A SPECIALTY LITERATURE REVIEW OF THE PREDICTIVE MAINTENANCE SYSTEMS

DRAGOS-ALEXANDRU ANDRIOAIA[1*], VASILE GHEORGHITA GAITAN[1]

[1] *Stefan cel Mare University of Suceava, 13 University Street, Suceava, 720229, Romania*

Abstract: Within the industrial standard 4.0, predictive maintenance has an essential role in production activities, by increasing equipment uptime and decreasing maintenance costs. Predictive maintenance monitors assets through sensors for optimal planning of maintenance operations to keep assets functional. In this paper, the authors perform an analysis of predictive maintenance system, proposed in the specialized literature, highlighting their component elements.

Keywords: predictive maintenance, PdM, RUL prediction, defect identification, IoT, machine learning

1. INTRODUCTION

The need to achieve as much production as possible, at the best possible quality and with the lowest possible costs, has determined an improvement in maintenance policies within companies focused on production. Maintenance is a set of activities aimed at keeping the equipment in a system in working order [1].

Maintenance strategies can be divided into two main branches, thus we have, reactive maintenance strategies and proactive maintenance strategies. Applying a reactive maintenance plan involves making repairs after equipment has broken down. Reactive maintenance plans are the most expensive [2]. Proactive maintenance strategies involve making repairs in advance with the aim of keeping the asset functional throughout the duration of the work. Within proactive maintenance strategies we can have preventive maintenance strategies and predictive maintenance (PdM) strategies [3]. PdM strategies involve applying a planned maintenance service before a failure occurs. Any operation done in advance to avoid failure and unnecessary wear and tear can be considered a preventive maintenance strategy. It can be based on calendar time or operating time. PdM is part of industry standard 4.0 and has become the desired industry standard by most factories. Repairs are made only when necessary [4].

PdM arose due to the shortcomings of reactive and preventive maintenance [5]. The PdM strategy is based on monitoring the equipment with the help of measurement systems capable of evaluating its condition during operation, permanently or in a certain period. PdM assesses the health of the asset to provide information that facilitates the repair, replacement of an asset, or leaving it untouched [6]. PdM brings several advantages such as: eliminates accidental shutdowns, increases equipment life, reduced maintenance costs, and reduces equipment downtime and environmental safety. Thus, maintenance costs can be reduced by applying a PdM policy with a percentage between 25 % and 35 %.

PdM systems whose decision-making system uses machine learning allow detecting the defect long before the functional failure occurs [5, 7]. According to the report prepared by the company IoT Analytics, the PdM

[*] Corresponding author, email: dragos.andrioaia@ub.ro https://doi.org/10.29081/jesr.v29i4.002

systems market will grow from 4.77B $ to 23.53 B $ during the period 2019 - 2024 [8]. Among the companies offering PdM services we have: IBM, SAP, Microsoft and Siemens.

In this work, the authors carry out a constructive but also functional analysis of PdM systems. Thus, the general structure of the PdM systems will be highlighted as well as their main achievements presented by the authors in the specialized literature.

2. STRUCTURE OF PDM SYSTEMS

PdM systems can detect changes in the physical condition of equipment (signs of failure) to carry out maintenance work, with the aim of increasing the life of equipment and decreasing the probability of a functional failure.

In the first step, PdM periodically or continuously monitors an asset through sensors and then performs signal pre-processing in the second step. In the third step, it applies an algorithm to detect anomalies [9].

In general, PdM systems are composed of the following modules (Figure 1): (1) The module used for data acquisition; (2) Data preprocessing and storage module; (3) The data set analysis module; (4) Decision support module and (5) Maintenance program implementation module [3, 10-12].

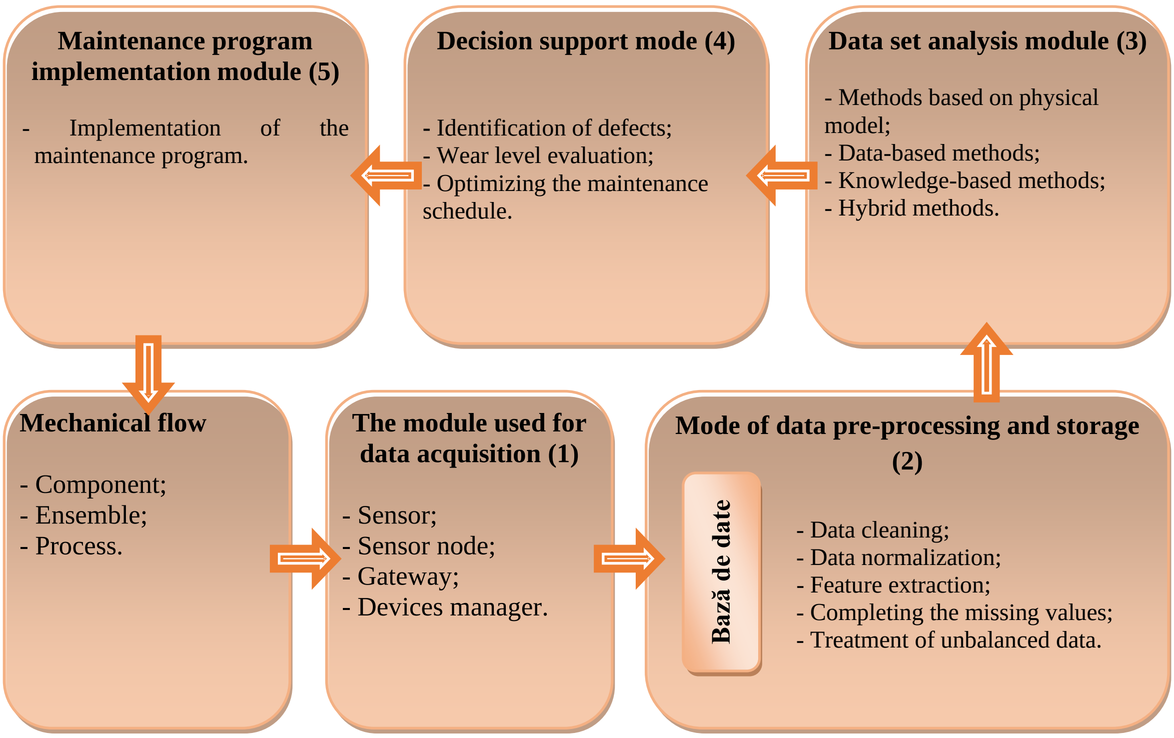

Fig. 1. Block diagram of PdM systems [3, 11, 12].

The sensor data acquisition module allows the collection of sensor data. The sensors transmit information about the state of the monitored equipment to the sensor hub devices, and these in turn transmit the information to another level with a higher processing capacity [10-12]. This module can be implemented using Internet of Things (IoT) technology.

Data preprocessing and storage module, all collected data will be preprocessed and stored in a database for the purpose of extracting diagnosis and prognosis. Data pre-processing involves the operations of: data cleaning, data normalization, feature extraction, filling in missing values, and handling unbalanced data [3, 11-13]. Data cleaning is the process of detecting and correcting inaccurate or corrupt records in the database, it involves removing outliers, removing noise, etc. [11, 13]. Data normalization involves standardizing the value ranges of the data from the sensors. Feature extraction involves the analysis of data with the aim of extracting feature of defects. The signals from the sensors can be analyzed in the time domain, in the frequency domain and in the time-frequency domain.

Completing the missing values involves approximating the missing values from the data series taken from the sensors. Treating unbalanced data involves balancing the classes when the data set contains classes with an unbalanced number of features [11, 13].

The data set analysis module mainly focuses on fault detection, classification and prediction to implement a PdM strategy. To perform maintenance before functional failure, the overall objective of PdM is to predict future failures early enough [11]. Within easy-to-solve problems, a short failure prediction period is required, and when the problem involves more complex equipment that could be replaced, the prediction period should be longer. After analyzing the data, we get the diagnosis and the prognosis. Diagnosis is based on the detection, isolation and identification of defects [3].

Prognostication is focused on predicting the time remaining before a machine component or manufacturing system ceases to perform its intended function due to the propagation and progression of defects/wear. The remaining life time is mentioned in the specialized literature as the RUL (Remaining Useful Life) index [14].

For data analysis, in order to predict RUL and identify defects, the following methods can be used: model-based methods, data-based methods, knowledge-based methods and hybrid methods [1].

Methods based on a physical model, involved the creation of a physical model that detects, depending on the data from the sensors, the remaining time until a failure occurs [1, 13].

Data-driven methods are the most used methods. Unlike physical model-based methods, data-based diagnosis and prognosis do not require a deep understanding of the underlying physics of the processes. These types of methods use historical data that is obtained from equipment monitoring to predict equipment degradation. Data-driven models include, machine learning [10, 13, 15, 16] etc.

Machine learning encompasses all algorithms that can make predictions based on data. Depending on the training process we can have supervised, unsupervised and semi-supervised machine learning algorithms [1]. In supervised machine learning algorithms learn patterns and relationships between input and output data, use labeled data. There are two types of supervised learning algorithms, Classification and Regression.

Classification is used to classify defects and regression is used to estimate RUL. Unsupervised machine learning models learn behavior from unlabeled data. The main advantage of these methods would be that they manage to cluster the data in an efficient way. Semi-supervised learning models are a combination of the first two types. Supervised learning models produce more accurate results than unsupervised learning but require human interaction when labeling the data.

Knowledge-based models include fuzzy logic and can be related to hybrid models. These types of methods include algorithms that combine model-based methods with data-based methods and knowledge-based methods. These methods are suitable for situations where we do not have enough historical data to develop a data-based model, and for this reason combining data-based methods with physical model-based methods and knowledge-based methods can generate a satisfactory result [1, 17]. The type of a method is chosen according to the type of system on which we want to implement a PdM policy.

Decision support and maintenance schedule implementation module, this module displays the results obtained from the data analysis module and provides us with a maintenance schedule. The results obtained using the data analysis module can be displayed using a color-based chart. Also within this module, the maintenance program is optimized so that activity interruption times are minimal. At the end, the maintenance program will be implemented after the decision makers choose the maintenance strategy [3, 11, 12].

The maintenance program implementation mode deals with the implementation of the maintenance program [3, 11, 12].

3. ANALYSIS OF PDM SYSTEMS PROPOSED IN SPECIALTY LITERATURE

Because PdM can create a more sustainable, safer and more profitable industry, companies have started investing in machines with self-diagnostic capabilities. In the Table 1, the main PdM systems from the specialized literature, proposed by the researchers, are presented.

From the specialized papers analyzed, it is found that there is a high interest of researchers in estimating the RUL and identifying the defects of the elements that make up the airplanes. Most authors focus on RUL estimation of components. Because bearings have a short life compared to other elements in a mechanical assembly there is a high interest of researchers in estimating the RUL in bearings.

Most authors use data-driven methods to estimate RUL and identify defects. Supervised machine learning algorithms are the most widely used for RUL estimation and defect identification. When training supervised machine learning models, it was found that the accuracy of the model would increase if we had data based on monitoring components from as many sensors as possible over a longer period of time.

In contrast to reactive and preventive maintenance policies, the application of predictive maintenance policies leads to a substantial reduction in maintenance expenses.

Table 1. PdM systems from the specialized literature.

Author	Predictive measure type, equipment	Data	Data set analysis module	Accuracy of the model/ Advantages of using the model
Lee J. and Mitici M. [18]	RUL, aircraft engines.	Aircraft turbofan engine degradation data, dataset: Commercial Modular Aero-Propulsion System Simulation (C-MAPSS).	Data-driven method, Multi-channel CNN with Monte Carlo dropout.	Reduces total maintenance cost by 29.3%. Prevents 95.6% of unscheduled engine replacements.
de Pater I. and Mitici M.[19]	RUL, aircraft cooling units.	Data from sensors monitoring Aircraft Cooling Units.	Model-based method.	It reduces costs compared to a maintenance strategy: reactive by 48% and preventive by 30%.
Al-Naggar, Y.M., et al [20]	Classification of CNC operating states, (good, satisfactory, unsatisfactory, unacceptable).	Data from spindle vibration monitoring of four CNC machines collected using IoT.	Condition monitoring.	It reduces maintenance costs and increases the uptime of CNC machines.
Kimera D. and Nangolo F.N. [21]	RUL, ballast pumps of floating docks.	Date, back pressure, flow rate, amperage, RPM and suction pressure monitored for 40 weeks.	Data driven method, Support Vector Machine – (SVM), Principal Component Analysis (PCA).	Reduces maintenance costs.
Rivera D.L. et al [22]	Identify defects, hydraulic pump of an injection molding machine.	Data from vibration sensors.	Model-based method	Reduces maintenance costs and increases uptime.
Yang C. et al T. [23]	RUL, rolling bearing.	Data from vibration sensors.	Data-driven method, Generalized Regression Neural Network (GRNN).	The prediction has an error between 5.7% and 1.4%
Zhao K., et	RUL, aero-engine.	Aerodynamic engine	Data-driven method,	The method has better

al [24]		degradation data, C-MAPSS data set.	Multi-Scale Integrated Deep Self-Attention Network (MSIDSN).	results than other models in the specialized literature.
Zhou J., et al [25]	RUL, bearings.	Bearing degradation data, IEEE 2012 PHM bearing data sets.	Data-driven method, Reinforced Memory Gated Recurrent Unit (RMGRU) network.	The authors demonstrate that the RMGRU method is superior to classical time series forecasting methods.
Rathore M.S. and Harsha S.P. [26]	RUL, bearings.	Bearing degradation data, dataset from the PRONOSTIA platform.	Data-driven method, Stacked Bi-directional Long Short Term Memory (SBiLSTM).	Comparison results indicate that the method has superior performance compared to other state-of-the-art methods.
Viale L., et al [27]	RUL, NASA turbofan.	Data from NASA Commercial Modular Aero-Propulsion System Simulation (N-CMAPSS), called Turbofan Engine Degradation Simulation.	Data-driven method, K-Nearest Neighbors Interpolation (kNNI).	It effectively reduces maintenance costs while encouraging safety.
Galarza-Urigoitia N., et al [28]	It identifies cracks in low-speed wind turbine shafts.	Dates of the ultrasonic sensors.	Model-based method.	Extends the useful life of the shaft by 50%. The system creates a failure alert when the shaft has reached 96% of its useful life.

4. CONCLUSIONS

Unlike the other types of maintenance activities, under industry standard 4.0, PdM has become the desired industry standard in most markets. Service activities take place only when necessary.

The use of PdM presents a series of advantages such as: increasing the life of equipment, eliminating accidental stops, reducing the downtime of machines, reduced maintenance costs, improving the quality of products and safety in the exploitation of the environment.

In smart factories, IoT technology is an essential enabler for PdM. Through the use of IoT sensors, smart factories come to life, with connected machines that can communicate with each other and people that can take action when needed.

Unlike physical model-based methods, data-based diagnosis and prognostication do not require a deep understanding of the underlying physics of the processes and do not require a complete knowledge of the system's behavior. Data-driven methods can predict defects long before other methods. For fault prediction and diagnosis, most authors of specialized papers using data-driven methods use machine learning algorithms. In machine learning, regression algorithms are used to predict RUL and classification algorithms are used to identify defects.

Within PdM, the most monitored components are those that have the shortest life span, such as bearings, shafts, etc. Due to strict safety standards, the interest in designing PdM systems for the aeronautical industry has increased substantially.

ACKNOWLEDGMENT

The work of Andrioaia Dragos-Alexandru was supported by the project "PROINVENT", Contract no. 62487/03.06.2022 - POCU/993/6/13 - Code 153299, financed by The Human Capital Operational Programme 2014–2020 (POCU), Romania.

REFERENCES

[1] Gouriveau, R., Medjaher, K., Zerhouni, N., From prognostics and health systems management to predictive maintenance 1: monitoring and prognostics, Wiley-ISTE, 2016.
[2] Li, Z., Wang, K., He, Y., Industry 4.0 - Potentials for predictive maintenance, Proceedings of the 6th International Workshop of Advanced Manufacturing and Automation, 2016, p. 42-46.
[3] Wang, K., Dai, G., Guo, L., Intelligent predictive maintenance (IPdM) for elevator service- through CPS, IOTaS and data mining, International Workshop of Advanced Manufacturing and Automation (IWAMA 2016), 2016, p. 1-6.
[4] Jimenez Cortadi, A., Irigoien, I., Boto, F., Sierra, B., Rodriguez, G., Predictive maintenance on the machining process and machine tool, Applied Sciences, vol. 10, no. 1, 2019, p. 224.
[5] Es-sakali, N., Cherkaoui, M., Mghazli, M.O., Naimi, Z., Review of predictive maintenance algorithms applied to HVAC systems, Energy Reports, vol. 8, 2022, p. 1003-1012.
[6] Ruiz-Sarmiento, J.-R., Monroy, J., Moreno, F.-A., Galindo, C., Bonelo, J.-M., Gonzalez-Jimenez, J., A predictive model for the maintenance of industrial machinery in the context of industry 4.0, Engineering Applications of Artificial Intelligence, vol. 87, 2020, art. no. 103289.
[7] Shetty, R., Predictive maintenance in the IoT era, Prognostics and health management of electronics: fundamentals, machine learning, and the internet of things, John Wiley and Sons Ltd, 2018, p. 589-612.
[8] Analytics, I., IIOT platforms for manufacturing 2019-2024, https://iot-analytics.com/wp/wp-content/uploads/2019/04/IIoT-Platforms-for-Manufacturing-2019-2024-vSample.pdf (23.07.2021).
[9] Koraei, M., Cebrian, J.M., Jahre, M., Near-optimal multi-accelerator architectures for predictive maintenance at the edge, Future Generation Computer Systems, vol. 140, 2023, p. 331-343.
[10] Wang, J., Liang, Y., Zheng, Y., Gao, R.X., Zhang, F., An integrated fault diagnosis and prognosis approach for predictive maintenance of wind turbine bearing with limited samples, Renewable Energy, vol. 145, 2020, p. 642-650.
[11] Li, Z., Wang, Y., Wang, K.-S., Intelligent predictive maintenance for fault diagnosis and prognosis in machine centers: Industry 4.0 scenario, Advances in Manufacturing, vol. 5, no. 4, 2017, p. 377-387.
[12] Wang, K., Intelligent predictive maintenance (IPdM) system – industry 4.0 scenario, WIT transactions on engineering sciences, vol. 113, no. 1, 2016, p. 259-268.
[13] Lughofer, E., Sayed, M.M., Predictive maintenance in dynamic systems advanced methods, decision support tools and real-world applications: advanced methods, decision support tools and real-world applications, Predictive Maintenance in Dynamic Systems, 2019.
[14] Wu, D., Liu, S., Zhang, L., Terpenny, J., Gao, R.X., Kurfess, T., Guzzo, J.A., A fog computing-based framework for process monitoring and prognosis in cyber-manufacturing, Journal of Manufacturing Systems, vol. 43, 2017, p. 25-34.
[15] Brigitte Chebel-Morello, J.-M.N., Varnier, C., From prognostics and health systems management to predictive maintenance 2: knowledge, reliability and decision, Wiley-ISTE, 2017.
[16] Niu, G., Data-driven technology for engineering systems health management, Ed. Science Press Beijing, 2017.
[17] Galar, D., Thaduri, A., Catelani, M., Ciani, L., Context awareness for maintenance decision making: A diagnosis and prognosis approach, Measurement, vol. 67, 2015, p. 137-150.
[18] Lee, J., Mitici, M., Deep reinforcement learning for predictive aircraft maintenance using probabilistic remaining-useful-life prognostics, Reliability Engineering and System Safety, vol. 230, 2023, art. no. 108908.
[19] de Pater, I., Mitici, M., Predictive maintenance for multi-component systems of repairables with remaining-useful-life prognostics and a limited stock of spare components, Reliability Engineering and System Safety, vol. 214, 2021, art. no. 107761.
[20] Al-Naggar, Y.M., Jamil, N., Hassan, M.F., Yusoff, A.R., Condition monitoring based on IoT for predictive maintenance of CNC machines, Procedia CIRP, vol. 102, 2021, p. 314-318.

[21] Kimera, D., Nangolo, F.N., Predictive maintenance for ballast pumps on ship repair yards via machine learning, Transportation Engineering, vol. 2, 2020, art. no. 100020.
[22] Rivera, D.L., Scholz, M.R., Fritscher, M., Krauss, M., Schilling, K., Towards a predictive maintenance system of a hydraulic pump, IFAC-PapersOnLine, vol. 51, no. 11, 2018, p. 447-452.
[23] Yang, C., Ma, J., Wang, X., Li, X., Li, Z., Luo, T., A novel based-performance degradation indicator RUL prediction model and its application in rolling bearing, ISA Transactions, vol. 121, 2022, p. 349-364.
[24] Zhao, K., Jia, Z., Jia, F., Shao, H., Multi-scale integrated deep self-attention network for predicting remaining useful life of aero-engine, Engineering Applications of Artificial Intelligence, vol. 120, 2023, art. no. 105860.
[25] Zhou, J., Qin, Y., Chen, D., Liu, F., Qian, Q., Remaining useful life prediction of bearings by a new reinforced memory GRU network, Advanced Engineering Informatics, vol. 53, 2022, art. no. 101682.
[26] Rathore, M.S., Harsha, S.P., An attention-based stacked BiLSTM framework for predicting remaining useful life of rolling bearings, Applied Soft Computing, vol. 131, 2022, art. no. 109765.
[27] Viale, L., Daga, A.P., Fasana, A., Garibaldi, L., Least squares smoothed k-nearest neighbors online prediction of the remaining useful life of a NASA turbofan, Mechanical Systems and Signal Processing, vol. 190, 2023, art. no. 110154.
[28] Galarza-Urigoitia, N., Rubio-García, B., Gascón-Álvarez, J., Aznar-Lapuente, G., Olite-Biurrun, J., López-Germán, A., Rubio-Botía, J., Predictive maintenance of wind turbine low-speed shafts based on an autonomous ultrasonic system, Engineering Failure Analysis, vol. 103, 2019, p. 481-504.