp. 295 - 304, 2009.

97. Orchard, M., Wu, B. and Vachtsevanos, G.: A particle filtering framework for failure prognosis, Proceedings of WTC2005, World Tribology Congress III, WA D.C., USA, 2005.

98. Orsagh R., Roemer M. and Sheldon J.: A comprehensive prognostics approach for predicting gas turbine engine bearing life, Proceedings of the 10th National Turbine Engine High Cycle Fatigue Conference, New Orleans, LO, 2004.

99. Orsagh R.F., Sheldon J., and Klenke C.J.: Prognostics/Diagnostics for gas turbine engine bearings, Proceedings of the IEEE Aerospace Conference, Vol. 7, pp.3095 - 3103, Big Sky, MT, March, 2003.

100. Paris P.C. and Erdogen F.: A critical analysis of crack propagation laws, Journal of Basic Engineering, Vol. 85, pp. 528 - 534, 1963.

101. Patrick R., Orchard, M., Zhang, B., Koelemay, M., Kacprzynski, G., Ferri, A., and Vachtsevanos, G.: An integrated approach to helicopter planetary gear fault diagnosis and failure prognosis, 42nd annual Systems Readiness Technology Conference, AUTOTESTCON 2007, Baltimore, MA, 2007.

102. Pecht, M. G.: Prognostics and Health Management of Electronics, New York, NY, Wiley, 2008.

103. Pérez P., Vermaak J., and Blake A.: Data fusion for visual tracking with particles, Proceedings of the IEEE, Vol. 92, No. 3, pp. 495–513, 2004.

104. Pusey H. C., Roemer M.J.: An assessment of turbo machinery condition monitoring and failure prognosis technology, The Shock and Vibration Digest, Vol.31, No.5, pp. 365 - 371, 1999.

105. Qiu H., Lee J., Lin J. and Yu G.: Robust performance degradation assessment methods for enhanced rolling element bearing prognostics, Advanced Engineering Informatics, Vol. 17, No. 3-4, pp. 127 - 140, 2003.

106. Qiu J., Set B.B., Liang S.Y., and Zhang C.: Damage mechanics approach for bearing life time prognostics, Mechanical Systems and Signal Processing, Vol. 16, No.5, pp. 817 – 829, 2002.

107. Rao M., Srinivas J., Raju V. and Kumar K.V.S.: Coupled Torsional-Lateral vibration analysis of geared shaft systems using mode analysis, Journal of Sound and Vibration, Vol. 261, No.2, pp. 359 - 364, 2003.

108. Rao T.: On the theory of bilinear models, Journal of the Royal Statistical Society, Series B, Vol. 43, No., pp. 244 - 255, 1981.

109. Rhoads M. and Bashyam M.: Engine Hybrid Ceramic Bearings, WL–TR–95–4081, Wright Patterson AFB, OH, 1994.

110. Roemer M. and Sheldon J.: A Comprehensive Prognostics Approach Predicting Gas Turbine Engine Bearing Life, Impact Technologies Report, Impact Technology LLC., Rochester, NY.

111. Ross, S.M.: Introduction to Probability Models, San Diego, CA, Academic Press, 1989.

112. Saha B. and Goebel K.: Modeling Li-ion battery capacity depletion in a particle filtering framework, Annual Conference of the Prognostics and Health Management Society, San Diego, CA, 2009.

113. Saha, B., Goebel, K., Poll, S., and Christophersen, J.: Prognostics methods for battery health monitoring using a Bayesian framework, IEEE Transactions on Instrumentation and Measurement, Vol. 58, No. 2, pp. 291 - 296, 2009.

114. Samanta B., Al-Balushi K. R. and Al-Araimi S. A.: Artificial neural networks and genetic algorithm for bearing fault detection, Soft Computing, Vol. 10, No. 3, pp. 264 - 271, 2006.

115. Sanjeev M.A., Maskell S., Gordon N. and Clapp T.: A tutorial on particle filterings for online nonlinear/non-Gaussian Bayesian tracking, IEEE Transactions on Signal Processing, Vol. 50, No. 2, pp. 174 - 188, 2002.

116. Schomig A. and Rose O.: On the suitability of the Weibull distribution for the approximation of machine failures, Proceedings of the Industrial Engineering Research Conference, Portland, OR, 2003.

117. Shao Y. and Nezu K.: Prognosis of remaining bearing life using neural networks, Proceedings of the Institution of Mechanical Engineers, Systems and Control Engineering, Vol. 214, No. 3, pp.217 - 230, 2000.

118. Shin H.J., Eom D.H. and Kim S.S.: One-class support vector machines—an application in machine fault detection and classification, Computers & Industrial Engineering, Vol. 48, No. 2, pp. 395 - 408, 2005.

119. Sohn H., Farrar C. R., Hemez F. M., Shunk D. D., Stinemates D. W., and Nadler B. R.: A Review of Structural Health Monitoring Literature: 1996-2001, Los Alamos National Laboratory Report, LA-13976-MS, 2004.

120. Spengler M. and Schiele B.: Toward robust multi-cue integration for visual tracking, International Workshop Computer Vision Systems, Vancouver, BC, Canada, 2001.

121. Stoneburner M.: Hybrid Ceramic Bearings: More Mettle than Metal, Applied Industrial Technologies Corporation, Cleveland, OH, 2005.

122. Sun B. and Ma J.: Comparison of system reliability models for electronics, the Annual of Aeronautics & Astronautics Science and Technology for Ph. D (in Chinese), pp. 122 – 129, Beijing, China, June, 2006.

123. Sunnersjo C.S.: Rolling bearing vibrations—the effects of geometrical imperfections and wear, Journal of Sound and Vibration, Vol. 98, No. 4, pp. 455 - 474, 1985.

124. Takebayashi H.: Bearings for extreme environments - part 3, basic performance of ceramic (silicon nitride) bearings, KOYO Engineering Journal English Edition, No. 158E, 2001.

125. Tong H. and Lim S.: Threshold auto-regression, limited cycles and cyclical data, Journal of the Royal Statistical Society, Series B, Vol. 42, No. pp. 245 - 292, 1980.

126. Tse P. and Atherton D.: Prediction of machine deterioration using vibration based fault trends and recurrent neural networks, Transactions of the ASME: Vibration and Acoustics, Vol. 121, No.3, pp. 355 - 362, 1999.

127. Tse P., Peng Y., and Yam R.: Wavelet analysis and envelope detection for rolling element bearing fault diagnosis - their effectiveness and flexibilities, Journal of Vibration and Acoustics, Vol. 123, No.3, pp. 303 - 310, 2001.

128. Vachtsevanos G., Lewis F., Roemer M., Hess A., and Wu B.: Intelligent Fault Diagnosis and Prognosis for Engineering Systems, Hoboken, NJ, Wiley, 2006.

129. Wackerly, D., Mendenhall, W. and Scheaffer, R.: Mathematical Statistics with Applications, Belmont, Buxbury Press, 1996.

130. Wang L., Snidle R.W. and Gu L.: Rolling contact silicon nitride bearing technology, Wear, Vol. 246, No. 1, pp. 159 - 173, 2000.

131. Wang P. and Vachtsevanos G.: Fault prognostics using dynamic wavelet neural networks, Artificial Intelligence for Engineering Design, Analysis and Manufacturing, Vol. 15, No.4, pp. 349 - 365, 2001.

132. Wang W. Q., Golnaraghi M. F., and Ismail F.: Prognosis of machine health condition using neuro-fuzzy systems, Mechanical Systems and Signal Processing, Vol. 18, No. 4, pp. 813 - 831, 2004.

133. Wang W.: A model to predict the residual life of rolling element bearings given monitored condition information to date, IMA Journal of Management Mathematics, Vol. 13, No.1, pp. 3 - 16, 2002.

134. Wang W.: An adaptive predictor for dynamic system for easting, Mechanical Systems and Signal Processing, Vol. 21, No.6, pp. 809 - 823, 2007.

135. Wang W.J. and McFadden P.D.: Application of wavelets to gearbox vibration signals for fault detection, Journal of Sound and Vibration, Vol. 192, No.5, pp. 927 - 939, 1996.

136. Warrier S.G., Jarmon D.C. and Chin H.A.: Finite element analysis of the critical flaw size in hybrid silicon nitride bearing ball, Proceedings of ASME Turbo Expo 2000, No. 2000-GT-65, Munich, Germany, 2000.

137. Wemhoff, E., Chin, H., and Begin, M.: Gearbox diagnostics development using dynamic modeling, AHS 63rd Annual Forum, Virginia Beach, VA, 2007.

138. Wereszczak A.A., Wang W., Wang Y.: Hadfield M.K., Kirkland W. T.P. and Jadaan M., Rolling Contact Fatigue of Ceramics, ORNL/TM-2006/521 Report, 2006.

139. Westwick-Farrow: Predictive/preventive maintenance, http://www.inmotiononline.com.au/inmotion/latest_news/article.asp?id=7611, 2006

140. Wren C., Azarbayejani A., Darrell T., and Pentland A.: Real-time tracking of the human body, IEEE Transaction Pattern Annual Machine Intelligence, Vol. 19, No.7, pp. 780 - 785, 1997.

141. Xie J.: Proposal for Developing a Physics-of-Failure-Based Reliability Prediction Methodology for Electronic Devices, CALCE Electronic Products and Systems Center, University of Maryland, College Park, MD, USA, 2004.

142. Yam R.C.M., Tse P.W., Li L., and Tu P.: Intelligent predictive decisions support system for CBM, The International Journal of Advanced Manufacturing Technology, Vol. 17, No.5, pp. 383 - 391, 2001.

143. Yan J., Koç M. and Lee J.: A prognostic algorithm for machine performance assessment and its application, Production Planning and Control, Vol. 15, No.8, pp. 796 - 801, 2004.

144. Zakrajsek, J.: An Analysis of Gear Fault Detection Method as Applied to Pitting Fatigue Failure Damage, NASA Technical Memorandum 105950, 1993.

145. Zaretsky E.V.: Tribology for aerospace applications, Society of Tribologists and Lubrication Engineers, Park Ridge, IL, 1997.

146. Zhang B., Sconyers C., Patrick R., and Vachtsevanos G.: A multi-fault modeling approach for fault diagnosis and failure prognosis of engineering systems, Annual Conference of the Prognostics and Health Management Society, San Diego, CA, 2009.

147. Zhang S., Ma L., Sun Y., and Mathew J.: Asset health reliability estimation based on condition data, Proceedings of the 2nd WCEAM and the 4th ICCM, pp. 2195 - 2204, Harrogate, UK, 2007.

148. Zhang X., Xu R., Kwan C., Liang S.Y., Xie Q., and Haynes L.: An integrated approach to bearing fault diagnostics and prognostics, Proceedings of American Control Conference, pp. 2750 - 2755, Portland, OR, 2005.

149. Zhang, B., Georgoulas, G., Orchard, M., Saxena, A., Brown, D., Vachtsevanos, G., and Liang, S.: Rolling element bearing feature extraction and anomaly detection based on vibration monitoring, 16th Mediterranean Conference on Control and Automation – MED'08, Ajaccio, Corsica, France, 2008.

150. Zhang, B., Sconyers, C., Byington, C., Patrick, R., Orchard, M., and Vachtsevanos, G.: A probabilistic fault detection approach: application to bearing fault detection, IEEE Transactions on Industrial Electronics, Vol. 58, No. 5, pp. 2011 - 2018, 2011.

151. Zio, E. and Peloni, G.: Particle filtering prognostic estimation of the remaining useful life of nonlinear components, Reliability Engineering and System Safety, Vol. 96, pp. 403 - 409, 2011.

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RESEARCH INTERESTS

Operations Research and Statistics
System Reliability Analysis and Modeling
Equipment Health Monitoring, Diagnosis, and Prognosis
Mechanical System CBM
Electronic Component Failure Analysis and Testing Design

WORK EXPERIENCE

The Academy of China Aerospace Times Electronics Corporation
Aug., 2002 –Aug., 2005

TEACHING EXPERIENCES

Sep, 2011- Dec., 2011	Teaching Assistant of – Work Productivity Analysis
Jan., 2011- May, 2011	Teaching Assistant of – Facilities Planning
Sep., 2009- Dec., 2009	Teaching Assistant of – Probability and Statistics for Engineers
Jan., 2010- May, 2010	Teaching Assistant of – Numerical Method in Mechanical Engineering

MAIN PROJECTS

Aug.,2009-Dec.,2011	Online Nonlinear/Non-Gaussian Bayesian Tracking: Rotating Mechanical System Diagnosis and Remaining Useful Life Prediction by Particle Filter Methodology
Aug.,2009-Sep.,2010	Study of a Novel Configuration-driven Data Mining Framework for Health and Usage Monitoring Systems
Jan.,2010-Oct.,2011	Study of an Integrated Prognostics Methodology with An Application to Hybrid Ceramic Bearing Life Prediction

Sep.,2010-Mar.,2011	Algorithm Study for Lithium-ion Battery Life Prediction with Particle Filtering Framework
Jan.,2011-Aug.,2011	The Remaining Useful Life Prediction of Gearbox by Integrating Oil Debris and Vibration Feature
Jan.,2011-May,2011	Optimum Layout Design of the Loading Dock at the Production Line of Caterpillar Co. Ltd
Sep.,2009-Aug.,2011	Instruct Three Undergraduate Students at University of Illinois at Chicago for Graduation Projects: Modal Testing and Analysis
Jan.,2006-Oct.,2008	ESD Failure Mechanism Analysis of IC by Simulation and Experiment
Apr.,2007-Aug.,2007	CPU Failure and Reliability Analysis for HAIER Washing Machine
Jan.,2006-Oct.,2007	Flow and Case Analysis of PHM for Technical Framework and Process Flow of Prognostic Health Management System (Fundamental Research for National Defense)
Sep.,2005-Dec.,2007	Responsible for Failure Analysis of 12 Electronic Components
Jan.,2006- Oct.,2007	Responsible for the ESD Failure Mode Characteristics, Mechanisms Research of the Identification and Selection Methods for High Reliability Components (Fundamental Research for National Defense).
Sep.,2005-Sep.,2006	The Development of Methodology for On-line Health Monitoring and Prognostic.

INTERNSHIP AND VOLUNTEER EXPERIENCE

Apr., 2010	Assistant for the 2010 IEEE International Conference on Networking, Sensing and Control
Sep., 2009-Dec.,2011	Research Assistant for Intelligent Systems Modeling & Development Laboratory
Aug.,2006–Aug.,2007	RelEng Technologies Corporation
Sep., 2005–Aug., 2007	AVIC1 Reliability Technology and Management Center

PUBLICATIONS

[1] David He, Eric Bechhoefer, **Jinghua Ma**, and Ruoyu Li, Particle Filtering Based Gear Prognostics Using One-Dimensional Health Index, Annual Conference of the Prognostics and Health Management Society, 2011.

[2] A Novel Configuration-Driven Data Mining Framework for Health and Usage Monitoring Systems, David He, Eric Bechhoefer, Mohammed Al-Kateb, **Jinghua Ma**, Pradnya Joshi and Mahindra Imadabathuni, ISBN: 978-953-307-547-1, Publisher: InTech, Publishing date: January 2011.

[3] M. Dalal, **J. Ma**, and D. He, Lithium-ion battery life prognostics health management system using particle filtering framework, pp 81-90, Vol 225, Issue 1, March 2011 ISSN 1748-006X.

[4] **Jinghua Ma**, David He, 2010, Development of Integrated Prognostics: An Application to Hybrid Ceramic Bearing Life Prediction, 2010 International Conference On Circuit and Signal Processing, pp.10-13.

[5] Ruoyu Li, **Jinghua Ma**, Arvind Panyala and David He, 2010, "Hybrid Ceramic Bearing Prognostics using Particle Filtering", 2009 Conference of The Society For Machinery Failure Prevention Technology, Huntsville, Alabama.

[6] David He, Arvind Panyala, Ruoyu Li, and **Jinghua Ma**, 2010, "The Use of Vibration Signals for Ceramic Bearing Prognostics", Proceedings of the 2010 Industrial Engineering Research Conference, Cancun, Mexico, June 5 – 9.

[7] **Jinghua Ma**, 2006, "Methodology for Health Monitoring and Prognostic for Electronic Products", The Annual Reliability of China Aeronautics Association, pp. 325 - 333.

[8] Bo Sun, **Jinghua Ma**, 2006,"Comparison of system reliability models for electronics", The Annual of Aeronautics & Astronautics Science and Technology for PHD, pp. 122 - 129.

PATENTS

Patent: "The Implementation Approach of a Digital Image Difference for a Specific Image Deforming".

HONORS & AWARDS

Awarded $1500 by the Prognostics and Health Management (PHM) Society to make a presentation in the 2010 PHM Society Doctoral Consortium at the 2010 PHM Conference, Portland, Oregon, October 10, 2010

"Excellent Scientific Paper", Aug., 2006, China Reliability Society

"Excellent Undergraduate Thesis", Beihang University, Jun., 2002

"Excellent Graduate Student", National Defense, Jul., 2002

"Guanghua Scholarship", Beihang University, Oct., 2001

"Renmin Scholarship", Beihang University, Oct., 1999

"Excellent Student Leader", Beihang University, Oct., 1999