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Review of predictive maintenance algorithms applied to HVAC systems

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Abstract

Predictive maintenance is a preventive maintenance approach that is performed based on an online health assessment and allows for timely pre-failure interventions. It can diminish the cost of maintenance by reducing the frequency of maintenance as much as possible to avoid unplanned reactive maintenance, without incurring the costs associated with too frequent preventive maintenance. The main objective of predictive maintenance of heating, ventilation, and air conditioning (HVAC) systems is to predict when the HVAC equipment failure may occur. The benefits are numerous: planning of maintenance before the failure occurs, reduction of maintenance costs, and increased reliability. For this, the predictive maintenance of the HVAC systems is based on the historical data of the system for predicting the state of health of the system. The process of predictive maintenance application is composed of the Internet of Things (IoT) sensors that are installed inside the HVAC system, then the IoT platforms that help in collecting the signals coming from the sensors and converting them to existing databases. Afterward, the algorithms of application of predictive maintenance could be either knowledge-based approaches, physics-based approaches, or even data-driven-based approaches. A systematic literature review on the existing algorithms of HVAC predictive maintenance application is conducted in this paper to summarize the most used approach for predicting future failures in HVAC systems and to explain the benefits and limits of these algorithms.

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Keywords: Predictive maintenance; Machine learning; Deep learning; HVAC systems

1. Introduction

The building sector is considered one of the main factors affecting energy expenditure and greenhouse gas emissions, approximately with a range rate of 20%–40% of the total energy consumption [1]. The HVAC system plays a major role in the overall energy consumption of buildings and represents 50%–60% of the energy used in buildings [2–5]. Maintenance of these HVAC systems accounts for more than 65% of annual facility management

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Nomenclature

AE	Autoencoder
AHU	Air handling unit
AI	Artificial intelligence
ANN	Artificial Neural Networks
BPNN	Back-propagation neuron network
CBM	Condition-based maintenance
CNN	Convolutional Neural Network
DBN	Deep Belief Network
DT	Decision Tree
EKF	Extended Kalman filter
FDD	Fault detection and diagnosis
GAN	Generative Adversarial Network
GBDT	Gradient Boosting Decision Tree
HSMM	Hidden Semi Markov Model
HVAC	Heating, Ventilation, and Air Conditioning
IoT	Internet of Things
KF	Kalman filter
KPCA	Kernel principal component analysis
LSTM	Long Short-Term Memory
MEP	Mechanical, Electrical, and Plumbing
ML	Machine learning
PCA	Principal Component Analysis
RF	Random Forest
RNN	Recurrent Neural Network
RUL	Remaining useful life
SAE	Supervised autoencoder
SFDD	Sensor Fault Detection and Diagnosis
SPC	Statistical Process Control
SVM	Short Vector Machine
TTF	Time to failure
UKF	Unscented Kalman filter
VAV	Variable air volume

costs [6]. Effective maintenance strategies can reduce building maintenance costs and even extend the life of building components. So, it is crucial to prepare a maintenance plan when the equipment or the machine starts to have alerts of probable future failures before it totally breaks down, and also, we need to make sure that we are not replacing the equipment before exploiting its fully potential lifecycle. This is important because the maintenance costs can reach up to 75% of the global maintenance costs during the lifecycle of the system [7]. Thus, the planning of maintenance needs to be applied just in the exact time needed. Traditional maintenance is usually applied based on a schedule maintenance planning which does not take into consideration the actual and real health state of the equipment. Therefore, we cannot exploit the full lifespan of the equipment since the majority of the time we replace parts that are still useful, which makes traditional maintenance strategies not efficient and requires high costs.

So, thanks to the enormous disadvantages of the corrective and preventive sorts of maintenance, predictive maintenance have appeared to improve the quality of equipment maintenance and reduce unnecessary costs related to maintenance procedures. Many researchers, such as [8], have confirmed that predictive maintenance can diminish the cost of maintenance by a rate ranging from 25% to 35%, defeat breakdowns by a rate of 70% to 75%, decrease the time of breakdowns with a rate of 35% to 45% and boost the production with a rate ranging from 25% to 35%.

To plan a predictive maintenance strategy there are lots of steps that should be applied correctly and precisely in order to have an accurate prediction result of the anomalies that could occur to equipment [9]. First of all, many IoT sensors should be installed on the system, such as vibration, acoustic, temperature, pressure, flow rate, CO_2 concentration, and many other sensors that depend on the type of equipment and the type of anomaly or the failure that we desire to predict. The second step is related to the collection and storage of data in an existing database. Then, these huge amounts of data should be cleaned and classified in the following step. After that, the essential step is the selection and the programming of the most adequate prediction model. Then, the coming step is related to the training of the model and its datasets to improve the quality of the predicting model. And the final step is the programming of the maintenance schedule plan. The most difficult part of the application of a predictive maintenance plan is related to the programming of the predictive model. This is due to a large amount of the existing models that differ from one model to another with the accuracy of the predicting results or the complexity of the datasets training.

Thus, the main objective of this article is to conduct a systematic literature review on the existing algorithms of predictive maintenance application on HVAC systems. These predictive maintenance algorithms could rely either on knowledge-based approaches, physics-based approaches, or even data-driven-based approaches. The motivation of this work has been identified from the existing gaps and limitations in the literature, such as reviews and surveys that are restricted to one specific scope. A lot of studies have focused either on data-driven-based algorithms [10], or machine learning-based algorithms [11,12] for predictive maintenance applications. Nevertheless, the majority have not taken into consideration the traditional existing algorithms, which are based on knowledge of physics models for predictive maintenance application on HVAC systems.

The rest of this paper is organized as follows; Section 2 provides a global overview of the predictive maintenance fields by explaining its benefits, its main goals, and the essential steps to apply it. Section 3, describes the knowledge-based models including the rule-based models and the fuzzy logic-based models. Section 4, explains the model-based models with illustrations of several studies from the literature that have developed these models in their surveys. Section 5, details the data-driven-based models and their sub-categories including machine learning-based models and deep learning-based models. Multi-based models are presented in Section 6, along with their possible combinations and their advantages. Finally, Section 7 summarizes the most used approaches for predicting future failures and anomalies in HVAC systems and explains the benefits and limits of these algorithms along with the main challenges of each approach.

2. Predictive maintenance

Predictive maintenance is the most recent sort of maintenance, that has gotten the attention of researchers and industries. This type of maintenance helps the industries to detect the failure of equipment before it occurs and to know exactly when it is going to happen and which part of the system is going to be affected. This intelligent sort of maintenance is creating a great revolution in the industry; industry 4.0; thanks to its benefits that lead to an enormous reduction in operation and maintenance costs of the whole system. Moreover, predictive maintenance has two crucial objectives which are diagnostic and prognostic. Diagnostics aims to predict and detect failures while extracting their causes and assessing the health state of the equipment. Prognostics aim to predict the future states of the system and the remaining useful life. The eventual goals of predictive maintenance are the estimation and the prolongation of the RUL and TTF of the equipment since it reduces the unplanned breakdown time of the machines and decreases the hall cost of the maintenance process. The TTF prediction serves to determine the lifespan of the equipment before having a failure [13]. Predictive maintenance is generally applied by adopting systems that collect data from sensors and actuators to establish diagnostics and prognostics analysis. OSA-CBM is a norm and standard that precise the most important steps that are needed to be followed in the predictive maintenance system for the estimation of the remaining useful life of any component exposed to one single failure mode [14]. These steps are data collection, data pre-processing, faults detection & identification, degradation assessment, RUL computation and finally making the report. These essential steps could be changed or modified in the predictive maintenance system according to the type of system studied [15]. As shown in Fig. 1, to apply predictive maintenance, there are several approaches to take into account; either knowledge-based approaches or physical-based model approaches, or even data-driven approaches. In addition to these single-based cited approaches, there are other hybrid types such as cloud-based [16], Deep Learning—based, IoT-based, Fleet-based, and Time-based.

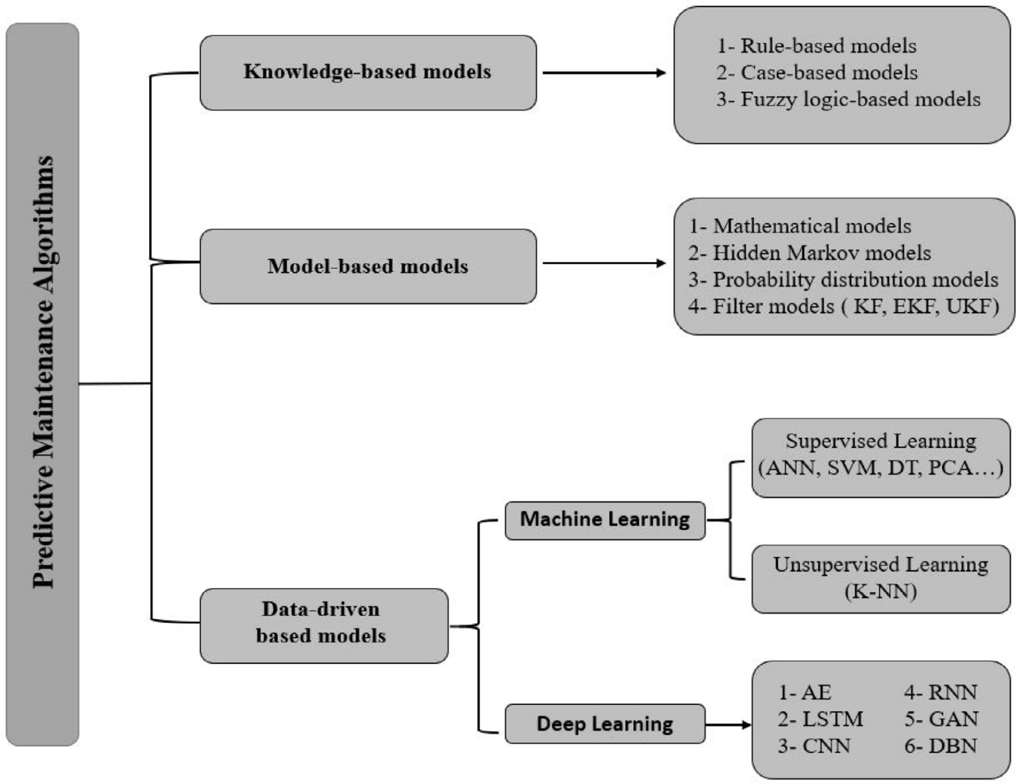

Fig. 1. Predictive maintenance algorithms.

3. Knowledge-based models

As soon as predictive maintenance appeared, traditional methods were used to apply it for fault diagnosis and prognosis and they were generally based on the knowledge and experience of the experts. The knowledge-based approach uses historical fault data as the ultimate tool for prediction. Otherwise, it does not take into account the mathematical or the physical models for prediction [17]. This model could be divided into three categories; rule-based or case-based and fuzzy knowledge-based algorithms. 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. In rule-based models, the knowledge is based on "IF-THEN" rules, which consist of a knowledge base containing many rules, a facts base, and an inference engine [18]. The knowledge base stores facts from the expert knowledge as inputs and the inference engine applies "IF-THEN" rules to the knowledge base to deduce new knowledge as outputs. This inference engine uses an iterative process that is repeated according to the inference engine frame until the end of the reasoning process. Visier et al. [19], has developed an expert system relying on a rule-based approach aiming at diagnosing faults in HVAC school systems. House et al. [20], has conducted a rule-based approach to detect the faulty state of the air handling units. Schein et al. [21], has also conducted a rule-based approach for FDD in AHU using mass balance and energy balance rules in the HVAC system studied. The drawback of these rule-based models is that the expert system is destinated to detect faults in a special type of HVAC system and it has not the ability to be generalized to all the HVAC systems. Since each type would have a different set of working rules that differs from one type to another (see Fig. 2).

Fuzzy-knowledge-based models (Fig. 3) are based on fuzzy logic and it uses approximately the same format of rules IF-THEN as rule-based systems. Fuzzy logic 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. Fuzzy logic is greatly linked to human perceptions [23]. And among the famous applications of fuzzy logic and fuzzy sets theory is the fuzzy inference system (FIS), which

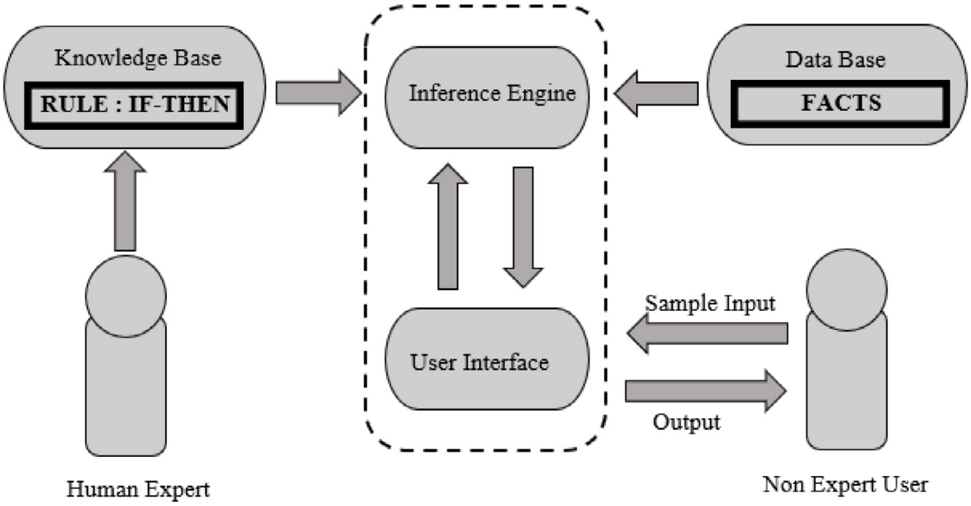

Fig. 2. RULE-based model system [22].

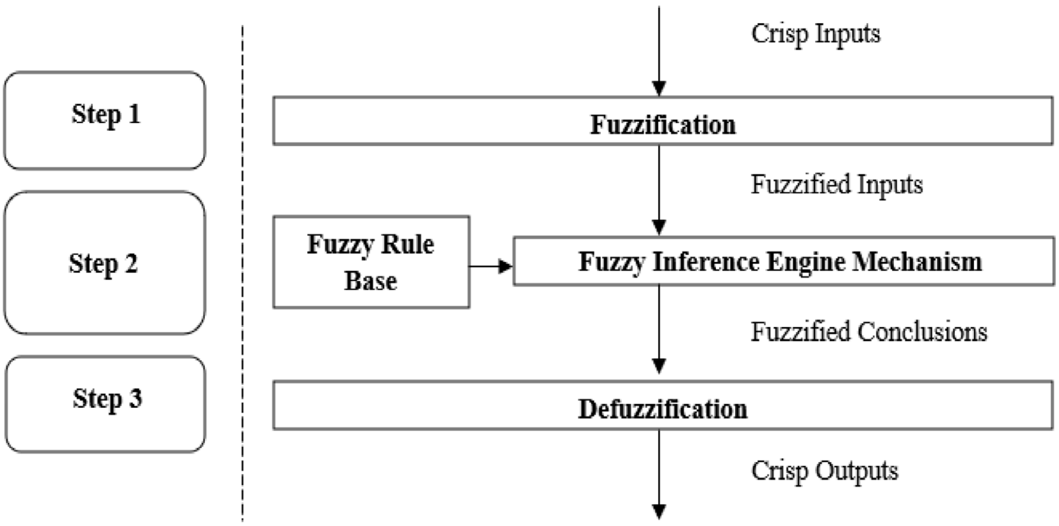

Fig. 3. Fuzzy logic process [25].

can deal with linguistic concepts, help with classification tasks, offline process simulation and diagnosis, and online decision support tools and processes. In literature, fuzzy-knowledge-based models have not been well used for predictive maintenance of HVAC systems. Few surveys have chosen to work with this type of knowledge-based model such as Dexter et al. [24], who have developed a multi-step fuzzy-based model for FDD of AHU to detect several faults and errors in the HVAC system.

4. Model-based models

Model-based or as also as known physics-based models use a physical understanding of the system to evaluate the remaining useful life of an equipment. The physics-based models could be divided into; the mathematical model, Hidden Markov model, Probability distribution model, and filter models such as KF, EKF, and UKF. The Hidden Markov models are destinated to systems that do not have a directly visible state, meaning that the state is hidden, but the output is visible and it depends on the internal states of the system. According to the literature, the model-based approach [26–29], is the most developed algorithm in the field of FDD of HVAC systems. Norford et al. [30], have conducted a demonstration of FDD on AHU systems based on a physical model to detect the common faults that occurred in these types of HVAC systems. Castro et al. [31], has also developed a physical model for FDD to detect faults in chiller systems. Furthermore, Wang et al. [32], have also proposed a model-based approach serving at SFDD in chilling plant systems.

5. Data-driven based models

In data-driven models, data is collected from the sensors installed in the equipment, components, and machines for fault prediction. The collected data features are extracted for processing, analysis, and degradation of information included in the data. To apply this model, the proper machine learning or deep learning algorithm should be selected according to the corresponding parameters of the equipment. ML is a subcategory of AI and it can be defined as an algorithm that can learn with the smallest support possible. ML-based models have many pros as they can deal with multivariate, high-dimensional data and can extract hidden relations among data. For ML models, various algorithms exist that can be classified into three categories. Either supervised learning algorithms such as ANN [33,34], SVM [35,36], PCA [37–39] and DT which includes GBDT [40] and RF [40]. Unsupervised learning algorithms such as k-NN. Those machine learning-based models could serve for classification, regression, or even clustering. Fig. 4, shows the architecture of the SVM algorithm.

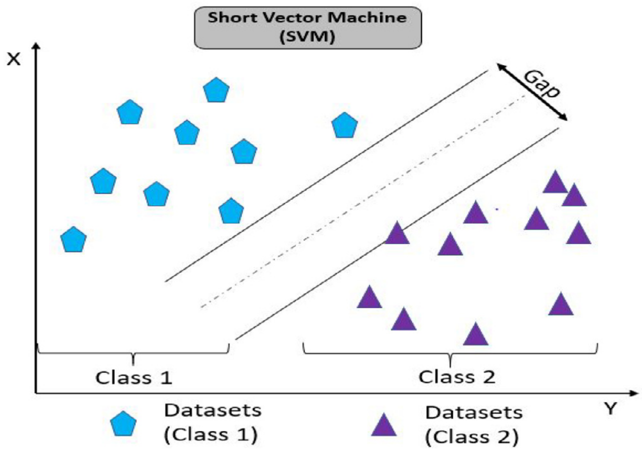

Fig. 4. The architecture of an example of ML data-driven based algorithm: SVM algorithm.

Data-driven based models have gotten the attention of many researchers recently due to their numerous advantages and benefices that do not depend on the accuracy of the mathematical and physical models or the development of a detailed experience rule. Among the several algorithms present and developed in data-driven models there are ANN algorithms, which are the most machine learning algorithms used and developed in the field of predictive maintenance for HVAC systems. Wang et al. [41], has developed an ANN algorithm for FDD in a VAV system. The findings have proved the accuracy of the algorithm in diagnosing the faults of outdoor air, supply air, and return airflow rate sensors. Moreover, West et al. [42], have conducted a novel statistic ML-based approach for FDD in HVAC systems. Turner et al. [43], have proposed a data-driven approach for automated FDD in residential HVAC systems based on a recursive algorithm for parameter estimation. Furthermore, Cheng et al. [44], have developed and compared two data-driven algorithms; ANN and SVM, to predict the future condition of MEP components that include HVAC systems. The study has shown a great potential for the SVM algorithm compared with the ANN algorithm in terms of the predicted results, condition, error, and accuracy. While, Montazeri et al. [45], have applied PCA and KPCA algorithms for sensor FDD of an AHU. As illustrated in Fig. 5, the authors have compared both developed PCA algorithms with the NN-based approach and have found that faults are detected and diagnosed by 60% using PCA algorithms and 62% using KPCA algorithms, and 98,7% using NN algorithms. Melendez et al. [46], have used MPCA (Multivariate Principal Component Analysis) for the FDD of an AHU (see Fig. 6).

Deep learning models are the second type of data-driven-based model. There are several DL algorithms in the literature such as AE, LSTM, CNN, RNN, DBN, GAN, and so on. Guo et al. [47], have established a fault diagnosis

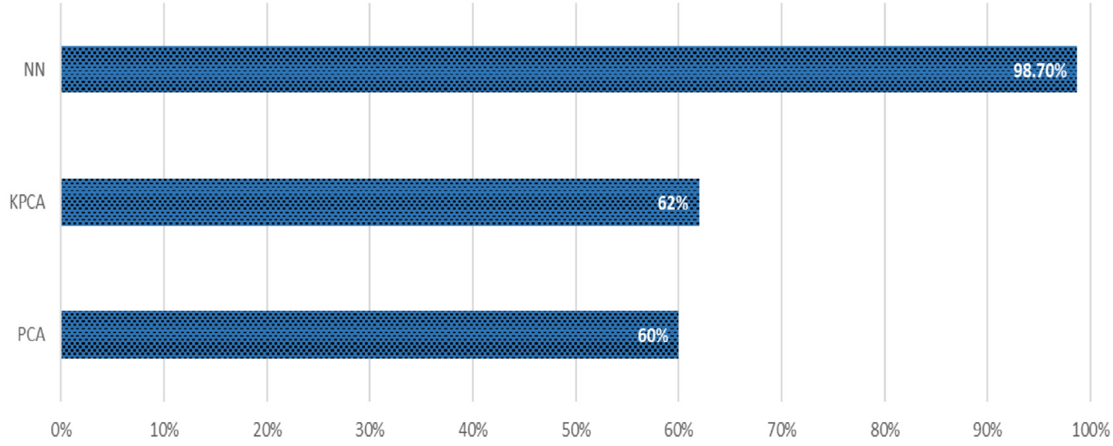

Fig. 5. Fault detection percentage for three different ML algorithms.

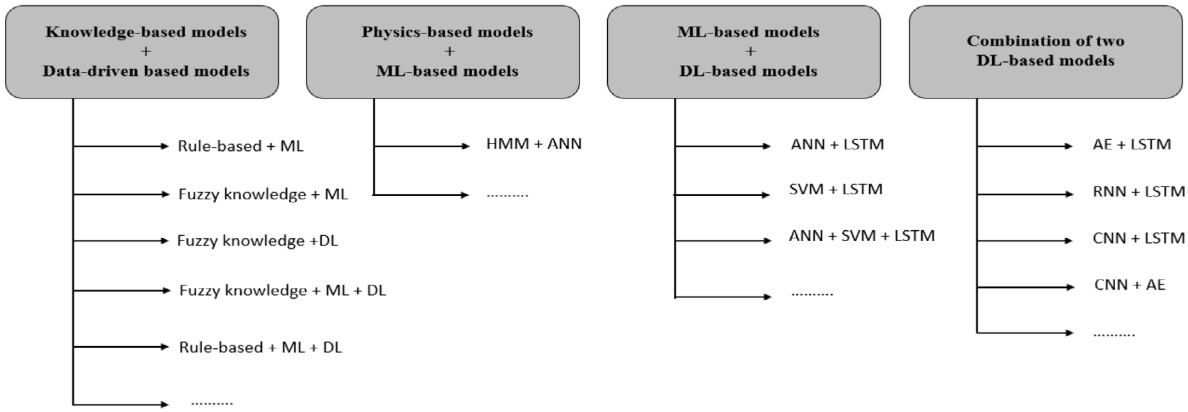

Fig. 6. Multi-based models' combinations.

model based on the DBN model. Fernandes et al. [48], have developed an LTSM model for predicting severe faults in boilers of the HVAC system. Yun et al. [49], have conducted a data-driven based model approach for fault detection and diagnosis of FDD of an AHU using the SAE algorithm. Then, the author compared the precision, sensitivity, and F1 score of the SAE algorithm used with other data-driven models such as ANN and SVM algorithms. Knowing that the F1 score is calculated by the weighted harmonic mean of precision and sensitivity. The findings of this study have proved that the proposed SAE algorithm has detected correctly the fault data of defined and undefined states with high performance. The SAE algorithm could be more accurate for FDD than the ANN and SVM algorithms. In addition, Li et al. [50], have used a semi-supervised FDD approach for constructing an HVAC system using modified GAN.

6. Multi-model approaches for predictive maintenance

To get and obtain real information about the equipment, several sensors such as pressure; temperature, humidity, and vibration, should be installed to collect and transmit data. But, some subsystems of the equipment cannot be always accessible or able to install sensors. Thus, this influences negatively data acquisition and then data-driven algorithms programming. To some up, the traditional predictive maintenance approach based on a single prediction method has several disadvantages and risks to not providing a fault prediction framework with higher accuracy and reliability. So, a hybrid approach has gotten the attention of many researchers recently, to take advantage and benefits of more than one single model and to avoid effectively the limits of each single model. Lots of studies use the multi-model approaches by combining two or more different models as illustrated in Fig. 3. Du et al. [51], have combined the BPNN with Subtractive clustering analysis to conduct a FDD of an HVAC system. Hassanpour et al. [52] have developed a hybrid approach combining the first principles of knowledge with a data-driven modeling algorithm for two fault case detection in the HVAC system. The first fault is relative to the return air temperature sensor and the second one is related to the mixed air temperature sensor. Yan et al. [53], have estimated the RUL of an AHU using the HSMM. And in order to improve the prognosis fault accuracy, the authors have combined the HSMM model with the SPC model to filter out the fault estimates of HSMM states. Bouabdallaoui et al. [54], have combined AE with LSTM algorithms to predict failures in a group of HVAC systems that include AHUs, boilers, and double pumps. Luo et al. [55], have proposed a hybrid approach framework, based on combining data-driven and model-based methods in order to obtain higher accurate prediction results and probability density functions.

7. Conclusion

With advancements in the industrial Internet of things and artificial intelligence, predictive maintenance has become more and more efficient. The core point to apply a predictive maintenance strategy successfully is to model and predict failure patterns accurately. Based on the systematic literature review conducted in this paper, it can be seen that this area has been well studied using many methodologies ranging from knowledge-based approaches to data-driven based approaches. However, the task of RUL is still challenging due to the complex, uncertain, nonlinear features and operational conditions. The main challenges can be summarized in several aspects such as the lack of input data because most data-driven models, especially machine learning approaches, predict the RUL based on the extracted data. And even though classification algorithms have shown excellent accuracy in distinguishing states, they need to be trained with a complete dataset of all failures. The algorithms are selected based on the developer's experience and this may influence the variability of the prediction results. SVM and ANN, are the most widely used ML algorithms in the literature. They have been successfully applied in several areas of predictive maintenance applications. Some papers have focused on ANN algorithms. Other papers have studied the SVM technique. Some authors have performed studies using the DT technique. However, it is observed that the DBN technique is less considered and there are only a few studies in the literature. Furthermore, conducting a study with only one prediction method may not show excellent results. Therefore, applying other methods to provide comprehensive results by applying hybrid a multi-based model. So, according to the conducted survey, it can be recommended to combine more than one single ML or DL model to provide a better prediction compared to using an individual model. Thus, classification and anomaly detection algorithms are also suggested to be combined to maintain the accuracy of classification models without losing the benefits of anomaly detection algorithms. In this way, predictive maintenance can be applied to different HVAC systems that do not have a large data set.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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