International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 03 | March - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Predictive Maintenance: Evolution, Purposes and Approaches for Industrial Systems - A Comprehensive Review

Punam J. Patil, Assistant Professor, Bharati Vidyapeeth College of Engineering, Navi Mumbai. Email: punam.patil@bvcoenm.edu.in Dr. Pankaj H. Zope, Associate Professor, SSBT's College of Engineering & Technology, Bambhori, Jalgaon. Email: phzope@gmail.com

---

Abstract—

This paper highlights the importance of maintenance techniques in the coming industrial revolution, reviews the evolution of maintenance techniques, and presents a comprehensive literature review on the latest advancement of maintenance techniques, i.e., Predictive Maintenance (PdM), with emphasis on system architectures, optimization objectives and approaches. Predictive Maintenance (PdM) has emerged as a transformative approach in the realm of industrial maintenance, particularly in process plants. By leveraging advanced technologies like IoT, AI, and machine learning, PdM enables proactive identification and resolution of potential equipment failures, significantly reducing downtime, optimizing resource allocation, and enhancing overall operational efficiency. This paper provides a comprehensive review of PdM, exploring its evolution, key technologies, benefits, challenges, and future trends.

Keywords: PdM, AI, Iot

I. Introduction

Maintenance as a crucial activity in industry, with its significant impact on costs and reliability, is immensely influential to a company's ability to be competitive in low price, high quality and performance. Any unplanned downtime of machinery equipment or devices would degrade or interrupt a company's business, potentially resulting in significant penalties and unmeasurable economic and reputation loss. For instance, Amazon experienced just 49 minutes of downtime, which cost the company $4 million in lost sales in 2013. On average, organizations lose $138,000 per hour due to data center downtime according to a market study by the ponemon Institute [24].

In industry 4.0, the existing traditional maintenance approaches (corrective and preventive) suffer from some as- 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 Min ing (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].

II. Survey

Evolution of Modern Techniques

The evolution of modern techniques (e.g., Internet of things, sensing technology, artificial intelligence, etc.) reflects a transition of maintenance strategies from Reactive Maintenance (RM) to Preventive Maintenance (PM) to Predictive Maintenance (PdM). RM is only executed to restore the operating state of the equipment after a failure occurs, and thus tends to cause serious lag and results in high reactive repair costs. PM is carried out according to a planned schedule based on time or process iterations to prevent breakdown, and thus may perform unnecessary maintenance and result in high prevention costs. In order to achieve the best trade-off between the two, PdM is performed based on an online estimate of the system "health" and can achieve timely pre-failure interventions. PdM allows the maintenance frequency to be as low as possible to prevent unplanned RM, without incurring costs associated with doing too much PM. Key benefits of this evolution [25, 26]:

•Reduced downtime: By proactively addressing equipment issues, unplanned outages and disruptions are significantly minimized.

Extended asset life: Early detection of anomalies allows for preventive measures, preventing major breakdowns and extending the lifespan of valuable equipment.

Improved operational efficiency: Optimized maintenance scheduling reduces unnecessary interventions and ensures resources are used effectively.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 03 | March - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

•Cost savings: Avoiding unplanned downtime, repairs, and part replacements translates to significant cost reductions.

Maintenances in Industry 4.0

PdM works in Smart Industrial systems:

***Data Acquisition*:** Sensors embedded in machines collect real-time data on vibration, temperature, energy consumption, and other parameters. Sensors are the backbone of data acquisition in predictive maintenance (PdM) for smart industrial systems. They act as the eyes and ears of the machines, constantly feeding the system with valuable information. Types of sensors commonly used for PdM: Vibration Sensors: These detect and measure vibrations in machinery expand more Increased vibration can indicate loose components, bearing wear, or misalignment, all of which can lead to failure expand more. Temperature Sensors: As the name suggests, they monitor temperature levels expand more Abnormal temperature readings can signal overheating due to friction, clogged filters, or cooling system issues. Current and Voltage Sensors: They track electrical parameters like current flow and voltage fluctuations. Deviations from normal ranges can indicate electrical problems, motor inefficiencies, or impending component failure. Acoustic Emission (AE) Sensors: These detect high-frequency sound waves emitted by machinery. Expand more AE signatures can reveal cracks, leaks, or other internal defects before they become critical expand more. Other Sensors: Depending on the specific machinery, additional sensors might be used to monitor factors like pressure, flow rate, or even air quality. The choice of sensor depends on the specific application and the type of data needed for effective PdM. By collecting real-time data from these diverse sensors, industrial systems gain a comprehensive understanding of the health and performance of their machines, enabling them to predict and prevent failures.

***Data Analysis*:** AI and machine learning algorithms analyze this data to identify patterns and anomalies that might signal potential equipment failure.

***Predictive Insights*:** Based on the analysis, the system predicts when a machine is likely to fail and recommends maintenance actions.

III. FUNDAMENTAL ASPECTS CONSIDERED IN THE CONTEXT OF PDM:

1) *System architecture*: With the advent of Industry 4.0, a variety of techniques have been involved in industrial systems, e.g., advanced sensing techniques, cloud computing, etc. In order to design efficient, accurate and universal maintenance systems by embracing these emerging techniques, PdM systems should:

a) Be compatible with various industrial standards,

b) Be easy to integrate with the emerging or future techniques, and

c) Satisfy the basic requirements of PdM, e.g., data collecting, fault diagnosis, and prognosis, etc.

2) *Optimization objective*: Cost and reliability are two common purposes for PdM approaches. These different purposes are often used in insulation, and may very well be in conflict. For example, for multicomponent systems, when the minimum system maintenance cost is obtained, the corresponding system reliability/availability may be too low to be acceptable [27]. Therefore, the purposes of PdM for a specific system or component should be well jointly investigated and set.

3) *Optimization method*: The existing approaches widely varied with the used algorithms, such as algorithms based on Artificial Neural Network (ANN), Support Vector Machine (SVM), auto-encoder, and Convolutional Neural Network (CNN), etc. Also, issues of PdM are different across industries, plants and machines. Therefore, the fault diagnosis and prognosis approaches in the context of PdM must be re- designed and tailored for specific applications.

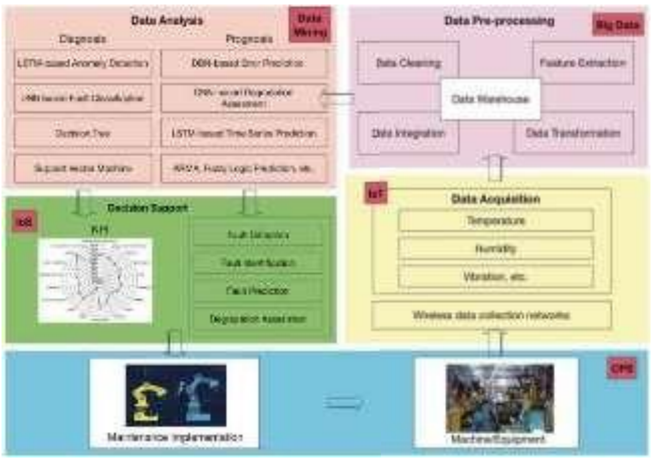

Fig 1. System architecture for the intelligent and PdM 4.0. [28]

IV. 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 2.

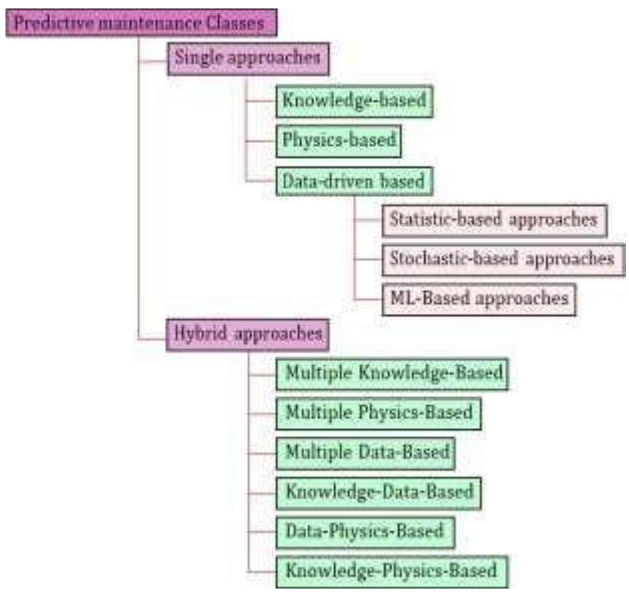

Fig. 2. The classification of predictive maintenance approaches according to the literature [8, 16, 13, 22, 20].

A. *Data-Driven approaches*

Data-driven techniques propose pre-processing steps to transform the data from sensors into a set of useful features. Subsequently, Machine Meaning (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.

i. *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, Re- gression 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 tobe 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].

ii. *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].

iii. *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 ac- curacy. 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 disadvantages 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.

iv. *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].

v. *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 combination of labeled and unlabeled data to train amodel, one-class classification to learn a model of normalequipment behavior, or using density-based anomaly detection to identify deviations from normal behavior as potential indicators of equipment failure.

vi. *Supervised Learning-based approaches*

Based on Supervised ML, this approach detects anomalies by creating a set of grouping rules that help to predict futuredata. Thus, supervised ML is usually employed in scenarios with labeled data availability [2] and uses classification or regression methods. SVM is a separate hyper plane 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 method 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 Auto encoders (AE), Restricted Boltz- man Machine (RBM), DBN, Vector Auto encoder(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.

B. 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].

i. 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, Nunez and Borat [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.

ii. 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. Vizier 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. Vaeznejad 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 designated to detect faults in special type of system and it has not the abilityto be generalized to all the systems.

iii. 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.

C. 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].

V. OPTIMIZATION CRITERION

A. Cost Minimization

The cost model varies with the applied maintenance strategy. For RM strategy, maintenance action for repairing equipment is performed only when the equipment has broken down or been run to the point of failure, thus there only exists corrective replacement cost (Cc). For PM strategy, sequential maintenance actions are scheduled the involved cost items often consist of preventive replacement cost (Cp), inspection cost (Ci), unit downtime cost (Cd) as well as the corrective replacement cost (Cc). Specifically [49], Grill et al. propose a cost model applying these cost items for continuous-time PM that aims at finding optimal preventive replacement threshold and inspection schedule based on system state. The objective cost function is to minimize the long comprehensive cost for the production task throughout the planning.

B. Availability/Reliability Maximization (ARM)

Predictive maintenance specifically targets ARM by leveraging data analysis to forecast potential equipment failures before they occur. This enables maintenance to be performed proactively, at the optimal time, preventing breakdowns and subsequent downtime.

Here's how predictive maintenance contributes to ARM:

Early detection of issues: By continuously monitoring equipment health through sensors and data collection, predictive maintenance identifies arising problems in their early stages. This allows for intervention before they escalate into critical failures that would necessitate lengthy repairs and outages.

•Reduced downtime: By addressing issues before they cause complete equipment failure, predictive maintenance significantly minimizes downtime. This translates into increased operational efficiency and availability. Optimized maintenance scheduling: Predictive maintenance programs determine the ideal timing for maintenance based on equipment condition, rather than following a fixed schedule. This eliminates unnecessary preventive maintenance that might have been conducted even when the equipment was healthy, and ensures critical maintenance is performed precisely when needed.

In essence, predictive maintenance provides the foresight to optimize maintenance activities around ARM goals. By proactively addressing equipment health, organizations can maximize system availability, reliability, and overall effectiveness [50].

C. Multi-Objective Optimization

Besides the aforementioned criterions, many others such as risk, safety and feasibility are commonly used in a PdM model. Usually, just one of these criterions is used as the optimization objective, e.g., minimizing maintenance cost, maximizing system reliability or minimizing equipment downtime, etc. However, such single-objective optimization approaches are often not enough to find the optimal solution that best represents the operator's preference on optimization objectives. For example, given a multi-component system, when the minimum maintenance cost is achieved, the reliability of a certain component may be too low to be acceptable. This is because that the components may be heterogeneous and diverse, the maintenance costs and degradation processes are also different. In this case, multi- objective optimization approaches are promising to achieve a better trade-off among different optimization objectives [47].

Optimization for even greater impact:

•Continuous improvement: Regularly review and refine predictive models based on new data and real-world experiences.

Integration with other systems: Connect predictive maintenance programs with enterprise resource planning (ERP) systems to streamline maintenance workflows and resource allocation.

Human-AI collaboration: Leverage the strengths of both AI and human expertise for more accurate diagnoses and informed maintenance decisions.

VI. DISCUSSION

Predictive maintenance has undergone a remarkable transformation, evolving from a reactive approach to a proactive and data-driven strategy for cost minimization, availability/reliability maximization and multiple objectives. This journey has been fueled by advancements in technology, particularly the rise of:

Sensor technology: Sensors embedded in equipment continuously gather real-time data on performance and health.

Big Data analytics: Advanced algorithms analyze vast amounts of collected data to identify patterns and predict potential failures.

Machine Learning (ML) and Artificial Intelligence (AI): These technologies learn from historical data and sensor readings to refine predictions and recommend optimal maintenance actions.

Predictive maintenance (PdM) is a game-changer for smart industrial systems. It's a shift from reactive maintenance (fixing things when they break) to proactive maintenance (addressing issues before they cause problems). This is achieved through the power of data analysis and artificial intelligence (AI).

The PdM approaches based on a single prediction method have several disadvantages. they risk to not providinga 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].

VII. Conclusion

This paper presents the most recent reviews found in the literature and related works on predictive maintenance. A classification and a comparison of the existing approaches is also proposed. Predictive maintenance 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 literature 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 jointlyinvestigated 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 anomalydetection 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- timebig 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 pro- duction 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 deBeuvron, 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 maintenancein industry4.0. Robotics and Computer-Integrated Manufacturing 74, 102281.URL: https://www.sciencedirect.com/science/article/pii/S073658452100161 7, 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. Buildingand Environment 73, 1–11.

[10] Ehrlinger, L., Wo¨ß, 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/S2352 484722013944,doi:https://doi. org/10.1016/j.egyr.2022.07.130. technologies and Materials for Renewable Energy, Environment andSustainability.

[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 applica- tions], 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., Salau¨n, M., 2020. Towards multi- model approaches to predictive mainte- nance: A systematic literature survey on diagnostics and prognostics. Journal of Manufacturing Systems 56, 539–557.URL: https://www.sciencedirect.com/science/article/pii/S027861252030118 7, doi:https://doi.org/10.1016/j.jmsy.2020.07.008.

[17] Nun˜ez, D.L., Borsato, M., 2018.Ontoprog: An ontology-based model for implementing prognostics healthmanagement in mechanicalmachines. 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 Remain- ing 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. Fastpredictive maintenance in industrial internet of things (iiot) withdeep 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 ofindustry 4.0. Frontiers in Big Data 4.https://www.frontiersin.org/articles/10.3389/fdata.2021.6 63466, 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. Advancesin Mechanical Engineering 14(6), 1–14.doi:10.1177/16878132221101009.

[25] Theissler, A., Pe´rez-Vela´zquez, J., Kettelgerdes, M., Elger, G., 2021. Predictive maintenance enabled by machinelearning: 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).

[29] L. Jiadi, H. Yang, L. Huan, Z. Xinli and L. WenJing, "Research on Data Center Operation and Maintenance Management Based on Big Data," 2020 International Conference on Computer Engineering and Application (ICCEA), Guangzhou, China, 2020, pp. 124-127, doi: 10.1109/ICCEA50009.2020.00033. Cost of data center outages. Laura Swanson. Linking maintenance strategies to performance

[30] International journal of production economics, 70(3):237–244, 2001.

[31] Y. Ran, J. Yang, S. Zhang, and H. Xi. Dynamic iaas computing resource provisioning strategy with qos constraint. IEEE Transactions on Services Computing, 10(2):190–202, March 2017.

[32] Hongzhou Wang and Hoang Pham. Reliability and optimal maintenance of series systems with imperfect repair and dependence. Reliability and Optimal Maintenance, pages 91–110, 2006.

[33] Ana Cachada, Jose Barbosa, Paulo Leitn˜o, Carla AS Gcraldcs, Leonel Deusdado, Jacinta Costa, Carlos Teixeira, Joa˜o Teixeira, Anto´nio HJ Moreira, Pedro Miguel, et al. Maintenance 4.0: Intelligent and pre-dictive maintenance system architecture. In 2018 IEEE 23rd Interna- tional Conference on Emerging Technologies and Factory Automation (ETFA), volume 1, pages 139–146, 2018.

[34] Tianwen Zhu, Yongyi Ran, Xin Zhou, Yonggang Wen “A Survey of Predictive Maintenance: Systems, Purposes and Approaches” IEEE Communication surveys & Tutorials, 22 Mar 2024