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IoT-Based Prognostics and Systems Health Management for Industrial Applications

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ABSTRACT Prognostics and systems health management (PHM) is an enabling discipline that uses sensors to assess the health of systems, diagnoses anomalous behavior, and predicts the remaining useful performance over the life of the asset. The advent of the Internet of Things (IoT) enables PHM to be applied to all types of assets across all sectors, thereby creating a paradigm shift that is opening up significant new business opportunities. This paper introduces the concepts of PHM and discusses the opportunities provided by the IoT. Developments are illustrated with examples of innovations from manufacturing, consumer products, and infrastructure. From this review, a number of challenges that result from the rapid adoption of IoT-based PHM are identified. These include appropriate analytics, security, IoT platforms, sensor energy harvesting, IoT business models, and licensing approaches.

INDEX TERMS Internet of things, maintenance, prognostics and systems health management, reliability, remaining useful life.

ACRONYMS

PHM	Prognostics and Health Management
IoT	Internet of Things
MEMS	Micro Electronic Mechanical Systems
RFID	Radio Frequency IDentification
CBM	Condition-Based Maintenance
RUL	Remaining Useful Life
PoF	Physics of Failure
FMMEA	Failure Modes, Mechanisms, and Effects Analysis
TTF	Time to Failure
MRO	Maintenance, Repair and Operations
IVHM	Integrated Vehicle Health Management
NFF	No Fault Found

I. INTRODUCTION

Reliability is the ability of an asset to perform under expected performance requirements for a specified period of time in field use conditions [1]. Customers expect their purchases to be reliable, and reliability influences their willingness to pay. Manufacturers need to balance customer expectations and profit expectations by designing for reliability and quality goals. Infrastructure (e.g., roads, ports) and utility (e.g., water, power, gas) operators providing services for their communities need to balance the costs, risks, and performance of their assets. The direct costs and reputation loss caused by poor asset reliability can significantly impact organizational performance. The ability to predict an asset's reliability is therefore a core capability.

This organizational capability is enabled by appropriate prognostics and systems health management (PHM) practices. PHM originates the idea that the ''health'' (or degradation) of assets can be determined and the reliability (and remaining useful performance over the life of the asset) predicted with the aid of in situ sensing [2]. PHM methodologies are based on several key elements in which sensors provide the capability of monitoring failure precursors and environmental loading conditions (e.g. stresses).

Asset manufacturers and operators have used sensors for decades to collect health data on assets, defined as "an item, thing or entity that has potential or actual value to an organization" [3]. Data collection today is often conducted using sensors hard-wired to industrial control systems to aid in assessing operational performance. In addition, technicians take readings from a machine to check its performance and may then discard the data [4]. However, developments in the IoT offer a new paradigm in which sensor data is streamed wirelessly from "things," which may be systems, sub-systems, or assets, to remote servers in the cloud. In this manner, all data relevant to health estimation (e.g., environmental conditions, maintenance, and operating data) are available for health monitoring and prognostic assessment. This sharing of information across assets and platforms enables the development of a complete operating picture and the flexibility to assess and manage new and even previously unknown risks.

The term IoT was reportedly first used in 1997 [5] so it is not a new idea. The Institution of Electrical and Electronic Engineers (IEEE) defines IoT as "a network of items, each embedded with sensors, which are connected to the Internet" [6]. This network enables the connection of geographically dispersed people and assets. Today, IoT is developing momentum due to a number of technical, cost, and standardization drivers and developments [7], [8]. The size and cost of sensors are decreasing due to advances in microelectronic-mechanical systems (MEMS) technology. In 2011, the number of interconnected devices (things) on the planet overtook the number of people [8]. Gartner, Inc., forecasts that 6.4 billion connected things will be in use worldwide in 2016, up 30% from 2015, and that number will reach 20.8 billion by 2020. In 2016, 5.5 million new things are estimated to be connected every day [9]. Access to real-time data is increasing due to wireless technologies, including radio frequency identification (RFID) tags and embedded sensors, and the proliferation of wireless sensor networks and addressing schemes that give each "thing" a unique address. The cost of connectivity is also decreasing, and, as more spectrum becomes available, the ability to communicate with more and different sensors is increasing. Furthermore, consumer confidence in, and use of, cloud computing and the reduction of the cost of data storage enables storing of massive datasets and provides a platform for the data analytics and machine learning algorithms used by the prognostics and system health monitoring models.

This paper shows how IoT and PHM can be integrated. We also discuss the opportunities that the IoT offers, and present some unique business innovations being implemented in industrial applications.

The remainder of this paper is organized as follows: Section II provides a brief overview of PHM methodologies and their applications. Section III introduces IoT-based PHM approaches for industrial applications and discusses potential benefits according to representative industry sectors. Section IV discusses the challenges of IoT-based PHM and potential financial benefits. Finally, concluding remarks and suggestions are presented in Section V.

II. OVERVIEW OF PROGNOSTICS AND SYSTEMS HEALTH MANAGEMENT (PHM)

For asset owners and operators, the health management strategy for a particular asset is dependent on the asset's failure behavior (failure modes) and the consequence of failure. There are generally considered to be four types of management strategies: corrective, fixed-interval preventative, failure-finding, and condition-based maintenance. Of these, condition-based maintenance (CBM) requires the highest level of asset management maturity. Rather than waiting until an asset fails or replacing it at a fixed interval, CBM uses sensor data and models to detect deterioration and select an appropriate time for maintenance. A successful CBM program relies on effective PHM.

PHM can be an effective solution for detecting anomalies and faults, diagnosing failures, predicting residual (remaining) lifetimes, and estimating the reliability of assets. Some examples of successful applications of PHM include electronics [10], [11], rotating machinery [12]–[14], and linear assets such as transport, water, and electrical distribution [15], [16]. PHM consists of four dimensions: sensing, diagnosis, prognosis, and management, as shown in Fig. 1.

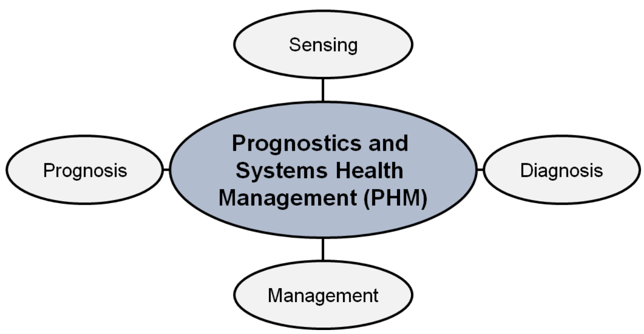

FIGURE 1. Four dimensions of PHM.

Sensing enables anomaly detectability by selecting and appropriately locating sensors that provide the capability to collect a history of time-dependent degradation of materials or environmental stresses. Anomalies do not necessarily indicate a failure. Changes in operating conditions, as well as asset performance degradation, can influence data to show anomalous behavior. However, even this type of anomaly information is valuable to asset management.

Diagnosis extracts fault-related information from the sensor signals caused by anomalies in asset health. Anomalies may result from material degradation, as well as changes in use conditions. Diagnosis relates the signal anomalies to a failure mode(s), and identifies the quantity of damage that has occurred as a health indicator. The results from this anomaly diagnosis can provide advanced warnings of failure, referred to as failure precursors.

Prognostics or remaining useful performance over the life of the asset [sometimes referred to as remaining useful life (RUL)] estimation methods use algorithms to predict the progression of a specific failure mechanism from its incipience to failure within appropriate confidence intervals. This step often requires additional information not traditionally provided by sensors, such as maintenance history, past and future operating profiles, and environmental factors [17], but available within the IoT.

The final key aspects of PHM are to effect appropriate decision making; to prevent catastrophic failures; to increase asset availability by reducing downtime and no-fault-founds; to extend maintenance cycles and execute timely repair actions; to lower life-cycle costs from reductions in inspection, repair, and inventory costs; and to improve system qualification, design, and logistical support.

PHM integrates component lifetime estimation and reliability prediction, enabling the reliability of an asset to be evaluated and providing the opportunity to manage the asset risk. A successful PHM execution relies on the selection of appropriate prognostic approaches. Currently, there are many prognostic techniques, and their usage must be tuned for each application. Prognostic methods can be classified by the following three approaches: physics-of-failure (PoF)-based, data-driven, and fusion.

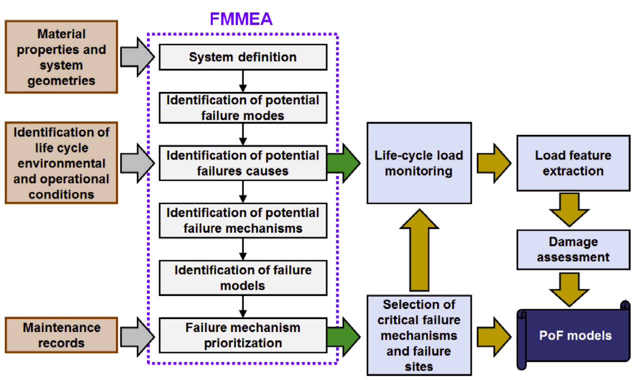

FIGURE 2. **PoF-based PHM methodology [18].**

A. PHYSICS-OF-FAILURE (PoF) APPROACHES

A PoF approach uses knowledge of how things degrade and fail. This knowledge is based on physical laws linked with a mathematical model [18]. As shown in Fig. 2, the PoF approach requires understanding of the process by which physical, electrical, chemical, and mechanical stresses act on materials to induce failure. The procedure of conducting PHM using a PoF approach can be summarized in the following five steps [19]:

Step 1: Identify the critical failure mechanisms and failure sites using failure modes, mechanisms, and effects analysis (FMMEA) [1];

Step 2: Monitor the life-cycle loads that may lead to performance or physical degradation and the associated asset responses;

Step 3: Extract features from the variables that change in response to deterioration associated with the failure mechanisms identified at *Step 1*;

Step 4: Assess damage and calculate remaining life using the PoF models of the failure mechanisms; and,

Step 5: Estimate uncertainty and predict the time-to-failure (TTF) as a distribution.

FMMEA provides a list of potential failure modes, mechanisms, and the corresponding models of an asset. According to the occurrence, severity, and detectability, FMMEA assigns scores to each potential failure mode, and ranks them to identify the critical failure modes. Life-cycle load monitoring establishes a history of loading conditions of the asset, such as thermal, mechanical, chemical, physical, and electrical loading conditions. Sensors are used to collect data from which features are extracted to represent and quantify the failure. The extent of damage is assessed using the PoF model for the various failure mechanisms. Uncertainty analysis of the life prediction enables risk-based decisions. Uncertainty sources include measurement errors, model parameter estimates, failure criteria, and future usage. A Monte- Carlo simulation can be used to provide the TTF as a distribution based on probabilistic damage assessment.

The main advantage of a PoF approach is the ability to incorporate an engineering-based understanding of the system into PHM by using knowledge of the materials and geometries of an asset, as well as the load conditions (e.g., thermal, mechanical, electrical, chemical) over the life cycle. PoF models tend to be failure mechanism-specific, therefore, they are sometimes not available in new designs where an up-front design for reliability was not implemented.

B. DATA-DRIVEN APPROACHES

Data-driven approaches use data analytics and machine learning to determine anomalies and make predictions about the reliability of assets based on internal and/or external covariates (also called endogenous and exogenous covariates). Internal covariates (e.g., temperature, vibration) are measured by sensors on the asset and are only present when the asset is operating. External covariates (e.g., weather data) are present whether or not the asset is operating [20]. The data-driven approach analyzes asset performance data based on a training database of internal and/or external covariates. This may be implemented either by obtaining data under healthy conditions or from data-mining techniques.

Data-driven approaches for PHM are used for both the diagnosis and prognosis stages, often .based on statistical and machine learning approaches [21]. These may include use of (1) multivariate statistical methods [22]–[25]; (2) black-box methods [26], [27]; (3) graphical models [28], [29]; (4) self-organizing feature maps; (5) time-domain methods; and (6) fuzzy rule-based systems. Reviews of these different models and more examples of their applications are found in [2] and [30]. Model selection depends on the requirements and objectives of the anomaly detection, diagnostics, and prediction. The following questions need to be considered during model selection: How well does the model describe the reality? How accurate is the prediction? How robust is the modelling approach?

Compared to PoF approaches, data-driven approaches do not necessarily need asset-specific information. Data-driven approaches can learn the behavior of the asset based on the data collected, and can be used to analyze intermittent faults by detecting changes in asset features. The approaches can also be used in complex assets with multiple and potentially competing failure modes as long as the asset exhibits repeatable behavior. In other words, the strength of data-driven approaches is their ability to transform high-dimensional noisy data into lower-dimensional information for diagnostic and prognostic decisions. However, data-driven approaches have some limitations, the main drawback being a reliance on historical data on the failure modes or mechanisms the analyst seeks to detect. This can be an issue especially when the consequence of failure is high, resulting in reliance on simulated or laboratory rather than field data for the training dataset. Reliance on historical data is also an issue for new products for which an extensive field failure history is not available.

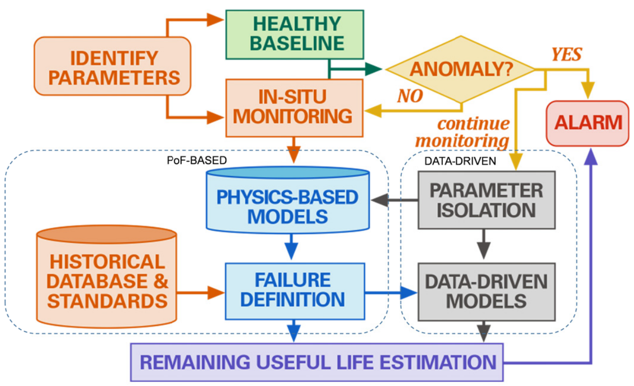

FIGURE 3. Fusion PHM methodology.

C. FUSION (PoF-BASED/DATA-DRIVEN HYBRID) APPROACHES

The fusion approach shown in Fig. 3 combines the advantages from the PoF-based and data-driven approaches to allow better RUL prediction capability [31]. This approach reduces the reliance on historical datasets and addresses the issue of previously unseen failure modes.

In fusion PHM, the first step is to determine which variables to monitor. The variables consist of external covariates, including operational and environmental loads, as well as internal covariates based on sensor data. The next step is to identify the features of these variables. Then, in situ measurements and deviations from the features associated with healthy states are used to detect anomalous behavior (e.g., Mahalanobis distance [32], [33], sequential probability ratio test [34], and self-organizing map). Once anomalies are detected, isolation techniques identify features that significantly contribute to the abnormal status. These features are further used as inputs of PoF models for RUL prediction. For the purpose of feature isolation, various data-mining and machine learning-based techniques (e.g., principal component analysis [35], mutual information-based feature selection, and support vector machine [36]) can be employed.

PoF models are used to assess in situ degradation of the asset under particular environmental and operating conditions. In fact, a number of potential failure mechanisms may exist in the use of the asset. Hence, it is theoretically necessary to have PoF model(s) corresponding to each failure mechanism for accurate assessment of in situ degradation, which may not always be the case. So, the fusion PHM scheme basically identifies and prioritizes the potential mechanisms for the asset under certain environmental and operational conditions. Then, PoF models can be identified from the database involving pre-defined PoF models.

Failure definition is considered as a process of defining the criteria of failure. Additionally, failure definition is based on PoF models, historical usage data, asset specifications, or related standards for each potential failure mechanism. In Fig. 3, degradation modeling is defined as a process of learning (or predicting) the behavior of the model parameters highly correlated with failure. To predict a parameter degradation trend, techniques such as relevance vector machine [37], hidden Markov model, and filters [38] (e.g., Kalman filter [39] and particle filter [40]) can be used. Finally, the RUL is predicted by determining if the predictive parameters meet the failure criteria resulting from failure mode definition. TTF can also be predicted using statistical and machine learning models.

Owing to the aforementioned advantages, the fusion approach has been successfully applied to RUL estimation for electronics, avionics, and structures. For instance, the fusion PHM approach successfully predicted the RUL of multilayer ceramic capacitors that can be found in a wide array of applications, including consumer electronics, telecommunications, data processing, personal computers, hard disks, video cameras, mobile phones, and general electronic circuits [41]. The fusion PHM approach was also used to predict the RUL of lithium-ion batteries, resulting in information that can be used for scheduling battery recharge and replacement for emerging electric and aerospace vehicles [42]. The RUL estimation based on the fusion PHM approach for avionics systems, insulated-gate bipolar transistors (IGBTs), and corrosion fatigue of physical structures was reported in the literature [43]–[45].

III. IoT-BASED PHM FOR INDUSTRIAL APPLICATIONS

The smart, connected elements of IoT require an appropriate technology infrastructure. This infrastructure is represented as a ''technology stack'' and is shown in Fig. 4. A technology stack facilitates data exchange between the asset and the user, integrates data from business systems and external sources, serves as the platform for data storage and analytics, runs applications, and safeguards access to assets and the

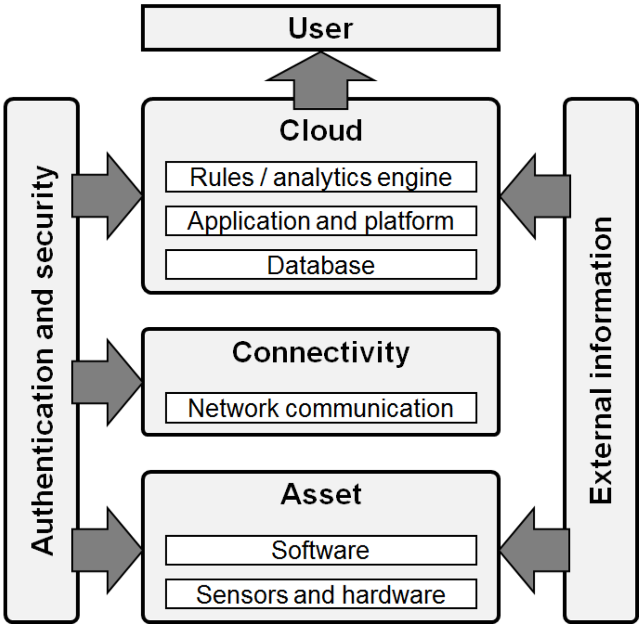

FIGURE 4. Technology stack for supporting IoT.

data flowing to and from them [46]. The lower half of the technology stack describes the elements associated with the asset. There are two parts—software and hardware. One of the evolutions currently underway is the addition of embedded sensors, RFID tags, and processors built into the asset. Collectively, this enables new data to be collected for PHM. This data needs to be transmitted, and therefore network connectivity, as shown in the central block, is a key feature of IoT. The data collected and transmitted has to be stored and processed in an efficient and interpretable way. This is increasingly being done using cloud computing services, represented by the top block in the technology stack. The user, shown at the top of the figure, includes people who access the results of the analysis as well as those involved in the development and maintenance of the technology stack elements and the models it supports. The blocks on either side of the stack identify the importance of authentication and security at all levels in the technology stack as well as the potential relationships with other systems and sources of information.

The following section considers how IoT has been and will be applied in the near future for PHM applications in different industrial sectors.

A. MANUFACTURING

Manufacturing is a major source of economic benefit in many countries. The manufacturing industry has traditionally focused on product quantity for mass production. In order to strengthen competitiveness, the manufacturing paradigm is now shifting towards combining sales with maintenance service enabled by IoT [4]. There is a significant shift underway from a focus on products alone to a focus on platforms. In a platform approach, a company's product operates as a facilitator and the product's value is created by the participants instead of the company itself. Examples include platform-based businesses such as Apple, Uber, and AirBnB. A prerequisite for a successful platform is a company's ability to build a value proposition around an ecosystem and not only around its own products [47]. The effect of this ability on manufacturers' relationships with customers is discussed in Section III.B.

In the manufacturing industry, Industrie 4.0 and its associated Smart Factory program are initiatives of the German government to assist in the development of cyber-physical platforms that enable IoT developments [48]. Cyber-physical platforms change the traditional manufacturing processes by integrating devices, equipment, and platforms in a factory, connecting factory-to-factory and integrating operational and information technologies [49]. Examples of platforms that support these ideas include the Siemens Totally Integrated Automation portal [50], GE's Predix platform [4], [51], and SAP Hana [52].

Japanese manufacturers tend to collaborate with IT companies to develop IoT-based manufacturing systems. For example, Toshiba Machine has developed an IoT-based PHM system with NEC. Customers' products send failure and operating information to NEC data centers, and Toshiba Machine then uses the cloud to propose maintenance services. By resolving the root causes of failure offsite, travel expenses for troubleshooting are reduced by 15%. Nidec has developed a similar IoT-based system in conjunction with IBM. A machine at Nidec sends operating information to the data center managed by IBM. The data center provides diagnosis of the machine based on the data collected [53], [54].

B. HEAVY INDUSTRY: MOBILE ASSETS

Mobile assets in heavy industry include airplanes, ships, and construction and mining equipment. These industries have embraced opportunities provided by IoT because their equipment is mobile and therefore data needs to be transmitted in real time in order to enable management decision making. Mobile assets are increasingly connected across the fleet, and the use of IoT allows for remote management of both maintenance and operational processes.

The "smart" ships shown in Fig. 5 are a good example of a value-added asset for heavy industry, whereby sensor information from the environment (e.g., sea waves, tidal currents, and winds), the ship itself (e.g., devices, modules, and systems), and other ships (e.g., routes), are analyzed to provide the captain with the optimal (e.g., fast and economic) route information, maintenance plans, and safe fleet management [55].

Construction and mining equipment products, such as excavators, wheel loaders, and backhoe loaders, are embracing the benefits of connectivity and monitoring [56]. Because construction sites are often in remote or even isolated locations, connectivity and real-time monitoring are required and PHM is becoming a more critical function. For example, Komatsu monitors and diagnoses faults in their construction

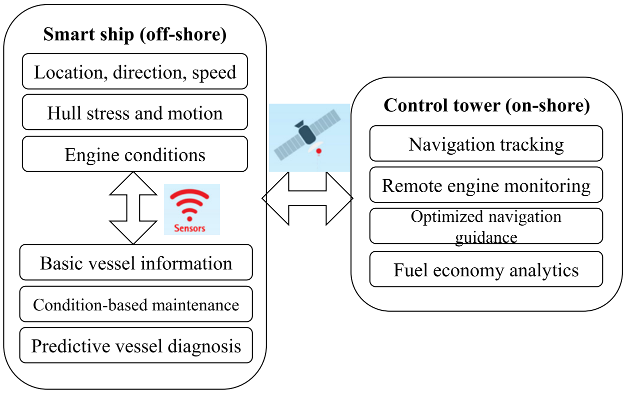

FIGURE 5. **Conceptual representation of smart ships.**

equipment products in the field via satellite communications [57]. Similarly, GE monitors their gas turbines in the field and collects more than 30,000 hours of operation data per day from their power plants installed world-wide. The monitoring system triggers alarms when the monitoring variables, such as noise, vibration, and temperature, show anomalous behavior. GE reported that PHM application saved more than \$70 million in 2014 [58]. Rolls-Royce now offers a business model that charges an hourly service fee for their jet engines. They monitor their products in the field in real time and provide their customers with optimized maintenance because it is forecasted as needed, rather than scheduled or, worse yet, conducted after a failure has occurred [59]. Thus, IoT-based PHM adds values to products and systems in the field, and can be used as a marketing strategy to differentiate businesses.

C. ENERGY GENERATION

The energy-generation industry consists of nuclear, thermal power, and renewable energy. Thermal power (oil, coal, and natural gas) generates 81.4% of the world's supply, biofuels 10.2%, nuclear 4.8%, hydro 2.4%, and renewables (geothermal, wind, and heat) 1.2% [60].

Power generation is a significant contributor to CO_2 emissions, responsible for about 50% globally. Hence, significant effort is going into improving the efficiency of generation and distribution. Cloud computing is enabling the development of so-called "smart grid" computing. Smart grids use large numbers of networked sensors, power electronic devices, distributed electricity generators, and communications appliances. As a result, the electric grid is becoming smarter and more complex, but requires integration of a large quantity of real-time information and data processing [61]. IoT-based PHM is an integral part of a smart grid as engineers seek to monitor the health of key components in the network.

Renewable energy includes wind, hydro, solar, and biofuel energy generation. Among these, wind energy generation often encounters reliability issues. In order to deliver desired capacity, wind power plants often require long blades and high towers, which increase the load and stress, and may eventually cause wind turbine failure. Many wind farms are located in remote locations, such as offshore or on a mountain, where accessibility is limited. A number of organizations, for example, GE (Digital Wind Farm) and Siemens (Wind Service Solutions), now provide IoT service solutions for wind farms. These solutions aim to optimize turbine performance and equipment life by using RUL estimation models to predict maintenance requirements [62].

IoT-based PHM in the energy-generation industry can change the maintenance paradigm by supporting the use of more CBM. It can increase plant reliability and availability, stabilize the power supply with fewer power interruptions, and eventually provide the industry with a good reputation and customer trust. In addition, IoT-based PHM plays a role in ensuring that aging power infrastructure is appropriately monitored for unplanned failures and that deteriorated assets are replaced at cost- and risk-effective intervals.

D. TRANSPORTATION AND LOGISTICS

IoT is playing an increasing role in the transportation and logistics industries as more physical objects are equipped with barcodes, RFID tags, and sensors. Transportation and logistics companies now conduct real-time monitoring as they move physical objects from an origin to a destination across their supply chain. From an IoT-based PHM perspective, the ability to see how long an item has been in storage and under what conditions (e.g., heat, vibration, humidity, and contaminating environments) enhances the ability to predict failures. An asset may undergo several loading conditions or even fail during transportation and storage due to unexpected exposure to mechanical shock and vibration, cosmic radiation, or being in a too dry, wet, or humid environment.

Commercial aviation spends more than 50% of its total expenses on maintenance, repair, and operations (MRO) [63]. Aircraft component failure results in significant loss of safety, profit, as well as reputation. Integrated vehicle health management (IVHM) is a unified system that assesses the current and future states of vehicles, and has evolved over the last 50 years [64]. IVHM with PHM capability has the potential to influence aircraft design by reducing system redundancy, resulting in fewer subsystems and modules on an aircraft. IoT-based PHM application in aviation can reduce unplanned maintenance and no-fault-found (NFF) events, and can improve aircraft availability and safety [65].

E. INFRASTRUCTURE ASSETS

Infrastructure assets (e.g., water, gas, power) are often geographically dispersed and hence reliant on remote monitoring and sensor telemetry. In the water industry, the ability to place an IoT solution on a flow meter allows real-time data to predict and adjust consumption. The ability to link operational data to condition-monitoring data enables predictive analytic solutions to be run in the cloud and prediction of network failures.

Infrastructure organizations are exploring ways in which sensors unconnected with the asset can be used to provide relevant asset health monitoring information, for example, the use of accelerometers in drivers' mobile phones to detect potholes and other road defects [66]. Cities and local governments are at the forefront of making data they collect publically available. Often called ''smart cities'' programs, these initiatives enable developers to create applications that enhance management of public infrastructure assets [67], [68].

F. AUTOMOBILES

The automobile industry is driving innovation in the application of technology that enables consumers to get advanced notice of problems with their vehicles as well as real-time diagnostics support. For example, cars made by General Motors, Tesla, BMW, and other manufacturers now have their own application programming interfaces (APIs). The APIs allow applications built by third parties to interface with the data collected on the car. This enables the development of applications for IoT-based PHM that add value by increasing connectivity, availability, and safety.

IoT allows ''smart'' cars in the field to connect to the network, enabling real-time navigation, remote vehicle control, self-diagnosis, and in-vehicle infotainment service. Smart cars can connect to other cars, as well as infrastructure, to share their route information for efficient route planning. Smart cars are evolving as a connected device, and in the future users may be able to purchase mobility through a driverless car network rather than having to own a car [69]. The reliability of a future smart car network will depend on appropriate use of IoT-based PHM. Cars with deteriorating health will need to be scheduled out of the system, so that unplanned in-service failures, which may affect the car network performance, can be avoided.

G. MEDICAL CONSUMER PRODUCTS

Medical devices are another area where consumer needs are increasing, and the consequences of their failures can be critical. For example, failures of in- vivo devices, such as pacemakers, can cause patient death. Medical devices can fail due to battery performance degradation. Patients with pacemakers are required to check at a fixed-time interval to ensure the device is functioning correctly. IoT-based PHM allows medical consumer products to be monitored and diagnosed continuously and remotely, and therefore can help these patients by reducing the number of intervals required for regular checking. IoT-based PHM of medical devices can also facilitate remote patient monitoring, homecare service for the elderly, and chronic disease management [70], [71].

H. WARRANTY SERVICES

Conventionally, customers seek warranty services when their assets fail. However, seeking a remedy to failure after the failure has occurred is costly for both the customers and maintainers. The customer loses operational availability, and the maintainers must conduct corrective maintenance, which is generally more expensive than predictive maintenance due to collateral damage, scheduling, diagnosis, and spare parts availability. In addition, waiting until an asset fails can pose safety (and liability) issues.

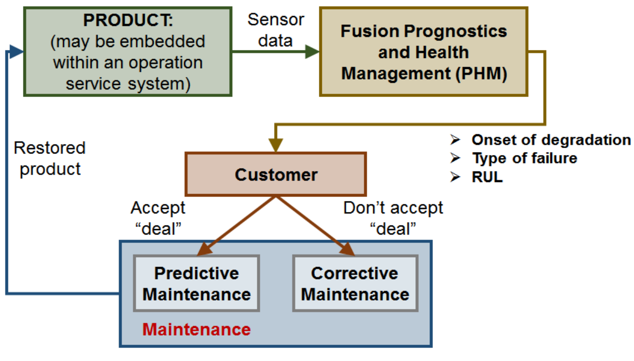

FIGURE 6. Inclusion of IoT-based PHM in predictive warranty service.

Fig. 6 overviews a predictive warranty service, where the asset is one that the customer has a significant investment in and for which the operational availability of the asset is of critical importance to the customer (e.g., cars and aircraft). The inclusion of IoT-based PHM into warranties can augment the customer's ability to make a decision about whether to seek warranty service prior to asset failure by offering useful information, such as the onset of the asset's degradation, type of failure, and RUL. Consequently, IoT-based PHM can facilitate effective logistical support by showing where and how the customer's asset is degrading [72].

I. ROBOTICS

Robots use a combination of sensors and actuators to fulfil their functions. These sensors can also be used for PHM when tied into an IoT system. The robotics market is expanding in many countries. For example, the U.S. government released the national robotics initiative in 2011 to accelerate the development and use of robots. In 2014, the E.U. launched a research and innovation project in the field of robotics through collaboration between the European Commission and around 180 private companies [73]. The Japanese government also released their robot strategy in 2015 [74]. The Japanese government advocates a five-year plan that aims at implementing next-generation robots through the advancement of sensor and artificial intelligence (AI) technologies.

IoT enables robots to connect to other robots and devices. FANUC's Intelligent Edge Link Drive (FIELD) system is an example of IoT-based PHM [75]. It is a platform that connects not only robots, but also peripheral devices and sensors. FANUC is collaborating with Cisco, Rockwell Automation, and Preferred Networks to establish the platform.

IoT expands the definition of robots from simple task performers to autonomous ones with self-learning abilities. This transformation has the potential to make robots play an important role in interacting with humans. IoT-based PHM can be a key technology for autonomous robots. It enables robots to diagnose themselves based on collecting data and AI technologies as a self-cognizant electronic system.

IV. MAKING IoT-BASED PHM WORK

The previous section described a number of current and significant business opportunities for IoT-based PHM. This section discusses some of the key challenges, in particular, analytics, security, IoT platforms, energy harvesting, IoT business models, and licensing and entitlement management.

A. ANALYTICS: MACHINE LEARNING AND DATA MINING

In an IoT-based PHM environment, the ever-growing use of sensors and networked things can result in the continuous generation of high-volume, high-velocity, and high-variety data, which is known as "big data" [76]. Conventional analytical approaches have been shown to be inadequate and need to be extended and adapted to deal with the challenge of scale, diversity, and the distributed nature of the data [77], [78]. Some of the major challenges include learning in distributed settings, learning from very high-dimensional data, and learning from heterogeneous and complex data. Hence, novel frameworks such as the alternating direction method of multipliers [79] are being introduced to enable optimization, a core functionality of many learning algorithms, in such distributed settings. Advances have enabled versions of successful machine learning algorithms such as convolutional neural nets [80], restricted Boltzman machines [81], support vector machines [82], and regression [83] for large-scale settings.

In addition, there have been advances in methods aimed at analyzing big data at scale for anomaly detection and time-series forecasting. These are needed for use cases that require online learning or where the models need to be adapted to evolving realities. Feature extraction is also one of the challenges that has resurfaced since it is no longer feasible for learning features to be designed or discovered using conventional techniques. Novel approaches are enabling automated feature extraction and learning in cases where generalized models can be built from extremely large distributed datasets. One of the most promising developments has been in learning sophisticated networks and auto-encoders via deep learning methods [84]. Deep learning is starting to show significant promise in PHM [85]–[87].

B. SECURITY

In the IoT-based PHM scheme, data are collected by wireless sensors and transmitted to a base system (e.g., a local server or a server in the cloud) or computer for post-analysis. Many wireless technologies have been recently used for data transmission, such as RFID, Bluetooth, Wi-Fi (IEEE 802.11), Ultra-Wideband, WiMax (Worldwide Interoperability for Microwave Access and IEEE 802.16), and ZigBee (IEEE 802.15.4) [88]. Reliability and affordability of IoT-based PHM applications is closely associated with connection robustness, security, and real-time data access.

However, the problem faced in data transmission is that malicious software might disturb data integrity. That is, the leakage of security-critical information (e.g., a system's usage record and performance information) can affect the trustworthiness of the IoT-based PHM system. Accordingly, security is one of the major issues to be addressed in IoT-based PHM.

C. IoT PLATFORMS

IoT platforms help reduce the cost of developing IoT-based services and applications. Without an IoT platform, the challenges of building an IoT application are significant: developing the application logic user interface and database, and developing data analytics. However, IoT platform providers leverage the underlying technologies and assets they have, while taking into consideration their business models and customers. Understanding what each provider offers is required when evaluating IoT platforms because selection of the underlying platform can be a critical decision for an IoT-based service developer. In general, switching platforms can be messy, expensive, time-consuming, and painful.

One of the issues for the IoT community has been the proliferation of architectures and communication protocols. However, standardization bodies such as the IEEE Standards Association [89], [90], the Internet Protocol for Smart Objects Alliance [91], the Industrial Internet Consortium [92], and the Open Interconnect Consortium [93] are working on common architectures and communication protocols.

D. ENERGY HARVESTING

Despite their potential, the reliability of IoT assets is often impeded by limited energy supply if these devices are deployed in energy-scarce locations or where no human intervention is possible. Accordingly, to address such energy constraints, re-generating power for IoT assets (also known as energy harvesting) is required. Energy harvesting is defined as the process of scavenging or hunting energy from the environment, such as solar, wind, or vibration, so that the device can be powered without an additional power source [94]. Considerable research is currently being directed to low-power or energy-harvesting support for sensors and associated connectivity systems [95].

E. NEW BUSINESS MODELS FOR IoT-BASED PHM

The combination of IoT and PHM will need new business models to support its effective implementation. There are a number of dimensions to consider, including:

- Speed of decision making: The opportunity to collect appropriate real-time data on asset health allows for a faster response to changing asset conditions. However, internal business processes for faster and more risk-based decisions are necessary. Currently, prognostics decisions are still largely made by experienced engineers who then need to pass on alerts and recommendations through a chain of command. This slows down the response time. In addition, the current structure of performance measures for maintenance organizations is based around metrics such as % schedule compliance

and % planned maintenance. Adherence to target values for these metrics means that ''schedule breakers'' such as actions coming from PHM that need rapid response will not be welcomed by the managers who are accountable for meeting target values for these performance measures.
- Trust and accountability: At present, for most organizations analysis of health data is done either internally or by trusted consultants. In the new paradigm, analysis will be done by models sitting in the cloud, and recommendations will be based on these models and reviewed by analysts sitting in remote operations centers. There are all sorts of questions about who has the authority in this process and how to build trust between the local asset operator and the remote analysts, who may know little about the actual asset or operation. These analysts may be employed by the company, the original equipment manufacturer (OEM), or even a third party.
- Liability: With so many groups involved in the process described in Fig. 4, how is liability determined in the event of a major asset failure? To support this evolving paradigm, a new style of risk- and performance-based contracts will be needed to support the tighter coupling between the multiple parties involved.
- Workforce competency: The process of IoT-based PHM described here will require a suite of new skills for which the current workforce is not necessarily ready. Many workers currently involved in traditional CBM roles will no longer be needed. Data will be collected by sensors rather than by data collectors, analysis will be done by models rather than by people, and decisions will be made by analysts with specialist modelling and engineering skills. These analysts may well work for third parties, making the current on-site workforce redundant. Supporting changes to incorporate new PHM-based IoT skill sets for both employees and third-party providers may require a significant change in current organizational structures [78].

F. LICENSING AND ENTITLEMENT MANAGEMENT

Licensing and entitlement management technology provides the locking capabilities that enable manufacturers to protect the embedded software intellectual property (IP) running on connected intelligent devices. Manufacturers faced with increasing global competitive pressure to reduce manufacturing costs can leverage the value created with Internet-connected products to increase revenue. However, manufacturers need to protect the IP contained in their applications and monetize it. This can be achieved through licensing and entitlement platforms that control access to the Internet-connected device, its functions, and features. These licensing and entitlement platforms will enable features such as dynamic pricing, bespoke bundling of features, and near-real-time software upgrades. These features should help manufacturers be more competitive by increasing the speed to market for new products, new feature combinations, and product enhancements.

V. CONCLUSIONS AND FUTURE DIRECTIONS

This paper introduced the opportunities and challenges of IoT-based PHM for industrial applications. While this paper presented many examples of companies successfully implementing IoT-based PHM, a major impediment is still the human capital to develop, validate, and maintain the models necessary for prognostics. These models require the engineering, statistics, and machine learning communities to work together. PHM requires the ability to link the anomalous patterns in the data to the failure modes and make connections to the underlying physics of failure (e.g. the failure mechanisms). One of the challenges with big data is that given enough data, one will always be able to find relationships, also called ''spurious correlations'' [96]. In PHM, only some of those relationships will make engineering sense.

To accelerate IoT-based PHM development, datasets on real asset failures need to be available. These datasets will enable the development of new algorithms and the validation of existing algorithms for specific applications. Condition-monitoring data alone is often not sufficient for PHM; metadata about the asset, its operating environment, and the external covariates that influence its deterioration would also be required. Of particular importance is the collection of failure modes and mechanisms for failure events. This data has usually been stored in separate systems to the sensor data. The advent of IoT enables these datasets to be merged and made available for analysis. Recent moves to develop a global prognostics data library will assist in making fit-for-purpose datasets more widely available [97].

A common feature of IoT platforms is a focus on open architecture. These open access platforms enable development of applications by third parties. This transition to open access is a paradigm shift for many businesses that have previously relied on proprietary products for competitive advantage. A number of international businesses and government groups are also now experimenting with open competitions using the platforms Kaggle and Hackathons to make datasets available for predictive analytics [98].

Although there are challenges to the implementation of IoT-based PHM, most of the issues are not insurmountable. Sensors are becoming small enough that they do not interfere with the product functions and have connectivity with lower power consumption. To process the data, hardware and software support using advanced statistical and machine learning methods is improving. Cloud computing capacity and speed have also increased significantly to meet the needs. Perhaps the biggest concern is with respect to the security of data [99].

The key conclusion is that IoT-based PHM is expected to have significant influence on the implementation of reliability assessment, prediction, and risk mitigation, and create new business opportunities.

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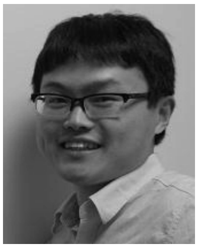

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