International Journal of Industrial Engineering & Supply Chain Management, Vol. 6, Issue 1, (2019) 38-61

University of Hormozgan

International Journal of Industrial Engineering & Management Science

Journal homepage: www.ijiems.com

Prognostics and Health Management in Machinery: A Review of Methodologies for RUL prediction and Roadmap

Saeed Ramezani[a], Alireza Moini [b,*], Mohamad Riahi[c]

[a,b] Department of Industrial Engineering, Iran University of Science and Technology, Tehran, Iran
[b] Department of Mechanical Engineering, Iran University of Science and Technology, Tehran, Iran

Keywords:

Prognostics and Health Management
Model-based approaches
Data-driven approaches
Remaining useful life
Condition Based Maintenance

ABSTRACT

By the advent of maintenance science, Prognostics and Health Management has gradually penetrated into all the domains of engineering equipment. Machinery prognostics is one of the major tasks in condition based maintenance (CBM), which aims to predict the remaining useful life (RUL) of machinery based on condition information. Costly repairing strategies and Preventive Maintenance are increasingly replaced by modern strategies such as PHM. This strategy, generally, consists of functional modules: data acquisition, data processing, feature extraction/selection, health assessment, diagnosis and prognosis. Although many different methods have been developed in the literature and implemented in different applications for each of the above modules, there is still a need for a comprehensive approach in this matter. This paper attempts to review recent studies in diagnosis and prognostics, as well as data-driven, model-based and hybrid approaches. Finally, the paper provides discussions on current situation of PHM and a roadmap for future trends for researchers in this field is presented.

1- Introduction

These days, advanced tools such as sensors, Metrics, controllers, and computer devices are used to diagnose the advances machines. Sophisticated diagnosis approaches are applied to determine the root cause of machine failures. Diagnosis is a passive method among maintenance decisions and it focuses on failures that have already been occurred and therefore, it cannot prevent the failures of machines and their costly consequences. In order to decrease maintenance costs and maximize the availability of machines, maintenance approaches should be subject to proactive method. In other words, maintenance strategies should follow prognosis-preventive approaches rather than traditional failure repairing ones. Prognostics has been used in the field of maintenance in the past 10 years though most of its applications are related to Remaining Useful Life

(RUL), which covers only one aspect of Prognostics and Health Management (PHM). As an engineering method, the goal of PHM is to provide an integrated perspective of the state of the machine or the health of the whole system for the user.
PHM is a maintenance strategy for solving reliability problems that has recently drawn attentions regarding design complexities, and operational and environmental conditions. Diagnosis lies within the PHM and can be summarized as the process of identifying and determining the relationship between cases and effects of failures in performance of equipment. Prognostics can be interpreted to have the form of health assessment and prediction process that consists of identification of incipient failures and prediction of RUL. The main goal of prognostics is the prediction of an accident its possible occurrence, and therefore, time is a vital variable in the prognostics, whereas this variable has a less important role in diagnosing processes. Health management is a continuous process over time that provides appropriate maintenance actions accurate supply decisions based on the output of diagnosis and prognosis. Health management is focused on assessing as well as minimizing the impacts of failures.
Identification and decomposition of incipient failures of components, providing a tool for monitoring and predicting the failures, and finally, making it possible to establish a schedule for maintenance as well as asset management are expectations from an efficient PHM system. By implementing such system, the health state of a machine or its components in any point in time is specified, possible failures are predictable and preventable, and achieving the zero failure performance is possible. The unnecessary and costly Preventive Maintenance (PM) can be eliminated, maintenance schedule can be optimized, and waiting time of the spare parts and resources can be reduce; all of these lead to a significant saving in costs.

This paper investigates various approaches and techniques in the field of PHM and is organized as follows: in section 2, the transition from traditional methods and orientations to proactive methods and transition to PHM is verified. In section 3, the general target and main functional modules of PHM are introduced and their relation with RUL is investigated. Section 4 introduces three main approaches to PHM, including data-driven, model-based, and hybrid approaches. In section 5, by presenting a detailed table, recent researches in the field of PHM, from the type of approach point of view as well as functional modules are reviewed. In section 6, the relationship between uncertainty and PHM is considered and a road map for future studies is developed. Finally, conclusions are presented in section 7.

2- Transformation of maintenance and development of PHM

2-1- Background

Historically, the concept of PHM is first presented in medicals. Prognostics in the field of medicals is in the form of prediction of health state of the patient after the illness period that can be due to the natural trend or treatment (Abu-Hannah and Lucas 2001). Also, in industries, PHM was first introduced in the Department of Energy and Department of Defense. The major motivation of its implementation was the reduction of Operating and Support costs (O&S) of military and industries of USA simultaneously with increasing the availability of these systems. These days, many studies in the field of PHM, as a tool for providing advanced warning systems, have been conducted. Defense Advanced Research Projects Agency (DARPA) aims to develop self-aware systems. Applied research lab of Pennsylvania University has worked in the field of Condition Based Maintenance (CBM) as well as health monitoring of equipment for years. Society of Machinery Failure Preventions Technology (MFPT) hold annual meetings with the subject of PHM (Z. Chen, Yang, and Hu 2012). In the past 10 years, several prognosis methods have been developed. Analysis of vibration signal (C. S. Byington et al. 2009) and Analysis of Oil (Muir and Taylor 1997) have drawn attention due to their unique capability in describing machine performance. Other techniques such as temperature analysis, Acoustic Emission and Acousto-Ultrasonic techniques have been vastly developed (Tan, Irving, and Mba 2007). Sensor Fusion, due to its inherent excellence in combining and interpreting the data of several different sensors has been vastly used (Crow et al. 2007).

2-2-Transition from traditional methods to PHM

The concept and the target of PHM is adopted from known maintenance and diagnosis methodologies such as PM, Reliability Centered Maintenance (RCM) and CBM. PM is a time based maintenance strategy in which, maintenance schedule for the machine or component is based on mean time between failures (MTBF). This method assumes that the system operates under deterministic and static conditions and therefore, it cannot be implemented in dynamic systems that operate in various functional regimes. This method may lead to an inappropriate maintenance schedule that is not optimum. CBM consists of data acquisition and processing (condition monitoring) based on information resulted from maintenance decisions made, and therefore, prevents unnecessary maintenance actions. This method can be implemented in systems where first, it can be considered as a deterministic system in some aspects, second, it can be static, and third, appropriate health indicators can be derived from its signal variables.

If the system is not stochastic, a communicative model cannot simply be established between input variables and output indicators. Therefore, future behaviors of the system cannot be accurately predicted based on past observations nor domain knowledge. In such a situation that hidden uncertainty exists in the system, the application of RCM is more suitable. RCM focuses on the proper functioning capability of the system with expected reliability value in a certain period of time and uses statistical tools such as failure modes and effect criticality analysis (FMECA) to retrieve information that can aid the identification of failure modes. Since RCM relied on statistical estimations of expected service life, it can reduce the uncertainty and unplanned maintenance actions.

If the uncertainty is more complex, such as in dynamic systems that have variable behavior over time, robust design should be considered. In this scenario, instead of relying on inspection for quality assurance, resources should be allocated to design process. Therefore, product performance will have little sensitivity to changes in raw materials, manufacturing processes, and operation process, due to the process design.

Transformation map of maintenance is shown in figure 1 in which, different maintenance strategies in complex and non-deterministic systems are presented.

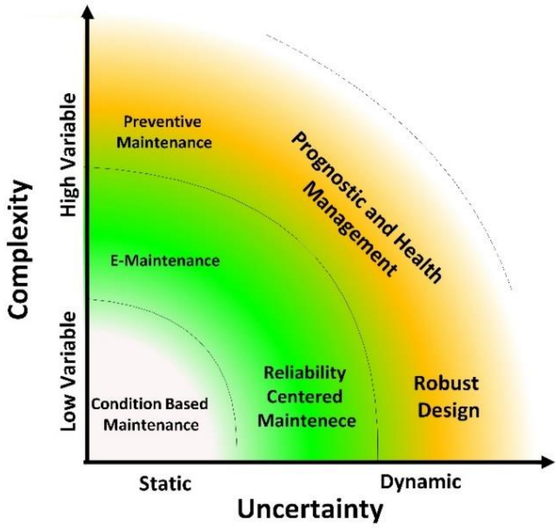

Figure 1: map of maintenance transformation

As shown figure 1, if the system is very complicated, as many variables such as vibration, velocity, stress, flow and … define its different aspects, eMaintenance is preferred over CBM. By using internet as well as communication technologies, eMaintenance is able to reach the zero failure performance. Moreover, by connecting to commercial-industrial systems, eMaintenance is able to line maintenance processes with business, production process, and asset management but if the complexity of the system is so high that only non-intrusive approaches can be applied, PM will be chosen.
During a workshop that was held by National Institute of Standard and Technology, in year 2002 (Andrew Hess, Stecki, and Rudov Clarck 2008) weaknesses related to application of traditional CBM methods were identified to be as the following:

- Inability to monitor the machines continually
- Inability to estimate the RUL accurately and reliably.
- Inability of maintenance systems to learning and identifying failures as well as to introducing the required reactions.

3- Target of PHM and functional modules

3-1- main layers and cycle of PHM

PHM can be referred to as a developed version of CBM. CBM techniques can provide input of prognostics in PHM. PHM relates studies of failure mechanisms (erosion, fatigue, extra loads, etc.) to life cycle management of the product. Regarding its ability to assess the health state as well as to predict the occurrence of failures, PHM can be considered to be basis of maintenance techniques in advanced fields.
The term PHM consists of two parts:

1. Prognostics that is referred to as extrapolation or prediction of the process with the aid of modeling the growth of failure based on assessing the current and the future operating conditions.
2. Health management that is referred to as maintenance activities and supplying actions, done in an intelligent manner based on the information of prognostics.

PHM is a novel maintenance strategy. It enables different industries to achieve their desired goals. Some of the key advantages of PHM are as follows:

- Higher availability and lower operational costs in order to optimize maintenance actions
- Improvement of system safety or prevention of undesirable effects
- Improvement of decision makings in order to increase the remaining service life of machines

PHM uses past, present, and future information in order to assess degradations, diagnosing failures, prognosis, and management of failures. PHM is described as to be the combination of seven balanced stages of open system architecture. These seven stages can be divided into three main layers: 1) Observation, 2) Analysis, and 3) Action.

- Observation
    1. Data acquisition: collecting appropriate data of condition monitoring (CM) and using the sensors.
    2. Data processing: data monitoring, eliminating noises, extracting and choosing appropriate analysis.
- Analysis
    3. Condition assessment: assessing current condition of the machine and determining the degradation level.
    4. Diagnosis: applying diagnosis techniques for discovering, categorizing, and recognizing the failures
    5. Prognosis: applying prognosis techniques for estimating RUL, and relevant confidence intervals.
- Action
    6. Decision support (offline): appropriate actions for maintenance and supply (quality of services), (online), system configuration (safety actions).
    7. Human machine interface: shows the relation between different stages such as prognosis with decision support and warnings.

In figure 2, PHM cycle is shown schematically (Lebold and Thurston 2001).

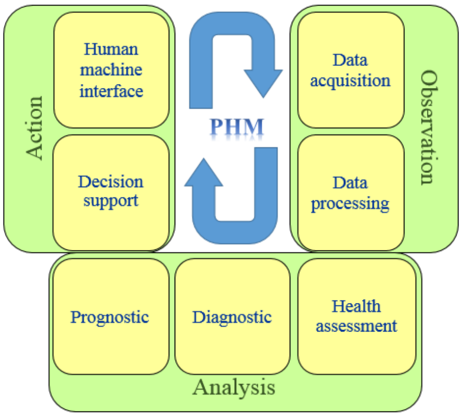

Figure 2: PHM cycle

2-3- Relation between prognostics and RUL

In the literature, several; definitions are presented for prognostics:

1. Ability of early identification of initial failure of component as well as having the tool and technology of managing and predicting the progression of that failure (Engele et al. 2000)

2. Predictive prognosis in a way that includes estimation of RUL or acceptable service life of the component (Anne Hess et al. 2006)
3. Predicting the future health condition based on assessing current health condition, past trends, and expected usage load of the equipment or the process in the future (Wu, Hu, and Zhang 2007)
4. Prognostics includes the prediction of system degradation based on the observed condition of the system (Luo et al. 2003)
5. Prediction of the RUL of the asset, its future conditions, or the end of life (EOL) risk (Heng et al. 2009).

In the above definitions, prediction of life cycle is a mutual concept. Also, International Organization for standardization has presented the following definition:

> Prognosis is the estimation of risk as well as time to failure of one or more present or future failure types (Tobon-meja et al. 2010).

In order to introduce RUL, consider the left side of figure 3 in which, for simplification, degradation is assumed to be a single dimension signal. In this case, after the identification of degradation (t_D), RUL is calculated as the time distance between current moment (t_c) and the moment (t_f) in which, the degradation signal is predicted to cross the failure threshold (FT). FT does not necessarily show the complete failure, but it shows a failure condition with the risk of losing the performance that occurs earlier than the EOL. Hence, RUL is defined based on relation (1):

$$RUL = t_f - t_c \tag{1}$$

Where t_f is the random variable of time to failure and t_c is the current time.

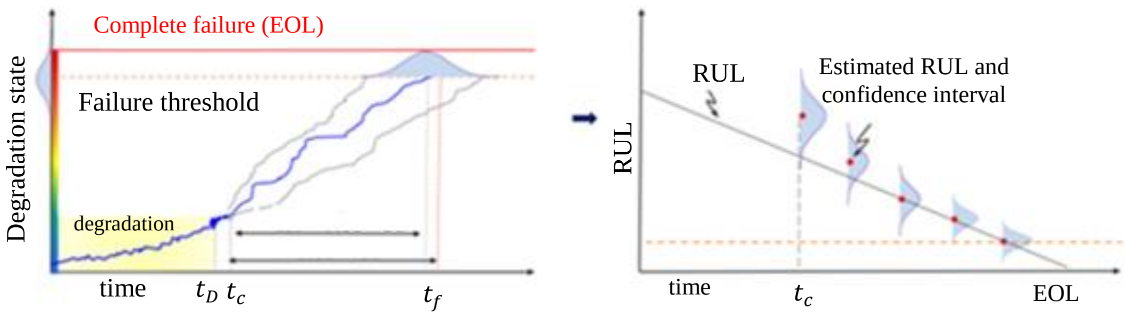

Figure 3: schematic presentation of prognosis and estimation of RUL

Due to the inherent uncertainty in degradation process, consideration of a confidence interval for the estimation is necessary. Therefore, decision making should be based on RUL confidence interval rather than RUL point estimation. There is an uncertainty in the determination of FT. the right side of figure 3 shows the conditions that are updated by obtaining new values for RUL.

4- PHM approaches

Current PHM approaches can be divided into three domains, called model-based, data-driven and hybrid approach. Model-based approach consists of generation of data from simulation models under nominal and degradation conditions (Gaspel et al. 2011). System RUL is predicted based on different functional condition. In a reliable or accurate model is not available, data-driven approaches are exerted. In this approach, failure progression pattern is verified and the time it takes to cross a predetermined threshold is predicted (Mosallam, Medjaher, and Zerhouni 2014).

Hybrid approach integrates the model-based and data-driven approaches and benefits from the advantages of both of them (J. Liu et al 2012).

4-1- model-based approach

Model-based approach, which is also called physics of failure and White Box model, describes the physics of system and failure modes using explicit mathematical relation. In this approach, unlike statistical techniques of reliability estimation, past performance data are not required. Predictions are made based on component specifications such as characteristics of materials, geometrical features, activation energy for degradation process, environmental stresses and etc. this approach is able to identify prevalent modes and mechanisms of failure. FMECA is the basis of this approach for identifying and prioritizing the degradation process (Varde and Pecht 2012).
A general form of model-based approach can be in the form of relation (2):

$$t_{50} = f(x_1, x_2, \dots, x_n) \tag{2}$$

, where t_{50} is the medium of life and x_i is a model parameter.
As an example, Paris model, which is a well-known crack growth model, is in the form of relation (3):

$$\frac{da}{dN} = C(\Delta K)^m, \qquad \Delta K = \Delta\sigma\sqrt{\pi a} \tag{3}$$

, where a is half of the length of the crack, N is the number of cycles, ΔK is the domain of intensity of stress, and the rest of the parameters are model constants that have a certain value. Crack growth and spall propagation (storm diffusion) are two of the well-known models. By combining knowledge of system mechanisms, failure growth model, and monitoring data, these models predict the state of the system.
Study of (Y. Li, Kurfess, and Liang 2000) considers the failure growth rate of rolling element bearing as well as the size of failure area using Paris formula. Reference (C. J. Li and lee 2005) uses the Paris formula to model the crack growth gearwheel. Reference (Oppenheimer and Loparo 2002) model the crack growth of rotor shaft using linear elastic failure of Foman. Although it is not possible to observe the size of failure area without a delay in machine operations, these models assume that the size of failure area can be directly estimated from vibration data. Reference 9Orsagh et al. 2004) use a random version of Yu-Harris equation of bearing life in order to estimate the initial values of spall propagation.
Model-based approach is suitable for situations where high accuracy is of great importance (e.g. in aircrafts). However, since choosing the right model is usually a hard task, it is not done in a proper manner because failure modes are different for different components. Moreover, knowledge related to system specifications such as material types and geometrical features may not be available (Javed 2014). In this case, model-based approach may not be appropriate due to the assumptions, errors, and uncertainties. For this reason, this method is combined with data-driven methods so that the model parameters are updated in an online manner.

4-2- data-driven approach

Data-driven approach can be considered as a Black Box that learns the behavior of the system directly from the collected state monitoring data (e.g. vibration, voice diffusion, force, and …). This approach is based on the assumption, according to which, statistical characteristics of system of the data are relatively deterministic unless the system operates improperly. Such methods convert raw data of state monitoring into appropriate information and system behavioral models (including degradation). Since these methods depends on data flow, they act powerfully in predicting the behavior of machines in near future, especially in their final years of life (Dawn An, Kim, and Choi 2015).

Data-driven approach is divided intor two parts: (1)Artificial Intelligence (AI) that itself, consists of Neural Networks (NN) (Ahmadzadeh and Lundberg 2013) and fuzzy logic (Silva et al. 2014); and (2)Statistical approach that includes Gaussian Process (GP) regression (Datong Lie et al. 2012), Support Vector Machine (Benkedjouh, Medjaher, Zerhouni, Rechak, et al. 2013), Least Squares Regression (Coppe, Haftka, and Kim 2011), Gama Process (Xiaolin Wang, Balakrishnan, and Guo 2013), Wiener Processes (X. S. Si et al. 2013), and Hidden Markov Model (Q. Liu and Dong 2012).

4-2-1- AI approach

NN can be labeled as the representative of AI methods. This algorithm, by retrieving inputs such as time, functioning conditions, and failure data, learns the quality of outputs such as level of degradation or life cycle. When NN learns adequately about the relationship between input and output, it can be used for diagnosis and prognosis. Input and output variables are shown by input and output layer nodes and the number of the nodes of the hidden layer should be chosen in a way that determines mechanisms of the connections between them appropriately. Since all the existing information can be considered as the input variable, determination of the number of input nodes is always a problem and usually, failure data is considered as the input. The next issue is the determination of weights and deviations. In NN, the complexity of relationship between input and output is not important and it is always possible to describe this relationship by increasing the nodes and hidden layers. Also, the uncertainties in data, which occur as a result of noise or deviations in data should be considered. Here, deviation is the error of measurement, taken by sensors (e.g. calibration error). This type of deviation cannot be verified by data-driven approaches since none of its parameters exist in the algorithm [24].

4-2-2- statistical approach

This approach, by fitting a stochastic model over collected data, and extrapolation of fitted curve in a way that exceeds the failure threshold, estimates the RUL. Similar to AI approach, this approach need adequate state monitoring data in order to learn degradation behavior of the machine. If in some cases, data is incomplete, this approach will have significant error though the nature of data is also important here. In reference [33] this approach is reviewed and categorized based on state monitoring data. Gaussian Process Regression is the most prevalent method amongst regression based methods in statistical approach.

In table 1, different methods in the model-based approach along with their advantages and limitations are presented.

Table 1. pros and cons of PHM method

Method	Pros.	Cons.
• 1) Reliability: uses event data (data related to history of failure times / replacement of units)		
Traditional reliability models (Weibull, Poisson, Exponential, …)	• Information of characteristics of the society makes long-term predictions viable • Does not require state monitoring	• Only provides general estimation for all units of population, which is not necessarily accurate for individual units.
• 2) PHM: uses data related to state monitoring (vibration, temperature, …)		
a) model-based approach	• If the physical model is consistent throughout the system, it can be fully accurate • Needs less amount of data compared to data-driven approach	• Physical models of actual life cycle are mostly stochastic and very complicated • They are limited to a certain failure type.
a.1) Paris formula in the crack growth model (Y. Li, Kurfess, & Liang, 2000)) ‹C. J. Li and Lee 2005)	• Least squares method provides the possibility of adaptation of the model parameters to changes in conditions	• It is assumed that failure area has linear correlation with vibration signal • Least squares method is similar to single step method in prediction of time series
a.2) Forman law in modeling the crack growth (Oppenheimer and Loparo 2002)	• Relates state monitoring as well as physics of crack growth to life cycle models	• Simplifying assumptions should be verified • For complicated situations, the model parameters should still be determined (e.g. pressure area of shaft and plastic areas)
a.3) spall propagation model (Orsagh et al. 2004)	• Calculated time to next storm as well as time from start to failure • Estimates cumulative failure from installation time, based on operational conditions	• Several parameters should be determined in the model.
b) data-driven approach	• Does not require experiential assumptions or estimations for physical parameters	• Usually requires large amount of accurate data
b.1) prediction of time series using NN (Ahmadzadeh and Lundberg 2013)	• Presents a quick analysis on multi-variable problems • Provides an appropriate planning for non-linear systems • Does not require initial knowledge	• Assumes that by crossing the predetermined threshold, failure occurs • Forecasting horizon is short-term • Assumes that state indicators describe the actual state of the system
b.2) fuzzy logic (Silva et al. 2014)	• Can be implemented for incomplete, noisy, and inaccurate data • Is more consistent with human processes, compared to other methods • Is suitable for complicated and unknown systems	• Not suitable for cases where calculation of membership function is complicated • It is possible that verbal expressions eliminate part of the accuracy of the model
b.3) Gaussian Process regression (Datong Liu et al. 2012)	• Can extract the hidden process from noisy data • Uses experience for learning	• Is not used for the cases where distribution of the considered feature is not similar to Gaussian
b.4) support vector machine (Benkedjouh, Medjaher, Zerhouni, Rechak, et al. 2013)	• Is suitable for high-volume data and instant analysis • In especial cases, due to maximization of decision boundaries, it has high accuracy	• There is no standard method for choosing the Kernel function, which is the main key of implementing support vector machine.
b.5) Hidden Markov model (Q. Liu and Dong 2012)	• Can be taught in a way that identifies all failure modes and states.	• The lack of a defined relationship between the change of health state and real failure progression points • The prediction depends on failure threshold.

4-3- Hybrid approach

This approach, by integrating model-based and data driven approaches, attempts to benefit from both of the approaches. The main idea behind hybrid approach is achieving a prognosis model in a way that is able to manage the uncertainties in order to accurately estimate RUL. (Javed 2014) divides this approach into two parts: series approach, and Parallel approach.

4-3-1- Series approach

Series approach, also known as systematic modeling approach, integrates the model-based approach that has prior knowledge of the process and the data-driven approach that is suitable for estimating unmeasurable parameters of the process. This approach is used in [27].

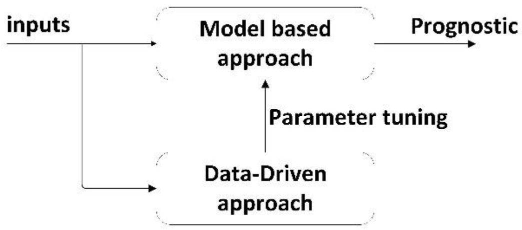

Figure 4: hybrid series approach

The series approach cannot be considered as a sole model-based approach because its parameters are adjusted using a data-driven method. In [36], the crack growth model is combined with Particle Filter method in a way that observed data is used to determine the model parameters. In [37], based on Particle Filter method, the spall propagation rate is predicted.

4-3-2- Parallel approach

Model-based approach uses the specific knowledge of the system while the data-driven approach uses state monitoring data for predictions. Both of these approaches has their own advantages and limitations. The hybrid approach attempts to benefit from the advantages of both of these models so that a more accurate output is obtained. The parallel approach uses a data-driven method to estimate the residuals that cannot be explained by the model-based approach.

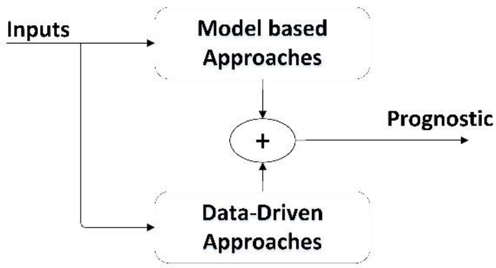

Figure 5: hybrid parallel approach

(Cheng and Pecht 2009) use hybrid approach for predicting the failure of multi-layer capacitators and (Pecht and Jaai 2010) propose a road map for electronic and information systems and show its application in assembling printed electronic cards.
In figure 6, different cateories of prognosis approaches are shown.

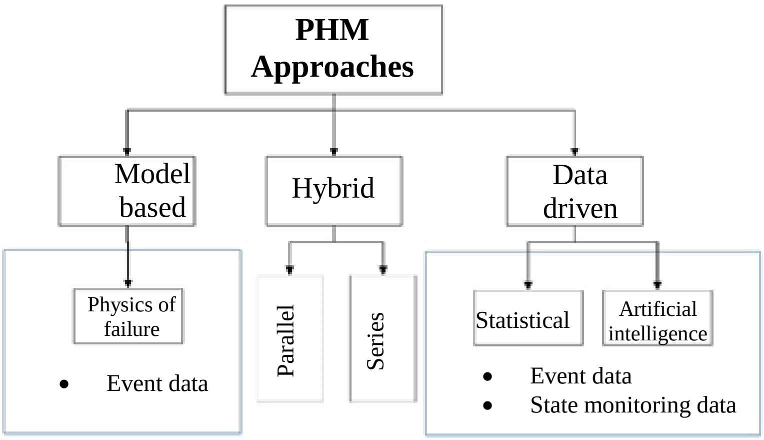

Figure 6: categorization of PHM approaches

5- Functional modules of prognostics algorithm

As previously mentioned, PHM consists of three performance layers: observation, analysis, and action. In details, these layers have several functional modules:

- Sensors and data acquisition: collecting and sorting useful data of machines for monitoring their states. This data can be divided into two types:
    1. Event data that includes events such as installation, failures, repairing, oil changing, and etc. acquiring some parts of this data is very costly.
    2. Condition monitoring data that is related to the health of system and includes a wide spectrum: sound, vibration, temperature, pressure, humidity, environmental conditions and …
- Signal processing: is a process in which, distortions and irrelevant data in a signal are eliminated and the signal take a condition under which, features are shown more clearly. This is done by methods such as Wavelet Transform, Fast Fourier Transform, and Empirical Mode Decomposition.
- Feature representation: Data obtained from signal processing, is rarely applicable due to its huge volume. Hence, presentation of data in the form of its features is a way to decrease its dimension. Depending on the data type of time domain analysis, frequency domain analysis, or time frequency domain, the feature representation module can be used.
- Feature extraction/selection: in this module, a small subset of all features that are obtained from previous stages is selected in a way that is necessary and adequate for describing the condition of the machine. By doing so, not only the categorization of failures is accelerated, but also the quality of diagnosis is improved. Eventually, these features will be used as inputs of diagnosis and prognosis. Various methods such as Principle Component Analysis (PCA) and
- Diagnosis: Diagnosis is used to analyze the trends that are set in the features, and to determine the root cause of failures and machine degradation. The applied methods in this step are Self-organizing Feature Map Neural Network (SOM), Support Vector Machine (SVM), Adaptive Neuro Fuzzy Integrated Systems (ANFIS), and …
- Health assessment: provides failure threshold or unacceptable performance levels for machine components in a way that appropriate maintenance operation is done prior to failure.
- Prognosis: includes estimation of RUL, reliability, and future condition of a machine based on assessing the trends of past data that have been analyzed in previous modules, which eventually results in prediction of failures and estimation of RUL.

- Auto-Regression Moving Average (ARMA), Dempster-Shafer Regression, SVM, and ANFIS are some of the methods that are used in this stage.

All of the above mentioned stages (modules) are provided in the form of a human machine interface that can be remotely controlled(Cassity, Aven, & Parker, 2012).
In table 1, conducted researches are broken down according to steps and methods.

Table 2. Categorization of conducted researches in the field of PHM according to steps and methods.

Ref.	Case study	D	M	Data Driven Data acquisition	Feature representation	Feature extraction	Diagnostic	Prognostic	Model base Physical model
(Tran & Yang, 2012)	Induction motor	●		Vibration	Mean, RMS, shape factor	ICA, Kernel ICA, PCA, Kernel PCA	W-SVM		
	Methane compressor	●		Acceleration (axial, vertical, horizontal)	RMS		SOM	SVM, PHM	
(Ahmadzadeh & Lundberg, 2013)	grinding mill liner	●		Metso mineral for wear measurement, Boliden mineral for affecting factors		PCA		FFBPNN	
(D. An, Choi, & Kim, 2012)	Aircraft panel		●	crack size				Bayesian inference, MCMC	
(Dawn An, Choi, & Kim, 2013)	Lithium-ion battery		●	capacity data				Particle filter	exponential growth model
	infinite plate		●	crack size				Particle filter	Paris model
(Dawn An, Kim, & Choi, 2015)	infinite plate		●	crack size				PF, Bayesian Method	Huang's model, Paris model
	infinite plate	●		crack size				NN, GP	-
(Babbar, Ortiz, Syrmos, & Arita, 2009)		●		Exhaust Gas Temperature (EGT), Oil Pressure	RMS, Mean, SD			Double Exponential Smoothing	
(Barad et al., 2012)	gas turbine engine	●		Vibrations, Pressures, temperatures, Speed of the rotor, Blade tip clearances, derived parameter	RMS levels, first order synchronous response			NN	
(Baraldi, Cadini, Mangili, & Zio, 2013)	Gas Turbine blade	●	●	Degradation info.				PF, bootstrap model	creep growth model
(Benkedjouh, Medjaher, Zerhouni, & Rechak, 2013)	Cutting tool	●		vibrations, force, acoustic emissions		EM-PCA, ISOMAP, wavelet packet decomposition (WPD)		SVR	
(Byington, Watson, & Bharadwaj, 2008)	gas turbine engine Accessory	●	●	Pump/ valve parameter	Mean, SD			double exponential smoothing	
(Caesarendra, Niu, & Yang, 2010)	Methane compressor		●	vibration				PF, Bayesian estimation	
(B. Chen, Matthews, & Tavner, 2013)	Wind turbine	●		Wind speed, rotor speed, blade angel, blade motor torque, power output			APK-ANFIS	SCADA Alarm	
(Z. Chen, Yang, & Hu, 2012)	Gearbox	●		Vibration			ED	EP	
(Cheng & Pecht, 2009)		●	●	Temperature, humidity			concept		
(Choi, An, Joo, & Kim, 2010)			●	Crack size				Bayesian	
(Coppe, Pais, Haftka, & Kim, 2012)	Finite plate, plate with hole		●	Crack size				Bayesian	Paris model
(Daigle & Goebel, 2011)			●	Crack size				PF	

(El-Koujok, Benammar, Meskin, Al-Naemi, & Langari, 2014)	Continuous-Flow Stirred-Tank Reactor (CFSTR)	●		inlet feed stream, temperature		Takagi–Sugeno	Multiple Sensor Fault Detection and Isolation (MSFDI)		
(Filev & Tseng, 2006)			●					fuzzy k-Nearest Neighbor clustering, Gaussian Mixture Model	
(Garga et al., n.d.)	Helicopter Gearbox	●	●	Vibration	RMS, kurtosis, crest factor, enveloping demodulation			NN, Expert sys, fuzzy logic	
(Gebraeel, Lawley, Liu, & Parmeshwaran, 2004)	Bearing	●		Vibration	RMS		Fuzzy C-mean clustering	NN	
(Greitzer et al., 1999)	Gas turbine	●		Temperature, pressure, leakage			NN	Linear regression	
(Gu, Azarian, & Pecht, 2008)	Ceramic	●		Temperature, humidity, bias				Regression residual detection and prediction analysis (RRDP), AR, ARIMA	
(D. He, Banerjee, & Bechhoefer, 2006)	helicopter rotor	●		Vibration, torque, speed, temperature				hidden semi-Markov model (HSMM)	
(W. He, Williard, Osterman, & Pecht, 2011)	lithium-ion batteries	●		Capacity				NLSR, EKF	
(Heng et al., 2009)	Centrifugal pump	●		Vibration	RMS			FFNN, Kaplan–Meier (KM)	
(Javed, Gouriveau, & Zerhouni, 2014)	Multiple benchmark test	●		Multiple input				SWELM	
(Javed, Gouriveau, & Zerhouni, 2013)	Turbo fan engine	●			26 features			SWELM, S-MEFC	
(Kumar, Torres, Chan, & Pecht, 2008)	Electronics product	●	●	Temperature, humidity, fan speed, …					FMMEA
(Lee, Ni, Djurdjanovic, Qiu, & Liao, 2006)	roller bearing			Vibration, oil	RMS, Kurtosis				PHM
(Lee et al., 2014)	alternator component	●		Vibration, energy, voltage,	54 feature: RMS, …		Logistic regression, SOM		
	airport chiller	●		OPC data, vibration			Wavelet Packet Analysis (WPA), Gaussian Mixture Model (GMM)		
	spindle bearing	●		Vibration			SOM		
	Engine	●		Operating, event, environmental, condition data				ARMA, BBN, fuzzy logic	
(D. Li, Wang, & Ismail, 2013)	Material fatigue	●		Relative voltage				enhanced fuzzy-filtered neural network, (EFFNN)	
(Y. G. Li & Nilkitsaranont, 2009)	Gas turbine	●		Temperature, pressure, fuel flow				Quadratic and linear regression	

(Lim & Mba, 2014)	Helicopter gearbox bearings	●		TRGB grease lubricated				Switching Kalman filter(SKF)	
(J. Liu, Wang, Ma, Yang, & Yang, 2012)	battery	●		Capacity				Fusion NN, NF, recurrent neural fuzzy (RNF), PF	
(Jie Liu, Saxena, Goebel, Saha, & Wang, 2010)	Lithium-ion Batteries	●		capacity				adaptive recurrent neural network (ARNN)	
(K. Liu, Gebraeel, & Shi, 2013)	aircraft gas turbine engine	●		Temp., press., core speed, fuel air ratio, …				Fusion, Exponential Function, …	
(Q. Liu & Dong, 2012)	hydraulic pump	●		Acceleration, flow discharge				HSMM by using sequential Monte Carlo (SMC)	
(Lu, Xiang, & Xu, 2014)	grinder	●		Force, acoustic		Wavelet transform		artificial immune algorithm	
(Medjaher, Moya, & Zerhouni, 2009)	pulley		●					Dynamic Bayesian Networks (DBN)	exponential
(Miao, Xie, Cui, Liang, & Pecht, 2013)	lithium-ion battery	●		capacity				unscented particle filter (UPF)	
(Moghaddass & Zuo, 2014)	turbofan engines	●				PCA		NHCTHSMP	
(Mohanty, Das, Chattopadhyay, & Peralta, 2009)	aluminum alloy		●	crack length				Gaussian Process	Bayesian Framework
(Niu & Yang, 2010)	methane compressor	●		vibration	RMS, envelop	SOM NN, wavelet decomposition		DSR, LS SVR	
(Niu, Yang, & Pecht, 2010)	Elevator motor	●		Vibration, current	14 feature: Mean, RMS,		SVM, LDA RFA, ART-KNN	DSR, LS SVM	
(M. E. Orchard & Vachtsevanos, 2007)	Planetary carrier plate		●	Crack length				Particle filter	Paris model
(M. Orchard & Vachtsevanos, 2007)	Turbine Engine		●	Crack length				Particle filter	
(M. J. J. Roemer & Kacprzynski, 2000)	Turbine blade						NN (Kohonen Map)		
(M. J. Roemer, Byington, & Rochester, 2007)	Turbine engine and bearing	●	●	Spall growth, vibro-acoustic	RMS, Kurtosis	FFT		Progression model	Spall initiation model
(Safizadeh & Latifi, 2014)	Bearing	●		Acceleration, load signal	10 parameter: RMS, Kurtosis, skewness, …		K-Nearest Neighbor (KNN)		
(Sankavaram et al., 2009)	Lithium-ion battery	●	●	Capacity, temp. CPU load, …		Wavelet transform	SVM	NN, time series, Markov model	Randles circuit
(Sarkar, Jin, & Ray, 2011)	aircraft gas turbine engines	●		Pressure, temp., speed, …			KNN		
(Si, Wang, Hu, Zhou, & Pecht, 2012)	Inertial Navigation Plat-form, Aluminum Alloy		●	Drift degradation, crack length					Nonlinear diffusion
(Silva et al., 2014)	PEM fuel cell	●		Voltage				ANFIS	

(Son et al., 2013)	automotive batteries		●	Degradation signal					DSPM, RDSPM, JPM
(Sotiris & Pecht, 2007)	Electronic product	●				PCA	SVC	SVR	
(J. Sun, Zuo, Wang, & Pecht, 2012)	gas turbine		●	degradation				Monte-Carlo	State space model
(Y. Sun, Ma, & Mathew, 2009)	Repairable system		●					Analytic Model for Interactive Failure (AMIF)	
(D. Liu, 2012)	Lithium-ion battery		●	State of health (EOH)					Gaussian process regression
(Tian, Jin, Wu, & Ding, 2011)	wind turbine components	●		Age value, condition monitoring				ANN	
(Tobon-Mejia, Medjaher, & Zerhouni, 2012)	CNC machine tool	●	●	Acceleration, AE emission			k-means	MoG-HMMs and DBN	
(Xiaolin Wang, Balakrishnan, & Guo, 2013)			●	Two fatigue crack length				bivariate gamma process	
(Xiaoxin Wang, Hu, & Zhang, 2014)	pneumatic conveying line	●		capacitive signals, electrostatic signals	Mean, RMS			ANFIS	
(Xu, Wang, & Xu, 2014)	Aircraft Engines	●	●	Temp., pressure, speed, …				SVM. RNN,	BM, DSR
(Xu & Xu, 2011)	avionics system	●	●	Time to failure data			FMMEA	SVM, FNN, ARMA	
(Yan, Liu, Han, & Qiu, 2013)	Wind power	●		Mean wind farm output				ORVM, GA-ANN	
(Zhao, Quan, & Cai, 2014)	Li-ion batteries	●		Remaining charge cycle (RCC)				Markov model	
(Zio & Di Maio, 2010)	Nuclear power plant	●		Temperature				Fuzzy logic modeling	

6- PHM and uncertainty

Uncertainty is the condition of having limited knowledge in which, accurate description of current or future state of the system is not possible. There are two sources of uncertainties: (1) Aleatory uncertainty, which is related to the inherent variation of the physical system under study and its environment, and is not due to the lack of information, and therefore, it cannot be reduced. This type is also known as variation or stochastic uncertainty. And (2) Epistemic uncertainty, which is due to the lack of information or incomplete information about the system and its environment. It is also known as subjective or deductible uncertainty (Lopez and Sarigul-Klijn 2010). In figure 7, sources of uncertainties are shown.

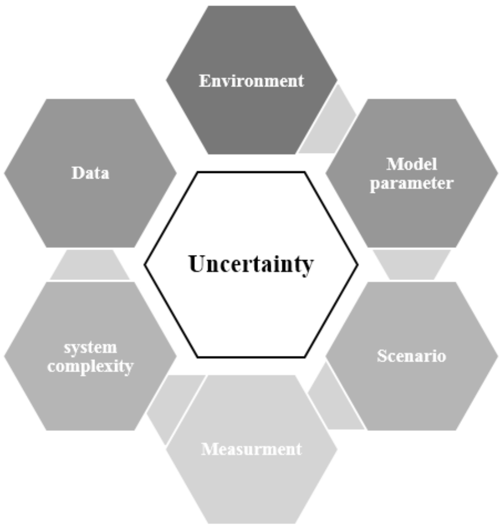

Figure 7. Sources of uncertainty and their analysis approaches

In practice, wear out process of machines in a dynamic environment is a complicated and frequently non-linear phenomena of usage, time, and environmental conditions (Uckun, Goebel, and Lucas 2008). State monitoring data (e.g. vibration, temeraure, humidity, pressure, etc) is usually noisy and due to the direct and indirect impacts of environmental conditions, hast high variation. In other words, prognosis of the machines, whether based on collected data, or degradation mechanisms, is under high levels of uncertainty. Available quantification methods of uncertainty in prognostics and RUL estimation is generally divided into two categories: 1) test-based prognotics, and (2) condition-based prognostics. The first category includes methods that perform the prognosis based on rigouros tests. Before or after the operation of a system. (offline). On the other hand, the second cateory perform the prognosis based on the performance of the system during the operation (online) (Sankararaman 2013).

Various references have focused on quantification of uncertainty in crack growth analysis (Sankararaman, Ling, and Mahadevan 2011), prediction of structural damage (Coppe et al. 2010), and mechanical bearings (Liao, Zhao, and Guo 2006), and they are categorized as the test-based prognosis approaches. Such an approach may be suitable for small components that have low-cost run to failure, but it is not viable for systems in larger scales. Quantification of uncertainty in prediction of RUL of batteries (Saha and Goebel 2008) and Pneumatic Valves (Daigle and Goebel 2010) are examples of researches that have been conducted in the performance monitoring approach. some of the researches have attepmted to quantify the uncertainty for online health monitoring by using Baysian filter, Kalman filter, and particle filter techniques. The main key in prognostics is the etimation of future degradation based on health state analysis and therefore, filtering techniques are not suitable for this matter since they estimate health state based on data (Sankararaman 2013).

7- Applicability to various case study

Different PHM approaches were discussed in the previous sections. Now the question is whether it is possible to implement a single prognostics model in multiple applications? The answer is definitely positive. Many of the prognostics methods have been developed in the past decades and they have been implemented in various systems. It should be mentioned that finding the best mathematical model for operators or craftsmen for prognosis is not a simple task.

Several applications of PHM are shown in the column related to case studies, in table 2.1. As an example, (B. Chen, Matthews, and Tavner 2013) propose a data-driven method for prognosis for failure of components of wind turbines (figure 8.a) using APK-ANFIS algorithm whose purpose is the automatic identification of failures related to pitch of gear, which is an important failure mode in wind turbines. (Javed 2013) use an improved data-driven model for prognosis of turbofan (figure 8.b). This model introduce a failure threshold for the system, and prediction of RUL is obtained by integrating Summation Wavelet Extreme Learning Machine (SWELM) and Subtractive-Maximum Entropy Fuzzy Clustering (S-MEFC) algorithms.

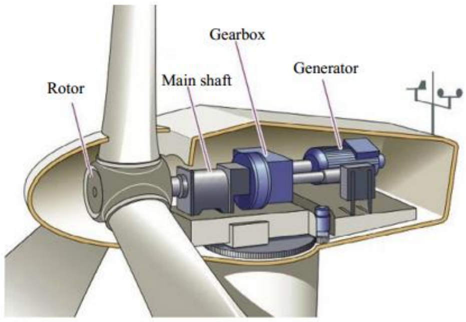

FIGURE 8.A. DRIVER SYSTEM OF WIND TURBINE

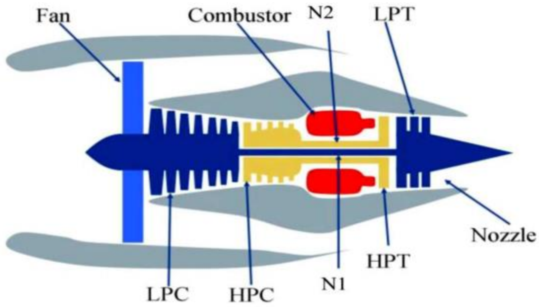

FIGURE 8.B. SIMPLIFIED DIAGRAM OF TURBOFAN

8- Arguments

In figure 9, the mega trend of expectations development of maintenance has shown schematically. In each phase specific strategies have used. Before 1950 maintenance strategies focused on repairing equipment after its failure, after that, need for higher accessibility derived industries to take action before failure happen and preventive maintenance come to the light. By implementing preventive maintenance higher up time and lower cost of maintenance achieved. At the late of 1970 health assessment of machines become attractive to implementer and condition based maintenance strategies developed. Although health assessment can project current statement of machines but it cannot predict future behavior of equipment. On the other hand, need for more safety, quality and accessibility and force for less cost and environmental impact urged practitioner to extend health assessment of equipment to future and modern strategies such as PHM, which be emerged lately.

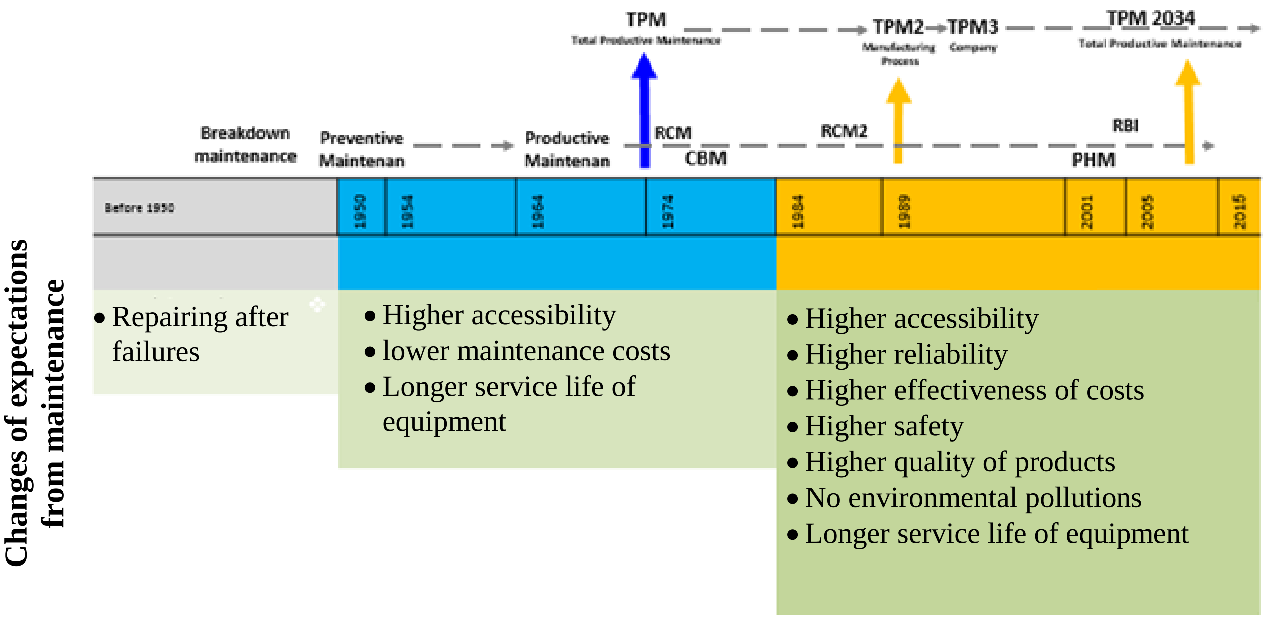

Figure 9. map of changes in expectations from maintenance

In figure 10, this mega trend excavates more elaborately and tools, techniques, advantage and disadvantage of each strategy discussed in detailed. By repairing failed equipment after failure, first generation of maintenance was easy schedule, even its better to say there is no schedule. No past and present data was available and due to this fail-fix approach, management of spare part ignored. In second generation, scheduling of maintenance action handled by time based approaches, which lead to unnecessary repairing action and spare part ordered only when it was needed but lead-time of supply for spare part was another problem. Condition based maintenance was a paradigm that based on data analysis in third generation of maintenance. It used well-known tool such as FMEA, FMECA, and FMMEA, which become a footstone of failure analysis techniques. In this era by using fast computer and expert system, costly and unpleasant failures prevented and management of spare part become more directed. Despite of all these improvement, the future behavior of systems was in ambiguous situation. Risk of production, losing of market sharing, heavy investment on equipment and dynamic environment put through practitioners to develop techniques, which have predict future behavior of systems. Prognostic and health management eventually emerged at the next millennium. It's a next generation class of maintenance approach which manage these risks, extend useful life, raise up safety and reliability, recline cost more and more, at the same time try to impact less on environment as possible. Zero based budgeting, zero environmental pollution, and near zero down time is manifest of this modern approach.

9- Conclusions

This paper attempts to comprehensively introduce, summarize, categorize, and review recent researches ion PHM. In this paper, recent researches in each of the functional modules of PHM were reviewed closely and step by step. By processing past and process monitoring data, PHM is able to predict future state and failure of the system, and provide appropriate warnings in the right time. Model-based approaches perform physical identification and modeling the degradation process of the system by identifying and separating vital parameters and failure modes, and prioritizing potential failure mechanisms. On the other hand, data-driven methods recognize and prognosticate by using process monitoring data, establishing health baseline, comparing parameters with the baseline, and identifying irregular cases. These two approaches has their own advantages and limitations, and they can be used based on the problem. Hybrid approaches, by simultaneous application of the two methods in the problem, attempt to overcome the limitations of each approach by accumulating their advantages and capabilities. These three approaches are carefully reviewed in the six following steps: parameter identification, data acquisition, feature representation, feature extraction/selection, diagnosis, and prognosis. Each of the functional modules was investigated the techniques that applied to it were introduced. Finally, regarding the increasing complexity and uncertainty of systems and development of maintenance procedures, a road map for future studies was presented.

References

Ahmadzadeh, F., & Lundberg, J. (2013). Remaining useful life prediction of grinding mill liners using an artificial neural network. *Minerals Engineering*, *53*, 1–8. https://doi.org/10.1016/j.mineng.2013.05.026

An, D., Choi, J.-H., & Kim, N. H. (2012). Identification of correlated damage parameters under noise and bias using Bayesian inference. *Structural Health Monitoring*, *11*(3), 293–303. https://doi.org/10.1177/1475921711424520

An, D., Choi, J. H., & Kim, N. H. (2013). Prognostics 101: A tutorial for particle filter-based prognostics algorithm using Matlab. *Reliability Engineering and System Safety*, *115*, 161–169. https://doi.org/10.1016/j.ress.2013.02.019

An, D., Kim, N. H., & Choi, J.-H. (2015). Practical options for selecting data-driven or physics-based prognostics algorithms with reviews. *Reliability Engineering & System Safety*, *133*, 223–236. https://doi.org/10.1016/j.ress.2014.09.014

Babbar, A., Ortiz, E. M., Syrmos, V. L., & Arita, M. M. (2009). Advanced diagnostics and prognostics for engine health monitoring. *IEEE Aerospace Conference Proceedings*, 1–10. https://doi.org/10.1109/AERO.2009.4839657

Barad, S. G. S. ., Ramaiah, P. ., Giridhar, R. ., Krishnaiah, G., P.V., R., R.K., G., & G., K. (2012). Neural network approach for a combined performance and mechanical health monitoring of a gas turbine engine. *Mechanical Systems and Signal Processing*, *27*, 729–742. https://doi.org/10.1016/j.ymssp.2011.09.011

Baraldi, P., Cadini, F., Mangili, F., & Zio, E. (2013). Model-based and data-driven prognostics under different available information. *Probabilistic Engineering Mechanics*, *32*, 66–79. https://doi.org/10.1016/j.probengmech.2013.01.003

Benkedjouh, T., Medjaher, K., Zerhouni, N., & Rechak, S. (2013). Health assessment and life prediction of cutting tools based on support vector regression. *Journal of Intelligent Manufacturing*, (Afnor 2005), 1–11. https://doi.org/10.1007/s10845-013-0774-6

Byington, C. S., Watson, M. J., & Bharadwaj, S. P. (2008). Automated Health Management for Gas Turbine Engine Accessory System Components. *2008 IEEE Aerospace Conference*, 1–12. https://doi.org/10.1109/AERO.2008.4526610

Caesarendra, W., Niu, G., & Yang, B.-S. (2010). Machine condition prognosis based on sequential Monte Carlo method. *Expert Systems with Applications*, *37*(3), 2412–2420. https://doi.org/10.1016/j.eswa.2009.07.014

Cassity, J., Aven, C., & Parker, D. (2012). Applying Weibull Distribution and Discriminant Function Techniques to Predict Damaged Cup Anemometers in the 2011 PHM Competition. *International Journal of Prognostics and Health Management*, *3*, 1–7.

Chen, B., Matthews, P. C., & Tavner, P. J. (2013). Wind turbine pitch faults prognosis using a-priori knowledge-based ANFIS. *Expert Systems with Applications*, *40*(17), 6863–6876. https://doi.org/10.1016/j.eswa.2013.06.018

Chen, Z., Yang, Y., & Hu, Z. (2012). A technical framework and roadmap of embedded diagnostics and prognostics for complex mechanical systems in prognostics and health management systems. *Reliability, IEEE Transactions on*, *61*(2), 314–322.

Cheng, S., & Pecht, M. (2009). A fusion prognostics method for remaining useful life prediction of electronic products. *… and Engineering, 2009. CASE 2009. IEEE …*, 102–107.

Choi, J., An, D., Joo, J., & Kim, N. H. (2010). Bayesian approach for parameter estimation in the structural analysis and prognosis. *Annual Conference on the Prognostics and Health Management Society 2010*, 1–8.

Coppe, A., Pais, M. J., Haftka, R. T., & Kim, N. H. (2012). Remarks on Using a Simple Crack Growth Model in Predicting Remaining Useful Life. *Journal of Aircraft*, *49*(6), 1965–1973. https://doi.org/10.2514/1.C031808

Daigle, M., & Goebel, K. (2011). Multiple damage progression paths in model-based prognostics. *IEEE Aerospace Conference Proceedings*. https://doi.org/10.1109/AERO.2011.5747574

El-Koujok, M., Benammar, M., Meskin, N., Al-Naemi, M., & Langari, R. (2014). Multiple sensor fault diagnosis by evolving data-driven approach. *Information Sciences*, *259*, 346–358. https://doi.org/10.1016/j.ins.2013.04.012

Filev, D. P., & Tseng, F. (2006). Real Time Novelty Detection Modeling for Machine Health Prognostics. *NAFIPS 2006 - 2006 Annual Meeting of the North American Fuzzy Information Processing Society*, 529–534. https://doi.org/10.1109/NAFIPS.2006.365465

Garga, A. K. a. K., Mcclintic, K. T., Campbell, R. L. R. L., Lebold, M. S. M. S., Hay, T. a. T. A., Byington, C. S. C. S. C. S., & Yang, C. (n.d.). Hybrid reasoning for prognostic learning in CBM systems. *2001 IEEE Aerospace Conference Proceedings (Cat. No.01TH8542)*, *6*, 2957–2969. https://doi.org/10.1109/AERO.2001.931316

Gebraeel, N., Lawley, M., Liu, R., & Parmeshwaran, V. (2004). Residual Life Predictions From Vibration-Based Degradation Signals: A Neural Network Approach. *IEEE Transactions on Industrial Electronics*, *51*(3), 694–700. https://doi.org/10.1109/TIE.2004.824875

Greitzer, F. L., Kangas, L. J., Terrones, K. M., Maynard, M. a, Wilson, B. W., Pawlowski, R. a, … Brown, N. B. (1999). Gas Turbine Engine Health Monitoring and Prognostics. *Current*, 1–7.

Gu, J., Azarian, M. H., & Pecht, M. G. (2008). Failure prognostics of multilayer ceramic capacitors in temperature-humidity-bias conditions. *2008 International Conference on Prognostics and Health Management, PHM 2008*, (C). https://doi.org/10.1109/PHM.2008.4711464

He, D., Banerjee, P., & Bechhoefer, E. (2006). Probabilistic Model Based Algorithms for Prognostics. *2006 IEEE Aerospace Conference*, 1–10. https://doi.org/10.1109/AERO.2006.1656122

He, W., Williard, N., Osterman, M., & Pecht, M. (2011). Prognostics of Lithium-ion Batteries using Extended Kalman Filtering. *IMAPS Advanced Technology Workshop on High Reliability Microelectronics for Military Applications*, 1–4.

Heng, A., Tan, a. C. C., Mathew, J., Montgomery, N., Banjevic, D., & Jardine, a. K. S. (2009). Intelligent condition-based prediction of machinery reliability. *Mechanical Systems and Signal Processing*, *23*, 1600–1614. https://doi.org/10.1016/j.ymssp.2008.12.006

Javed, K., Gouriveau, R., & Zerhouni, N. (2013). Novel failure prognostics approach with dynamic thresholds for machine degradation. *IECON 2013 - 39th Annual Conference of the IEEE Industrial Electronics Society*, 4404–4409. https://doi.org/10.1109/IECON.2013.6699844

Javed, K., Gouriveau, R., & Zerhouni, N. (2014). SW-ELM: A summation wavelet extreme learning machine algorithm with a priori parameter initialization. *Neurocomputing*, *123*, 299–307. https://doi.org/10.1016/j.neucom.2013.07.021

Kumar, S., Torres, M., Chan, Y. C., & Pecht, M. (2008). A hybrid prognostics methodology for electronic products. In *Proceedings of the International Joint Conference on Neural Networks* (pp. 3479–3485). https://doi.org/10.1109/IJCNN.2008.4634294

Lee, J., Ni, J., Djurdjanovic, D., Qiu, H., & Liao, H. (2006). Intelligent prognostics tools and e-maintenance. *Computers in Industry*, *57*, 476–489. https://doi.org/10.1016/j.compind.2006.02.014

Lee, J., Wu, F., Zhao, W., Ghaffari, M., Liao, L., & Siegel, D. (2014). Prognostics and health management design for rotary machinery systems—Reviews, methodology and applications. *Mechanical Systems and Signal Processing*, *42*(1–2), 314–334. https://doi.org/10.1016/j.ymssp.2013.06.004

Li, C. J., & Lee, H. (2005). Gear fatigue crack prognosis using embedded model, gear dynamic model and fracture mechanics. *Mechanical Systems and Signal Processing*, *19*(4), 836–846.

Li, D., Wang, W., & Ismail, F. (2013). Enhanced fuzzy-filtered neural networks for material fatigue prognosis. *Applied Soft Computing Journal*, *13*(1), 283–291. https://doi.org/10.1016/j.asoc.2012.08.031

Li, Y. G., & Nilkitsaranont, P. (2009). Gas turbine performance prognostic for condition-based maintenance. *Applied Energy*, *86*(10), 2152–2161. https://doi.org/10.1016/j.apenergy.2009.02.011

Li, Y., Kurfess, T. R., & Liang, S. Y. (2000). Stochastic prognostics for rolling element bearings. *Mechanical Systems and Signal Processing*, *14*(5), 747–762.

Lim, C. K. R., & Mba, D. (2014). Switching Kalman filter for failure prognostic. *Mechanical Systems and Signal Processing*, *52–53*, 426–435. https://doi.org/10.1016/j.ymssp.2014.08.006

Liu, D. (2012). Data-driven prognostics for lithium-ion battery based on Gaussian Process Regression. *Proceedings of the IEEE 2012 Prognostics and System Health Management Conference (PHM-2012 Beijing)*, 1–5. https://doi.org/10.1109/PHM.2012.6228848

Liu, J., Saxena, A., Goebel, K., Saha, B., & Wang, W. (2010). An Adaptive Recurrent Neural Network for Remaining Useful Life Prediction of Lithium-ion Batteries, 0–9.

Liu, J., Wang, W., Ma, F., Yang, Y. B., & Yang, C. S. (2012). A data-model-fusion prognostic framework for dynamic system state forecasting. *Engineering Applications of Artificial Intelligence*, *25*(4), 814–823. https://doi.org/10.1016/j.engappai.2012.02.015

Liu, K., Gebraeel, N. Z., & Shi, J. (2013). A Data-Level Fusion Model for Developing Composite Health Indices for Degradation Modeling and Prognostic Analysis. *IEEE Transactions on Automation Science and Engineering*, *10*(3), 652–664. https://doi.org/10.1109/TASE.2013.2250282

Liu, Q., & Dong, M. (2012). Online health management for complex nonlinear systems based on hidden Semi-

Markov model using sequential Monte Carlo methods. *Mathematical Problems in Engineering*, *2012*, 331–348. https://doi.org/10.1155/2012/951584

Lu, Z.-J., Xiang, Q., & Xu, L. (2014). An Application Case Study on Multi-sensor Data fusion System for Intelligent Process Monitoring. *Procedia CIRP*, *17*, 721–725. https://doi.org/10.1016/j.procir.2014.01.122

Medjaher, K., Moya, J.-Y., & Zerhouni, N. (2009). Failure prognostic by using dynamic Bayesian networks. *Dependable Control of Discrete Systems*, *2*, 257–262.

Miao, Q., Xie, L., Cui, H., Liang, W., & Pecht, M. (2013). Remaining useful life prediction of lithium-ion battery with unscented particle filter technique. *Microelectronics Reliability*, *53*(6), 805–810. https://doi.org/10.1016/j.microrel.2012.12.004

Moghaddass, R., & Zuo, M. J. (2014). An integrated framework for online diagnostic and prognostic health monitoring using a multistate deterioration process. *Reliability Engineering and System Safety*, *124*, 92–104. https://doi.org/10.1016/j.ress.2013.11.006

Mohanty, S., Das, S., Chattopadhyay, A., & Peralta, P. (2009). Gaussian Process Time Series Model for Life Prognosis of Metallic Structures. *Journal of Intelligent Material Systems and Structures*, *20*, 887–896. https://doi.org/10.1177/1045389X08099602

Niu, G., & Yang, B. S. (2010). Intelligent condition monitoring and prognostics system based on data-fusion strategy. *Expert Systems with Applications*, *37*(12), 8831–8840. https://doi.org/10.1016/j.eswa.2010.06.014

Niu, G., Yang, B. S., & Pecht, M. (2010). Development of an optimized condition-based maintenance system by data fusion and reliability-centered maintenance. *Reliability Engineering and System Safety*, *95*, 786–796. https://doi.org/10.1016/j.ress.2010.02.016

Orchard, M. E., & Vachtsevanos, G. J. (2007). A Particle Filtering Approach for On-Line Failure Prognosis in a Planetary Carrier Plate. *International Journal of Fuzzy Logic and Intelligent Systems*. https://doi.org/10.5391/IJFIS.2007.7.4.221

Orchard, M., & Vachtsevanos, G. (2007). A particle filtering-based framework for real-time fault diagnosis and failure prognosis in a turbine engine. *Control & Automation, 2007. …*.

Roemer, M. J., Byington, C. S., & Rochester, I. T. (2007). prognostic and health management software for gas turbin engine bearings. *Architecture*, 1–8. https://doi.org/10.1115/GT2007-27984

Roemer, M. J. J., & Kacprzynski, G. J. J. (2000). Advanced diagnostics and prognostics for gas turbine engine risk assessment. *2000 IEEE Aerospace Conference. Proceedings (Cat. No.00TH8484)*, *6*, 345–353 vol.6. https://doi.org/10.1109/AERO.2000.877909

Safizadeh, M. S., & Latifi, S. K. (2014). Using multi-sensor data fusion for vibration fault diagnosis of rolling element bearings by accelerometer and load cell. *Information Fusion*, *18*, 1–8. https://doi.org/10.1016/j.inffus.2013.10.002

Sankavaram, C., Pattipati, B., Kodali, A., Pattipati, K., Azam, M., Kumar, S., & Pecht, M. (2009). Model-based and data-driven prognosis of automotive and electronic systems. *2009 IEEE International Conference on Automation Science and Engineering, CASE 2009*, 96–101. https://doi.org/10.1109/COASE.2009.5234108

Sarkar, S., Jin, X., & Ray, A. (2011). Data-Driven Fault Detection in Aircraft Engines With Noisy Sensor Measurements. *Journal of Engineering for Gas Turbines and Power*, *133*(August 2011), 81602. https://doi.org/10.1115/1.4002877

Si, X.-S., Wang, W., Hu, C., Zhou, D.-H., & Pecht, M. G. (2012). Remaining useful life estimation based on a nonlinear diffusion degradation process. *IEEE Transactions on Reliability*, *61*(1), 50–67.

Silva, R. E., Gouriveau, R., Jemeï, S., Hissel, D., Boulon, L., Agbossou, K., & Yousfi Steiner, N. (2014). Proton exchange membrane fuel cell degradation prediction based on Adaptive Neuro-Fuzzy Inference Systems. *International Journal of Hydrogen Energy*, *39*, 11128–11144. https://doi.org/10.1016/j.ijhydene.2014.05.005

Son, J., Zhou, Q., Zhou, S., Mao, X., Salman, M., & Member, S. (2013). Evaluation and Comparison of Mixed Effects Model Based Prognosis for Hard Failure, *62*(2), 379–394.

Sotiris, V., & Pecht, M. (2007). Support vector prognostics analysis of electronic products and systems. *AAAI Fall Symposium on Artificial Intelligence for …*.

Sun, J., Zuo, H., Wang, W., & Pecht, M. G. (2012). Application of a state space modeling technique to system prognostics based on a health index for condition-based maintenance. *Mechanical Systems and Signal Processing*, *28*, 585–596. https://doi.org/10.1016/j.ymssp.2011.09.029

Sun, Y., Ma, L., & Mathew, J. (2009). Failure analysis of engineering systems with preventive maintenance and failure interactions. *Computers & Industrial Engineering*, *57*(2), 539–549. https://doi.org/10.1016/j.cie.2008.08.007

Tian, Z., Jin, T., Wu, B., & Ding, F. (2011). Condition based maintenance optimization for wind power generation systems under continuous monitoring. *Renewable Energy*, *36*, 1502–1509. https://doi.org/10.1016/j.renene.2010.10.028

Tobon-Mejia, D. a., Medjaher, K., & Zerhouni, N. (2012). CNC machine tools wear diagnostic and prognostic by using dynamic Bayesian networks. *Mechanical Systems and Signal Processing*, *28*, 167–182. https://doi.org/10.1016/j.ymssp.2011.10.018

Tran, V. T., & Yang, B. S. (2012). An intelligent condition-based maintenance platform for rotating machinery. *Expert Systems with Applications*, *39*(3), 2977–2988. https://doi.org/10.1016/j.eswa.2011.08.159

Wang, X., Balakrishnan, N., & Guo, B. (2013). Residual life estimation based on bivariate non-stationary gamma degradation process, (January 2015), 37–41. https://doi.org/10.1080/00949655.2013.824448

Wang, X., Hu, H., & Zhang, A. (2014). Concentration measurement of three-phase flow based on multi-sensor data fusion using adaptive fuzzy inference system. *Flow Measurement and Instrumentation*, *39*, 1–8. https://doi.org/10.1016/j.flowmeasinst.2014.04.003

Xu, J., Wang, Y., & Xu, L. (2014). PHM-oriented Integrated Fusion Prognostics for Aircraft Engines based on Sensor Data, *14*(4), 1124–1132.

Xu, J., & Xu, L. (2011). Health management based on fusion prognostics for avionics systems. *Journal of Systems Engineering and Electronics*, *22*(3), 428–436. https://doi.org/10.3969/j.issn.1004-4132.2011.03.010

Yan, J., Liu, Y., Han, S., & Qiu, M. (2013). Wind power grouping forecasts and its uncertainty analysis using optimized relevance vector machine. *Renewable and Sustainable Energy Reviews*, *27*, 613–621. https://doi.org/10.1016/j.rser.2013.07.026

Zhao, Z., Quan, Q., & Cai, K.-Y. (2014). A Profust Reliability Based Approach to Prognostics and Health Management. *IEEE Transactions on Reliability*, *63*(1), 26–41. https://doi.org/10.1109/TR.2014.2299111

Zio, E., & Di Maio, F. (2010). A data-driven fuzzy approach for predicting the remaining useful life in dynamic failure scenarios of a nuclear system. *Reliability Engineering and System Safety*, *95*(1), 49–57. https://doi.org/10.1016/j.ress.2009.08.001