Building Research & Information

ISSN: 0961-3218 (Print) 1466-4321 (Online) Journal homepage: www.tandfonline.com/journals/rbri20

A data-driven predictive maintenance model for hospital HVAC system with machine learning

Raid Al-Aomar, Marah AlTal & Jochen Abel

To cite this article: Raid Al-Aomar, Marah AlTal & Jochen Abel (2024) A data-driven predictive maintenance model for hospital HVAC system with machine learning, Building Research & Information, 52:1-2, 207-224, DOI: 10.1080/09613218.2023.2206989

To link to this article: https://doi.org/10.1080/09613218.2023.2206989

Published online: 16 May 2023.

BRI BUILDING RESEARCH & INFORMATION
2024, VOL. 52, NOS. 1–2, 207–224
https://doi.org/10.1080/09613218.2023.2206989

Routledge Taylor & Francis Group

Check for updates

A data-driven predictive maintenance model for hospital HVAC system with machine learning

Raid Al-Aomar[a], Marah AlTal[b] and Jochen Abel[c]

[a]School of Applied Technical Sciences, Industrial Engineering, German Jordanian University, Amman, Jordan; [b]Faculty of Engineering, Aqaba University of Technology, Aqaba, Jordan; [c]Faculty of Architecture, Civil Engineering & Geomatics, Frankfurt University of Applied Sciences, Frankfurt, Germany

ABSTRACT

Corrective and preventive maintenance strategies are typically employed to maintain an efficient functionality of different facility systems. This entails the evaluation of current conditions and the prediction of future conditions. Such prediction is highly needed for critical building systems such as Heating, Ventilation, and Air Conditioning (HVAC) of hospitals to maintain their functionality and extend their lifetime. Current literature highlights the benefits of adopting machine-learning algorithms for predictive modelling. Literature also reveals a gap in predictive modelling based on real-time sensor data and the prediction of both short-term and long-term future conditions. This paper presents a data-driven predictive maintenance model of a hospital's HVAC system with a focus on the Air Handling Units (AHUs). The developed model adopts machine-learning using the sensor data acquired by the BMS and the database of the hospital's CMMS. Support Vector Machine (SVM), Decision Trees (DT), and K-Nearest Neighbours (KNN) algorithms are used for the prediction of AHU's short-term conditions. Prophet Forecasting and Seasonal Auto-Regressive Integrated Moving Average (SARIMA) algorithms are then used to predict the AHU's long-term future conditions. The study also highlights the benefits of adopting the proposed model in terms of reduced maintenance cost and improved operational effectiveness of hospital AHUs.

ARTICLE HISTORY
Received 6 January 2023
Accepted 20 April 2023

KEYWORDS
Predictive modelling; maintenance planning; machine learning; building management; air handling unit

Introduction

Building maintenance is an essential part of Facility Management (FM) for maintaining operations and attaining sustainability. Typically, maintenance accounts for 65% of the buildings' operating expenses (Sacks et al., 2018). Most buildings undertake a mix of corrective and preventive maintenance procedures. Corrective maintenance is performed after fault recognition and it can be either immediate or deferred depending on the time aspect (European Committee for Standardization, 2010). This typically results in increased shutdown and maintenance expenses associated with restoring or replacing failed components. Preventive maintenance, on the other hand, conducts inspection, replacement, and repairs according to a scheduled plan in order to reduce or prevent shutdowns and extend the components' lifetime (Cheng et al., 2020). However, preventive maintenance without an accurate prediction of faults has a limited detection power and typically involves unnecessary inspections and replacements that generally increase the facility's operational costs (Susto et al., 2015). According to Mobley (2002), maintenance inspections and actions that are carried out unnecessarily represent one-third of the maintenance expenses.

An effective maintenance strategy is, therefore, essential to reduce operational costs and prolong the lifespan of building systems. Expert systems for predictive maintenance have emerged as an effective maintenance strategy that can extend service life while reducing the costs of inspections, materials, and labour (Carvalho et al., 2019).

Hospitals are an example of complex buildings that utilize various specialized and complex systems to provide patients with safe and sustainable healthcare services (Lavy & Shohet, 2009). Hospitals are non-stopping operating facilities and their efficiency is vital since any system failure may lead to multiple health complications (Mwanza & Mbohwa, 2015). Heating, Ventilation, and Air Conditioning (HVAC) is one of these essential systems that provides adequate hospital environment and maintain good Indoor Air Quality (IAQ) (Au-Yong et al., 2014). IAQ is considered an essential human health determinant in complex facilities such as hospitals (Norhidayah et al., 2013). The

CONTACT Raid Al-Aomar raid.alaomar@gju.edu.jo

potential failures of HVAC systems could affect the building's economic, environmental, and performance aspects (Sánchez-Barroso & García Sanz-Calcedo, 2019). Therefore, adopting a predictive maintenance strategy is particularly essential to predict and prevent potential failures in the hospital's HVAC system and to optimize its operational cost.

The increased availability of industrial data has facilitated the ways in which predictive maintenance could be developed and deployed (Costello et al., 2017). Building Management System (BMS) can greatly help in monitoring and controlling building systems through sensor data. Several previous studies utilized the BMS to predict the condition of HVAC systems. For example, Kukkonen (2018) used BMS to obtain sensor data for an Air Handling Unit (AHU) and applied fuzzy expert rules and recursive density estimation for automatic fault detection. Computerized Maintenance Management System (CMMS) could be also used to improve the efficiency of maintenance management systems. Such computerized systems along with the availability of sensor data have also facilitated the utilization of machine learning in predictive maintenance.

Reviewed literature reveals a noticeable progress in adopting machine learning in predictive maintenance in general and for HVAC systems in particular. Recently, Cheng et al. (2020) developed a data-driven predictive maintenance framework that utilizes machine-learning algorithms to predict the future conditions of a chiller in an HVAC system. The framework focused on predicting the chiller's long-term future condition based on data collection and data integration of the Building Information Modelling (BIM), Facility Management (FM) system, and Internet-of-Things (IoT) technologies. Cheng et al. (2020) recommended to extend the framework application to other HVAC systems and to utilize other machine learning algorithms that predict both short-term and long-term conditions. Furthermore, reviewed literature also revealed the need for studies that integrate BMS sensor data and CMMS database for the predictive maintenance of HVAC systems in hospitals especially the AHUs.

This paper contributes to this research gap through the development and testing of a data-driven predictive maintenance model based on the framework developed by Cheng et al. (2020). The proposed model utilizes the sensor data of BMS and CMMS database to evaluate and predict the conditions of the hospital AHUs using a set of machine-learning algorithms. The model is intended to effectively perform and plan the corrective and preventive maintenance based on an accurate prediction of the AHU's short-term and long-term conditions. This is expected to result in reducing the AHU's maintenance expenses while optimizing the system efficiency and preserving the hospital's IAQ.

Literature review

Predictive maintenance strategies predict faults and errors before they occur (Carvalho et al., 2019). They are mainly based on the analysis of known characteristics as well as an evaluation of significant parameters of the items' deterioration. It is often associated with the prognostic capability in terms of forecasting the future system conditions and the Remaining Useful Life (RUL) (Puglisi, 2019). RUL is defined as the period of time that the equipment will continue to function according to its design specifications (Zio, 2013).

Fault diagnosis is the method used for identifying the system's physical fault factors while fault prognosis can be used to predict the RUL and future condition of systems (Mirnaghi & Haghighat, 2020).

As discussed in Yan et al. (2020b), fault prognosis prevents unexpected failures, optimizes the resources of maintenance actions, and consequently leads to reduced maintenance costs. This also enables dynamic maintenance scheduling considering system operation and results in a lower energy cost and higher equipment reliability (Sullivan et al., 2010).

HVAC system and AHU in hospitals

HVAC is an essential system in hospitals and buildings in general. It provides adequate ventilation, air conditioning, and good IAQ to the building users (Au-Yong et al., 2014). Such functionality is crucial to hospitals to ensure proper air flow, temperature and humidity control, and a healthy environment. Key HVAC system components include chillers, pumps, insulated steel pipes for water distribution, AHU, duct fan, air terminal, dampers for air distribution, control systems, and electrical distribution systems (Buys & Mathews, 2005).

As a crucial element of HVAC systems, numerous researches have been dedicated to identifying and diagnosing various malfunctions that may occur in AHUs (Yan et al., 2016). AHU connects the main heating/cooling system to the different building zones. AHU faults could, therefore, lead to many undesired outcomes like indoor discomfort, poor IAQ, occupant complaints, and energy waste (Zhao et al., 2017). Further details on AHU functionality can be found in Du et al. (2014) and Yan et al. (2020a).

Many developments in the management systems of hospitals and healthcare facilities mandate the continuous assessment of healthcare buildings and their air-conditioning systems with numerous studied on the connection between the patients' degrees of recovery and their surroundings (Moscato et al., 2017). These studies emphasized the importance of maintaining IAQ in hospitals through efficient AHUs and other HVAC systems.

However, building HVAC systems are often disturbed by many problems including device faults, improper control, and poor maintenance. These problems generally lead to significant energy waste (Zhao et al., 2019) and increase the costs of system installation, operation, and maintenance (Moscato et al., 2017). Thus, effective preventive maintenance strategies through predictive modelling are increasingly considered to increase the efficiency of AHU and HVAC system and to reduce their maintenance and operational costs and prolong their lifespan.

BMS and CMMS in maintenance

BMS is a system used to remotely control and monitor the building functionalities and building systems such as the HVAC systems, fire systems, and electrical systems (Kučera & Pitner, 2018). It can assist facility managers, engineers, and operators in controlling, monitoring, and maintaining building systems, which typically results in reducing energy consumption and improving occupant satisfaction (Domingues et al., 2016). BMS functions by connecting a variety of sensors to different system components to collect relevant data and notify decision makers of any need to check the system condition and to respond appropriately (Brambley et al., 2005). According to Kastner et al. (2005), the architecture of the BMS system is organized into three layers:

(1) Field layer, which contains sensors, valves, dampers, actuators that send and receive signals from the controller.
(2) Control layer (the middle layer), where measurements are processed, this layer contains the controller, also known as the Direct Digital Control (DDC).
(3) Management layer, which provides a sufficient data presentation and visualization level to enable operators to determine the system status.

In addition to the BMS, the CMMS provides operational assistance to FM by helping with the daily building operations, such as maintenance, waste management, and cleaning services. These systems support decision-making in asset management, inventory management and space management (Kučera & Pitner, 2018). Therefore, integrating both technologies can greatly help in operating and maintaining the critical building systems such as HVAC and AHUs (Kučera & Pitner, 2018). Examples of systems that support such integration include E-facility (eFACiLiTY, 2020) and (Ecodomus, 2020).

The BMS and CMMS can record a vast amount of HVAC system operation and maintenance data. This typically includes key parameters and variables such as temperatures, flow rates, and pressures along with maintenance and failures records. Kukkonen (2018) used BMS to obtain AHU sensor data and to investigate various techniques for detecting potential faults. Yan et al. (2018) also used sensor data from BMS for the fault detection of AHU. Finally, Cheng et al. (2020) used sensor data obtained from the BIM model to predict the chiller's future condition. Nonetheless, when advanced data analysis technology is not adopted, recorded data are not fully utilized in the maintenance of AHU and HVAC systems. Machine learning methods can, therefore, be integrated with BMS and CMMS to establish an expert system for predictive maintenance.

Predictive maintenance with machine learning

Machine learning, within artificial intelligence, has emerged as a powerful tool for developing intelligent predictive algorithms in many applications including maintenance. Machine learning algorithms can manage high-dimensional, multi-variable data, and extract hidden connections between data in a complex and diverse environment (Wuest et al., 2016). Such capability can produce valuable information to decision makers and provide many advantages to system maintenance such as the reduction of maintenance cost, the continuity of operation, and the control of spare parts inventory (Peres et al., 2018).

Several machine-learning algorithms were used in literature to predict the condition of systems. Examples include Support Vector Machine (SVM), Decision Trees (DT), and K-Nearest Neighbour (KNN). SVM is a well-known machine-learning algorithm that performs classification and regression tasks with high accuracy and precision levels (Sexton et al., 2017). It analyzes regression and identifies patterns (different data classes) by creating an n-dimensional hyperplane that divides data into n groups/classes (Carvalho et al., 2019; Susto et al., 2013). DT also solves regression problems using a structured classification rule (Lin & Fan, 2019). It has demonstrated positive outcomes in multiple industries with accurate predictions. It can be used with high-dimensional categorical and numerical data with a proper combination of accuracy and speed (Syachrani et al., 2013). KNN approaches the classification by comparing and training the given tuples to define the nearest sample point (Kiran Naik et al., 2021).

There are other algorithms that can be used for long-term forecasting in predictive maintenance, such Prophet forecasting and Seasonal Auto-Regressive Integrated Moving Average (SARIMA). Prophet forecasting is a model for time-series forecasting that Facebook released and shared with the public in 2017 (Shawon et al., 2020). It works best with time-series that have strong seasonal effects in historical data (Aditya-Satrio et al., 2021) and considers outliers and missing values in time-series data (Ye, 2019). It is customizable to a wide variety of applications (Taylor & Letham, 2018). SARIMA can also perform seasonal time-series forecasting as an extension of the Auto-Regressive Integrated Moving Average (ARIMA) model which was developed to predict future values using time-series autocorrelation analysis (Jeong et al., 2014). The SARIMA model is often applied when the data has seasonality-periodic fluctuations (Farsi et al., 2021).

For predictive maintenance, these machine-learning tools hold the potential to conveniently analyze and interpret thousands of sensor data points from hundreds of different system sources. This can increase the efficiency of the data-driven predictive maintenance as it surpasses humans in the ability to form decisions based on complex data. However, such applications' feasibility depends on the selected machine-learning algorithm, the system or application, and the available or accessible data (Carvalho et al., 2019).

Predictive maintenance of HVAC system

For HVAC systems, numerous studies on data-driven methods for Fault Detection and Diagnosis (FDD) were conducted using machine-learning algorithms. Yan et al. (2020a) developed a framework for FDD in AHUs based on sensor data and by using Generative Adversarial Network (GAN) as an unsupervised machine-learning technique. Also, Yan et al. (2018) proposed a semi-supervised SVM machine-learning algorithm for FDD of AHU. The proposed model achieved an accuracy between 80% and 89%. Similarly, Trivedi et al. (2019) used a machine-learning algorithm for the predictive maintenance of AC systems. They applied SVM and DT algorithms to detect system faults using real monitoring data. The outcomes showed that the DT model had a higher accuracy of 93.6% than the SVM model.

However, there was a shortage in research addressing fault prognosis of HVAC systems especially in hospitals. Cheng et al. (2020) developed a framework for data-driven predictive maintenance for chillers as an integral component of the HVAC system. SVM and Artificial Neural Network (ANN) machine-learning algorithms were used in the analysis. They were both highly accurate for short-term prediction. Yan et al. (2020b) designed a semi-Markov physics-based model to predict the RUL of cooling coils in AHU. Experimental results revealed that their method could predict the RUL of the components and systems with high accuracy with a focus on discrete parameter condition states.

The review of such limited research revealed a gap in frameworks that utilize machine learning for both short-term and long-term predictive maintenance of the AHUs in hospitals. There is also a gap in models that utilize sensor data from both BMS and CMMS. This paper builds on the work of Cheng et al. (2020) and contributes to these research gaps. The focus is on the predictive maintenance of the AHUs in hospitals. It also contributes to studies that utilize and evaluate the performance of machine-learning algorithms for predictive maintenance.

Methodology

A systematic methodology is used for developing and testing a predictive maintenance model. As shown in Figure 1, the model consists of three main elements: data collection, condition monitoring and prediction, and maintenance performance and planning. The condition monitoring and prediction function is divided into two sub-systems: The first sub-system is condition monitoring using GUI in the BMS. This sub-system has two sub-modules (1) Current condition assessment of the AHU using a machine-learning algorithm for classification purposes. The second module is (2) Future condition prediction using time-series forecasting algorithm based on cumulative condition data generated by the machine-learning algorithm in the first module. The second sub-system is condition monitoring and prediction using CMMS. It predicts the AHU's short-term condition, which helps the FM and maintenance staff in updating their near-term maintenance plans and preparing the appropriate tools and items required for corrective maintenance in advance. The third function in the proposed model is maintenance performance (based on the short-term prediction) and maintenance planning (based on the long-term prediction).

Data collection

For data collection, field devices measure, collect the AHU's sensor data and send signals to the DDC. The DDC processes the sensor data and transmits it to the

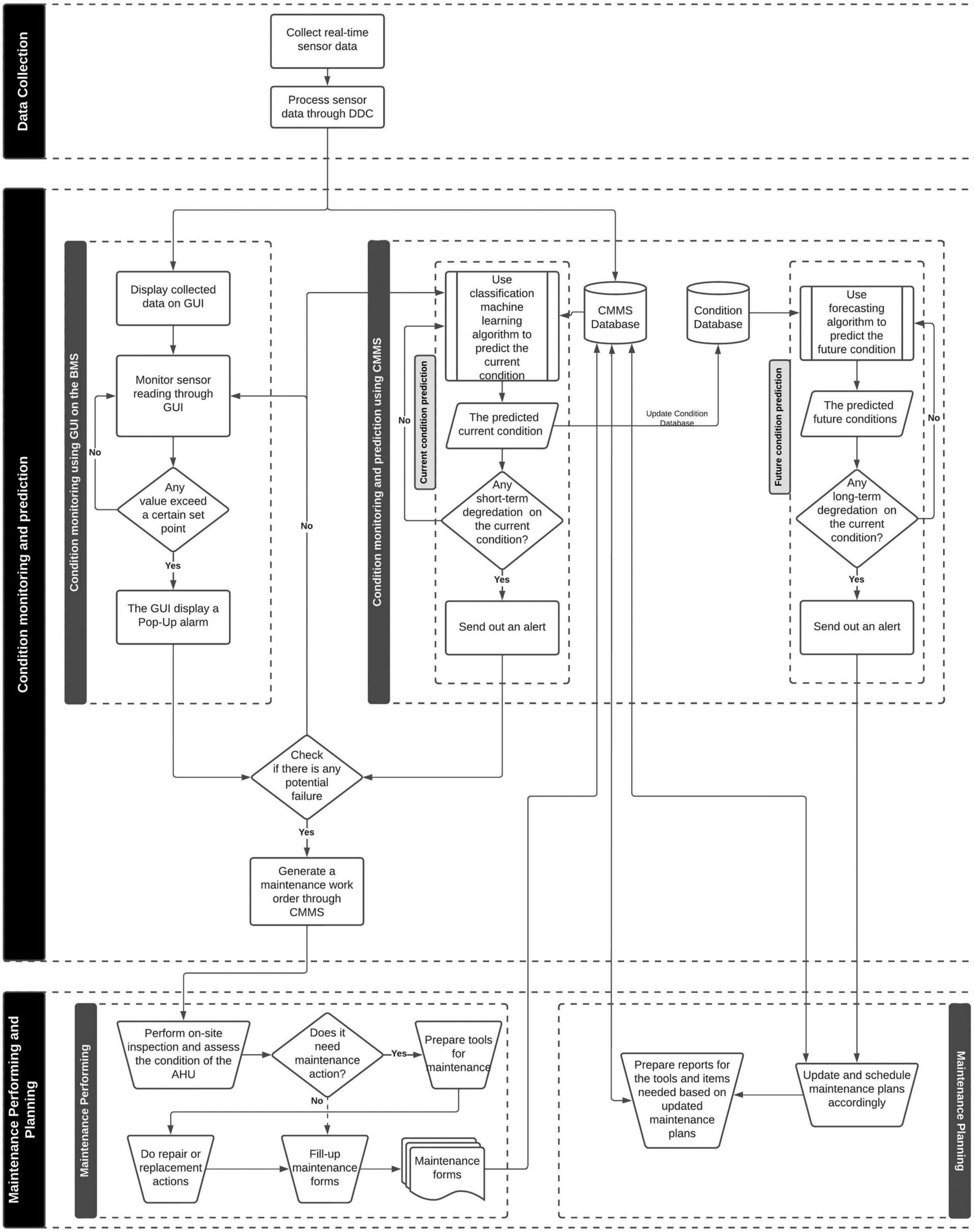

Figure 1. Data flow and methodology of the developed model.

Graphical User Interface (GUI) of BMS and CMMS database for condition monitoring and prediction. The databases is saved on a SQL server. Data collected from the field devices of AHUs include the temperature, pressure, CO^2, and airflow sensor data in addition to unit name and location. Sensor data is sent to the DDC which converts them into numerical information and transmits them to the GUI of the BMS and the CMMS database. As shown in Figure 2, the DDC sends sensor data using the Building Automation

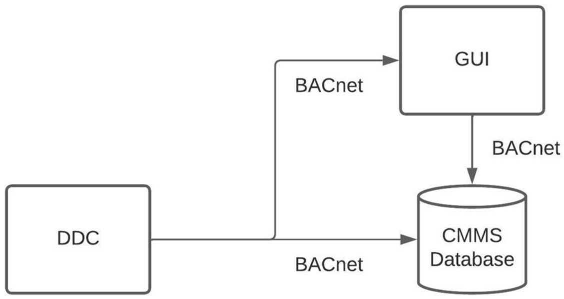

Figure 2. Functionality of data collection phase.

Control Network (BACnet) protocol, which is designed to meet the communication requirements of the building automation and control systems such as HVAC, lighting, access, and fire detection control systems. The BACnet protocol provides mechanisms for computerized equipment with various functions to exchange information (ASHRAE, 2019). The data is transferred via a plug-in created and installed in the CMMS software to import and store data from the DDC. It should be noted that the attribute names of the imported data and the CMMS should match in order to facilitate the mapping of the imported data from the BMS to the CMMS system. The CMMS and condition databases are designed using the SQL data model and are stored on a server for centralized management. Data retrieval from the database is facilitated using SQL queries, a standard mechanism for requesting and processing specific data from relational databases.

Condition monitoring and prediction

Condition monitoring collects and analyzes relevant AHU parameters to determine if the AHU's conditions have changed in comparison to the normal operating conditions (i.e. whether the AHU's condition has deteriorated). This occurs when real-time sensor readings or the assessment of current/future condition of an AHU exceeds a certain level set by the FM staff according to the ASHRAE (2019) standards. If so, an alarm or warning signal will be displayed indicating that the device has or will have a problem. The FM staff will then inspect the AHU for possible failures and develop a maintenance work-order to perform on-site maintenance and inspection. The FM staff will start looking for potential failures based on their previous experience with AHU faults.

Figure 1 showed that the functionality of the condition monitoring and prediction phase is mainly divided into two sub-systems: (1) Condition monitoring using GUI in the BMS. (2) Condition monitoring and prediction using CMMS.

Condition monitoring using GUI in the BMS

In this sub-system, the FM staff will follow the corrective maintenance procedure. The system monitors real-time sensor data directly and sends an alert in the case of a sudden failure (abnormal event). The FM staff will monitor the AHU sensor readings using the BMS's GUI. The GUI enables the FM staff to read and control the AHU sensors. If any sensor reading (temperature, pressure, etc.) exceeds the specific limit, the GUI will display a pop-up alarm to warn the FM staff. The specified limits are case-based, but for example, if the temperature for the air coming out of the supply fan exceeds the set point by ±2°C, the GUI will display a pop-up alarm to warn the FM staff.

Condition monitoring and prediction using CMMS

In this sub-system, the FM staff will follow the preventive maintenance procedure. It provides decision support for maintenance planning by predicting the AHU's current and future conditions on the CMMS using machine-learning algorithms. The objective is to reduce both time and expenses related to unnecessary inspections in the preventive maintenance procedures and to increase the overall AHU efficiency. If the predicted current/future condition deteriorates, the CMMS will display an alert to notify the FM staff. This methodology in this sub-system is based on two modules: (1) Current condition prediction and classification using machine-learning algorithm, and (2) Future condition prediction using time-series forecasting algorithm.

Machine-learning for short-term prediction

This module intends to predict failures that will occur in the short-term by monitoring the current condition of the AHU sensor readings. To this end, three classification machine-learning algorithms (SVM, DT, and KNN) were evaluated and compared. The SVM, KNN, and DT algorithms were chosen due to their ability to handle different types of data, their simplicity and flexibility, and their interpretability. The prediction process was developed using Python programming. Figure 3 illustrates the process of AHU short-term condition prediction using SVM, DT, and KNN. The inputs to the prediction process are values of six variables obtained from the CMMS database (two textual variables representing AHU name/number and its location and four sensor numerical values representing temperature, pressure, airflow, and CO^2 level). The output of this process is a condition index scaled from (1 to 10) that represents the current condition of the AHU.

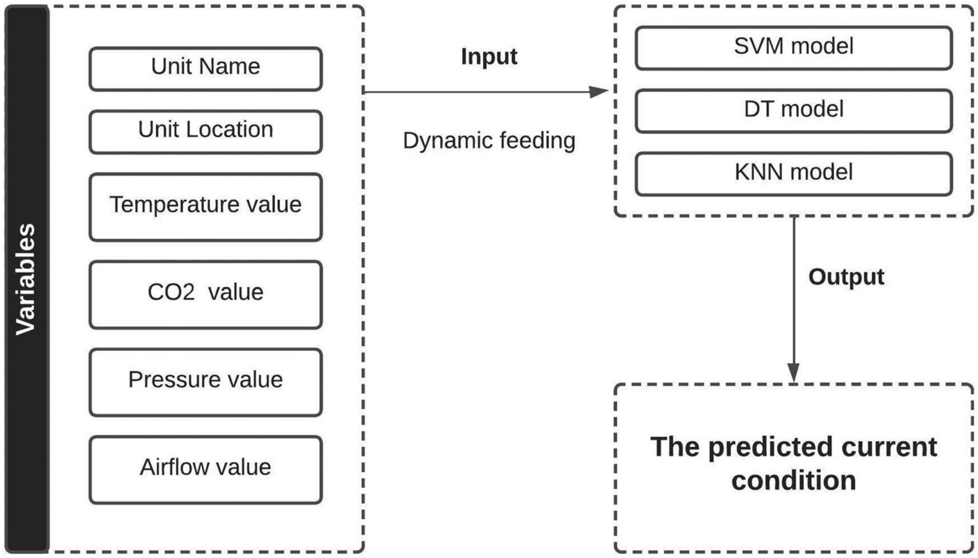

Figure 3. Short-term condition prediction of AHU.

Figure 4 describes the training approach of the SVM, DT, and KNN algorithms. The input data were divided into two sets: 70% for the algorithms' model training and 30% for model testing. These percentages were chosen to prevent overfitting, according to the findings of Gholamy et al. (2018). Historical data is used for training the model on recognizing inherent patterns, while real-time data is used for predictions.

The 1–10 condition scale is presented in Table 1. It is the scale used by Cheng et al. (2020) to assess the HVAC system condition based on the Facility Condition Assessment Guidebook (Federal Transit Administration, 2015) and FM practitioners' interviews. According to Cheng et al. (2020), this scale can be feasible for most building components in general, including chillers and AHUs. Furthermore, a qualified FM engineer evaluated, reviewed, and adjusted the adopted scale.

Table 1 represents the scale of the HVAC system's condition, its corresponding description, and the required maintenance actions. For instance, when a building facility's condition index is between 9 and 10, this indicates that the AHU is in excellent condition and no maintenance action is needed. When the status index is between 7 and 9, maintenance technicians must inspect the AHU regularly. When the condition index is between 3 and 5, the components' condition is severely degraded, and maintenance technicians must undertake extensive repairs as soon as possible. If the condition index is less than 3, the AHU is not operating, and one or some of its components has failed.

In the developed model, the CMMS monitors the output of the machine-learning algorithm. If there is any degradation in a predefined value between the previous and the current output, the CMMS sends an alert revealing the issue. The output is stored in the condition database at CMMS for future condition prediction.

Time-series forecasting for long-term condition prediction

This prognosis module predicts 'long-term' conditions of the AHU based on the 'short-term' estimates generated by the current condition prediction module and stored in the CMMS condition database. Predicting the long-term future conditions enables the FM staff to update the AHU maintenance plans and prevent failures. It also enables FM staff to prepare requests for the tools and items needed for future maintenance and set the maintenance actions according to the situation.

Since the time-series of AHU condition data often has seasonality and changes over time, two time-series forecasting algorithms (Prophet forecasting and SARIMA) were evaluated and compared. Prophet forecasting uses a simple additive regression algorithm $y(t)$ with three main components: piecewise trend, seasonality, and holiday effects. Based on Taylor and Letham (2018), $y(t)$ can be expressed as follows:

$$y(t) = g(t) + s(t) + h(t) + \in (t) \tag{1}$$

Where $g(t)$ is the trend function that models the linear changes over time, $s(t)$ captures the periodic changes over historical data (i.e. seasonality), $h(t)$ reflects abnormal predictable days of the year which occur on irregular schedules, and $\varepsilon(t)$ represents noise which the model

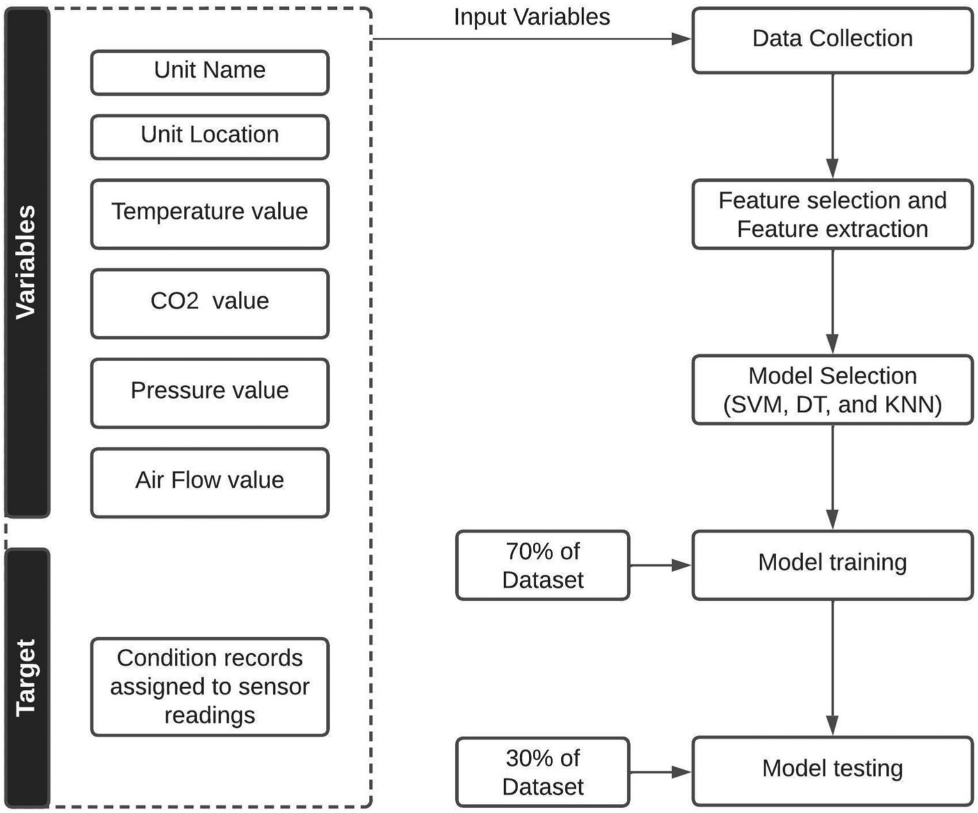

Figure 4. Training and testing of the SVM, DT, and KNN algorithms.

Table 1. The condition assessment scale of the HVAC system.

Overall AHU condition index	Scale	Condition description	Maintenance action required
9–10	Excellent	• no defects • As new condition	Regular monthly inspection. New construction, no visible defects or damage. Meets efficiency and capacity goals and maintains desired temperature and indoor air quality throughout the facility.
7–9	Good	• Minor defects • Major maintenance not required • Some deterioration to finishes	Minor improvement needed. Minor deterioration or defect with no functional impact typically addressed through routine maintenance.
5–7	Fair	• Average condition • Services are functional but need attention • Components require maintenance • Significant defects are evident • Deferred maintenance work exists	Repairs are needed; some deterioration exists, and maintenance needs are significant. With this, the system meets the need, still within its useful life.
3–5	Poor	• Badly deteriorated • Major defects • Components fail frequently	The system fails to meet standards or needs. Components need extensive repair at a minimum.
0–3	Critical	• The building has failed components • Not operational	The system has critical defects affecting function and is well past its useful life; its issues are beyond repair and warrant detailed review.

Adapted from Cheng et al. (2020).

does not accommodate. Similarly, SARIMA model requires selecting hyper-parameters for both the trend and seasonal elements of the series. The trend and seasonal hyper-parameters of the model can be configured using the grid search approach. The Akaike Information Criteria (AIC) metric is used to evaluate and compare parameters configuration where the model parameter configuration with lower AIC value has the best performance. Both were implemented using Python programming.

Figure 5 illustrates the process of AHU future condition prediction using Prophet forecasting and SARIMA algorithms. The input to the prediction process is the time-series data of the AHU condition obtained from the condition database. This process generates a condition index scale from 1 to 10, reflecting the AHU's future condition for several periods (e.g. one month, three months, one year, etc.). For the SARIMA model, the input data is divided into two sets; 70% for model training and 30% for model testing.

After predicting the AHU's future condition, the CMMS will monitor its output. If there is a difference in a predefined value between the previous and current output, the CMMS will send a warning to alert the FM staff. The FM staff will then update the plans for long-term preventive maintenance.

Maintenance performance and planning

As shown in Figure 1, this phase consists of two functions: (1) performing maintenance for sudden and short-term failures and (2) planning maintenance for long-term failures.

Maintenance performance

Suppose that the predicted current condition indicates a deterioration in the AHU performance or a real-time sensor reading exceeds a specific limit, in such a case, an alert will be sent from the GUI in the BMS or from the CMMS to notify the FM staff. The FM staff will then check whether a potential short-term failure is present and create a maintenance work-order accordingly. Later, the maintenance staff will conduct an on-site inspection to examine the AHU's condition. If the AHU needs maintenance (repair or replacement), the FM staff will act accordingly. Afterward, staff will fill out the required maintenance forms and relevant data (labour, cost, time, tools, and items). The CMMS database will be also updated with the information in the maintenance forms.

Maintenance planning

Predictive maintenance is expected to lead to a cost-effective preventive maintenance plan. Predicted values provide insights on the AHU's future condition before any repairs are required. If the predicted future condition changes, the CMMS will send an alert notifying the FM staff to develop a preventive maintenance plan and prepare for the tools and items required for maintenance. This is expected to result in an effective preventive maintenance that would improve the AHU's condition, reduce the system failures, and minimize the costs associated with a sudden failure. This step also allows the FM staff to plan their spare parts' inventory in advance and avoid the expenses involved with ordering urgent replacement parts. For example, if the AHU's future condition has deteriorated from 8 to 6 in the next three months, then significant repairs and maintenance are needed to avoid further AHU's condition degradation.

Results of model application

The developed data-driven predictive maintenance model, shown in Figure 1, was applied to the AHUs of the HVAC system in a hospital in Jordan. The multi-specialty hospital has a total built-up area of 94,000 m^2 distributed over 35 floors. It consists of 200 beds, 10 operating rooms, 20 intensive care units, 14 cardiac care units, 100 clinics, laboratories, emergency units, and other support facilities. Figure 6 shows the hospital zones and services.

The hospital has a total of 42 AHUs to regulate the IAQ in different hospital zones. Four types of sensors are installed to monitor the AHU: (1) Temperature sensors, (2) Pressure sensors, (3) Airflow sensors, and (4) CO^2 sensors. Honeywell (2020) for BMS and E-Facility (eFACiLiTY, 2020) for CMMS are used to control the overall hospital's operations and functions. The model

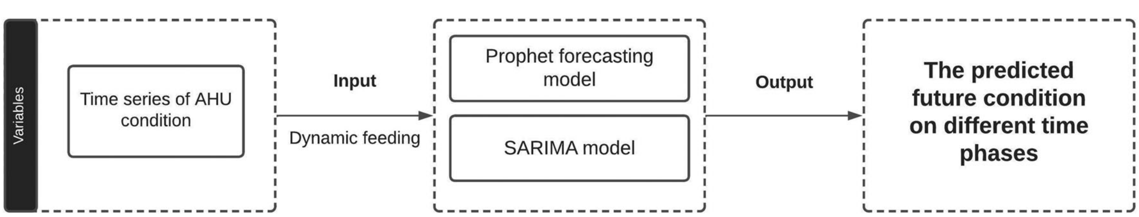

Figure 5. The long-term condition prediction process for the AHU.

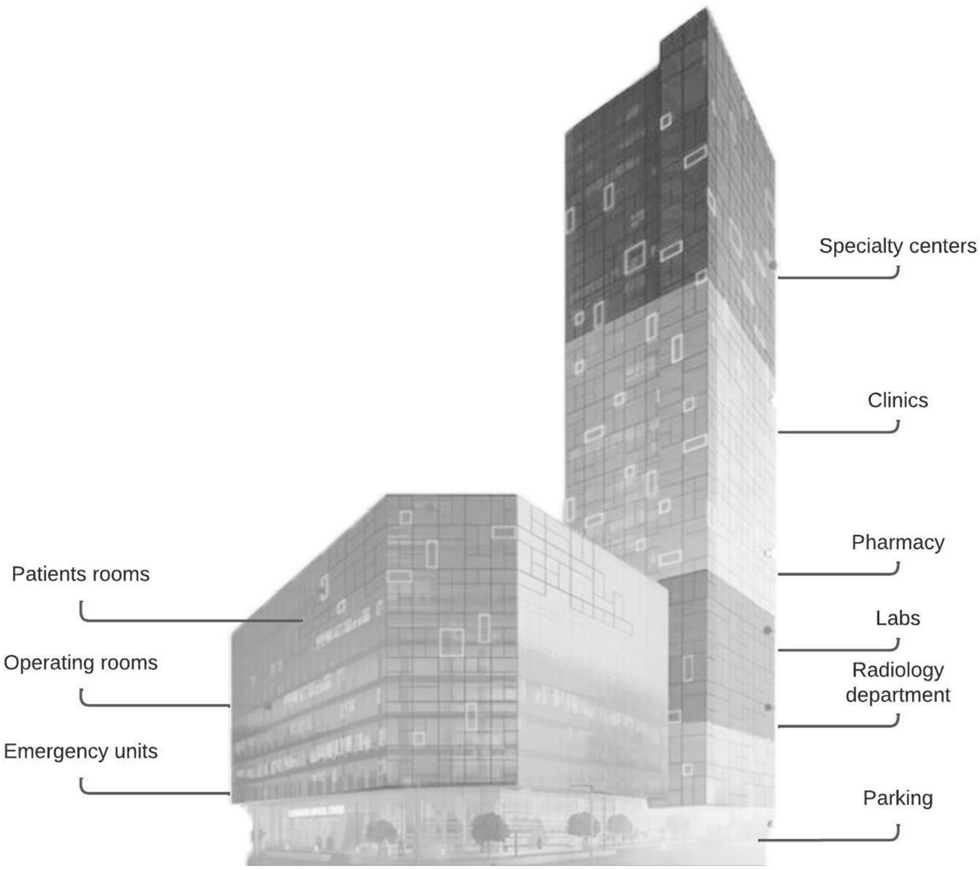

Figure 6. Hospital zones and facilities.

application to AHUs includes data collection, condition monitoring and prediction, and maintenance performance and planning.

AHU sensor data collection

The sensor data were collected in the period of August 2019 to August 2020 from the field devices and processed in the DDC for one of the hospital's AHUs. This includes temperature, pressure, airflow, and CO^2 values along with unit name and location. These parameters represent the currently used indicators of AHU's conditions and can be retrieved from the BMS. Currently, maintenance engineers review the data manually and assign a condition scale accordingly. Table 2 shows a sample of the extracted sensor data stored in an Excel sheet.

Figure 7 shows graphs of the complete sensor data gathered from August 2019 to August 2020. The temperature set-point value is 20°C and the values increase and decrease with time and according to the season. The pressure and the temperature patterns are very similar and the pressure's set-point value is 750 Pascal. The airflow values are inversely proportional to the pressure values with a set point of 8000 L/s. The CO^2 set point is 400 parts per million. Since hospitals are active operating facilities, there should be no sudden fluctuations in a steady performance of the AHU.

AHU condition monitoring and predication

The DDC sends sensor readings to the GUI and CMMS database to monitor and predict the AHU's condition. The GUI and CMMS will directly monitor real-time sensor data and send an alert in case of a sudden failure

Table 2. A sample of extracted sensor readings of the AHU.

Date/time	Temp	Pressure	Air flow	CO^2	Condition
2019-08-01 12:00	20.1	753	7940	351	9.5
2019-08-01 18:00	20.3	753	7880	369	9.5
2019-08-02 0:00	20.1	754	7770	379	9.5
2019-08-02 6:00	20.2	756	7980	353	9.5
2019-08-02 12:00	21.0	757	7725	387	9.0
2019-08-02 18:00	20.8	760	7725	395	9.0
2019-08-03 0:00	20.6	759	7660	390	9.0
2019-08-03 6:00	20.7	761	7620	389	9.0
2019-08-03 12:00	20.8	757	7585	389	9.0
2019-08-03 18:00	20.9	762	7715	397	9.0
2019-08-04 0:00	20.6	760	7540	391	9.0
2019-08-04 6:00	21.1	775	7495	410	8.5
2019-08-04 12:00	21.1	778	7465	419	8.5
2019-08-04 18:00	21.1	779	7325	420	8.5

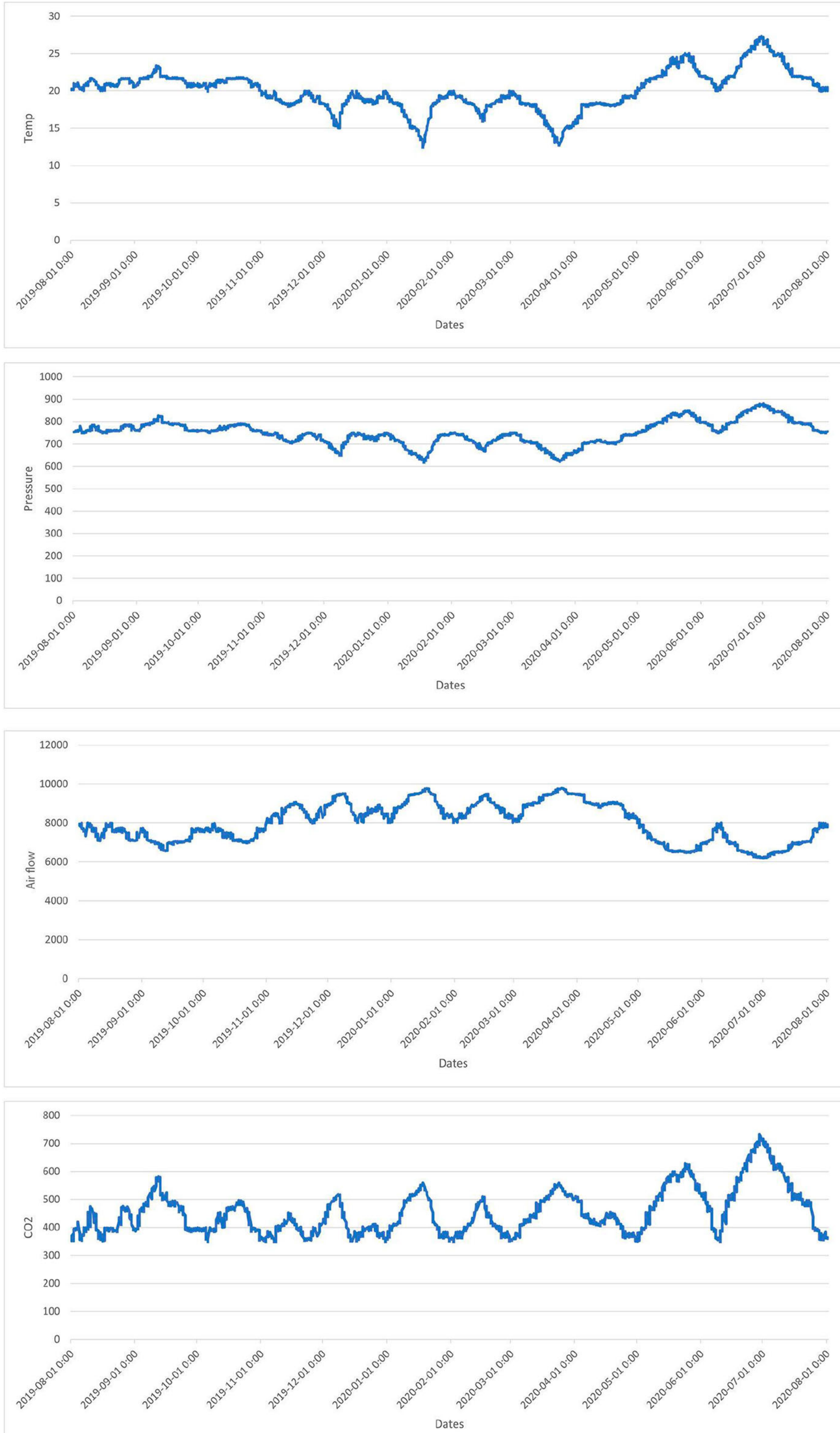

Figure 7. Patterns of sensor data collected from the AHU.

to initiate a corrective maintenance procedure. The AHU performance is visualized and monitored by FM staff through the GUI. Each sensor reading should not exceed a certain threshold set by the engineers according to the ASHRAE (2019) standard and the serving zone. If exceeded, the GUI displays an alarm to notify the FM staff to inspect a potential failure and, if needed, issue a maintenance work-order. Table 3

Table 3. An example of AHU set points and thresholds of sensors readings.

Sensor reading	The set point	The threshold
Temperature value	20°C	±2°C
Pressure values	750 Pa	±5%
CO^2	400 ppm	≥600 ppm

shows an example of the set points and thresholds of the sensor readings for the AHU in the hospital.

AHU short-term condition prediction

The collected sensor data from the AHU are approximately 1460 data points. The AHU current condition prediction was conducted using SVM, DT, and KNN machine learning algorithms. The three algorithms were developed using Python's built-in library (Sklearn). The algorithms were trained on the same dataset of sensor data. The condition index presented in Table 1 is assigned to sensor readings and used for the training of the three supervised machine-learning algorithms. The SVM model parameters are set to 'linear' kernel type with C value of 100. A default setting is used for other SVM parameters. Default settings are also used for DT and KNN models' parameters.

Algorithms' training results are calculated based on four parameters. True Positive (TP) and True Negative (TN) to denote the number of predictions in which the classifier correctly predicts the same class and False Positive (FP) and False Negative (FN) to denote the number of predictions where the classifier incorrectly predicts the wrong class. Means of precision, recall, and F-1 score were used as performance measures for comparing the three machine-learning algorithms. The precision measures assess the machine-learning algorithm ability to only predict actual positive classes as positive. The recall measure represents the proportion of correctly classified positive classes among the ones classified as positives (i.e. the TP rate). Finally, the F-1 score captures the harmonic mean of precision and recall (i.e. it seeks a balanced measure between precision and recall) when there is imbalanced class distribution. The following formulas are used to calculate the accuracy, precision, recall, and F-1 score:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FN} + \text{TN} + \text{FP}} \tag{2}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{3}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{4}$$

$$\text{F1 score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5}$$

Table 4. Average performance measures of tested machine-learning algorithm.

Machine-learning algorithms	SVM	DT	KNN
Accuracy	93.56%	99.90%	95.68%
Precision	93.40%	98.40%	87.22%
Recall	92.50%	97.80%	86.22%
F-1 score	92.50%	97.90%	85.11%
Computational time (seconds)	00:10.58	00:08.32	00:07.50

Table 4 presents a summary for the performance results of training the SVM, DT, and KNN, respectively. Ten trials were initially used to train the machine-learning algorithms. Accuracy, precision, recall, and F-1 score were calculated for each trail. The accuracy measure was used to prove that it is a misleading measure in this case. Even though the accuracies were high, the precision, recall, and F-1 scores were low. The DT has the highest F-1 score, which indicates that it has the best performance in predicting the AHU's current condition. The KNN has the lowest processing time while the SVM has the highest.

Furthermore, tests of hypothesis at a Confidence Interval (CI) of 95% were performed based on F-1 score and using a two-sample *t*-test. Results revealed that SVM has better performance than KNN and DT has better performance than SVM model. This confirms that DT superiority as reported in Table 4.

Consequently, DT is adopted in the CMMS to monitor the current condition of AHU. Based on the predicted condition, a condition index scaled from 1 to 10 is assigned to the AHU's current condition (i.e. Table 1). If there is any change to the predefined value between the previous and the current output, CMMS will send a warning indicating the problem. The output of the DT algorithm is also saved in the condition database for future condition prediction.

AHU long-term condition prediction

In this step, accumulated current condition database is used to predict the future condition of the AHU. To this end, Prophet forecasting and SARIMA algorithms were trained and compared using records (time-series data) of the AHU's condition from August 2019 to August 2020 and records from August 2020 to December 2020 (i.e. a total of 2070 data points). Prophet forecasting was developed using the built-in library (Prophet) in Python and SARIMA was developed using (Statsmodels) library.

For the prophet forecasting training, the available data is split between in-sample data for training the algorithm and out-sample data to predict the future condition, as shown in Figure 8. The bold line in the figure represents the machine condition and the black dots refer to the recorded

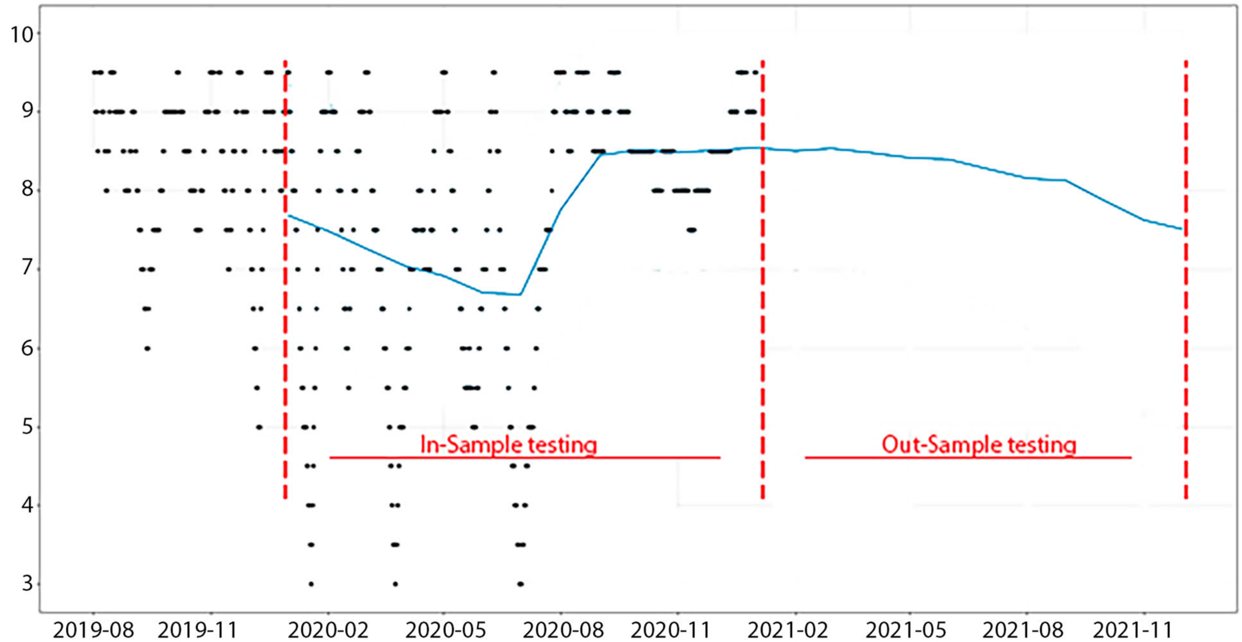

Figure 8. AHU predicted future conditions based on Prophet forecasting.

and saved condition. For SARIMA model, the training data set was used to first set its optimal parameters.

The metrics used to evaluate and compare the performance of Prophet forecasting and SARIMA algorithms are Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) (Shawon et al., 2020). The lowest yielded value from both metrics indicate a better performance of machine-learning. Formulas of the used metrics are as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum\nolimits_{i=1}^{N} (y_i \hat{y}_i)^2} \tag{6}$$

$$\mathrm{MAPE} = \frac{1}{N}\sum\nolimits_{i=1}^{N} \frac{|y_i - \hat{y}_i|}{y_i} \times 100\% \tag{7}$$

$$\text{Prediction Accuracy} = 100\% - \mathrm{MAPE} \tag{8}$$

Table 5 presents the results of the Prophet forecasting and SARIMA algorithm performance compared to the actual conditions recorded in each month from January 2020 to December 2020. The APE in this Table refers to the Absolute Percentage Error, whereas the SE is the Squared Error. As shown in Table 5, the Prophet forecasting achieved a better performance in terms of RMSE and MAPE. Moreover, the computational time for SARIMA model was higher than Prophet forecasting.

Consequently, Prophet forecasting algorithm was adopted to predict the AHU's future conditions for the next four proposed periods (3, 6, 9 months, and 1 year), respectively. Predicted conditions were also shown in

Table 5. Results of evaluating Prophet Forecasting and SARIMA algorithms.

		Prophet forecasting algorithm			SARIMA algorithm		
	Actual	Predicted	APE	SE	Predicted	APE	SE
1	6.806	7.676	12.87%	0.756	8.085	18.78%	1.634
2	8.009	7.479	6.51%	0.280	7.405	7.53%	0.364
3	6.185	7.262	17.17%	1.159	7.262	17.41%	1.159
4	7.583	7.038	6.09%	0.297	7.183	5.28%	0.160
5	6.770	6.912	3.13%	0.020	6.270	7.38%	0.250
6	6.538	6.696	3.00%	0.025	7.381	12.90%	0.711
7	6.621	6.672	1.09%	0.003	6.970	5.27%	0.122
8	9.048	7.746	13.86%	1.696	7.299	19.33%	3.059
9	8.958	8.479	4.70%	0.230	7.077	21.00%	3.538
10	8.343	8.418	1.41%	0.006	7.210	13.57%	1.282
11	8.013	8.5	6.24%	0.238	7.121	11.13%	0.795
12	8.960	8.522	4.22%	0.192	7.178	19.88%	3.173
MAPE (%)			6.69%			13.29%	
Prediction accuracy (%)			93.31%			86.71%	
RMSE			0.639			1.163	
Computational time			00:29.08			00:40.33	

AHU number	Visual inspection for supply air motor (noise and vibration)	Visual inspection for return motor (noise and inspection)	Visual Inspection for the belts of supply fan	Visual inspection for the belts of return fan	Visual Inspection for UV lamp	Visual Inspection for pressure and temperature gauges	Visual inspection for any water of air leaks	Visual inspection for the PICV		DPS reading		Comments	Condition
								HW	CHW	Pleated filter	Bag filter		
AHU 03	none	none	good	good	good	normal	normal	30	10	250	200	filters need cleaning	8.9

Figure 9. The AHU maintenance checklist.

out-sample forecast in Figure 9. The CMMS will monitor the output of Prophet forecasting and if there is a degradation in values (comparing the previous levels), the CMMS will send a warning to indicate the issue.

AHU maintenance performance and planning

As mentioned previously, this phase includes (1) performing maintenance for the AHU short-term failures and (2) maintenance planning for the AHU long-term failures.

AHU maintenance performance

If the GUI displays a pop-alarm or the predicted current condition changes based on a predefined value, the FM staff begins to inspect the AHU condition and check potential failures. If any is detected, the FM staff generates a maintenance work-order that includes information of the request, the equipment, the required work details, and a confirmation of work completion. The work-order also includes the cost details associated with the performed maintenance.

Once the work-order is generated, the FM staff performs an on-site inspection of the AHU and evaluates its condition using a pre-prepared checklist, as shown in Figure 9. This checklist contains certain metrics that the maintenance staff use to evaluate the AHU's condition. If the AHU needs repairing, the maintenance staff will fix or replace the failed part and fill out the maintenance work-order, including the tools, materials, labour, and maintenance expenses. For example, and as shown in Figure 9, the condition of the maintained AHU is 8.9. FM staff will then use the form to address the comments and update the CMMS database accordingly.

AHU maintenance planning

Based on the predicted future condition of the AHU, an in case of any predicted degradation, the CMMS sends a warning to the FM staff. The staff will accordingly initiate a maintenance work-order in advance and prepare the expected tools and materials needed to performance maintenance. The future maintenance plan will be constantly updated and modified based on each predicted condition. Table 6 present the forecasted values for 3, 6, 9 months, and 1 year, respectively.

As shown in Table 6, the AHU's current condition is 8.9, indicating that it requires minor improvements and maintenance. Prediction also indicates that it will remain at the same performance level for the next three months. Still, the FM staff should keep the monitoring to avoid any sudden degradation in condition. After 6 months, the AHU's predicted condition will drop to 8.3 indicating a state of minor degradation but still in good condition (i.e. no significant maintenance is needed and a monthly inspection is recommended for the next 6 months). After 9 months, the future condition drops to 7.8 indicating an apparent degradation is expected and an inspection order should be generated. If the FM staff only conducts monthly inspections with no repairs, the condition will degrade to 7.2 one year later, which is a major degradation. To prevent any failures, facility managers should raise the frequency of the regular inspections to twice a month. Overall, in the developed model, the FM staff will immediately note the changes or degradation in condition, prepare the tools and material needed in advance, and update the maintenance plan according to each predicted condition.

Table 6. AHU predicted future condition at different time phases.

		Predicted future condition			
	Current condition	3 months later	6 months later	9 months later	1 year later
AHU	8.9	8.9	8.3	7.8	7.2

Discussion, conclusion, and directions for future work

Reviewed literature has emphasized the need for an integration between building information systems and machine learning to increase the effectiveness of maintenance in hospitals. A data-driven predictive model was, therefore, proposed in this paper using machine learning and sensor data from the hospital's BMS and CMMS. The model was applied for the preventive maintenance of the AHU component of the hospital's HVAC system. The model was developed based on the framework proposed by Cheng et al. (2020) and was functionally structured using three modules: data collection, condition monitoring and prediction, and maintenance performance and planning. These modules have contributed to the BMS and CMMS integration with machine learning, the combination of short-term and long-term predictions, and the balance of cost and operational effectiveness of maintaining critical systems in hospitals.

The proposed model has therefore contributed to the framework proposed by Cheng et al. (2020). Different machine learning algorithms were utilized for the prediction, BMS and CMMS were used to support the prediction, and the framework application was extended to the hospital's AHUs. Furthermore, the proposed model has utilized both current and future condition predictions in order to optimize the prediction process and has also demonstrated the cost implications of applying the model to real-world systems.

Three machine learning algorithms (SVM, KNN, and DT) were evaluated based on their characteristics and relevance to AHU and HVAC systems in the reviewed literature. SVM typically strikes a balance between configuration simplicity and accuracy achieved in predicting the conditions of HVAC systems (Han et al., 2019). KNN has an ability to replace missing AHU sensor data with credible values (Batista & Monard, 2002). Lastly, DT was found reliable in fault diagnosis based on the used testing data and the HVAC expert opinion (Yan et al., 2016). These algorithms were, therefore, adopted in the proposed model for the predictive maintenance of HVAC and AHU systems.

The performance of the three machine learning algorithms was evaluated for prediction accuracy. Results showed that the DT algorithm was found to be the best in predicting the AHU's short-term condition with 97.90% F-1 performance score. Results were in line with Trivedi et al. (2019) who showed that DT outperforms SVM with an accuracy of 93.6%. Cheng et al. (2020) achieved an accuracy of 96.422% when using SVM to predict the future condition of a chiller. For future condition prediction, two time-series forecasting algorithms (Prophet forecasting and SARIMA) were trained and compared based on RMSE and MAPE. The Prophet forecasting achieved the best performance in predicting the AHU's future condition with a lower RMSE value of 0.639, a lower MAPE value of 6.69%, and a prediction accuracy of 93.31%. The obtained results were found to be acceptable compared to the limited availability of benchmark models.

Nonetheless, the proposed model was developed to support the integration of other machine learning algorithms and techniques that can improve the accuracy of the prediction. This includes algorithms such as Extreme Gradient Boosting (XGB) and Random Forest (RF) which are tree-based ensemble learning methods (Sagi & Rokach, 2021). Although noted for their overfitting and sensitivity to outliers, these algorithms have been widely adopted in the industry for their ability to handle complex data and deliver high-accuracy results (Meas et al., 2022).

In terms of practical implications, the proposed framework paves the way for developing an expert system for the effective performance and planning of both corrective and preventive maintenance. The presented functionalities in the model enable the continuous feeding of real-time sensor data for both short-term and long-term prediction. This establishes a platform for the realistic assessment of AHU's current and future conditions, a proactive decision-making process, and a dynamic update of maintenance plans.

Model adoption can also greatly benefit from the advantages of IoT wireless technologies in collecting real-time sensor data for enabling BMS monitoring of various building systems. The developed model can, therefore, be adapted to other HVAC components in the hospital as well as to other facility systems (e.g. medical equipment) which capitalizes on the technology investment and extends model applicability. Ultimately, this leads to effective preventive maintenance, quality IAQ, and sustainable hospital operations.

However, adopting machine learning in predictive maintenance of hospital systems is still relatively underdeveloped and the contribution of this work to this field can be further improved by addressing few limitations. For example, the quality and quantity of the collected dataset have an impact on the reliability of the prediction results. The collected dataset in this study is only for one year and the number of faulty conditions reported during this relatively short time may not be sufficient. Further studies may increase the size of the training data set in order to enhance the accuracy of the prediction and to improve the overall reliability of the adopted maintenance plans. Also, the developed model was only tested on the AHU as part of the hospital HVAC system. Different system parameters and sensor data may affect the model's application to other HVAC components. For example, a CO^2 sensor is not typically used for monitoring the chiller. Future studies may, therefore, consider testing the model on other HVAC components such as chillers and comparing results to reported performance and prediction accuracy. Finally, the proposed framework was set to be versatile and enabled to support other machine learning algorithms. This encourages data scientists and developers to explore a broader range of techniques and approaches for solving classification and prediction problems. However, the method's structure should be adapted to accommodate the collected data sets and the functionality of the predicted component.

Disclosure statement

No potential conflict of interest was reported by the author(s).

References

Aditya-Satrio, C. B., Darmawan, W., Nadia, B. U., & Hanafiah, N. (2021). Time series analysis and forecasting of coronavirus disease in Indonesia using ARIMA model and PROPHET. *Procedia Computer Science*, *179*, 524–532. https://doi.org/10.1016/j.procs.2021.01.036

American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHARE). (2019). *The standards for ventilation and indoor air quality* (ANSI/ASHRAE Standard 62.1-2019). https://www.ashrae.org/technical-resources/bookstore/standards-62-1-62-2#:~:text=ANSI%2FASHRAE%20Standards%2062.1%20and,adverse%20health%20effects%20for%20occupants

Au-Yong, C. P., Ali, A. S., & Ahmad, F. (2014). Improving occupants' satisfaction with effective maintenance management of HVAC system in office buildings. *Automation in Construction*, *43*, 31–37. https://doi.org/10.1016/j.autcon.2014.03.013

Batista, G. E., & Monard, M. C. (2002). *A study of K-nearest neighbor as an imputation method*. International Conference on Health Information Science.

Brambley, M. R., Haves, P., McDonald, S. C., Torcellini, P., Hansen, D., Holmberg, D. R., & Roth, K. W. (2005). *Advanced sensors and controls for building applications: Market assessment and potential R&D pathways*. https://doi.org/10.2172/1217909

Buys, J. H., & Mathews, E. H. (2005). Investigation into capital costs of HVAC systems. *Building and Environment*, *40*(9), 1153–1163. https://doi.org/10.1016/j.buildenv.2004.11.011

Carvalho, T. P., Soares, F. A. A. M. N., Vita, R., Francisco, R. D. P., Basto, J. P., & Alcalá, S. G. S. (2019). A systematic literature review of machine learning methods applied to predictive maintenance. *Computers & Industrial Engineering*, *137*, 106024. https://doi.org/10.1016/j.cie.2019.106024

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. https://doi.org/10.1016/j.autcon.2020.103087

Costello, J. J. A., West, G. M., & McArthur, S. D. J. (2017). Machine learning model for event-based prognostics in gas circulator condition monitoring. *IEEE Transactions on Reliability*, *66*(4), 1048–1057. https://doi.org/10.1109/TR.2017.2727489

Domingues, P., Carreira, P., Vieira, R., & Kastner, W. (2016). Building automation systems: Concepts and technology review. *Computer Standards & Interfaces*, *45*, 1–12. https://doi.org/10.1016/j.csi.2015.11.005

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. https://doi.org/10.1016/j.buildenv.2013.11.021

EcoDomus. (2020). *Building information modeling (BIM)*, San Francisco, USA. https://www.ecodomus.com

eFACiLiTY®. (2020). *Enterprise Facility Management Software is a globally recognized CAFM/EAM/CMMS software*. SIERRA ODC. https://www.efacility.in

European Committee for Standardization. (2010, November). *UNI EN 13306: Maintenance – maintenance terminology* (BS EN 13306:2010). British Standards Institution. http://irma-award.ir/wp-content/uploads/2017/08/BS-EN-13306-2010.pdf

Farsi, M., Hosahalli, D., Manjunatha, B., Gad, I., Atlam, E. S., Ahmed, A., & Ghoneim, O. A. (2021). Parallel genetic algorithms for optimizing the SARIMA model for better forecasting of the NCDC weather data. *Alexandria Engineering Journal*, *60*(1), 1299–1316. https://doi.org/10.1016/j.aej.2020.10.052

Federal Transit Administration. (2015). *Facility condition assessment guidebook*. Department of Transportation USA. https://www.transit.dot.gov/sites/fta.dot.gov/files/docs/Facility%20Performance%20Assessment%20Guidebook.pdf

Gholamy, A., Kreinovich, V., & Kosheleva, O. (2018). *Why 70/30 or 80/20 relation between training and testing sets: A pedagogical explanation*. ScholarWorks@UTEP. https://scholarworks.utep.edu/cgi/viewcontent.cgi?article=2202&context=cs_techrep

Han, H., Cui, X., Fan, Y., & Qing, H. (2019). Least squares support vector machine (LS-SVM)-based chiller fault diagnosis using fault indicative features. *Applied Thermal Engineering*, *154*, 540–547. https://doi.org/10.1016/j.applthermaleng.2019.03.111

Honeywell. (2021). *Honeywell has the Niagara Framework-based building management solution (BMS) that takes all aspects of your building and occupant needs into consideration to maximize energy efficiency and make management of your facility simpler and more user-friendly*. Honeywell International Inc. https://www.honeywell.com

Jeong, K., Koo, C., & Hong, T. (2014). An estimation model for determining the annual energy cost budget in educational facilities using SARIMA (seasonal autoregressive integrated moving average) and ANN (artificial neural network). *Energy*, *71*, 71–79. https://doi.org/10.1016/j.energy.2014.04.027

Kastner, W., Neugschwandtner, G., Soucek, S., & Newman, H. M. (2005). Communication systems for building automation and control. *Proceedings of the IEEE*, *93*(6), 1178–1203. https://doi.org/10.1109/JPROC.2005.849726

Kiran Naik, B., Chinthala, M., Patel, S., & Ramesh, P. (2021). Performance assessment of waste heat/solar driven membrane-based simultaneous desalination and liquid desiccant regeneration system using a thermal model and KNN machine-learning tool. *Desalination*, *505*, 114980. https://doi.org/10.1016/j.desal.2021.114980

Kučera, A., & Pitner, T. (2018). Semantic BMS: Allowing usage of building automation data in facility benchmarking. *Advanced Engineering Informatics*, *35*, 69–84. https://doi.org/10.1016/j.aei.2018.01.002

Kukkonen, V. (2018). *Condition-based maintenance of air handling units*. Aalto University. https://aaltodoc.aalto.fi/handle/123456789/32441

Lavy, S., & Shohet, I. M. (2009). Integrated healthcare facilities maintenance management model: Case studies. *Facilities*, *27* (3/4), 107–119. https://doi.org/10.1108/02632770910933134

Lin, C. L., & Fan, C. L. (2019). Decision Tree analysis of the relationship between defects and construction inspection grades. *International Journal of Materials, Mechanics and Manufacturing*, *7*(1), 27–32. https://doi.org/10.18178/ijmmm.2019.7.1.423

Meas, M., Machlev, R., Kose, A., Tepljakov, A., Loo, L., Levron, Y., Petlenkov, E., & Belikov, J. (2022). Explainability and transparency of classifiers for air-handling unit faults using explainable artificial intelligence (XAI). *Sensors*, *22* (17), 6338. https://doi.org/10.3390/s22176338

Mirnaghi, M. S., & Haghighat, F. (2020). Fault detection and diagnosis of large-scale HVAC systems in buildings using data-driven methods: A comprehensive review. *Energy and Buildings*, *229*, 110492. https://doi.org/10.1016/j.enbuild.2020.110492

Mobley, R. K. (2002). Impact of maintenance [kindle]. In *An introduction to predictive maintenance* (2nd ed, pp. 1–22). USA: Plant Engineering, Butterworth Heinemanm, Elsevier Science.

Moscato, U., Borghini, A., & Teleman, A. A. (2017). HVAC management in health facilities. In S. Capolongo, G. Settimo, & M. Gola (Eds.), *Indoor air quality in healthcare facilities* (1st ed., pp. 95–106). Springer Briefs in Public Health, Springer.

Mwanza, B. G., & Mbohwa, C. (2015). An assessment of the effectiveness of equipment maintenance practices in public hospitals. *Procedia Manufacturing*, *4*, 307–314. https://doi.org/10.1016/j.promfg.2015.11.045

Norhidayah, A., Chia-Kuang, L., Azhar, M., & Nurulwahida, S. (2013). Indoor air quality and sick building syndrome in three selected buildings. *Procedia Engineering*, *53*, 93–98. https://doi.org/10.1016/j.proeng.2013.02.014

Peres, R. S., Dionisio Rocha, A., Leitao, P., & Barata, J. (2018). IDARTS – Towards intelligent data analysis and real-time supervision for industry 4.0. *Computers in Industry*, *101*, 138–146. https://doi.org/10.1016/j.compind.2018.07.004

Puglisi, A. (2019). *Proactive maintenance framework for complex building service equipment: A predictive maintenance approach for hospital buildings facility management services*. Polytechnic University of Milan. https://www.politesi.polimi.it/handle/10589/152346?fbclid=IwAR3vJ1lTpKEzNxwN46J6kUXSB6kisupUMkT5le0_coPzwjnnFOtypWdSHzU

Sacks, R., Eastman, C., Lee, G., & Teicholz, P. (2018). BIM for owners and facility managers. *BIM Handbook: A guide to building information modeling for owners, designers, engineers, contractors, and facility managers* (3rd ed., pp. 130–173). Wiley.

Sagi, O., & Rokach, L. (2021). Approximating XGBoost with an interpretable decision tree. *Information Sciences*, *572* (2021), 522–542. https://doi.org/10.1016/j.ins.2021.05.055

Sánchez-Barroso, G., & García Sanz-Calcedo, J. (2019). Application of predictive maintenance in hospital heating, ventilation and air conditioning facilities. *Emerging Science Journal*, *3*(5), 337–343. https://doi.org/10.28991/esj-2019-01196

Sexton, T., Brundage, M. P., Hoffman, M., & Morris, K. C. (2017). Hybrid datafication of maintenance logs from AI-assisted human tags. In *2017 IEEE International Conference on Big Data (Big Data)* (pp. 1769–1777). https://doi.org/10.1109/BigData.2017.8258120

Shawon, M. M., Akter, S., Islam, M. K., Ahmed, S., & Rahman, M. M. (2020). Forecasting PV panel output using Prophet time series machine learning model. In *2020 IEEE Region 10 Conference (TENCON)* (pp. 1141–1144). https://doi.org/10.1109/TENCON50793.2020.9293751

Sullivan, G., Pugh, R., Melendez, A. P., & Hunt, W. D. (2010). *Operations & maintenance best practices – A guide to achieving operational efficiency (Release 3)*. U.S. Department of Energy Office of Scientific and Technical Information. https://doi.org/10.2172/1034595

Susto, G. A., McLoone, S., Pagano, D., Schirru, A., Pampuri, S., & Beghi, A. (2013). Prediction of integral type failures in semiconductor manufacturing through classification methods. In *2013 IEEE 18th Conference on Emerging Technologies & Factory Automation (ETFA)* (pp. 1–4).

Susto, G. A., Schirru, A., Pampuri, S., McLoone, S., & Beghi, A. (2015). Machine learning for predictive maintenance: A multiple classifier approach. *IEEE Transactions on Industrial Informatics*, *11*(3), 812–820. https://doi.org/10.1109/TII.2014.2349359

Syachrani, S., Jeong, H. S. D., & Chung, C. S. (2013). Decision tree-based deterioration model for buried wastewater pipelines. *Journal of Performance of Constructed Facilities*, *27* (5), 633–645. https://doi.org/10.1061/(ASCE)CF.1943-5509.0000349

Taylor, S. J., & Letham, B. (2018). Forecasting at scale. *The American Statistician*, *72*(1), 37–45. https://doi.org/10.1080/00031305.2017.1380080

Trivedi, S., Bhola, S., Talegaonkar, A., Gaur, P., & Sharma, S. (2019). Predictive maintenance of air conditioning systems using supervised machine learning. In *2019 20th International Conference on Intelligent System Application to Power Systems (ISAP)*. https://doi.org/10.1109/isap48318.2019.9065995

Wuest, T., Weimer, D., Irgens, C., & Thoben, K. D. (2016). Machine learning in manufacturing: Advantages, challenges, and applications. *Production & Manufacturing Research*, *4*(1), 23–45. https://doi.org/10.1080/21693277.2016.1192517

Yan, K., Huang, J., Shen, W., & Ji, Z. (2020a). Unsupervised learning for fault detection and diagnosis of air handling units. *Energy and Buildings*, *210*, 109689. https://doi.org/10.1016/j.enbuild.2019.109689

Yan, K., Zhong, C., Ji, Z., & Huang, J. (2018). Semi-supervised learning for early detection and diagnosis of various air handling unit faults. *Energy and Buildings*, *181*, 75–83. https://doi.org/10.1016/j.enbuild.2018.10.016

Yan, R., Ma, Z., Zhao, Y., & Kokogiannakis, G. (2016). A decision tree based data-driven diagnostic strategy for air handling units. *Energy and Buildings*, *133*, 37–45. https://doi.org/10.1016/j.enbuild.2016.09.039

Yan, Y., Luh, P. B., & Pattipati, K. R. (2020b). Fault prognosis of key components in HVAC air-handling systems at component and system levels. *IEEE Transactions on Automation Science and Engineering*, *17*(4), 2145–2153. https://doi.org/10.1109/TASE.2020.2979166

Ye, Z. (2019). Air pollutants prediction in Shenzhen based on ARIMA and Prophet method. In T. Fang & V. Khaletski (Eds.), *E3s Web of Conferences* (p. 05001). https://doi.org/10.1051/e3sconf/201913605001.

Zhao, Y., Li, T., Zhang, X., & Zhang, C. (2019). Artificial intelligence-based fault detection and diagnosis methods for building energy systems: Advantages, challenges and the future. *Renewable and Sustainable Energy Reviews*, *109*, 85–101. https://doi.org/10.1016/j.rser.2019.04.021

Zhao, Y., Wen, J., Xiao, F., Yang, X., & Wang, S. (2017). Diagnostic Bayesian networks for diagnosing air handling units faults – Part I: Faults in dampers, fans, filters and sensors. *Applied Thermal Engineering*, *111*, 1272–1286. https://doi.org/10.1016/j.applthermaleng.2015.09.121

Zio, E. (2013). Prognostics and health management of industrial equipment. *Diagnostics and Prognostics of Engineering Systems: Methods and Techniques*, 333–356. https://doi.org/10.4018/978-1-4666-2095-7.ch017