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Review

Recent advances in prognostics and health management for advanced manufacturing paradigms

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ABSTRACT

Manufacturing paradigms have played their important roles in modern industry. In recent 20 years, production systems of advanced manufacturing paradigms (e.g. mass customization, reconfigurable manufacturing, sustainable manufacturing and service-oriented manufacturing) have been developed to exceed the traditional "mass production" paradigm. The reasons that make system health management especially difficult include individual machine deteriorations, different system structures, diverse production characteristics and exponential scheduling complexity. To address these gaps, we provide a review of the prognostics and health management (PHM) field focusing on prognostics approaches for asset health, and maintenance policies for more "informed" decisions. This paper addresses recent advances in PHM for advanced manufacturing paradigms to forecast health trends, avoid production breakdowns, reduce maintenance cost and achieve rapid decision-making. Furthermore, an in-depth look at future research interests is provided.

1. Introduction

The conception of prognostics and health management (PHM) was proposed from the Medical Science, and then be introduced into the Mechanical Science [27,51]. Like medical prognostics focuses on the prediction of potential diseases and the pre-treatment for patient health, PHM in the Mechanical Science aims to provide an integrated framework for degradation prediction and machinery maintenance. Specially, the contents in PHM have been studied a lot by integrating prognostics techniques and maintenance policies, such as condition based maintenance (CBM), predictive maintenance (PM) and on-condition maintenance (OM). Research focusing on accurate health predictions and efficient maintenance decisions in PHM field has been a very important research hotspot [15,100]. Over the past several decades, reliability engineering has covered many fields of research [13,37,96]. Yang et al. [124] reviewed condition monitoring for device reliability in power electronic converters. Jiang, Hong and Cui [41] introduced the advantages and disadvantages of degradation modeling, and then summarized the related research of degradation modeling. Our review does not cover all the articles in the prognosis and maintenance fields, but we do cover a broad area of latest studies for advanced manufacturing paradigms that have pushed development in PHM forward.

As an emerging field in the Mechanical Science, PHM is gaining interest from the industry and academia. An effective PHM framework normally includes the health prognostics and the maintenance management. For the health prognostics, more and more professional and hi-tech instruments (e.g. smart sensors, meters, controllers and computational devices) have been applied to collect and analyze the signals from individual machines [99,128]. Prognostics techniques, such as vibration monitoring, oil analysis, temperature detection, acoustic emission and ultrasonic inspection, have also been widely employed to measure the status of a machine. Many valuable prognostics approaches have thus been proposed to generate a rational estimation of the remaining useful life (RUL) or the potential degradation process [21,26]. For the maintenance management, complex systems have been equipped and operated in advanced manufacturing paradigms, such as mass customization, reconfigurable manufacturing, sustainable manufacturing and service-oriented manufacturing. System-level maintenance policies are facing the challenges from structural, stochastic and economic dependencies [119,138]. Therefore, machine interactions and production characteristics should be investigated and modeled to identify maintenance opportunities for achieving a cost-effective maintenance scheme.

Due to recent developments in the manufacturing paradigms, PHM methodologies for traditional manufacturing systems need to be extended. We noticed an increasing interest in integrating PHM with advanced manufacturing paradigms. Besides the classical dependencies

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of multi-unit manufacturing systems, new production characteristics should be considered to extend the PHM notion from a systemic view [10,19,30,72]. With the technique innovations, enterprises apply mass customization, reconfigurable manufacturing, sustainable manufacturing and service-oriented manufacturing to maintain competitiveness and meet customer needs. More targeted PHM methodologies enable the industry to lower the possibility of unexpected breakdowns and the cost of maintenance. Thus, novel PHM methodologies for advanced manufacturing paradigms are vital for enterprises with foresight. This state of the art review provides an extensive literature overview on this topic of recent advances in PHM. Throughout this research, we focus on the distinctive production characteristics of each advanced manufacturing paradigm, where the corresponding prognostics approaches and maintenance policies are illustrated.

In recent years, some valuable review articles have been published to promote the PHM applications through different perspectives [4,108]. Shafiee and Chukova [90] published the first identifiable academic literature review to deal with warranty and maintenance. Wang et al. [109] reviewed and summarized the research developments on the fault detection, diagnosis and prognostics of rotating machines in the perspective of the spectral kurtosis technique. Keizeret al. [46] provided an extended classification scheme focusing on various dependencies of economic, structural, stochastic and added resource dependence. Different from remarkable review studies above, our main contributions include that we propose a new classification in the PHM field in the perspective of various advanced manufacturing paradigms (e.g. mass customization, reconfigurable manufacturing, sustainable manufacturing and service-oriented manufacturing). Thus, we provide the review on PHM methodologies for the corresponding order-oriented, reconfiguration-oriented, energy-oriented and lease-oriented PHM mechanisms. Furthermore, we locate gaps in the literature that require further studies to achieve an effective implementation of PHM in practice.

This article reviews various prognostics approaches and maintenance policies in PHM field, and illustrates methodologies for conducting PHM. The reminder of this paper is organized as follows: In Section 2, we discuss the relationship between PHM and manufacturing systems, and the challenge factors are introduced. Section 3 includes the review of developed and applied prognostics approaches (physics-based, data-driven and hybrid approaches). Accurate health prediction of an individual asset is the cornerstone of efficient maintenance decisions for manufacturing systems. Section 4 introduces the targeted maintenance policies suitable for advanced manufacturing paradigms. The relationships between production characteristics and maintenance policies are explained. Section 5 concludes the current gaps in the literature. The aim of this state of the art review is to understand not only the current practices toward PHM, but also the opportunities that exist in PHM development for future manufacturing paradigms.

2. PHM in manufacturing systems

In order to conduct the design and deployment of a PHM framework, manufacturing systems are analyzed as the monitored and scheduled objects. In the modern manufacturing industry, a manufacturing system usually consists of various machines, which undergo increasing degradation and wear with aging. In the view of the structural dependence, the unnecessary breakdown or a maintenance action of one machine may affect upstream/downstream machines, or increase the potential unavailability of parallel and k-out-of-N systems. The system performance is determined by both the performance of the machines and their configuration within the system [28,46,52]. The degradation of identical machines differ drastically, with deterioration processes typically accompanied by specific physical phenomena from sensor-driven condition monitoring technologies [32,86,142]. Thus, for each individual machine, prognostics approaches are adopted to convert monitored multivariate data to abstracted health information. RUL distributions and the potential degradation processes are essential to the decision-making of machinery maintenance and system management. For the whole system, maintenance policies are much more complex, since the interactions and dependencies among machines should be integrated from a system-wide look. Thus, performing PHM becomes more interesting because it is likely to benefit from dynamic determinations of system-level maintenance opportunities.

More importantly, enterprises have been pursuing a shift to the advanced manufacturing paradigms to ensure the competitive ability. The advanced manufacturing paradigms mainly include: (1) Mass customization, which has been applied to respond quickly to customer demands. It has changed the manufacturing process from "push" pattern to "pull" pattern. (2) Reconfigurable manufacturing, which has been invented to take the advantage of reconfigurable structures to make diverse products within limited time in a cost-effective manner. (3) Sustainable manufacturing, which has aroused great concern on green and sustainable technologies to avoid unnecessary energy waste and contaminated natural environment. (4) Service-oriented manufacturing, which is emerging with the increasing dependence on leased machines and systems. The service contracts offered by original equipment manufacturers (OEMs) have predominantly focused on maintenance and upkeep activities for machines. In summary, the novelty of these advanced manufacturing paradigms has been shown in Table 1.

All the manufacturing paradigms above play their important roles in promoting the technological innovations in industry. However, these shifts have also brought new challenges for conducting PHM. There are the main factors that make this problem especially difficult with the applications of advanced manufacturing paradigms:

(1) Individual machine deterioration. Most of the existing policies are developed based on population-specific reliability characteristics (i.e., historical failure time distributions). Such characteristics only consider the degradation information from the whole population and ignore the unique information from each individual machine. By means of conducting condition monitoring on an individual component, it is possible to achieve prognostics for the individual. The collected condition monitoring data contains plenty of real-time health information for explaining the uncertainties and thereby making decisions that are more "informed". Besides, by fusing different condition monitoring data, the deterioration estimation of a component can be more accurate. The prognostics for an individual component is important, since changes in any component may affect the entire system directly. Furthermore, it is practical to consider the deterioration of components in a system from the view of operation and market, especially in power systems

Table 1
Characteristics of advanced manufacturing paradigms.

Paradigms	Mass customization	Reconfigurable manufacturing	Sustainable manufacturing	Service-oriented manufacturing
PHM mechanism	Order-oriented	Reconfiguration- oriented	Energy-oriented	Lease-oriented
System structure	Rigid	Flexible	Rigid	Rigid
Paradigm characteristic	Variable orders	Changeable structures	Energy consumptions	Outsourcing maintenance
Decision-making objective	Cost reduction	Cost reduction	Energy reduction	Profit increase
Maintenance opportunity	Batch-changing work	Reconfiguration duration	Standby duration	Personnel dispatch

[64].

(2) Different system structure. Traditionally, we have to rebuild different system-level maintenance policies for various stationary structures (e.g. series system, parallel system, series-parallel system, k-out-of-N system, arbitrary structure and redundancy). Facing changeable structures, the traditional manner not only causes the intractable scheduling complexity, but also weakens the rapid responsiveness. The open-ended design for rapid changes in system structure is a new issue in the perspective of PHM methodologies.

(3) Diverse production characteristics. An effective PHM methodology should consider not only real-time deteriorations of individual machines, but also production characteristics of manufacturing systems. Maintenance opportunities identified in diverse production characteristics are used to optimize maintenance scheme from a systematic view. Dynamically utilizing production characteristics (e.g. variable orders in mass customization, changeable structures in reconfigurable manufacturing, energy consumptions in sustainable manufacturing, outsourcing maintenance in service-oriented manufacturing) can lead to cost/energy-effective PHM solutions.

(4) Exponential scheduling complexity. Traditional opportunistic maintenance policies calculate all possible machine combinations and their corresponding maintenance cost-savings. Thus, the scheduling complexity for a J-unit manufacturing system will be at least $O(2^{(J-1)})$, which means the complexity (O) grows exponentially with the increase of the machine number (J). In practice, dynamic scheduling and rapid responsiveness of PHM methodologies are essential to employ those advanced manufacturing paradigms into the industry.

In summary, the diagram of the manufacturing path to advanced manufacturing paradigms has been illustrated in Fig. 1. In the following sections, prognostics approaches for accurate health prediction of individual machine, and maintenance policies suitable for advanced manufacturing systems are reviewed and a conclusion with respect to future PHM developments is arrived at.

3. New technical developments in health prognostics

Accurate health prognostics based on continuous state monitoring can provide real-time maintenance schemes and avoid economic losses led by unexpected breakdown. Prognostics is the fundamental task, it mainly refers to predicting reliability or probability of failure of an asset at future times and RUL [143]. Due to its importance, prognostics attracts a lot of researchers' attention. Some review literatures on prognostics approaches have appeared from different perspectives [39,45,51,54,92,93,98,112,135]. Roughly, prognostics approaches can be categorized into physics-based approaches, data-driven approaches and hybrid approaches.

Physics-based approaches are referred to model-based approaches that assume the behavior of a damage development of a component can be physically modeled, and the model parameters could be obtained based on measured data. Data-driven approaches rely on the information from previously observed or collected data to map the characteristics of damage/degradation state to predict future trend. Hybrid approaches integrate the advantages of different approaches.

3.1. Physics-based approaches

Physics-based approaches utilize mathematical models to describe the physical models or degradation models of a machinery component. These models are constructed and configured based on first principles, domain experience, failure mechanism, and a series of requisite assumption. Physics-based approaches include but not limited to the following methods: physical models, structural analysis, contact analysis, cumulative damage model, cycle fatigue, crack growth model, spalling growth estimation model and so on [2,18]. These methods could reflect the degradation process directly by the application of mathematical models according to the specific type or failure mode of the component. The precision of the substitution mathematical models is crucial to the prognostic accuracy. In addition, certain parameters of the models are determined initially based on the domain experience or updated continually according to real-time condition of the machinery to enhance prognostic accuracy.

Various physics-based approaches are presented for numerous types

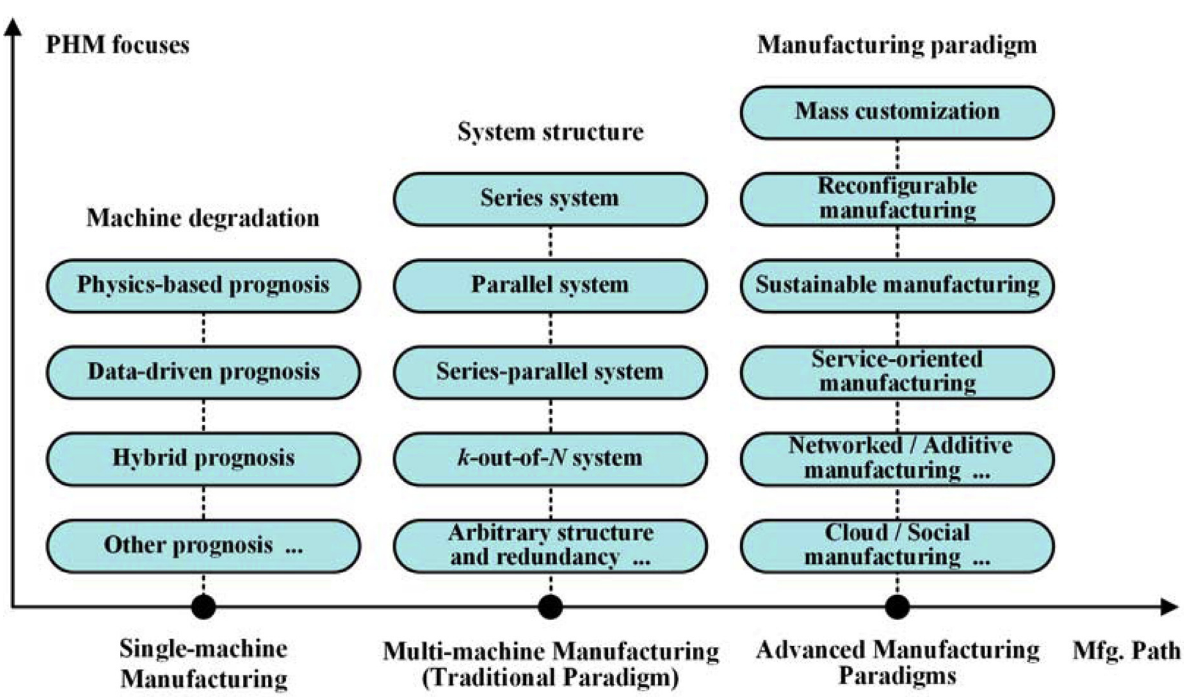

Fig. 1. Manufacturing path to advanced manufacturing paradigms.

Table 2
Advantages and disadvantages of physics-based approaches.

Category	Method	Advantage	Disadvantages	Reference
Physics-based approaches	Single degree of freedom model	Reflect the degradation process of bearing accurately	Require training test to determinate unknown parameter	[67]
	Interval observers and ellipsoid algorithms	Consider the slow behavior of degradations	Model specificity	[83,130]
	Dynamic model with a virtual defect	Introduce a virtual defect to present its development	Difficult to build accurate and proper virtual defect	[17,73]
	Interacting multiple model	Track the undetectable failure	Non-universal to different functioning modes	[61,81]
	Online approximator	Achieve failure isolation	Need practice verification	[102,133]

of machinery component in recent research [67]. Some literatures focus on the failure modes of the complex machinery system to improve the prognostic capability. For the hidden failure mode, Luo et al. [61] presented an interacting multiple model (IMM) to track the undetectable failure. For the complex and multi-failure modes, Thumati and Jagannathan [102] proposed online approximator in discrete time. Its application scope was expanded to the complex machinery system. More publications using physics-based approaches for prognostics are referred to Table 2.

The advantages and disadvantages of physics-based approaches are also shown in Table 2. Obviously, the main drawbacks of the physics-based approaches can be summarized as follows:

- The construction of the substitution mathematical models depends on the domain experience excessively, such as the thorough awareness of the component structure, the exhaustive exploration of the degradation process and so on. Thus, human error could make an extreme influence on the accuracy of the model.
- The correlation among the variables is obscure to model in a statistical relation. Moreover, discrete and nonlinear relations lead the model optimization more difficult.
- The parameters of the models, especially the influential factor of the component degradation like workload, as well as the external factors like the production environment, are difficult to estimate or measure. In most condition, artificial assumptions are required.
- The component specialty of the substitution mathematical models limits their application scope of failure prognostic, or even forces their application into failure detection [103].

3.2. Data-driven approaches

Data-driven prognostics approaches deduce asset degradation/state behavior directly from monitoring data. It is not necessary to understand the mechanics and propagation of a damage. Some studies classified these approaches into artificial intelligence approaches and statistical approaches [7,55]. Meanwhile, other studies classified the prognostics approaches into machine learning and statistical approaches [39]. The advantages and disadvantages of these approaches are listed in Table 3.

3.2.1. Machine learning approaches

- Artificial neural network (ANN) methods

ANN is one class of the most representative data-driven methods that use training samples to obtain desired outputs, such as degradation trend, residual lifetime and so on. There are many different categories of the ANNs, for example, back propagation neural network (BPNN), recurrent neural network (RNN), fuzzy neural network (FNN) and extreme learning machine (ELM), etc. A typical ANN is composed of an input layer, hidden layer(s) and an output layer. ANN has strong ability for nonlinear simulation, strong robustness and self-study ability. Due to these merits, ANNs are widely used in fault diagnosis and prognosis [105,139]. Pan et al. [76] realized the real-time prediction of machine health condition via online dynamic FNNs. Mazidi et al. [62] utilized an ANN to detect anomalies in the performance of the wind turbine. Xiao et al. [121] proposed a degradation prediction approach based on BPNN to solve the problem without failure or suspension histories as training samples.

Even though there are many merits about ANNs, some issues should not be ignored due to the nature of the algorithms themselves. First, there is no theoretical standard to determine the structure of networks, for example the number of hidden layers and the associated number of neurons. Moreover, most networks require sufficient amount of data for training and the training process is time-consuming. Furthermore, the precision of prognosis depends on the training samples. It is worth noting that the results from the well trained networks may be different even though the training samples are same. In addition, the prognostics results cannot support the confidence limit.

- Support vector machine (SVM) methods

SVM is one of the most popular algorithms on classification and regression analysis. It is a supervised learning method. The basic motivation of SVM is to find out an optimized separation hyperplane, so that the distance from it to the nearest data point on each side is maximized. The high performance of SVM on non-linear classification is due to its kernel trick that implicitly maps inputs into high-dimensional feature spaces. Compared with ANNs, SVM can avoid over fitting effectively and the training process is faster. SVM performs efficiently for large dataset and real-time analysis. Besides, the kernel trick of SVM can be determined based on expert knowledge. Furthermore, SVM is defined by convex optimization.

Due to the advantages, SVM is widely used on prognostics. Widodo and Yang [111] developed machine health prognostics models using survival probability and SVM. Lu et al. [60] focused on the estimation of degradation trend of a slewing bearing with small sample data based on proposed least squares SVM. Khelif et al. [47] used support vector regression to estimate the RUL of an equipment directly from sensor values without the necessity of estimating degradation states or a failure threshold.

Even though SVM is widely used on prognostics due to its good generalization capacity, the main concern about SVM is that there is no theoretical guidance to determine the kernel function/trick in SVM. Besides, the method is also without consideration of confidence limit.

- Bayesian methods

Bayesian inference utilizes the probability to represent all forms of uncertainty. A Bayesian network is a probabilistic acyclic graphical model that represents a set of random variables and their probabilistic interdependencies [93]. The kernel theory of Bayesian methods is conditional probability. Hence, the prior knowledge or root causes of a failure must be known. Bayesian methods provide confidence limits, intrinsically. These methods capture and integrate expert knowledge. Meanwhile, the relationships among events or failures are considered.

Table 3
Advantages and disadvantages of data-driven approaches.

Category	Subcategory	Method	Advantage	Disadvantages	Reference
Data-driven approaches	Machine learning approaches	ANN	● Strong ability for nonlinear simulation	● No theoretical standard for structure determination	[62,76,105,121,139]
			● Strong robustness	● Require sufficient amount of data for training	
			● Strong self-study ability	● Confidence limit is not considered	
		SVM	● Over fitting is avoided effectively	● No theoretical guidance for kernel function/trick	[47,60,111]
			● Performs efficiently for large dataset		
			● Defined by convex optimization	● Confidence limit is not considered	
		Bayesian methods	● Based on systematic theory	● Depend on the prior knowledge/data and root causes excessively	[42,44,69,94,110].
			● Uncertainty is considered	● Prior distribution is very sensitive	
			● Over fitting is avoided effectively	● Require a number of training samples or measurement data	
			● Incompleteness of data sets can be readily managed		
		Markov models	● Tolerate the incomplete and multivariate data	● A large volume of reasonable data is required for training	[59,66,97,132]
			● Have the Bayesian property	● Depend on the required assumption	
	Statistical approaches	ARMA	● Historical failure data and failure mechanism are not required	● Less reliable for long-term prognostics	[79]
		(Regressive method)	● Computationally efficient	● linear assumption is implied in the algorithm	
			● Accurate results for short-term prediction	● Confidence limit is not considered	
		Gamma processes	● The mathematical calculations are easily to be understood	● The processes are adequate for monotonic processes	[77,88,89,95])
		(Regressive method)			
		Wiener processes	● Easy to explain	● Time homogeneous process	[35]
		(Regressive method)	● A Wiener process can describe non-monotone deterioration trace	● Only employ the information contained in the current degradation data rather than the entire of the observations	
			● Have Markovian property		
		Proportional hazards model	● Models are easy to be developed and explained	● Difficult to measure covariates without historical failure	[104,129,136]
				● Parameter selection of the models is time consuming	

For the methods themselves, over fitting is effectively avoided, while multivariate and dynamic processes are modeled. Moreover, the incompleteness of data sets can be managed.

Bayesian methods include many configurations and architectures that are widely used in prognosis, for example, discrete Bayesian, Bayesian belief networks (BBN), Particle filter [44], Kalman filter [94] and so on. Bayesian methods consider the uncertainty when estimating degradation state or RUL based on prior knowledge/data or root causes. Jin et al. [42] studied the degradation assessment and residual life prediction of secondary batteries in spacecraft using a two-phase method. Mosallam et al. [69] proposed a two-phase prognostic method for direct RUL prediction.

For Bayesian methods, if the prior knowledge/data or root causes are unknown, these methods cannot be modeled convincingly. In addition, the prognostics results are very sensitive to the prior distribution. Bayesian methods require a number of training samples or measurement data. Another concern of Bayesian methods is the intensive computation caused by variants for non-linear systems.

- Markov models

Markov models assume that a system or component should be in a single state among a finite number of states. The component transits from one state to another with associated probability. For a basic Markov chain, the sum of probabilities of leaving one state and entering into the different states must be equal to one. For semi-Markov models, they do not require that the time spent in a particular state obeys exponential distribution, but rather can obey arbitrary distribution [93]. Thus, the sum of probabilities of leaving one state and entering different states can be less than one [53]. Hidden Markov chain is an extension of Markov chain where not all states are directly observable and thus respective transition probabilities are indirectly assignable [97,132]. Hidden semi-Markov models revise the assumption that the failure rate is inconstant, thus hidden semi-Markov chains are more suitable for prognostics. Mazidi et al. [66] used Markov models to address the uncertainty in the nature of the operation and component degradation for wind turbines. Liu et al. [59] presented an integrated framework for multi-sensor equipment diagnosis and prognosis based on adaptive hidden semi-Markov model (AHSMM).

The advantages and disadvantages of Markov models are similar with the ones of Bayesian methods. Markov models can deal with the incomplete and multivariate data, and provide accurate prognostics results if the root causes of a failure are known. Besides, Markov methods consider the states of a machine and the transit among the states. Markov methods need a large volume of reasonable data for training. In addition, some assumptions of Markov methods, for example single monotonic, non-temporal failure degradation pattern, and the distribution of failure progression time, make the Markov models unsuitable in many cases.

3.2.2. Statistical approaches

Statistical data-driven approaches estimate RUL or degradation by using event data or monitoring data. Event data means the recorded failure event or suspension data. However, some critical assets are not allowed to run to failure, thus event data may be scarce. Monitoring data is more informational and practical for prognostics. The typical statistical approaches, such as some trend evaluation methods, Gaussian processes and Wiener processes, can be divided into regressive methods and proportional hazards models.

- Regressive methods

Autoregressive moving average (ARMA) is a typical regressive model that is composed of two parts: an autoregressive (AR) part and a moving average (MA) part. It is widely applied to time series data. The advantages of ARMA are that historical failure data and failure mechanism are not required. However, one disadvantage is that the algorithm performs badly for long-term prediction. Thus, Pham et al. [79] presented a hybrid improvement of nonlinear autoregressive with exogenous input (NARX) model and ARMA model for long-term machine state forecasting. In addition, this algorithm has the linear assumption, its application is thus limited if the non-monotone degradation trace is extracted. Furthermore, the confidence limit is not considered.

Gamma processes have the monotonic property and are usually used to describe the deterioration of a component with a sequence of positive increments over time [77,89]. Shafiee and Finkelstein [88] developed a proactive group maintenance policy, where the propagation of damage was formulated by Gamma process. Son et al. [95] modeled a non-homogeneous Gamma process for estimating RUL with considering a noisy observed degradation data and by using the Gibbs sampling technique. Gamma processes are adequate for monotonic processes, for example damage size and other measurements (crack growth, total metal concentrations). Nevertheless, in practical applications, not all the degradation processes are monotonic processes. Hence, Gamma processes are restricted for modeling degradation.

Wiener processes are the extension of standard Brownian motion. A Wiener process predicts failure upon the first passage time (FPT) of the degradation model exceeding a predetermined threshold. The distribution of FPT can be well explained and analyzed as inverse Gaussian distribution. A Wiener process can be regarded as random motion of particles in fluids and air. Therefore, Wiener processes have mathematical advantages to describe non-monotone deterioration trace. Huang et al. [35] proposed an adaptive skew-Wiener model for RUL prediction, which is much more flexible than traditional stochastic process models. However, there are also some limitations about Wiener processes. A Wiener process is a time homogeneous process, while not all degradation processes have this property. In addition, Wiener processes only employ the information contained in the current degradation, rather than the information of entire sequence of observations.

- Proportional hazards model

Proportional hazards model is one of the most frequently applied models for prognostics. It formulates a component degradation as the product of a baseline hazard rate and a positive function that reflects the effect of operating condition on the baseline hazard. Proportional hazards model implies two important assumptions. One assumption is that “times to failure” are independent and identically distributed. The other assumption is that the covariates affecting the life of an item do not influence the “times to failure” of any other items. You et al. [129] divided an equipment lifecycle into a stable zone and a degradation zone, and developed a two-zone proportional hazard model to predict equipment RUL. Tian and Liao [104] proposed a multi-component system condition-based maintenance policy based on proportional hazards model. Zhang et al. [136] proposed a mixture Weibull proportional hazard model (MWPHM) to predict the failure of a mechanical system with multiple failure modes using lifetime and monitoring data.

Due to the assumptions above, proportional hazards model is not always practical in some cases. In some situations, the failure histories or associated covariate data are not occurred. The failure modes have interactions among components and covariates that cannot be measured. Moreover, sometimes the parameter selection of the models is time consuming.

3.3. Hybrid prognostics approaches

Hybrid prognostics approaches integrate the merits of different methods and make the prognostics more accurate. The hybrid prognostics approaches can be mainly categorized into two classes: (1) Physics-based approaches combined with data-driven approaches, and (2) data-driven approaches combined with other data-driven

Table 4
Advantages of hybrid approaches.

Category	Advantage	Subcategory	Method	Reference
Hybrid approaches	● Integrate the merits of different methods and avoid their weakness ● The prognostics more accurate	Physics-based approaches combined with data-driven approaches	● Results from different types of approaches achieve prognostics together	[82]
			● Use the data-driven approaches to estimate the health condition, use physics-based approaches to predict degradation or RUL	[134]
		Data-driven approaches combined with data-driven approaches	● Different approaches achieve prognostics together	[16,25,63]
			● Different approaches achieve different part of prognostics	[9,22,65,106,110,122,140]

approaches. The advantages of these two types of approaches are shown in Table 4.

- Physics-based approaches combined with data-driven approaches

The hybrid approaches of physics-based approaches combined with data-driven approaches mainly include two types. One type is that the prognostics results from physics-based approaches and data-driven approaches are fused together. The other type is that the data-driven approaches are used to estimate the current/future health state/index, then physics-based approaches are used to predict degradation or RUL.

For the first type, Qian et al. [82] revised phase space warping (PSW) by enhanced multi-dimensional auto-regression model to describe defect tracking on a fast-time scale. Paris crack growth model was modified by a time-piecewise algorithm to characterize the defect propagation on a slow-time scale. For the second type, Zhang et al. [134] developed a novel hybrid approaches in which data-driven method was used to “calibrate” the physics-of-failure model. Meanwhile, the physics-of-failure model was used to define failure criteria and thresholds for data-driven method, and RUL prediction was based on data-driven results.

- Data-driven approaches combined with data-driven approaches

Similar with above hybrid approaches, this type of hybrid approaches can also be categorized into two types. One type fuses the results from different data-driven methods into a final prognostic result [16]. The other type uses one data-driven method to estimate current/future health state/index, and then utilizes another data-driven approach to predict degradation or RUL [22,122,140].

For the first type, Gebraeel et al. [25] mapped the relationship between vibration signals and the bearing operating time by using BPNNs. RUL prediction was accomplished by weighting the outputs of all the neural networks. Mazidi et al. [63] proposed a hybrid approach based on ANNs and a proportional hazards model. A combination of the models’ outcomes can offer the possibility to evaluate asset management policies. For the second type, Tran et al. [106] proposed a three-stage RUL prediction approaches by integrating ARMA, proportional hazard model and SVM. Wang et al. [110] used Wiener process to model system degradation, then Kalman filter was used for RUL estimation. Mazidi et al. [65] proposed a hybrid health condition model where ANNs were created to simulate normal behavior and then the signal was applied through a proportional hazards model to create the health condition function. Baptista et al. [9] presented the RUL estimation method in aeronautics by combining data-driven and Kalman filtering.

Developing hybrid approaches has two main advantages. One advantage is that the hybrid approaches can capture both failure mechanism/failure mode/defect propagation and merits of algorithms. The other advantage of the hybrid approaches is that these hybrid approaches can avoid the weakness of different methods/algorithms.

4. New methodological developments in maintenance policies

Nowadays, with the applications of advanced manufacturing paradigms, there has been a growing interest in the new developments of maintenance policies. By pulling the real-time results of health prognostics, decision-makers should investigate and model the different system structures, the diverse production characteristics and the exponential scheduling complexity. Due to the difficulty in dealing with these issues, maintenance policies for advanced manufacturing paradigms developed slowly in the early years. With the actual demands in the industry, new PHM scheduling has gaining more and more popularity.

4.1. Mass customization

In today's competitive market, mass customization is widely applied to deliver products and services that respond quickly to customer demands and best meet individual needs with near mass production efficiency [24]. As a manufacturing paradigm focusing on the broad provision of personalized products/services, mass customization has changed the manufacturing from "push" mode to "pull" mode [34]. In mass customization, batch orders with variable lot sizes are processed, and it is important to provide individually designed batches through process agility, flexibility and integration. Major companies like General Motors, Ford, Chrysler, Toyota and others have been implementing this paradigm in their manufacturing lines. Different from the traditional flow-line production, mass customization has the following production characteristics. First, according to the different requirements of every customer, batch orders are independent with variable lot sizes. Second, these sequential batches processed in a system are normally ordered only a short time beforehand. Third, for handling the sequential batches cycle by cycle, a set-up work happens when one batch switches to another. Fourth, facing the new trends of customer demand volatility, frequent market shifts and increased quality requirements, each batch production prefers no interruptions during the current cycle.

It is worth noting that mass customization has changed the production from "made-to-stock" to "made-to-order" [125]. This requires the conventional system-level maintenance policies to be improved for the "high-variety-low-volume" production. Recent advances in prediction methods allow for processing massive data into real-time information for explaining the uncertainties and thereby making decisions that are more "informed". Due to the complexity of jointly scheduling for maintenance actions and production orders, studies of this problem at system level are urgently required [14,20,107,120]. However, according to mass customization characteristics, there remain some issues need to be addressed. First, most of existing production & maintenance policies suffer from the intractability when the number of machines grows. Second, classical maintenance-driven policies have not extensionally analyzed the consequences of advancing or postponing PM activities in mass customization. Third, real-time and cost-effective scheduling at system level is required in industrial companies that makes various products in large and discrete batches, when the demands and production processes are stochastic.

Therefore, other than classical maintenance policies, novel maintenance policies are required to eliminate unnecessary production stops, achieve significant cost reduction and overcome complexity of system-level scheduling in mass customization [5,71]. Jin and Ni [43] tried to make joint decisions on the preventive maintenance level and production quantity for manufacturing systems. Maintenance decisions were integrated with production decisions to accommodate the demand uncertainty. Fitouhi and Nourelfath [23] developed an integrated lot-sizing and preventive maintenance strategy to minimize the sum of preventive and corrective maintenance costs, setup costs, holding costs, backorder costs and production costs. It also satisfied the demand for all products over the entire horizon. Xia et al. [113] proposed a bi-level maintenance policy for mass customization with degrading machines. The maintenance scheduling considered not only individual machine deteriorations, but also the batch production with variable lot size. Yu et al. [131] emphasized that the development of mass customized products demands various activities, such as design, manufacturing process planning, manufacturing resource planning and maintenance process planning, to be considered and coordinated. Liu and Yao [57] further introduced Mobike, a bike-sharing service provider in China, integrated maintenance support into its platform to fulfill multi-dimensional customer requirements. In sum, in the system-level maintenance policies for mass customization, the key issue that how to react rapidly to practical changes and updates of batch orders needs to be further studied, especially in the global competitive market.

4.2. Reconfigurable manufacturing

Facing increasingly unpredictable market changes, reconfiguration concept has been widely studied to handle rapid product upgrades and variable product demands [48]. To stay competitive with market fluctuations, reconfigurable manufacturing systems (RMS) have been developed with their new characters. A RMS is designed with the ability of dynamic adjustments of the manufacturing functionality, and open-ended reconfigurations of the system structure and its machines [3]. In traditional mass production, a system structure will rarely be adjusted after the original system design. In reconfigurable manufacturing, manufacturing systems should be designed to offer high-quality products, and respond rapidly to consumer needs. By combining the high throughput of a dedicated manufacturing line (DML) with the flexibility of a flexible manufacturing systems (FMS), a RMS can respond to variable product demands by adapting its reconfigurable structures and related machines in a limited time [11]. The RMS techniques constitute a novel type of systems characterized by the adjustable structure, and thus help to achieve future manufacturing system's flexibility and responsiveness [29].

However, the production characteristics of a RMS with its reconfigurable structures also bring the challenges in the system-level maintenance scheduling. It is essential for operating a RMS and its machines healthily for reconfigurable manufacturing. It is worth noting that changing needs of capacity and functionality not only cause diverse reconfigurations of a RMS, but also separate the production process into sequential manufacturing stages with corresponding system structures. In practice, the economic, stochastic and structural dependences of different types of systems have led to the scheduling complexity. Even those maintenance policies in term of various fixed structures are of huge value and high difficulty, no matter the policies for reconfigurable structures. Most existing system-level maintenance strategies were developed in term of different system structures like series, parallel, series-parallel and k-out-of-N systems [6,85,118]. It can be seen that most previous studies are devoted to the fixed structure problem, and thus cannot be suitable for the reconfigurable structure problem.

For proposing an effective maintenance policy for reconfigurable manufacturing, the core production characteristics of a RMS should be considered. Meanwhile, the rapid responsiveness provides a key advantage for a RMS by adjusting production capacity when the market grows, and adding functionality when the product changes [74]. The key issue is that separated manufacturing stages caused by diverse reconfigurations have their own system structures, which are designed for current production requirements. If the system-level maintenance policy has to be rebuilt with sequential reconfigurations for those different structures, the RMS responsiveness and flexibility will be weakened. Therefore, some groundbreaking maintenance studies for reconfigurable manufacturing have been published by comprehensively investigating RMS characteristics and maintenance opportunities. Zhou et al. [141] incorporated reconfiguration into PM actions for improved system performance. The expected total cost of implementing the integrated reconfiguration and age-based maintenance (IRABM) policy was minimized. Renna [84] utilized a simulation environment to test how the level of flexibility and preventive maintenance policy affect the performance of RMSs that are designed with customized flexibility. Xia et al. [114] considered the operation process rebuilding (OPR) of operation systems and an opportunistic maintenance (OM) policy was proposed according to OPR activities. Xia et al. [117] developed a reconfigurable maintenance time window (RMTW) strategy for those reconfigurable structures of a RMS. Koren et al. [49] emphasized that the agility and speed of maintenance may play a significant role in the system design for next generation manufacturing with six RMS characteristics. In sum, the system-level maintenance policies for reconfigurable manufacturing should be designed to efficiently adapt to system reconfigurations, decrease scheduling complexity, avoid unnecessary breakdowns and optimize maintenance cost.

4.3. Sustainable manufacturing

With increasing concerns on the human ecology, the industry's responsibility to apply sustainable manufacturing has been required. Sustainable manufacturing means that the increasing demands have resulted in greater efforts toward energy consumption control to satisfy government legislations for green manufacturing and future needs for sustainable globalization. In fact, nowadays the industry has occupied more than 37% of the global total energy. Meanwhile, industrial activities have caused about 19% of the greenhouse gas emissions, where manufacturing processes play an important role [1]. Therefore, innovating sustainability has become a new standard, while manufacturing systems have shifted from focusing solely on cost reduction to balancing cost, energy, and other social objectives.

In recent years, energy consumption control has become the research hotspot in industry and academy. It is worth noting that unnecessary energy wastes lead to more carbon emissions, higher production costs and contaminated natural environment. This requires the manufacturers to take the responsibility for applying new green/sustainable technologies to reduce industrial emissions to the atmosphere [40]. Facing the challenges of balancing cost priorities against sustainable responsibilities, decision makers should handle the changes in economic, environmental and social factors, which are all important for sustainable manufacturing. That is, the energy-efficient health management will be urgently required to avoid environmental taxes and penalties [31]. A PHM methodology needs to be developed to comprehensively consider machine deteriorations, production characteristics and energy interactivities.

On the one hand, sustainability indicators are required in the maintenance decision-making to better control and maintain the machines/systems to be consistent with sustainable requirements. Developed based on the energy consumption and the useful output, energy efficiency indicator (EEI) can be considered as a main performance for sustainable performance, which should be compliant with “sustainable manufacturing” orientation defended in industry. At machine level, EEI approaches associated with machines are often evaluated based on the behavior of several features, like voltages, temperature and harmonics [58]. At system level, systemic EEI approaches consider not only the machines’ behaviors and their interactions, but also the behaviors of the whole system regarding to the performance to be served [33]. The latter approaches are usually directly integrated with the maintenance decision-making.

On the other hand, there have been many valuable ways to reduce energy consumption for sustainable manufacturing. First, the design phase has been researched to improve the machine and upgrade the structure. Mori et al. [68] proposed a new acceleration control method to reduce energy consumption by synchronizing spindle acceleration with the feed system. Second, some studies focused on optimizing the manufacturing process parameters to reduce energy consumption. Oda et al. [75] reported their findings on cutting condition improvement for 5-axis machine tools, specifically addressing tool angles and cutting speed in an effort to reduce energy consumption. Third, the production optimization has been viewed as the most fast-speed and cost-effective way to achieve energy reduction in manufacturing systems. Shui et al. [91] presented a mathematical model to estimate both production frontier and energy demand frontier, and evaluated the energy efficiency in the automotive manufacturing sector using plant-level production and utility consumption data. Fourth, the maintenance issues have been studied to optimize maintenance schemes for reducing energy consumption [123]. Lindström et al. [56] addressed intelligent and sustainable production in the sense of combining and integrating online predictive maintenance and continuous quality control. Kumar et al. [50] developed a big data driven sustainable manufacturing framework for condition-based maintenance prediction. The big dataset was generated from a sophisticated simulator of a gas turbine propulsion plant. Zhang et al. [137] studied an overall architecture of big data-based analytics for product lifecycle (BDA-PL) by focusing on cleaner manufacturing and maintenance processes of complex products. Xia et al. [115] proposed an energy saving window (ESW) policy to reduce the energy consumption of a whole production line. Energy consumption interactivities, batch production characteristics, and system-layer maintenance opportunities were comprehensively integrated. In sum, it should be noticed that a lot of energy is used in the background processes, including maintenance activities and machine startups. Thus, an energy-oriented maintenance policy could be proposed by enabling technologies both at machine level and at system level. Besides, maintenance and startup issues could be integrated in sustainable manufacturing.

4.4. Service-oriented manufacturing

With the intense market competition, many manufacturing companies have been increasingly relied on leased equipment and machinery. Increasing economic stress, equipment technical complexity and machine availability/criticality have made equipment leasing a good option [70]. Meanwhile, leading OEMs, such as GE and Pratt &Whitney, have their customer facilities (lessees), who lease physical assets and require maintenance service all over the world. Therefore, outsourcing maintenance has been a growing paradigm shift in many industries due to several advantages. Firstly, lessees who lease and utilize high-technology equipment can avoid high purchase investment. Secondly, OEMs who designed and manufactured the machines are arguably the best source for maintaining these assets over the lifecycles. Thirdly, diversified choices of those leased machines can promote the achievement of flexible manufacturing according to customer demands and preferences. Fourthly, extra costs of in-house maintenance department (crew salary, staff training and sensor procurement, etc.) can be significantly reduced.

In this situation, many OEMs are turning to product-service packages where they deliver (typically lease) the physical assets, and offer an integrated service contract for the asset. However, there is still a great challenge for OEM to manage the big data of machine statuses due to the lack of professional asset knowledge and smart prognostic tools [78]. Leased systems have been widely used in mining plants, processing plants, manufacturing plants and power plants. In 2011, U.S. equipment leasing permeability (leasing equipment investment/ total equipment investment) has reached 21%. Performing outsourcing maintenance requires cost, and it is a significant part of the operating budget of customer facilities (lessees). For developing an industrial Internet of Things (IoT) framework for maintenance and operations management, we need to notice that manufacturing facilities are equipped with different machines that undergo complex degrading processes. These degradations will finally cause machine failures and interrupt facility operations. Most OEMs schedule maintenance actions to improve the states of leased machines and thus reduce unnecessary failures and corresponding penalties [126]. Thus, OEMs have been required to extend the machine lifetime, minimize the crew dispatches and reduce the maintenance costs in useful ways [107].

In the maintenance literatures for service-oriented manufacturing, most of the studies focus on maintenance decision-making for a single leased machine [38,87]. Pongpech and Murthy [80] developed a periodic PM policy that achieves a tradeoff between maintenance costs and lease penalties. Yeh et al. [127] investigated several important optimal preventive-maintenance policies for leased equipment. PM actions were performed sequentially with a fixed maintenance degree. Chang and Lo [12] integrated the influence of lease period length into a maintenance model by considering the machine's residual value. Hung et al. [36] took the penalty of changing market environment into account for the expected total cost model of preventive maintenance to obtain an optimization strategy for leased equipment. In all, these works play a great role in maintenance scheduling for service-oriented manufacturing. However, one of the unique aspects in manufacturing settings is that recent leased system is often not a single machine, but instead a multi-unit manufacturing system. Teixeira et al. [101] described a research project to investigate how PHM could support effective fulfilment for product-service systems (PSS) contracts. Askri et al. [8] developed a correlated group preventive maintenance policy correlated to production for parallel leased machines by using the gravity center approach (GCA). Xia et al. [116] proposed a leasing profit optimization (LPO) maintenance policy to schedule Early PM optimizations for the series system by utilizing maintenance opportunity. In sum, system structure interactivities, group maintenance opportunities and leasing service contracts could be integrated to achieve the profit maximization and the dispatching reduction for service-oriented manufacturing.

5. Conclusions and directions for further researches

This overview aims at providing a comprehensive review on the recent advances in the PHM field in the perspective of various manufacturing paradigms. Advanced manufacturing paradigms rise with the global competition and technique innovations to maintain enterprise competitiveness and meet customer needs. This trend delivers an urgent requirement of more targeted PHM methodologies, from both theoretical and practical points of views. This review focuses on two aspects, these being prognostics approaches and maintenance policies. The power of mathematics and statistics has been used to develop different kinds of prognostics approaches and various maintenance policies. The challenges and gaps in PHM methodologies for advanced manufacturing paradigms have been summarized in Table 5.

For the health prognostics, prognostics approaches with their merits and disadvantages are analyzed in this review: (1) physics-based approaches achieve prognostics by using mathematical models to describe the degradation mechanics or damage propagation. (2) Data-driven approaches use the collected data (usually condition monitoring data) to map the characteristics of damage/degradation state to achieve prognostics. (3) Hybrid approaches combine the advantages of different approaches to improve the prediction accuracy or extend prognostics model applications.

For the maintenance management, the relationship between production characteristics and policy designs are studied: (1) Mass customization policies integrate production and maintenance, thus rapidly react to market changes and updates of batch orders. (2) Reconfigurable manufacturing policies can adapt to system reconfigurations, avoid RMS breakdowns and reduce maintenance cost. (3) Sustainable manufacturing policies are designed to control and maintain systems in an energy-efficient way. (4) Service-oriented manufacturing policies integrate maintenance opportunities and lease contracts to achieve the profit maximization and the dispatching reduction.

The following are the thoughts based on the above review, regarding the future research topics or directions. These thoughts are not exhaustive, but may shed some light for those interested in PHM research and applications.

First, prognostics techniques in previous literature still have some weaknesses that limit their practical values in PHM applications, and lead to the situation that many researches are still resting at the theoretical phase:

- For data acquisition, most existing prognostics methods need a large quantity of historic data for model training. Not only normal state data, but also failure or even fatal data is required. This makes data collection a high-cost and difficult task.
- For method establishment, many prognostics methods are updated only by real-time input data, other than the models themselves. There requires a fast-speed method that can achieve online updating of the prognostics model.
- For industrial application, each prognostics method is usually designed for a specific domain and lacks generality. There lacks a general prognostics method to promote PHM practical applications.
- For accuracy detection, a consistent way to compare and evaluate different prognostics methods is lacking. There requires a criterion to judge the accuracy and precision for various prognostics methods.

Therefore, future topics on prognostics techniques to effectively measure and forecast machine degradation and RUL may include that holistic methods, other than domain specific models, should be proposed to adapt to the fast equipment upgrading. Another direction is that the error between real RUL and predicted RUL should be fed back to reestablish the prognostics method. Seamless integration of degradation prediction and machinery maintenance is also a research direction that needs further exploration. Accurate forecasting for machine health prognosis is essentially required to achieve more effective maintenance schedules.

Second, designing maintenance policies for advanced manufacturing paradigms is still a new research field in PHM. Few of them have been used in practical applications successfully. The required extensions include:

- For mass customization, most joint scheduling policies of maintenance and production handle sequential batch/job orders with pre-determined lot sizes. It is still a difficult task to model the uncertainty of customer demand volatility.
- For reconfigurable manufacturing, the complexity of many opportunistic maintenance policies grows exponentially with the machine number gaining. Reconfigurable structures bring more challenges than fixed system structures.
- For sustainable manufacturing, the linking of maintenance with

Table 5
Summary of challenges and gaps in the PHM field.

Area	Sub-area	Gap	Challenge
Health prognostics (Machine level)	Physics-based approaches	Excessive dependence of specific domain experience and modeling techniques, and lack of universality	Accuracy increase of modeling and parameter estimation, and consideration of external factors
	Data-driven approaches	Need of a large quantity of historic data for data training, including state data, and failure or even fatal data	Real-time prediction and balance of prognosis accuracy, data volume and calculation time
	Hybrid approaches	Selection of various prognostics methods to improve the accuracy and precision for more effective maintenance schedules	Consistent way to compare, evaluate and integrate different prognostics methods
Maintenance management (System level)	Mass customization	Trends of customer demand volatility, frequent market shifts and increased quality requirements	Joint scheduling of cost-effective maintenance actions and variable batch orders
	Reconfigurable manufacturing	Ability of dynamic adjustments of reconfigurable structure and open-ended system reconfigurations	Efficient adaption to various system reconfigurations and responsiveness of model reconstructions
	Sustainable manufacturing	Demand of reducing energy consumption other than focusing solely on maintenance cost reduction	Energy-efficient integration of system maintenance opportunities and energy interactivities
	Service-oriented manufacturing	Rise of outsourcing maintenance where OEMs are required to provide maintenance service in time	Comprehensive consideration of group maintenance, leasing contracts and profit maximization

energy consumption control under a system view is a potential topic. A consistent criterion of the measurement for energy reduction and energy interactivities is lacking.

- For service-oriented manufacturing, most of the studies focus on maintenance decision-making for a single leased machine. However, current outsourcing maintenance has to serve multi-unit leased systems, even multiple systems all around the world.

Therefore, future research directions on maintenance policies for manufacturing paradigms include in-depth analysis of production characteristics and integration of multi-level decision-makings. At machine level, the linking of unique information from each individual machine with maintenance scheme for the whole system is a topic that needs further exploration. At system level, open-ended maintenance optimizations for rapid changes in system structure needs to be further explored to push a theoretical concept into commercial uses. The above two topics are for the problems of single-location maintenance planning with opportunistic maintenance policies. Now facing global business, there are still some problems needed to be studied for multi-location maintenance optimization, integrating spare part inventory, logistics path planning and human resource scheduling.

Beyond that, advanced manufacturing paradigms are still developing with the rapid upgrading and innovation of manufacturing, information, and management technologies. This transformation provides motivation for improving maintenance policies. The connections of PHM methodologies with new manufacturing paradigms will be the research directions for future exploration.

- For networked manufacturing, during the entering the global market, manufacturers adopt the spatial expanding model that builds multiple local clusters of supply chain and forms a global manufacturing network. The key challenge is how to integrate different maintenance resources into regional/global production systems involving many locations.
- For additive manufacturing, further study of this technology is necessary in the view of spare parts supply for real-time maintenance scheduling. The research direction can be how to evaluate the potential impact of additive manufacturing improvements on the configuration of spare parts supply chains.
- For cloud manufacturing, the developed maintenance policy should be combined with cloud computing with a manufacturing perspective. The key challenge can be summarized as the capability of providing distributed, fast-responding, on-demand and quantifiable maintenance services.
- For social manufacturing, maintenance scheduling has to be suitable for the new paradigm. It promotes socialized resources configuration, social interaction, business collaboration and all-around production management to accomplish product lifecycle tasks efficiently and flexibly.

It is seen that PHM methodologies for advanced manufacturing paradigms has a positive cascading effect in upgrading future industries and increasing their competitiveness. They would be systematic methodologies consisting of recent advances in prognostics techniques and maintenance policies. The successful PHM applications in the industry require the contributions from not only the field of reliability engineering, but also the field of manufacturing engineering. It could be anticipated that more PHM methodologies for advanced manufacturing paradigms will appear, and this overview can serve as a reference point for future studies.

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