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Prognostics and Remaining Useful Life Prediction of Machinery: Advances, Opportunities, and Challenges

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Abstract: As the fundamental and key technique to ensure the safe and reliable operation of vital systems, prognostics with an emphasis on the remaining useful life (RUL) prediction has attracted great attention in the last decades. In this paper, we briefly discuss the general idea and advances of various prognostics and RUL prediction methods for machinery, mainly including data-driven methods, physics-based methods, hybrid methods, etc. Based on the observations from the state of the art, we provide comprehensive discussions on the possible opportunities and challenges of prognostics and RUL prediction of machinery so as to steer the future development.

Keywords: prognostics; remaining useful life; data-driven; machine learning; degradation modeling

I. INTRODUCTION

This paper reflects the important aspects in the field of prognostics and remaining useful life (RUL) prediction of machinery. Opportunities and challenges, as well as future directions are discussed. Section II on overview of prognostics research and future research opportunities was completed by Professor Nagi Gebraeel from Georgia Institute of Technology. Section III on opportunities and challenges in RUL prediction of machinery was written by Professor Yaguo Lei and Dr. Naipeng Li from Xi'an Jiaotong University. Section IV on opportunities and challenges in statistical data-driven prognostics was presented by Professor Xiaosheng Si from Rocket Force University of Engineering. Section V on prediction of RUL: future directions was written by Professor Enrico Zio from PSL Research University and Politecnico di Milano.

II. OVERVIEW OF PROGNOSTICS RESEARCH AND FUTURE RESEARCH OPPORTUNITIES

A. OVERVIEW

There is a plethora of work centered on prognostics and estimating remaining lifetime. Much of the work conducted over the past two to three decades has been recorded in several comprehensive survey papers such as [1–4]. These papers provide multiple perspectives on how to classify the current literature in prognostics and remaining life predictions. Figure 1 attempts to provide a simple overarching taxonomy of existing works in prognostics. Our taxonomy is more or less consistent with the traditional categorization of modeling approaches into model-based frameworks, data-driven models, and hybrid approaches that combine the two. We provide two additional dimensions. The first deals with the modeling assumptions about the environmental and/or operational covariates and their impact on remaining life predictions. The second focuses on data dimensionality starting with univariate and multivariate time series and moving on to profile and image data.

B. METHODOLOGIES USED DEVELOPING PROGNOSTIC MODELS

1) MODEL-BASED PROGNOSTICS. Model-based approaches assume the existence of a mathematical model that exploits physical knowledge of a system to derive phenomenological equations that characterize system degradation. In this context, prognostics are typically split into two sequential problems: a state-estimation problem where system health is assessed based on data observations, and a prediction problem that utilizes filtering techniques, such as Kalman filter, unscented Kalman filter, and particle filter to simulate the state distribution forward in time to RUL [4–6]. Model-based prognostics have been successfully implemented in diverse applications ranging from batteries [5,7,8] to various types of rotating machinery [9,10].

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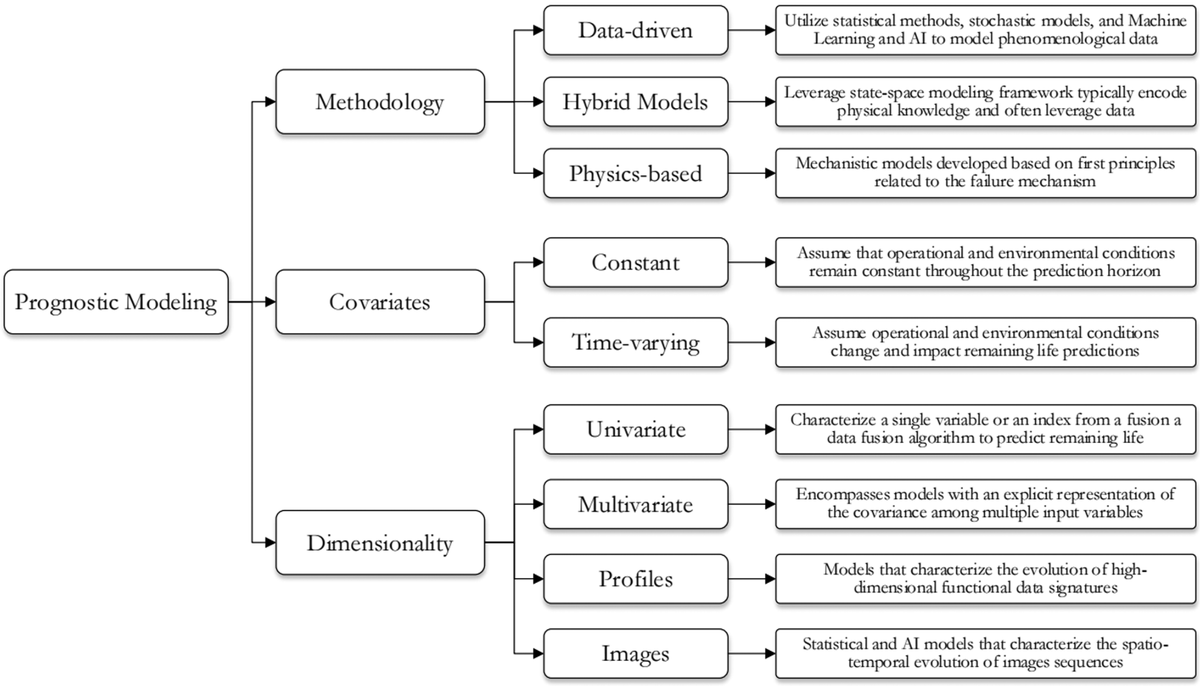

Fig. 1. Classification of prognostic models.

Model-based prognostics offer some key benefits. They often show good prediction accuracy when the model degradation parameters are estimated accurately. They can also estimate RUL conditional on the future operational and/or environmental conditions by modeling incorporating them as external inputs to the state-space equations. However, the model-based approach relies almost exclusively on the existence and the estimation of a parametric mathematical representation of the system dynamics and its degradation process. This is often hard to derive for complex systems and also difficult to generalize. The propagation of the system state forward in time can also become computationally prohibitive, especially for systems with high-dimensional state-space representation. Additionally, a substantial amount of data is required for parameter estimation.

2) DATA-DRIVEN PROGNOSTICS. Data-driven approaches attempt to learn certain patterns and statistical characteristics present in historical data that can be indicative of the component's state of health. These patterns and trends can be utilized to estimate the component's RUL. RUL estimation is generally performed through multivariate pattern matching or by extrapolating the current state of health to a predefined threshold [4]. In contrast to model-based approaches, data-driven approaches generally do not require specific domain knowledge and expertise, or complex phenomenological models that describe a system's physics. This makes them a popular choice when modeling complex systems for which creating a physical model might be extremely difficult, or even impossible.

Data-driven prognostic models can be loosely classified into two types: statistical-based approaches and machine learning (ML)-/artificial intelligence (AI)-based frameworks. Statistical approaches generally attempt to learn existing techniques between the variables in the data (such as the relationship between a degradation signal and operating time) and utilize those relationships to make predictions about future behavior [3]. Regression-based models and Markov processes are two of the most predominant techniques that rely on statistical/probabilistic frameworks for modeling degradation. These techniques are based on mapping the state of health of a component (treated as the dependent variable) to a set of independent variables (e.g., time, usage, environment, etc.). The mapping is then used to predict how the state of health of the system will behave to certain changes in the independent variables. A large portion of the literature in this space tries to predict RUL by estimating the time it takes to cross some predefined critical degradation threshold [3,4]. Many Markov-based techniques usually define some hidden Markov model with a finite number of states and an observed process that depends on the hidden one [1]. This approach is suited for applications where degradation states are not directly observable, yet the data still depend on the degradation state [3].

ML and AI are very powerful tools when it comes to data-driven prognostic models [3]. They are usually very generalizable and can be quite effective when the data are abundant and curated properly. Another benefit of ML-/AI-based appears clearly when modeling high-dimensional data such as spectral and image data. Such applications need careful feature extraction to extract informative features that are correlated with the underlying physical degradation. There are numerous feature extraction methods and techniques, some commonly used tools include principal component analysis (PCA), functional-PCA, wavelets, convolutional neural networks (CNNs), and variational autoencoder. It is noteworthy to mention that the accuracy of many RUL predictions is highly dependent on the efficacy of the feature extraction process. Additionally, the effectiveness of ML/AI models relies on the availability of large volumes of properly curated data – something that is often a major challenge in many industrial applications.

Interpretability is often a key limitation in many data-driven frameworks. Most statistical and ML-based models generally lack physical interpretability [3]. This poses serious challenges in building trust between human operators and predictions generated by these models.

3) HYBRID PROGNOSTICS MODELS. Hybrid approaches are usually a combination of model-based and data-driven approaches. A review on hybrid prognostics is presented in [11]. One common approach in hybrid prognostics algorithms is the use of data-driven methods (e.g., neural network [NN], long short-term memory network LSTM, radial basis function network RBF) to create a mapping from sensor measurements to the state space and then using a state-space model to model the evolution of the degradation state [12,13]. Such approaches are more comprehensive and combine the benefits of both frameworks. However, they are still deeply rooted in building customized models that are relatively application specific. The creation of a truly generalized hybrid modeling framework is still an illusive endeavor.

C. PROGNOSTIC MODELS AND COVARIATES

Generally speaking, harsh environments tend to accelerate the degradation mechanisms that occur prior to failure as compared to milder environments. Yet, as noted by [14], the vast majority of conventional failure models assume that prevailing environmental conditions are temporally invariant or have no effect on deterioration and failure processes. The limited number of failure models that do consider environmental effects generally belong to one of two groups: (1) hazard rate function models that treat environmental conditions as model covariates [15–17] and (2) stochastic wear and/or shock models in which the wear and/or shock intensities are modulated by the environment (cf. [18,19]). However, even these models have certain features that limit their applicability. First, the hazard rate function is only useful for making inferences about a large population of components, but not about specific components as it cannot be easily observed or measured for individual components [20]. The second group of models is useful for deriving analytical lifetime distributions (or their transforms) and assessing, probabilistically, the full or residual lifetime of the component. However, these models treat failure as a random event and do not provide information about the evolution of the physical degradation process that occurs prior to failure [21].

1) TIME-VARYING PROGNOSTIC MODELS. Few models have studied predicting RUL under time-varying environmental and operating conditions; examples include load-dependent degradation models such as batteries [8,22,23] and bearings [24–26]. [27] proposed a methodology for modeling degradation signals from components functioning under dynamically evolving environment conditions where in-situ sensor signals related to the degradation process as well as the future environment conditions were utilized when predicting the components RUL. The model assumed that the time-dependent degradation rate where a component's degradation signal increases (or decreases) is affected by the severity of the environmental condition. These conditions are assumed to evolve as a continuous-time Markov chain. [26] extended this work by considering a state-space modeling framework where changes in the degradation rate are part of a state transition function, and jumps in the degradation signals due to environmental changes are part of a measurement function. The separate analysis of these two factors made it possible to distinguish the unique contribution of these two aspects resulting in reducing the false alarms and improving the prediction accuracy. Additional works that considered a similar setup include [28–30].

D. DIMENSIONALITY OF DEGRADATION DATA

Popular prognostics modeling frameworks involve modeling how degradation signals evolve over time and using that information by estimating the time remaining for the signal to cross a predefined failure threshold. Typically, a degradation signal is computed from specific features obtained from the raw sensor data. Most prognostic models developed in the literature are designed to model a univariate signal representing a time series of degradation-based data evolving over time.

1) MULTIVARIATE DEGRADATION SIGNALS. Multisensor application often involved complex equipment that typically undergo multifaceted degradation processes. Using multiple sensors can potentially capture different aspects of the complicated degradation processes that usually involve different failure modes. Overall, the data in such cases are much richer and can lead to more accurate failure predictions. One of the key aspects in this setting is how to systematically combine information from multiple sensors from the same equipment, otherwise known as fusion. [1] provides a review of multi-sensor data fusion approaches and classifies the techniques based on the level at which fusion is performed: data, feature, and decision levels.

Data-level fusion directly integrates information of the raw data from multiple sensors. Feature-level fusion combines feature information extracted from the raw data. Decision-level fusion focuses on integrating different diagnostic or prognostic results. A large portion of the fusion literature utilizes AI approaches, such as NN and fuzzy logic. However, most of these models have been used for fault detection and diagnostics, much less prognostics. A few examples of recent prognostic models for multi-sensor applications can be found in [31–34]. Some of the approaches relies on computing an aggregate composite health index [31]. Typically, a univariate aggregate signal is constructed by taking a weighted combination of various degradation signals from individual sensors. In other cases, the data fusion is performed through a state-space modeling framework that is used to represent the overall degradation state of a system [32,33]. Work developed by [34] was among the first to formally leverage the covariance structure governing a multivariate stream of degradation signals. Other multivariate degradation models rely on clustering analysis where historical data are divided into different subsets that characterize the health states at different degradation levels [35,35–37].

2) IMAGE-BASED DEGRADATION SIGNALS. Imaging is one of the fastest growing technologies for condition monitoring and industrial asset management. Conventional approaches that utilize random coefficients models, Brownian motion, gamma process, and functional data analysis to model how degradation signals evolve over time are not suitable for characterizing the spatio-temporal correlations that exist in image data. One of the key challenges with modeling image data revolve around the analytical and computational challenges associated with modeling high-dimensional data streams. The high dimensionality arises from the fact that a single image streams may consist of a large sequence of images (observed across the life cycle of an equipment) coupled with the large numbers of pixels embedded in each image. Another challenge is the complex spatial–temporal structures within these image streams. Pixels are spatially correlated within a single image and temporally correlated across sequential images. In recent work by [38], degradation-based image data streams were modeled as a spatio-temporal process. [39] proposed two deep-learning methods for estimating time-to-failure in industrial systems using image sensor data. The authors utilized CNN and autoencoder to collect useful information from images, which are high dimensional, and then train a LSTM-based regression model to predict time-to-failure. [40] developed a methodology to predict residual useful lifetime of a system based on a sequence of degradation images. The methodology has two main steps. First, it projects the image tensors onto a low-dimensional space. Next, the projected tensors are regressed against time-to-failure via penalized location-scale tensor regression. The coefficient tensor is decomposed using CANDECOMP/PARAFAC (CP) and Tucker decompositions, thereby enabling parameter estimation in a high-dimensional setting. [41] trained different NNs (deep neural network DNN, LSTM, and CNN) to capture the correlation between the degradation image stream and its remaining lifetime. They additionally implemented a multiple weighted time window policy to increase the prediction accuracy of the NN. This policy takes into account not only the most recent monitoring data but previous observations as well. The proposed image stream-based regressors are validated by using two datasets of degradation infrared images, showing that the LSTM achieves the best performance on the accuracy.

E. SOME OPEN QUESTIONS IN PROGNOSTICS

There have been significant research advances in the field of prognostics and predictive modeling. Given these advances, there are still some open topics that still require more exploration and research. Below are some topics that the authors believe are understudied, yet seem to be important to advancing the field of prognostics.

1) PROGNOSTICS OF SYSTEMS WITH INTERDEPENDENT DEGRADATION PROCESSES. Predicting the remaining lifetime of multi-component systems requires an accurate evaluation of the degradation states of its constituent components. More importantly and perhaps significantly, more challenging is the need to characterize failure and degradation interactions among the critical components of the system. Characterizing these interdependencies is indeed very difficult, so much so that many reliability prediction models have circumvented this challenge by assuming that component lifetimes (within a given system) are independent. Although such assumptions help to obtain mathematically tractable models, they remain unrealistic, especially for applications where dependencies are indeed present.

Most conventional models that study component dependencies can be divided into two main groups. The first group encompasses models that study how the failure of one component affects the failure rate of other components [42,43]. The second group focuses on models that employ a more statistical approach by developing multivariate distributions of system component lifetimes, especially in the context of shocks and load sharing scenarios [44]. Other models have studied economic and stochastic dependence in the context of opportunistic maintenance. A review of optimal maintenance of multi-component systems can be found in [45]. The paper states that interactions between components complicate the modeling and optimization of maintenance but offer an opportunity to group maintenance which may save costs.

From the viewpoint of this paper, one of the understudied topics in prognostics has to do with predicting RUL of systems comprised of components with interdependent degradation processes. One of the key questions is how specific levels of degradation in one component affect the degradation rates of other components in the system. The characteristics of these interactions may vary from one system to another. Some interactions may be triggered by specific degradation levels where others can be more subtle and evolve continuously over time. Consequently, the ability to formally characterize these interdependencies and account for their behavior over time and perhaps even over different levels of component degradation would be worth investigating. Additionally, predicting the RUL of each component independently versus the RUL of the system is rich topics of research. Model-based approaches might prove more successful than data-driven ones in performing prognosis on systems with multiple interacting components due to their ability to fully capture the underlying physics phenomena of the system and the interactions between the components. However, such models would be extremely challenging, if not impossible, to generate for the complex systems in consideration.

2) PROGNOSTICS AND DATA SPARSITY. Many prognostic models have been developed on the premise that the degradation signals are observed with high fidelity at frequent time steps. In reality, however, degradation observations often contain outliers as well as missing and corrupt data that result from the harsh industrial environments that equipment operate in. For example, there are numerous issues with data communication, network connectivity, read/write, storage formats, etc. Developing models that are robust to high levels of missing and corrupt data is needed for accurate predictions of RUL.

Another important topic related to data sparsity is the lack of failure time data. In many practical applications, components and systems are repaired preventively before any catastrophic failure. In fact, catastrophic failures are so rare in industry because many critical equipment that require prognostics often operate in a risk-averse ecosystem. As a result, many practical applications only have partial degradation signals with “censored” failure times. What makes this problem even more challenging is that most of these partial degradation signals are of different lengths and do not conform to a fixed threshold, since replacement and repairs are not triggered by a predefined threshold. These settings present a unique challenge for ML-based prognostics models that rely on supervised learning (labeled failure times) that utilize large volumes of data [46]. Some recent works have approached this problem from the perspective of few-shot learning [47,48]. However, this topic is still one of the open problems that has not yet been formally investigated.

While recently there have been many works that attempt to develop prognostic models for a wide array of applications using varying techniques, there are still some areas that have not been fully explored yet. One such area is the prognosis of systems with multiple interacting, gradually degrading components. This is because when the components interact, the degradation of one component can significantly affect the rate of degradation of the others, either increasing or decreasing their individual RULs. This leads to the utilization of the current state of health to extrapolate the degradation trajectory of the system to predict its RUL becoming a much more challenging task. Therefore, while there are works such as [49] where the authors successfully utilize data-driven approaches to diagnose the state of health of such systems, performing system prognosis utilizing similar approaches remains a largely unexplored area.

3) COMPONENTS THAT EXHIBIT INTERMITTENT FAULTS. Another area that has not been fully explored yet is the prognosis of components that exhibit intermittent faults. Intermittent faults are faults that occur randomly during the component's operation and then disappear shortly after without the need for any repair activities. An example of such fault is a valve that randomly gets stuck in a certain position during its operation and then returns back to the operational state without any intervention. Such components do not exhibit the traditional degradation signal where the occurrence of a certain fault marks the start of degradation, and then a sensor reading monotonically and gradually changes over time to reflect the worsening of said fault. Instead, degradation in these components manifests as a gradual increase in the frequency or the intensity of the intermittent faults. It must also be noted that the intermittent faults might not be obviously visible in the sensor data, which introduces another challenge in analyzing it. There are a few examples in literature where the authors successfully utilize either model-based or data-driven approaches to perform prognosis on components that exhibit intermittent faults. Examples include [50] where the authors utilize an extreme learning machine to predict the RUL of an electrical connector in vibration environments, [34] where the authors utilized a Bond graph to preform prognosis on an electric scooter, and [51,52] where the authors utilize a linear model to predict the remaining time until a threshold on the proportion of time that a component spends at a faulty state is crossed. While all of these approaches, and many others, have proven successful in their individual applications, they all share the same limitation: lack of generalizability. This is because most of the current works utilize specific knowledge and information about the components under study to build their prognosis technique, making them only applicable to a certain component or a class of components. To eliminate the need to create a new approach for each individual components or class of components, there should exist a prognosis approach that is generalizable so that it can be utilized for a wide variety of components that exhibit intermittent faults. Such approach would need to be data-driven instead of model based to maximize the generalizability and to ensure applicability to highly complex components.

4) PROGNOSTICS-BASED DECISION MODELS. The final goal of prognostics algorithms is to provide insights to decision makers, thereby helping them make condition-based decisions regarding system operations, maintenance scheduling, and even spare parts logistics. Existing prognostics algorithms, however, are usually designed and tested without considering their use in decision-making. These prognostics algorithms are trained to maximize prediction accuracy, which might not necessarily guarantee their effectiveness when integrated with decision optimization models [53]. In this regards, the development of decision models that can leverage RUL predictions is one of the future directions that need to be examined and explored carefully.

III. OPPORTUNITIES AND CHALLENGES IN RUL PREDICTION OF MACHINERY

A. A BRIEF INTRODUCTION

Operational maintenance plays a major role in keeping the safety and reliability of machinery. With the development of the sensor technology and Internet of Things (IoTs), condition-based maintenance (CBM) has become the most popular and effective maintenance strategy in industrial practice [54]. The basic idea of CBM is to estimate the health state of machinery by capturing on-line monitoring signals using different kinds of sensors, such as vibration signals, temperatures, motor currents, and acoustic emissions, and conduct maintenance schedule based on real-time monitoring results. To prepare spare components in advance and schedule a precise time of repair, industrial managers need to know the RUL of the machinery in-service at its early degradation stage. RUL prediction aims to forecast the time left before the machinery reaches the final failure.

RUL prediction is actually a tough issue in most industrial scenarios, since the damage, degradation, and failure of machinery are usually affected by various uncertainty resources, such as the operational conditions, the quality of the product, the working environment, and the service task. It is really difficult to forecast the future degradation trend based on historical observations and provide an accurate RUL prediction result. To deal with this tough issue, lots of research work have been conducted in recent years.

In terms of technical processes, RUL prediction can be divided into the following four steps. The first step is to capture condition monitoring signals which reflect the degradation behavior of machinery. The second step is to construct health indicators (HIs) from monitoring signals to quantify the degradation severity. The failure criterion is generally defined based on a specified failure threshold of corresponding HIs. The third step is to divide the health stages according to the varying degradation trends of HIs. The purpose of this step is to identify some important time stamps including the first degradation time, the first predicting time [55], the stage switching time, etc. The last step is to conduct RUL prediction at degradation stages by mapping different models and the degradation data. More details about the technical processes can be found in the systematic review paper regarding to RUL prediction [28].

In terms of modeling theories, prognostic methods can be broadly classified into physics model-based methods, data-driven methods, and their hybrid methods. Physics model-based methods describe degradation processes of machinery by constructing functional models on the basis of the failure mechanisms or the first principle of damage. In real practice, it is actually a big challenge to construct a high-precision physical model to describe the degradation behavior of machinery. With the increase of complexity and integration of mechanical systems, the damage of each component will interact with each other. It becomes more and more difficult to understand the physics of damage and formulate the degradation behavior of machinery.

Conversely, data-driven prognostic methods have been developed broadly with the advancement of condition monitoring technology.

Data-driven prognostic methods mainly include statistical data-driven methods and ML)-based methods [28,56]. A systematic review about the basic idea and major processes of statistical data-driven methods has been provided in the review paper [56]. As a kind of prognostic methods developed from statistical theory, they are superior in describing the stochastic characteristics of degradation processes and quantifying the uncertainty of prediction results. Some research works have been conducted to deal with different kinds of uncertainty resources, including the unit-to-unit variability [57], the temporal variability [58,59], the measurement noises [60], the time-varying operational conditions [55,61,62], etc. The major idea of uncertainty description is to describe the uncertainty resources by introducing random parameters into the degradation model. Then, the model parameters are estimated according to real-time condition monitoring data. The uncertainty of the degradation process is further transmitted into the probability density function of the predicted RUL. It is of crucial importance to analyze the dominant uncertainty resource in particular cases and quantify its contribution to the RUL prediction result. For example, both measurement noises and time-varying operational conditions can introduce amplitude fluctuation in the condition monitoring data. However, the mechanisms of these two factors are absolutely different with each other. To be specific, the measurement noises are caused by the inherent characteristic of data acquisition systems and the interference of environment. They are generally presented as random fluctuation and assumed to be normally distributed. The fluctuation caused by the operation conditions is highly correlated with the condition profiles, which can be reduced by using a kind of baseline condition transformation strategy [55]. As a result, the degradation trend of the health state can be highlighted while the impact of operational conditions can be ruled out, which is helpful for improving the precision and reliability of prediction result.

ML-based RUL prediction methods introduce the advanced techniques of ML into the area of RUL prediction. They attempt to learn the degradation patterns from available observations automatically without depending on the first principle of degradation or expert knowledge. Therefore, this kind of approaches is more suitable to deal with prognostic issues where no prior knowledge is available. The basic requirement is that sufficient data need to be provided for model training. However, it is a tough requirement for the task of RUL prediction, since the collection of whole-life degradation data is time consuming, and it is sometimes impossible in cases where serious failure is not allowed. The interpretability is also a major concern in the application of ML-based approaches. ML models generally care more about the mapping relationship between the input data and output data. They do not care about the inherent interpretability of the relation. Because of the lack of transparency, they are always named as "black boxes". However, in industrial scenarios, the interpretability of prediction result is significant for maintenance decision. It is difficult to convince operators to accept the prediction result if it is uninterpretable.

The development history ML-based RUL prediction is highly influenced by the advances in ML techniques. The early techniques introduced into RUL prediction include the artificial neural network, neural fuzzy system, support vector machine, K-nearest neighbor, Gaussian process regression, etc. They are named as traditional ML techniques hereafter for simplicity. Nowadays, with the advances of deep learning (DL) techniques, such as CNNs, recurrent neural networks (RNNs), and Bayesian deep learning, it has attracted more and more attention in this research field. Traditional ML-based prognostic methods generally work together with a feature extraction process. A set of features are first extracted from condition monitoring data. Then, the features are input into the ML models to conduct the RUL prediction task. DL techniques have the capability of analyzing high-dimensional data and extracting features automatically from data. Thus, they can realize the "end-to-end" RUL prediction, that is, input the original data into the model and output the RUL result directly. According to data processing strategies, ML-based RUL prediction approaches can be roughly classified into the following three categories.

(1) Constructing a fusion HI for RUL prediction. A HI with obvious monotonic and stable degradation trend is helpful to facilitate the RUL prediction process. Some researchers [63,64] attempt to construct a good HI by employing ML techniques. This strategy utilities the high capability of ML techniques in nonlinear relation mapping to construct HIs from condition monitoring data for RUL prediction. The major task is to map the high-dimensional original data into a one-dimensional HI sequence which is able to represent the degradation process of machinery. To ensure the high quality of the HIs, the construction process is generally guided by some evaluation criteria such as the monotonicity, trendability, and robustness. New criteria can also be developed and involved into the model according to different requirements of prediction tasks.

(2) Predicting the degradation process using the strategy of time series forecasting. In this strategy, the ML techniques are used to learn the recurrent relationship between the time series data of HIs, which can be formulated using the generalized expression $x_{i+1} = f(x_i, x_{i-1}, \cdots, x_{i-p})$, where $\mathrm{f}(\cdot)$ represents the mapping relationship function, $(x_i, x_{i-1}, \cdots, x_{i-p})$ is the input of the model that is the HI observations of previous time steps, and x_{i+1} is the output of the model that is the HI value in the next time step. The RUL can be predicted by inputting the predicted HI values step by step until exceeding a specified failure threshold.

(3) Predicting the RUL using a straightforward mapping strategy toward RUL. Different from the time series prediction, this strategy maps the relationship between current health states to the RUL values. The input variables can be original data or HIs extracted from them, which represent the current health state of the system. The output is the RUL value or its ratio to the total lifetime. This strategy can achieve the RUL prediction directly. It is more straightforward than the previous one in terms of procedure. However, it puts forward higher requirements for the nonlinear mapping capacity of the prognostic model.

B. OPPORTUNITIES AND CHALLENGES

There is no doubt that great advancements have been achieved in the RUL prediction of machinery. However, most research is conducted in the laboratory environment wherein the working parameters are controllable. The real practice scenarios are generally more complicated than laboratory environment. Current academic research in RUL prediction is still far from practical application. To promote the development of RUL prediction technique in industrial practice, there are still lots of big challenges in the future research. Some suggested research directions are provided as follows.

(1) Self-data-driven prognostic approaches

It is seen from the above introduction that most data-driven prognostic approaches need sufficient whole-life degradation data to train models. Although data acquisition becomes more easier with the advances of sensor techniques, it is still a tough issue to capture high-quality and -quantity whole-life degradation data in industrial practice. The first reason is that the life time of an industrial system is generally many years. It is time-consuming and high cost to capture condition monitoring data during the whole life of the system. The next reason is that, for some systems with high requirement on safety, such as aircraft, aerospace plane, and nuclear power equipment, they are not allowed to operate under serious fault stages. We can only capture partial degradation data for this kind of systems. Even if the whole-life data of several failed units are captured, it is unable to promise the similarity of the degradation pattern between the training units and the test unit. The degradation behaviors of industrial systems are influenced by many uncertainty resources, leading to the unit-to-unit variability of the degradation pattern among different units. It highly restricts the applicability and flexibility of training data-dependent prediction approaches. An effective strategy to deal with this issue is to predict the RUL of a system driven by its own condition monitoring data without depending on training data from failure events, which is also defined as self-data-driven RUL prediction [55]. To facilitate the self-data-driven prognostic process, a model base involving various degradation models needs to be prepared in advance. During the online prediction process, an optimal model is selected according to the degradation characteristics of the in-service unit, and the model parameters are updated according to the real-time data. The major challenges in self-data-driven prognostics may include: (1) how to construct a diversified model base and (2) how to select a suitable model adaptively according to the degradation pattern of the in-service unit.

(2) Dataset accumulation and publication

As mentioned above, whole-life degradation data are the basic resource for RUL prediction. It is time consuming to accumulate degradation data under normal operational conditions. Therefore, accelerated degradation tests are often employed to accumulate whole-life degradation data. Some research institutes have published prognostic datasets on websites, which are free to download for academic researchers. For example, the prognostic data repository of NASA has collected and published many accelerated degradation datasets including some typical mechanical and electrical components and systems [65]. In addition, some international societies such as the Prognostics and Health Management (PHM) society and the Institute of Electrical and Electronics Engineers (IEEE) reliability society often organize prognostic challenges in international conferences, which provide valuable datasets and competition opportunities for researchers. Some scholars [66] also voluntarily share their datasets to promote the development of prognostic research. Thanks to these published datasets, researchers can develop various prognostic approaches and compare their approaches with existing ones using the same benchmark datasets. This is significant for the development of the prognostic theories and methodologies. However, most of existing accelerated degradation datasets are generated in the laboratory environment that are totally different from the industrial scenarios. The degradation behaviors of systems in real industrial cases suffer from more complicated uncertainties, including the time-varying operational conditions and the interference from outside environment. Therefore, researchers are encouraged to conduct more degradation tests under realistic operational conditions and publish the degradation dataset. In addition, we also appeal to the companies to accumulate and share the degradation datasets of their real industrial equipment. It would not only promote the development of prognostic research but also help to advertise and update their products. Both researchers and companies can benefit from the voluntary data share.

(3) RUL prediction of machinery with complex degradation behaviors

Generally speaking, there are two different kinds of prognostic strategies. The first strategy is to forecast the future degradation trend of machinery based on its historical degradation trajectory. This strategy requires that the machinery must share the same degradation pattern during the whole lifetime. Otherwise, the prediction result will deviate far from the actual curve. The second strategy is to predict the RUL of an in-service unit using a prognostic model trained by a group of failure units. This strategy requires that the test unit must have the similar degradation pattern with training units. These above two strategies both require that the degradation pattern of machinery is simple enough to be derived from historical observations. We also find so many demonstration cases in literature with perfect gradual degradation trends. These demonstration cases are generally ideal cases selected from experimental degradation tests. In most industrial cases, however, the degradation behavior of machinery is complex or even irregular. The prognostic models will suffer from various strange degradation cases in real practice. It is a big challenge to keep the robust and stable performance of the prognostic models in the RUL prediction of complex degradation behaviors in industrial practice.

IV. OPPORTUNITIES AND CHALLENGES IN STATISTICAL DATA-DRIVEN PROGNOSTICS

A. A BRIEF INTRODUCTION ON STATISTICAL DATA-DRIVEN PROGNOSTICS

In engineering practice, particularly lots of systems are designed to perform particular missions and required to operate safely during their whole life cycle. However, no matter how reliable they are, the deterioration of their quality and performance due to aging, varying loads, and operating environments will gradually impair them and finally result in their ultimate failures. Such systems are also known as the stochastic degrading systems. PHM has emerged as an essential and efficient approach for improving the operating safety and reducing the operational costs for such stochastic degrading systems [67]. In the PHM framework, prognostics with an emphasis on the RUL prediction have long been recognized as the fundamental and key technique to implement the health management of stochastic degrading systems [68,28].

Driven by the desire to ensure the safe and reliable operation of stochastic degrading systems, especially for vital systems, various methods to achieve prognostics have been developed. In general, prognostic methods for stochastic degrading systems can be broadly divided into physics model-based methods, data-driven methods, and their fusion. With advances in sensing and condition monitoring techniques, the monitoring data of the system's performance degradation process can be more easily obtained. As a result, the data-driven prognostic methods have become the emerging topic in the PHM field. In the past 15 years, extensive efforts have been made to developing various data-driven prognostics methods. Data-driven prognostic approaches mainly include ML and statistical data-driven approaches [28,69]. Due to advantages in reflecting the uncertainty and randomness of the degradation process and providing the probability distribution of the RUL to quantify the prediction uncertainty, significant advances have been witnessed in statistical data-driven prognostic approaches since this kind of methods can provide a natural description of the random failure of the practical system. Therefore, we focus mainly on the statistical data-driven approaches in the following discussions.

The basic idea of statistical data-driven prognostic approaches for stochastic degrading systems is as follows: Based on the monitoring data of degrading systems, the RUL of the system can be predicted based on stochastic models by fitting the evolution law of the system performance degradation variable and extrapolating it to the failure threshold. Generally, there are three key components to achieve statistical data-driven prognostics, respectively, described as follows:

(1) Stochastic degradation modeling. The performance deterioration of degrading systems will be inevitable due to mutual effects of various random factors including aging, loads, and varying environments. The deterioration process is accumulated over the operating time and will lead to the final failures of these systems. Therefore, the degradation variable of the system will randomly evolve during the system operating process. As such, adopting stochastic models to characterize such randomly evolving process is a natural choice.

(2) Parameter estimating of stochastic degradation models. Because the adopted stochastic models is selected according to the statistical characters of the concerned systems, the model parameters are unknown. In this case, to perform the prognostics, the model parameters of the used stochastic models should be first estimated based on the monitoring degradation data. The widely used methods for parameter estimation include the maximum likelihood estimation method, the Bayesian method, the expectation maximum algorithm, etc.

(3) Solving the probabilistic distribution of the RUL. Based on the stochastic degradation modeling and the associated parameter estimating, to solve the probabilistic distribution of the RUL is the key task for prognostics. Generally, the probabilistic distribution of the RUL can be solved by the distribution of the degradation variable or by the first hitting time of the degradation process characterized by the stochastic model. The difference between the solutions derived by the distribution of the degradation variable or by the first hitting time of the degradation process can be found in [69].

In current studies on statistical data-driven prognostic approaches, the implementation processes of components (2) and (3) are basically fixed or seldom changed. In contrast, there are significant variants on stochastic models for characterizing the degradation processes of systems, and thus more discussions are deserved. Despite many variants on stochastic models used for degradation modeling, they can be generally described as $X(t) = x_0 + g(t;\boldsymbol{\theta}) + \varepsilon(t)$, where $X(t)$ is the degradation variable of the system reflecting the degradation state at time t, x_0 is the initial degradation, $g(t;\boldsymbol{\theta})$ is the time-dependent function with parameter vector $\boldsymbol{\theta}$ to model the time-varying trend of the degradation process, and $\varepsilon(t)$ is the random term to model the temporal uncertainty or randomness of the degradation process. According to the modeling principles for the degradation trend $g(t;\boldsymbol{\theta})$, statistical data-driven prognostic approaches can be divided into being parametric, semi-parametric, and nonparametric models-based methods. Based on the functional form of $g(t;\boldsymbol{\theta})$, statistical data-driven prognostic approaches include linear models-based methods and nonlinear models-based methods, where linear models-based methods adopt linear models with time to represent the degradation progression and nonlinear models-based methods adopt nonlinear models with time. Besides the degradation trend modeling, modeling the random term $\varepsilon(t)$ is another important aspect in prognostics since the degradation process of the system has the inherent randomness due to the impacts of various uncertain factors. According to difference in modeling $\varepsilon(t)$ by stochastic processes, statistical data-driven prognostic approaches mainly include random-effect regression models, Gamma processes, inverse Gaussian processes, Wiener processes, and recently developed beta processes, Tweedie exponential dispersion process, Student-t processes, etc. The detailed discussions on these statistical data-driven prognostic approaches can be found in several comprehensive review papers such as [28,70], and some technical papers like [71–73].

B. DISCUSSIONS ON OPPORTUNITIES AND CHALLENGES

It is observed from the above brief discussions that great advances have been made on statistical data-driven prognostic approaches and such methods are still in the stage of fast development. Nevertheless, there are some new opportunities and challenges required to be aware and addressed in the future, as discussed in the following.

(1) Prognostics via stochastic degradation model calibration

Statistical data-driven prognostic approaches generally adopt the stochastic model to characterize the evolving progression of the degradation variable. In existing studies with such methods for degradation modeling and RUL prediction, the appropriate functional form of $g(t;\boldsymbol{\theta})$ should be determined in advances [74]. Then, the model parameters are estimated or updated by the degradation monitoring data of the concerned system to perform the model calibration. However, selecting the functional form of $g(t;\boldsymbol{\theta})$ is itself a challenging problem. More importantly, when the selected functional form of the degradation model is inappropriate, it is difficult and ineffective to calibrate the degradation model simply by updating the model parameters, and the prediction accuracy will be thus affected. Hence, how to achieve simultaneous calibration of the functional form and parameters of the degradation model is an important direction holding promise to improve the prognosis accuracy and overcome the difficulty in selecting the functional form of $g(t;\boldsymbol{\theta})$.

(2) System-level prognostics with multiple degradation variables coupling

Although significant advances in statistical data-driven prognostic approaches have been witnessed, most of these studies are tailored to component-level prognostics in which an important potential prerequisite is that the health state of the concerned component can be simply reflected by a single performance degradation variable. The univariate hypothesis provides great convenience and flexibility for the degradation process modeling and RUL prediction [75]. However, this may not be practical for the system-level prognostics. As for a complex system, its health state is often codetermined by multiple variables related to the system performance and the health state can rarely be exactly described by a single performance degradation variable. In this case, considering multiple performance variables is a must in prognostics. However, compared with widely studied component-level prognostics, the system-level prognostics are much more sophisticated. The primary challenges in system-level prognostics may include: (1) how to model the degradation process of the system particularly for coupled multiple performance variables; (2) how to define the system failure in the multiple performance variables case; and (3) how to estimate the model parameters by the coupled degradation monitoring data of multiple performance variables if indirect component-level observations are utilized for system-level prognostics. All these aspects introduce the difficulty applying component-level prognostic methods to predict the RUL of complex systems. Thus, new framework for system-level RUL prediction should be developed in the future by considering the above challenges.

(3) Fusion of DL and statistical data-driven prognostic approaches

The success of statistical data-driven prognostic approaches is dependent heavily on the performance of the degradation feature or the degradation trend of the monitored variable. With the good degradation feature, stochastic degradation models can be effectively constructed and output the prediction RUL in probabilistic distribution forms to quantify the prognosis uncertainty. This is also known as the major advantage of statistical data-driven prognostic approaches. Recently, with great advances in Industry 4.0 and the IoTs, a large number of monitoring data can be obtained providing abundant information on the system's health state and the RUL. However, statistical data-driven prognostic approaches are difficult to directly apply to the big data case unless the additional degradation feature engineering is introduced. Therefore, it is not surprising to observe that DL-based prognostics methods have attracted much attention in the big data case [76]. By DL techniques, the abstract degradation features can be automatically extracted for prognostics or the end-to-end prognostics can be achieved directly by mapping the original data into the RUL to remove the feature engineering. Nevertheless, the RUL corresponds to predicting the future failure event and thus has the inherent uncertainty. Unlike statistical data-driven prognostic approaches, DL-based prognostics methods have the limited capability in characterizing the prognosis uncertainty. As a result, fusing DL and statistical data-driven prognostic approaches will hold great promise to pave the way on prognostics for big data cases. A possible avenue is to apply DL techniques to extract the degradation feature and then model the progression of such feature with stochastic models. To do so, the capability of quantifying prognosis uncertainty and handling the big data can be jointly achieved. Therefore, fusion of DL and statistical data-driven prognostic approaches is an important development direction, but the challenge lies in how to establish the effective and explainable fusion mechanism.

V. PREDICTION OF RUL: FUTURE DIRECTIONS

A. INTRODUCTION

The RUL of a component or system is the time left before it will no longer be able to perform its intended function. The task of predicting the RUL is called prognostics. For RUL prognostics to be adopted in practice, the question of which predictive models to use is fundamental. Specifically, the prediction capability of a prognostic model must be gauged with respect to the ability to provide trustable RUL predictions, which must possess the quality characteristics required and the confidence level necessary for allowing to use them for taking decisions. Indeed, trust of the predictions heavily influences the decision makers' attitude toward taking the risk of using the predicted RUL values to inform their decisions. The choice of which method to use is typically driven by the data and/or the physics-based models available, taking into account the cost–benefit considerations related to the implementation of the predictive system. A set of Prognostic Performance Indicators, measuring different predictive characteristics, must be used to guide the choice of the modeling approach.

Eventually, to arrive at taking reliability and safety decisions based on RUL predictions in practice, it is necessary to understand and quantify the impacts and benefits of the development of a predictive system, including avoiding unexpected catastrophic failures, reducing maintenance frequency, optimizing spare parts and storage, optimizing resources, etc. Clearly, given the increasing complexity, integration, and informatization of modern engineering component and systems, RUL prediction capabilities can no longer be isolated additions in support to maintenance but must be closely linked to the other parts of the overall system (structural, power, electromechanical, information and communication technology, control). Then, such predictive capabilities must be included since the beginning in the system conceptualization and design, to meet the overall operation and performance requirements [77].

Up to date, the main development efforts in RUL prediction have been devoted to the hardware (e.g., IoTs, smart meters, etc.) and to the software for tracking the health state of monitored equipment (e.g., data analytics, platforms for IoT interconnection and clouding for computing, etc.). On the other hand, the full deployment of PHM in practice involves other aspects, including design (e.g., the use of smart components may lead to different reliability allocation solutions), and impacts various work units involved in maintenance decisions and actuations (e.g., workers can use smart systems, maintenance engineers can analyze big data), including the supporting logistics (spare parts availability and warehouse management can be driven by the RUL predictions) [78].

B. CHALLENGES

A number of challenges still remain to be overcome to render effective the use of RUL predictions in practice. Some of these challenges are inherent in the complexity of the components and systems degradation processes, which are not fully known, are dynamic, and highly nonlinear; this makes their understanding, characterization, and modeling quite difficult. On the other hand, the data used to develop and calibrate the predictive models are collected in the field and are affected by inevitable limitations including missing data and erroneous data from malfunctioning sensors, scarcity, and incompleteness of data, often unlabeled with respect to the state of degradation of the component or system, changing operational and environmental conditions.

In practical applications, the RUL predictions, and the models that provide them, must satisfy a number of requirements to meet diverse objectives. Certainly, accuracy and precision are required to the level needed for the decisions that they support: in some cases, very high accuracy and precision are necessary to take confident decisions (e.g., of anticipating or postponing a scheduled maintenance based on accurate RUL predictions); in other cases, accuracy and precision need not be so high and may be compromised for other objectives. For example, transparency, explainability, and interpretability of RUL predictive models can be of particular interest for decision making or are even demanded as a regulatory prerequisite in safety-critical applications. Also, security issues regarding data integrity, data confidentiality, and authentication exist. Finally, any RUL prediction must be accompanied by an estimate of its uncertainty, in order to confidently take robust decisions based on such prediction.

C. FUTURE DEVELOPMENTS

Surely, DL will continue to be developed and used to allow incorporating feature engineering in the process of predictive model training, by automatic data processing and feature extraction: whereas encouraging results have been obtained already in the application of DL for fault detection and diagnostics, RUL prediction still remains a bit of a challenge for DL in practice.

Other developments for the deployment of RUL prediction in practice include:

- RNNs for time series predictive analysis, combined also with data transformation into images so as to allow exploiting methods of image processing (including CNNs)
- Signal reconstruction methods (including autoencoders) of unsupervised and semi-supervised learning for degradation prediction in practical cases of unlabeled data
- Optimal Transport methods and unsupervised adaptation techniques to cope with the difference between the test data distribution and the training data one, which is a quite common situation in practice
- Bayesian neural networks and deep Gaussian processes to provide the RUL predictions with estimates of their uncertainty
- Methods for obtaining transparency and interpretability of RUL predictions for building trust on their use for decision making, especially in safety-critical applications. In particular, methods for injecting physical information in learning models (e.g., Physics-Informed Neural Networks), post-hoc sensitivity approaches, and visualization techniques are being studied to provide interpretability from different perspectives, including explaining the learned input-output relation representations, explaining the individual model outputs, and explaining the way the output is produced by the model.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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