Abstract

This paper reviews current literature in the field of predictive maintenance from the system point of view. We differentiate the existing capabilities of condition estimation and failure risk forecasting as currently applied to simple components, from the capabilities needed to solve the same tasks for complex assets. System-level analysis faces more complex latent degradation states, it has to comprehensively account for active maintenance programs at each component level and consider coupling between different maintenance actions, while reflecting increased monetary and safety costs for system failures. As a result, methods that are effective for forecasting risk and informing maintenance decisions regarding individual components do not readily scale to provide reliable sub-system or system level insights. A novel holistic modeling approach is needed to incorporate available structural and physical knowledge and naturally handle the complexities of actively fielded and maintained assets.

Contents

1 Introduction 2
2 Complex Assets 3
  2.1 Critical Capabilities ........................................... 5
3 Review of Reviews ........................................... 5
4 Primary Literature ........................................... 6
  4.1 Condition Estimation and Forecasting ........................................... 7
    4.1.1 Bearings, spinning, and cutting ........................................... 7
    4.1.2 Gearboxes ........................................... 8
    4.1.3 Turbines ........................................... 8
    4.1.4 Vehicles ........................................... 9
    4.1.5 Industrial plant operations ........................................... 10
    4.1.6 Other ........................................... 10
    4.1.7 No sensors ........................................... 10
    4.1.8 No sensors and no faults ........................................... 11
  4.2 Maintenance and Operational Planning ........................................... 11
  4.3 Maintenance scheduling ........................................... 11
  4.4 Performance quantification ........................................... 12
  4.5 Supply planning ........................................... 12
5 Gap Analysis ........................................... 12
  5.1 Modeling Interactions ........................................... 14
    5.1.1 Dependability Modeling and Analysis ........................................... 14
    5.1.2 Primary literature focused on complex assets ........................................... 14
  5.2 Maintenance ........................................... 14

*Both authors are with the Auton Lab, Carnegie Mellon University. Copyright (c) 2019 Carnegie Mellon University.
1 Introduction

Predictive maintenance describes an approach to equipment management that focuses on exploiting sensing, inspection, and maintenance data to forecast future degradation state, remaining-useful-life, or similar quantity characterizing expected future performance of the equipment. Such forecasts are then used to optimize maintenance planning, supply chain, and other maintenance, design, and engineering activities. As a conceptual framework, it has gained significant popularity in recent years. This is not least due the very attractive claim that predictive maintenance can significantly improve over the state-of-practice by more closely aligning maintenance effort with maintenance need, thereby saving significant amounts of money and time while decreasing unplanned downtime and uncertainty. In applications with limits on equipment availability and/or budgets, predictive maintenance promises to enable intelligent planning to effectively and efficiently satisfy such constraints.

Predictive maintenance is sometimes abbreviated PMx or PdM and sometimes referred to as predictive/prognostic health management (PHM). It is closely associated with condition based maintenance (CBM) and reliability centered maintenance (RCM). Figure 1 shows the number of predictive maintenance related academic publications by year. Note the low count in 2019 is an artifact due to the date of the query. Table 1 lists the top 5 countries of origin by article count. Table 2 lists the top 10 funding agencies acknowledged by article count. These publication records demonstrate a growing interest in the field, which is likely correlated with advances in machine learning and artificial intelligence, and a reduction in data storage and processing costs over the past decade.

This vast amount of literature makes a comprehensive review challenging. Rather, we review the recent literature on predictive maintenance with a focus on complex equipment at the system and fleet/enterprise levels, examples of which include airlines, truck fleets, etc. The costs, repair time, number of components, variation in use/duty/load, and amount and scope of available data, are all dramatically higher in such scenarios as compared to analysis of individual components. With an increase in the problem complexity and scope, it may not be effective to craft data processing pipelines, data featurizations, and predictive models, for individualized components and failure modes, as is commonly demonstrated in the literature [Rögnvaldsson et al., 2018].

The remainder of this document is structured as follows. In Section 2 we provide our view on what differentiates predictive maintenance of complex assets from individual components. In Section 3 we review other relevant review articles, highlighting recent conceptual trends and industrial foci. In Section 4 we review primary research, organized by principal concepts in predictive maintenance; condition estimation, forecasting, planning/scheduling, and performance quantification. In Section 5 we characterize the gap between prior work and the needed capabilities for system-level PMx and review relevant existing work. In Section 6 we conclude with promising future directions.

Table 1: Top 5 leading countries by publication count.

| Country                        | Number of publications | % of publications |
|--------------------------------|------------------------|-------------------|
| United States Of America       | 1578                   | 25.402            |
| People’s Republic China        | 1544                   | 24.855            |
| France                         | 421                    | 6.777             |
| United Kingdom                 | 327                    | 5.264             |
| Canada                         | 245                    | 3.944             |

1Web of Science query (conducted on 2019-03-01): TS=(*predictive maintenance* OR *condition estimation* OR *remaining useful life* OR *degradation model* OR *failure prediction*) AND SU=(*ENGINEERING OR COMPUTER SCIENCE OR SCIENCE TECHNOLOGY OTHER TOPICS OR MATHEMATICS OR MECHANICS OR ROBOTICS OR OPERATIONS RESEARCH MANAGEMENT SCIENCE*)
Figure 1: Count of predictive maintenance related academic publications by year (as of March 1, 2019).

Table 2: Top 10 leading funding agencies by publication count, after some de-duplication.

| Agency                                                      | Country     | Number of publications | % of publications |
|--------------------------------------------------------------|-------------|------------------------|-------------------|
| National Natural Science Foundation of China                 | China       | 561                    | 9.034             |
| National Science Foundation of China                         | China       | 111                    | 1.787             |
| National Science Foundation                                  | USA         | 96                     | 1.546             |
| Fundamental Research Funds for the Central Universities      | China       | 93                     | 1.498             |
| Natural Sciences and Engineering Research Council of Canada  | Canada      | 39                     | 0.628             |
| National Basic Research Program of China 973 Program         | China       | 35                     | 0.564             |
| China Scholarship Council                                    | China       | 34                     | 0.548             |
| China Postdoctoral Science Foundation                        | China       | 27                     | 0.435             |
| Fundamental Research Funds for the Central Universities of China | China   | 22                     | 0.354             |
| European Union                                              | EU          | 18                     | 0.290             |

Figure 2: Model components for fleet level predictive maintenance of complex equipment

2 Complex Assets

We differentiate between predictive maintenance applied to a single component with that applied to a complex asset. By complex asset we mean a system of several interacting components. In most cases, component interactions such as redundancies make application of predictive maintenance focused on each constituent component, an unsatisfying solution at the system level. Here, we itemize several fundamental distinctions between component level and system level problem elements to emphasize the importance
of this differentiation.

**Faults.** In single component analysis, faults are typically not enumerated. Rather, failure is the only outcome. On the other hand, complex assets may present numerous and varied faults, to the degree that novel fault types may be wholly unobserved in training data. Additionally, for complex assets, faults are typically observed at the sub-system or system level. For example, it may be recorded that an engine fails to start, but not that a particular valve gasket has ruptured. Further, it may be that no individual component fails outright, but rather in their degraded state multiple components fail to work together.

**Degradation state.** For individual components, degradation state is synonymous with wear and tear, and is tightly connected with remaining useful life (RUL). It is typical that degradation state is modeled as a single-dimensional quantity that monotonically increases with use. For complex systems this notion must be extended, for example modeling degradation state as a multidimensional vector encoding the wear state of each constituent component. Additionally, the relationship between degradation state and failure can be complex and non-linear. This relationship is the object of study in the discipline of reliability analysis. The use of reliability models such as fault trees and Bayesian networks in predictive maintenance is briefly touched upon in Section 5.1.1.

**Data.** Unlike isolated components, it is typically not cost-effective or not feasible to conduct run-till-failure experiments. As a result, observed data are collected from machines operating in a production environment or in the field, which likely includes significant variation in operating loads. These sources of variation may need to be accounted for in predictive models to achieve desired levels of predictive performance.

Degradation state is almost surely not directly observed in complex assets. Direct observation is sometimes assumed for analysis of individual components, but the volumes of data that would be required to directly record degradation state of all of the individual components in a complex asset would likely be prohibitive to say nothing of large sensing array that would be required. Rather, degradation state will be indirectly observed or perhaps partially observed. Additionally, data will typically reflect sub-system behavior rather than individual component state.

**Maintenance actions.** Maintenance can often be ignored in the context of individual components. If training data consist of run-till-failure experiments, maintenance is not performed. In other cases maintenance may consist of replacing a component near failure, in which case the effect of maintenance is to return a part to like-new condition as is often modeled in the literature [Yildirim et al., 2016a, Yildirim et al., 2016b, Hao et al., 2017b, Peng et al., 2017a]. In training data this can be viewed as censoring observations and maintenance type and effect need not be explicitly considered. In contrast, complex assets may be actively maintained with both repair and replacement of components, impacting degradation state and/or degradation rates, as well as their estimates, in non-trivial ways.

As a direct result of maintenance, examples of failure may be rare or absent in available training data. In safety-critical systems, components will be serviced or replaced prior to actual failure events. In down-time sensitive applications maintenance may be performed opportunistically during available maintenance windows rather than in correlation with impending failure. Therefore, it is important to account for the effects of maintenance during the development of predictive models.

**Fleet.** A fleet of individual components is often treated as a set of identical pieces, the observations of which can be pooled into a single training set. However, with long lived complex assets, individual histories of maintenance, asset-specific usage histories and aging, customization, and modifications, may result in a set of similar but not identical assets. If the degree of similarity is moderate, due to say unit customization, model training procedures will have to be adapted to reflect the resulting subjectivity. Transfer learning or multi-task learning frameworks may be needed for sharing information across the fleet. Additionally, long lived assets may show additional forms of concept drift. For example, replacement parts may be sourced from a new supplier with slightly different tolerances or operational characteristics. In such a situations, historical data may not be perfectly reflective of the current reality.  

---

2 Perhaps measured in accumulated load and/or use, as opposed to wall clock time.
Planning. As with fleets of individual components, fleet-level planning for systems requires taking all assets into consideration for making optimal maintenance decisions. This is typically because finite maintenance resources induce a coupling across maintenance decisions for each asset. However, with complex assets, additional couplings always exist between components of a given asset. If maintenance is to be performed on one component, it may induce or block a maintenance window for another component, and may impact the effective duration of jointly performed maintenance actions.

2.1 Critical Capabilities

Generally, predictive maintenance can be described as failure risk forecasting combined with maintenance planning. There are a number of sub-problems that must be solved to realize PMx capabilities. The importance of each of these sub-problems can vary significantly depending on the use case under consideration. The principal components of PMx are described in Figure 2. Data must be collected and curated for use, requiring infrastructure for data collection, storage, and analysis. One common consideration in the literature is how to facilitate data collection through cloud solutions and IoT technology [Meraghni et al., 2018, Chukwueke et al., 2016], although cloud solutions are not immediately applicable to some asset types or scenarios due to safety and security concerns. Once data is available, it can be used to estimate historical, current, and future condition or failure risk. As noted in Section 2 these are not synonymous, though often conflated. Given ones belief of the future risks, operational and maintenance plans can be formulated to optimize global objectives.

This viewpoint is fundamentally asset-centric. Figure 2 does not call out the need to estimate uncertainties in supply chain (e.g. shipping lead times, etc.) or in maintenance itself (e.g. time to repair). This focus on asset-centric capabilities is typical of the literature reviewed. The majority of academic research in the PMx field has focused on condition and failure risk forecasting. Maintenance scheduling has been addressed, but to a lesser extent. Operational planning, such as e.g. assigning vehicles to delivery routes [Biteus and Lindgren, 2017], has been briefly touched upon. Cost-benefit analysis of predictive capabilities (e.g. [Busse et al., 2018]) appears also to be currently understudied.

3 Review of Reviews

There exist several reviews of CBM and PMx. Most of these reviews walk the reader through the basic pipeline of data acquisition, processing and feature extraction, modeling and prediction, and finally decision support. Usual points under discussion are classes of data types, tools, and techniques that are commonly used. We give a brief overview of these reviews here to build out a description of the current state of the field.

[Si et al., 2011] is one of the most frequently cited papers in the field. The authors review several families of RUL prediction approaches. The methods are stratified by whether (degradation) state is directly or indirectly observed. For directly observed state, reviewed approaches include regression based models, Wiener processes, Gamma processes, and Markovian models. For indirect observation, the authors describe filtering-based methods, hazard models, and hidden Markov models.

[Lei et al., 2018] gives a recent review of data acquisition and RUL prediction. The authors identify four technical processes; data acquisition, health indicator construction, health stage segmentation, and RUL prediction. The authors review four commonly used public data sets for RUL prediction: The NASA turbofan dataset [Saxena and Goebel, 2008], the FEMTO bearing dataset [Nectoux et al., 2012], the IMS bearing dataset [Qiu et al., 2006, Lee et al., 2007], and a milling dataset [Agogino and Goebel, 2007]. For each dataset [Lei et al., 2018] give a description, list of important properties, and recounts applications. [Eker et al., 2012] additionally describes a Li-ion battery dataset [Saha and Goebel, 2007], a Insulated Gate Bipolar Transistor (IGBT) dataset [Celaya et al., 2009], and the Vickler dataset [Virkler et al., 1979]. Most of these datasets are from the NASA Ames prognostics data repository [NASA, 2019], which currently hosts 16 datasets. [Lei et al., 2018] summarizes performance metrics used in RUL prediction and concludes with future challenges including data volume (either limited or overwhelming), handling multiple failure modes, system level RUL prediction, and others.

Several reviews focus on Industry 4.0 and the “digital-twin” concepts. The digital-twin is meant to be a “living model” which can forecast effectively the behavior (including failure) of its real-world asset counterpart. [Liu et al., 2018] describes the development of the digital-twin concept in aerospace, while

\[3\] The idea of a digital twin is also found within the U.S. Department of Defense under the banner of the Digital Engineering Transformation (DET) and is spelled out in the Digital Engineering strategy by the Office of the Deputy Assistant Secretary of Defense for Systems Engineering, 2018.
sensor data information as pause to discuss the issues that arise when different types of data are or are not available. We categorize We now turn to a detailed review of literature highlighting each PMx task. Before jumping in however, we

4 Primary Literature

We turn to a detailed review of literature highlighting each PMx task. Before jumping in however, we pause to discuss the issues that arise when different types of data are or are not available. We categorize information as sensor data, which describe the current behavior of an asset, maintenance logs which
describe the actions taken with the intent to extend the utility of an asset or set of assets, and fault records which describe observed failures.

When fault records are unavailable or insufficient in number to support statistical analysis, the PMx effort is called unsupervised in contrast to supervised. In the supervised setting direct RUL prediction is the most common approach. In the unsupervised setting anomaly detection is the principal approach. In contrast, most planning algorithms presume a failure risk forecast.

4.1 Condition Estimation and Forecasting

The bulk of the academic literature in the field focuses on condition estimation and forecasting, often specializing to application domain. For this reason, we structure these studies according to domain and primary PMx sub-task; condition estimation and fault detection or RUL prediction. We make note of whether techniques are supervised or unsupervised, grouping similar methods together. Finally, we note special cases where sensor data and/or fault records are not available.

4.1.1 Bearings, spinning, and cutting

Condition estimation [Jia et al., 2019] uses a WS-ZHT1 multifunctional rotor test rig to simulate faults, generating supervised data. The authors evaluate infrared thermography (IRT) for condition estimation of bearings. They conclude that IRT base condition estimation is more effective than traditional vibration based methods. Other authors working in the supervised setting focus on vibration data. [Sezer et al., 2018] fit a model to predict roughness from vibration and temperature data in CNC machines. [Kateris et al., 2014] performs condition monitoring of bearings in rotating machinery using vibration data. The authors use neural networks to identify and locate (inner/outer race) faults using fully labeled data collected on a test machine.

[Ferreiro et al., 2016] describes unsupervised predictive maintenance in the spinning tool setting. The authors use a finger-print learning method using supervised data to train a fault detector and an envelope analysis to detect outliers.

RUL prediction Supervised RUL prediction methods for bearings or rotating machinery very often use data from run-till-failure bench-top experiments. Occasionally, partially damaged bearings will be used to accelerate failure in order to gather more failure examples or explore specific failure modes. [Yan et al., 2017] describes a data processing pipeline for predictive maintenance in the industrial setting. The authors demonstrate predicting tool wear and tool RUL on CNC machines. While the authors describe processes for creating structured data from semi-structured or un-structured data common in the industrial setting, their demonstration focuses on the use of featurized vibrations data via envelope analysis and similar strategies. [Li et al., 2019a] developed a state-space based RUL prediction algorithm that is robust to varying operating conditions. The approach uses a particle filter with linear drift term. The linear term is modulated by operating conditions. A pair of operating condition dependent jump coefficients are introduced to the observation model, to account for jump discontinuities or change points in the observed degradation signal. In earlier work, [Bian et al., 2015] model degradation in a randomly-evolving environment modeled as a continuous-time Markov chain. The authors argue that most hazard models and prior research considers only static environments, which can lead to model-mismatch and degraded model performance if environments do vary. [Hao et al., 2017a] consider a serial processing line in which tool wear impacts production quality and production quality of preceding steps effects tool wear rates of downstream steps. A linear relationship between burr size and tool wear is presumed. The approach is demonstrated on simulated data. [Fumeo et al., 2015] uses an online-support vector regression machine to efficiently learn/predict RUL on railway bearings. The authors use vibration and temperature as inputs from run-to-failure data. [Liao et al., 2016] develop feature extraction capabilities for improved RUL prediction on bearing systems, again using run-till-failure experiments. [Luo et al., 2019] demonstrates RUL and wear prediction on spinning tools. The authors use advanced dynamic identification techniques to process vibrations data coupled with deep learning methods to produce their final predictive model. [Fang et al., 2018] develop tensor-based methods for RUL prediction from streams of infrared images of bearings. When stacked, these images form a rank-3 tensor. The approach is to project the tensors to a low-dimensional tensor subspace and then apply a penalized location-scale regression using RUL as the dependent variable. [Guo et al., 2017] apply recurrent neural networks to RUL estimation on bearings in the supervised setting. The authors conclude that RNNs give superior performance to self organizing maps.
Kanawaday and Sane, 2017 analyzed industrial cutting tools. The authors used unsupervised techniques to establish outliers. They then trained supervised models to forecast the occurrence of these outliers.

4.1.2 Gearboxes

Condition estimation [Zhao et al., 2019] develops supervised methods for fusing wavelets and deep learning approaches. The authors demonstrated their method on planetary gearbox fault diagnosis. [Wade et al., 2017] use vibration data to estimate condition of nose gearboxes (NGBs). Authors cite prior work indicating that vibration exceedences are a sub-optimal condition estimator due to variation in individual aircraft and components. The authors develop aerospace specific metrics for model selection. Data represents 600 assets with 40 ground-truth faults. Authors describe several metrics including bookmakers informedness (TPR FPR), historical based TNR, asset based TNR, in-sample informedness, cross-validation informedness, absolute difference between in-sample and cross-validation informedness, and position shuffle. [Wade et al., 2015] describes data preparation for health status prediction of engine output gearboxes and turbo shaft engines. Health and Usage Monitoring System (HUMS) data are used as predictors, including Outside Air Temperature (OAT), Turbine Gas Temperature (TGT), Torque, Compressor Speed (NG), Power Turbine Speed (NP), Anti-Ice, Indicated Airspeed (IAS), and Barometric altitude. The predictive target is engine removal events for reason of low power/low torque (LPLQ).

[Oehling and Barry, 2019] suggest that the state-of-art for informing safety from flight data is to monitor for exceedences of established thresholds. The authors use unsupervised outlier detection to identify potentially safety-relevant occurrences from flight data and compare to the exceedence-based approach. Outlier detection is shown to have good utility.

RUL prediction [Martin-del Campo et al., 2019] demonstrates an unsupervised dictionary learning based approach for faults in wind farms. Data are gearbox vibration records for six turbines (publicly available). Condition evaluation is effected by building anomaly detection capability using learned dictionaries by means of a “dictionary distance.” Dictionaries are realized as a sparse coding model.

4.1.3 Turbines

Condition estimation [Rahman et al., 2018] use a supervised signature based algorithm for detecting and characterizing faults. Fault signatures are produced by simulating different fault types. Rausch et al., 2007 also used supervised learning to detect and classify faults and used these classifications to adjust flight parameters in real-time for improved flight safety. Training data was again produced using numeric simulations.

[Yan, 2016] uses unsupervised anomaly detection of redundant (simultaneous) temperature measures to diagnose combustor issues in gas turbine engines. Data is sampled at 1/60 Hz and an extreme learning machine (ELM) is adapted for anomaly detection. Michelassi et al., 2018 presents a very similar work. Michau et al., 2018 uses deep-learning based anomaly detection methods to identify potential faults in gas turbine data. The authors also explore the use of “sub-fleets” creating appropriate cohorts for comparison.

RUL prediction [Xue et al., 2008] developed a fuzzy-similarity based method for estimating RUL on aircraft turbine engines. Authors analyzed cases of high pressure turbine shroud burn faults. Their algorithm identifies peer groups based on exhausted gas temperature (EGT), fuel flow (WF), and core speed (N2) after correcting for flight envelopes. Observed RUL from from identified peers is then aggregated to estimate the RUL of a target engine. Many supervised RUL prediction studies use the NASA turbofan dataset [Saxena and Goebel, 2008] as benchmark. Fang et al., 2017b develop methods for improved multivariate RUL regression, including feature selection. Cao et al., 2018 proposes a change point detection modeling a (linear) gradual degradation to a subset of sensor streams (p0), where observations before and after the change point k are assumed to be i.i.d. normal. The detection is based on a generalized likelihood ratio (GLR) statistic considering average run length (ARL) and expected detection delay (EDD). Several extensions of the technique are proposed e.g. non i.i.d. case and modelling adaptive subset of crushed sensors p0. The method is demonstrated on stock bidding trend detection as well as the NASA turbofan dataset. Fang et al., 2017a, Fang, 2018 uses functional Principal Component Analysis (FPCA) and location-scale regression are used to predict time to failure (RUL) of partially degraded equipment. A multivariate FPCA and hierarchical FPCA is used for data fusion on a massive dataset. One of the
key contributions is that the scalability of (multivariate) FPCA is enhanced by exploiting Randomized Low-rank Approximation (RLA) without knowing the rank of the RLA in advance. Zhang et al., 2018 use a 3-layer LSTM for gas turbine engine RUL prediction. The authors define a health index as the output of a single ReLU neuron, fit to predict 1 at the beginning of an engine’s time series and 0 at time of failure, regularized against first differences. This regularization encourages smooth health index trajectories. Finally, the 3-layer LSTM is trained for a one-step forecast task. By repeated forecasts at test time, RUL is inferred. Ragab et al., 2016 use a discrete logic approach for RUL prediction given observed operating parameters and condition indicators. Li et al., 2019b describes an ensemble RUL prediction approach, using Random Forest, CART, RNN, and several other algorithms as constituents of the ensemble. The authors show that the ensemble is able to predict RUL on the NASA turbofan dataset with high accuracy.

4.1.4 Vehicles
Condition estimation
Atamuradov et al., 2018 describes supervised health indicator (HI) construction, assessment, and prognostics for railway applications. Rögnvaldsson et al., 2018 describes a life-long learning approach to fault detection, arguing that it is economically infeasible to use human experts to build, evaluate, and field predictive models for each failure mode. This is especially true for novel failure modes or (potentially) occasionally modified equipment. The paper gives a good review of unsupervised methods. The authors remark that most of the prior work presumes high-quality features are provided (presumably by experts) and that little work in the unsupervised space accounts for inter-asset variation. The authors’ approach is based on Consensus Self-organizing Models (COSMO), and the basic elements of the strategy are to first identify interesting (in an information theoretic sense) functional transformation of raw sensor data and then to compare these derived values across the fleet. One or a few outliers were there is general consensus otherwise in one or more derived signal suggests a fault. The authors conclude that there is a significant need to improve the quality of data in service records. Dubrawski and Sondheimer, 2011 demonstrate detection of escalating maintenance issues by comparing event counts with historical counts as well as with similar cohorts.

RUL prediction
Bonissone and Varma, 2005, Bonissone et al., 2005 present a fuzzy-similarity based model to identify peer groups for a fleet of 1100 locomotives. Peers are similar in maintenance history, usage, and expected behavior. Observed RUL is aggregated across peers to estimate RUL for target locomotives. The authors use an evolutionary framework for model optimization to maintain an up-to-date similarity measure. Teixeira et al., 2015 models the evolution of fault magnitude in components, using their supervised model to disregard apparent faults that do not follow expected evolutionary behavior. The result is that their model successfully disregards most cases of “no fault found.” Le et al., 2017 use ML models to predict RUL for engine oil in land based military vehicles. Data collected from VHUMS included engine RPM, temperature, throttle position, oil temperature, among others. Oil condition was measured by means of laboratory tests. Data included 16 vehicles with a total of 30 oil test results. Rule-learning gave very good performance in stratified cross-validation (number of folds was unspecified). Nascimento and Viana, 2019 proposes an LSTM with monotonic damage accumulation. The utility of the model is demonstrated by synthetic simulation. Training data are “far field stresses,” and labels are periodic inspections for cracks. Magargle et al., 2017 gives and in-silico demonstration of digital-twin methodology in support of predictive maintenance for automotive breaks. By reference to the digital twin, wear rate is inferred from data and RUL predictions are made. Prytz et al., 2015 describes the application of predictive maintenance to a fleet of trucks. Three years of data are used to demonstrate the approach. The authors describe common difficulties; data is co-opted for mining, maintenance records are incomplete and free-text based, etc. The authors note that the feature distribution used for predicting future faults is age dependent, and apply modeling strategies to correct for equipment age. They also discuss issues arising of dependence among observations in the data set and recommend a leave-one-vehicle out cross-validation approach. Nixon et al., 2018 describes predictive maintenance analysis on diesel engines for military vehicles. Input data consists coarsely sampled measures from the engine management computer. Predictive targets were created by grouping
unscheduled maintenance actions by failure mode. Baptista et al., 2019 studies how Kulman filtering can be used to smooth RUL estimates over time, reducing noise and improving overall accuracy. Cipollini et al., 2018 evaluate several ML approaches for engine health analysis on naval vessels. The authors conclude that unsupervised anomaly/outlier detection methods are the most appropriate as they can be realized with minimal ground-truth. A public dataset is available for this work.

### 4.1.5 Industrial plant operations

#### Condition estimation

Amruthnath and Gupta, 2018 explores some unsupervised methods for fault detection using vibration data from a cooling fan. Graß et al., 2019 proposes an unsupervised approach for anomaly detection in time-series data representing configuration-based electronics production lines. Hendrickx et al., 2018 describes an unsupervised clustering approach for comparing similar machines in industrial environments. Anomalies are detected by means of monitoring similarity among machine equivalence classes. Kroll et al., 2014 describes an anomaly detection strategy based on discrete-continuous hybrid automata.

#### RUL prediction

Mattes et al., 2012 evaluates Bayesian networks, Random Forest, and linear regression for supervised RUL prediction using equipment specific sensor data. Susto et al., 2015 presents a supervised model for predicting failure within m iterations using data from run-to-failure experiments for an ion implanter tool. Susto and Beghi, 2016 explores the application of a time-series featurization approach to RUL prediction. Bastos et al., 2014 describes an ML framework for predictive maintenance of a nuclear plant. Features consist of monitoring data reported at 1 Hz frequency. The prediction target are failures, recorded in maintenance records.

#### Other

Poosapati et al., 2019 proposes a rule-based strategy for processing anomalies in predictive maintenance applications. Their goal is to develop cognitive reasoning capabilities that can recognize patterns and suggest courses of action.

#### RUL prediction

Cristaldi et al., 2016 evaluates a few models for supervised RUL prediction of a “fleet” of circuit breakers. Models have access to an observed health condition (HC), and forecast the point at which the HC reaches the end-of-life level using observed time-series as inputs. Fleet level data is used to learn probability distributions over HC variation. Cline et al., 2017 review 19 years of inspection data for swivels and valves on oil and gas equipment. Authors noted that they were unable to compute residual life of the majority of components due to the fact that most components never failed. Failure within next year was selected as the most viable target. Features included wear-index, derived values thereof, and counts of previous failure or inspection events. Bey-Temsamani et al., 2009 suggests that data engineering and feature selection through case studies can be used to facilitate later development of prognostic models. The authors demonstrate RUL prediction on copy machines. Mishra et al., 2018 apply hierarchical Bayesian modeling to forecasting battery performance. The hierarchical modeling structure effects a peer-to-peer comparison, and can make predictions without sensing data based on a battery’s peer group (i.e. its prior). Xin et al., 2017 extends Bayesian hazard modeling for fire and industrial accidents to include dynamics.

### 4.1.7 No sensors

In the absence of sensor data, researchers have used maintenance and/or failure data to uncover patterns that can forecast future failures.

Baptista et al., 2018 proposes an ARMA based model for supervised prediction of RUL/failure risk aimed at reducing unnecessary removals and avoiding failure. The authors use an ARMA model and PCA to feature time-series of past removal/failure events and pass this through a predictive model which forecasts RUL. They demonstrate on a data set of 584 engine bleed valve removals. Sipos et al., 2014 uses distribution-classification to predict upcoming failure from the distribution of observed fault codes in log-data collected from medical equipment. Service notifications are used to denote failure. Korvesis et al., 2018 parse post-flight event logs to predict landing gear faults in aircraft. Kraisangka and Druzdzel, 2016 Kraisangka and Druzdzel, 2018 show how Bayesian networks can be used to model hazard rates, leading to more powerful models. Wang et al., 2017 demonstrate a classification based approach for predictive maintenance in automated teller machines (ATM). The authors use statistics of
error message occurrences, occurrences of temporal patterns of error messages, and individual machine characteristics (model, installation date, etc.). Error message type is extracted from error codes present in the ATM log files. Labels are determined by the occurrence of a maintenance ticket.

[Salo et al., 2018] present a poster describing an NLP pipeline for extracting useful information from free-text maintenance write-ups in wind farm data. The approach cluster text descriptions into equivalence classes, grouping write-ups that describe the same/similar maintenance actions.

4.1.8 No sensors and no faults

If neither explicit failures nor sensor data are available, one can predict future maintenance using historical maintenance. For example, [Gardner et al., 2017] uses tensor decomposition to data-mine maintenance data for patterns. A rank-3 tensor is created out of vehicle ID, maintenance action type, and time. An LSTM is trained to forecast maintenance actions as well, treating each vehicle’s time series as an observation.

4.2 Maintenance and Operational Planning

Most work in predictive maintenance does not consider variable workloads, operating conditions, or equipment use. Further, those that do explicitly take these issues into account [Hao et al., 2017b, Li et al., 2019a, Bian et al., 2015] generally do not forecast use and/or modify usage plans in consideration of degradation status. [Biteus and Lindgren, 2017] is an exception. The authors describe an end-to-end predictive maintenance program that predicts failure risks, schedules maintenance actions, and creates condition-aware plans of utilization (route planning) for a fleet of trucks. Maintenance actions are broken down into the smallest possible units and transformed into constraint rules. A random forest is used to predict failure risk, and constrained optimization strategies are used to produce maintenance and route plans. The approach is demonstrated on a fleet of 80,000 trucks and a single component (air dryer purge valve) for which failures are observed in 1.6% of records. Data are publicly available in UCI repository [Dua and Graff, 2017].

4.3 Maintenance scheduling

[Maillart, 2006] applies a POMDP framework, assuming that without maintenance, system state degrades stochastically, over discrete states, according a known transition function. Maintenance costs are differentiated according to whether they are preventive or reactive. Both types of actions are assumed to return the system to like-new condition. POMDP formulations are also explored by [Ghasemi et al., 2007, Jiang et al., 2015, Li and Pozzi, 2019].

[Yildirim et al., 2016a, Yildirim et al., 2016b] represent a two-part paper. In part I, the authors assume the ability to observe a degradation signal which is given by a parametric degradation function plus additive noise. Observation of the degradation signal allows inference of the asset-specific degradation parameters, some of which are shared across a fleet. A Bayesian model is presumed, and the distribution of RUL for each asset is inferred from the observed degradation signal. A cost function relates RUL to cost by dictating a different (lower) cost for planned maintenance than for failure events. A maintenance action (planned or otherwise) is presumed to return the asset to “new” status (note assets are treated as single-component systems). A mixed-integer program is defined for characterizing total maintenance costs. A constraint on labor capacity couples maintenance actions across assets. In part II, the mixed-integer program is extended to include constraints on asset commitments and loads. These can encode constraints on the number of up/down transitions, total availability or capacity, etc. Experiments demonstrate significant improvement in reliability and reduced costs over standard practice. [Yildirim et al., 2017] demonstrates a very similar approach to [Yildirim et al., 2016a, Yildirim et al., 2016b] for a fleet of wind turbines. The authors add constraints that limit location visits on the part of the maintenance crew, constraints of maintenance effort, and constraints on turbine output which couples the maintenance effort across turbines encouraging concurrent maintenance actions. This leads to cost optimization.

[Yildirim et al., 2016a, Yildirim et al., 2016b] extend the mixed-integer programming planning algorithm of [Yildirim et al., 2016a, Yildirim et al., 2016b] to include a probabilistic constraint on availability. This constraint ensures that the likelihood of too many assets in maintenance simultaneously is low. The purpose of this constraint is to guard against the risks and costs of unexpected failures. [Moghaddass and Ertekin, 2018] solves the joint condition estimation and maintenance planning problem for single-component systems. The authors assume preventative maintenance is less expensive than failure and maintenance actions require a certain lead time. The approach is demonstrated with numerical simulations. [Yang et al., 2018]
describes a genetic-algorithm optimization approach for scheduling maintenance actions based on noisy RUL predictions. Rajora, 2018 is a dissertation largely focusing on solving hierarchical coupled constraint optimization problems that arise in maintenance scheduling and assembly planning problems. Hao et al., 2017b presumes that system degradation is a function of workload (increased workload increases degradation). The authors develop a control system that dynamically modulates workload between multiple machines, based on posterior degradation belief distributions. The controller seeks to guide failure of machines in such a way that they do not overlap, reducing risk of work-stoppage. The approach is demonstrated on simulated stamping machines.

Lin et al., 2018 argues that most CBM-oriented research in the aerospace domain focus on minimizing cost or maximizing availability of single aircraft in isolation, and rarely consider both objectives simultaneously much less that for an entire fleet. The authors propose a model for doing just that. The model assumes a simple deterministic damage function (of time) and cost function. The authors use support vector regression to effect the multi-objective optimization. Feng et al., 2017a describes a learning game-theoretic approach to fleet-level maintenance strategy aimed a minimizing cost under an availability constraint. The game is focused on learning strategies of when to replace line-replaceable modules, given failure probabilities. The authors also touch on the NP-hard nature of the fleet level CBM problem. Feng et al., 2017b extends this work to include dispatched and standby sets of aircraft. Again, game theory is used to search for optimal decision strategies.

4.4 Performance quantification

It is advisable to understand the level of predictive performance necessary for a predictive maintenance effort to yield positive utility. Such measures serve the important function of defining success both for proofs-of-concept predictive models and system performance while scaling solutions to the enterprise level. Toward that end, Busse et al., 2018 demonstrates an a priori cost-benefit-analysis for predictive maintenance capabilities. This is significant, as such analyses can provide the aforementioned understanding. The authors use a Wiener process with linear drift to model the predictions of a hypothetical RUL prediction module. They then push sampled predictions through different maintenance planning strategies, and compute total costs using a hypothetical cost model. The demonstration is conducted for a single component machine with single failure mode.

Lei et al., 2018 reviews performance metrics for RUL prediction. The authors divide metrics into offline and online measures. Offline metrics measure accuracy of RUL estimations or failure risks for example. The proposed online metrics, in contrast, do not require knowledge of future failures, comparing the current RUL estimate to its recent estimates.

4.5 Supply planning

Boev et al., 2019 sketch out a constrained optimization based approach for prescribing maintenance plans and spare part availability.

5 Gap Analysis

In the reviewed literature, the asset under study is sometimes simple such as a bearing or cutting tool and sometimes complex such as a gas turbine or automotive engine. However, when complex assets are considered, it is largely the case that either only a small number of simple components or a small number of failure modes are studied. As such, these complex assets are treated using methods analogous to those for individual components. This approach has the advantage that methods and insights developed using run-till-failure bench experiments on bearings say, can be utilized on larger systems where run-till-failure is not realistic. Further, it could be argued that one could repeat such a process for all the major components and/or failure modes of a complex asset. It has been pointed out however, that this approach could be prohibitively expensive due to the resources needed to build and maintain the numerous required models. Rögnvaldsson et al., 2018. Further, if dependencies between failure modes are to be taken into account, then there is little justification for not starting with a comprehensive model approach.

In our view, the primary gaps between our view of PMx for complex assets and current literature, center on the handling of condition and failure risk estimation/forecasting. We identify two principal gaps: failure to incorporate inter-component interactions, and failure to address the effects of maintenance.
5.1 Modeling Interactions

Modeling interactions between components can enable sub-system or system level models of failure risk, facilitating PMx for fleets of complex assets. This is not a new concept. We review some initial work in detail below. But first, we highlight work from Dependability Modeling and Analysis, a closely related discipline that specializes in this area.

5.1.1 Dependability Modeling and Analysis

Reliability and dependability analysis is standard practice in product design. The term describes the problem of quantifying the risk and nature of failures of (typically complex) equipment. Generally, the goal of dependability modelling is to relate basic events, which often represent failure of individual components, to overall sub-system and system level behavior. Such models can be used to determine the criticality of different components, overall system robustness, as well as to diagnose, correct, and avoid failures. Common methods include Failure Mode and Effects Analysis (FMEA), Failure Modes, Effects and Criticality Analysis (FMECA), (dynamic) fault-trees, (dynamic) Bayesian networks, and stochastic Petri-nets. These methods are currently being integrated into the DoD digital engineering strategy [Boydston et al., 2015] on the Future Vertical Lift (FVL) program. Of particular note on the FVL efforts is the use of modeling at both the system and subsystem level.

[Chemweno et al., 2018] gives a recent review of dependability modelling with a focus on the treatment of uncertainty, both uncertainty of predictions (aleatory) and uncertainty of the model (epistemic) [Fox and Ulkün, 2011]. The authors find that dynamic fault-tree analysis and dynamic Bayesian networks are the most common methods, together accounting for 44% of the dependability modelling literature (as measured by count of articles). They note that while Bayesian methods are naturally suited for combining evidence from different sources, limited reliability data necessitates quantifying the epistemic uncertainty beyond typically analysis of posterior distributions. Toward that end, the authors review fuzzy analysis, interval analysis, and Dempster-Shafer evidence theory (DSTE) for quantifying epistemic uncertainty. DSTE is the most common such method accounting for 46% of articles that address epistemic uncertainty. Finally, the authors identify inclusions of predictive models of failure probability into reliability models as a key future research direction.

In that respect, there are several degrees of potential integration between these distinct modeling exercises. One may build RUL and/or failure risk forecasting capability for individual components, treating each as independent. The forecast risks can then be fed into a reliability model to more comprehensively inform risk assessment process. [Lee and Pan, 2019] can be viewed as a step in this direction. The authors combine estimates of failure probability via a Markov model with a reliability model using a tree-structured Bayesian network. If significant dependencies exist in the failure risks of basic events, they will have to be taken into account. Sub-system or system level faults may impact the degradation rates of components (e.g. adjusting workloads or operating conditions due to a fault). In such circumstances is may be desirable to model basic failure risk and system reliability jointly. This could be accomplished using dynamic Bayesian networks, for example. [Chiacchio et al., 2016a, Chiacchio et al., 2016b] join stochastic hybrid automaton with dynamic fault-trees to jointly model age of components and failure risk under dynamic operating conditions. However, no learning is performed as the governing equations of the approach are given upfront.

5.1.2 Primary literature focused on complex assets

Some authors have begun to address the challenges that arise when considering complex assets. Often this means modeling the relationship between sensing and component state and component-component interactions.

[Rodrigues, 2017] introduces a particle filter model wherein the observation function is informed by system architecture. Incorporating this system-level model allows the method to relate system level performance indicators to component health state. The authors model the component health state as a gamma process. The method is demonstrated on two simulated data sets; a simplified multi-pump hydraulic system and a multi-component air conditioning system.

[Lee and Pan, 2019] assume the degradation state of each component is described by a discrete vector with \( h_i \in \{0, 1, \ldots, f_i\} \), where \( i = 1, \ldots, N \) enumerates components and \( f_i \in \mathbb{N} \) is the failure state for component \( i \). These so-called health states are presumed to be increasing in severity, until failure. Health state values are forecast \( n \) time steps into the future using a Markov model, for which the transition matrices \( P_i \) are known (or learned from historical data) for each component. The \( P_i \) also encode the assumption of non-decreasing state transitions, i.e. no spontaneous repair. Let \( \tilde{h}_i \) be a one-hot vector...
encoding the current health state for component $i$, then $P_i^{n+1} h_i$ is the posterior health state distribution for component $i$. Finally, probability of the system or a sub-system level failure is computed by a tree-structured Bayesian network, for which the parameters (conditional probability tables) are presumed known a priori.

[Barde et al., 2019] demonstrates a classical reinforcement learning strategy for maintenance of a fleet of trucks. The authors consider 8 components, and use a model-free approach with tabular $Q$ function to learn the optimal maintenance policy under different choices of reward function. This type of reinforcement learning does have optimality guarantees in the limit of sufficient state-action space exploration. However, the main advantage may be that it is easy to integrate complex logistics and incorporate the effects of multiple concurrent maintenance actions. Unfortunately, this kind of approach can only work if (i) the state-action space is discrete and of low enough arity that it can be sufficiently explored, (ii) ample observed data or realistic simulations of equipment histories are available, and (iii) failures are observed. If maintenance is largely preventative, the learning agent will not effectively be able to directly learn policy since it will not encounter penalties associated with failure. Additionally, in real-world complex equipment, the state-action space is likely to be at least partly continuous and complex, requiring function approximation techniques to learn the $Q$ function. In practice, these conditions would require massive amounts of trials to find good policies. Further, current opinion in the field is that reinforcement learning using model approximation can be very difficult to tune properly and can produce sporadic unanticipated behavior. This is unacceptable in safety critical applications such as e.g. aerospace.

[Lin et al., 2018] focuses on maintenance planning for a fleet of aircraft. The authors presume that a probability-of-failure model is given for each component, which is a function of the component’s damage level. Aircraft failure probability is taken as the maximum component level failure probability. This assumption may be in error and the aircraft failure probability depends on the statistical dependency between components. In any case, the authors define a repair cost function, dependent on the damage level of a component and a wasted [RUL] function. Finally, they optimize a two-objective decision model under the constraint that failure probability is very small.

[Hao et al., 2015] consider sub-system level sensing, e.g. vibration measurements, and study how one can isolate component-level degradation signals. The authors use independent component analysis (ICA) to separate the degradation signals for a known number of components and demonstrate [RUL] prediction on synthetic data. [Blancke et al., 2018] describes the use of Petri-nets for failure risk forecasting on complex systems. Their approach relies on expert knowledge of failure physics, and models fault propagation using a colored Petri net. Modeling the fault propagation allows for prescriptive diagnostic inference as well.

5.2 Maintenance

Maintenance of complex assets raises two primary issues. The first is that maintenance censors future failure events. Second, maintenance actions could alter the latent degradation state and its trajectory in non-trivial ways. Yet, little to no work has been put toward modeling the impact of maintenance on the latent degradation state.

Figure 3 illustrates this concept. The trajectories of three assets in the latent degradation space are shown. The failure boundary reflects the level of degradation that results in an observed failure. Asset 1 degrades and fails. For this asset, time-till-failure would be retrosepectively available. Asset 2 degrades, but transitions to another point of the state-space due to maintenance action, after which it degrades to failure along a different trajectory. For this asset time-till-failure would be misleading for early observations as they are confounded by the effect of the maintenance. No failure is observed for Asset 3, making it unusable for simple supervised [RUL] based methods.
Figure 3 represents a Markovian viewpoint. But the existence of such a latent state is well motivated by the predictive state representation (PSR) approach to partially observable Markov decision processes (POMDP) [Littman and Sutton, 2002; Singh et al., 2003; Boots et al., 2011]. Our perspective is that modeling the degradation process in this way neatly addresses the effects of maintenance on system evolution towards failure. We can structure this formulation as a representation learning task. The objective would be to learn an embedding function that would map an asset’s history into a latent vector representation. The evolution of these vectors could be presumed (e.g. incremented by cumulative historical load), or modeled. Finally, the effect of each maintenance action could also be modeled. This approach naturally makes use of all available data whether or not failures are observed. It can be realized in many ways. For example, one could use deep recurrent networks to map histories to the latent state and model maintenance as additive functions of current state and action type. Finally, structural, physical, or reliability models of the assets can be incorporated into this modeling exercise to reduce data-driven model learning costs and improve accuracy.

6 Conclusion

We reviewed current literature in the field of predictive maintenance. We identified several fundamental differences between condition estimation and failure risk forecasting as applied to simple components such as bearings and cutting tools from the capabilities needed to solve the same tasks on complex assets. These differences stem from complex latent degradation states, active maintenance programs, increased coupling between maintenance actions, and higher monetary and safety costs for failures.

As a result, methods that are effective for forecasting risk and informing maintenance decisions for individual components do not readily scale to sub-system or system level insights. A holistic modeling approach is needed that incorporates available structural and physical knowledge and naturally handles the complexities of actively fielded and maintained assets.

References

[Agogino and Goebel, 2007] Agogino, A. and Goebel, K. (2007). Milling data set. NASA Ames Prognostics Data Repository, BEST Lab: Berkeley, CA, USA.

[Amruthnath and Gupta, 2018] Amruthnath, N. and Gupta, T. (2018). A research study on unsupervised machine learning algorithms for early fault detection in predictive maintenance. In 2018 5th International Conference on Industrial Engineering and Applications (ICIEA), pages 355–361. IEEE.

[Atamuradov et al., 2018] Atamuradov, V., Medjaher, K., Camci, F., Dersin, P., and Zerhouni, N. (2018). Railway point machine prognostics based on feature fusion and health state assessment. IEEE Transactions on Instrumentation and Measurement.

[Baptista et al., 2019] Baptista, M., Henriques, E. M., de Medeiros, I. P., Malere, J. P., Nascimento Jr, C. L., and Prendinger, H. (2019). Remaining useful life estimation in aeronautics: Combining data-driven and Kalman filtering. Reliability Engineering & System Safety, 184:228–239.

[Baptista et al., 2018] Baptista, M., Sankararaman, S., de Medeiros, I. P., Nascimento Jr, C., Prendinger, H., and Henriques, E. M. (2018). Forecasting fault events for predictive maintenance using data-driven techniques and ARMA modeling. Computers & Industrial Engineering, 115:41–53.

[Barajas and Srinivasan, 2008] Barajas, L. G. and Srinivasan, N. (2008). Real-time diagnostics, prognostics and health management for large-scale manufacturing maintenance systems. In Asme 2008 international manufacturing science and engineering conference collocated with the 3rd jsme/asme international conference on materials and processing, pages 85–94. American Society of Mechanical Engineers.

[Baraldi et al., 2012] Baraldi, P., Mangili, F., and Zio, E. (2012). A Kalman filter-based ensemble approach with application to turbine creep prognostics. IEEE Transactions on Reliability, 61(4):966–977.

[Barde et al., 2019] Barde, S. R., Yacout, S., and Shin, H. (2019). Optimal preventive maintenance policy based on reinforcement learning of a fleet of military trucks. Journal of Intelligent Manufacturing, 30(1):147–161.

[Basciftci et al., 2018] Basciftci, B., Ahmed, S., Gebraeel, N. Z., and Yildirim, M. (2018). Stochastic optimization of maintenance and operations schedules under unexpected failures. IEEE Transactions on Power Systems, 33(6):6755–6765.
[Bastos et al., 2014] Bastos, P., Lopes, I., and Pires, L. (2014). Application of data mining in a maintenance system for failure prediction. *Safety, Reliability and Risk Analysis: Beyond the Horizon: 22nd European Safety and Reliability*, 1:933–940.

[Bey-Temsamani et al., 2009] Bey-Temsamani, A., Engels, M., Motten, A., Vandenplas, S., and Om-pusunggu, A. P. (2009). A practical approach to combine data mining and prognostics for improved predictive maintenance. *Data Min. Case Stud.*, 36.

[Bian et al., 2015] Bian, L., Gebraeel, N., and Kharoufeh, J. P. (2015). Degradation modeling for real-time estimation of residual lifetimes in dynamic environments. *IEE Transactions*, 47(5):471–486.

[Biteus and Lindgren, 2017] Biteus, J. and Lindgren, T. (2017). Planning flexible maintenance for heavy trucks using machine learning models, constraint programming, and route optimization. *SAE International Journal of Materials and Manufacturing*, 10(3):306–315.

[Bian et al., 2015] Bian, L., Gebraeel, N., and Kharoufeh, J. P. (2015). Degradation modeling for real-time estimation of residual lifetimes in dynamic environments. *IEE Transactions*, 47(5):471–486.

[Bey-Temsamani et al., 2009] Bey-Temsamani, A., Engels, M., Motten, A., Vandenplas, S., and Om-pusunggu, A. P. (2009). A practical approach to combine data mining and prognostics for improved predictive maintenance. *Data Min. Case Stud.*, 36.

[Bian et al., 2015] Bian, L., Gebraeel, N., and Kharoufeh, J. P. (2015). Degradation modeling for real-time estimation of residual lifetimes in dynamic environments. *IEE Transactions*, 47(5):471–486.

[Biteus and Lindgren, 2017] Biteus, J. and Lindgren, T. (2017). Planning flexible maintenance for heavy trucks using machine learning models, constraint programming, and route optimization. *SAE International Journal of Materials and Manufacturing*, 10(3):306–315.

[Bian et al., 2015] Bian, L., Gebraeel, N., and Kharoufeh, J. P. (2015). Degradation modeling for real-time estimation of residual lifetimes in dynamic environments. *IEE Transactions*, 47(5):471–486.

[Bey-Temsamani et al., 2009] Bey-Temsamani, A., Engels, M., Motten, A., Vandenplas, S., and Om-pusunggu, A. P. (2009). A practical approach to combine data mining and prognostics for improved predictive maintenance. *Data Min. Case Stud.*, 36.

[Bian et al., 2015] Bian, L., Gebraeel, N., and Kharoufeh, J. P. (2015). Degradation modeling for real-time estimation of residual lifetimes in dynamic environments. *IEE Transactions*, 47(5):471–486.

[Bey-Temsamani et al., 2009] Bey-Temsamani, A., Engels, M., Motten, A., Vandenplas, S., and Om-pusunggu, A. P. (2009). A practical approach to combine data mining and prognostics for improved predictive maintenance. *Data Min. Case Stud.*, 36.

[Bian et al., 2015] Bian, L., Gebraeel, N., and Kharoufeh, J. P. (2015). Degradation modeling for real-time estimation of residual lifetimes in dynamic environments. *IEE Transactions*, 47(5):471–486.

[Bey-Temsamani et al., 2009] Bey-Temsamani, A., Engels, M., Motten, A., Vandenplas, S., and Om-pusunggu, A. P. (2009). A practical approach to combine data mining and prognostics for improved predictive maintenance. *Data Min. Case Stud.*, 36.
[Chukwuekwe et al., 2016] Chukwuekwe, D. O., Schjølberg, P., Rødseth, H., and Stuber, A. (2016). Reliable, robust and resilient systems: towards development of a predictive maintenance concept within the industry 4.0 environment. In EFNMS Euro Maintenance Conference.

[Cipollini et al., 2018] Cipollini, F., Oneto, L., Coraddu, A., Murphy, A. J., and Anguita, D. (2018). Condition-based maintenance of naval propulsion systems: Data analysis with minimal feedback. Reliability Engineering & System Safety, 177:12–23.

[Cline et al., 2017] Cline, B., Niculescu, R. S., Huffman, D., and Deckel, B. (2017). Predictive maintenance applications for machine learning. In 2017 Annual Reliability and Maintainability Symposium (RAMS), pages 1–7. IEEE.

[Coraddu et al., 2016] Coraddu, A., Oneto, L., Ghio, A., Savio, S., Anguita, D., and Figari, M. (2016). Machine learning approaches for improving condition-based maintenance of naval propulsion plants. Proceedings of the Institution of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment, 230(1):136–153.

[Cristaldi et al., 2016] Cristaldi, L., Leone, G., Ottoboni, R., Subbiah, S., and Turrin, S. (2016). A comparative study on data-driven prognostic approaches using fleet knowledge. In 2016 IEEE International Instrumentation and Measurement Technology Conference Proceedings, pages 1–6. IEEE.

[Dua and Graff, 2017] Dua, D. and Graff, C. (2017). UCI machine learning repository.

[Dubrawski and Sondheimer, 2011] Dubrawski, A. and Sondheimer, N. (2011). Techniques for early warning of systematic failures of aerospace components. In 2011 Aerospace Conference, pages 1–9. IEEE.

[Eker et al., 2012] Eker, Ö. F., Camci, F., and Jennions, I. K. (2012). Major challenges in prognostics: study on benchmarking prognostic datasets. PHM Society, 3(4).

[Enrico et al., 2019] Enrico, Z., Mengfei, F., Zhiguo, Z., and Rui, K. (2019). Application of reliability technologies in civil aviation: Lessons learnt and perspectives. Chinese Journal of Aeronautics, 32(1):143–158.

[Fang, 2018] Fang, X. (2018). Predictive Analytics for Complex Engineering Systems Using High-Dimensional Signals. PhD thesis, Georgia Institute of Technology.

[Fang et al., 2017a] Fang, X., Gebrael, N. Z., and Paynabar, K. (2017a). Scalable prognostic models for large-scale condition monitoring applications. IISE Transactions, 49(7):698–710.

[Fang et al., 2017b] Fang, X., Paynabar, K., and Gebrael, N. (2017b). Multistream sensor fusion-based prognostics model for systems with single failure modes. Reliability Engineering & System Safety, 159:322–331.

[Fang et al., 2018] Fang, X., Paynabar, K., and Gebrael, N. (2018). Real-time predictive analytics using degradation image data. In 2018 Annual Reliability and Maintainability Symposium (RAMS), pages 1–6. IEEE.

[Fang et al., 2019] Fang, X., Paynabar, K., and Gebrael, N. (2019). Image-based prognostics using penalized tensor regression. Technometrics, pages 1–29.

[Feng et al., 2017a] Feng, Q., Bi, W., Chen, Y., Ren, Y., and Yang, D. (2017a). Cooperative game approach based on agent learning for fleet maintenance oriented to mission reliability. Computers & Industrial Engineering, 112:221–230.

[Feng et al., 2017b] Feng, Q., Bi, X., Zhao, X., Chen, Y., and Sun, B. (2017b). Heuristic hybrid game approach for fleet condition-based maintenance planning. Reliability Engineering & System Safety, 157:166–176.

[Ferreiro et al., 2016] Ferreiro, S., Konde, E., Fernández, S., and Prado, A. (2016). Industry 4.0: Predictive intelligent maintenance for production equipment. In European Conference of the Prognostics and Health Management Society, pages 1–8.
[Fox and Ülkümen, 2011] Fox, C. R. and Ülkümen, G. (2011). Distinguishing two dimensions of uncertainty. *Perspectives on thinking, judging, and decision making*, pages 21–35.

[Fumeo et al., 2015] Fumeo, E., Oneto, L., and Anguita, D. (2015). Condition based maintenance in railway transportation systems based on big data streaming analysis. *Procedia Computer Science*, 53:437–446.

[Galán and Gómez, 2018] Galán, M. H. and Gómez, E. A. M. (2018). A review of maintenance management models: Application for the clinic and hospital environment. *The International Journal of Engineering and Science (IJES)*, 7(9):1–17.

[Galar et al., 2015] Galar, D., Thaduri, A., Catelani, M., and Ciani, L. (2015). Context awareness for maintenance decision making: A diagnosis and prognosis approach. *Measurement*, 67:137–150.

[Gardner et al., 2017] Gardner, J., Koutra, D., Mroueh, J., Pang, V., Farahi, A., Krassenstein, S., and Webb, J. (2017). Driving with data: Modeling and forecasting vehicle fleet maintenance in Detroit. *arXiv preprint arXiv:1710.06839*.

[Gerdes et al., 2016] Gerdes, M., Scholz, D., and Galar, D. (2016). Effects of condition-based maintenance on costs caused by unscheduled maintenance of aircraft. *Journal of Quality in Maintenance Engineering*, 22(4):394–417.

[Ghasemi et al., 2007] Ghasemi, A., Yacout, S., and Ouali, M. (2007). Optimal condition based maintenance with imperfect information and the proportional hazards model. *International journal of production research*, 45(4):989–1012.

[Graß et al., 2019] Graß, A., Beecks, C., and Soto, J. A. C. (2019). Unsupervised anomaly detection in production lines. In *Machine Learning for Cyber Physical Systems*, pages 18–25. Springer.

[Guo et al., 2017] Guo, L., Li, N., Jia, F., Lei, Y., and Lin, J. (2017). A recurrent neural network based health indicator for remaining useful life prediction of bearings. *Neurocomputing*, 240:98–109.

[Hao et al., 2017a] Hao, L., Bian, L., Gebraeel, N., and Shi, J. (2017a). Residual life prediction of multistage manufacturing processes with interaction between tool wear and product quality degradation. *IEEE Transactions on Automation Science and Engineering*, 14(2):1211–1224.

[Hao et al., 2015] Hao, L., Gebraeel, N., and Shi, J. (2015). Simultaneous signal separation and prognostics of multi-component systems: The case of identical components. *IIE Transactions on Automation Science and Engineering*, 14(2):1042–1052.

[Hao et al., 2017b] Hao, L., Liu, K., Gebraeel, N., and Shi, J. (2017b). Controlling the residual life distribution of parallel unit systems through workload adjustment. *IEEE Transactions on Automation Science and Engineering*, 14(2):101–110. Springer.

[Jia et al., 2019] Jia, Z., Liu, Z., Vong, C.-M., and Pecht, M. (2019). A rotating machinery fault diagnosis method based on feature learning of thermal images. *IEEE Access*.

[Jiang et al., 2015] Jiang, Y., Chen, M., and Zhou, D. (2015). A POMDP based decentralized maintenance for multi-state system with heterogeneous components. In *2015 Chinese Automation Congress (CAC)*, pages 2057–2062. IEEE.

[Kanawaday and Sane, 2017] Kanawaday, A. and Sane, A. (2017). Machine learning for predictive maintenance of industrial machines using IoT sensor data. In *2017 8th IEEE International Conference on Software Engineering and Service Science (ICSESS)*, pages 87–90. IEEE.

[Kateris et al., 2014] Kateris, D., Moshou, D., Pantazi, X.-E., Gravalos, I., Sawalhi, N., and Loutridis, S. (2014). A machine learning approach for the condition monitoring of rotating machinery. *Journal of Mechanical Science and Technology*, 28(1):61–71.

[Korvesis et al., 2018] Korvesis, P., Besseau, S., and Vazirgiannis, M. (2018). Predictive maintenance in aviation: Failure prediction from post-flight reports. In *2018 IEEE 34th International Conference on Data Engineering (ICDE)*, pages 1414–1422. IEEE.

[Kraisangka and Druzdzel, 2016] Kraisangka, J. and Druzdzel, M. J. (2016). Making large Cox’s proportional hazard models tractable in Bayesian networks. In *Conference on Probabilistic Graphical Models*, pages 252–263.
[Kraisangka and Druzdzel, 2018] Kraisangka, J. and Druzdzel, M. J. (2018). A Bayesian network interpretation of the Cox’s proportional hazard model. International Journal of Approximate Reasoning, 103:195–211.

[Kroll et al., 2014] Kroll, B., Schaffranek, D., Schriegel, S., and Niggemann, O. (2014). System modeling based on machine learning for anomaly detection and predictive maintenance in industrial plants. In Proceedings of the 2014 IEEE Emerging Technology and Factory Automation (ETFA), pages 1–7. IEEE.

[Le et al., 2017] Le, V. T., Lim, C. P., Mohamed, S., Nahavandi, S., Yen, L., Gallasch, G. E., Baker, S., Ludovici, D., Draper, N., Wickramanayake, V., et al. (2017). Condition monitoring of engine lubrication oil of military vehicles: A machine learning approach. In 17th Australian International Aerospace Congress: AIAA 2017, page 718. Engineers Australia, Royal Aeronautical Society.

[Lee and Pan, 2019] Lee, D. and Pan, R. (2019). Evaluating reliability of complex systems for predictive maintenance. arXiv preprint arXiv:1902.03495.

[Lee et al., 2015] Lee, J., Bagheri, B., and Kao, H.-A. (2015). A cyber-physical systems architecture for industry 4.0-based manufacturing systems. Manufacturing Letters, 3:18–23.

[Lee et al., 2014a] Lee, J., Kao, H.-A., and Yang, S. (2014a). Service innovation and smart analytics for industry 4.0 and big data environment. Procedia CIRP, 16:3–8.

[Lee et al., 2007] Lee, J., Qiu, H., Yu, G., and Lin, J. (2007). Rexnord technical services: Bearing data set. Moffett Field, CA: IMS, Univ. Cincinnati. NASA Ames Prognostics Data Repository, NASA Ames.

[Lei et al., 2018] Lei, Y., Li, N., Guo, L., Li, N., Yan, T., and Lin, J. (2018). Machinery health prognostics: A systematic review from data acquisition to rul prediction. Mechanical Systems and Signal Processing, 104:799–834.

[Li et al., 2019a] Li, N., Gebraeel, N., Lei, Y., Bian, L., and Si, X. (2019a). Remaining useful life prediction of machinery under time-varying operating conditions based on a two-factor state-space model. Reliability Engineering & System Safety.

[Li et al., 2014b] Li, Z., Goebel, K., and Wu, D. (2014b). Degradation modeling and remaining useful life prediction of aircraft engines using ensemble learning. Journal of Engineering for Gas Turbines and Power, 141(4):041008.

[Liao et al., 2016] Liao, L., Jin, W., and Pavel, R. (2016). Enhanced restricted boltzmann machine with prognosability regularization for prognostics and health assessment. IEEE Transactions on Industrial Electronics, 63(11):7076–7083.

[Lin et al., 2018] Lin, L., Luo, B., and Zhong, S. (2018). Multi-objective decision-making model based on CBM for an aircraft fleet with reliability constraint. International Journal of Production Research, 56(14):4831–4848.

[Littman and Sutton, 2002] Littman, M. L. and Sutton, R. S. (2002). Predictive representations of state. In Advances in neural information processing systems, pages 1555–1561.

[Liu and Goebel, 2018] Liu, Y. and Goebel, K. (2018). Information fusion for national airspace system prognostics. In PHM Society Conference, volume 10.

[Liu et al., 2018] Liu, Z., Meyendorf, N., and Mrad, N. (2018). The role of data fusion in predictive maintenance using digital twin. In AIP Conference Proceedings, volume 1949, page 020023. AIP Publishing.

[Luo et al., 2019] Luo, B., Wang, H., Liu, H., Li, B., and Peng, F. (2019). Early fault detection of machine tools based on deep learning and dynamic identification. IEEE Transactions on Industrial Electronics, 66(1):509–518.
[Magargle et al., 2017] Magargle, R., Johnson, L., Mandloi, P., Davoudabadi, P., Kesarkar, O., Krishnaswamy, S., Batteh, J., and Pitchaikani, A. (2017). A simulation-based digital twin for model-driven health monitoring and predictive maintenance of an automotive braking system. In Proceedings of the 12th International Modelica Conference, Prague, Czech Republic, May 15-17, 2017, number 132 in Linköping Electronic Conference Proceedings, pages 35–46. Linköping University Electronic Press.

[Maillart, 2006] Maillart, L. M. (2006). Maintenance policies for systems with condition monitoring and obvious failures. IIE Transactions, 38(6):463–475.

[Martin-del Campo et al., 2019] Martin-del Campo, S., Sandin, F., and Strömbergsson, D. (2019). Dictionary learning approach to monitoring of wind turbine drivetrain bearings. arXiv preprint arXiv:1902.01426.

[Mattes et al., 2012] Mattes, A., Schöpka, U., Schellenberger, M., Scheibelhofer, P., and Leditzky, G. (2012). Virtual equipment for benchmarking predictive maintenance algorithms. In Proceedings of the 2012 Winter Simulation Conference (WSC), pages 1–12. IEEE.

[Meraghni et al., 2018] Meraghni, S., Terrissa, L. S., Ayad, S., Zerhouni, N., and Varnier, C. (2018). Post-prognostics decision in cyber-physical systems. In 2018 International Conference on Advanced Systems and Electric Technologies (IC_ASET), pages 201–205. IEEE.

[Merizalde et al., 2019] Merizalde, Y., Hernández-Callejo, L., Duque-Perez, O., and Alonso-Gómez, V. (2019). Maintenance models applied to wind turbines. A comprehensive overview. Energies, 12(2):225.

[Michau et al., 2018] Michau, G., Palmé, T., and Fink, O. (2018). Fleet PHM for critical systems: Bi-level deep learning approach for fault detection. In Proceedings of the Fourth European Conference of the Prognostics and Health Management Society, volume 4.

[Michelassi et al., 2018] Michelassi, V., Allegorico, C., Cioncolini, S., Graziano, A., Tognarelli, L., and Sepe, M. (2018). Machine learning in gas turbines. Mechanical Engineering Magazine Select Articles, 140(09):S54–S55.

[Mishra et al., 2018] Mishra, M., Martinsson, J., Rantatalo, M., and Goebel, K. (2018). Bayesian hierarchical model-based prognostics for lithium-ion batteries. Reliability Engineering & System Safety, 172:25–35.

[Moghaddass and Ertekin, 2018] Moghaddass, R. and Ertekin, Ş. (2018). Joint optimization of ordering and maintenance with condition monitoring data. Annals of Operations Research, 263(1-2):271–310.

[NASA, 2019] NASA (2019). PCoE Datasets. https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/. Accessed: 2019-04-06.

[Nascimento and Viana, 2019] Nascimento, R. G. and Viana, F. A. (2019). Fleet prognosis with physics-informed recurrent neural networks. arXiv preprint arXiv:1901.05512.

[Nectoux et al., 2012] Nectoux, P., Gouriveau, R., Medjaher, K., Ramasso, E., Chebel-Morello, B., Zerhouni, N., and Varnier, C. (2012). PRONOSTIA: An experimental platform for bearings accelerated degradation tests. In IEEE International Conference on Prognostics and Health Management, PHM’12, pages 1–8. IEEE Catalog Number: CPF12PHM-CDR.

[Nixon et al., 2018] Nixon, S., Weichel, R., Reichard, K., and Kozlowski, J. (2018). A machine learning approach to diesel engine health prognostics using engine controller data. In PHM Society Conference, volume 10.

[Oehling and Barry, 2019] Oehling, J. and Barry, D. J. (2019). Using machine learning methods in airline flight data monitoring to generate new operational safety knowledge from existing data. Safety Science, 114:89–104.

[Office of the Deputy Assistant Secretary of Defense for Systems Engineering, 2018] Office of the Deputy Assistant Secretary of Defense for Systems Engineering, D. O. D. (2018). Digital engineering strategy. https://fas.org/man/eprint/digeng-2018.pdf.

[Patwardhan et al., 2016] Patwardhan, A., Verma, A. K., and Kumar, U. (2016). A survey on predictive maintenance through big data. In Current Trends in Reliability, Availability, Maintainability and Safety, pages 437–445. Springer.

[Poosapati et al., 2019] Poosapati, V., Katneni, V., Manda, V. K., and Ramesh, T. (2019). Enabling cognitive predictive maintenance using machine learning: Approaches and design methodologies. In Soft Computing and Signal Processing, pages 37–45. Springer.
[Prytz et al., 2015] Prytz, R., Nowaczyk, S., Rögnvaldsson, T., and Byttner, S. (2015). Predicting the need for vehicle compressor repairs using maintenance records and logged vehicle data. *Engineering applications of artificial intelligence*, 41:139–150.

[Qiu et al., 2006] Qiu, H., Lee, J., Lin, J., and Yu, G. (2006). Wavelet filter-based weak signature detection method and its application on rolling element bearing prognostics. *Journal of sound and vibration*, 289(4-5):1066–1090.

[Ragab et al., 2016] Ragab, A., Yacout, S., and Ouali, M.-S. (2016). Remaining useful life prognostics using pattern-based machine learning. In *2016 Annual Reliability and Maintainability Symposium (RAMS)*, pages 1–7. IEEE.

[Rahman et al., 2018] Rahman, M., Zaccaria, V., Zhao, X., and Kyriamidis, K. (2018). Diagnostics-oriented modelling of micro gas turbines for fleet monitoring and maintenance optimization. *Processes*, 6(11):216.

[Rajora, 2018] Rajora, M. (2018). *INTELLIGENT MANUFACTURING FOR PRODUCTION PLANNING BASED UPON HIERARCHICALLY COUPLED CONSTRAINED AND MULTIMODAL OPTIMIZATION*. PhD thesis, Georgia Institute of Technology.

[Rausch et al., 2007] Rausch, R. T., Goebel, K. F., Eklund, N. H., and Brunell, B. J. (2007). Integrated in-flight fault detection and accommodation: A model-based study. *Journal of Engineering for Gas Turbines and Power*, 129(4):962–969.

[Rezvanizaniani et al., 2014] Rezvanizaniani, S. M., Liu, Z., Chen, Y., and Lee, J. (2014). Review and recent advances in battery health monitoring and prognostics technologies for electric vehicle (EV) safety and mobility. *Journal of Power Sources*, 256:110–124.

[Rodrigues, 2017] Rodrigues, L. R. (2017). Remaining useful life prediction for multiple-component systems based on a system-level performance indicator. *IEEE/ASME Transactions on Mechatronics*, 23(1):141–150.

[Rögnvaldsson et al., 2018] Rögnvaldsson, T., Nowaczyk, S., Byttner, S., Prytz, R., and Svensson, M. (2018). Self-monitoring for maintenance of vehicle fleets. *Data mining and knowledge discovery*, 32(2):344–384.

[Saha and Goebel, 2007] Saha, B. and Goebel, K. (2007). Battery data set. *NASA AMES prognostics data repository.*

[Sakib and Wuest, 2018] Sakib, N. and Wuest, T. (2018). Challenges and opportunities of condition-based predictive maintenance: A review. *Procedia CIRP*, 78:267–272.

[Salo et al., 2018] Salo, E., McMillan, D., and Connor, R. (2018). Value from free-text maintenance records: converting wind farm work orders into quantifiable, actionable information using text mining. *Analysis of Operating Wind Farms 2018*.

[Saxena and Goebel, 2008] Saxena, A. and Goebel, K. (2008). Turbofan engine degradation simulation data set. [http://ti.arc.nasa.gov/project/prognostic-data-repository](http://ti.arc.nasa.gov/project/prognostic-data-repository)

[Schmidt et al., 2016] Schmidt, B., Galar, D., and Wang, L. (2016). Context awareness in predictive maintenance. In *Current trends in reliability, availability, maintainability and safety*, pages 197–211. Springer.

[Schmidt and Wang, 2018] Schmidt, B. and Wang, L. (2018). Cloud-enhanced predictive maintenance. *The International Journal of Advanced Manufacturing Technology*, 99(1-4):5–13.

[Sezer et al., 2018] Sezer, E., Romero, D., Guedea, F., Macchi, M., and Emmanouilidis, C. (2018). An industry 4.0-enabled low cost predictive maintenance approach for SMEs. In *2018 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC)*, pages 1–8. IEEE.

[Si et al., 2011] Si, X.-S., Wang, W., Hu, C.-H., and Zhou, D.-H. (2011). Remaining useful life estimation—a review on the statistical data driven approaches. *European journal of operational research*, 213(1):1–14.

[Singh et al., 2003] Singh, S. P., Littman, M. L., Jong, N. K., Pardoe, D., and Stone, P. (2003). Learning predictive state representations. In *Proceedings of the 20th International Conference on Machine Learning (ICML-03)*, pages 712–719.

[Sipos et al., 2014] Sipos, R., Fradkin, D., Moerchen, F., and Wang, Z. (2014). Log-based predictive maintenance. In *Proceedings of the 20th ACM SIGKDD international conference on knowledge discovery and data mining*, pages 1867–1876. ACM.
[Susto and Beghi, 2016] Susto, G. A. and Beghi, A. (2016). Dealing with time-series data in predictive maintenance problems. In 2016 IEEE 21st International Conference on Emerging Technologies and Factory Automation (ETFA), pages 1–4. IEEE.

[Susto et al., 2015] Susto, G. A., Schirru, A., Pampuri, S., McLoone, S., and Beghi, A. (2015). Machine learning for predictive maintenance: A multiple classifier approach. IEEE Transactions on Industrial Informatics, 11(3):812–820.

[Tambe et al., 2015] Tambe, S., Bayoumi, A.-M. E., Cao, A., McCaslin, R., Edwards, T., and Center, C.-B. M. (2015). An extensible CBM architecture for naval fleet maintenance using open standards. In Intelligent Ship Symposium, Boston, USA.

[Teixeira et al., 2015] Teixeira, R. E., Morris, K. E., and Sautter, F. C. (2015). Probabilistic machine learning could eliminate no fault found. Procedia CIRP, 38:124–128.

[Trodd, 1998] Trodd, G. (1998). Practical implementation of predictive maintenance. In Conference Record of 1998 Annual Pulp and Paper Industry Technical Conference (Cat. No. 98CH36219), pages 29–37. IEEE.

[Virkler et al., 1979] Virkler, D. A., Hillberry, B., and Goel, P. (1979). The statistical nature of fatigue crack propagation. Journal of Engineering Materials and Technology, 101(2):148–153.

[Vogl et al., 2019] Vogl, G. W., Weiss, B. A., and Helu, M. (2019). A review of diagnostic and prognostic capabilities and best practices for manufacturing. Journal of Intelligent Manufacturing, 30(1):79–95.

[Wade et al., 2017] Wade, D., Vongpaseuth, T., Lugos, R., Ayscue, J., Wilson, A., Antolick, L., Brower, N., Krink, S., Szeliwistowski, M., and Albarado, K. (2015). Machine learning algorithms for HUMS improvement on rotorcraft components. In Proceedings of the 71st Annual Forum of the American Helicopter Society.

[Wade et al., 2017] Wade, D. R., Wilson, A. W., et al. (2017). Applying machine learning-based diagnostic functions to rotorcraft safety. In 17th Australian International Aerospace Congress: AIAC 2017, page 663. Engineers Australia, Royal Aeronautical Society.

[Wagner et al., 2016] Wagner, C., Saalmann, P., and Hellingrath, B. (2016). An overview of useful data and analyzing techniques for improved multivariate diagnostics and prognostics in condition-based maintenance. In Proceedings of Annual Conference of the Prognostics and Health Management Society, pages 3–6.

[Wang et al., 2017] Wang, J., Li, C., Han, S., Sarkar, S., and Zhou, X. (2017). Predictive maintenance based on event-log analysis: A case study. IBM Journal of Research and Development, 61(1):11–121.

[Xin et al., 2017] Xin, P., Khan, F., and Ahmed, S. (2017). Dynamic hazard identification and scenario mapping using Bayesian network. Process Safety and Environmental Protection, 105:143–155.

[Xue et al., 2008] Xue, F., Bonissone, P., Varma, A., Yan, W., Ekland, N., and Goebel, K. (2008). An instance-based method for remaining useful life estimation for aircraft engines. Journal of failure analysis and prevention, 8(2):199–206.

[Yan et al., 2017] Yan, J., Meng, Y., Lu, L., and Li, L. (2017). Industrial big data in an industry 4.0 environment: Challenges, schemes, and applications for predictive maintenance. IEEE Access, 5:23484–23491.

[Yan, 2016] Yan, W. (2016). One-class extreme learning machines for gas turbine combustor anomaly detection. In 2016 International Joint Conference on Neural Networks (IJCNN), pages 2909–2914. IEEE.

[Yang et al., 2008] Yang, Z. M., Djurdjanovic, D., and Ni, J. (2008). Maintenance scheduling in manufacturing systems based on predicted machine degradation. Journal of intelligent manufacturing, 19(1):87–98.

[Yildirim et al., 2017] Yildirim, M., Gebraeel, N. Z., and Sun, X. A. (2017). Integrated predictive analytics and optimization for opportunistic maintenance and operations in wind farms. IEEE Transactions on Power Systems, 32(6):4319–4328.

[Yildirim et al., 2016a] Yildirim, M., Sun, X. A., and Gebraeel, N. Z. (2016a). Sensor-driven condition-based generator maintenance scheduling—part i: Maintenance problem. IEEE Transactions on Power Systems, 31(6):4253–4262.

[Yildirim et al., 2016b] Yildirim, M., Sun, X. A., and Gebraeel, N. Z. (2016b). Sensor-driven condition-based generator maintenance scheduling—part ii: Incorporating operations. IEEE Transactions on Power Systems, 31(6):4263–4271.
[Zhang et al., 2018] Zhang, J., Wang, P., Yan, R., and Gao, R. X. (2018). Deep learning for improved system remaining life prediction. Procedia CIRP, 72:1033–1038.

[Zhao et al., 2019] Zhao, M., Kang, M., Tang, B., and Pecht, M. (2019). Multiple wavelet coefficients fusion in deep residual networks for fault diagnosis. IEEE Transactions on Industrial Electronics, 66(6):4696–4706.

A Acronyms

ARL Average Run Length
ARMA Autoregressive Moving Average
ATM Automated Teller Machine
CART Classification And Regression Trees
CBM Condition Based Maintenance
CNC Computer Numerical Control
COSMO Consensus Self-Organizing Models
DET Digital Engineering Transformation
DSTE Dempster-Shafer Evidence Theory
EDD Expected Detection Delay
EGT Exhausted Gas Temperature
ELM Extreme Learning Machine
EU European Union
FEMTO Franche-Comté Electronics Mechanics Thermal Science and Optics
FMEA Failure Mode and Effects Analysis
FMECA Failure Modes, Effects and Criticality Analysis
FPCA Functional Principal Component Analysis
FPR False Postive Rate
FVL Future Vertical Lift
GLR Generalized Likelihood Ratio
HUMS Health and Usage Monitoring System
IAS Indicated Airspeed
ICA Independent Component Analysis
IGBT Insulated Gate Bipolar Transistor
IMS Intelligent Maintenance Systems
IRT Infrared Thermography
LPLQ Low Power/Low Torque
LSTM Long Short-Term Memory
N2 Core Speed
NASA National Aeronautics and Space Administration
NG Compressor Speed
NGB Nose Gearboxe
NLP Natural Language Processing
NP Power Turbine Speed
OAT Outside Air Temperature
PCA Principle Component Analysis
PdM Predictive Maintenance
PHM  Predictive/Prognostic Health Management
PMx  Predictive Maintenance
POMDP Partially Observable Markov Decision Process
PSR  Predictive State Representation
RCM  Reliability Centered Maintenance
RLA  Randomized Low-rank Approximation
RNN  Recurrent Neural Network
RPM  Rotations Per Minute
RUL  Remaining Useful Life
TGT  Turbine Gas Temperature
TNR  True Negative Rate
TPR  True Positive Rate
UCI  University of California, Irvine
USA  United States of America
VHUMS Vehicle Health and Usage Monitoring System
WF  Fuel Flow