Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 220 (2023) 645–650

Procedia Computer Science

www.elsevier.com/locate/procedia

The 6th International Conference on Emerging Data and Industry (EDI40), March 15-17, 2023, Leuven, Belgium

Predictive Maintenance for Smart Industrial Systems: A Roadmap

Hafsi Meriem[a,*], Hamour Nora[a], Ouchani Samir[a]

[a] *CESI LINEACT, 15C Av. Albert Einstein, Villeurbanne, 69100, France*

Abstract

The advent of Industry 4.0 and propelled the application of Artificial Intelligence in different industrial fields and contexts, such as predictive maintenance (PdM). Through its ability to assess the condition of equipment to detect signs of failure and anticipate them, PdM brings several potential benefits in terms of reliability, safety and maintenance costs among many other benefits. Different approaches are proposed in the literature. They are based on data, physic models or knowledge but several problems and limits persist, in particular, to override this dependence on a particular context, to utilize data and business knowledge considering the challenges of applying existing solutions to another context, difficulties associated with data analysis, and uncertainty management. In this context, the goal of this paper is also to highlight the challenges faced in the area of PdM, both for implementation and use-case. PdM remains a hot topic in the context of Industry 4.0 but with several challenges to be better investigated in the area of machine learning, knowledge representation and semantic reasoning applications.

Keywords: Predictive maintenance, Prognostic and Health Management, Hybrid approach, Knowledge-based, Data-driven, Industry 4.0

1. Introduction

In industry 4.0, the existing traditional maintenance approaches (corrective and preventive) suffer from some assumptions and limits, such as high costs, inadequate or inaccurate mathematical degradation processes and manual feature extraction. With the trend of smart manufacturing and the development of Internet of Things (IoT), Data Mining (DM) and Artificial Intelligence (AI) and semantic representations, predictive maintenance (PdM) is proposed as a novel type of maintenance paradigm to perform maintenances only after the analytical models predict certain failures or degradations [20]. Therefore, IoT is used for data acquisition, Big data techniques for data pre-processing, Advanced Deep Learning methods for fault diagnostics and prognostics, Deep Reinforcement Learning for decision making and Powerful hardware for complex computing [20]. PdM research has a lot of attention in the industry due to its potential benefits in terms of reliability, safety, and maintenance costs among many other benefits [16].

* Corresponding author. Tel.: +33-670-305-524 .
E-mail address: mhafsi@cesi.fr

1877-0509 © 2023 The Authors. Published by Elsevier B.V.

10.1016/j.procs.2023.03.082

In this article, we present a review of existing approaches of PdM to estimate the remaining useful life (RUL) of a component [22]. We propose a classification of these approaches based on the recent reviews and works on PdM.

2. Maintenance in Industry 4.0

2.1. Classification of the main approaches in predictive maintenance

According to the literature review, three main types of PdM are considered in Industry 4.0: data-based, knowledge-based and physics-based PdM. A PdM approach can be single or hybrid, the latter combining two or more of those mentioned above. The scientific community has agreed on the approaches classification as shown in Figure 1.

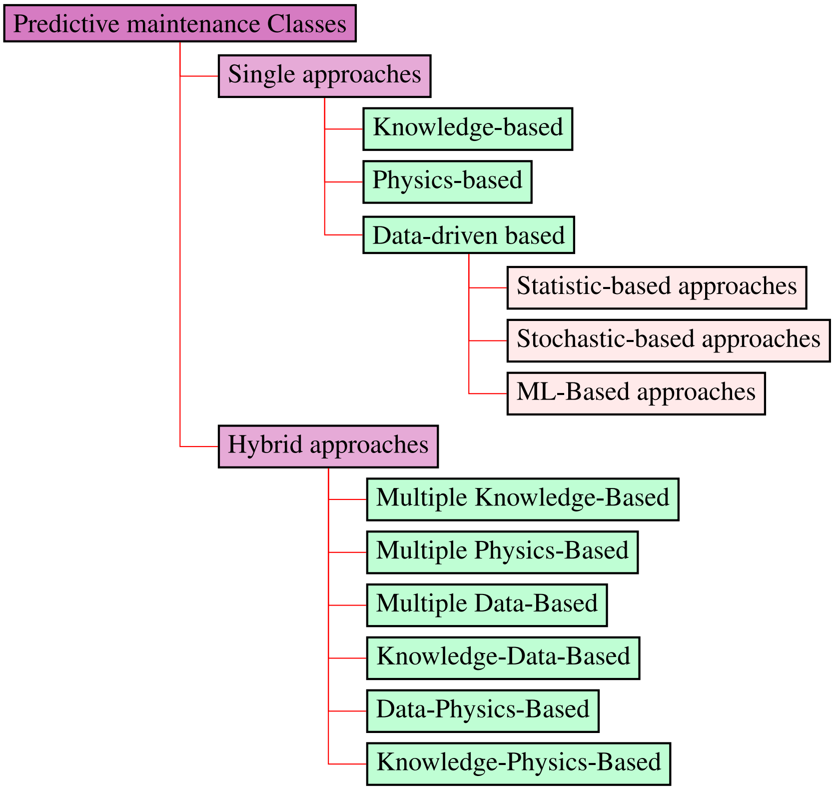

Fig. 1. The classification of predictive maintenance approaches according to the literature[8, 16, 13, 22, 20].

2.2. Data-Driven approaches

Data-driven techniques propose pre-processing steps to transform the data from sensors into a set of useful features. Subsequently, Machine Mearning (ML) models can be trained by using the features. In contrast, knowledge-driven techniques require domain and background knowledge to accurately identify the true causes of anomalies, which commonly involve human experts [8]. Several existing Data-driven approaches are presented in the following.

2.2.1. Statistic-based approaches

Based on statistical models, this approach is based on the degradation analysis of random variables which aims to determine a correlation with operational time or any other non-random variables that describe the lifecycle of the system [25]. This correlation will show the evolution of degradation along the life cycle. For prognostics, Regression analysis will help to determine the existing relationship between the random variables and the system life cycle. Besides regression analysis, there are two other statistical approaches that stand out: Autoregressive models in which a future value of a random variable is assumed to be a linear function of past observations and random errors, and Bayesian models. Despite the advantages offered by these models, some drawbacks concern the need for enough previous data to build a reliable model and uncertainty management [16]. Lastly, new directions are devoted towards statistical-traditional ML techniques, such as SVM, Random Forest, Gradient Boosting and Extreme Gradient Boosting approaches, to predict the failure machine [13].

2.2.2. *Stochastic-based approaches*

Stochastic models are probability models which determine the evolution of random variables over time. The building blocks of stochastic models are stochastic processes [16]. Model-based RUL (Remaining Useful Life) prognostics assume that the degradation of components is characterized by a stochastic process [18]. For diagnostic and prognostic faults, three main stochastic processes were identified in the literature: Gaussian, Markov, and Levy processes [16].

2.2.3. *Machine Learning-Based approaches*

One of the main approaches used for prognostic, diagnostic and anomaly detection is ML techniques [19, 20]. Commonly called Data-driven approaches, they use various data such as sensor measurement, to RUL prediction without the knowledge of physical structure and degradation. ML approaches allow the prediction of the future state of equipment by using old data and continuously adapting to incoming data, which leads to better prediction accuracy. the main advantages of such approaches lie in their ability to process large amounts of data and take into account many factors in the prediction, which can improve their quality[8]. In addition, they can be automated and easily integrated into existing maintenance systems. However, there are also some disavantages to consider: the need for sufficient quality and quantity of data to train the ML model, which can be expensive and difficult to obtain in some situations. Some applications are done in the literature in the manufacturing context, for example, by including auto-regressive integrated moving average–based (ARIMA) models, hidden Markov models (HMMs), support vector regression (SVR) models, artificial neural networks (ANNs), and random forest (RF) regression [22]. The ML-Based PdM approaches can use supervised, unsupervised, semi-supervised learning.

2.2.4. *Unsupervised Learning-based approaches*

Used if there is no feedback provided from anyone and the algorithm finds patterns in unknown data sets (clustering, association rules, self-organized maps) and so, unlabeled data are used for training purposes [2]. K-Means clustering is used to expedite the labeling process when it comes to anomaly detection [8].

2.2.5. *Semi-Supervised Learning-based approaches*

A semi-supervised PdM would involve using a small amount of labeled data to train a model to predict the failure, and then using this model to make predictions on the rest of the data [3]. This can be useful when there is a limited amount of labeled data available. Several different techniques can be used for semi-supervised PdM, including using a combination of labeled and unlabeled data to train a model, one-class classification to learn a model of normal equipment behavior, or using density-based anomaly detection to identify deviations from normal behavior as potential indicators of equipment failure.

2.2.6. *Supervised Learning-based approaches*

Based on Supervised ML, this approach detects anomalies by creating a set of grouping rules that help to predict future data. Thus, supervised ML is usually employed in scenarios with labeled data availability [2] and uses classification or regression methods. SVM is a separate hyperplane formally defined as a discriminative classifier. Naive Bayes classification method is based on the Bayesian Theorem and is primarily compatible when the dimensionality of the input is high. K-Nearest Neighbor (k-NN) algorithm is an example of supervised ML methods adapted to solve classification and regression issues by assuming similarities in devices deployed in a proximate location. Regression algorithms use the input features to predict the data's output values faded into the system. The Decision Tree approach constructs regression or classification techniques in a tree structure [1].

Deep learning (DL) is defined as a subset of ML that has networks capable of supervised learning from data that are unstructured. However, the demands of advanced prediction make it impossible for the traditional data-driven methods to handle the data complexity and growth. DL–based models have recently received great attraction as they offer several benefits such as better performance of RUL prognostics, i.e., high prognostics accuracy and automatic feature extraction. In the context of PdM, the convolutional neural network (CNN) is predominately used for the acquisition of high-level spatial features from sensor signal data. Moreover, Long Short-Term Memory (LSTM) neural networks are specifically used for extracting sensor temporal information [22][20]. Choice of DL because of its robustness to noise as long as the models are trained with high data quality [8]. Recent advancement in DL techniques has made it also possible to largely improve PdM performance compared to the classical approaches. In [21], DL models are categorized into three mains families [15]: (1) generative approaches such as Autoencoders (AE), Restricted Boltzmann Machine (RBM), DBN, Vector Autoencoder(VAE). (2) discriminative approaches like RNN, Long Short-Term Memory (LSTM) [4], Convolutional Neural Network (CNN) and finally, (3) hybrid DL model such as: Generative Adversarial Network (GAN) [20] and Ladder Net.

2.3. Knowledge-based approaches:

The principle of knowledge-based systems is the maintaining of a knowledge base that stores the symbols in the form of statements about the domain and performs reasoning by manipulating these symbols. These systems measure the similarity between a new observation and a database of previously described situations and deduce appropriate decisions. Knowledge-based approaches can be classified into three classes: knowledge graphs, rule-based systems, and fuzzy systems [11].

2.3.1. Knowledge graph

Knowledge graph is a structured semantic knowledge base used to describe concepts and their relationships in the physical world in symbolic form. A typical knowledge graph describes usually knowledge as multi-relational data and is expressed as a triple fact (head entity, relationship, and tail entity) which is the relationship between two entities [12]. Entities are connected to each other through relationships. The term knowledge graph is often used as a synonym for ontology [10]. Ontologies provide reasoning capabilities by which new knowledge can be inferred. To facilitate PdM, Nuñez and Borsato [17] proposed an ontology-based model for implementing Prognostics Health Management in mechanical machines. The proposed generic ontology (OntoProg) is capable of being used in several types of mechanical machines, of different types of manufacturing, the possibility of storing the knowledge contained in events of real activities that allow through consultations in SPARQL for decision-making which enable timely interventions of maintenance in the equipment of a real industry. In [5], a domain ontology for smart condition monitoring was presented. Formalizing the condition monitoring for manufacturing processes domain knowledge, it is developed into three ontology modules: the Manufacturing Module, the Context Module, and the Condition Monitoring Module. The effectiveness and usability of the ontology were tested on a conditional maintenance task of bearings in rotating machinery. After that, the domain ontology is further extended in the literature [6], where a domain ontology named Manufacturing Predictive Maintenance Ontology (MPMO) is developed and used together with sequential pattern mining techniques to enable anomaly detection and prediction on production lines. The proposed ontology is tested on a real-world data set collected from a semiconductor manufacturing process.

2.3.2. Rule-based models

In this model, the knowledge is based on rules, which consist of a knowledge base containing many ”if-then” rules, a facts base, and an inference engine [16]. The knowledge base stores facts as inputs and the inference engine apply the rules to deduce new knowledge as outputs. This inference engine uses an iterative process that is repeated until the end of the reasoning process. Visier et al. [28], has developed an expert system relying on a rule-based approach aiming at diagnosing faults in HVAC (heating, ventilation, and air conditioning) school systems. Vaezi-nejad and Whitcomb [27] developed a rule-based approach to detect the faulty state of the air handling units. Schein et al. [23], has also conducted a rule-based approach for Fault detection and diagnosis using mass balance and energy balance rules in the system studied. The drawback of these models is that the expert system is destinated to detect faults in a special type of system and it has not the ability to be generalized to all the systems.

2.3.3. Fuzzy-knowledge-based models

These systems are based on fuzzy logic and it uses the same format of rules IF-THEN. Fuzzy logic is linked to human perception. It can be explained as a collection of traditional Boolean logic designed to deal with partial truth values that are intermediate values between true values and false values that aims to describe the level of truth or falsehood of a statement [14]. In literature, fuzzy-knowledge-based models have not been well used for predictive maintenance. The disadvantage of knowledge-based models is their low accuracy and can hardly be applied to complex systems. Still, the use of this predictive maintenance approach can be effective and provide an advantage for simplified cases.

2.4. Physics-based approaches

These models called model-based approaches, use the laws of physics to assess the degradation of components. They demand high skills on mathematics and physics of the phenomena for the application [16]. In fact, mathematical models of pieces of equipment or a process that involve numerous differential equations are realized to form physics-based models from first principles. With accurate models, predictive models can be designed to provide reliable predictions [24].

3. Discussion

The PdM approaches based on a single prediction method have several disadvantages. they risk to not providing a fault prediction framework with higher accuracy and reliability since their predictions are based on the quality and availability of Data coming from different sensors. So, a hybrid approach has gotten the attention of many researchers recently. In the literature, a hybrid model-based PdM task can be classified into series and parallel approaches. As an example of a series approach, a physical model is first used to establish prior knowledge about the monitored manufacturing process. On the other hand, data-driven methods behave like state estimators to capture unmeasured process parameters. Within this process, data-driven methods serve as an online parameter estimation technique to continuously update model parameters when new data is available [26]. A parallel approach takes advantage of the strong computational capability of data-driven models to predict residuals that are not explained by first principle models [7]. Most of the literature work uses a fusion process to integrate the outputs of physical model-based and data-driven approaches. Du et al. [9], have combined the BPNN with Subtractive clustering analysis to conduct an FDD of the system. Different combinations of hybrid approaches were proposed in the literature: Multiples knowledge-based models, knowledge-based models with data-driven models, knowledge-based models with physics-based models, Knowledge-based models with data-driven models and physics-based models. more details can be found in [16].

4. Conclusion

This paper presents the most recent reviews found in the literature and related works on predictive maintenance. A classification and a comparaison of the existing approaches is also proposed. Predictive maintenace stay an open domain of research. Many challenges were dressed in different surveys and reviews [8, 16]. One of the common challenges is the lack of labeled failure data in the manufacturing industry, uncertainty management, the lack of a systematic approach to design and develop predictive maintenance systems, the extrapolation of existing solutions to complex system applications, including multiple components, and their associated faults, the fusion of large and different sources of condition monitoring data, the incorporation of external influence data, formalization and sharing of knowledge, In fact, three fundamental problems in the context of PdM are souligned in the litterature review : (1) PdM system architectures should be compatible with various industrial standards, be easy to integrate with the emerging of future techniques, satisfy the basic requirements of Pdm. (2) The purposes of PdM should be well jointly investigated and set. Finally, (3) The approaches for fault diagnostic and prognostic must be designed and tailored for specific problems [20].

References

[1] Al-amri, R., Murugesan, R.K., Man, M., Abdulateef, A.F., Al-Sharafi, M.A., Alkahtani, A.A., 2021. A review of machine learning and deep learning techniques for anomaly detection in iot data. Applied Sciences 11. URL: https://www.mdpi.com/2076-3417/11/12/5320, doi:10.3390/app11125320.

[2] Angelopoulos, A., Michailidis, E.T., Nomikos, N., Trakadas, P., Hatziefremidis, A., Voliotis, S., Zahariadis, T., 2020. Tackling faults in the industry 4.0 era—a survey of machine-learning solutions and key aspects. Sensors 20. URL: https://www.mdpi.com/1424-8220/20/1/109, doi:10.3390/s20010109.

[3] Ariyaluran Habeeb, R.A., Nasaruddin, F., Gani, A., Targio Hashem, I.A., Ahmed, E., Imran, M., 2019. Real-time big data processing for anomaly detection: A survey. International Journal of Information Management 45, 289–307. URL: https://www.sciencedirect.com/science/article/pii/S0268401218301658, doi:https://doi.org/10.1016/j.ijinfomgt.2018.08.006.

[4] Bampoula, X., Siaterlis, G., Nikolakis, N., Alexopoulos, K., 2021. A deep learning model for predictive maintenance in cyber-physical production systems using lstm autoencoders. Sensors 21. URL: https://www.mdpi.com/1424-8220/21/3/972, doi:10.3390/s21030972.

[5] Cao, Q., Giustozzi, F., Zanni-Merk, C., de Bertrand de Beuvron, F., Reich, C., 2019. Smart condition monitoring for industry 4.0 manufacturing processes: An ontology-based approach. Cybernetics and Systems 50, 82–96.

[6] Cao, Q., Zanni-Merk, C., Samet, A., Reich, C., de Bertrand de Beuvron, F., Beckmann, A., Giannetti, C., 2022. Kspmi: A knowledge-based system for predictive maintenance in industry 4.0. Robotics and Computer-Integrated Manufacturing 74, 102281. URL: https://www.sciencedirect.com/science/article/pii/S0736584521001617, doi:https://doi.org/10.1016/j.rcim.2021.102281.

[7] Cheng, J.C., Chen, W., Chen, K., Wang, Q., 2020. Data-driven predictive maintenance planning framework for mep components based on bim and iot using machine learning algorithms. Automation in Construction 112, 103087.

[8] Cheng, X., Chaw, J.K., Goh, K.M., Ting, T.T., Sahrani, S., Ahmad, M.N., Abdul Kadir, R., Ang, M.C., 2022. Systematic literature review on visual analytics of predictive maintenance in the manufacturing industry. Sensors 22. URL: https://www.mdpi.com/1424-8220/22/17/6321, doi:10.3390/s22176321.

[9] Du, Z., Fan, B., Jin, X., Chi, J., 2014. Fault detection and diagnosis for buildings and hvac systems using combined neural networks and subtractive clustering analysis. Building and Environment 73, 1–11.

[10] Ehrlinger, L., Wöß, W., 2016. Towards a definition of knowledge graphs. semantics (posters, demos, success). Metallurgy-Proceedings 48.

[11] Es-sakali, N., Cherkaoui, M., Mghazli, M.O., Naimi, Z., 2022. Review of predictive maintenance algorithms applied to hvac systems. Energy Reports 8, 1003–1012. URL: https://www.sciencedirect.com/science/article/pii/S2352484722013944, doi:https://doi.org/10.1016/j.egyr.2022.07.130. technologies and Materials for Renewable Energy, Environment and Sustainability.

[12] Hou, J., Qiu, R., Xue, J., Wang, C., Jiang, X.Q., 2020. Failure prediction of elevator running system based on knowledge graph, in: Proceedings of the 3rd International Conference on Data Science and Information Technology, pp. 53–58.

[13] Jagatheesaperumal, S.K., Rahouti, M., Ahmad, K., Al-Fuqaha, A.I., Guizani, M., 2021. The duo of artificial intelligence and big data for industry 4.0: Review of applications, techniques, challenges, and future research directions. CoRR abs/2104.02425. URL: https://arxiv.org/abs/2104.02425, arXiv:2104.02425.

[14] Luo, J., Namburu, M., Pattipati, K., Qiao, L., Kawamoto, M., Chigusa, S., 2003. Model-based prognostic techniques [maintenance applications], in: Proceedings AUTOTESTCON 2003. IEEE Systems Readiness Technology Conference., Ieee. pp. 330–340.

[15] Mohammadi, M., Al-Fuqaha, A.I., Sorour, S., Guizani, M., 2017. Deep learning for iot big data and streaming analytics: A survey. CoRR abs/1712.04301. URL: http://arxiv.org/abs/1712.04301, arXiv:1712.04301.

[16] Montero Jimenez, J.J., Schwartz, S., Vingerhoeds, R., Grabot, B., Salaün, M., 2020. Towards multi-model approaches to predictive maintenance: A systematic literature survey on diagnostics and prognostics. Journal of Manufacturing Systems 56, 539–557. URL: https://www.sciencedirect.com/science/article/pii/S0278612520301187, doi:https://doi.org/10.1016/j.jmsy.2020.07.008.

[17] Nuñez, D.L., Borsato, M., 2018. Ontoprog: An ontology-based model for implementing prognostics health management in mechanical machines. Advanced Engineering Informatics 38, 746–759. URL: https://www.sciencedirect.com/science/article/pii/S1474034617306080, doi:https://doi.org/10.1016/j.aei.2018.10.006.

[18] de Pater, I., Reijns, A., Mitici, M., 2022. Alarm-based predictive maintenance scheduling for aircraft engines with imperfect Remaining Useful Life prognostics. Reliability Engineering and System Safety 221. URL: https://ideas.repec.org/a/eee/reensy/v221y2022ics0951832022000175.html, doi:10.1016/j.ress.2022.10834.

[19] Ramotsoela, D., Abu-Mahfouz, A., Hancke, G., 2018. A survey of anomaly detection in industrial wireless sensor networks with critical water system infrastructure as a case study. Sensors 18. URL: https://www.mdpi.com/1424-8220/18/8/2491, doi:10.3390/s18082491.

[20] Ran, Y., Zhou, X., Lin, P., Wen, Y., Deng, R., 2019. A survey of predictive maintenance: Systems, purposes and approaches. URL: https://arxiv.org/abs/1912.07383, doi:10.48550/ARXIV.1912.07383.

[21] Rieger, T., Regier, S., Stengel, I., Clarke, N., 2019. Fast predictive maintenance in industrial internet of things (iiot) with deep learning (dl): A review, in: CERC.

[22] Sang, G.M., Xu, L., de Vrieze, P., 2021. A predictive maintenance model for flexible manufacturing in the context of industry 4.0. Frontiers in Big Data 4. URL: https://www.frontiersin.org/articles/10.3389/fdata.2021.663466, doi:10.3389/fdata.2021.663466.

[23] Schein, J., Bushby, S.T., Castro, N.S., House, J.M., 2006. A rule-based fault detection method for air handling units. Energy and buildings 38, 1485–1492.

[24] Shukla, K., Nefti-meziani, S., Davis, S., 2022. A heuristic approach on predictive maintenance techniques: Limitations and scope. Advances in Mechanical Engineering 14(6), 1–14. doi:10.1177/16878132221101009.

[25] Theissler, A., Pérez-Velázquez, J., Kettelgerdes, M., Elger, G., 2021. Predictive maintenance enabled by machine learning: Use cases and challenges in the automotive industry. Reliability Engineering and System Safety 215. URL: https://ideas.repec.org/a/eee/reensy/v215y2021ics0951832021003835.html, doi:10.1016/j.ress.2021.10786.

[26] Turner, W., Staino, A., Basu, B., 2017. Residential hvac fault detection using a system identification approach. Energy and Buildings 151, 1–17.

[27] Vaezi-nejad, H., Whitcomb, J., 2001. An expert rule set for fault detection in air-handling units. ASHRAE Transactions 107.

[28] Visier, J.C., Vaezi-Nejad, H., Corrales, P., 1999. A fault detection tool for school buildings. Technical Report. Centre Scientifique et Technique du Batiment, Champs-sur-Marne (FR).