Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 107 (2022) 77–82

www.elsevier.com/locate/procedia

55th CIRP Conference on Manufacturing Systems

A Decision-Based Framework for Predictive Maintenance Technique Selection in Industry 4.0

J.Li[a], D. Schaefer[b], J. Milisavljevic-Syed[a]*

[a]Systems Realization Laboratory, School of Engineering, University of Liverpool, Brownlow Hill, Liverpool L69 3GH, United Kingdom

[b]School of Engineering, University of Lincoln, Brayford Pool, Lincoln, LN6 7TS, United Kingdom

* Corresponding author. Tel.: +44 151 795 7362. *E-mail address:* j.milisavljevic-syed@liverpool.ac.uk

Abstract

Maintenance is defined as the actions that allow machines and equipment to work for an extended period of time by retaining and restoring equipment to its original state. In Industry 4.0 context, Predictive Maintenance (PdM) is a strategy that utilizes digitized sensor data and data analytics to continuously monitor the state of machine components or processes to determine when and where maintenance actions may be required. There are five key types of PdM techniques being used in practice: experience-based, model-based, physical-based; data-driven; and hybrid. Selecting the most suitable PdM technique for a given setup or scenario is critical for any successful PdM implementation in industry to optimize cost and time. To help businesses in identifying and selecting the most appropriate PdM technique for their specific purposes, the authors propose a corresponding decision-making framework based on several critical factors to be considered in the process. They also discuss how the framework might best be used in industrial strategic planning processes and elaborate on its limitations and challenges.

Keywords: Predictive Maintenance, Industry 4.0, Maintenance 4.0, Decision Making,

1. Introduction

Maintenance is defined as the combination of all the technical and administrative actions, including supervision, intended to retain an item or restore it to a state in which it can perform its required function [1]. In Industry 4.0 context, Predictive Maintenance (PdM) is a strategy that utilizes digitized sensor data along with data analytics to continuously monitor the state of machine components or processes to determine when and where maintenance may be required. According to Zhang et al. [2], predictive maintenance can both minimize maintenance costs and maximize a device's service life.

Industry 4.0 is driven by technologies such as Internet of Things (IoT), Big data, Cyber-Physical Systems (CPS), Artificial Intelligence (AI), etc. machine operation Data such as speed and power and environment data such as humidity is often continuously measured and recorded. PdM is realized by analyzing such data. PdM can realize high-quality maintenance operations and reduce maintenance cost and improve product quality and increase customer satisfaction. In addition, generating new sources of income is also a potential advantage of PdM.

10.1016/j.procir.2022.04.013

Although the advantages of PdM have been widely recognized, there are several barriers to implementation in practice. One of the main barriers is a lack of systematic methods to support enterprises in selecting the most suitable PdM technique for their specific needs. There are five types of PdM techniques used in practice: experience-based, model-based, physical-based; data-driven; and hybrid. Each one has its particular requirements in terms of hardware, software, information, etc. Accordingly, implementation cost and time for each PdM technique vary, as does their capability spectrum. PdM technique capability refers to each technique's tasks, such as accurate component state prediction, fault prognostic, and assets service live extension. Selecting the most suitable PdM technique for a given setup or scenario is critical for any successful implementation in industry for cost and time optimization and, of course, overall financial viability and return on investment in the long run. A brief overview of the five main PdM techniques being used is provided as follows.

Experience-based PdM techniques are, as the name suggests, derived from experience. Human experts gain experience and derive specific rules and other factors through years of practical experience in maintaining technical systems [3]. In experience-based PdM, tacit knowledge identifies faults, describes component wear and tear, and predicts component failure [4]. Computer-aided experience-based PdM systems can help perform automated diagnostics and prognostics runs and be implemented at modest cost and varying levels of complexity, such as Excel spreadsheet protocols or rule-based expert systems. Another strength of experience-based techniques is that they provide explicative results [5]. In contrast, a weakness of experience-based techniques is that their capability in terms of prognostics is rather limited [4].

Data-driven PdM techniques represent the other end of the spectrum. In Industry 4.0, manufacturing systems are equipped with sensors that can continuously measure and record operational data such as vibrations, humidity, noise, and more. The data obtained from these sensors can then be analyzed to monitor and assess component wear and derive prognostics on the remaining service life or a component or tool [4]. Several approaches have been used to build data-driven PdM systems in practice, for example, Artificial Neural Network (ANN), Support-Vector Machines (SVM), Decision Trees (DT), and more. Most of them exhibit high accuracy in fault prediction and component remaining useful life (RUL) estimating [6-9].

Model-based PdM techniques rely on mathematical models that can be used to describe/capture the state of degeneration of systems or components. Model-based techniques for fault diagnosis and prognosis use residuals as features, in which the analytical model is used to check the consistency between the measured results and the expected behaviour of the process [10]. Some commonly used models include Markov chains, Gaussian, linear system, and Wiener. These models are suitable for component RUL estimation since they are regression models. In addition to the high prediction accuracy, the most significant advantage of model-based techniques is their reusability [10]. On the other hand, model-based techniques are computationally expensive and require advanced mathematical understanding for their development. Another drawback of model-based techniques is that mathematical models can only describe a limited number of wear and tear types.

Physics-based PdM techniques are based on the laws of physics to assess the degeneration of components. They generate highly accurate component wear and tear simulations using physics behaviour models [4]. The physics-based and model-based techniques can both be described by mathematical equations. However, model-based techniques do not necessarily have anything to do with physical law or phenomenon, and they can be statistical or stochastic equations. Physics-based models can monitor and assess part wear and tear utilizing computational simulations. However, only limited physics wear and tear phenomena can be described and simulated accurately, such as fatigue and crack for mechanical components, rotor cage damage and degradation evaluation of industrial robots. In addition, the external environment, such as temperature and pressure, may influence the prediction accuracy [11], and the physics-based technique also requires advanced knowledge in physics to develop.

Hybrid PdM techniques. In Industry 4.0 context, manufacturing systems are becoming more complex. They often include multiple manufacturing stations or facilities to realize the ever-growing demand for high-quality products with increased customizability up to a lot size of one, at a competitive cost, and decreasing lead times. Not all components of such highly sophisticated manufacturing systems can be assessed with a single model and thus require using several PdM techniques in concert [4,12]. For example, Dulaimi et al. [13] present multiple data-driven systems on a simulated jet engine; Grabot [14] combines experience-based techniques with data-driven techniques for complex systems. However, the main drawback of the hybrid approach is that it is far more expensive to implement than any of the single technique PdM systems.

Although in the proceeding a basic overview of the general characteristics of different PdM techniques is presented, their successful implementation depends on many other factors, such as the machinery to be equipped with PdM technology, the exact types of wear and tear to be monitored, implementation cost and cost of staff training, the enterprise's long-term strategy, return on investment, etc. To date, there is no specific one-size-fits-all method to allow enterprises to evaluate their specific PdM needs effectively and efficiently and to identify the most feasible solution(s). To bridge this gap, the authors conducted an in-depth critical literature review to identify several key factors to be considered in PdM technique selection and implementation. Based on this, the authors propose a corresponding decision-based framework for helping decision-makers in industry to devise the right PdM strategy and solutions for their specific needs. The remainder of this paper is organized as follows. In Section 2, a review of actual industrial PdM implementation cases as a baseline to identify or deduct relevant factors. The decision-based framework is proposed in Section 3, followed by a discussion on limitations, future work, and conclusions in Section 4.

This is a resupply of March 2023 as the template used in the publication of the original article contained errors. The content of the article has remained unaffected.

2. Literature Review

In this section, a summary of the relevant literature review pertaining to the identification of key PdM technique selection and implementation factors is provided. Accordingly, the following research questions are postulated:

- RQ1: What are the key factors affecting PdM technique selection and implementation in industry?
- RQ2: How do these factors affect the selection of the most suitable PdM technique(s)?

Papers covering real life PdM selection and implementation case studies of the last ten years are selected for this review. Cases in the experimental environment are excluded, as are simulated cases. The databases used for the search are IEEEXplore Digital Library, ScienceDirect, and Springer. Two quality criteria are used for paper selection which are: 1. The paper includes the preparation phase (defining the goal of PdM implementation, defining critical components, and determining the parameter(s) that indicate deterioration). 2. The paper includes the data acquisition phase (hardware infrastructure design and data availability). These two phases include most of the information related to PdM technique selection and implementation. Key factors identified for consideration in the PdM selection and implementation process are as follows.

Data availability is the most frequently-mentioned factor in the reviewed literature. It can be divided into two categories. The first one is historical data availability. Historical data in maintenance can be defined as data gathered from technical knowledge, inspection, and historical records. In terms of PdM under Industry 4.0, historical data refers to the recorded system condition, including working parameters (speed, force, etc.), environment (temperature, pressure, humidity, etc.) and fault record. Historical data has a crucial effect on building Data-driven PdM systems since training, and testing prediction models is required [6-9]. The second category is data acquisition which refers to acquiring required data. Each type of PdM technique, including experience-based, data-driven, model-based and physics-based, requires a particular amount and quality of data to operate. They differ in terms of data type, and their amount and quality vary from one PdM technique to another. In the data acquisition process, engineers need to consider whether the required data can be collected. For example, from machine operation records [15-17] or installed sensors to monitor required parameters [6,17,18]. Data acquisition is vital to selecting and implementing any type of PdM technique because all of them need data to conduct prediction.

Critical components in maintenance refer to the components that significantly impact maintenance cost, system availability, product quality, and safety. For each scenario, the most relevant primary factors need to be chosen. Since each technique has its limitations and some can only be applied to select components, the most critical components need to be identified before evaluating the suitable techniques.

Expert knowledge refers to the knowledge that supports the PdM selection and implementation process. Using expert knowledge is the primary way to identify critical components, define mathematical models in model-based systems [19] or physical wear and tear models in physics-based systems [20-22], and to develop data-driven prediction models [16,18,23]. Typically, most companies can benefit from vast internal expert knowledge gained from years of experience. However, if such knowledge is not readily available, it may be necessary to derive it from past production and maintenance records or look for external alternatives.

Secondary data has a similar function and effect as expert knowledge when selecting and implementing PdM. However, the source of secondary data and expert knowledge can be different. For example, secondary data can be research results from research publications, patents or published company reports [15,22,24].

Cost. Most of the reviewed literature is focused on verifying PdM techniques or systems in practice but lacks detailed cost consideration. Albeit cost is one of the most significant factors for a successful PdM implementation from a cost-benefit analysis or return of investment point of view. The cost of PdM implementation includes the cost of sensors, system installation, IT systems for data analysis, training for operators, consulting, etc. PdM will not be the suitable maintenance approach if the cost cannot be justified.

External support refers to help from research groups or professional consultants. Enterprises may need external help in any phase of the selection and implementation process. Seeking external help is because the enterprise-internal knowledge and experience cannot support the whole implementation process.

The review in this paper covered publications related to real-world predictive maintenance applications. Six factors that were considered by most of the authors and impact PdM technique selection are identified in the selection and implementation process. However, no research pointed out the direct link between factors and technique selection. The following section presents the PdM technique selection framework to link the identified factors and PdM technique selection.

3. The Decision-Based Framework for Predictive Maintenance Technique Selection

A Decision-Based Framework for Predictive Maintenance Technique Selection is presented in this section (Figure 1).

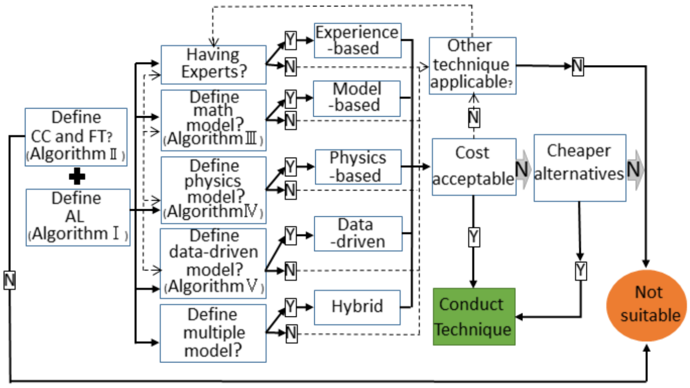

Fig. 1. The Decision-Based Framework for Predictive Maintenance Technique Selection.

The framework is supported by five algorithms that help make critical decisions in the PdM implementation process. These algorithms are:

(1) Algorithm to Define PdM Implementation Ambition Level (Algorithm I),
(2) Algorithm to Define PdM Implementation Critical Component (Algorithm II),
(3) Algorithm to Check if Model-based PdM Technique is Applicable (Algorithm III),
(4) Algorithm to Check if Physics-based PdM Technique is Applicable (Algorithm IV); and
(5) Algorithm to Check if Data-driven PdM Technique is Applicable (Algorithm V).

They are presented in Sections 3.1-3.5, respectively.

Any enterprise using the framework first needs to evaluate their ambition using Algorithm I and check the suitable techniques for their ambition level. In industry 4.0, PdM implementation ambition level referees to ambition or objective of enterprise for PdM implementation. Most of the enterprises do not claim they have a specific ambition level or objective when implementing PdM. However, it is identified that enterprises have specific tasks to achieve when developing PdM systems, such as diagnosing component accurate future state, predicting component RUL and extending assets service life. The cost, knowledge, skill, resource and experience requirements of achieving these tasks vary case to case basis. In this paper, the authors defined four ambition levels based on the tasks that enterprises are aimed to achieve to describe different implementation ambition levels:

- AL 1: diagnose assets fuzzy future state;
- AL 2: diagnose single component accurate future state and RUL;
- AL 3: diagnose multiple component accurate future state and RUL; and
- AL 4: extend assets service life through optimized maintenance actions.

Next, critical components (CC) and fault types (FT) need to be defined using Algorithm II. After that, the applicability of suitable techniques on the defined critical components needs to be evaluated (using Algorithms III, IV or V, respectively). After the applicable technique is defined, the required hardware and software can be determined. Next, the implementation cost must be evaluated. The PdM technique can be selected and implemented if the cost is acceptable. If the cost is not acceptable, the other applicable techniques or cheaper hardware or software alternatives need to be considered.

3.1 Algorithms to Define PdM Implementation Ambition Level (Algorithm Ⅰ)

For enterprises, the ambition level needs to be defined before the selection and implementation process because the required cost, knowledge, recourse and time for these levels are different. In addition, each PdM technique is only suitable for some of these ambition levels. The Algorithms to Define PdM Implementation Ambition Level and the Ambition level and PdM technique relationship map are presented in this section (Figure 2).

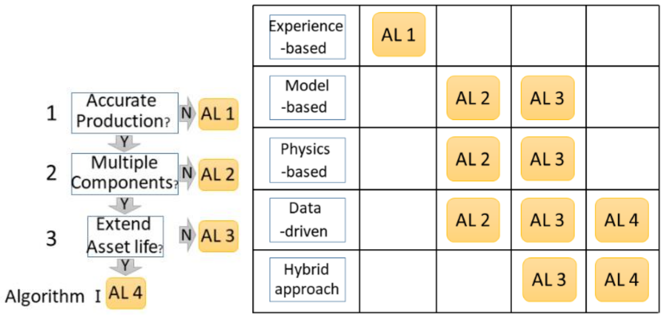

Fig. 2. Algorithms to Define PdM Implementation Ambition Level (Algorithm I) and the Ambition level and PdM technique relationship map.

The Step 1 is to decide whether there is a need to predict the system's future state accurately. If not, then ambition level is AL1; if yes, then the next is Step 2, predicting multiple components, for example, tools, spindle and bearing of one milling machine. If there is no need for predicting on multiple components, the ambition level is AL 2; if there is, then the next is Step 3, extending the assets service life, for example, delaying the retirement time of machine. If there is no need for extending the assets service life, then the ambition level is AL 3. Otherwise, the ambition level is AL 4.

Each PdM technique is only suitable for some of these ambition levels. Experience-based technique is mapped with AL 1. Enterprises with AL 1 only aimed at predicting system or component fuzzy future state. In AL 1, typically, enterprises aim at making sure no fault will happen on their devices before finishing a specific job. In this case, accurate system or component RUL prediction is not required. Although all PdM techniques can achieve such fuzzy predictions, the experience-based technique is the only one that requires relatively low cost and effort to develop. Other techniques except experience-based are not cost-effective for AL 1.

AL 2 is mapped with model-based, physics-based and data-driven techniques. Enterprises with AL 2 aim to diagnose and prognosticate fault of a single component accurately. The successful implementation of model-based [19,24], physics-based [20-22] and data-driven [6,7,9] PdM techniques is presented in several publications. The results showed that these three techniques can accurately diagnose and predict fault for various components. However, model-based and physics-based may be limited by use cases because they can only describe limited part wear and tear. The hybrid approach also can achieve such tasks. On the one hand, applying a hybrid approach to a single component cannot increase prediction accuracy, increasing implementation cost and effort.

AL 3 is mapped with a model-based, physics-based, data-driven and hybrid approach. Enterprises with AL 3 aimed at accurately diagnosing and prognostic fault of multiple components. As described in the preceding paragraph, these techniques can accurately diagnose and prognose the fault of various components since many successful implementations have been published. Compared to data-driven techniques and hybrid approaches for multiple components cases, the model-based and physics-based techniques have limited capability because they can only describe limited part wear and tear.

AL 4 is mapped with a data-driven and hybrid approach. Enterprises with AL 4 aimed to extend assets service life through optimized maintenance actions. Usually, the assets service life extension is realized by diagnostic and prognostic on several systems or components of assets and optimizing maintenance planning, for example, rail systems. The quantity of components monitored for AL 4 is usually larger than AL 3. In this case, model-based and physics-based techniques usually cannot predict many components since they can only describe limited part wear and tears. In this case, a hybrid approach that combines different techniques is typically employed to compromise the difficulty of predicting many components.

3.2 Algorithm to Define PdM Implementation Critical Component (Algorithm Ⅱ)

The second algorithm to support PdM technique selection is the Algorithm to Define PdM Implementation Critical Component (Figure 3). As presented in Section 2, critical components substantially impact PdM technique selection because each technique has its characteristics, and some part wear and tear cannot be accurately described by physical law or mathematical model. Therefore, critical components need to be defined before evaluating the suitable techniques. Step 1, is to determine is their available knowledge within the enterprise to define critical components, and fault types need to be examined. The most applied methods to define critical components uses internal expert knowledge and experience to determine critical components and fault types [16,18,23]. If unable to define critical components with internal knowledge, the next is Step 2, checking whether the enterprise has history maintenance record data to define critical components and fault types. Evaluating the components with the highest maintenance rate, cost or effort from history maintenance records is another method that defines critical components and fault types [18,20,23]. If the history maintenance record is unavailable, the next is Step 3, determining critical components and fault types from secondary data (published research or industry report). Enterprises engineers can learn what critical components to select from the published research or industry report. Finally, suppose the secondary data is unavailable. In that case, the next is Step 4, evaluating if the enterprises can receive external research groups or consultants to help to define critical components and fault types.

3.3 Algorithm to Check if Model-based PdM Technique is Applicable (Algorithm Ⅲ)

The third support algorithm is the Algorithm to Check if Model-based PdM Technique is Applicable (Figure 3). This algorithm starts with Step 1, checking available mathematical models to predict component states within the enterprises. The reusability of the previously developed mathematical model within the enterprise on new cases needs to be checked. If there are no available mathematical models within the enterprise, the next is Step 2, evaluating whether the enterprise has the expert knowledge to develop the mathematical models. For example, an enterprise can check if they can develop a Markov chain, Gaussian, linear system, or Wiener part wear model. If the enterprise cannot create such models, the next is Step 3, checking whether such mathematical models can be learned from secondary data. The secondary data here refers to the published mathematical model from research or industry reports. For example, if an enterprise predicts fatigue crack growth in fuselage panels, they can learn from [19]. If secondary data is unavailable, the next is Step 4, evaluating if the enterprise can receive external research groups or consultants to help define such models. After the model is defined, the required data to run the model can be determined. The last is Step 5, checking if such data can be acquired from the system by examining sensor type and location.

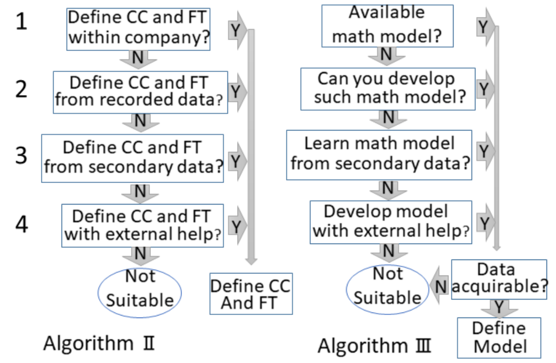

Fig. 3. Algorithm to Define PdM Implementation Critical Component (Algorithm II) and Algorithm to Check if Model-based PdM Technique is Applicable (Algorithm III).

3.4 Algorithm to Check if Physics-based PdM Technique is Applicable (Algorithm Ⅳ)

The following algorithm to support PdM technique selection is the Algorithm to Check if Physics-based PdM Technique is Applicable (Figure 4). The phases of algorithm Ⅳ are precise as algorithm III. The only difference between them is that algorithm IV exam the availability, exciting knowledge, secondary data and external help for the physics wear and tear model.

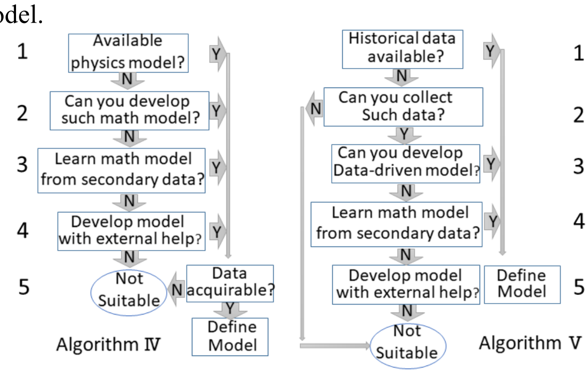

Fig. 4. Algorithm to Check if Physics-based PdM Technique is Applicable (Algorithm IV) and Algorithm to Check if Data-driven PdM Technique is Applicable (Algorithm V)

3.5 Algorithm to Check if Data-driven PdM Technique is Applicable (Algorithm Ⅴ)

The last algorithm to support PdM technique selection is the Algorithm to Check if Data-driven PdM Technique is Applicable (Figure 4). This algorithm starts with Step 1, checking if recorded historical data can be used to train the data-driven model within the enterprise. If not, the next is Step 2,

This is a resupply of March 2023 as the template used in the publication of the original article contained errors. The content of the article has remained unaffected.

checking whether these data can be recorded for a period of time. If the answer is yes, then the next is Step 3, checking whether the data-driven prediction model can be developed. If not, the next is Step 4, to check if the data-driven model can be defined by learning from secondary data. Here, secondary data refers to the models updated to the open-source databases or published by researchers and companies. At last, if the secondary data is not available, the last is Step 5, to consider seeking external research groups or consultants help. It should be noticed that support Algorithm III, IV and V cannot help to decide what specific mathematical, physics or data-driven model to use for each technique.

4. Discussion and Conclusions

In industry 4.0, selecting the most suitable PdM technique is critical for any successful PdM implementation in the industry that leads to cost and time reduction. No method allows enterprises to select PdM techniques considering their situations, such as knowledge and experience on PdM and ambition level. Hence, in this paper, we introduced the Decision-Based Framework for Predictive Maintenance Technique Selection.

The Decision-Based Framework for Predictive Maintenance Technique Selection is a process reference framework supported by five algorithms for the implementation of predictive maintenance. It guides enterprises to select a suitable PdM technique in the implementation process considering several factors identified from the literature review. The identified factors are Data Availability, Critical Component, Expert Knowledge, Secondary data, Cost and External Assistant. This paper linked these factors with the PdM techniques, allowing enterprises to assess their situation and select suitable PdM techniques.

The limitations of this proposed framework are:

- It is mainly based on research and secondary data from the literature. Actual industry data will be analyzed in the next phase of the project for refinement and validation.
- It has not yet been fully validated using real-world test cases.
- In this paper, the PdM techniques are applied to critical components only. However, some critical components may not be benefitted from PdM. In this paper, the method for selecting suitable components for PdM is not included.

As for future work, the focus is on validating the applicability and adaptability of the Decision-Based Framework for Predictive Maintenance Technique Selection conclusively in the first place. In addition, in future work, the target is to develop a method to select suitable components for PdM considering cost efficiency, technology limitation, and uncertainty.

References

[1] British Standard Glossary of terms 1993.
[2] Zhang W, Yang D, Wang H. Data-driven methods for predictive maintenance of industrial equipment: A survey. IEEE Systems Journal. 2019;13:2213-27.
[3] Hao L, Jinsong Y, Ping Z, Xingshan L. A review on fault prognostics in integrated health management. 2009 9th International Conference on Electronic Measurement & Instruments: IEEE; 2009. p. 4-267-4-70.
[4] Jimenez JJM, Schwartz S, Vingerhoeds R, Grabot B, Salaün M. Towards multi-model approaches to predictive maintenance: A systematic literature survey on diagnostics and prognostics. Journal of Manufacturing Systems. 2020;56:539-57.
[5] Vogl GW, Weiss BA, Donmez MA. Standards for prognostics and health management (PHM) techniques within manufacturing operations. National Institute of Standards and Technology Gaithersburg United States; 2014.
[6] Wöstmann R, Barthelmey A, West N, Deuse J, Schüppstuhl T, Tracht K, et al. A retrofit approach for predictive maintenance. Tagungsband des Kongresses Montage Handhabung Industrieroboter. 2019;4:94-106.
[7] Sai VC, Shcherbakov MV, Tran VP. Data-driven framework for predictive maintenance in industry 4.0 concept. Conference on Creativity in Intelligent Technologies and Data Science: Springer; 2019. p. 344-58.
[8] Ramesh P, Dutta SJ, Neog SS, Baishya P, Bezbaruah I. Implementation of predictive maintenance systems in remotely located process plants under industry 4.0 scenario. Advances in RAMS Engineering: Springer; 2020. p. 293-326.
[9] Shamayleh A, Awad M, Farhat J. IoT based predictive maintenance management of medical equipment. Journal of medical systems. 2020;44:1-12.
[10] Ran Y, Zhou X, Lin P, Wen Y, Deng R. A survey of predictive maintenance: Systems, purposes and approaches. arXiv preprint arXiv:191207383. 2019.
[11] Schmidt B, Wang L. Predictive maintenance: literature review and future trends. The International Conference on Flexible Automation and Intelligent Manufacturing (FAIM), 23-26 June 2015, University of Wolverhampton, UK: The Choir Press; 2015. p. 232-9.
[12] Alaswad S, Xiang Y. A review on condition-based maintenance optimization models for stochastically deteriorating system. Reliability engineering & system safety. 2017;157:54-63.
[13] Al-Dulaimi A, Zabihi S, Asif A, Mohammadi A. A multimodal and hybrid deep neural network model for remaining useful life estimation. Computers in Industry. 2019;108:186-96.
[14] Grabot B. Rule mining in maintenance: Analyzing large knowledge bases. Computers & Industrial Engineering. 2020;139:105501.
[15] Woldman M, Tinga T, Van Der Heide E, Masen MA. Abrasive wear based predictive maintenance for systems operating in sandy conditions. Wear. 2015;338:316-24.
[16] Florian E, Sgarbossa F, Zennaro I. Machine learning-based predictive maintenance: A cost-oriented model for implementation. International Journal of Production Economics. 2021:108114.
[17] Li R, Verhagen WJ, Curran R. Stakeholder-oriented systematic design methodology for prognostic and health management system: Stakeholder expectation definition. Advanced Engineering Informatics. 2020;43:101041.
[18] Gbadamosi A-Q, Oyedele LO, Delgado JMD, Kusimo H, Akanbi L, Olawale O, et al. IoT for predictive assets monitoring and maintenance: An implementation strategy for the UK rail industry. Automation in Construction. 2021;122:103486.
[19] Yiwei W, Christian G, Binaud N, Christian B, Jian F. A model-based prognostics method for fatigue crack growth in fuselage panels. Chinese Journal of Aeronautics. 2019;32:396-408.
[20] Rivera DL, Scholz MR, Fritscher M, Krauss M, Schilling K. Towards a predictive maintenance system of a hydraulic pump. IFAC-PapersOnLine. 2018;51:447-52.
[21] Tinga T, Loendersloot R. Physical model-based prognostics and health monitoring to enable predictive maintenance. Predictive Maintenance in Dynamic Systems: Springer; 2019. p. 313-53.
[22] Aivaliotis P, Arkouli Z, Georgoulias K, Makris S. Degradation curves integration in physics-based models: Towards the predictive maintenance of industrial robots. Robotics and Computer-Integrated Manufacturing. 2021;71:102177.
[23] LaRose J, Barker J, Finlay B, Trinidad A, Guyer C, Weinstein J, et al. Predictive Maintenance of Pump and Abatement Equipment in a 300mm Semiconductor Fab. 2021 32nd Annual SEMI Advanced Semiconductor Manufacturing Conference (ASMC): IEEE; 2021. p. 1-4.
[24] Bonci A, Longhi S, Nabissi G. Fault Diagnosis in a belt-drive system under non-stationary conditions. An industrial case study. 2021 IEEE Workshop on Electrical Machines Design, Control and Diagnosis (WEMDCD): IEEE; 2021. p. 260-5.

This is a resupply of March 2023 as the template used in the publication of the original article contained errors. The content of the article has remained unaffected.