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Diagnostics and prognostics for complex systems: A review of methods and challenges

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Abstract

Diagnostics and prognostics have a significant role in the reliability enhancement of systems and are focused topics of active research. Engineered systems are becoming more complex and are subjected to miscellaneous failure modes that impact adversely their performability. This ever-increasing complexity makes fault diagnostics and prognostics challenging for the system-level functions. A significant number of successes have been achieved and acknowledged in some review papers; however, these reviews rarely focused on application to complex engineered systems nor provided a systematic review of diverse techniques and approaches to address the related challenges. To bridge the gap, this paper first presents a review to systematically cover the general concepts and recent development of various diagnostics and prognostics approaches, along with their strengths and shortcomings for the application of diverse engineered systems. Afterwards, given the characteristics of complex systems, the applicability of different techniques and methods that are capable to address the features of complex systems are reviewed and discussed, and some of the recent achievements in the literature are introduced. Finally, the unaddressed challenges are discussed by taking into account the characteristics of automotive systems as an example of complex systems. In addition, future development and potential research trends are offered to address those challenges. Consequently, this review provides a systematic view of the state-of-the-art and case studies with a reference value for scholars and practitioners.

KEYWORDS

complex engineered system, fault diagnostics, prognostics, remaining useful life

1 | INTRODUCTION

The increasing complexity of engineered systems, such as industrial processes, aircraft, road vehicles, manufacturing systems, electrical and electronic equipment, brings challenges associated with the exposure to diverse failure modes, affecting the systems' reliability, safety, and performability. Hence, there is an essential need to develop diagnostics and prognostics methods to implement for complex systems, operating in real-world conditions. The diagnostics tasks are

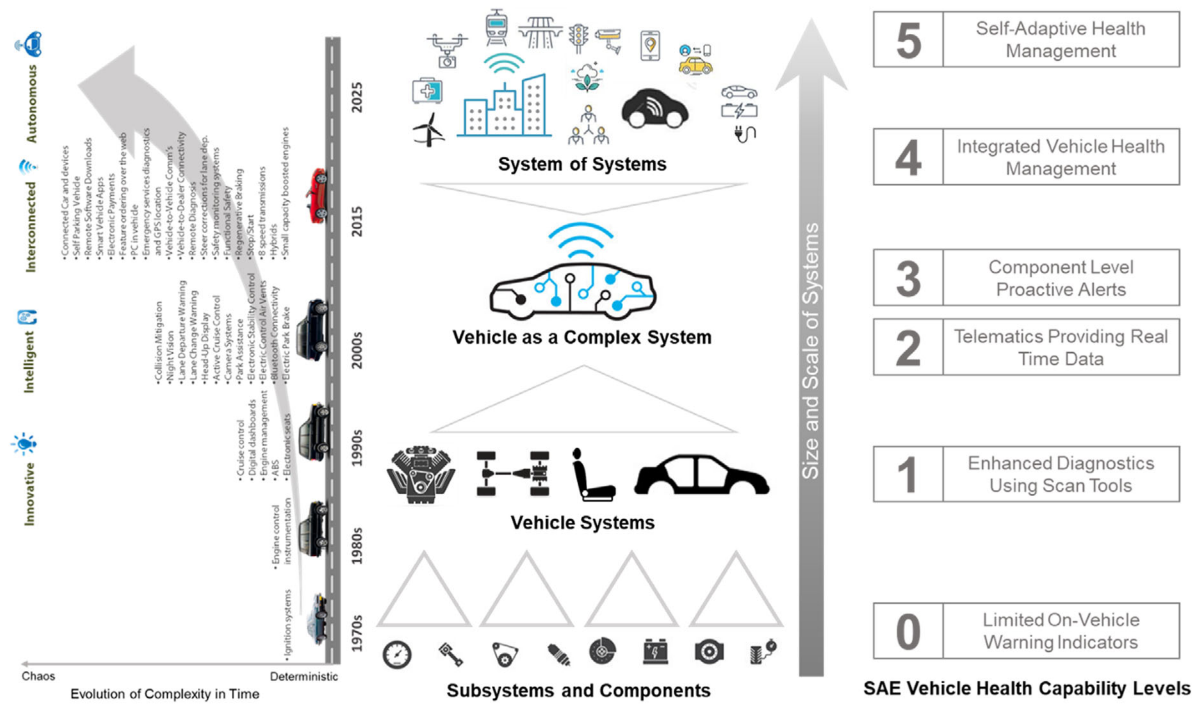

FIGURE 1 Characteristics of complex automotive systems and SAE integrated vehicle health management capability levels[12]

focused on fault detection, fault isolation, and fault identification.[1] Fault detection is the task of identifying that something is going wrong in the monitored system as soon as a fault occurs, fault isolation determines which fault candidate can explain the observed abnormal behavior, and fault identification determines the magnitude and type of the fault when it is detected.[2] On the other hand, prognostics tries to estimate how likely the failure of a system is, given the current state of the system including diagnostics.[3,4] Remaining useful life (RUL) is the main prediction type in prognostics. RUL is the time left before the end of the useful life or before the health state of a system crosses a failure threshold, given the current health state of the system.[5] A complementary approach for prognostics is in relation to the probability of a system to operate fault-free until a specific future time, given the current health condition.[1] The benefits of diagnostics and prognostics for a complex system are significant; the biggest being that they are used to increase system safety and operational reliability and also to improve and optimize system design and development. They also have a powerful impact on the life-cycle cost, which reduce operating cost and increase revenue.[6]

Diagnostics and prognostics are the most important aspects of not only condition-based maintenance (CBM), prognostics and systems health management (PHM), and system reliability optimization[1,7-9] but also play important roles in emerging system health-related programs, standards and technologies such as integrated vehicle health management (IVHM).[10] IVHM technology is introduced to solve the fault diagnostics and prognostics difficulties for complex systems. IVHM is a strategy to integrate subsystems' condition monitoring (CM), fault diagnosis, fault mitigation, fault prediction, and maintenance planning strategy of a vehicle together to prevent accidents, raise safety, enhance ground maintenance, and reduce maintenance cost.[10] In aerospace and automotive recommended practice JA6268,[11] a six-level reference scale is provided to define a prescriptive vehicle health capability guide. These levels are illustrated in Figure 1,[12] along with the evolution and decomposition of the automotive system as a system of systems. In the last two levels (vehicle level health management and self-adaptive health management), diagnostics and prognostics play the most important roles,[11] where Level 5 is the road map for complex automotive systems as a system of systems.

Figure 2 illustrates the number of articles related to diagnostics and prognostics in seven engineering fields (electrical and electronic, mechanical, multidisciplinary, biomedical, chemical, industrial, and manufacturing engineering), published during the last two decades, which is based on the search results from Web of Science. The distribution of the articles reveals the increasing trend in the number of research works carried out for diagnostics and prognostics. Among around 18,000 published articles in these seven areas of engineering, electrical and electronic, mechanical, and multidisciplinary research areas have the highest proportions. Despite the huge number of research works, both from academic researchers and industry engineers, current diagnostics and prognostics approaches are not able to fully address the characteristics of modern systems, and still, there are some unaddressed challenges.

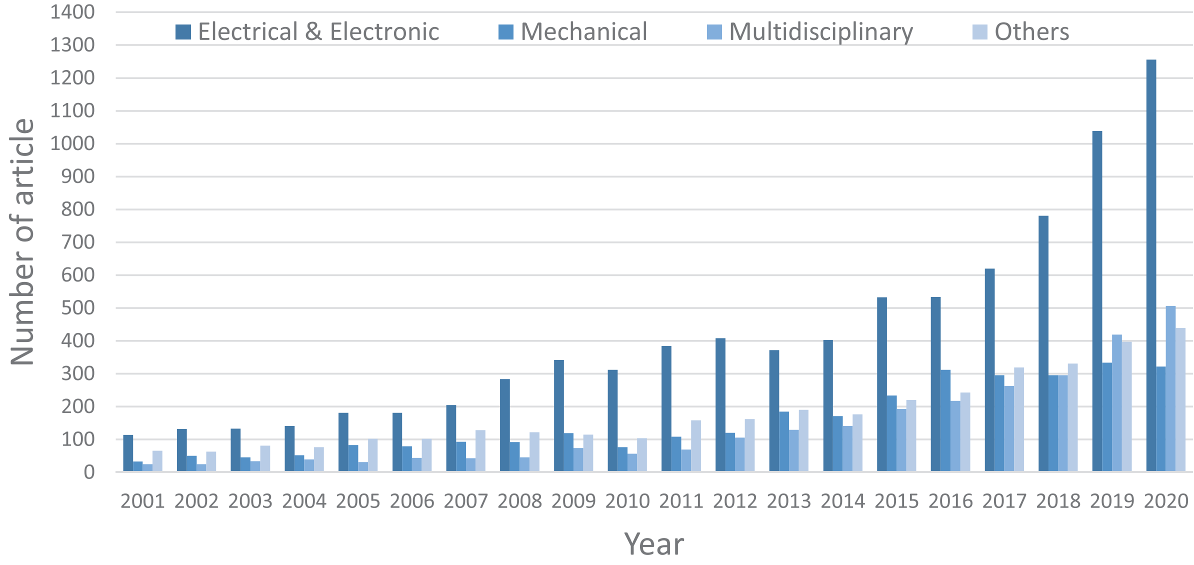

FIGURE 2 Distribution of published articles about diagnostics and prognostics in engineering research areas

1.1 | Complex engineered systems and their characteristics

Complex systems have been defined by many researchers from various fields (from physical to nonphysical systems) in fairly different ways. Hence, there is not a unique definition for complex systems, and also there are variations in the measures of complexity.[13] Diverse definitions are mostly because the complexity is a subjective notion to a high extent.[14,15] However, there is a common statement in almost all the definitions that "complex systems consist of many elements with complicated interactions." Similar to the definition, there are different characterizations for complex systems in different fields. However, in the literature,[14-22] the core set of properties pertaining to complex systems that are mutually exclusive and collectively exhaustive can be considered as consisting of many elements that usually engaged in many interactions, nonlinearity and dynamicity of interactions among the parts, multi-state and multi-objective, algorithmic and often nonergodic, order robustness, evolution and adaptation, hierarchy of system and sub-system, neither completely random nor completely ordered, high epistemic uncertainty, and so forth.

Industrial systems can be categorized into continuous and discrete systems.[23] Continuous systems mostly operate in a steady-state condition and produce constant outputs, whereas discrete systems work under different process conditions and the system's outputs depend on the process particularities. Considering the exhaustive features of complex systems, the characteristics of discrete industrial systems are sufficient enough to consider these systems as complex systems. Road vehicles, as a well-known example of discrete industrial systems, have seen significant transformations and modernization over the past few decades. Vehicles have become more complex following the integration of electronics, software, and networks as illustrated in Figure 1. These components and subsystems interact dynamically to deliver the functions of the automotive systems. Looking at a higher level, where various systems are integrated and the mechanism is controlled or monitored by computer-based algorithms (i.e., referring to cyber-physical systems,[24] which are the central topic in the era of Industry 4.0), the practical difficulties in reliability analysis rise significantly. The reliability analysis of vehicular cyber-physical systems is one of the most challenging research topics.[25]

Engineered systems are becoming more complex being generally composed of some interconnected subsystems/components, possessing high-nonlinear and stochastic dynamics, equipped with multiple control loops, operating under noisy environments, and varying loads.[25-27] The complex hardware and software structures are not the only reason for the complexity of a modern system, and the challenges in the information processes (monitoring, processing, management, etc.) of the system intensify the complexity.[28]

With the large amount of computationally diverse data released and shared, the world has entered the era of big data. These big data resources are able to capture the relationship between numerous systems and subsystems, which is unlikely to be fully observed otherwise.[29] On the other hand, building mathematical models to characterize the behavior of complex systems or using expert knowledge to describe their functionality is difficult and unrealistic,[28,30] as prior knowledge of process models is generally unavailable. Hence, it is worthwhile to focus on the features of complex system's data that are statistically complex.

The complicated interactions in complex systems lead to heterogeneous data with multifarious characteristics.[25] Systems in different industrial sectors have different big data characteristics. Taking into account all those characteristics, nonlinearity, dynamicity, nonstationarity, and non-Gaussianity are the most common data features mentioned in the literature for complex engineered systems[3,23,30-32] that are briefly described here:

- Nonlinearity: Unlike linear systems, the behavior of a nonlinear system is described by nonlinear differential equations.[3,31] The nonlinearity of data is becoming higher and more common by increasing the complexity of modern engineered systems.
- Dynamic behavior: The pattern of data in complex systems changes over time. These changes are because of the feedback control systems.[23] Autocorrelation and cross-correlation properties between different sampling points of the measurement variables lead to dynamic changes in the behavior of data.[26]
- Nonstationary behavior: Different from a stationary process in which the probability distributions of the ensemble (or sub-records) and correlation functions are independent of absolute time, in general, the means and variances of data in complex systems shift over time.[32] Both linear and nonlinear systems can have data with nonstationary behavior.[3]
- Non-Gaussian data characteristics: Although Gaussian distribution is a suitable model for many cases, and it is commonly used for continuous data, data in complex systems are generally non-Gaussian because of multiple modes/states or operating conditions.[33]

Diagnostics and prognostics of complex engineered systems, taking into account the complicated structural principles, varying operational conditions, and multifarious data characteristics, are difficult tasks. Therefore, proposing the adequate method, given the features of the system under study and pertaining data, is pivotal to enhance the accuracy of results.

1.2 | A brief survey over the existing reviews

Over the last two decades, several review papers have been published in the context of diagnostics and prognostics. Some reviews are broad and cover different approaches.[1,4,8,34-36] Some reviews particularly concentrated on diagnostics[37-40] or prognostics,[3,4,8,41-45] and some others focused on a certain diagnostics and prognostics approach, like data-driven,[5,46,47] knowledge-based,[48,49] model-based,[50,51] and hybrid approaches.[52] Some others, exclusively concentrated on a technique, such as artificial intelligence,[37,43,53] machine learning (ML),[54] computational methods,[55] particle filter (PF),[56] Bayesian Network (BN).[57,58] Some reviews specifically focused on diagnostics and/or prognostics of a particular system, like wind turbines,[59] gas turbine,[60] bearing,[61] rotating machinery,[1,3,8,41] trains,[62] and electronic products.[52]

The published review papers are broad and cover the majority of diagnostics- and prognostics-related topics. However, there is no such comprehensive review that discusses the opportunities and challenges of implementing different models and techniques to address the characteristics of complex engineered systems (i.e., nonlinearity, dynamicity, nonstationarity, and non-Gaussianity), for both diagnostics and prognostics purposes. To narrow this gap, this paper systematically presents the general concepts and features of various methods within a modified classification as well as reviewing the recent research studies. These research works include many journal publications as well as a few conference proceedings and PhD theses. The paper attempts to provide the review without a focus on a specific model or a particular type of application or system. After the abstract introduction of the methods and comparing their merits in relation to the application of engineered systems, the techniques that are able to address the characteristics of complex engineered systems are reviewed and some of the recent developments are highlighted. This review provides comprehensive references for researchers, helping them develop advanced research in diagnostics and prognostics fields.

The remainder of this paper is organized as follows. Section 2 reviews and discusses four main diagnostics and prognostics approaches (i.e., physics-based, data-driven, knowledge-based, and hybrid) in detail, through collecting a fairly large number of references. Section 3 gives a comprehensive review of the applications of different techniques to diagnostics and prognostics of complex engineered systems. Section 4 discusses the new challenges and unaddressed characteristics of complex systems and also identifies the prospects of different techniques in diagnostics and prognostics of complex engineered systems. Conclusions are drawn in Section 5.

2 | DIAGNOSTICS AND PROGNOSTICS APPROACHES

Diagnostics and prognostics methods in the literature can be classified into four main approaches: data-driven, physics-based, knowledge-based, and hybrid approaches. The existing review papers adopted slightly different classifications depending on the viewpoints of the researchers based on the problems and application areas considered. In addition to the dissimilarity of terminologies and context in each community, these nonhomogeneous classifications are also influenced by the different sets of reviewed and discussed papers and the area of application. Table 1 summarizes the classifications proposed in the key review papers. These review papers are collectively exhaustive in diagnostics and prognostics methods. These reviews that are from the last two decades have covered both PHM and CMB context, providing quite a few applications from different industrial sectors.

Diagnostics is an independent analysis on its own, while prognostics relies on diagnostics outputs and cannot be done without diagnostics.[4] The implementation processes of diagnostics and prognostics are similar, and the difference is on the purposes. Taking into account these matters, in this paper, the methods for diagnostics and prognostics are tried to classify and review collectively. As shown in Figure 3, a modified classification is proposed for diagnostics and prognostics related methods that consist of four main classes and related subclasses. The general concepts and recent development of these methods, along with their pros and cons are discussed in this section.

2.1 | Physics-based approaches

The application of general physics-based approaches is based upon the understanding of the physics-of-failure (e.g., crack growth) in a system.[8] These approaches are suitable where the accurate mathematical models are available for a system, based on its physical fundamentals. The underlying assumption in physics-based approaches is that there is a physical model that characterizes the evolvement of degradation or damage. Hence, the physical model is often referred to as a degradation model, and consequently, the physics-based prognostics and the model-based prognostics are used interchangeably.[63] Fault detection and isolation (FDI) and and Diagnosis (DX) are two distinct communities for classic model-based fault detection and diagnosis.[27,64] FDI is based on control theory and statistical decision-making,[65,66] while the DX is based on soft computing and artificial intelligence.[67]

Physics-based approaches are mostly application (failure mode) specific,[4,35] and it is hard to classify further. However, a limited number of diverse classifications can be found in the literature (e.g.,[45,46,51,62,68]). The clear disagreement in the classifications is a confirmation that physics-based approaches are item-specific. Considering this matter, instead of classifying physics-based approaches, their applications for fault diagnostics and prognostics have been separately reviewed in this paper.

2.1.1 | Diagnostics application of physics-based approaches

The model-based diagnostic approaches are applicable when mathematical models of the system can be constructed from the first principles. These approaches evaluate residuals as outcomes of consistency checks between the sensed measurements of system performance and the predictions from the mathematical model.[69,70] They indicate the inconsistencies between the actual and expected behavior of a system. The fault diagnostics is based on the assumption that the residuals are large in the presence of malfunctions and small in the presence of noise, normal disturbances, and modeling errors. Statistical techniques are used to define the thresholds for detecting the presence of faults.[50] Figure 4 illustrates the general structure of model-based diagnostics.

Parameter estimation, diagnostic observers (fault detection filters), and parity relations (parity space) are the leading methods for residual generation.[50,69] In practice, the process parameters are not known, or they are not known exactly enough. Therefore, they require to be determined with parameter estimation methods. The methods are based upon measuring the input and output signals, if the basic structure of the model is known. The least square method, extended least squares method, and recursive least square method are the most used techniques for parameter estimation.[71]

The observer-based approach is one of the mostly applied model-based schemes for fault detection in a system. This technique compares the process outputs and the corresponding estimates to obtain the residual signal. Fault detection filter is a class of diagnostic observer, which can be used for state estimation as well as diagnostic purposes.[66,72]

TABLE 1 A comparison of proposed classifications in the literature

Reference	Proposed classification	Review context	Area of application
Bektas et al.[55]	Physics-based models Knowledge-based models • Expert systems • Fuzzy logics • Similarity-based Data-driven models • Stochastic algorithms • Statistical algorithms • Artificial neural network and deep learning Hybrid applications	Prognostic for complex systems under dynamic regimes	Complex systems under dynamic regimes
Kordestani et al.[45]	Model-based prognosis • Kalman filtering based prognosis • Particle filtering based prognosis • Model-based observers for prognosis Data-driven prognosis • Regression-based prognosis • Intelligent-based prognosis • Probabilistic-based prognosis • Markov-based prognosis Knowledge-based prognosis • Signal processing based prognosis • Fuzzy-based prognosis Hybrid methods for prognosis	CBM of complex and safety-critical engineering systems	Batteries, Rotating Machinery Systems and Safety-Critical Systems
Peng et al.[42]	Physical model-based methodology Knowledge-based methodology • Expert systems • Fuzzy logic Data-driven methodology • ANN-based methodology • Statistical approaches Combination model	Machine prognostics in CBM	General
Jardine et al.[1]	Diagnostics • Statistical approaches • Artificial intelligent approaches • Model-based approaches Prognostics • Statistical approaches • Artificial intelligent approaches • Model-based approaches	CBM of mechanical systems	Machinery diagnostics and prognostics
Sutharssan et al.[46]	Data-driven • Statistical approach • Machine learning (ML) approach Model-driven • Physics of failure • System model Fusion	Prognostics and systems health management for engineered systems	General
Liao and Köttig[52]	Experience-based model • Expert systems • Fuzzy logic Data-driven model • Statistical models • Reliability functions • Artificial intelligence models Physics-based model • First principles • Statistical methods for parameter identification Hybrid approach	Prognostics of engineered systems	Batteries

(Continues)

TABLE 1 (Continued)

Reference	Proposed classification	Review context	Area of application
Zhong et al.[23]	Model-based methods, Knowledge-based methods Data-driven methods • Machine-learning algorithm • Statistical pattern recognition-based methods • Artificial intelligence models	Fault prognosis for industrial systems	General industrial systems
Sikorska et al.[4]	Knowledge-based • Expert systems • Fuzzy systems Life expectancy • Stochastic models • Statistical models Artificial Neural Networks • Direct RUL forecasting • Parametric estimation for other models Physical models	RUL estimation by industry	General engineering assets

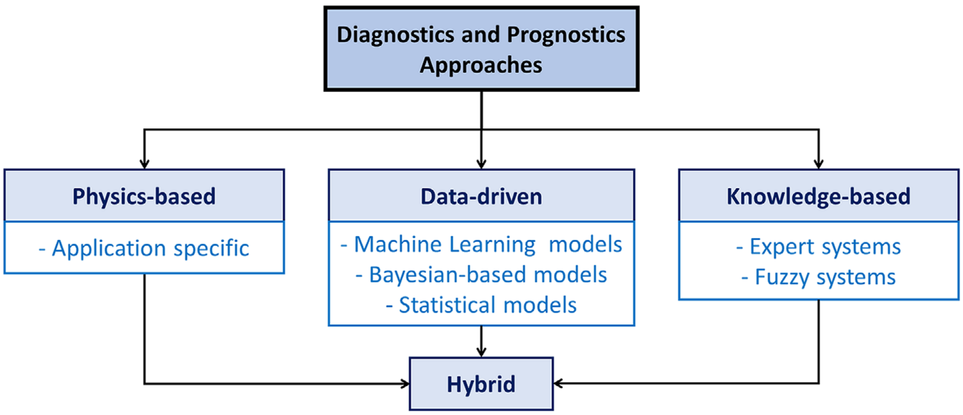

FIGURE 3 Classification of diagnostics and prognostics approaches

Kalman filter (KF),[73,74] and some modified KF methods have been successfully applied for diagnostic purposes in the practical application of engineered systems, for example, extended KF (EKF),[75] unscented KF (UKF),[76] and PF.[77]

The parity space technique is one of the strategies to construct a model-based fault diagnosis. In this technique, a group of so-called parity relations (i.e., modified system equations) is obtained, taking into account measured process signals. These parity relations decouple the residuals from the system states and among each other. This helps to improve the detectability of faults. The inconsistency in the system equations is the indication of the presence of a fault.[50,69] This fault diagnosis scheme has been widely employed in the past decades.[78-80]

In general, it is hard to compare different residual generation approaches for fault detection as the application of a particular approach depends on several factors such as the system itself, availability of the model, and the application sensitivity. Generally, the structure of the model is required to be known in the parameter estimation technique, while observer-based and parity space approaches assume that the model and the related parameters are known. Input excitation is required in the parameter estimation technique, whereas the others do not have such limitations. On the other hand, the parameter estimation approach is a better choice for the detection of multiplicative faults. Another key difference is that among these three approaches, only the parameter estimation technique is able to detect and isolate several faults based on single output information.[71] In terms of dealing with measurement noises, parity space is more sensitive than the other two approaches.

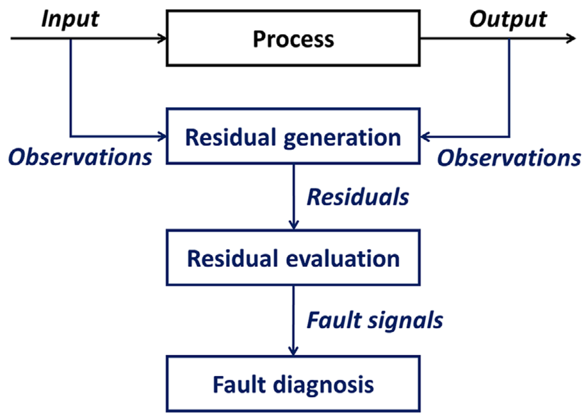

FIGURE 4 Structure of physics-based fault diagnostics

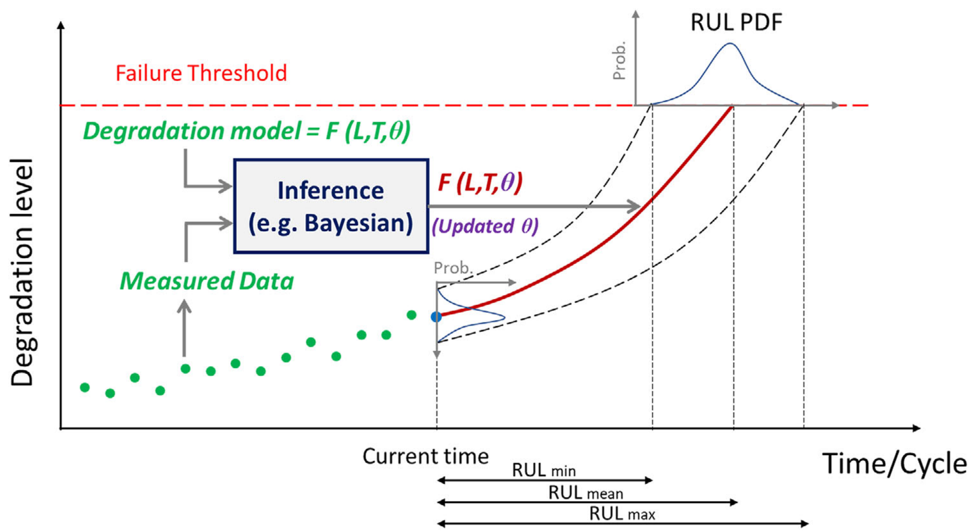

FIGURE 5 Illustration of physics-based prognostics for remaining useful life prediction

2.1.2 | Prognostics application of physics-based approaches

Physics-based prognostics models integrate mathematical models describing the physics of a system and failure modes (i.e., the evolution of damage or degradation) as well as CM data to provide a knowledge-rich prognosis.[41] When there is an accurate physical model of a system that characterizes damage degradation as a function of time/cycle, the prognostics is principally complete. Because progressing the degradation model in the future time can determine the future behavior of damage.[63] In practice, the degradation model is not deterministic (i.e., not complete) due to the uncertain environmental and operating conditions in the future. Figure 5 illustrates the physics-based prognostics utilizing measured data and the degradation model. The model is represented as a function of operating condition (L), elapsed time/cycle (T), and mathematical model parameters (θ).[4] The physics-based degradation modeling approach usually considers available physics-of-failure models, such as Arrhenius, Eyring, and Inverse Power models.[81]

Model parameters can be identified employing estimation algorithms based on measured data. The key concept of physics-based prognostics is to exploit measured data to decrease the uncertainty in degradation model parameters. For this purpose, mostly Bayesian inference algorithms like KF,[82] the EKF,[83] the PF,[84,85] and the Bayesian method[86,87] are used. There are also frequentist approaches in which only historical data are used to estimate the model parameters of interest.[88] However, the Bayesian approach is more effective as it combines the measured data with a prior belief to derive a posterior distribution of the model parameters.[36] Therefore, most model-based prognostics methods have their foundation on Bayesian inference.[63]

Failures of a complex engineered system may be caused by multiple degradation processes. Therefore, it is important to consider multiple degradation processes simultaneously. In practice, assuming independent degradation processes may not be realistic and can lead to poor modeling of multiple degradations in a complex system. To address this issue, several distributions and tools have been adapted and employed to model multivariate degradation, such as multivariate normal distribution[89] and Bayesian Markov Chain Monte Carlo method.[90]

2.1.3 | Summary

Physics-based methods are quite useful in general owing to their ability to capture a physical phenomenon. There are some advantages that these methods can outperform others, once the mathematical model is identified accurately. They provide a better means to handle the bias in measured data and are able to explain the behavior of a system in a wide range of operating conditions. Moreover, they require a relatively small number of data and can make a long-term prediction. On the negative side, a complete understanding of the failure mechanisms and theories is required. Therefore, it is difficult to develop such models for the damage evolution processes of complex systems. In addition, the quality of data and parameter estimation are two key issues in physics-based methods to be practical.

2.2 | Data-driven approaches

Data-driven approaches utilize a (preferably large) amount of collected data at previous and current operating conditions (i.e., testing and training data) in order to learn a system behavior and predict the future trend, independently from physics or engineering principle about the system.[5] Data-driven approaches use systems' CM data (instead of human expert models or physical models) to build a mathematical function based on the correlations and dependencies between the output variable of interest and the vector of sensed variables, in order to extrapolate prediction. The efficiency of these methods depends on training data, which requires volumes of data. It is quite difficult to specify how much data are fairly useful for the prognostics, without a detailed knowledge about the system.

Data-driven approaches have a variety of algorithms based on the type of mathematical functions and how to utilize the given information.[47] In practice, algorithms of physics-based approaches mostly can be used for data-driven approaches since a mathematical function can be employed instead of a physical model.[63] Data can also be artificially generated for training and testing purposes (e.g., in the case of unbalanced datasets).

In the literature, different classifications are introduced for data-driven methods (e.g.,[42,46,55]). In terms of search strategies, this paper broadly classifies them as ML methods, Bayesian-based models, and other statistical models.

2.2.1 | Machine learning methods

ML–as a subfield of artificial intelligence–plays an important role in different diagnostics and prognostics methods.[37,38] ML algorithms such as support vector machine (SVM), decision tree (DT), and artificial neural network (ANN) are some of the most popular data-driven approaches utilized in the literature. Deep learning (DL) algorithms and transfer learning (TL) are recently taken into consideration for diagnostic and prognostic applications.[53,91,92]

An SVM is a popular supervised ML model that employs classification algorithms for two-group classification problems.[93] The objective of the SVM algorithm is to find a hyperplane in an N-dimensional space (N is the number of features) that distinctly classifies the data points.[94] SVMs have been successfully applied to a wide variety of diagnostics[95,96] and prognostics[97,98] applications. Although SVM is a state-of-the-art technique for regression and classification[99] and has a better generalization ability than the neural networks (NNs),[98] it suffers from a number of disadvantages, one of which is the lack of probabilistic outputs that make more sense in health monitoring applications.[23]

A DT-based model is an effective supervised ML technique to implement the classification methods in high-dimensional data space. In DT models, the input and the corresponding output in the training data are explained, and the data is continuously split based on a specified parameter.[100] DTs are used effectively in many diverse areas such as medical diagnosis, remote sensing, and speech recognition. They are also successfully applied for diagnostics and prognostics applications. Their application for diagnostics and prognostics is also wide, and they have been applied for many systems such as electric products,[101] rotating machinery,[102] and chemical industry.[103] One of the main features of DT is its capability to break down a complicated decision-making process into a set of simpler decisions; therefore, it provides a solution that is often easier to interpret.[100] However, there are a few issues that limit DT's application for complex systems like, instability (a small change in the data can lead to a large change in the structure of the optimal DT), difficulty in dealing with continuous attributes, and the relatively low accuracy.

ANNs represent one of the most popular and highly effective data-driven approaches for diagnostics[95,104] and prognostics[105-108] in engineered systems. DL models, as a branch of ML, which is based on ANN with representation learning, are also applied for diagnostics and prognostics purposes.[109,110] These algorithms are popular in computing science communities, and in recent years, their applications are increasing in engineering communities. TL is also utilized for diagnostics and prognostics, which is an ML method, where a model designed for a task is reused as the starting point for a model on a similar task.[92] The applications of ANN and DL/TL are discussed in more detail, respectively, in Sections 3.1 and 3.2. There are some other ML algorithms such as k-nearest neighbors[111] and random forest,[112] which also adequately applied for diagnostics and prognostic.

2.2.2 | Bayesian-based models

Bayesian-based data-driven models estimate the state of a process with a minimum prediction covariance received from data. The results of these methods are presented in the form of probability distributions rather than precise estimations. They are able to estimate the current and future states of complex systems.[113] These models are based on Bayes' theorem, which explains the probability of an event ($P(A)$), based upon prior knowledge of conditions, which may be related to the event[55]:

$$P\ (AB) = \frac{P(B|A)P\,(A)}{P\,(B)}, \tag{1}$$

where A and B are events and $P(B) \neq 0$.

There is an increasing trend of Bayesian-based models' application for diagnostics and prognostics, owing to their advantages over other methods, such as the capability for modeling complex systems and being applicable for both diagnostics and prognostics.[114] In different review papers, other names are also used for this class of methods, for example, probabilistic reasoning[45] and stochastic algorithms.[55] BN, hidden Markov models, KF, and PF are the most common types of these probabilistic approaches.

BN is a probabilistic graphical model, which explains the relations between faults and symptoms, both visually and conceptually. Even though BN modeling is not the solution to all problems, it is fairly versatile and applicable for a wide range of applications. This is due to its ability to represent the complex inter-relationships (i.e., causal-effect relationship) among the related variables of a system. BNs[115] and dynamic BN[116] have been quite effectively utilized for diagnostics and prognostics in various applications, for example, rotating machines,[117] industrial process,[118] aeronautics industry,[119] and power systems.[120] Despite numerous merits, there are some limitations in implementing BN such as data preprocessing requirements and difficulties in dealing with multidimensional data.

Hidden Markov modeling (HMM) is a stochastic method built upon the principles of Markov chains (i.e., the probability of each event only depends on the state attained in the previous event) for modeling a system with unobservable states.[121] HMM can be represented as the simplest dynamic BN. An HMM can be defined completely by the parameters N, D, A, B, $and\ \pi$ (for simplicity $\lambda = A, B, \pi$, which is called the model parameter). Where N is the number of states in an HMM, D is the number of different observations for each state, A is the state transition probability, B is the observation probability, and π is the initial state probability. HMM has been utilized in some applications adequately, for example, speech processing and handwriting recognition, and in the past two decades in industrial systems for diagnostics and prognostics.[122-125] Practically, defining the discrete states for a continuous degrading system and estimating corresponding transition probabilities is one of the major challenges that restrict wider applications of HMM.

The KF is a set of mathematical equations providing a computationally efficient (recursive) tool to estimate the state of a process so that the mean of the squared error is minimized.[126] KF is a type of Bayesian filtering in which the variables are normally distributed, and the transitions are linear. In the literature, the application of KF for diagnostics and prognostics purposes is broad.[73,127] However, in practical applications where the process to be estimated and/or measurement models are not linear, the KF is not the appropriate tool. EKF[128] and UKF[129] are two modified KF for nonlinear estimations. Both EKF[83] and UKF[130] have been used for diagnostics and prognostics of industrial systems.

The PF is another well-known filtering algorithm that can effectively solve the state estimation problem of non-Gaussian noise and nonlinear state-space systems.[56] Because of these capabilities, this filter has been developed for various applications of diagnostics and prognostics.[131-133]

In general, unlike many other methods, the Bayesian-based probabilistic methods can represent the complex causal relationship amongst the variables of interest of a system and also can be used to model multistate, dynamic processes with incomplete and noisy measurements. Given these advantages, they have a high contribution in the diagnostics and prognostics of complex systems. However, they face difficulties in dealing with multidimensional data, and a data preprocessing phase is normally required before applying these methods. Moreover, they might be computationally intensive, especially for modeling a system with a large number of states.

2.2.3 | Statistical models

There are some more techniques that have been employed for diagnostics and prognostics purposes (e.g., Monte Carlo methods).[134-136] Here, a few of them that can be classified under statistical models have been reviewed.

A regression-based data-driven approach is a set of statistical processes to estimate the relations between a dependent variable and one or more independent variables. The Gaussian process regression is a linear regression and one of the commonly used regression-based methods.[137] Support vector regression (SVR)[130,138] and k-nearest neighbor regression algorithm[139] are also promising algorithms for diagnostics and prognostics because they are easy to implement and can easily process small training sets and multi-dimensional data.

Principal component analysis (PCA) is a statistical technique for dimensionality reduction that is able to identify correlations and patterns in a dataset so that it can be transformed into a lower dimension dataset without losing any important information. Independent component analysis (ICA) is used to find a representation of data as independent sub-elements. PCA[140,141] and ICA[142,143] are both effective tools in diagnostics and prognostics processes. These two techniques can be classified under ML methods as well.

There are a few more data-driven techniques that have not been reviewed here as their applications for diagnostics and prognostics are sparsely discussed in the literature.

2.2.4 | Summary

From a practical point of view, data-driven approaches are fast and easy to implement. In fact, there are many available packages for data mining and ML that increase the speed and simplicity of the implementation. Identifying relationships that were not previously considered is possible by collecting enough data. Moreover, these methods can consider all relationships without any prejudice since they work with objective data. However, the data-driven method requires a large amount of data that includes all possible failure modes for the same or similar systems. The results of data-driven methods might be counter-intuitive since physical knowledge is not involved; hence, it is risky to accept the related result without understanding the source of the problem. In addition, the methods can be computationally intensive in both analysis and implementation. The reliability of data-driven approaches is low comparing with physics-based approaches, which perform well even with a small size of data. The issue is that the reliable physics model is not available always. In such a case, if enough data is available, then a data-driven approach can be implemented, which does not require a physics model. However, if there is not enough data or data is not fully relevant or balanced, there are no reliable approaches and then the health assessment process will be unreliable or partly applicable. Table 2 summarizes the merits and limitations of the reviewed data-driven methods.

2.3 | Knowledge-based approaches

Knowledge-based models rely on engineering experience and historical events, which provide intuitive results by comparing an observed situation with a library of previously defined failures to find the similarity.[4] These models are applicable

TABLE 2 A brief comparison of data-driven methods

Data-driven method		Advantage	Disadvantage
ML methods	ANN	• Is able to model complex, nonlinear systems • Is able to use many types of input data, though particularly normalized numerical values • Has high classification accuracy • Has the ability to work with incomplete knowledge • Has parallel processing capability	• Requires a large amount of data for training • Might be time-intensive in determining the appropriate model and data training • Is not suitable for categorized or symbolic data • Has no physical meaning • Has a high risk of over-fitting • Unable to represent causality
	SVM	• Has high classification accuracy • Works well with even unstructured and semi structured data • Has a lower risk of over-fitting	• Has no physical meaning • Has low efficiency in dealing with big data • Is computationally expensive, thus runs slow
	Decision tree	• Is easy to understand and interpret • Requires less effort for data preparation as there is no need for normalization or scaling of data • Is able to handle missing values	• Is instable in facing with even small changes • Encounters difficulty in dealing with continuous attributes • Has relatively low accuracy for large domains • Unable to represent causality
	DL	• Has automatic features extraction • Has higher robustness to noise • Has more accurate results • Has low risk of over-fitting	• Requires a large amount of data • Has time-consuming training • Has no physical meaning • Unable to represent causality
Bayesian-based models	Bayesian network	• Is fairly versatile and applicable for a wide range of applications • Is able to represent the complex inter-relationships (i.e., causal-effect relationship) • Presents results in the form of probability distributions rather than precise estimations • Is able to provide good prediction accuracy even with rather small sample sizes • Can be easily combined with decision-analytic tools • Has low risk of over-fitting of data	• Requires data preprocessing • Faces difficulties when encountering multidimensional data • Requires discretization in dealing with continuous data • Requires expert knowledge for effective model representation • Requires extensive data collection
	Hidden Markov modeling	• Is suitable to model multivariate, dynamic processes • Is appropriate for multi-failure mode • Has strong statistical foundation • Is computationally efficient • Is able to model spatial and temporal data • Has efficient learning algorithms • Individual models can be trained using global data only • Has wide variety of applications • Can be used for fault diagnosis on nonstationary signals and dynamic system	• Faces difficulty when encountering non-Gaussian noise • Is not able to express dependencies between hidden states • Requires a large amount of data for training • Encounters difficulties in defining the discrete states for a continuous system • Faces difficulties in estimating transition probabilities

(Continues)

TABLE 2 (Continued)

Data-driven method	Advantage	Disadvantage
Kalman filter	• Is very fast • Is computationally efficient • Is able to provide the quality of the estimate (i.e., the variance) • Capable to deal with incomplete and noisy data	• Is not appropriate for nonlinear applications • Is limited in dealing with non-Gaussian distributions • Has slow reaction speed in facing rapid change situations
Particle filter	• Is suitable to model multivariate, nonlinear processes • Is effective in dealing with non-Gaussian noise • Has more accurate results than other filtering methods	• Is more computationally intensive than KF • Require enough historical data and time in dealing with higher dimensions • Has the risk of particle depletion phenomenon

whenever deep knowledge about the system under study is available. As these models correlate engineering experience and knowledge, it is also called "experience-based models" in some references (e.g.,[52]). Expert systems and fuzzy logic can be considered as two sub-classes of knowledge-based models, since both rely on domain knowledge.

2.3.1 | Expert systems

Expert systems are computer programs that imitate expert knowledge to solve a problem in a particular field.[4] It normally contains the collection of experience from domain experts and a rule base to apply that knowledge to particular problems. The rules are represented as IF condition, THEN consequence. Conditions (which are inputs in the statement) are normally the facts about the system and consequence is the related outcome.[42] Each set of conditions has to have only one output and all possible combinations of conditions must have an output.[144] The usefulness of the model depends on the consistency, how exact it is, and frequently updating the knowledge. Expert systems are employed for diagnostics and prognostics purposes such as for intelligent monitoring a control procedure of a cogeneration plant in support of fault detecting and predicting purposes[145] and for detecting failure and predictive maintenance.[146]

The outputs of expert systems are understandable, and conditions can be obtained for a specific consequence. However, it is not always easy to acquire knowledge for a particular field and even harder to establish rules as increasing the number of inputs and outputs may result in a combinatorial explosion.[147]

2.3.2 | Fuzzy systems

The Boolean statement used by expert systems is not able to define sets (i.e., true or false) realistically in many cases.[144] To get over this issue, fuzzy logic can be used. Fuzzy logic is considered as a superset of standard conventional Boolean logic which is extended to deal with the partial truth. It contains a few steps (e.g. fuzzification and defuzzification) and after completing the different steps, the resulting fuzzy model needs to be validated.[4]

In addition to the applicability of fuzzy systems for control, it is also successfully applied to diagnostics and prognostics models.[148,149] Fuzzy logic is also combined with other modeling tools and techniques for diagnostics and prognostics purposes, such as ANNs.[144]

Unlike expert systems, the applications of fuzzy logic are broad and give the opportunity for considering descriptive rules that are intentionally imprecise.[148] Fuzzy logic models are most effective to model the behavior of a system with continuous variables. They are also efficient for the cases with no available mathematical model or in dealing with highly noisy data.[42,149] Relying heavily on the domain of expert knowledge to specify the rules and develop the fuzzy sets is the main hindrance for fuzzy systems wider applicability.

TABLE 3 Advantages and disadvantages of different knowledge-based methods

Knowledge-based approach	Advantages	Disadvantages
Expert system	• Understandable outputs • Conditions can be obtained for a specific consequence	• Not easy to acquire knowledge • Combinatorial explosion for complex systems • Highly uncertain results
Fuzzy system	• Less uncertainty (compared to the expert system) • Broader application • Ability to consider descriptive rules (to cope with Boolean logic) • Effective to model the behavior of a system with continuous variables, noisy data • No need for a mathematical model	• Validate is needed • Requiring a proper design of the system's functions • Relying heavily on the domain expert knowledge • Not easy to acquire knowledge or requires additional knowledge transformation • Computationally expensive

2.3.3 | Summary

Knowledge-based models are mainly based upon the capability of the domain expert, and building these models is really challenging. Because of the combinational explosion problem, it seems even impossible for complex system applications. This reality limits the application domain of knowledge-based models. Accordingly, not many papers have focused on knowledge-based models, in comparison to physics-based, and especially data-driven approaches[45] and the existing works are quite old. However, knowledge-based models are more associated with hybrid approaches rather than independent diagnostics and prognostics techniques in recent years. This integration adds some flexibility to the modeling process.[150,151] Table 3 compares different knowledge-based methods by summarizing their generic advantages and disadvantages.

2.4 | Hybrid approaches

To leverage the advantages of different diagnostics and prognostics models (physics-based, knowledge-based, and data-driven), hybrid approaches attempt to integrate the strengths of these three approaches, where it is possible. The results of hybrid approaches are claimed to be more accurate and reliable.[52] Using physics-based, knowledge-based, or data-driven approaches alone for practical complex systems might not be efficient. As an alternative, a combination of these approaches can maximize the prediction capability and increase the reliability of results. As an example, the knowledge of physical behavior can allow to establish the mathematical model in a data-driven method.

In terms of classification, hybrid approaches can be classified into series and parallel models.[35] For example, in a series model, parameter tuning for physics-based is performed by data-driven methods, and in a parallel model, the residuals that are not explained by the first principle model are trained by a data-driven model.

Another classification for hybrid models, which is more specific, is based on the different combination sets of physics-based, knowledge-based, or data-driven models. In the literature, five different combinations of these models can be found for diagnostics and prognostics applications.[52]

- Knowledge-based and data-driven models have been combined to deal with the limitations of knowledge-based models since data-driven models can handle continuous data and learn the behavior of a system only from data.[152,153]
- Some researchers have used the output of the knowledge-based model to provide supplementary support to improve the physics-based model.[154]
- Multiple data-driven models have also been broadly combined as another type of hybrid approach. In these approaches, one data-driven method is used for feature extraction of a system, when it is not directly measurable (so-called offline training), and the other data-driven models are employed to predict the future state of the system based on the offline training.[125,155-158]
- The combination of data-driven and physics-based models are widely used among researchers for diagnostics and prognostics. As these two models are individually capable for both diagnostics and prognostics, their different combinations have been exploited extensively in the literature.[127,159-161]

- Combination of all three - knowledge-based, data-driven, and physics-based models, is sought in order to exploit the full advantages of different models.[52] However, integrating all three models is very difficult and challenging and impractical for the majority of cases.

Accurate diagnostics and prognostics are consequential for industrial systems, and over the years, different models individually have been used for these ends. Combining different models can improve the related results by leveraging the advantages of those models. However, hybrid approaches depend on a specific application domain, and there are a few challenges that restrict the applicability of hybrid models such as higher computational costs, determining the best combination of methods given the available data and information, which reduce the uncertainty in the results.

In this paper, some of the reviewed papers under physics-based, data-driven, or knowledge-based approaches can also be considered as hybrid models since they combine tools from different approaches.

2.5 | Comparison of different approaches

In the previous subsections, the details of the different methods were reviewed. In order to choose the appropriate method, in addition to the requirements and restrictions of research, the main advantages and disadvantages of each model needs to be understood. In Table 4, different methods are compared, and their pros and cons are summarized.

3 | CRITICAL REVIEW OF DIAGNOSTIC AND PROGNOSTICS APPLICATIONS TO COMPLEX SYSTEMS

Characteristics of complex engineered systems significantly reduce the application of knowledge-based and physics-based approaches. This is due to the fact that diverse interconnected subsystems/components, the multiplicity of processes, their concurrency, and their reliance on embedded intelligence lead to an unmanageable number of parameters in knowledge-based approaches. They also complicate significantly the construction of mathematical models for physics-based approaches.[28,30] On the other hand, the availability of ample data and relatively higher computational powers imply the use of data-driven methods for complex engineered systems. Hence, this section will review and discuss different data-driven diagnostics and prognostics methods that have been applied to address one or more characteristics of complex systems.

For the application of complex engineered systems, different methods have been employed. These methods are mostly based upon the traditional statistical, probabilistic and especially artificial intelligence methods, which have been enhanced and adapted or combined with other methods to address the characteristics of complex systems. Here, for the purpose of review, these methods are classified into classic methods, optimised classic methods, and hybrid methods.

3.1 | Classic methods

Some of the data-driven methods are able to cope with some of the features of complex systems since there are fundamentally nonlinear and/or dynamic modeling tools. Here, some of these methods are reviewed and their applications for complex systems are discussed.

An ANN is a class of model that is usually nonlinear in which a group of interrelated functional relationships between input stimuli and desired output are established where the parameters of the functional relationship are required to be adjusted for optimum performance.[162] Feedforward[163] and recurrent networks[164] are two typical network architectures of ANN-based predictors, which both have been employed in engineering applications. NNs have several advantages, including the ability to work with incomplete knowledge, parallel processing capability, the ability to implicitly detect complex nonlinear relation between dependent and independent variables, and having fault tolerance. Disadvantages include its black box nature (i.e., unexplained behavior of the network), greater computational burden, the difficulty of showing the problem to the network, risk of overfitting, and the experimental characteristics of model development.[53,91] The features of ANN, particularly, its capability to implicitly detect complex nonlinear relationships between dependent and independent variables, make it a suitable method for diagnostics and prognostics analyses of complex systems.[104,106-108] However, the adaptive forms of ANN are widely used for complex systems' applications, which are discussed in Section 3.2.

TABLE 4 Comparison of techniques for diagnostics and prognostics

Methods	Advantages	Disadvantages
Data-driven models	• Are easy and fast to implement • Do not need to mathematically formulate the process • Can consider all relationships without any prejudice since they work with objective data • Are easy to implement for complex systems where it is hard to build the physics-based models	• Require a large amount of data that includes all possible modes of failure for the same or similar systems • The results might be counter-intuitive • The unanticipated failure modes cannot be modeled • Can be computationally intensive in both analysis and implementation • It might be challenging to explain the result and find a physical meaning to the results • The reliability of results is lower in comparison to physics-based models
Physics-based models	• Can provide the most accurate and precise results, in the case of the availability of sufficient knowledge about the system behavior • The outputs are easy to understand • Require less data than data-driven models	• Require comprehensive knowledge of system behavior • Are computationally expensive in the case of complex systems • Are extremely challenging to extract mathematical knowledge about the complex system • Require extensive and expensive empirical data for model parameter identification • Are problem-specific
Knowledge-based models	• Do not need models • Are easy to understand and interpret the results • Require less programming and training • Provide an intuitive way of representing and reasoning with incomplete and inaccurate information	• Are highly dependent on the human experts • Do not have memory and are not able to learn • Require obtaining domain knowledge and convert it to rules which are challenging in practice • Suffer from the combinational explosion problem for complex systems • Normally cannot be applied in prognostics without incorporating other techniques
Hybrid models	• Benefit from the advantages of combined methods • Have higher reliability and accuracy of results • Can outperform other models, if carefully design	• May have higher computational costs, which limits their applicability • Determining the appropriate type of integration, given heterogeneous information is challenging • Face difficulties in aggregating results from various participant models

The applications of PF are becoming wider because of the high potential of PF in dealing with dynamic systems characterized by non-Gaussian and nonlinear natures. In the literature, there are quite a few research works that employed PF for diagnostics and prognostics of complex nonlinear systems.[132,133,165,166] There are a few other methods like, HMM, hidden semi-Markov model (HSMM), BN, dynamic BN, and ICA that also have been used for complex systems applications. However, they are not able to fully address the characteristics of modern complex systems, and they are mostly integrated with other tools in the form of hybrid methods. These methods are discussed in Section 3.3.

3.2 | Optimised classic methods

Many algorithms and approaches have been extended, improved, enhanced, and adapted in order to address the characteristics of complex systems. In the literature, there are many modified and adapted methods that have wide applications in diagnostics and prognostics of complex engineered systems, which are the topics of active research. Here, widely used adapted or improved methods for prognostics and diagnostics of complex engineered systems are discussed, and some of the related research works have been introduced.

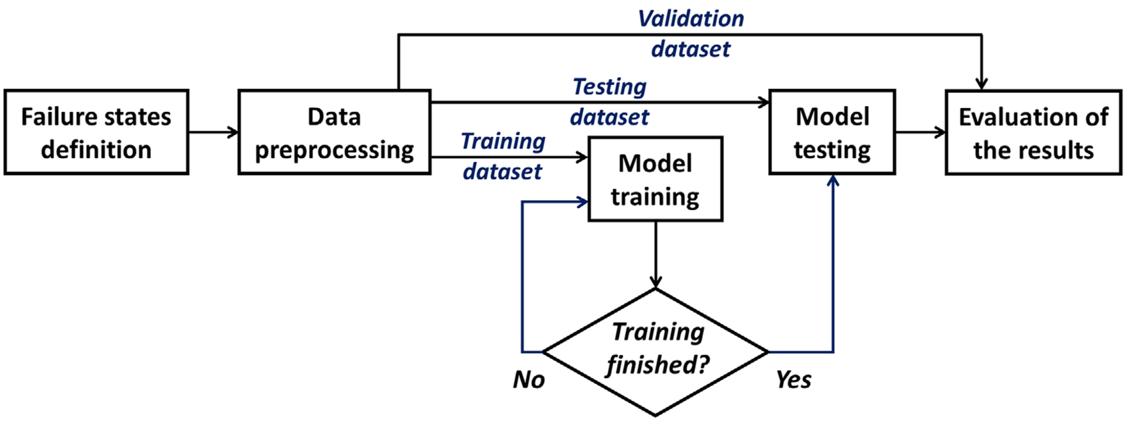

FIGURE 6 The high-level procedure of diagnostics and prognostics framework using deep learning

3.2.1 | Deep learning

As an ML method, DL is based on ANN, which is featured by multiple nonlinear processing layers in which hierarchical representations of data are tried for learning.[167] DL algorithms are becoming more popular for diagnostics and prognostics applications due to their potential advantages in dealing with nonlinear dynamics in time-series data.[53,91] Unlike traditional algorithms, DL is a powerful self-learning model that does not require a manual feature extraction step. Figure 6 illustrates the high-level procedure of DL diagnostics and prognostics framework.

There are a few DL algorithms; however, the main algorithms include the convolutional NN (CNN), recurrent NN (RNN), deep belief network (DBN), and deep NN.[168] Different DL architectures have been applied to fault diagnosis and prognosis fields; however, the most popular ones for the application of complex engineered systems have been reviewed here.

Convolutional Neural Network

CNNs are basically standard NNs that have been extended across space using shared weights. CNNs provide effective methods to work with raw signals directly by weight sharing and local connections without feature extractors.[109]

Despite the advantages of CNN, it suffers from a few limitations for the applications of diagnostics and prognostics. To alleviate the limitations of traditional CNN and enhance the performance, new frameworks have been presented. Zhu et al.[169] introduced a multiscale CNN for RUL prediction to synchronously keep the global and local information, compared to a traditional CNN. To consider temporal dependencies in different degradation states and quantify the uncertainty in RUL estimation, which cannot be addressed by CNN, Wang et al.[170] presented a recurrent CNN framework for RUL prediction in machinery systems. Han et al.[171] developed a dynamic ensemble CNN combined with a multi-level wavelet packet for fault diagnostics of a gearbox. The results revealed the effectiveness of the framework for the case even the sufficient fault data is not available. To address the imbalanced distribution of machinery health conditions, Jia et al.[172] proposed a new learning method named deep normalized CNNs to classify the faults of bearing.

Deep Belief Network

DBN, which is based on the restricted Boltzmann machine (RBM)[110] has become a common approach in ML and more recently for diagnostics and prognostics purposes due to its promising advantages such as learning algorithm and fine-tuning procedure. DBN, which is a probabilistic generative model, employs a multi-layered feed-forward NN that contains several RBMs. The layer-by-layer, unsupervised learning algorithm of RBMs can efficiently pre-train the model and adjust its parameters through the fine-tuning procedure.[173]

Zhang and Zhao[174] introduced a DBN-based fault diagnosis model for fault classification in Tennessee Eastman (TE) process. Using the mutual information approach, they extracted individual fault features in both temporal and spatial domains using DBN sub-networks. Liu et al.[175] proposed a DBN-based model for real-time diagnosis and quality monitoring framework for the manufacturing process. The DBN model for quality spectra is set up in a training stage that is used to monitor and diagnose the process profiles in the online phase. To overcome the difficulty of DBN-based RUL estimation techniques in uncertainty quantifying, Hu et al.[30] introduced a two-phase model using the DBN and diffusion process for

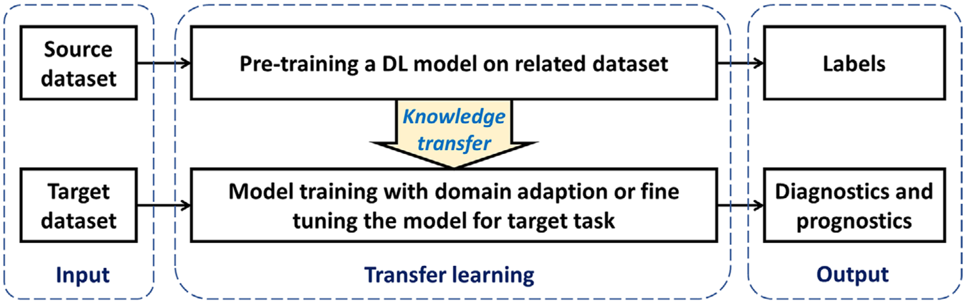

FIGURE 7 Deep transfer learning-based diagnostics and prognostics framework

prognostics of degraded bearings. First, deep hidden features are extracted using DBN, and then the probability density function of predicted RUL is presented employing the diffusion process. Wang et al.[176] introduced an extended DBN that utilizes all valuable information in the raw signal for fault classification in the TE process. This framework covers the limitation of traditional deep network models in which the layer-wise feature compression may filter the useful information in the raw data. To alleviate the limitations of traditional DBN in feature learning under different working conditions, Yan et al.[177] proposed a multiscale cascading DBN framework to automatically identify rotating machinery faults working in different operational conditions.

Recurrent Neural Network

An RNN is another DL technique that forms a directed graph along a temporal sequence from connections between nodes.[167] In recurrent network, signals can travel in both directions by introducing loops in the network. This characteristic helps to consider temporal dynamic behavior.[178]

The most important RNN is the long short-term memory network (LSTM) that is able to learn long-term dependencies. In recent years, LSTM networks have been widely employed for dynamic systems' application. Wu et al.[179] proposed an LSTM RNN-based approach to predict faults with the degradation sequence of equipment in which there is no need for predefining threshold or other ML methods. To alleviate the limitation of RUL estimation methods in learning the long-term dependencies within lithium-ion batteries' capacity degradations, Zhang et al.[180] proposed an LSTM network-based method. The method utilizes Monte Carlo simulation to generate a probabilistic RUL prediction. Wu et al.[181] employed vanilla LSTM RNN for RUL estimation of industrial systems, in order to increase the accuracy of prediction in the cases like complicated operations, model degradations, variable operating conditions, and highly noisy data. The results for aircraft turbofan engines show that the methods outperform RNN and gated recurrent unit (GRU) LSTM. GRU is another type of RNN that also has been utilized for diagnostics and prognostics applications.[182]

Despite the outstanding capability of DL for diagnostics and prognostics, these methods–like many other traditional frameworks for fault diagnosis–generally assume that the training and test samples have similar distributions. However, it is almost impracticable in real-world industrial applications, where the operating condition changes over time. Moreover, the quantity of the same distribution samples is normally insufficient to build qualified diagnostic and prognostics models (so-called distribution discrepancy issue). In addition, training a DL model requires huge amounts of labeled samples, in which collecting enough labeled training data is challenging and also expensive, especially for unseen conditions. Moreover, training a DL model from scratch requires notable computational and time resources, and it is challenging to meet the real-time requirements of some fault diagnosis and prognosis tasks.[38,183,184]

3.2.2 | Transfer learning

To overcome the limitations of DL, TL[92] has shown potential value in fault diagnostics and prognostics. TL possesses the capability to leverage the knowledge learnt from the massive source data to build diagnosis and prognosis models for the similar but smaller dataset. The idea behind TL is to adapt the distribution and improve the learning of the predictive model in the target domain using the knowledge contained in the source domain. Therefore, TL can transfer knowledge learnt from one task to facilitate fulfilling a different but similar task. Figure 7 illustrates the high-level procedure of diagnostics and prognostics framework using TL.

To cover the DL issues, Han et al.[183] introduced a deep transfer network as a new framework for fault diagnosis in industrial applications. The method, which generalizes the DL model for wider applications, performs based on extending the marginal distribution adaptation to joint distribution adaptation, in order to address the issue of the lack of labeled CM data and get more accurate results. Zhang et al.[185] proposed an RUL estimation method utilizing the TL algorithm with bi-directional LSTM NNs. The method is based on the exploitation of data samples from different but similar tasks for the RUL prediction of turbofan engines. Wen et al.[184] proposed a deep TL-based three-layer sparse auto-encoder for fault diagnosis, the proposed sparse auto-encoder achieved the higher accuracy than other algorithms (e.g., DBN, sparse filter, ANN, SVM), when the training and testing data are subject to different feature distributions. Mao et al.[186] introduced a two-phase method by integrated deep feature representation and TL for RUL prediction of rolling bearings with the inconsistent distribution of vibration data. The method improves the feature representation ability of faults and the degradation process and also enhances the RUL prediction accuracy.

3.2.3 | Non-Gaussian methods

For complex system process data, non-Gaussianity should be one of the most significant properties due to multiple process states or operating conditions. Therefore, the techniques that fundamentally assume that data follow a single Gaussian distribution (e.g., PCA or partial least squares, KF) are not suitable for the application of complex systems. For non-Gaussian modeling situations, an effective solution is to build finite mixture models in order to accommodate the various non-Gaussian behaviors. The most commonly used finite mixture model is the Gaussian mixture model (GMM) that can approximate any complex non-Gaussian probability density for the given enough weighted mixture components.[33] Some of the techniques (e.g., ANN and PF) have basically non-Gaussian data structure and are suitable for analyzing multivariate systems that exhibit non-Gaussian behavior. These techniques have been reviewed in the previous sections, and here, only some research studies that employed the non-Gaussian and mixture of Gaussian models have been reviewed.

Xu and Deng[187] introduced dynamic Bayesian ICA methods for fault detection in multimode, non-Gaussian dynamic processes. The method alleviated the limitation of ICA methods in considering dynamic characteristics of process data, as the assumption in ICA is that there is only one normal operation mode. Yan et al.[188] presented a semi-supervised GMM framework to diagnose faults in new data categories. The framework was successfully applied on a rotary machine and high-voltage electronic equipment for detecting and classifying the faults. Hong et al.[189] proposed an early fault diagnostics method for bearings using vibration data. Their method extracts features based on spectral kurtosis, filter the results using statistical approaches, and faults are evaluated by a GMM. Liu et al.[190] presented a Dirichlet process (DP) Gaussian mixture for online process fault detecting and identification, using sensor data. The outcomes of the method are fault detection and identification of specific process anomalies employing DP-based statistical process control and recurrent hierarchical DP unsupervised clustering.

3.2.4 | Kernel-based methods

The application of kernel-based methods is wide for nonlinear data processing. The kernel representation of data is transferring nonlinear data into a high-dimensional space where it is easier to separate the two classes of data. In a kernel function, the inputs vectors are taken into the original space and the dot product of the vectors in the feature space is returned.[191] SVM and kernel PCA (KPCA) are two kernel-based learning methods that have been successfully applied in diagnostics and prognostics fields. SVM has been introduced in Section 2.2.1.

Xu et al.[192] introduced a fault prognostics method based on local kernel PCA and multivariate time delay analysis for nonlinear processes. The application of the method for the TE process showed more accurate results, compared to other methods. Multi-block statistics local kernel PCA algorithm integrated with statistics pattern analysis is proposed by Zhou and Gu[193] for nonlinear process monitoring and fault detection. Their method is effective for single-mode process analysis. Hamrouni et al.[194] introduced a reduced interval kernel PCA method for fault detection in uncertain nonlinear processes to deal with uncertain data and reduce the computation complexity for large datasets. The method has a lower computational cost, compared to interval kernel PCA methods.

There are more kernel-based methods that have been employed for complex, nonlinear, and non-Gaussian systems such as modified robust total kernel partial M-regression,[195] performance-relevant kernel ICA,[143] auto-associative kernel regression.[196] The wide application of kernel-based techniques is because of their capabilities in dealing with high-dimension, nonlinear, non-Gaussian data with a reasonable computational cost. They also can be used for both supervised and unsupervised problems. However, the selection of an appropriate kernel to solve a problem is challenging and, in many cases, DL methods outperform kernel-based methods in terms of the accuracy of results.

3.2.5 | Dynamic methods

To address the time-varying behavior of complex systems, dynamic modeling is employed that generally represents the behavior of a system over time as a set of states that occur in a defined sequence. The dynamic forms of different methods have been exploited for prognostics and diagnostics of complex systems.

Dynamic BN is one of the widely used dynamic methods for reliability analysis of complex systems, which enables the reliability estimation based on a temporal aspect.[158] Lewis and Groth[197] investigated the capabilities of dynamic BNs for diagnostics and prognostics of complex engineered systems. Yu et al.[196] employed dynamic ICA (DICA) combined with auto-associative kernel regression for fault detection to address the nonlinearity and multimodality in complex industrial systems. Shi et al.[198] introduced an incipient fault detection method in gearbox systems using Deep Recursive Dynamic Principal Component Analysis, in order to detect faults in time-varying, noisy vibration signals. Ahmad et al.[199] introduced an RUL estimation method for bearing based on the dynamic regression models. In this method, in order to predict the RUL, the online vibration level is measured based on the normal value for vibration, and the developing trend of health indicator is captured via recursively updating the regression models. Kong and Yang[200] integrated an adaptive first predicting time selection approach with dynamic exponential regression for RUL estimation in rolling element bearings. This integration was proposed to overcome the limitations of existing methods in considering incipient faults and also the requirements for historical data for parameter estimation. Wang et al.[201] employed dynamic LSTM NN to indirectly predict the online RUL of satellite lithium-ion batteries. Instead of using the capacity of batteries, this method indirectly extracts the health indicator, using the Spearman correlation analysis method.

3.2.6 | Other adapted methods

Many tools and techniques are not able to address the characteristics of complex systems. Consequently, to suit the circumstances of the complex system under study, the adapted and enhanced forms of the tools–which are more flexible–have been employed to provide more reliable diagnostics and prognostics results. The application of adapted techniques for prognostics and diagnostics is wide and quite many research studies can be found, employing the modified forms of numerous techniques.

Liu et al.[202] proposed an adaptive HSMM for diagnostics and prognostics in multi-sensor systems to decrease computation and space complexity. In the adaptive training algorithm, the maximum likelihood linear regression transformation is used to represent the differences among the multiple sensors. Cheng et al.[203] presented an enhanced particle filtering algorithm to alleviate the particle impoverishment problem of PF in RUL prediction, which may cause unrealistic prediction results. In this method, an adaptive neuro-fuzzy inference system learns the state transition function in the fault degradation model using the fault indicator extracted from the monitoring data. Qian and Yan[204] proposed an enhanced PF approach for RUL estimation of rolling bearings that integrates an adaptive importance density function selection and a back propagation NN-based resampling smoothing. The method uses particles in each recursive step to identify an adaptive importance density function and employs a back propagation NN to improve the particle diversity before resampling. To increase the diagnostics accuracy in complex mechanical systems operating in diverse conditions, Han et al.[205] introduced an adaptive spatiotemporal pattern network (STPN) diagnostics approach. The STPN-based approach, which is integrated with CNNs, is capable to extract spatial and temporal features from different types of time-series data.

The general characteristics of complex systems and different operating conditions for a system under study challenge the application of conventional methods. As a result, the utilization of the adaptive form of diagnostics and prognostics techniques and methods is a more natural choice and is expected to have more accurate results than the non-adaptive counterparts.

3.3 | Hybrid methods

Hybrid methods integrate the advantages of two or more methods to maximize the estimation and prediction capabilities. Hybrid methods play a key role in the application of practical complex systems since one method is normally not enough to address the challenges faced in dealing with complex systems' diagnostics and prognostics. Therefore, combinations of data-driven methods (mostly their adaptive forms) are integrated to address dynamic, nonlinear, nonstationary, and non-Gaussian characteristics of complex engineered systems. In this section, hybrid methods have been classified into the different combinations of ML and statistical methods for the purpose of review. It is worth mentioning that some of the reviewed papers under adapted methods in Section 3.2 can be considered as hybrid models since they integrate two or more methods.

3.3.1 | Integration of ML methods

The integration of several ML techniques seems to be a promising implementation for complex engineered systems since they are capable tools for both data training and data processing.

Different hybrid methods have been proposed for prognostics and diagnostics of rotating machinery using vibration signals that are highly noisy and nonstationary in nature.[206] Merainani et al.[207] combined self-organizing feature map NN with Hilbert empirical wavelet transform and singular value decomposition to identify and classify faults in automatic gearboxes working in various operating modes, using nonstationary vibration signals. Bastami et al.[105] applied the wavelet packet transform for extracting the features of vibration CM signal and applied ANN for estimating the RUL of rolling element bearings. In another research study, SVM is combined with particle swarm optimization technique to estimate the RUL of aircraft engines such that the model requires only the information about the current status of the system, without requiring knowledge of the prior situation.[208]

Lithium-ion batteries have both dynamic and static characteristics, and their operating conditions (e.g., power, temperature) are variable. The RUL of lithium-ion batteries is predicted in[209] by a hybrid method, using false nearest neighbors and a hybrid NN. Han et al.[205] integrated STPN approach and CNN for feature learning and condition classification, for the purpose of fault diagnosis in complex systems operating in variable conditions. The obtained results revealed that the hybrid method has better performance than shallow learners ML algorithms.

3.3.2 | Integration of ML and statistical methods

To leverage the advantages of ML and statistical approaches, their combinations have been applied by many researchers in order to enhance the accuracy and reliability of the diagnostics and prognostics results.

Cho et al.[210] combined RNN and dynamic BN for fault detection and isolation in three-phase induction motors where RNN is used to model normal system behavior and various fault conditions, and BN is employed to evaluate the residuals. Jinglong et al.[182] introduced a fusion method based on KPCA and a GRU to estimate RUL of a nonlinear degradation process. In this method, nonlinear features are extracted by KPCA, and RUL is predicted by the GRU, as it is effective in describing a very complex system. Wang et al.[211] combined relevance vector machine regressions with exponential degradation models coupled with the Frechet distance to estimate the RUL of rolling element bearings exploiting nonlinear degradation data. To attain higher RUL estimation accuracy, Wu et al.[212] employed the combination of NN and bat-based PF for modeling and updating the related parameters of lithium-ion batteries' degradation trends under different working conditions. Wang et al.[213] introduced CNN-based hidden Markov models for fault detection in bearings. In this hybrid method, the features of nonlinear and nonstationary vibration data are learned by CNN, and HMMs are used as fault classifying tools. Deutsch et al.[131] integrated a DBN and a PF for more accurately predicting the RUL in hybrid ceramic bearings, using vibration data. Peng et al.[214] used a similar combination of tools (DBN and improved PF), to introduce a method for RUL prediction in aircraft engines, using degradation data. Yu et al.[196] integrated auto-associative kernel regression and dynamic ICA for fault detection in nonlinear multimode industrial processes. Auto-associative kernel regression is used for residual generation, as it is an effective technique for nonlinear and multimode applications. Dynamic ICA is employed to deal with the non-Gaussian distribution of residuals obtained from auto-associative kernel regression.

3.3.3 | Integration of statistical methods

To improve the accuracy of fault diagnostics and prognostics in complex systems, many statistical techniques have been integrated into various research studies to address some features of complex engineered systems.

Wei et al.[215] employed the fusion of SVR and PF for state-of-health detection and RUL prediction in lithium-ion batteries. SVR is used to simulate complex aging mechanisms of batteries, and degradation parameters are estimated using PF, as it can filter measurement noises. A combination of PCA and HMM are proposed by Georgoulas et al.[216] for broken rotor bar fault diagnosis in asynchronous machines. PCA is employed to extract a characteristic component, which shows the rotor symmetry caused by the broken bars, and HMMs process the component in two different classes (a multiclass and a one-class), for estimating the severity of the fault.

The integration of HMM and BN (or dynamic BN) have also been applied for diagnostics and prognostics in some research studies. Medjaher et al.[155] integrated a mixture of Gaussians HMMs (MoG-HMMs) and dynamic BNs as modeling tools for RUL estimation, considering that degradation in the critical components of a physical system is the only cause of failure. The method contains two learning and exploitation phases to estimate the RUL of bearings. Rebello et al.[158] presented a new methodology for functional reliability estimation of complex industrial systems. They used HMM to map the continuous data into unobservable state probabilities and dynamic BN to find the posterior system state probability by considering the component dependencies within a system. The method is based on the assumption that the degradation in underlying system components is the major cause of failure in the system. Galagedarage and Khan[156,157] integrated MoG-HMM and BN to detect, isolate, and predict identified faults in the TE process. The methods were based on the comparison between offline and online generated log-likelihood to predict the most likely future state of the system and utilizing the relevant information to identify the root cause of faults.

3.4 | Summary and discussion

Various methods with different applicability have been employed for diagnostics and prognostics, aiming at addressing one or a few of the features of complex engineered systems. Considering the feature of complex systems stated in Section 1.1 and the review of related research works, here, the capability of various methods to address those features are highlighted.

3.4.1 | Nonlinearity

Vibration data (mostly form bearings) analysis is one of the common and efficient techniques for diagnostics and prognostics. However, these data are highly nonlinear and often contain strong noise. This is because of the changes in friction, stiffness, fault excitation, and operational environment.[132,177] In addition, data for lithium-ion batteries, chemical processes, aircraft engine, and some other systems, which are nonlinear in general, have been analyzed for diagnostics and prognostics. Table 5 provides a summary of the applications of different methods to address the nonlinearity of complex systems for the reviewed research works in this section. For diagnostics and prognostics purposes dealing with nonlinear data, some methods have been widely employed. The table emphasizes the evidence that DL and TL (in general ANN-based methods), PF, SVM, kernel-based methods, and the fusion of these methods are the best for diagnostics and prognostics of complex engineered systems with nonlinear data. This is because of the fact that these methods have high potentials in dealing with complex systems characterized by nonlinear natures. However, these are not the only methods, and there are some other methods (e.g., HMM), which perform well on nonlinear processes.[182]

3.4.2 | Dynamicity

Dynamic modeling tools such as dynamic BN, dynamic ICA, and dynamic PCA are suitable methods to address the time-varying behavior of complex systems. DL and TL are other techniques, which their capabilities have been proved, for the analysis of data with dynamic behaviors. In Table 6, the application of these methods, which have been reviewed in this section, are summarized. The table confirms the sufficiency of dynamic statistical methods, state estimation methods (e.g., HMM and BN), and ANN-based methods (i.e., DL and TL) for fault diagnosis and prognosis in engineered systems with dynamic data behaviors.

3.4.3 | Nonstationarity and non-Gaussianity

Nonstationarity and non-Gaussianity are two more data features in complex engineered systems introduced before. Tables 7 and 8 show, respectively, these features of complex systems' data, addressed in the reviewed research papers

TABLE 5 Summary of the methods employed to address nonlinearity in data of complex engineered systems

Methods	Reference	Application
DL and TL	• Yan et al.,[177] Hu et al.,[30] Wen et al.,[184] Han et al.[183] • Wu et al.,[179] Wu et al.[181] • Zhang et al.,[180] Wang et al.[201] • Zhang and Zhao,[174] Wang et al.[176] • Wang et al.,[170] Liu et al.,[175] Han et al.[183]	• Bearings • Aircraft Engine • Electronic products • TE process • Other applications
ANN	• Laredo et al.,[107] Bektas et al.[106] • Khera and Khan[108] • Zhang and Wang[104]	• Aircraft Engine • Electronic products • Wind turbine
Kernel-based	• Hamrouni et al.,[194] Zhou and Gu,[193] Xu et al.[192] • Lee et al.,[141] Chu et al.,[195] Liu et al.[143]	• TE process • Chemical process
PF	• Li et al.,[132] Qian and Yan,[204] Cheng et al.[203] • Yu et al.[166] • Yu et al.[133] • Li et al.[165]	• Bearings • Lithium-ion batteries • Rotating machinery • Piston pumps
SVM	• Yan et al.[98] • Nieto et al.[208] • Gangsar and Tiwari[97]	• Bearings • Aircraft Engine • Lithium-ion batteries
Hybrid	• Jack and Nandi,[96] Wang et al.,[213] Bastami et al.,[105] Wang et al.,[211] Deutsch et al.,[131] Han et al.[205] • Jinglong et al.,[182] Peng et al.[214] • Ma et al.[209] Wei et al.,[215] Wu et al.[212] • Rebello et al.,[158] Galagedarage and Khan,[156,157] Yu et al.[196] • Han et al.,[205] Han et al.[171]	• Bearings • Aircraft Engine • Electronic products • TE process • Other applications

TABLE 6 Summary of the methods employed to address dynamicity in data of complex engineered systems

Methods	Reference	Application
DL and TL	• Yan et al.,[177] Zhu et al.,[169] Jia et al.[172] • Wu et al.,[179] Wu et al.[181] • Khera and Khan,[108] Zhang et al.,[180] Wang et al.[201] • Zhang and Zhao,[174] Wang et al.[176] • Liu et al.[175]	• Bearings • Aircraft Engine • Electronic products • TE process • Manufacturing process
Dynamic-based	• Ahmad et al.,[199] Kong and Yang[200] • Xu and Deng[187] • Lewis and Groth,[197] Shi et al.[198]	• Bearings • TE process • Other applications
Hybrid	• Deutsch et al.,[131] Medjaher et al.[155] • Cho et al.,[210] Georgoulas et al.[216] • Yu et al.,[196] Galagedarage and Khan,[156,157] Rebello et al.,[158] Yu et al.[196] • Wei et al.,[215] Han et al.[171]	• Bearings • Induction motors • TE process • Other applications

in this section along with their applications. Diverse methods have been exploited to deal with the nonstationary behavior of data in complex engineered systems such as wiener process, ICA, and SVR. However, ANN-based techniques have shown a higher potential to address this issue. Non-Gaussianity, which is mostly because of multiple modes/states or operating conditions in a system,[33] has been often addressed by GMMs, PF, and ICA in diagnostics and prognostics applications.

TABLE 7 Summary of the methods employed to address nonstationarity in data of complex engineered systems

Methods	Reference	Application
DL and TL	• Mao et al.,[186] Zhu et al.,[169] Han et al.[183] • Zhang et al.[185] • Wang et al.[201]	• Bearings • Aircraft Engine • Lithium-ion batteries
Hybrid	• Merainani et al.[207] • Malla et al.,[95] Wang et al.[213] • Wei et al.[215] • Yu et al.[196]	• Gearbox • Bearings • Lithium-ion batteries • TE process
Other methods	• Kong and Yang[200] • Bektas et al.,[106] Laredo et al.[107] • Xu and Deng[187] • Liu et al.[202]	• Bearings • Aircraft Engine • TE process • Hydraulic pumps

TABLE 8 Summary of the methods employed to address non-Gaussianity in data of complex engineered systems

Methods	Reference	Application
Gaussian mixture model	• Hong et al.[189] • Yan et al.[188] • Yan et al.[188] • Wu et al.[179] • Liu et al.[190]	• Bearings • Rotating machinery • Electronic equipment • Aircraft Engine • Chemical process
PF	• Li et al.,[132] Qian and Yan,[204] Cheng et al.[203] • Yu et al.[166]	• Bearings • Lithium-ion batteries
ICA	• Xu and Deng,[187] Zhang and Zhang[142] • Liu et al.[143]	• TE process • Chemical process
Hybrid	• Medjaher,et al.[155] • Wei et al.,[215] Wu et al.[212] • Galagedarage and Khan,[156,157] Rebello et al.,[158] Yu et al.[196]	• Bearings • Lithium-ion batteries • TE process

3.4.4 | Variable operating conditions

In practice, operating conditions and environment are most likely to change for a complex engineered system which affects the data characteristics.[217] Therefore, it is important to take into account the environment and operation conditions in analyzing the data. Table 9 summarizes the employed methods to address the variable operating conditions in the

TABLE 9 Summary of the methods employed to address variable operating condition in complex engineered systems

Methods	Reference	Application
DL and TL	• Yan et al.[177] • Yan et al.,[177] Han et al.[183] • Han et al.[183] • Wu et al.,[181] Zhang et al.[185] • Khera and Khan[108]	• Bearings • Gearbox • Wind turbine • Aircraft Engine • Electrolytic capacitors
Hybrid	• Merainani et al.[207] • Han et al.[205] • Han et al.[205] • Ma et al.,[209] Wu et al.[212]	• Gearbox • Bearings • Wind turbine • Lithium-ion batteries

reviewed papers. Similar to nonstationarity, ANN-based techniques have shown a higher potential to deal with the effects of variable operating conditions of complex engineered systems.

4 UNADDRESSED CHALLENGES AND FUTURE TRENDS

Substantial progressions have been accomplished in prognostics and diagnostics of complex engineered systems by employing diverse techniques and methods to address various features of these systems. In the literature, abundant research works can be found trying to deal with undesirable data characteristics of complex engineered systems such as nonlinearity, dynamicity, nonstationarity, non-Gaussianity, and also challenges like variable operating conditions. Despite the remarkable progressions and achievements, there are some serious challenges in diagnostics and prognostics of complex engineered systems that largely remain unaddressed. This is because of the higher demand and requirement on the reliability and safety of complex systems and also the incapability of current methods to fully cover the characteristics of these systems, working in real-world conditions. Based on the context of the discussed matters, currently, the main challenges of diagnostics and prognostics in complex engineered systems that have not been fully addressed or has been less addressed are as below:

- In the literature, mostly well-known systems like the TE process and rolling element bearings have been investigated, whereas for other complex systems like automotive systems, the literature is rare, as it is very difficult to address the related challenges and cover all the features. Moreover, the simplifications make the obtained results unrealistic since the interconnections are complicated and data quality is low. As an example, the cross-sensitivity of nitrogen oxides and ammonia sensors is one of the big challenges in the automotive aftertreatment system.[218] This issue is less in aerospace systems, as they are more safety-critical systems, compared to automotive, but for automotive systems, it is not cost-effective to spend huge amounts of money for high accuracy sensors. This adds another challenge to the study of automotive systems where it is needed to deal with highly uncertain data.
- As data has become an inevitable part of diagnostics and prognostics in complex engineered systems, dealing with miscellaneous data with multifarious characteristics is one of the main challenges. In the literature, some CM data have been studied (e.g., temperature, electric voltage, and current), where the major investigation is on vibration data. Although vibration or other measurements are valuable CM data for rotating machinery, it is not the case for most complex systems such as automotive systems. In automotive systems, mostly operational data, which are collected from various sensors, are stored in electronic control units. These operational data are more challenging to employ for diagnostics and prognostics purposes as defining the thresholds are difficult due to various operational modes of the system. As an example, for automotive aftertreatment system, parameters like nitrogen oxides level, carbon monoxide, hydrocarbons, particulate matter, exhaust gas mass flow rate, differential pressure, temperature, and so forth need to be measured.[218] Utilizing these variables instead of well-analyzed data (e.g., vibration) is far more challenging for the reliability analysis of a system. Moreover, most of the proposed approaches in research works are suitable for vibration signals only (e.g.,[139]).
- Handling real-world uncertainties are always one of the major challenges for the use of diagnostics and especially prognostics. Uncertainties in diagnostics and prognostics that lead to a significant variance of results from the actual situation can be grouped into three categories: (a) model uncertainty, (b) measurement and forecast uncertainty, and (c) inherent uncertainties. Though efforts have been made to describe the uncertainty bounds and confidence levels–given that big data have become an inseparable part of modern systems–further refinements and improvements in methods are expected as diagnostics and prognostics mature. For example, in the automotive industry, this becomes more important where data is collected from sensors with relatively low accuracy, in comparison to other safety-critical systems like systems in the aerospace industry.

In agreement with some other research works (e.g.,[23,38]), data-driven methods, especially DL and TL theories, will play a more substantial role in the diagnostics and prognostics of complex engineered systems. This is because of the availability of data and the capability of data-driven methods in dealing with the features of complex systems. Moreover, DL methods are able to deal with nonlinear dynamics automatically and extract and select features. In addition, TL methods have the capacity to transfer knowledge learned from one task to facilitate fulfilling a different but similar task. However, the lack of causal representations in these models is the main hindrance to their wider real-world application at the moment. In general, it is impossible to prescribe an approach or a method that works ideal for all cases. This is the matter of trade-off to find the best method, given the specifications of the system under study and the requirements of the research.

5 | CONCLUSION

Diagnostics and prognostics, which are the most important aspects of CBM, PHM, and IVHM, have received more attention among academic researchers and industrial engineers since the demand for more reliable and safer systems is increasing. This paper attempted to summarize recent research and development in diagnostics and prognostics of engineered systems. Different techniques and methods have been reviewed and their merits and limitations were discussed. Many recent research works were introduced for a wide variety of methods, which are of considerable reference value for scholars and practitioners who are new to the diagnostics and prognostics research areas.

Characteristics like dynamic behavior, nonlinearity, non-Gaussianity, nonstationarity, and variable operating conditions exist in complex engineered systems and related data. Indisputably, ignoring these features in diagnostics and prognostics processes makes the results unrealistic. Therefore, it is important to select an appropriate method given the features of the system under study to obtain more accurate results. To address this point, the second part of the paper focused on the diagnostics and prognostics for the application of complex engineered systems. After introducing different methods that have been employed to address the features of complex engineered systems, the unaddressed challenges were discussed and highlighted by taking into account the characteristics of automotive systems as a typical example of complex engineered systems. The discussed challenges can help researchers looking for potential research opportunities to fill the gaps in the literature.

Considering the features of complex systems and releasing and sharing the huge amount of data, which are able to describe the complicated relationship between numerous systems and subsystems, and also maturing data-driven approaches, especially ML, DL, and TL, it is believed that deep TL techniques will continue to be powerful and attractive for diagnostics and prognostics of complex engineered systems.

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CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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