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Survey Paper

Artificial intelligence in prognostics and health management of engineering systems

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ABSTRACT

Prognostics and health management (PHM) has become a crucial aspect of the management of engineering systems and structures, where sensor hardware and decision support tools are deployed to detect anomalies, diagnose faults and predict remaining useful lifetime (RUL). Methodologies for PHM are either model-driven, data-driven or a fusion of both approaches. Data-driven approaches make extensive use of large-scale datasets collected from physical assets to identify underlying failure mechanisms and root causes. In recent years, many data-driven PHM models have been developed to evaluate system's health conditions using artificial intelligence (AI) and machine learning (ML) algorithms applied to condition monitoring data. The field of AI is fast gaining acceptance in various areas of applications such as robotics, autonomous vehicles and smart devices. With advancements in the use of AI technologies in Industry 4.0, where systems consist of multiple interconnected components in a cyber–physical space, there is increasing pressure on industries to move towards more predictive and proactive maintenance practices. In this paper, a thorough state-of-the-art review of the AI techniques adopted for PHM of engineering systems is conducted. Furthermore, given that the future of inspection and maintenance will be predominantly AI-driven, the paper discusses the soft issues relating to manpower, cybersecurity, standards and regulations under such a regime. The review concludes that the current systems and methodologies for maintenance will inevitably become incompatible with future designs and systems; as such, continued research into AI-driven prognostics systems is expedient as it offers the best promise of bridging the potential gap.

Abbreviations

ANFIS	Adaptive network-based fuzzy inference system
ANN	Artificial Neural Network
ARNN	Adaptive Recurrent Neural Network
BNN	Bayesian Neural Network
CART	Classification and Regression Tree
CBM	Condition-Based Maintenance
C-MAPSS	Commercial Modular Aero-Propulsion System Simulation
CNC	Computer Numerical Control
CNN	Convolutional Neural Network
DBM	Deep Boltzmann Machine
DBN	Deep Belief Network
DRL	Deep Reinforcement Learning
EAD	Ethically Aligned Design
ELM	Extreme Learning Machine
EMD	Empirical Mode Decomposition
EN	Elastic Net
GPR	Gaussian Process Regression
GPU	Graphical Processing Unit
GRU	Gated Recurrent Unit
HAC	Health-Aware Control
HMM	Hidden Markov Model
ICA	Independent Component Analysis
KF	Kalman Filter
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MIMOSA	Machinery Information Management Open Sys-

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	tems Alliance
ML	Machine Learning
MLP	Multi-Layer Perceptron
MSE	Mean Squared Error
OEE	Overall Equipment Effectiveness
OSA-CBM	Open System Architecture for Condition-Based Maintenance
PCA	Principal Component Analysis
PDF	Probability Density Function
PHM	Prognostics and Health Management
PdM	Predictive Maintenance
PM	Preventive Maintenance
RBF	Radial Basis Function
RBI	Risk-Based Inspection
RBM	Restricted Boltzmann Machine
RF	Random Forest
RL	Reinforcement Learning
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
RUL	Remaining Useful Life
RVM	Relevance Vector Machine
RVM-NDM	Relevance Vector Machine New Design Matrix
RVR	Relevance Vector Regression
SCADA	Supervisory Control and Data Acquisition
SOM	Self-Organizing Map
SQP	Sequential Quadratic Optimization
SVM	Support Vector Machine
SVR	Support Vector Regression
TR	Technical Report
WPD	Wavelet Packet Decomposition

1. Introduction

The conventional maintenance practice in industries was corrective in nature, where an equipment was repaired or replaced upon failure. However, due to the high failure cost and downtime penalty, preventive maintenance (PM) strategies became very popular in the early 1980s. The PM includes performing various actions (such as replacing an oil filter in a machine) at predetermined time or usage intervals. This strategy is yet a predominant maintenance strategy in a lot of industries, including construction, mining, chemical and petrochemical (Shafiee, 2015). However, since equipment utilization may not be optimized by fixed-interval PM methodologies, risked-based methods are increasingly being adopted in industrial facilities so that resources can be assigned to equipment according to their criticality rankings. Specific reference can be made to the oil and gas industry, where the American Petroleum Institute (API) published recommended practices for the implementation of risk-based inspection (RBI) in oil and gas processing facilities; see API (2016a, b). The semi-quantitative approach offered by API makes extensive use of inspection data (where such data is available) to develop physics-based models for the equipment, incorporating expert knowledge from the operators and process engineers into the analysis. Therefore, RBI is effectively known as a hybrid of both model-driven and data-driven methods (Shafiee and Soares, 2020).

Despite being implemented in many fields, RBI is yet to be proven when used in the context of an ecosystem where large amounts of sensor data are constantly gathered from heterogeneous systems at a very high rate. In recent years, condition-based maintenance (CBM) has become popular in an effort to minimize unplanned maintenance, increase reliability and reduce operating costs. CBM recommends optimal maintenance actions based on asset condition information (Jardine et al., 2006). CBM involves the key tasks of diagnostics and prognostics, which both fundamentally involve collecting sensor data, processing the data and constructing the system health states based on the processed data. While the diagnostics task detects, identifies and isolates faults, the prognostics task uses diagnostics information along with past historical data to predict future health states of the equipment as well as determine the time to perform maintenance actions (An et al., 2015). Prognostic maintenance therefore means making maintenance decisions based on predicted time that a component or system can operate before encountering a failure — this time is known as the remaining useful life (RUL). The methods for predicting a system's future health state can be categorized into model-driven (where a physical model of system degradation behaviour is developed to estimate RUL); data-driven (where condition monitoring data is processed and used to estimate RUL); or a fusion of both approaches.

Data-driven techniques in PHM were mostly based on statistical methods. However, with advances in sensor technology and signal processing, artificial intelligence (AI) techniques have become increasingly popular. AI is the ability of a machine to display human-like intelligence, especially in response to inputs from its environment. The field of AI has received wide attention in recent years in various applications, particularly in cases where very large volumes of data are generated at a fast rate. In such cases, the conventional statistical methods become less useful as analytical tools. With respect to the area of predictive maintenance (PdM) and prognostics and health management (PHM), various AI algorithms have been proposed in the literature on how to predict the state of health of engineering systems. To this end, the RUL estimation at system, subsystem or component level is a critical task upon which the entire prognostics endeavour is based.

This paper provides a thorough state-of-the-art review of the AI techniques adopted for PHM of engineering systems. Most reviews covering the subject tend to focus on a specific algorithm or class of algorithms, or on specific use cases; hence, ignoring actual issues around real-life implementation of PHM in fielded systems. This review provides a broad perspective on the subject while delving into the soft issues that need to be addressed to enable adoption of AI-driven PHM technologies. The applications of various AI technologies in PHM are identified via a systematic literature review to aid practitioners in making well-informed decisions. Our review shows that a finite collection of PHM datasets is continuously used for the purpose of training and testing AI algorithms. These datasets have been mostly obtained from either numerical simulations or experimental measurements from accelerated degradation testing in research laboratories, and there seems to be dearth of real-life data from operational systems. So, there either is a lack of appreciable collaboration between the industry and academia or the actual level of collaboration is not accurately captured in the literature, perhaps due to confidentiality reasons. Our study also reveals that 'deep learning' algorithms are becoming very popular in recent years as they deliver very good results while eliminating the need to pre-process the data before feeding it into an algorithm or model. Of course, there are other enablers for the proliferation of deep learning algorithms, like availability of big data and high capability Graphical Processing Units (GPUs).

The remaining part of this paper is organized as follows: Section 2 outlines the procedure for using AI in PHM, including a brief overview of popular algorithms adopted in the literature for system prognostics. Section 3 presents the state-of-the-art of AI-driven PHM research, identifying the various datasets used to test the algorithms. Some metrics applied to measure the performance of the AI algorithms were also briefly discussed. Section 4 discusses the soft issues around the real-time implementation of AI in PHM which tends to generally be ignored in the literature. Section 5 discusses ideas for future research and, finally, Section 6 summarizes the discussion and concludes the paper.

2. Use of AI in PHM

There are quite a number of comprehensive reviews on data-driven prognostics in the published literature. Jardine et al. (2006) conducted a review of machinery diagnostics and prognostics and discussed how the entire CBM process aids in maintenance decision-making. Primitively, the tendency has been to concentrate on prognostics as a separate area that is yet to be fully explored. However, intuition suggest that one must be able to perform diagnostics (i.e., detect, isolate and identify faults) before attempting to perform prognostics (Schwabacher and Goebel, 2007; Jardine et al., 2006; Sikorska et al., 2011; An et al., 2015). This is inevitable in the case of developing data-driven PHM techniques because the existence of actual failure data is fundamental to the training process of AI algorithms. In general, most of the reviews in the literature (Jardine et al., 2006; Sikorska et al., 2011; An et al., 2015; Lei et al., 2018) delineate the procedure of deploying AI in PHM into three broad stages: (i) data collection and processing; (ii) development of algorithm, training and validation; and (iii) RUL prediction and maintenance decision-making. This procedure is illustrated in Fig. 1, and some important aspects of the three main stages are discussed in the following subsections.

2.1. The key: good quality data

Since AI approaches are purely data-driven, the results obtained will be only as good or as accurate as the quality of the dataset used for training the algorithm. PHM typically involves data collection, cleaning, preprocessing and features extraction, analytics, RUL prediction and, eventually, algorithm performance measurement using suitable RUL metrics. With the advancement of internet of things (IoT) technologies, it is now cheaper and easier to obtain large amounts of data from engineering systems (Lei et al., 2018; Zhao et al., 2019). However, some real challenges that are still being experienced with the availability of good quality data are outlined in below:

i. With thousands of sensors being deployed in engineering system to measure different physical parameters, a large amount of multi-dimensional data is generated. Several techniques for data dimensionality reduction have been developed over the years, including: principal component analysis (PCA), independent component analysis (ICA), self-organizing maps (SOM) and wavelet packet decomposition (WPD). However, the challenge in the PHM research is the need to process the data as and when they are collected (i.e., in real or close to real time). The operating conditions of the sensors need to be monitored, their calibration issues must be addressed, and noise in the data should be removed by pre-processing the signals.
ii. As a further point regarding data quality and preprocessing, it is important to state that not all the data collected for PHM purpose contain useful information for algorithm development. PHM practitioners who use AI algorithms for data-driven prognostics need to be aware of the relevance of feature engineering, especially how to eliminate redundant features that are not informative, as well as how to craft new features via computing different statistics or parameters from the collected data. Most of the popular libraries available for use like scikit-learn, TensorFlow with Keras, MATLAB, PyTorch, etc., include rich packages for data preprocessing and feature engineering.
iii. In industrial environments, it is not safe and economically feasible to run machines until they break down. As such, most data available for academic research are obtained from experiments, test beds and simulations, which might not be a true representative of real-life failure data.
iv. In real-life applications, machines are subject to varying environmental conditions. The ability to prune the data to discount for the attendant noise while at the same time taking credit for environmental loading is also a major challenge. All these issues with data reliability and quality help to emphasize the importance of uncertainty quantification when using such data for prognostics. Different categories of algorithms addressing uncertainty quantification are briefly discussed in Section 2.2.5.
v. In a few cases where real-life data have been provided by industry, as in the study by Carroll et al. (2019) on wind turbine gearbox failures, the details of the data were not provided due to confidentiality reasons.

The literature search conducted for this work identified some datasets commonly used for research on the use of AI in PHM. These datasets are briefly introduced below:

2.1.1. NASA C-MAPSS dataset

This dataset presents the NASA turbofan engine degradation problem and was first introduced for the PHM 2008 data challenge. The dataset was generated with a MATLAB Simulink tool called the Commercial Modular Aero-Propulsion System Simulation, C-MAPSS, producing a large amount of turbofan engine data (Saxena et al., 2008). The dataset comprises data for engine conditions under normal mode as well as faulty modes, with the fault being introduced at a given time and persisting till the end. The challenge is to identify the present health state of the various engine units and subsequently, the time-to-failure or RUL of the system. The dataset is useful for benchmarking, enabling the comparison between different AI algorithms. This is possible as four datasets out of the five datasets available in the C-MAPSS have a *training set, test set* and *ground truth RUL* values to measure performance. In the fifth dataset, the challenge dataset, the ground truth RUL values are not provided. Ramasso et al. (2015) provided a detailed guidance on the appropriate use of this dataset for research.

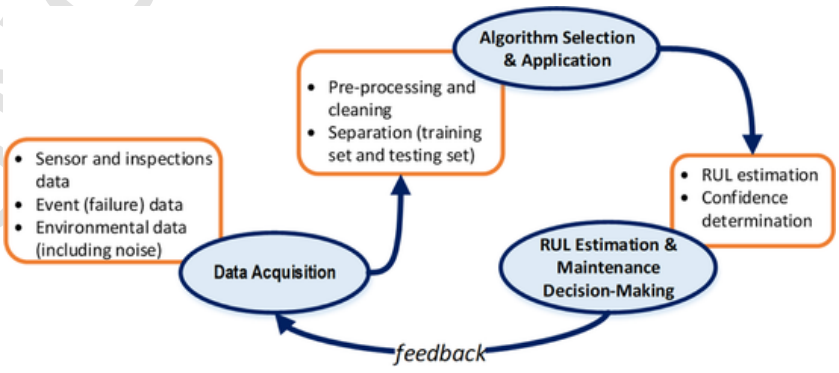

Fig. 1. A flow process for the use of AI in PHM.

2.1.2. FEMTO-ST bearings dataset on PRONOSTIA test bed

This dataset was introduced for the PHM 2012 data challenge during the IEEE International Conference on PHM. The data, which was provided by the Institute Franche-Comté Electronics Mechanics Thermal Processing and Optics–Sciences and Technologies (FEMTO-ST Institute, France), consists of 17 run-to-failure data of rolling element bearings generated from the PRONOSTIA test bed. Six of the datasets are full run-to-failure data, whereas the other 11 datasets are truncated. This makes the training of AI algorithms challenging and the accurate prediction of RUL difficult. Full details of the dataset from the PRONOSTIA testbed are presented by Nectoux et al. (2012).

2.1.3. Other datasets

The PHM 2010 data challenge presented data for high-speed Computer Numerical Control (CNC) milling machine with cutters used until a significant wear stage. The challenge was to accurately predict the RUL of the cutting tools. Other milling datasets are also available and have been used in previous publications. Another set of data for PHM research is the NASA battery data, which has been used in about 8% of the publications found in the literature. Most of the datasets discussed in this work are publicly available for download (see NASA's Prognostics Center of Excellence, 2017).

Although the above-mentioned datasets are collected from real accelerated life degradation experiments, it is remarkable that there is a paucity of research publications that have used data from actual operational engineering assets. Nevertheless, the obvious advantage of these common datasets is the ability for different researchers to compare the results obtained using different algorithms on the same dataset. Also, the researchers who experience difficulty in accessing data or designing their own experiments to obtain data can make use of these publicly available datasets for research. Fig. 2 shows the usage of various datasets in data-driven PHM research.

The papers in which common PHM datasets were used are given in Table 1.

2.2. AI algorithms for prognostics

As stated earlier, one of the reasons for the recent increase in popularity of the use of AI in PHM is due to the increased availability of data from sensors installed on engineering devices and systems. Other contributory factors are successes recorded in other applications, like e-maintenance, as well as the evolution of a rather large number of algorithms on different platforms like Python, TensorFlow with Keras (using Python), PyTorch, Sci-kit Learn, MATLAB, R, Java, C++ and Microsoft Azure Learning Studio. The availability of cross-platform libraries via the ability to import different libraries into different platforms has also helped to accelerate adoption. Some popular algorithms in use include Deep Learning, regular Artificial Neural Networks (ANNs), nearest neighbour algorithms (mostly k-NN), naïve Bayes, decision trees, and Support Vector Machine (SVM) (Ochella et al., 2021). For prognostic maintenance, ANNs (and other algorithms based on neural networks) have been used the most in the literature. Fig. 3 illustrates the broad categorization of common AI algorithms.

The AI algorithms used in majority of the published literature are discussed briefly below.

2.2.1. Deep learning

The deep learning architecture originated from ANN with the unique quality of having multiple layers stacked on each other, between the input layer and the output layer. This characteristic of deep learning also applies to the multi-layer perceptron (MLP), which is a neural network with multiple hidden layers trained via backward propagation. In that sense, the MLP can be said to be an instance of deep learning. However, what makes deep learning attractive, as compared to traditional machine learning (ML) algorithms, is the ability to skip the process of hand crafting features from the input data before being fed into the network. With deep learning, the input can be fed directly into the network and the network learns the features on its own. Deep learning was first introduced for use in natural language and image processing and recognition (LeCun et al., 2015). The deep learning algorithms that have been used for PHM research include autoencoders (and its variants), restricted Boltzmann machine with its variants being deep belief networks (DBN) and deep Boltzmann machine (DBM), convolutional neural network (CNN) and recurrent neural network (RNN). Variants of RNN, the long short-term memory (LSTM) and Gated Recurrent Units (GRU) have also been used in the literature for prognostics.

Different deep learning algorithms have also been combined together to solve PHM problems, exploiting the advantage of each algorithm to address an aspect of the problem that is amenable to the application of that particular algorithm. Yue et al. (2018) used CNN-LSTM to address the issue of blade icing on wind turbines. The extraction of features was performed using the CNN algorithm, and then LSTM was used to make time-series predictions based on the extracted features. Chen et al. (2018) applied a somewhat similar approach to the wind turbine blade icing prognostic problem using deep neural networks to learn and extract features while using k-NN to classify the learned features. The CNN architecture has an input layer, several hidden layers and an output layer. For most configurations, the hidden layers are the convolution layer, the pooling layer and a fully connected layer, beyond which a regression or classification algorithms is used to generate the output,

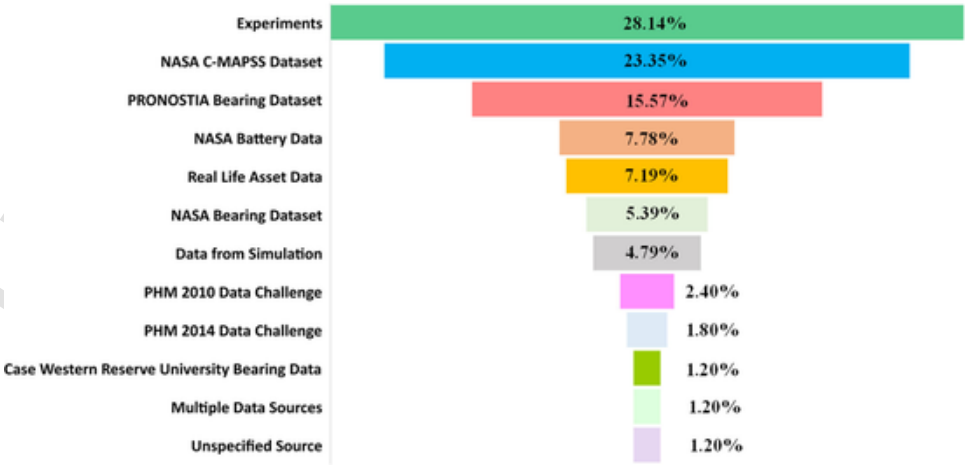

Fig. 2. Different datasets adopted in PHM research.

Table 1
The papers in which common PHM datasets were used.

Number of papers	Dataset	List of publications
38	NASA C-MAPSS dataset (*Details presented in* Section 2.1.1)	Heimes (2008), Peysson et al. (2009), Sun et al. (2010), Javed et al. (2013), Khelif et al. (2014), Bluvband and Porotsky (2015), Javed et al. (2015a), Ragab et al. (2016b), Lim et al. (2016), Sateesh Babu et al. (2016), Xiong et al. (2015), Yongxiang et al. (2016), Zhang et al. (2016b, 2017a), Jiang and Kuo (2017), Zhao et al. (2017), Yang et al. (2016b), Zheng et al. (2017, 2018a), Li et al. (2018b), Hsu and Jiang (2018), Zhang et al. (2018b, a), Lin et al. (2018), Shi et al. (2018), Mathew et al. (2018a), Li et al. (2018a), Wu et al. (2018a, c), Zhou et al. (2018), Ordóñez et al. (2019), Li et al. (2019b), Skordilis and Moghaddass (2020), Kozjek et al. (2020), Kraus and Feuerriegel (2019), Peng et al. (2020), Kim and Liu (2020), Cheng et al. (2021).
36	Experiments *(Experiments conducted by each researcher to generate data)*	Camci and Chinnam (2005), Saha et al. (2009), Camci and Chinnam (2010), Zhang and Kang (2010), Li et al. (2012), Ben Ali et al. (2015), Deng et al. (2016), Guha et al. (2016), Hu et al. (2016), Shaban and Yacout (2016), Thirukovalluru et al. (2016), Wu et al. (2016), Liu et al. (2016a), Yang et al. (2016a), Zhang and Gao (2016), Zhang et al. (2017b), Chen and Li (2017), Wu et al. (2017b, a), Dong et al. (2017), Wang et al. (2017a, b), Jiang et al. (2017), Laddada et al. (2017), Liao et al. (2017), Ma et al. (2017), Mansouri et al. (2017), Razavi-far et al. (2017), Zhang et al. (2017), Deutsch and He (2018), Elforjani and Shanbr (2018), Ma et al. (2018), Wang et al. (2018), Zhang et al. (2018c), Yan et al. (2018), Li et al. (2020).
26	FEMTO-ST PRONOSTIA bearing dataset (*See details in* Section 2.1.2)	Tobon-Mejia et al. (2011b, 2012a), Medjaher et al. (2012), Porotsky (2012), Benkedjouh et al. (2013), Mosallam et al. (2013), Zurita et al. (2014), Carino et al. (2015), Singleton et al. (2015), Liao et al. (2016), Ren and Lv (2016), Liu et al. (2016b), Guo et al. (2017), Liu et al. (2017a), Belmiloud et al. (2018), Cheng et al. (2018), Hinchi and Tkiouat (2018), Jin et al. (2018), Mao et al. (2018), Ren et al. (2018a), Zhao and Wang (2018), Jin et al. (2018), Patil et al. (2019), Ren et al. (2019), Li et al. (2019a), Zhu et al. (2019).
12	NASA battery data *(Data is publicly available online)*	Zhou et al. (2012), Liu et al. (2013), Zhou et al. (2013), Liu et al. (2015), Patil et al. (2015), Wang et al. (2016), Ding et al. (2017), Wu et al. (2017), Qin et al. (2017), Tang et al. (2018), Ren et al. (2018b), Zheng et al. (2018b).
11	Real life data *(Data from real life operational assets — wind turbine blades, gearbox; gas processing equipment; compressor; bearings; and batteries).*	Tran et al. (2012), Frisk and Krysander (2015), Ragab et al. (2019), Yang and Zhang (2016), Costello et al. (2017), Ren et al. (2017), Carroll et al. (2019), Chen et al. (2018), Niu et al. (2018), Song et al. (2018), Yue et al. (2018).
7	NASA bearing dataset *(Data is publicly available on NASA repository).*	Tobon-Mejia et al. (2011a), Hong and Zhou (2012), Liu et al. (2017b), Ahmad et al. (2017), Li (2017), Khan and Prosvirin (2018), Zhang et al. (2019).
7	Simulation	Wan and Li (2013), Xia et al. (2013), Krishnan et al. (2017), Zhu (2018), Xanthopoulos et al. (2018), Jha et al. (2019), Vega and Todd (2020).
5	Research lab data	Saha and Goebel (2008), Morando et al. (2013), Javed et al. (2015b), Benkedjouh (2016), Mezzi (2018).
4	PHM 2010 data challenge *(This dataset is from a CNC milling tool)*	Javed et al. (2012), Tobon-Mejia et al. (2012a), Zhu (2018), Wu et al. (2016).
3	PHM 2014 Data Challenge *(Degradation data from Proton Exchange Membrane Fuel Cell).*	Qiao and Xun (2015), Xue et al. (2016), Liu et al. (2019).
2	Case Western Reserve University bearing data	An et al. (2017), Qi et al. (2017).
2	Using multiple datasets to test algorithm	Wang et al. (2017c), Trinh and Kwon (2018).
2	Exact source not specified	Galar (2012), Fan and Tang (2013).

Review papers (~6% of papers) and a framework proposal (~0.6% of papers) were not captured in the publications in Table 2 above.

depending on the nature of the problem being addressed. Li et al. (2019b) and Zhu et al. (2019) used a multiscale feature extraction approach, where the CNN had several concatenated convolution and pooling layers. The aim was to gain better representation of different features of the raw data. Good results were obtained by the multiscale approach when applied to bearing data from the PRONOSTIA test bed and they were compared with those obtained using other deep learning approaches. Even though data can be fed directly to deep learning models without handcrafted features extraction, other approaches have involved some level of pre-processing of data before feeding to deep learning algorithms. Ren et al. (2018a) presented the spectrum-principal-energy-vector as a feature extraction method to obtain the eigenvector which they considered suitable for a deep CNN. Belmiloud et al. (2018) used wavelet packet decomposition (WPD) to extract features from bearings data and fed the extracted features to a deep CNN for training and RUL prediction.

Fundamentally, CNN has a feed-forward neural network architecture. RNN, on the other hand, is a deep learning algorithm which has memory in the sense that output from one layer is fed as input to the previous layer. As such, RNNs are more amenable to time-series data. However, RNNs can only capture recent memory and are poor at addressing the issue of long-term dependencies. As a variant of RNN, the LSTM addresses this problem by the introduction of three gates, namely, input gate, output gate and forget gate. The input gate selects key information to store in the internal state, the output gate determines output information and the forget gate discards redundant information — hence keeping important information for long-term use in the internal state of the network. Zheng et al. (2017) and Hsu and Jiang (2018) used LSTM to estimate the RUL of turbofan engines based on the C-MAPSS dataset. The results were compared with those obtained using MLP, SVM and CNN and it was shown that LSTM produced better results based on the root mean square error (RMSE) metric. Zhang et al. (2018a) used a bi-directional LSTM for the same C-MAPSS problem and they also obtained better results compared to MLP, SVM, deep CNN and the conventional LSTM. Other researchers, including Mao et al. (2018) and Zhang et al. (2019) used LSTM to predict RUL for bearings while Zhang et al. (2017) applied LSTM to RUL estimation of lithium-ion bat-

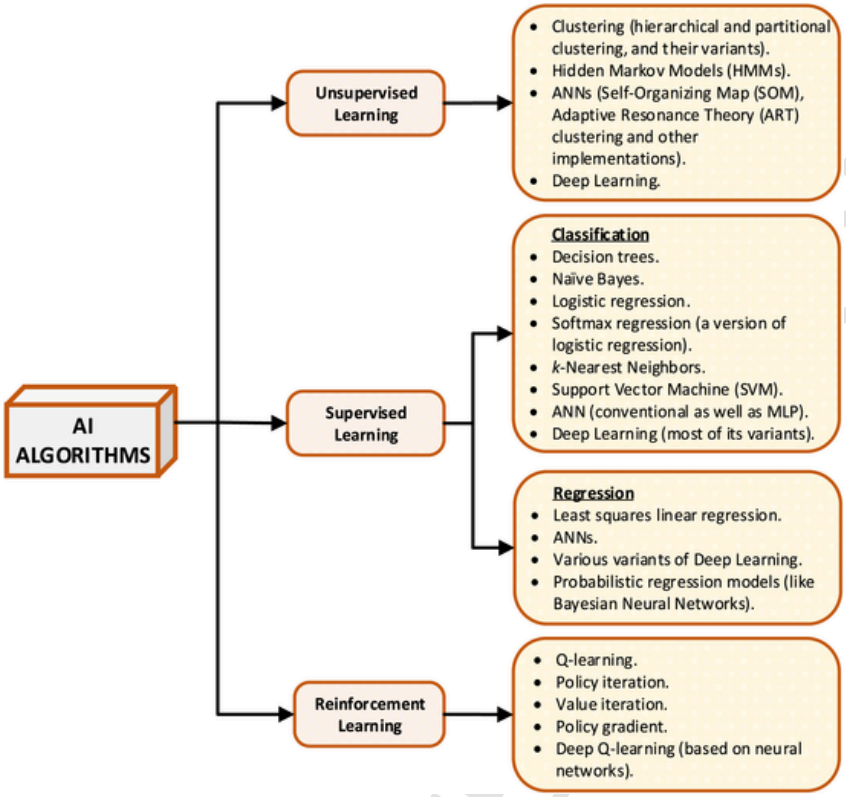

Fig. 3. Categorization of common AI algorithms.

teries. Overall, the key feature of addressing long-term dependencies was the major reason why researchers have used LSTM as against the standard RNN.

Other deep learning algorithms that have been used for PHM include deep coupling autoencoders, deep denoising autoencoders, restricted Boltzmann machine, deep belief networks and, most recently, probabilistic deep learning algorithms using variational inference or Monte Carlo dropout for approximating the posterior distributions. Most of the papers which used deep learning have been published rather recently, from 2016 onwards. This recent adoption clearly follows from the successes recorded by its use in image processing and recognition. Khan and Yairi (2018) and Zhao et al. (2019) conducted detailed reviews on deep learning algorithms used in the literature for PHM. A summary of these deep learning algorithms is shown in Fig. 4.

2.2.2. Hybrid/Fusion

Hybrid techniques involve the combination of model-driven and data-driven methods (in the context of this paper, data-driven methods are referred to as AI-based methods). Saha and Goebel (2008) used relevance vector machine (RVM), as a Bayesian treatment of SVM, for model identification and then provided estimates of RUL in the form of a probability density function (PDF) based on a particle filters framework built upon the RVM-trained model, statistical estimates of noise and projected operating conditions. Yang et al. (2016b) used a selective kernel ensemble-based RVM algorithm to obtain relevance vectors for degradation data in lithium-ion batteries and fit the relevance vector onto a physical model to extrapolate RUL values. When the results were compared to feed-forward ANN and SVM, the hybrid method showed superior performance. In another study, Zheng et al. (2018a) used a very similar approach with RVM on battery data to train a model, but instead they used Kalman Filters to make RUL projections. Ahmad et al. (2017) implemented a hybrid PHM approach by training an adaptive predictive model on the NASA bearing degradation data and then adopting a regression-based approach to predict the RUL. Other researchers such as Jin et al. (2018) used a self-organizing map (SOM) to train the degradation model for the bearings data from the FEMTO-ST PRONOSTIA test bed and then adopted an unscented Kalman Filters to estimate RUL using the trained model. In general, the hybrid approach combines the use of degradation data to train an AI algorithm to learn the parameters of a physical model, and then uses the learned model along with statistical or other approaches to make extrapolations or predictions. It must however be noted that hybrid methods only lend themselves to application areas where the underlying physics behind the system can be modelled, so that the training process effectively helps to approximate the model parameters. Hybrid models are therefore not directly applicable to complex systems where the physics of failure cannot be somewhat explicitly modelled. Fig. 5 presents two alternative routes for adopting a hybrid/fusion approach to estimate RUL of engineering systems.

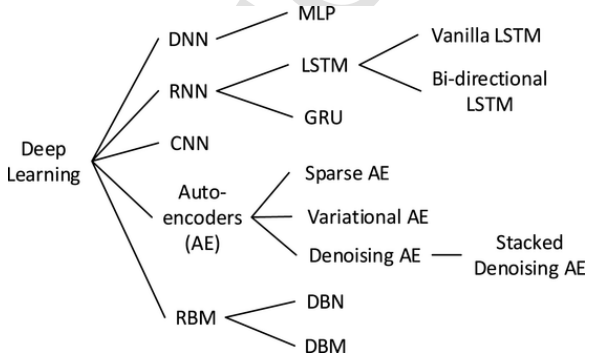

Fig. 4. Various deep learning algorithms used in the literature for PHM.

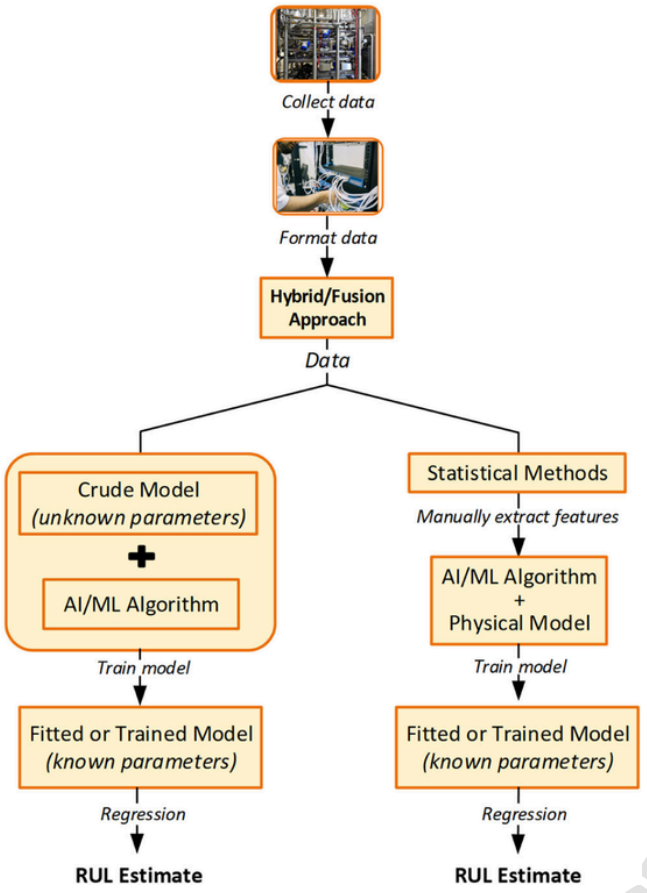

Fig. 5. Two alternative routes for adopting a hybrid/fusion approach to estimate RUL.

2.2.3. Support Vector Machine (SVM)

SVM is a technique used for classification and regression analysis by creating a hyperplane to separate data with different classes. The extracted features from the data are projected into a multi-dimensional space using a kernel function and then a hyperplane is generated such that there is maximum distance between the nearest training data and the hyperplane, thus providing good generalization capabilities. In relation to PHM applications, failure data can therefore be separated from healthy data. Benkedjouh et al. (2013) estimated the RUL of bearings by using an isometric feature reduction mapping technique to extract features from the PRONOSTIA bearings data. The errors obtained from using three kernel functions, namely Gaussian, polynomial and Radial Basis Function (RBF), were compared by projecting the features onto a multi-dimensional hyperplane. Eventually, the Gaussian kernel function was shown to produce the least error compared to other two functions. Carino et al. (2015) estimated the RUL of the same PRONOSTIA bearings, using the features selected based on the assumption that monotonically decreasing features are most likely to represent degradation patterns. A one-class SVM was then used to characterize an incremental degradation profile in the feature space, subsequently using the RMSE to measure the performance of the algorithm. The key implication of the two studies cited is that data from most physical systems are Gaussian, along with Gaussian noise and that monotonically decreasing or increasing features are most useful for RUL predictions. Non-Gaussian data can usually be transformed to Gaussian space to make them amenable to modelling, with the results going through an inverse transformation after predictions using the learned model.

One challenge with all datasets available for PHM, and indeed any dataset that may be obtained from engineering systems, is the difference in lengths of the run-to-failure data for each unit within the dataset. This difference reflects the fact that different equipment have different lifetimes, either due to design, different environmental factors or different operational or loading conditions. To address this challenge, Bluvband and Porotsky (2015) used SVM to predict the RUL for turbofan engines in a context of suspended time series, where a number of points in the data were missing. Shi et al. (2018) used a modified RVM with a new design matrix, called RVR-NDM which includes an additional column vector which represents the overall degradation pattern. The performance of the algorithm was measured using mean absolute percentage error (MAPE) and the RMSE. Several other studies have used the SVM technique to estimate the RUL of lithium-ion batteries, which are important components for energy storage in a wide variety of applications including consumer electronics, transportation, and large-scale energy production. In all these studies, the common approach involves the need to separately extract the features and establish a degradation pattern and subsequently applying the SVM algorithm. In general, these techniques have produced good results for use in both classification and regression problems.

2.2.4. Ensemble

Ensemble techniques combine several different configurations of the same base learner or algorithm to make a single prediction. Hu et al. (2012) conducted a study to demonstrate that using an ensemble of the data-driven AI algorithms for PHM yields more accurate results when compared to any sole algorithm within the ensemble. In the study, different weights were assigned for algorithms that are accuracy-based, the ones that are diversity-based, and those that are optimization-based. As shown in Fig. 6, ensemble methods include bagging, boosting and stacking. Bagging, also called bootstrap aggregating, assigns equal weights to each algorithm in the ensemble, with each algorithm trained using a random sample from the training dataset. The training data is sampled with replacement in the process of training each base algorithm. Random Forests is an example of bagging ensemble, with decision trees as the base learners. Wu et al. (2017a) used random forests as a bagging ensemble method for predicting the tool wear. Although the training times achieved were slightly long, the RMSE using random forests was much lower when compared to ANN and SVM. Cheng et al. (2021) used an ensemble of 80 different LSTMs to make RUL predictions for the C-MAPPS dataset, with each base LSTM having the same hyperparameters. Each base LSTM was also trained on a single, unique engine degradation data, and the results from 80 engines were aggregated to obtain the optimal LSTM configuration as well as RUL distribution parameters derived from the mean and variance of the 80 predictions. This approach produced a mean RUL prediction that is superior to any single prediction from each of the 80 LSTMs, thus taking full advantage of the bagging ensemble learning approach.

Boosting involves the process of progressively improving the results of a classifier with subsequent algorithms in the ensemble, with the sole purpose of more accurately predicting or classifying previously misclassified instances in the data. With boosting, the process is initialized with a uniform distribution so that all instances in the data have equal likelihood of being selected in the training dataset, while misclassified instances are returned to the distribution to improve their chances of correct classification with other algorithms in the ensemble. Zhang et al. (2017a) used a multi-objective DBN for RUL prediction using the C-MAPSS dataset. A DBN is a deep learning algorithm comprising RBMs stacked to form multiple layers. The ensemble method used in the study trained DBNs as base learners with two conflicting objectives, including accuracy and diversity. Accuracy is measured in terms of the error between the predicted RUL and the ground truth RUL while diversity checks the correlation between the output of each DBN to those of other DBNs within the ensemble. The various DBNs are gradually evolved through appropriate weighting to generate an optimal ensemble model that minimizes error and maximizes diversity.

Stacking involves the use of a heterogeneous mix of different base learners and then combining their results to produce a single prediction. The results can be combined with a classification algorithm or a regression algorithm, depending on the problem. Stacking is different from bagging in two ways; first, with stacking, the base learners are necessarily a heterogeneous set of algorithms or models and, second, each of the base learners are trained on the full set of training data unlike in bagging where the training data is sampled with replacement. Li et al. (2019a) used a stacking ensemble approach for RUL prediction and tested it on the C-MAPSS dataset. The study used as base learners: random forests (RFs), classification and regression tree (CART), recurrent neural networks (RNN), autoregressive (AR) model, adaptive network-based fuzzy inference system (ANFIS), relevance vector machine (RVM), and elastic net (EN). Particle swarm optimization (PSO) and sequential quadratic optimization (SQP) methods were then used to assign optimal weights to each base learner. The final RUL was obtained by taking the weighted sum of the RULs estimated by the base learners. In general, ensemble methods help to produce better accuracy while ensuring good generalization capabilities.

2.2.5. *BayesIan algorithms and uncertainty quantification*

The algorithms discussed so far make deterministic or point estimates of RUL, which are not necessarily near the "true" value. This is because point estimates have a fundamental flaw of not addressing the uncertainty in both the data and the model parameters. In practical terms, what this means is that an equipment with a predicted RUL of say 30 cycles, may end up failing earlier, after say 15 cycles or indeed last longer and fail after say 40 cycles. Such a scenario does not enable optimization of resources or efficient planning for maintenance and end-of-life treatment. Incorporating uncertainty in RUL predictions is the most effective way to address this flaw. Uncertainties in RUL prediction are of two types, aleatoric (or data) uncertainty and epistemic (or model parameters) uncertainty, both of which should be addressed, ideally (Adedipe et al., 2020). Attempts to incorporate uncertainties in RUL prediction have involved different approaches. Some proposals involve making several RUL predictions using the same algorithm and then calculating the mean prediction and the variance as representative values for the RUL distribution. Deutsch and He (2018) used a resampling technique by eliminating one training data for each run of a deep learning algorithm and repeated that process until the entire training data was covered, thereby obtaining several point estimates of RUL and the RUL distribution parameters therefrom. Liu et al. (2010) also used a similar approach by making 50 RUL prediction runs using an adaptive recurrent neural network (ARNN) and obtaining the RUL distribution parameters by computing the mean and variance of the 50 RUL point estimates. While this approach may capture, to some degree, the variability in the training and test data, it is however a heuristic approach that fails to directly account for uncertainty in a repeatable and systematic way.

Probabilistic techniques such as particle filtering (see Miao et al., 2013; Su et al., 2017; Chang and Fang, 2019), Kalman filtering and its variants (see Singleton et al., 2015; Son et al., 2016; Cui et al., 2020), and Hidden Markov Models (see Soualhi et al., 2016; Zhang et al., 2016b; Zhu, 2018) have also been used extensively for PHM. Although these methods are mathematically rigorous and more systematic than running several estimates and taking the average, they do not give RUL estimates as probability distributions with uncertainty estimates. To close this gap, Bayesian techniques like Gaussian Process Regression, GPR (Baraldi et al., 2015; Aye and Heyns, 2017; Richardson et al., 2017) enable uncertainty quantification in RUL prediction by providing probability distributions, with a mean and variance for the RUL at each time step. However, GPR derives the prior and the posterior distributions as multivariate normal functions, which does not always conform to data from engineering systems as they are not all multivariate normal. As such, a more contemporary approach is the use of Bayesian Neural Networks (BNNs) for RUL prediction. BNNs can be trained using any distribution as the prior. In addition, BNNs have gained traction recently for use in RUL prediction due to their superior performance in terms of both higher accuracies and outputs of RUL predictions that incorporate uncertainties in both data and model parameters. Another advantage of BNNs, and Bayesian techniques generally, is their interpretability, mainly because of their mathematically rigorous foundations. This helps to quell the common criticism of deep learning approaches as black-box approaches that cannot be interpreted. A few studies have been proposed using BNNs for RUL prediction. Reference can be made to Kraus and Feuerriegel (2019), Peng et al. (2020), Li et al. (2020), Kim and Liu (2020), and Vega and Todd (2020) for additional insight.

2.2.6. *Reinforcement learning*

The literature search produced only scant evidence of publications using reinforcement learning (RL) algorithms for PHM applications. In this algorithm, the learning agent is trained to act based on a reward system, depending on the outcome of the prediction. For that reason, it has found the most application in gaming. PHM applications are either classification (diagnostics or health state division), regression (RUL prediction) or, as it is in most cases, a combination of both problems. The main application of the RL technique is in maintenance policy formulation and decision-support systems. In such case, the outcome of maintenance actions taken based on the result of condition monitoring and RUL prediction are fed back to the learning agent in the form of re-

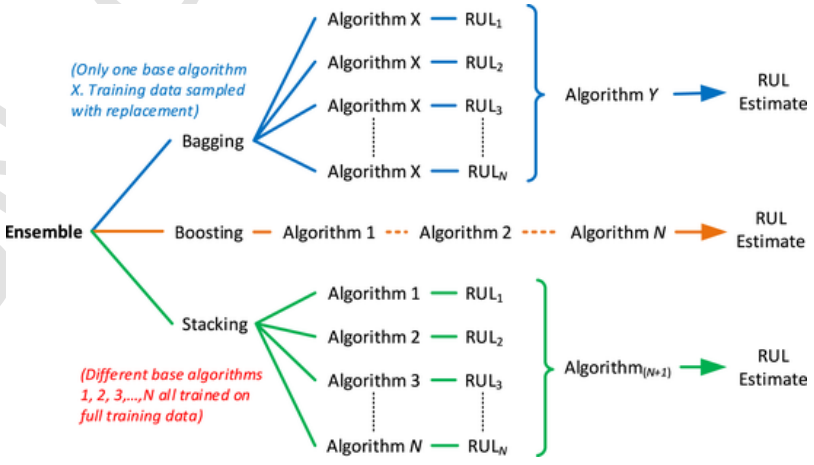

Fig. 6. Bagging, boosting and stacking approaches to ensemble AI learning.

wards, hence aiding the agent to subsequently make better, fully integrated decisions. Cheng et al. (2018) used RL strictly for health stage division by looking at highly trendable features from sensor data as multiple health indicators, and then considering their change points simultaneously as agents. The transition between health states was then modelled as a Markov Decision Process, and then an RL algorithm was used to determine the optimal change point transitions and hence, optimal health state division. Xanthopoulos et al. (2018) extended the use of RL approach beyond health stage division by using Q-learning to determine production-maintenance control policies via a reward mechanism for the algorithm that looks at system health states at different epochs and compares one state to the previous state and to a reward threshold, and, on that basis, makes decision as to whether to continue production or to trigger an alert for maintenance decision to be made. The application was strictly in the area of maintenance decision-making.

In furtherance of the application of the RL approach in PHM, Skordilis and Moghaddass (2020) extended the use of RL by combining Bayesian filtering and deep reinforcement learning (DRL). The Bayesian filtering algorithm was used to observe the system's latent degradation or health states based on multidimensional sensor data, with continuous updating. The DRL component of the algorithm made real-time maintenance decisions based on a framework designed based on the computed RUL value as well as costs of replacement versus that of failure. The advantages of the proposed method include dynamic and real-time monitoring of latent system degradation states, with uncertainty quantification due to the Bayesian approach, which also lends itself to interpretability as it is mathematically rigorous. Another study by Kozjek et al. (2020) used the RL approach to continuously adjust RUL predictions based on a reward system. RUL predictions by a primary regression algorithm uses the trend in system health states as input to make RUL predictions, which are then compared to the actual RUL, and the agent is then rewarded based on the delta between the two values, and the RUL is thereafter adjusted accordingly. Training is performed for different episodes, with RUL, safety, utilization level and maintenance planning as the respective reward objective for each episode. Another interesting development and new direction in the use of RL approach for PHM is in the area of health-aware control (HAC). HAC designs are now formulated around the use of results from data-driven PHM such as the system health states and RUL values as inputs into the cost functions to generate rewards which are then used by an RL algorithm to learn optimal system control and maintenance policy in the face of system degradation. Examples of such applications include the study conducted by Jha et al. (2019). Overall, the use of RL algorithms for PHM is nascent and largely unexplored.

3. Literature review process

In this Section, the results of our systematic literature review on the state-of-the-art in the use of AI algorithms for PHM will be presented. The methodology used in this study involves searching the indexed databases, such as Scopus, Web of Science, IEEE Xplore Digital Library and the American Society of Mechanical Engineers (ASME) Digital Collections, since they provide the best collection of peer-reviewed journals and conference papers. The following keywords and their combinations were used: "artificial intelligence", "machine learning", "diagnostics", "prognostics", "remaining useful life", and "maintenance". The focus of the literature study was to cover peer-reviewed publications; as such, books, book chapters, university dissertations and non-English publications were not in the inclusion criteria. Publications in the following professions were also excluded: health, medicine, environmental sciences, business and management, arts and humanities, and the social sciences. The search criteria were defined as presented above to sufficiently capture publications in the most relevant journals and conferences.

A combination of the results from all four databases initially generated a total of 342 references, which reduced to 192 after merging duplicates and deleting references that were not relevant to engineering assets. This number was pruned down to 178 after reading through the abstracts and in most cases, the full text of the papers to further establish their relevance to the study. Out of the 178 publications, 86 were journal articles while 92 were conference papers – published predominantly by IEEE and PHM Society – spanning from 2005 to March 2021. The results of the search were categorized to establish the distribution of AI algorithms used, the sources of data used to demonstrate the applicability of the algorithms, and the various equipment used as case studies.

3.1. Framework for categorization of the literature

In order to establish trends, the identified publications were categorized based on types of the AI algorithms used, source of data used for the research, the equipment or system used as a case study (where applicable) and the affiliation of the researchers.

3.1.1. AI algorithms used for PHM

The review carefully looked at the various AI algorithms or combination of algorithms used in the papers selected. When classifying the algorithms, the following notes were taken into consideration:

i. Algorithms that were similar, like support vector machine, support vector regression, support vector classification, relevance vector machine, were all grouped as SVM-based algorithms.
ii. The categories of algorithms or approaches under deep learning and ensemble methods are pretty much defined and they were grouped as such.
iii. Conventionally, hybrid/fusion approaches in condition monitoring and PHM combine model-based and data-driven approaches for RUL prediction. However, in the context of AI or ML, hybrid/fusion approaches are construed to be the combination of model-based or statistical approaches with AI algorithms for a single PHM purpose (i.e., to make only RUL prediction). "Single" in this context means putting together different algorithms to produce one RUL estimate rather than each algorithm producing its own RUL estimate and then choosing the 'best' estimate based on a performance metric (for example, RMSE).
iv. We also noted that with ensemble and hybrid/fusion techniques, multiple algorithms are used together to make a single prediction of RUL. As such, for this work, ensemble and hybrid/fusion techniques were classified differently from methods that used several different algorithms, separately, to perform prognostics, and then compared the results and chose the individual algorithm with the best performance. We classified such an approach as a comparison approach.

Upon classification, deep learning algorithms were ranked first as the most used type of AI algorithm for PHM research (about 29% of the publications). This is because the increased adoption of AI algorithms for data-driven PHM coincided with the time when deep learning was becoming the go-to algorithm for most other applications in other industries, enabled by availability of data to train the algorithms as well as computing resources capable of handling the training process. Hybrid/fusion approaches were ranked second (about 14% of the publications), ensemble techniques were third (in about 10% of the publications) and SVM-based algorithms were fourth (about 8.5% of the publications). Although it can be argued that deep learning and some of the ensemble techniques have their basis in neural networks, ANN-based techniques in its conventional form accounted for 4.2% of the publications. The publications in which these common algorithms were used

for PHM were introduced in more detail in Section 2.2, highlighting what each algorithm achieved, as well as their shortcomings. Table 2 presents the various algorithms along with the references in which the algorithms were used for research. The guidance for using Table 2 is to mainly serve as quick pointers to publications in which specific AI algorithms have been used in the literature for PHM so as to gain further insight into a specific approach or to aid comparison of research results.

3.1.2. Datasets

Publications in the literature show that researchers mostly used experiments data (~28%), closely followed by the NASA C-MAPSS dataset for turbofan engines (~23%) (Saxena and Goebel, 2008) and then the bearings dataset from FEMTO-ST PRONOSTIA test bed (~16%) (Nectoux et al., 2012). Both the NASA C-MAPSS dataset and the FEMTO-ST PRONOSTIA dataset are available for download at https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/. Data from real life operational assets constituted only about 7% of the publications, revealing the need for better collaboration between industry and researchers in terms of the provision of real operational asset data for data-driven PHM research. Furthermore, these percentages can serve as good pointers for those who need to benchmark their studies with some of the datasets for which a lot of studies have already been conducted.

3.1.3. Application areas

Data from rolling element bearings (~29%), turbofan engines (~21%), batteries (~20%) and cutting tools (~8%) were the most used in publications found in the literature. This is because most of the experiments conducted by researchers to obtain data for prognostics were conducted for bearings while the publicly available datasets were also from bearings and the other equipment mentioned above, mostly under test conditions or computer simulations. Wind turbine blades and wind turbine gearboxes were used in about 2% of the publications — all the data used for research on wind turbines were obtained from real life operational wind farms, but most could not be shared by the researchers for confidentiality reasons.

3.1.4. Epilog on algorithms

Some of the reasons for the popularity of deep learning algorithms were discussed in Section 2.2.1. However, an additional point to note is the aspect of hyperparameter tuning. Hyperparameters determine the architecture of any deep learning algorithm and they include: the number of layers, the number of nodes in each layer, the optimization algorithm, the learning rate for the optimization algorithm, the dropout rate (if dropout is implemented to reduce overfitting or as a Bayesian approach), etc. Earlier approaches towards hyperparameter tuning to determine the optimal values for each hyperparameter in a network involved manual assignments (manual search) by the algorithm developer and logging the output from the training process for any set of assignments. The developer then subsequently picks the value that yields the best results. However, tailored algorithms are now available for hyperparameter tuning or optimization, the most common of which are: random search, grid search, hyperband tuner, Bayesian optimization, gradient-based optimization, and early stopping (Bergstra and Bengio, 2012; O'Malley et al., 2019; Wu et al., 2019).

The advantages as well as the limitations of k-NN, naïve Bayes, SVM, ANN and deep learning algorithms were presented in the study by Liu et al. (2018). Furthermore, Sikorska et al. (2011) and Khan and Yairi (2018) both proposed a more detailed breakdown of the advantages and disadvantages of AI techniques and provided guidance on the suitability of any given algorithm. Table 3 lists some AI algorithms along with a synthesis of the pros and cons as presented in Sikorska et al. (2011), Khan and Yairi (2018) and Liu et al. (2018).

Table 2
Common AI algorithms used in PHM research.

Number of papers	Dataset	List of publications
48	Deep Learning	Heimes (2008), Liu et al. (2010), Morando et al. (2013), Deng et al. (2016), Liao et al. (2016), Thirukovalluru et al. (2016), Zhang and Gao (2016), Zhang et al. (2016b), Chen and Li (2017), Ding et al. (2017), Dong et al. (2017), Zhao et al. (2016), Guo et al. (2017), Jiang et al. (2017), Wang et al. (2017a), Jiang and Kuo (2017), Wang et al. (2017c), Krishnan et al. (2017), Liao et al. (2017), Ma et al. (2017), Qi et al. (2017), Ren et al. (2017), Zhang et al. (2017), Zheng et al. (2017), Belmiloud et al. (2018), Chen et al. (2018), Deutsch and He (2018), Hinchi and Tkiouat (2018), Hsu and Jiang (2018), Zhang et al. (2018b, a), Mao et al. (2018), Mezzi (2018), Remadna (2018), Ren et al. (2018a, b), Li et al. (2018b), Ma et al. (2018), Lin et al. (2018), Wu et al. (2018a), Zhang et al. (2018c), Yan et al. (2018), Yue et al. (2018), Zhao and Wang (2018), Ren et al. (2019), Li et al. (2019b), Zhang et al. (2019), Zhu et al. (2019).
23	Hybrid/Fusion	Camci and Chinnam (2005), Saha and Goebel (2008), Wan and Li (2013), Liu et al. (2013), Qiao and Xun (2015), Hu et al. (2016), Shaban and Yacout (2016), Yang et al. (2016b), Yang and Zhang (2016), Liu et al. (2016a), An et al. (2017), Ahmad et al. (2017), Wu et al. (2017), Liu et al. (2017a), Jin et al. (2018), Niu et al. (2018), Wang et al. (2018), Song et al. (2018), Trinh and Kwon (2018), Zheng et al. (2018a), Zhou et al. (2018), Liu et al. (2019), Ordóñez et al. (2019).
17	Ensemble	Sun et al. (2010), Zhang and Kang (2010, ?), Javed et al. (2013), Ben Ali et al. (2015), Frisk and Krysander (2015), Javed et al. (2015a, b), Wu et al. (2016, 2017b), Zhang et al. (2017a), Wang et al. (2017b), Li (2017), Wu et al. (2018c), Patil et al. (2019), Li et al. (2019a), Cheng et al. (2021).
14	SVM-based	Peysson et al. (2009), Galar (2012), Tran et al. (2012), Fan and Tang (2013), Benkedjouh et al. (2013), Zhou et al. (2013), Bluvband and Porotsky (2015), Carino et al. (2015), Patil et al. (2015), Wang et al. (2016), Qin et al. (2017), Mathew et al. (2018b), Tang et al. (2018), Shi et al. (2018).
7	Extreme Learning Machine (ELM)	Benkedjouh (2016), Liu et al. (2016b, 2017b), Laddada et al. (2017), Razavi-far et al. (2017), Xue et al. (2016), Zheng et al. (2018b).
7	Conventional ANN	Javed et al. (2012), Lim et al. (2016), Sateesh Babu et al. (2016), Zhao et al. (2017), Zhang et al. (2017b), Carroll et al. (2019), Khan and Prosvirin (2018).
7	Comparison of individual algorithms	Mathew et al. (2018a), Yang et al. (2016a), Wu et al. (2017a), Mansouri et al. (2017), Costello et al. (2017), Elforjani and Shanbr (2018), Li et al. (2012).
5	HMM	Camci and Chinnam (2010), Xia et al. (2013), Wu et al. (2018b), Soualhi et al. (2016), Zhang et al. (2016a)
5	Reinforcement Learning	Cheng et al. (2018), Xanthopoulos et al. (2018), Jha et al. (2019), Skordilis and Moghaddass (2020), Kozjek et al. (2020).
5	Bayesian neural networks	Kraus and Feuerriegel (2019), Peng et al. (2020), Li et al. (2020), Kim and Liu (2020), Vega and Todd (2020).
4	MoG-HMM	Tobon-Mejia et al. (2011a, b, 2012b), Medjaher et al. (2012).
2	Logical analysis of data (LAD)	Ragab et al. (2016a), Ragab et al. (2019).

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Table 2 (*continued*)

Number of papers	Dataset	List of publications
21	Others	Cross entropy optimization (Porotsky, 2012); Dynamic Bayesian network (Tobon-Mejia et al., 2012a); Gaussian process regression (Hong and Zhou, 2012; Baraldi et al., 2015; Aye and Heyns, 2017; Richardson et al., 2017); Sparse Bayesian Learning (Zhou et al., 2012); Adaptive neuro-fuzzy inference system - ANFIS (Zurita et al., 2014); Instance-based learning (Khelif et al., 2014); Kalman filter (Singleton et al., 2015; Son et al., 2016; Cui et al., 2020); k-NN (Xiong et al., 2015); Particle filter (Guha et al., 2016; Miao et al., 2013; Su et al., 2017; Chang and Fang, 2019); PCA (Yongxiang et al., 2016); Hidden semi-Markov model (Zhu, 2018); Light gradient boosting machine (Li et al., 2018b); Sparse coding (Ren and Lv, 2016).

Some of the algorithms appearing as being used in only one publication may actually have been used in multiple publications but have been grouped under fusion, hybrid or comparison approaches. Moreover, papers based on purely analytical statistical methods were excluded from the search.

3.2. RUL metrics

The key technical endeavour in the use of AI for PHM is the accurate prediction of RUL in engineering systems, sub-systems or components. RUL, simply put, is the time from the incipient stage of degradation to the point of failure. According to Jardine et al. (2006), RUL can be considered from two perspectives:

i. Probability that a system will operate without failure up to a given future time.
ii. Time to failure given the present health state and past operation profile.

RUL is random in nature and as such, RUL estimation may connote the determination of RUL distribution or the expected value of RUL. Whatever approach is adopted, it is important to have some measures in place to determine the level of confidence in the predicted value. Some of the RUL metrics used in the literature are discussed below:

(a) Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\widetilde{y}_i - y_i\right)^2}. \quad (1)$$

(b) Mean Absolute Error (MAE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\widetilde{y}_i - y_i\right|. \quad (2)$$

(c) Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|\widetilde{y}_i - y_i\right|}{y_i} \times 100\%. \quad (3)$$

where y_i and $\widetilde{y}_i$ are the true and predicted values of the RUL and n is the number of different models used or the number of different RUL predictions made if only one model is used.

Leão et al. (2008) developed a framework proposing a set of PHM performance metrics for use with a wide group of AI algorithms. The peculiar feature of the framework is amenability to bespoke definition by users so as to fulfil user requirements. Some of the metrics include prognostics hits score, false alarm rate, missed estimation rate, prognostic effectivity, average bias, average absolute bias and coverage. The definitions of these metrics and how to apply them were covered in the

Table 3
Pros and cons of common AI algorithms used in PHM.

Algorithm	Pros	Cons
k-NN	a. Mature theory and easy to implement b. Can be used for classification and regression	a. Large computation b. Need lots of storage space c. Selection of 'k' hugely influences outcome
Naïve Bayes	a. Robust for missing values situation b. Requires little storage space c. Easy to explain	a. Strong prior assumptions b. Computational challenges and combinatorial explosion c. Requires prior probability
SVM	a. Good classification accuracy b. Can handle multi-dimensional features	a. Low efficiency for large volumes of data b. Difficult to explain physical meaning
ANN	a. Good classification accuracy b. Good approximation of complex non-linear functions	a. Multiple parameters and amenable to over-fitting b. 'Black box' approach and difficult to explain
Deep Learning	a. Learn features and complex structures directly from data b. Automatically recognizes failure signatures in data	a. Need large amounts of data b. 'Black box' approach and difficult to explain c. Training times can be long. d. Need huge computational resources
• *Autoencoder*	a. Modifiable to learn richer representations b. Easy to implement c. Good for dimensionality reduction d. Easy to track loss/cost function during training	a. Training can require lots of data and data processing b. Learns to capture much information rather than much relevant information — may not be able to determine relevant information.
• *Denoising AE*	a. Good for denoising (feature extraction) because they are deterministic b. Implicitly designed to form a generative model	a. Randomly inserts noise at input level
• *Variational AE*	a. Learns what noise distribution to insert at code level b. Explicitly designed to form a generative model c. Can generate data using distributions	a. Can be difficult to optimize b. Can be difficult to implement
• *RBM*	a. Can create patterns if there are missing data b. Can learn a probability distribution from its set of inputs	a. Can be difficult to train b. Difficult to track the lost/cost function
• *DBM*	a. Parameters of all layers can be learnt jointly b. Handles uncertainty about ambiguous data	a. Training can be slow, as such joint optimization of parameters impractical for large datasets b. Approximate inference slow thus not favoured for features extraction
• *DBN*	a. Good for one-dimensional data b. Can extract the global feature from data c. Can consistently achieve high performance on raw data	a. Optimizing training is difficult, hence training can be slow and inefficient

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Table 3 (*continued*)

Algorithm	Pros	Cons
• *CNN*	a. Good for multi-dimensional data b. Good at local feature extraction	a. Complicated and hence takes a long time to train
• *RNN, LSTM and GRU*	a. Good for sequential data b. Can detect changes over time	a. Can be difficult to train and implement
• *BNN*	a. Mathematically rigorous, hence a bit explainable. b. Incorporates uncertainty quantification. c. Results tend to be more realistic for practical purposes	a. Can be computationally expensive. b. Selection of appropriate priors can be tricky.

study in details, including a case study application. Saxena et al. (2009) proposed four metrics to use in offline PHM performance evaluation, particularly to help with AI algorithm development. The metrics are sequential with time and should necessarily be determined in order as follows: prognostic horizon, α-λ performance, relative accuracy and convergence. A further addition to the discourse on prognostics performance metrics is the review conducted by Lei et al. (2018). The review catalogues metrics for determining the level of confidence in RUL predictions when several models are used. Some of these metrics include: confidence interval, relative accuracy, convergence, predictability, mean prediction error, overall average bias, overall average variability, reproducibility, online RMSE, online coverage and online width. The PHM data challenges by the PHM Society use scoring functions which are basically percentage errors on the actual RUL values, to measure the results obtained on the datasets provided. The key implication is that, for whatever model being deployed for RUL prediction, suitable metrics must be devised for the performance of the algorithm, and hence, the confidence in the entire PHM methodology. This is a valuable information for maintenance decision-making. An up-to-date and comprehensive review of PHM metrics, along with the suitability of each metric for use in different application scenarios is presented in the study by Ochella and Shafiee (2021).

4. Key enablers for AI in PHM

As mentioned earlier, most of the early successes recorded by AI are in the area of e-commerce (online shopping, hotel and airline reservation, social media, financial services, etc.). In terms of practical engineering applications, great advances have been recorded in the automotive industry, manufacturing industry and space exploration. In fact, an AI discussion paper by McKinsey Global Institute which surveyed senior AI executives in 3073 companies across ten countries and 14 sectors of the economy, showed that the automotive and assembly industry was among early leaders with high AI adoption (Bughin et al., 2017). For the energy and utilities industry, the report posits that the use cases for AI that potentially stand to yield the most benefits are the areas of operation and maintenance (O&M) optimization as well as prediction of consumer behaviour and energy utilization patterns. However, to exploit the full potentials of AI-enabled systems, the right enablers must first be in place. The authors have identified the issues of infrastructure, standards, security, regulations, and manpower as key requirements that must be addressed to provide the enabling platform for the application of AI in PHM. In what follows, a brief overview of these issues is provided.

4.1. Infrastructure

For large, established engineering companies, the cost of adopting AI technology may actually be huge and can serve as an initial barrier. Major challenges are likely to be compatibility of old systems with new ones, data storage, and the fact that each operating facility within a company's collection of assets is typically unique. Thus, there may be a need to set up unique, bespoke AI-driven PHM systems for each facility across the company's assets portfolio. Clearly, a way to go around this is a phased approach to adoption and implementation. Also, the concept of digital twins can be adopted, where physical assets are mimicked in a digital form and sensor readings and inspection data are fed to the digital version to observe the system's behaviour and make predictions. General Electric (GE) is already implementing the digital twin concept for wind farms (Woyke, 2017). The studies by Werner et al. (2019), Aivaliotis et al. (2019), He et al. (2021), and Meraghni et al. (2021) all demonstrate the use of digital twins for PHM of engineering systems. The concept, in terms of PHM, fundamentally provides a good alternative to obtain run-to-failure data and to observe the results of PHM in a simulated environment, in advance, so that proactive actions can be taken for the real, operational system.

4.2. Standards

Engineering practice is traditionally guided by standards set by professional bodies or national institutes. Similarly, engineering assets built for operation in the offshore environments are also typically qualified by classification bodies like Lloyds Register (LR), American Bureau of Shipping (ABS), Det Norske Veritas Germanisher Lloyd (DNV GL), Bureau Veritas (BV), Lloyds Register (LR), etc. A key consideration that has come up, in the discussion about AI and its application for engineering systems is that of standardization. The most common standard usually mentioned in the PHM field is the Machinery Information Management Open Systems Alliance (MIMOSA) which proposed the Open System Architecture for Condition-Based Maintenance (OSA-CBM). The OSA-CBM defines the various stages involved in PHM for engineering system in terms of functional layers, namely: data acquisition via sensors, data manipulation or preprocessing, diagnostics (comprising health stage detection, assessment, and division), prognostics and decision support and, finally, presentation (or machine–user interface). These stages or functional layers were used in the IEEE standard for PHM of electronic systems (IEEE, 2017), which referred to them as the elements of the PHM functional reference model. Vogl et al. (2014) comprehensively catalogued the list of International Organization for Standardization (ISO) and International Electrotechnical Commission (IEC) standards in relation to PHM of manufacturing systems. Other recent studies covering the issue of standards include the detailed work by Chang et al. (2018), Vogl et al. (2019) and Omri et al. (2020). Furthermore, the ISO/IEC JTC 1/SC 42 is the international standards committee that deals with the standardization of AI. It has published seven standards, one of which addresses AI use cases (ISO/IEC TR 20547-2:2018) while another addresses the assessment of the robustness of neural networks (ISO/IEC TR 24029-1:2021). The ISO standard related to PHM is ISO 13381-1:2015. It can be inferred from the recent studies and above-mentioned standards that there is no standard addressing AI-driven PHM technologies. The most common approach towards addressing the use of AI has been from the ethical perspective and the need for explainability and interpretability. In 2015, the IEEE Standards Association proposed "The IEEE Global Initiative on Ethics of Autonomous and Intelligent System" themed Ethically Allied Design (EAD). The EAD document (IEEE, 2018) catalogues various proposals for ethical considerations in the use of AI but does not address PHM systems. Overall, the general consensus is that such an important evolution in the way engineering systems are designed, built, operated and maintained, surely requires standardization.

4.3. Security

In an AI ecosystem where assets are interconnected in a cyber–physical space, a wide range of legal and cyber-security issues are likely to arise — incidents have actually been recorded in the power and utilities, transportation, petroleum and manufacturing industries (RISI, 2019). For designers of AI-based PHM systems, how to distinguish between real failures and failures due to cyber-attacks is a challenge to consider. A study by Tuptuk and Hailes (2018) discusses in detail the security issues around existing and future industrial cyber–physical systems. One of the vulnerabilities mentioned in the paper, amongst several others, involves attacks on data acquisition and storage systems which can adversely affect the accuracy of prognostics and also the availability of the PHM module, leading to potential lack of confidence in the entire PHM system. As such, the issue of safety, from the perspective of cybersecurity, needs to be duly considered for full deployment in fielded systems.

4.4. Regulations

There is clearly a need for governments and regulatory agencies to develop new sets of regulations that not only provide the opportunity for operators to obtain approval for the use of AI in PHM for safety-critical equipment, but also provide the environment where such systems are protected by law from malicious intrusion and attacks. A study by Ogie (2017) showed that the UK and the US appeared to have recorded the most cyber-attacks on industrial control systems. However, the study suggests that this may be as a result of openness to reporting on the part of both countries. Such openness to reporting may indeed be dictated by regulations. Therefore, regulations to be developed to guide the use of AI in PHM should as a minimum spell out reporting requirements whenever incidents are recorded. Moreover, regulations must require demonstrable evidence that safety and reliability of engineering systems using AI for prognostics are not compromised, especially when compared to conventional practice. In this regard, the issues of explainability and interpretability also re-surface as government regulations will require clear demonstration of responsibility on the part of asset owners regarding the safety of any system being deployed.

4.5. Manpower

To successfully adopt AI-driven PHM systems, there will be a need to re-skill engineers and operators. The McKinsey Global Institute report by Bughin et al. (2017) posits that an AI-ready culture needs to be established such that there is collaboration between operators and AI systems. Apart from operators, mid-level managers will also need training to become AI-aware and trust the system to deliver the results upon which safe and efficient maintenance decision-making will be made.

5. Future research

There is some degree of inertia being witnessed across different industries towards the implementation of AI in PHM. The clear gap between studies found in the literature and actual deployment in industries is the main evidence for this. This inertia may be primarily due to the economic risks of disrupting established technological systems being added to the uncertainties that are bound to exist during a transition phase. For instance, in the wind farms equipped with condition monitoring devices and Supervisory Control and Data Acquisition (SCADA) systems, terabytes of data are gathered every day, which pose several storage, processing and interpretation challenges. With respect to infrastructure, a practical approach for upgrading existing plants to support AI-enabled systems is to progressively improve on data acquisition capabilities by installing sensors and making robust plans for data storage and processing requirements. Also, prior considerations must be made at the concept stage of new projects to accommodate AI-driven PHM systems. Other challenges that will need further research are highlighted as follows:

i. Although attempts have been made at developing performance metrics relevant to the use of AI in PHM, their use in the literature is somewhat arbitrary, with researchers principally aiming at whatever metric will give an indication of less error. However, further research needs to be conducted to identify which particular metric best suits any given algorithm, with the intended PHM application in mind, so that performance measures are fairly standardized and therefore give values that are applicable to the real-life system being modelled.
ii. Deploying AI-driven PHM systems in new engineering assets with no operational or failure data is an area that requires further research. Even with prior consideration at the concept stage of developing such assets, the unavailability of condition monitoring data is an issue that has not yet been addressed in the literature. The digital twin concept potentially holds the key to addressing this challenge.
iii. Similar to the point raised in (ii) above, the context of managing design changes or retrofitting a system using AI-driven PHM tools needs to be addressed. Given that prior to any changes, the AI algorithm must have been trained using data from an older configuration, how to reconfigure and retrain the system for optimal performance needs to be methodical. It will be interesting to see how further research tackles the issue of seamless convergence of old systems with new ones as regards PHM modules running on AI algorithms.
iv. The soft issues around manpower needs and transitioning of skills, development of standards to guide the professional practice of using AI in PHM, as well as developing relevant regulations to help government provide the right support and controls are all areas that are at their nascent stages of research.
v. Another area of interest is the issue of explainability of the AI algorithms as well as interpretability of the results obtained from them. The black-box AI algorithms are often hard to explain and/or the results they produce can be hardly understood by humans. Therefore, white-box AI models are preferred over black-box models in estimating the RUL of engineering systems. In the same vein, the results require correct interpretation, with the full understanding of whatever assumptions may have been made in the training process. Mathematically rigorous formulations of AI algorithms based on Bayesian techniques offer very promising potentials for addressing these twin issues because the inner workings are explained to some extent by the mathematical background while the uncertainty quantification they provide will help with interpretability and correct application of results for PHM purposes.
vi. Deep reinforcement learning algorithms have achieved remarkable feats in gaming applications, with the most notable one being Google DeepMind's AlphaGo. It will be interesting to see how the concept of learning agents and reward systems are applied in prognostics, towards perhaps achieving very accurate, online RUL predictions for real-life applications. Such a scenario will help engineers achieve very high overall equipment effectiveness (OEE) for a lot of engineering systems, with potential implications for revolutionizing asset life extension models, going forward into the era of smart systems.

6. Conclusion

The field of artificial intelligence (AI) is no doubt poised to be at the heart of the unfolding technological revolution, termed industry 4.0.

The area of prognostics and health management (PHM) and its application in engineering systems is not being left behind, as revealed by the plethora of research publications in the literature, particularly in the past ten years. In this paper, we reviewed over 200 publications, with particular focus on 178 publications comprising 86 journal papers (~48%) and 92 conference papers (~52%), highlighting different approaches for the use of AI in PHM of engineering systems. Some of the metrics used to measure prognostics performance were also presented, emphasizing their importance in establishing confidence levels on estimated RUL values. The key considerations for the actual deployment of AI-driven PHM in engineering systems were also discussed. Analyses of the research publications in the literature reveals the need for increased collaboration between industry and researchers, especially as regards the availability of real-life data for research. Research must therefore progress to ensure that predictive maintenance as a practice is fully prepared to take on the inevitability of the smart factories and systems of the future.

Uncited References

Er et al. (2012)

CRediT authorship contribution statement

Sunday Ochella: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization, Project administration. **Mahmood Shafiee:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – review & editing, Visualization, Supervision. **Fateme Dinmohammadi:** Validation, Formal analysis, Investigation, Writing – review & editing, Visualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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