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Data-driven predictive maintenance planning framework for MEP components based on BIM and IoT using machine learning algorithms

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ABSTRACT

Facility managers usually conduct reactive maintenance or preventive maintenance strategies in building maintenance management. However, there are some limitations that reactive maintenance cannot prevent failure, and preventive maintenance cannot predict the future condition of MEP components and repair in advance to extend the lifetime of facilities. Therefore, this study aims to apply a predictive maintenance strategy with advanced technologies to overcome these limitations. Building information modeling (BIM) and Internet of Things (IoT) have the potential to improve the efficiency of facility maintenance management (FMM). Despite the significant efforts that have been made to apply BIM and IoT to the architecture, engineering, construction, and facility management (AEC/FM) industry, BIM and IoT integration for FMM is still at an initial stage. In order to provide a better maintenance strategy for building facilities, a data-driven predictive maintenance planning framework based on BIM and IoT technologies for FMM was developed, consisting of an information layer and an application layer. Data collection and data integration among the BIM models, FM system, and IoT network are undertaken in the information layer, while the application layer contains four modules to achieve predictive maintenance, namely: (1) condition monitoring and fault alarming module, (2) condition assessment module, (3) condition prediction module, and (4) maintenance planning module. Machine learning algorithms, ANN and SVM, are used to predict the future condition of MEP components. Furthermore, the developed framework was applied in an illustrative example to validate the feasibility of the approach. The results show that the constantly updated data obtained from the information layer together with the machine learning algorithms in the application layer can efficiently predict the future condition of MEP components for maintenance planning.

1. Introduction

Building maintenance is widely recognized as an integral part of facility management (FM), as maintenance costs account for more than 65% of the annual FM costs [1]. Effective maintenance strategies can reduce building maintenance costs and even extend the service lifetime of building components. Currently, reactive maintenance and preventive maintenance are adopted in building maintenance management. In reactive maintenance, FM staff perform maintenance actions after the failure happens. Preventative maintenance is a calendar-based approach that enables FM staff to inspect or replace the building component at predetermined intervals or periods of time. However, the reactive maintenance cannot prevent the failure and preventive maintenance cannot predict the future condition and repair components in advance to extend the lifetime of building components. Predictive maintenance, known as condition-based maintenance, aims to detect incipient failures and eventual degradation based on detection of trends of component conditions using historical data so that early actions can be taken [2]. Predictive maintenance can address the above disadvantages through predicting possible failures and repairing components ahead of time to extend the service lifetime, when building components are still in good working order. This approach is highly reliant on operational data collected and transmitted by sensors. Two main approaches for collecting condition data in a facility are by inspection (such as regular surveys) and by continuous surveillance (such as monitoring using sensors). Decision making for predictive maintenance requires the integration of various types of information such as monitoring data, maintenance records, work orders, causes, and the knock-on effect of failures, etc.

Besides these maintenance strategies, computer-based systems are used to improve the efficiency of facility maintenance management (FMM) activities. Currently, popular building maintenance systems,

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such as computerized maintenance management systems (CMMS) and computerized aided facility management systems (CAFM) mainly focus on capturing valuable information. However, paper-based records and Excel spreadsheets are still widely used for transferring FM information, which can cause a time delay in responding to service requests, resulting in inefficient operations and maintenance (O&M). In the AEC/FM industry, building information modeling (BIM) has been used to facilitate maintenance activities and store maintenance records, such as failure locations and problem type [1]. Therefore, BIM has the potential to improve the efficiency of FMM. In addition to BIM, data on facility conditions can be obtained from Internet of Things (IoT) such as sensor networks or radio frequency identification (RFID) systems. Sensor networks have been applied to monitor the conditions of building equipment and building environment, and the collected sensor data is valuable for predictive maintenance.

Researchers have studied aspects of predictive maintenance. Hao et al. [3] proposed the prototype of decision support system for corrective maintenance, preventative maintenance, and condition-based maintenance. However, the method of information integration in the decision support system and condition prediction algorithms was not considered. Wang et al. [4] investigated a cloud-based paradigm for predictive maintenance based on a mobile agent to enable timely information acquisition, sharing and utilization to improve the accuracy and reliability in fault diagnosis, remaining service life prediction, and maintenance scheduling. However, it did not include a reliable prediction algorithm for condition prediction. In addition, some studies were conducted on the condition predictive methods for maintenance. For example, Ren and Zhao [5] established an architecture based on IoT for product research and manufacturing, and O&M process data acquisition, using decision making methods for predictive maintenance, such as decision tree, k-Means, support vector machine (SVM), and neural network. However, they did not illustrate how to use these methods and the prediction process.

The aforementioned research gaps include (1) lack of information integration for predictive maintenance, (2) lack of reliable predictive algorithms, and (3) no description of prediction process. Based on these research gaps, a systematic way to implement BIM and IoT technologies for predictive maintenance of MEP components is necessary to improve the efficiency of FM. Therefore, this research develops an integrated data-driven framework based on BIM and IoT technologies for predictive maintenance of building facilities. The framework contains (1) a condition monitoring and fault alarming module, (2) a condition assessment module, (3) a condition prediction module, and (4) a maintenance planning module, providing a technological framework for decision making in FMM.

This study focuses on the mechanical, electrical and plumbing (MEP) components of building facilities, such as HVAC systems, electrical components, lighting, lifts, and elevators, which are essential elements to ensure the functionality of buildings [6]. Chiller of HVAC systems is used as an example to show how to use the proposed framework for MEP facilities, because chiller is a key component of HVAC systems to cool down a building and provide better building environment. The framework can monitor the condition of MEP components and capture real-time information from IoT network. It not only addresses the information integration issues among BIM, IoT and FM systems, but also handles the continuously training of prediction models using real-time sensor data, updated inspection records and maintenance records. Therefore, the predictive models can fit the practical situation and the prediction accuracy is improved. In addition, FM managers can schedule the maintenance plan and purchase the materials and tools ahead of time to perform the maintenance actions before the failure. Therefore, the proposed framework can prevent the failure and extend the lifetime of MEP components.

This paper is organized as follows: Section 2 reviews the current status and limitations of FMM and predictive maintenance based on BIM and IoT. Section 3 describes the proposed framework for predictive maintenance in detail. An illustrative example is presented in Section 4 to validate the feasibility of the proposed framework, followed by the conclusions in Section 5.

2. Related literature review

2.1. BIM-based facility maintenance management

The first type of BIM application for FMM is related to facility information management. Lee and Lin [7] studied how the BIM approach is applied to develop 3D models for managing and maintaining building facilities. However, these applications are limited and can only track and manage the most recent maintenance-related information, events, and problem descriptions in the 3D CAD-based models. However, there is no automatic condition monitoring and maintenance scheduling function to enable FM staff to make decisions for facility maintenance quickly. Motawa and Almarshad [8] investigated a number of case studies and developed an integrated system to capture information and knowledge of building maintenance using case base reasoning. However, the integrated system could not predict the failure of building components. Shen et al. [9] proposed a loosely coupled integration approach for decision support in facility management and maintenance. They described a framework to facilitate decision making for building maintenance, but details on how to use this framework and specific case studies were not provided. Motamedi et al. [10] utilized BIM visualization capabilities to solve maintenance problems and provided a data model for failure root cause detection. However, automatic decision making using BIM is not considered in this study. Chen et al. [11] proposed a framework for automatic scheduling of maintenance work orders based on BIM, by obtaining information from BIM models and FM systems to automatically generate maintenance schedules. However, this framework is only used for facility maintenance planning, but not for predictive maintenance.

The second type of studies on BIM application for FMM are mainly related to a combination of BIM with other technologies, such as geographic information system (GIS) and augmented reality (AR) to improve the efficiency of maintenance. Kang and Hong [12] proposed a software architecture for effective incorporation of BIM with a GIS-based FM system, and they created a BIM/GIS-based prototype that extracts, transforms and loads information from BIM and GIS to integrate FM data. Koch et al. [13] used marker-based AR technology to navigate the maintenance roads for facility staff. Lee and Akin [14] used marker-based AR technology to detect the condition of components. Cheng et al. [15] compared marker-based AR and marker-less AR for indoor maintenance and decoration. However, the application can only display maintenance and operational data, but does not include planning for maintenance. Overall, most of the above researchers studied information visualization and information extraction from BIM models, but not for facility condition analysis or facility maintenance planning.

Based on the aforementioned research gaps, this study describes a specific framework to show the dataflow and implementation process of predictive maintenance, and the study includes four modules that allow FM staff to make better decisions for maintenance.

2.2. BIM- and IoT-based predictive maintenance

Researchers have studied the possibilities of applying BIM to predictive maintenance. Hallberg [16] found that the possibilities of adopting predictive maintenance strategy depend on the availability of performance-over-time and service life forecasting models and methods. Hao et al. [3] developed a decision support system for integrating corrective maintenance, preventative maintenance and condition-based maintenance, and they mentioned the possibility of combining a condition monitoring system and BIM technology. Hallberg and Tarandi [17] discussed how open BIM facilitates the implementation of a predictive Lifecycle Management System (LMS) and adoption of long-term and dynamic maintenance strategy. This system was designed only for building structure maintenance and did not mention the specific degradation models and the specific approach used for condition prediction. Later on, Cheng et al. [18] developed a BIM-based decision support system for predictive maintenance of building facilities. However, there was no case study provided to validate the feasibility of the propose framework. Wang et al. [4] investigated a cloud-based paradigm for predictive maintenance based on a mobile agent to enable timely information acquisition, sharing and utilization for improved accuracy and reliability in fault diagnosis, remaining service life prediction, and maintenance scheduling. They claimed how to store and analyze these data with efficient predictive maintenance algorithms is a big challenge. This study illustrated a case of an electric motor and compared a healthy motor with a broken motor for fault diagnosing, but did not provide a prediction algorithm for condition prediction. Ren and Zhao [5] indicated that the challenges for maintenance using big data are lack of timely and accurate data of components, and lack of useful patterns and knowledge of the component lifecycle. However, they did not suggest the solution on how to collect timely and accurate sensor data. Civerchia et al. [19] proposed a framework of Intelligent Predictive Maintenance (IPdM) systems in Industry 4.0 and illustrated the functions of six modules in an IPdM system. However, no case studies were provided to validate the feasibility of this system. Schmidt and Wang [20] mentioned that cloud technology can enhance the predictive maintenance process, which indicated there was a lack of a systematic way in predictive maintenance implementation.

In addition, Wang and Wang [21] proposed a framework of predictive maintenance based on deep learning. However, they did not illustrate how the framework can be applied to practice. Gombé et al. [22] proposed a system based on wireless sensor network to monitor industrial systems in order to prevent faults and damages. They used this sensing architecture to measure the temperature of industrial machine components and evaluated the robustness of the method. The main limitation of interrogation range is emphasized in the link budget calculation. Francis and Mohan [23] studied the ARIMA model based on real time trend analysis for prediction processes of predictive maintenance. The automated system of the data capturing in the railway transportation will help in analyzing the evolution of fault trends and predicting the failure. Moreover, these researchers applied IoT and predictive algorithms for predictive maintenance, without BIM technology. Therefore, the aforementioned applications did not provide any reliable and practical methods for facility managers to predict the future condition and no practical case studies were provided.

In this study, reliable and practical machine learning algorithms for predictive maintenance methods are discussed in Section 2.3 and potential algorithms are selected to support this study.

2.3. Machine learning algorithms for predictive maintenance

Several machine learning algorithms, including artificial neural networks (ANN), SVM, and Markov chains, can be applied to predict the condition of building components. Recently, ANNs have been used as decision support tool because of the potential ability of predicting nonlinear time series trend. The ability of ANNs to capture and retain nonlinear failure patterns has been researched and documented extensively [24,25]. ANNs have been found to perform better than known classical auto-regressive models for trend prediction of nonlinear time series [26]. ANNs differ from traditional statistical techniques in their ability to successfully learn nonlinear features of a time series, and ANNs have been widely used in forecasting [27]. For example, El-Abbasy et al. [28] developed models that evaluate and predict the condition of pipelines based on several factors, including corrosion. Silva et al. [29] used multiple linear regression analysis and ANN to estimate the durability and service life of a facade coating, and established mathematical models to describe the facade degradation. However, Silva et al. [29] found that studies strongly relying on statistical data cannot be considered. SVM is a widely used classification technique based on statistical learning theory. Sousa et al. [30] evaluated the performance of ANNs and SVMs in predicting the structural condition of sewers, and indicated there were particular advantages in predicting the structural condition. Both methods are also dependent on the specific cases in the training and testing samples, and the SVM method is more sensitive to the values of the parameters. Morcous [31] used the Markov chain model to predict the future condition of the components of a bridge, and tried to predict the service life of the bridge. However, the Markov chain model has two limitations: (1) the model used discrete parameter. (2) It assumes that the future condition depends only on its present condition, not on its past condition. These limitations means the Markov chain is not appropriate for some building components, such as HVAC system.

In addition, Wang and Wang [21] discussed about the impact of artificial intelligence (AI) to future predictive maintenance, which is an important part of future advanced production systems. Specially, they discussed why people are interested in applying deep learning technology in predictive maintenance strategy. However, they mentioned that deep learning is not well suited to every problem. It typically requires large data sets for training. der Mauer et al. [32] mentioned predictive maintenance approaches usually require deep integration with the specific machine. In their study, the sound sequences were subsequently analyzed using neural networks developed in Keras and TensorFlow. It was described that the proposed approach can be applied to solve predictive maintenance tasks. However, their implementation was often associated with technical limitations related to solution complexity as well as to legal and financial restrictions. Carvalho et al. [33] mentioned the performance of predictive maintenance applications depends on the appropriate choice of the machine learning method. They presented a systematic literature review of machine learning methods applied to predictive maintenance, showing which were being explored in this field and the performance of the current state-of-the-art machine learning techniques. Therefore, based on the datasets we collected and these methods we compared, the ANN and SVM algorithms are selected on this study as the machine learning models to predict the future condition. In addition, both ANN and SVM depend on the number of datasets used to train the model network, and their efficiency increases with the number of datasets. The quality of the models is directly related to the amount of available data. Therefore, our study will improve the prediction process and make the prediction models to become data-driven models based on real-time data.

3. The proposed framework of data driven predictive maintenance planning based on BIM and IoT for building facilities

The proposed framework utilizes the functionality of BIM and IoT to achieve condition monitoring and prediction of the facility condition to support decision making for facility maintenance activities, as shown in Fig. 1. The predictive maintenance framework is based on the methodology in literature review and the newly developed methods, including information integration, information visualization, the proposed four modules of predictive maintenance, and machine learning algorithms. The predictive maintenance framework is integrated with new technologies, namely, BIM, IoT, and FM system. The framework includes two layers: the information layer and the application layer. The information layer contains the connection of various kinds of information from the as-built BIM models, IoT sensor network, and FM system, while the application layer includes four modules for (1) condition monitoring and fault alarming, (2) condition assessment, (3) condition prediction, and (4) maintenance planning. In addition, the data flow and implementation process of prediction maintenance is illustrated in Section 3.1.1, and details of four modules are discussed in Sections 3.2.1 to 3.2.4, respectively.

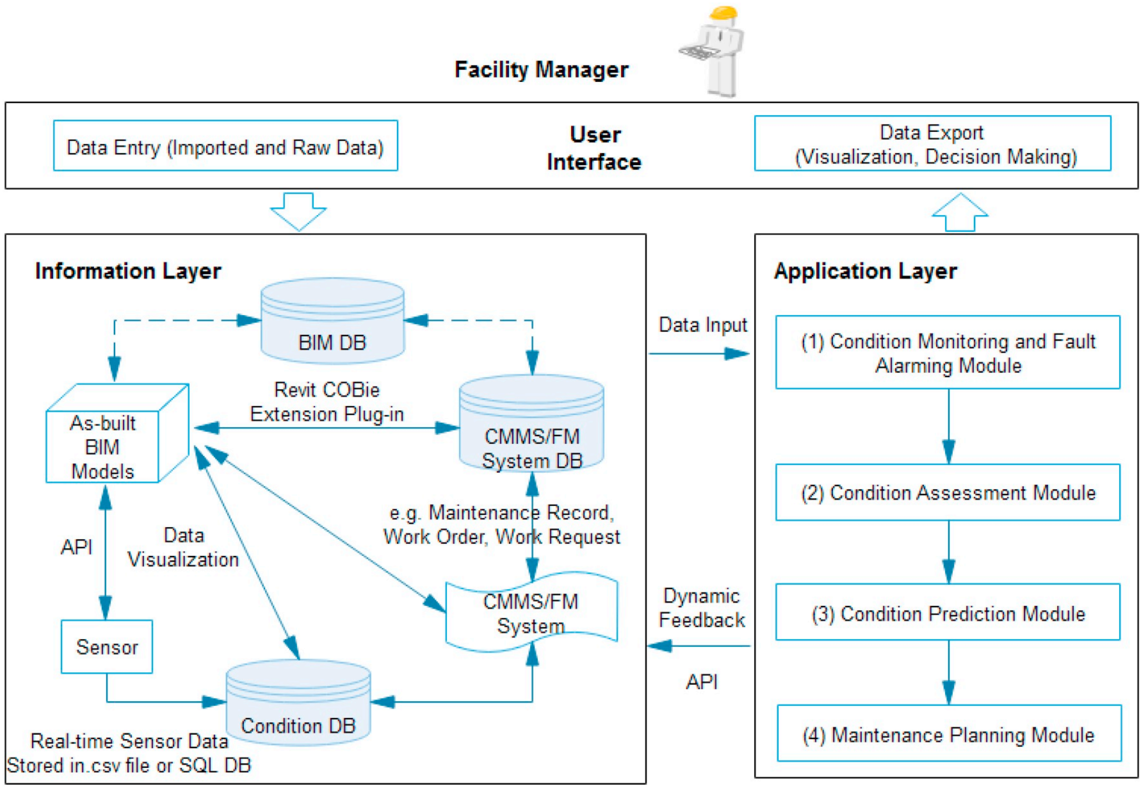


Fig. 1. Proposed data-driven predictive maintenance planning framework based on BIM and IoT for MEP components.

3.1. *Information layer*

According to the asset management standard PAS 1192-2:2013 [34], asset information contains graphical information, non-graphical information, and documentation data, which are usually stored in separate databases. In this framework, graphical information and part of the non-graphical information related to building facilities are stored in BIM models, while the other parts of the non-graphical information and documentation data (e.g., past maintenance records, work orders and requests) are stored in the FM system database. Sensor data are stored in an independent condition database.

3.1.1. *Data collection*

Component parameters related to predictive maintenance are identified based on the literature review. Flores-Colen et al. [35] studied on the criteria for prioritization of predictive maintenance of building facades, and these important criteria include (1) type of constructive solution, (2) external environment, (3) building age, (4) remaining service life, and (5) data of the last intervention on the area effected. Niu et al. [36] studied an optimized condition based maintenance system by data fusion, and suggested that health assessment of equipment is based on historical and condition monitoring values. The values of sensor data features, such as mean and root mean square frequency, are the important indexes to indicate the condition of the equipment. Bansal et al. [37] studied a novel real-time predictive maintenance system based on a neural network approach, and they mentioned that a large number of sensors were required to collect data relevant to all machine parameters. Sousa et al. [30] used parameters in sewer structures to predict the condition, including material, diameter, length, depth, slope, age, and velocity.

The required information is divided into three groups: (1) Geometric and semantic information (non-graphical information) of building facilities, such as type, dimensions, materials, capacity, location, and installation year. These data are exported from the BIM model, and they represent the inherent properties and indicate the inherent deterioration trend in the service period. (2) Operational data of each critical components and data on facility conditions, including sensor data of temperature, pressure, flow rate, obtained from an IoT sensor network. Sensors are used to monitor the operational condition of critical components, and the trend of sensor data can suggest the frequency of abnormal events and the usage pattern of components. (3) Maintenance-related data and documents, including inspection records and historical maintenance records, gathered from the FM system. Maintenance-related documents provide detailed parameters, including usage age, inspection times per year, abnormal times per year, minor maintenance times per year, and major maintenance time per year. These detailed parameters are important for evaluating the current condition and predicting the future condition when acting as the input for the prediction model. Information of these three groups is collected in the following sub-sections.

3.1.1.1. Data collection from BIM models. A BIM model includes both geometric and semantic information, which is valuable for FM and predictive maintenance. When the as-built model is delivered to the owner, the model should be verified and meet the facility information requirement based on PAS 1193-2: 2003 for O&M. Therefore, the as-built BIM models should contain specific graphical information and non-graphical information, so that these BIM models can provide accurate and complete information for predictive maintenance, including component type, dimensions, materials, capacity, location, and installation year.

In addition, COBie (Construction Operations Building Information Exchange) is an information exchange specification for the lifecycle capture and delivery of information needed by facility managers [38]. COBie can be applied to transfer BIM data from BIM models to the FM system, and a COBie extension for Revit was used to extract the required information from the BIM models for predictive maintenance. The sample of extracted COBie data is represented in the COBie spreadsheet, shown in Fig. 2. The COBie spreadsheet shows the information on Component Name, Created By, Created On, Type Name,

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Name	CreatedBy	CreatedOn	TypeName	SpaceNames	Description	tSystem	ExtObject	tIdentifier	SerialNumber	InstallationDate	TagNumber	rCode	setIdentifier
2	Door-100A	wchenau@connect.ust.hk	2018-11-04T11:08:38	Hardware Items	100A	Door Type D1		IfcDoor		000-01-1	2015-03-01			
3	Door-100F	wchenau@connect.ust.hk	2018-11-04T11:08:38	Hardware Items	100B	Door Type D1		IfcDoor		000-01-2	2015-03-01			
4	Door-100G	wchenau@connect.ust.hk	2018-11-04T11:08:38	Hardware Items	100A	Door Type D1		IfcDoor		000-01-3	2015-03-01			
5	Door-101A	wchenau@connect.ust.hk	2018-11-04T11:08:38	Hardware Items	100A, 101,	Door Type D1		IfcDoor		000-01-4	2015-03-01			
6	Door-102A	wchenau@connect.ust.hk	2018-11-04T11:08:38	Hardware Items	100B, 102	Door Type D1		IfcDoor		000-01-5	2015-03-01			
7	Door-103A	wchenau@connect.ust.hk	2018-11-04T11:08:38	Hardware Items	100A	Door Type D1		IfcDoor		000-01-6	2015-03-01			
8	Door-104A	wchenau@connect.ust.hk	2018-11-04T11:08:38	Hardware Items	100A, 104,	Door Type D1		IfcDoor		000-01-7	2015-03-01			
9	Door-105A	wchenau@connect.ust.hk	2018-11-04T11:08:38	Hardware Items	100A, 105	Door Type D1		IfcDoor		000-01-8	2015-03-01			
10	Door-100C	wchenau@connect.ust.hk	2018-11-04T11:08:38	Overhead Coiling Doors Assembly	100A	Overhead Door		IfcDoor		C600-012-01	2015-03-01			
11	Door-100D	wchenau@connect.ust.hk	2018-11-04T11:08:38	Overhead Coiling Doors Assembly	100A	Overhead Door		IfcDoor		C600-012-02	2015-03-01			
12	Door-100E	wchenau@connect.ust.hk	2018-11-04T11:08:38	Overhead Coiling Doors Assembly	100A	Overhead Door		IfcDoor		C600-012-03	2015-03-01			
13	Door-100B	wchenau@connect.ust.hk	2018-11-04T11:08:38	Overhead Coiling Doors Assembly	100A	Overhead Door		IfcDoor		C600-012-04	2015-03-01			
14	HP-1	wchenau@connect.ust.hk	2018-11-04T11:08:38	HVAC System Components and Equipment	100A	Heat Pump		objComponent		1000-00-1	2015-03-01			
15	RH-1	wchenau@connect.ust.hk	2018-11-04T11:08:38	HVAC System Components and Equipment	100A	Radiant Heater		objComponent		236S-300-1	2015-03-01	RH-1		
16	RH-2	wchenau@connect.ust.hk	2018-11-04T11:08:38	HVAC System Components and Equipment	100A	Radiant Heater		objComponent		236S-300-2	2015-03-01	RH-2		
17	RH-3	wchenau@connect.ust.hk	2018-11-04T11:08:38	HVAC System Components and Equipment	100A	Radiant Heater		objComponent		226S-200-1	2015-03-01	RH-3		
18	RH-4	wchenau@connect.ust.hk	2018-11-04T11:08:38	HVAC System Components and Equipment	100A	Radiant Heater		objComponent		236S-300-3	2015-03-01	RH-4		
19	RH-5	wchenau@connect.ust.hk	2018-11-04T11:08:38	HVAC System Components and Equipment	100A	Radiant Heater		objComponent		236S-300-4	2015-03-01	RH-5		
20	RH-6	wchenau@connect.ust.hk	2018-11-04T11:08:38	HVAC System Components and Equipment	100A	Radiant Heater		objComponent		226S-200-2	2015-03-01	RH-6		
21	RH-7	wchenau@connect.ust.hk	2018-11-04T11:08:38	HVAC System Components and Equipment	100A	Radiant Heater		objComponent		236S-300-5	2015-03-01	RH-7		
22	RH-8	wchenau@connect.ust.hk	2018-11-04T11:08:38	HVAC System Components and Equipment	100A	Radiant Heater		objComponent		226S-200-3	2015-03-01	RH-8		
23	RH-9	wchenau@connect.ust.hk	2018-11-04T11:08:38	HVAC System Components and Equipment	100A	Radiant Heater		objComponent		236S-300-6	2015-03-01	RH-9		
24	RH-10	wchenau@connect.ust.hk	2018-11-04T11:08:38	HVAC System Components and Equipment	100A	Radiant Heater		objComponent		236S-300-7	2015-03-01	RH-10		
25	RH-11	wchenau@connect.ust.hk	2018-11-04T11:08:38	HVAC System Components and Equipment	100B	Radiant Heater		objComponent		236S-300-8	2015-03-01	RH-11		
26	RH-12	wchenau@connect.ust.hk	2018-11-04T11:08:38	HVAC System Components and Equipment	100B	Radiant Heater		objComponent		236S-300-9	2015-03-01	RH-12		

Instruction | Contact | Facility | Floor | Space | Zone | Type | Component | System | Spare | Resource | Job | Document | Attribute | Coordinate | Connection ...

Fig. 2. The sample of COBie spreadsheet.

Space Name, Description, ExtObject, Serial Number, Installation Date, Tag Number, etc.

3.1.1.2. Sensor data collection from IoT sensor network. An IoT sensor network is established to gather sensor data from building facilities and environment during the operation period, as shown in Fig. 3. After data acquisition, a signal is decoded from the direct digital control (DDC) system to determine the condition and external environmental parameters. In addition, a dockable plug-in is developed in the BIM model to directly visualize real-time sensor data in a BIM model as well as storing real-time sensor data into the condition database, as shown in Fig. 3. The specific functions of the developed plug-in for data visualization and data storage are illustrated in Fig. 6 in Section 3.1.2. The developed plug-in is convenient for facility manager to read real-time sensor data in the BIM model and synchronously store sensor data into corresponding condition DB (MSSQL DB). FM manager can check the sensor data by clicking the "Sensor Data" button to see the current sensor data and the maximum value and minimum value of sensor data in the historical trend. FM manager can also check the sensor information, average value, and the historical value of the sensor from the condition database. The sensor data is stored synchronously by clicking the "StoreToDB" button, as shown in Fig. 6. In the last process as shown in Fig. 3, the sensor data are used in the FMM process for condition monitoring and prediction.

Fig. 4 shows a typical sensor and a DDC system in an IoT sensor network. In the sensor data collection system, the BACnet (Building Automation and Control Networks) protocol, commonly as a data communication protocol among different equipment, devices and sensors [39], is used to obtain real time operational data from the IoT sensor network. The types of operational data include operational logic, facility conditions, live data streams from deployed sensors, set points, control parameters, alarms, events, and trend logs. This study focuses on set-point data and sensor-derived condition data to indicate the status of equipment and facilities, because checking these types of data is important for diagnosing the current status of the equipment. In an IoT sensor network, BACnet supports various types of operation data, including temperature, pressure, flow rate and ON/OFF status. Four object types and their attributes are used to model various types of sensor-derived operation data: (1) Analog Input (AI), (2) Analog Output (AO), (3) Binary Input (BI), and (4) Binary Output (BO). Analog refers to a continuously changing voltage or current level signal. An AI is an analog signal from a sensor. The DDC system converts the AI into numerical information to represent AO, and AO is analog data for the device controls. Examples of analog signal are temperature (e.g., 23.7 °C) and humidity (e.g., 57%) data. A binary signal typically has an ON (0) and OFF (1) state. A BI signal contains the state of an input from devices such as an air conditioning switch or a door-closed switch. A BO signal contains the state of an output to devices such as a motor starter or panel signal light. AI, AO, BI, and BO signals can be extracted from the DDC system, as shown in Fig. 4.

3.1.1.3. Information collection from FM system. Most FM systems

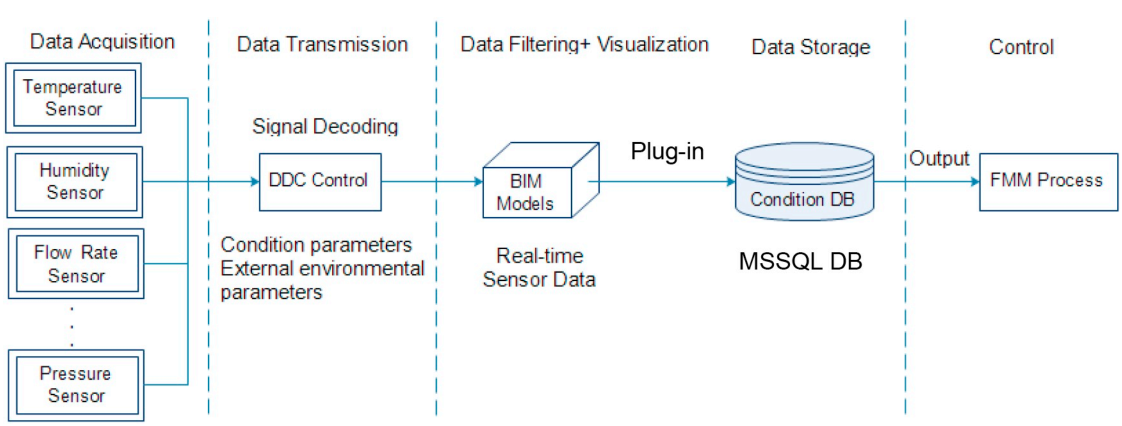


Fig. 3. The sensor data collection system.

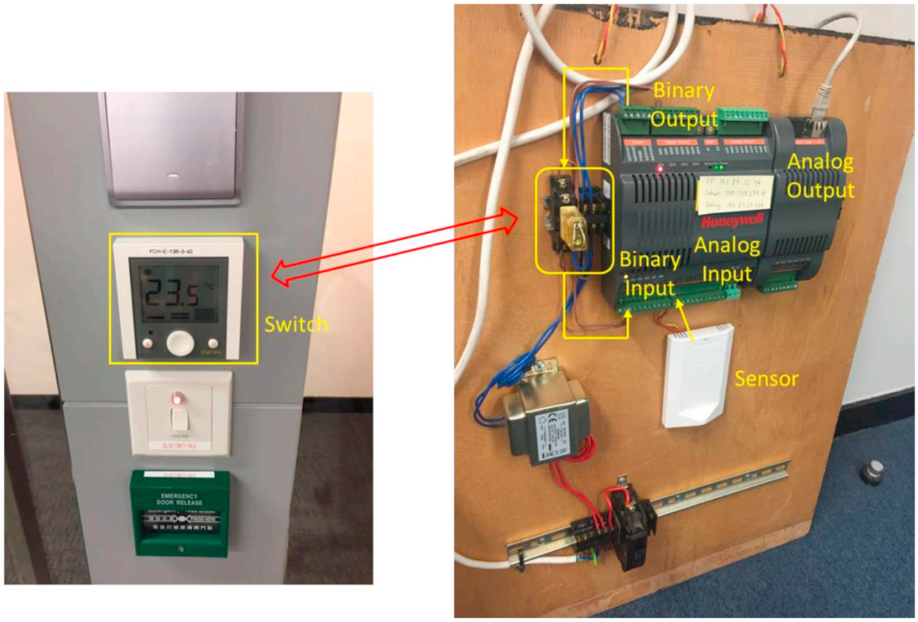


Fig. 4. The typical sensor and DDC system in an IoT sensor network.

contain several sub-systems for different functions, including space management, maintenance management, and asset management, etc. The maintenance management module is essential and indispensable. The information on inspection records, maintenance requests, maintenance work orders, and historical maintenance records, is extracted from FM systems for prediction in this step.

3.1.2. *Data integration and visualization*

The abovementioned three groups of information in Section 3.1.1 are integrated together and visualized in 3D BIM models and used for condition prediction and efficiency improvement of facility maintenance management. There are four steps in data integration and visualization: (1) BIM and FM data integration using COBie, (2) IFC extension of sensor entity and *IfcSensorType*, (3) development of sensor data schema, and (4) sensor model visualization and sensor data visualization.

3.1.2.1. BIM and FM data integration using COBie. COBie is an information exchange specification for the lifecycle capture and delivery of information needed by facility managers [38]. Therefore, COBie can be applied to integrate BIM data and FM data. In this framework, a Revit COBie extension plug-in is installed in BIM authoring software for data extraction from the BIM models to the FM system. Different types of information from BIM models are selected based on customized configurations, and then imported into COBie spreadsheets. Usually, the names of attributes in COBie spreadsheets are different from the facility data in FM systems. It is necessary to map the COBie data into FM systems based on the data schema of the FM relational database. In the data mapping process, the attribute names of COBie data are matched to the attribute names in FM database table. The attributes of the components in the COBie spreadsheet are then mapped with the corresponding attributes in the FM system using the COBie connector plug-in we developed. The connector plug-in can import data from COBie spreadsheets to the FM system column by column. This data mapping process is described in detail in Chen et al. [40].

3.1.2.2. IFC extension of sensor entities and IfcSensorType. In order to transfer sensor data from an IoT sensor network into a BIM model, some IFC entities need to be extended in the IFC schema, and a sensor data schema is herein proposed to represent data in BIM models, as explained in the following.

In *IfcBuildingControlsDomain* of IFC4, there are six types of entities and corresponding attributes that represent concepts related to building control system, namely, (1) actuator, (2) alarm, (3) controller, (4) sensor, (5) flow instrument, and (6) unitary control element. In order to correctly map the built-in Revit parameters and the relative IFC objects (e.g., IFC sensor entities), the *ifcSensorType* is created in IFC4 to represent the sensor. Each sensor modelled in Revit belongs to the *IfcDistributionControlElement* class. To specify the behavior of an object, its *IfcExportType* and *IfcExportAs* parameters must be set properly. *IfcExportType* defines the IFC object with a predefined type, and a sensor needs to be set to *IfcSensorType*, which contains common attributes shared by all types of sensors, as representations of shape or the composition of elements.

As an example, *IfcSensorType.TemperatureSensor* is an IFC entity of type *IfcDistributionControlElement* with its *IfcExportType* property set to *IfcSensorType* and its *IfcExportAs* property set to Temperature Sensor in the IFC4 edition. Based on the IFC schema and corresponding sensor properties, the BIM model can represent sensor entities and sensor attributes in 3D visualization. In addition, sensor attributes can be updated based on the extended IFC4 entities in the IFC schema, while the sensor value can be updated and visualized in the properties field in the BIM models through the developed plug-in. The condition monitoring allows an improvement of the regular and automatic updating of values in the model through the IFC representation, retrieving constantly updated data from the IoT sensor network.

3.1.2.3. Development of sensor data schema. The data exchange standard IFC4 is not complete. In the IFC 4, *IfcSensorType* has properties: *Pset_ElectricalDeviceCommon*, *Pset_Condition*, *Pset_EnvironmentalImpactIndicators*, *Pset_EnvironmentalImpactValues*, *Pset_PackingInstructions*, *Pset_ManufacturerOccurrence*, *Pset_ManufacturerTypeInformation*, *Pset_ServiceLife*, and *Pset_Warranty*. However, *IfcSensorType* does not include other properties and relations needed by the O&M phase such as operational status of sensors (e.g., “active”, “broken”, and “decommissioned”), downtime information, and failure cause. Therefore, the sensor schema is created for data representation, as shown in Fig. 5. In addition, the condition database is used to store and manage data efficiently.

In the information layer, the sensor related information, such as sensor name, sensor ID, sensor type, sensor value, the location of

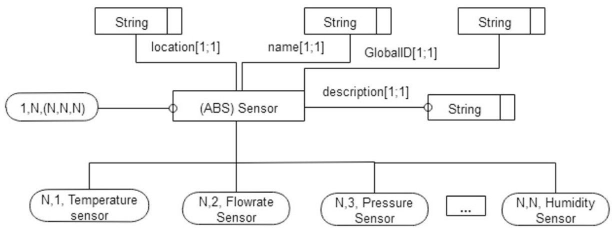


Fig. 5. General sensor schema of representative in BIM model.

sensor, and the description of sensor, are gathered in the condition database. However, not all of these data are necessary for condition prediction. The proposed framework can help the FM manager to select the necessary information for condition prediction. For example, when analyzing the condition of a chiller, the relevant sensors (e.g., temperature sensor, pressure sensor, flow rate sensor) are selected based on the sensor name and the location of the sensor in the chiller. Sensor name, sensor ID, sensor value, and sensor type are collected in the condition database for future prediction.

3.1.2.4. Sensor visualization and sensor data visualization. Several types of sensor are selected for condition monitoring, such as the temperature sensor, flow rate sensor, and pressure sensor. Different sensors are used for monitoring different equipment. Each sensor modelled in BIM belongs to the *ifcSensorType* class. A plug-in of Autodesk Revit was developed using Revit API (Application Programming Interface) to map sensor data into BIM models as well as to visualize the sensor model. The visualized sensor data and sensor models are shown in Fig. 6. Sensor information, the current value of the sensor, the maximum, minimum, average values, and the historical value of the sensor in the condition database are shown in this plug-in. The data trend of the sensor data is also displayed for fault alarming. For example, in Fig. 6, when the sensor data exceeds the threshold (10 °C), there is a warning in the data trend, which indicates a potential failure happens.

Maintenance documents are stored in FM system. Real-time sensor data collected from IoT system is visualized in BIM model and it is finally stored in condition database. Each building element/component has the unique element ID and the element ID is the "key to connect the maintenance documents and sensor data in the relational database". Based on the connection, FM manager can quickly query the necessary data for condition prediction to do better decisions. Therefore, it supports the establishment and control of predictive maintenance projects.

3.2. Application layer

The application layer performs data analysis for four purposes: (1) condition monitoring and fault alarming, (2) condition assessment by analyzing inspection records and monitored condition, (3) predicting the conditions of components by analyzing a) condition data gathered by sensors, b) various attributes from BIM models, and c) historical maintenance records, and (4) generating a rescheduled maintenance plan. Details of these four modules are illustrated in the following sections.

Fig. 7 illustrates clearly the dataflow and implementation process in the application layer. Firstly, FM staff obtain attributes and parameters, such as location, dimension, material, type, etc. from an as-built BIM model. Then, in the condition monitoring stage, real-time data from sensors are gathered and then visualized in the BIM model for real-time monitoring in a 3D environment. If there is an abnormal signal, the framework analyzes the potential failure based on historical maintenance records and sensor data. If a potential failure exists, the FM staff will assess the condition of components according to inspection records, maintenance standards, and monitored condition in the second stage.

Following that, in the condition prediction stage, machine learning algorithms are applied to predict the future condition, using historical maintenance records, sensor data, geometric information and attributes, and the assessed condition index from module 2. After predicted condition generated, the maintenance plan is rescheduled according to the predicted condition from module 3, in order to extend the lifetime of MEP components. The maintenance actions are decided based on the

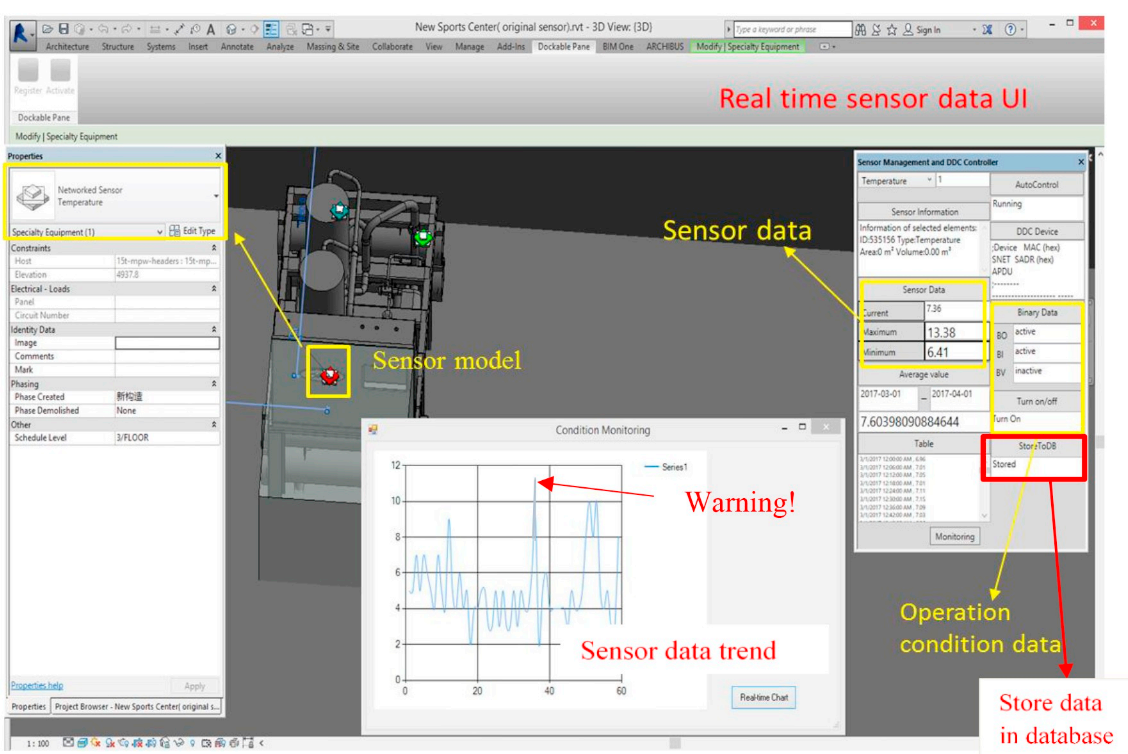


Fig. 6. The user interface BIM platform for sensor management.

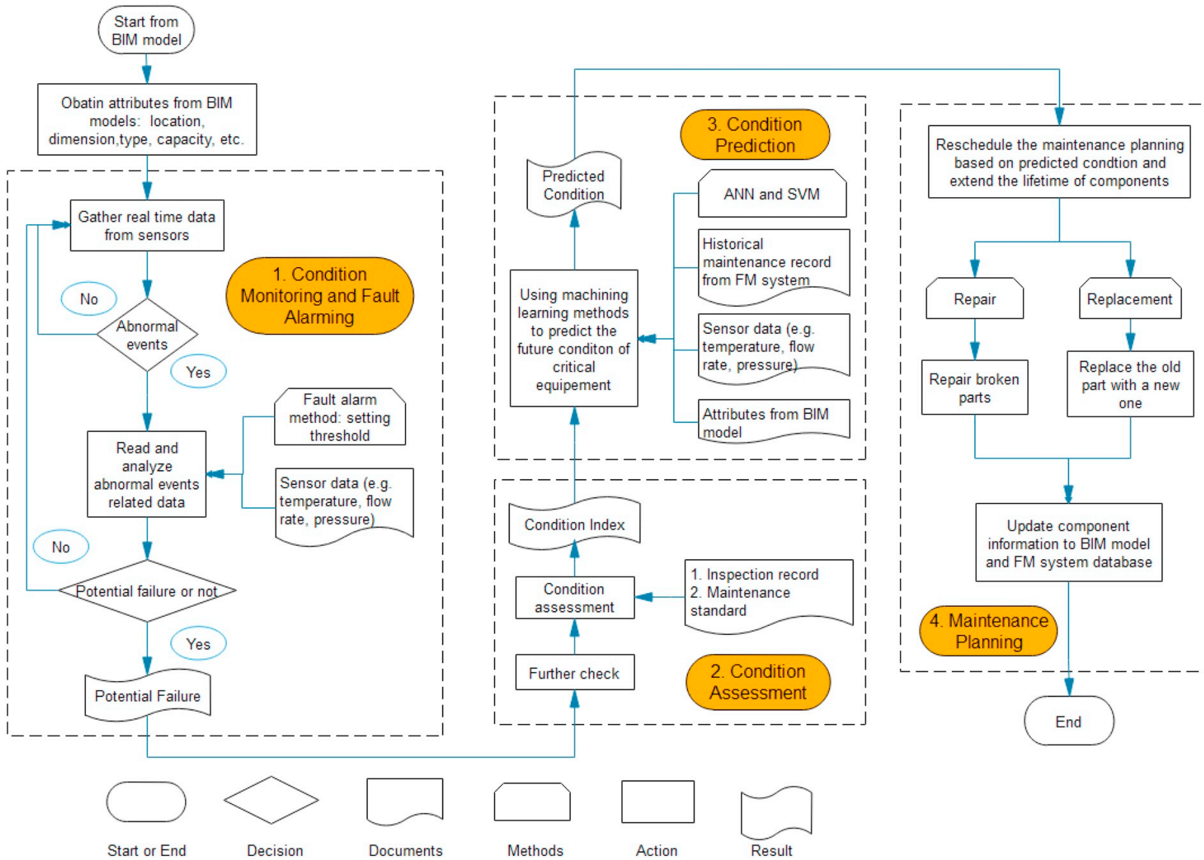


Fig. 7. The detailed dataflow and implementation process in the application layer of the proposed framework.

predicted condition and failure condition index. Finally, the FM staff update the information in the BIM model and database for further operation.

3.2.1. Condition monitoring and fault alarming module

Condition monitoring is defined as the collection and interpretation of the relevant component parameters for the purpose of identification of the state of component changes from normal conditions and the health trends of the equipment. Condition monitoring and fault alarming is the first step for predictive maintenance. Fig. 6 shows the developed plug-in in Autodesk Revit for (1) sensor data visualization and condition monitoring, and (2) fault alarming. Firstly, the developed plug-in enables FM staff to retrieve sensor data from the plug-in directly, monitor the condition of each equipment, and track any real-time data trends in the BIM model for automatic control.

Secondly, fault alarming is mainly based on abnormal events from the MEP components, such as an abnormal temperature of a chiller or an abnormal vibration of a machine. The basic rule of predictive maintenance is that if the parameter value or sensor data of the MEP component reaches a certain threshold, there is an alarming or warning to indicate something wrong with the component. Facility managers will then inspect the component on site and find the possible fault and causes of this component based on experience, the facility maintenance handbook [41], and references to the historical data trend.

In this plug-in, if the value of sensor data exceeds the threshold, an alarm is triggered, which activates the prediction process in module 3 to predict the future conditions. Once the alarm is triggered, the time stamp and value of the abnormal event are automatically recorded in the condition monitoring module, and will be used for further assessment and prediction.

3.2.2. Condition assessment module

Many research studies on building facility assessment have been directed toward setting the criteria for evaluating the performance of building components [42,43]. However, regardless of the criteria and the degree of detail, the results of any assessment largely depend on the accuracy of subjective field inspection. Existing systems must have their assets inspected by experienced inspectors (against certain criteria). Hiring such inspectors is very costly and the process of inspection is time-consuming. In order to quantify the condition of MEP facilities, we developed a scale of conditions (Table 1), based on the facility condition assessment guidebook [44], building maintenance practical code in Hong Kong [45], and interview with FM practitioners. The scale of conditions in Table 1 is conveniently used for both inspection and maintenance. The process of condition assessment is also suitable for other mechanical systems and components.

HVAC systems are used as an example, and the condition scale is applicable for most building components in general. The condition scale of a building HVAC system, its corresponding description, and required maintenance actions are illustrated in Table 1. After assessing the condition of each system, the inspectors assign a value to indicate what maintenance action needs to be taken. In addition, in the proposed framework, some of inspection data have been inputted into BIM models with storing and presenting the inspection data directly in 3D environment. Attributes such as “data of inspection” and “condition index” have been added to BIM models as additional attributes.

The common deterioration curve of MEP components is illustrated in Fig. 8. The repair or replacement action is corresponded according to different condition indexes [46]. When the condition index of a building facility is 9–10, it means the condition is excellent and no action is needed. A maintenance technician needs to conduct regular inspection for the building facility when the condition is good (condition index of 7–9). When the condition index is between 3 and 5,

Table 1
The condition assessment scale of an HVAC system.

Overall chiller condition index	Scale	Condition description	Maintenance action required
9–10	Excellent	1) No defects 2) As new condition and appearance	Regular monthly inspection New construction, no visible defects or damage. Meets efficiency and capacity goals and maintains desired temperature and air quality throughout the facility.
7–9	Good	1) Minor defects 2) Superficial wear and tear 3) Some deterioration to finishes 4) Major maintenance not required	Minor improvement needed, may be slightly outdated and less efficient and consistent. Minor deterioration or defect with no functional impact typically addressed through routine maintenance.
5–7	Fair	1) Average condition 2) Significant defects are evident 3) Worn components require maintenance 4) Services are functional but need attention 5) Deferred maintenance work exists	Repairs are needed; some deterioration exists, and maintenance needs are significant. With these, the system meets need, still within its useful life.
3–5	Poor	1) Badly deteriorated 2) Potential structural problems 3) Poor appearance 4) Major defects 5) Components fail frequently	System has exceeded its useful life; fails to meet standards or needs. Components need extensive repair at a minimum. Currently does not appear to be any safety issue.
0–3	Critical	1) Building has failed components 2) Not operational 3) Not viable 4) Unfit for occupancy or normal use 5) Environmental/contamination/ pollution issues exist	System is well past its useful life and has critical defects affecting function; its issues are beyond repair and warrant detailed review.

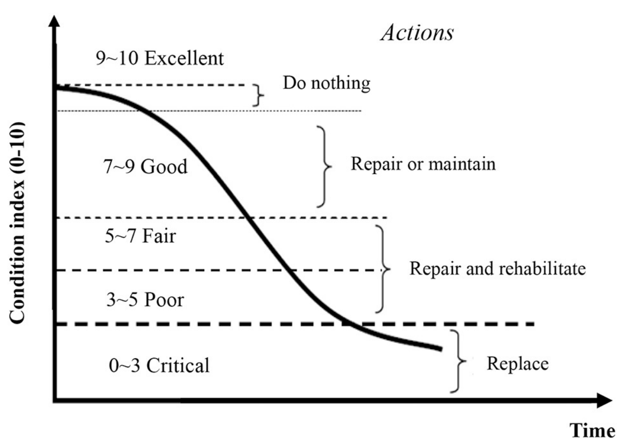


Fig. 8. The relationship between condition and corresponding maintenance actions.

component has deteriorated quite badly and its components need extensive repair and rehabilitation as soon as possible by a maintenance technician. When the condition index is under 3, the building component should be replaced. Based on the different conditions, the facility manager decides the appropriate maintenance action and maintenance priority. The condition index is lower, and the building component has higher priority.

3.2.3. *Condition prediction module*

The aim of predictive maintenance is to provide decision support for maintenance scheduling by diagnosing the defects and predicting the condition of building components. The condition monitoring data measured by its particular sensors, the FM data collected from FM system, BIM data, and the assessed condition in Section 3.2.2, will be used in condition prediction.

In this study, ANN and SVM algorithms are selected as the machine learning algorithms to predict the future condition of MEP components, as mentioned in Section 2.3. Fig. 9 shows the predictive maintenance algorithm process. The input of this prediction process is 15 variables, which are collected from three systems, e.g., BIM models, FM systems and IoT sensor networks. These 15 variables are listed, as follows: (1) chiller type, (2) dimension, (3) material, (4) capacity, (5) location, (6) installation year, (7) temperature sensor value, (8) pressure sensor value, (9) flow rate sensor value, (10) usage age, (11) inspection times per year, (12) abnormal event times per year, (13) minor repair times per year, (14) major repair times per year, and (15) problem type. In addition, different MEP components have different variables. For example, a chiller is monitored by temperature sensor, pressure sensor and flow rate sensor, while an elevator is monitored by vibration sensor. The output of this prediction process includes (1) the condition index of MEP components in buildings, and (2) triggers and alarms for the required maintenance actions.

In the proposed BIM- and IoT-based data-driven predictive maintenance planning framework, the model training and prediction are dynamic and continuous. In the process, the prediction models are trained based on the continuously updated real-time sensor data and the accumulated maintenance record. Therefore, the parameters of the prediction models are adjusted and modified gradually to accord with the new conditions of the facilities that they model, as shown in Fig. 10. Afterwards, the new prediction model is used for condition prediction. In this way, the predicted result based on the data-driven prediction maintenance planning framework is more accurate than the traditional prediction maintenance method.

The process of the condition prediction approach is shown in Fig. 10. The preparation steps include (1) datasets collection and (2) machine learning algorithm selection. The prediction process includes four steps: (1) training, (2) cross validation, (3) testing, and (4) prediction. These aforementioned 15 variables, consisting of the input datasets, are used to train and test the prediction model, illustrated in the Fig. 10.

The collected data sets (input datasets) of the selected variables are used to train the ANN and SVM algorithms to obtain data-driven ANN prediction models and data-driven SVM prediction models. The input datasets are randomly divided into three sets: (1) 80% for model training, (2) 10% for cross validation, and (3) 10% for model testing. The division percentage and method are based on previous studies [47,48]. The training set is used to train the machine learning models, whereas the testing set is used to test the trained models and to continuously correct it by adjusting the weights of the machine learning

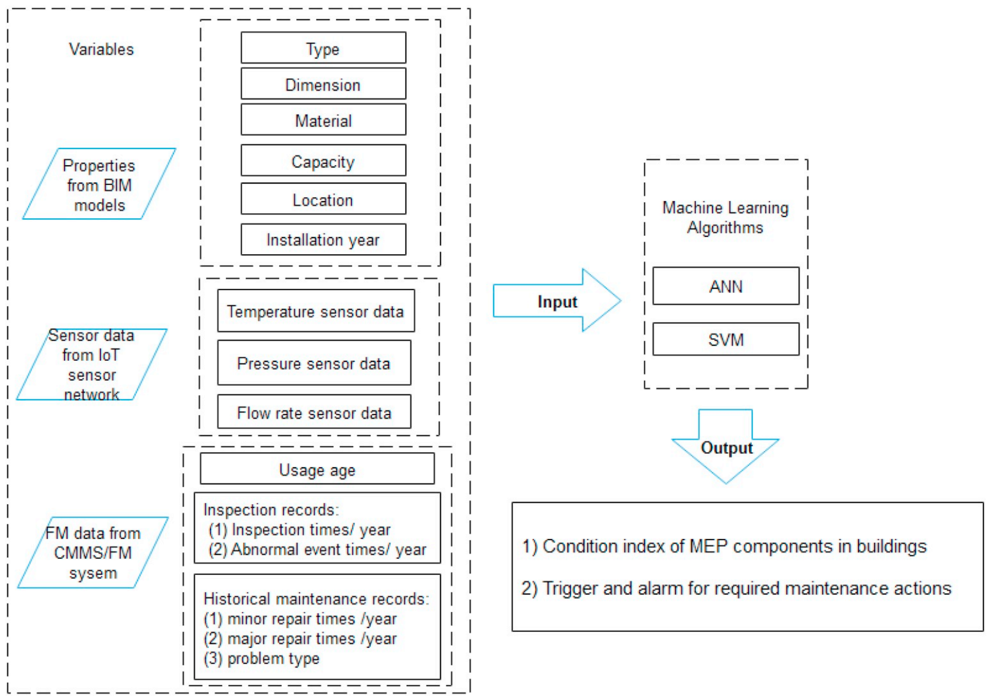


Fig. 9. The predictive maintenance algorithm process.

algorithm links. The rest of data set (10%) is used to validate the trained model. In the process, the trained models are correspondingly adjusted based on dynamic updating data, including the collected dynamic sensor data and the accumulated updated maintenance records, to become data driven-based models. Finally, the well-trained models are applied to predict the future condition of components.

3.2.3.1. Artificial neural networks (ANNs). ANNs have been used to

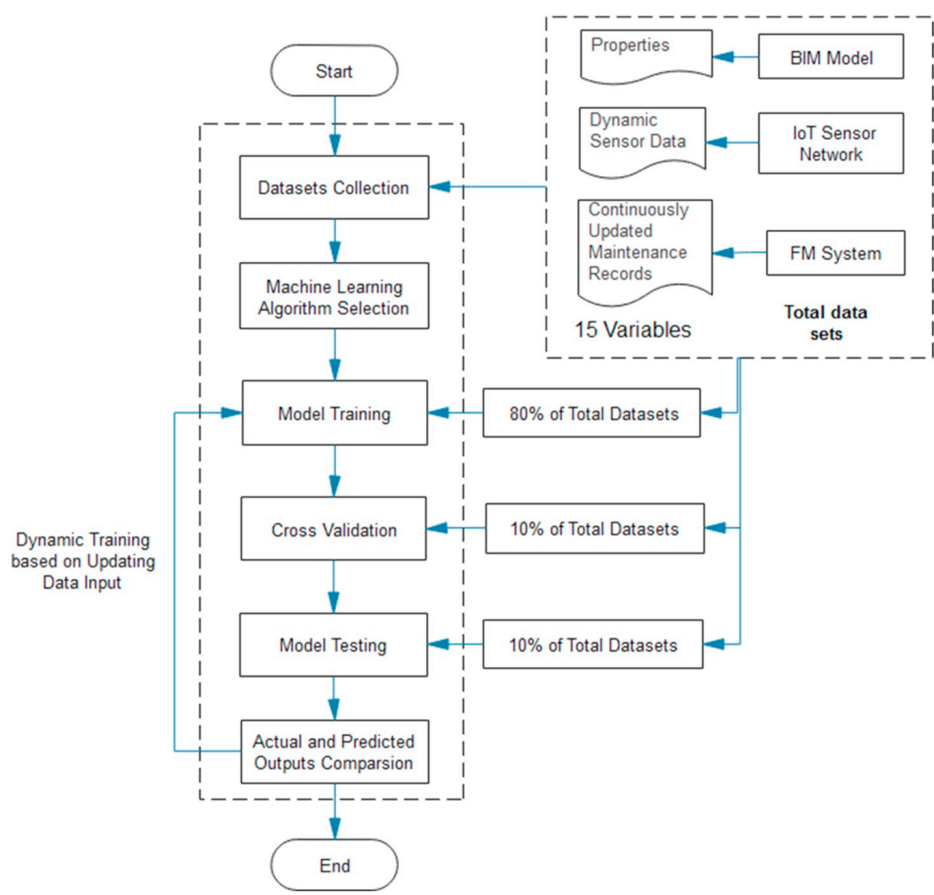


Fig. 10. The data-driven condition prediction approach.

successfully solve complex problems in various application fields, including civil engineering, and operations and maintenance process [49]. These several studies have used ANN computational models for the analysis of the service life of building components [50] and new materials in civil engineering [51]. Among the various types of ANNs, multilayer perceptron networks (MLP networks) and radial basis function networks (RBF networks) are two of the most commonly used as universal approximators [30]. In this study, the MLP networks method is used to predict the condition of equipment in buildings because it has been shown to be suitable for prediction [30]. An MLP is a network with three or more layers of neurons: (1) an input layer, (2) one or more hidden layers, and (3) an output layer. MLPs are fully connected feed-forward networks: each neuron in each layer is linked to all neurons in the next layer. The neurons usually have an extra input (called bias) unrelated to the other neurons, and normally improve the network's performance. In the study, the input of ANN algorithm includes the aforementioned 15 variables. The hidden layer includes three layers: the first layer has 5 nodes, the second layer has 20 nodes, and the third layer has 10 nodes. The output of ANN algorithm is the predicted condition.

3.2.3.2. Support vector machine (SVM). SVM is a supervised learning model used for classification tasks, developed by Cortes and Vapnik [52] from Vapnik and Chervonenkis's statistical learning theory [53]. SVM classification methods are developed based on the principle of the optimal separation of classes. Originally, the SVM was developed for classifying linearly separable classes by selecting the linear classifiers minimizing the generalization error, or at least an upper bound on this error, derived from structural risk minimization. In this concept, the decision hyperplane that characterizes the SVM leaves a maximum margin between the two classes, where the margin is defined as the sum of the distances of the hyperplane from the closest point of the two classes [54]. The reason why SVM insists on finding the maximum margin hyperplanes is that it offers the best generalization ability. It allows not only the best classification performance (e.g., accuracy) on the training data, but also leaves much room for the correct classification of future data. SVM is a widely used pattern classification technique based on statistical learning theory [55].

In this study, the maximum margin hyperplanes to do better classification is described in the following function with respect to $\vec{w}$ and b.

$$L_p = \frac{1}{2}\,||\vec{w}|| - \sum\nolimits_{i=1}^{t} a_i y_i(\vec{w} * \vec{x_i} + b) + \sum_{i=1}^{t} a_i \tag{1}$$

where t is the number of training examples, and a_i, $i = 1, \ldots, t$, are non-negative numbers such that the derivatives of Lp with respect to a_i are zero. a_i are the Lagrange multipliers and Lp is called the Lagrangian. In Eq. (1), the vectors $\vec{w}$ and constant b define the hyperplane. $\vec{w}$ is the vector normal to the hyperplane; b is the hyperplane offset parameter.

In this study, the input of SVM algorithm is the same 15 variables. The output of SVM classification is the predicted condition.

3.2.4. Maintenance planning module

Fig. 10 illustrates the maintenance planning and possible deterioration curves of MEP components in predictive maintenance, reactive maintenance and preventive maintenance, respectively. It compares the changes of condition index in different maintenance strategies when performing maintenance actions within a few times.

As shown in Fig. 11(a), the best condition of each building component is C_{satrt} (condition index of 10) at T_0, and then the condition gradually decreases. The deterioration curve in predictive maintenance includes the red solid part (representing the curve before prediction) and the red dash part (representing the predicted curve after prediction). A prediction trigger (condition $C_{trigger}$) is set in the monitoring system to indicate the timing for taking prediction actions. When the condition reaches the threshold $C_{trigger}$ at T_{d1}, the prediction trigger is activated and FM staff use the proposed framework to predict the future condition. The outcomes of the prediction module (red dash curve) include the future condition and the predicted repair date (T_{d2}). According to the predicted condition, the maintenance staff schedule the maintenance plan in advance and then perform repair actions at T_{d2}. After repair, the condition of component recovers to $C_{pstart1}$, which is less than C_{start}, because the repaired component is usually not as good as the original one due to damage. The similar situations happen at T_{d4}, T_{d6}, and T_{d8}. The period from T_{d1} to T_{d2}, similar with the period from T_{d3} to T_{d4} and the period from T_{d5} to T_{d6}, enables FM staff to predict future condition, schedule maintenance tasks, and perform maintenance actions. Since the prediction accuracy depends on the algorithm selection, collected datasets, and model structures, the predicted condition may be not exactly same to the actual condition, which is explained in Sections 4.2.4 and 4.3. For example, the predicted condition at T_{d2} is C_{repair}, which is higher than the actual condition. It means the deterioration of the component appears earlier than the expected and the maintenance actions need to be performed early.

Reactive maintenance usually performs replacement or repair after failure, and the deterioration curve for reactive maintenance is shown in black line in Fig. 11(a). At time T_{r1}, the condition reaches the failure line $C_{failure}$, which indicates the component is out of functioning. Facility staff or users report the failure to the facility maintenance office. It takes time for maintenance staff to respond so that they replace the component at T_{r2}. After replacement, the condition recovers to C_{start} at T_{r2}. Reactive maintenance action is usually performed when the condition is poor (condition index is around 3, referred to Fig. 8) and the component is not functioning, likely causing lots of loss.

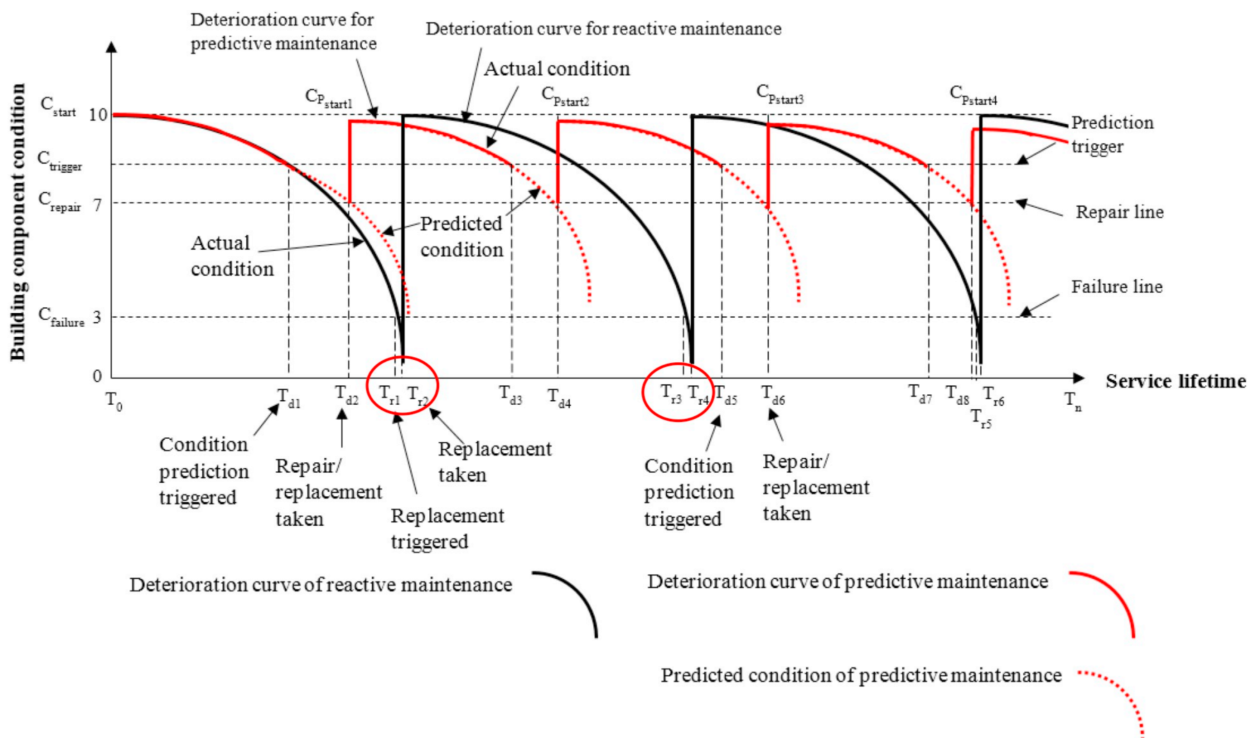
In preventive maintenance, facility staff set the condition C_{repair} (condition index of 7) as the repair line, and regular inspection is performed in the time interval of ($T_{in} - T_{i(n-1)}$) as shown in Fig. 11(b), which is normally constant for a type of components. At T_{i1}, as the condition has not reached C_{repair}, the inspector continues to perform regular inspection. Once the condition decreases to C_{repair} at time T_{p1}, the inspector reports this situation to the facility management office. After a while, maintenance staff perform repair action at time T_{p2} and the condition of component recovers to C_{start1}, less than C_{start}. However, preventive maintenance cannot find the precise repair timing every time. For example, when maintenance staff inspect the facility at T_{i11}, the condition C_a is higher than C_{repair}, so repair/replacement action is not needed. In the next inspection at T_{i12}, the condition C_b at T_{i12} is already lower than C_{repair} (at T_{p5}) so that the repair action is late. Similarly, another scenario is even worse when the failure is found at T_{i16} and maintenance action is performed at T_{p4}. Fig. 11(b) suggests that preventive maintenance performs the periodic inspection and tries to prevent the failure. However, it cannot prevent the failure every time and periodic inspection costs manpower, money and time [2,56].

When compared with reactive maintenance and preventive maintenance, predictive maintenance can not only predict the future conditions, highlighted in dash red curves, as shown in Fig. 11(a), but also can undertake scheduling and maintenance actions before the condition reaches the repair line. In general, predictive maintenance can predict the failure in advance and save scheduling time so as to prevent further failure.

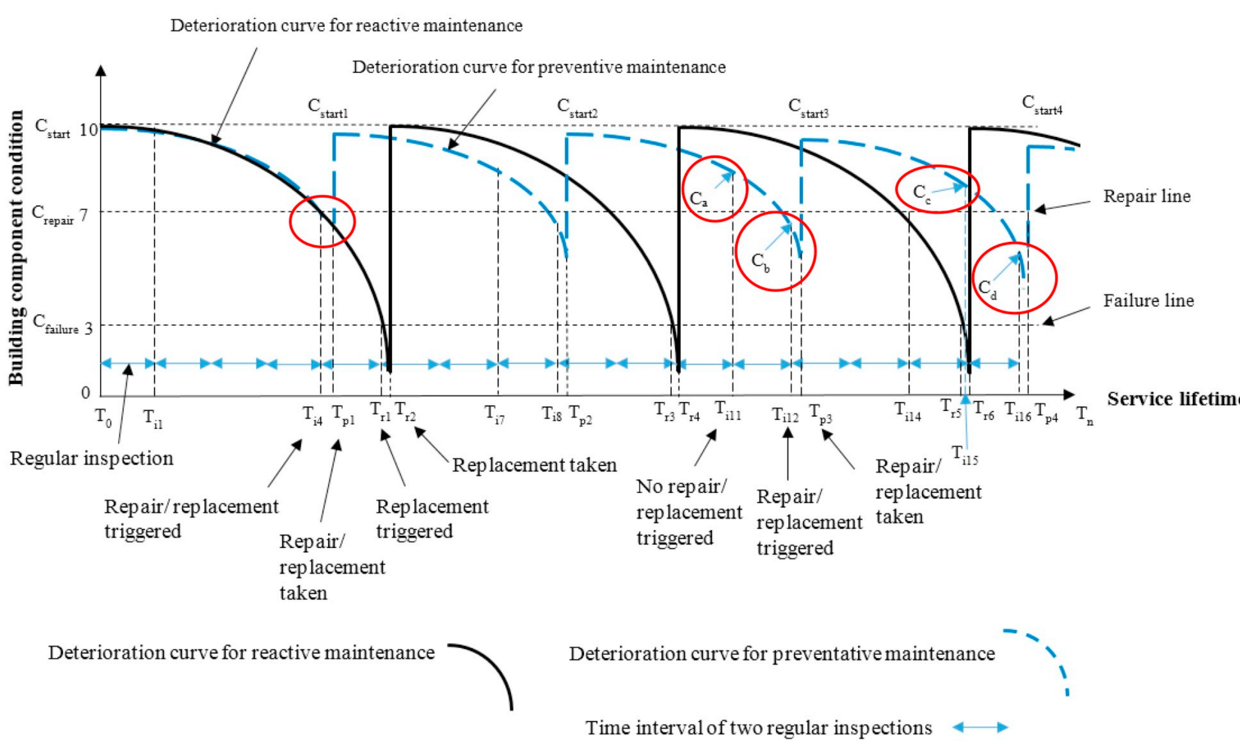
4. Case study

4.1. Case background

To validate the proposed data-driven predictive maintenance planning framework, three academic buildings on the Hong Kong University of Science and Technology (HKUST) campus were studied and used as an illustrated example. There are 4 chillers (WCC1-WCC4) serving three campus buildings (IAS building, NABN building, and NABS building). WCC1 to WCC 3 are all rated at 1800 kw, while WCC 4 is 350 kW. Three types of sensor have been installed to monitor the chillers: (1)



(a) Reactive Maintenance VS Predictive Maintenance



(b) Reactive maintenance VS Preventive maintenance

Fig. 11. The maintenance planning and deterioration curves of building components using different maintenance strategies and actions.
(a) Reactive maintenance VS predictive maintenance.
(b) Reactive maintenance VS preventive maintenance. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

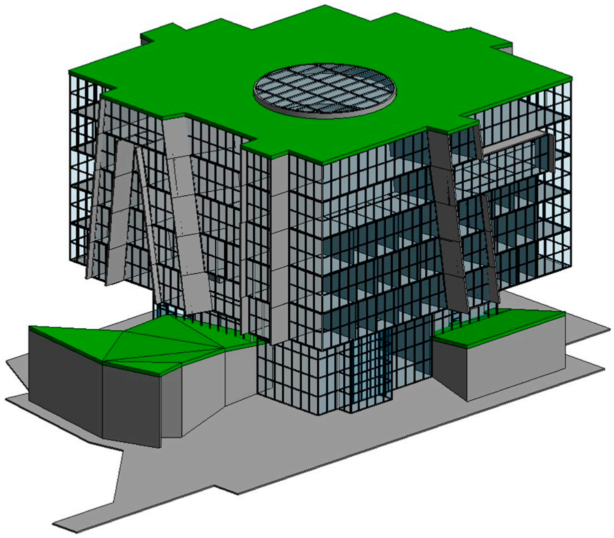


Fig. 12. The BIM model of IAS building in HKUST campus.

temperature sensors, (2) pressure sensors, and (3) flow rate sensors. The signals from the sensors and DDC system were collected and sent through a sensor network to the BIM models. The BIM model created for the IAS building in HKUST is selected as an example and is shown in Fig. 12.

4.2. The application process

4.2.1. Data collection

4.2.1.1. Data from BIM model. The FM manager and maintenance technicians can obtain the properties including voltage, frequency and electrical load of the chillers from the BIM model, as shown in Fig. 13. This information is used for condition inspection and condition assessment, in which the real time mechanical information is gathered from the IoT sensor network, including evaporator outlet temperature, evaporator inlet temperature, condenser outlet temperature, condenser inlet temperature, chilled evaporator flow rate, and chilled condenser flow rate.

4.2.1.2. Data from IoT sensor network. The IoT sensor network of the HVAC systems has two main functions: monitoring the status of HVAC system and controlling the operation of HVAC system. Functions are provided by the IoT sensor network using the developed plug-in to connect the DDC system and BIM models, via the BACnet communication protocol for HVAC systems, as follows. The monitoring function contains eight monitoring parameters: (1) ON/OFF status, (2) mode (cool/dry/heat/fan), (3) air direction, (4) temperature set point, (5) room temperature, (6) filter alarm, (7) fault alarm, and (8) auto/manual status. The operation function contains four controlling parameters: (1) ON/OFF control, (2) mode selection (cool/dry/heat/fan), (3) air direction, and (4) temperature set point. Table 2 shows the set points of the IoT sensor network in the chillers.

The values of temperature, flow rate, and pressure (e.g., evaporator outlet temperature, evaporator inlet temperature, condenser outlet temperature, condenser inlet temperature, chilled evaporator flow rate, and chilled condenser flow rate.) are collected from the IoT sensor network and visualized in the BIM models, as shown in Fig. 13. According to Fig. 5 in Section 3.1.1, the sensor data as well as the data trends are visualized in the BIM model for the FM manager to operate the HVAC system. Sensor data between January 1 and May 2, 2017 were obtained to illustrate how long-term trends in sensor data are used to predict the future conditions of a chiller. Abnormal signals in the data indicate possible malfunctioning of equipment at particular time instants; and abnormal events are recorded in the FM system to be used for predicting future conditions. Fig. 14 illustrates three types of sensor

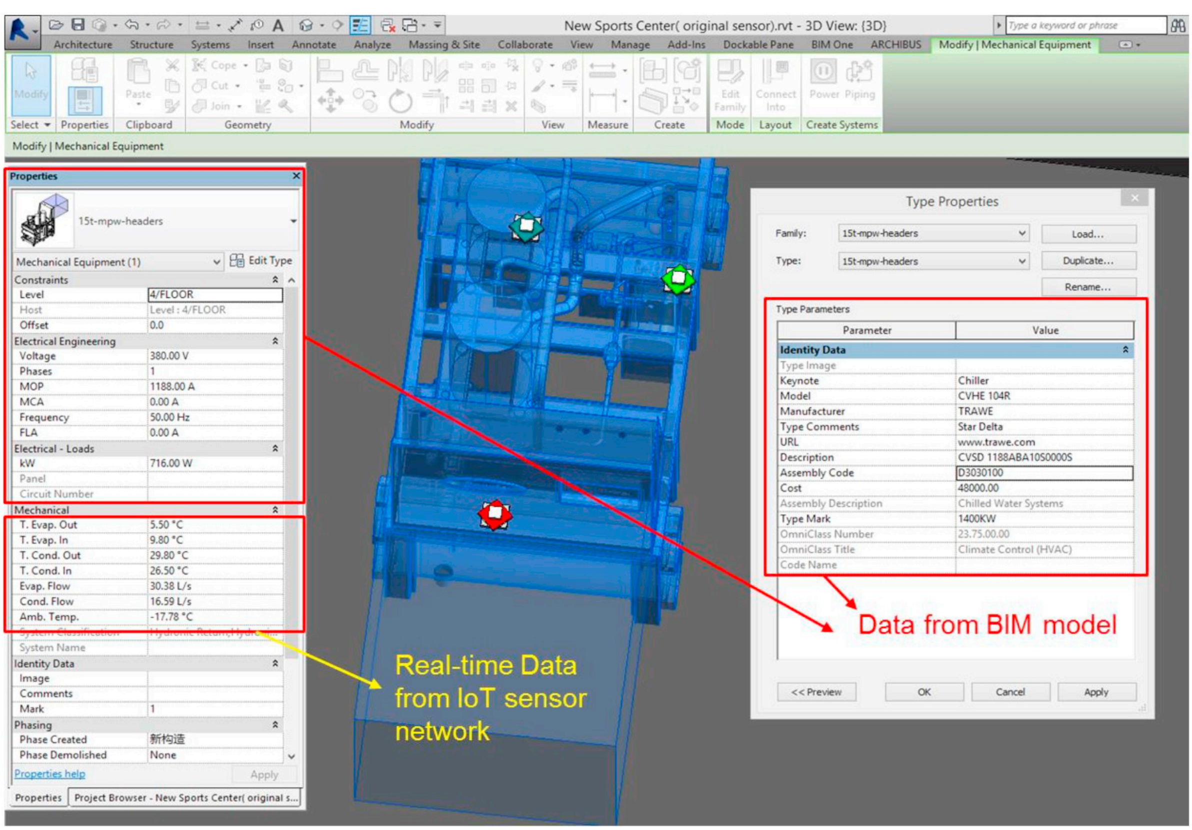


Fig. 13. The characters of the chillers in the BIM model.

Table 2
The set points of IoT sensor network in the HVAC system.

Heat pump boiler and fluid cooler system		Set points			
Parameters	Description	AI	AO	BI	BO
SP1	FC PUMP COMMAND				1
SP1S	FC PUMP STATUS			1	
SP1F	FC PUMP PRESSURE	1			
SPIP	FC PUMP FLOWRATE	1			
FLC1D	FLUID COOLER DAMPER				1
FLC1	FLUID COOLER FAN START/STOP				1
FLC1FS	FLUID COOLER STATUS			1	
FLCP11S	PUMP 11 STATUS			1	
FLCP11	PUMP 11 COMMAND				1
FLCP11P	PUMP 11 PRESSURE	1			
FLCP11F	PUMP 11 FLOWRATE	1			
CWS	CHILLED WATER SUPPLY TEMPERATURE	1			
CWR	CHILLED WATER RETURN TEMPERATURE	1			
T.Evap.Out	TEMPERATURE of CHILLED EVAPORATION.OUT	1			
T.Evap.In	TEMPERATURE of CHILLED EVAPPRATION.IN	1			
T.Cond.Out	TEMPERATURE of CHILLED CONDENSER.OUT	1			
T.Cond.In	TEMPERATURE of CHILLED CONDENSER.IN	1			
Evap.FLOW	CHILLED EVAP.FLOWRATE	1			
Cond.FLOW	CHILLED COND.FLOWRATE	1			
FLC1	FLUID COOLER FAN MODULATION		1		
FLC1HZ	FLUID COOLER FAN SPEED	1			

data (temperature, pressure, and flow rate) from 1 April to 30 April of 2017, and shows the working days, weekends, and holidays. Fig. 14 shows the usage pattern of the HVAC system. For example, when the temperature value suddenly increased to the peak value or dropped down quickly, it suggests the user turned on or turned off the HVAC system at that time. Therefore, we can see there was a peak temperature in chiller at the beginning of working day periods. When the temperature value remained in the upper level, it meant the HVAC was running. When the temperature value remained at a lower level, it represented that the HVAC was off or running at a low rate of energy consumption. The pattern of pressure is similar to the temperature. In addition, the trend of temperature and pressure was plat in weekends and Easter holiday, it suggests that no occupant changed the temperature, leading to no fluctuation.

The pattern of flow rate is different from others because it relates to the inlet temperature of HVAC the occupants set. When the flow rate value was very high, it suggests the occupants set the inlet temperature of HVAC low and the HVAC was running at a high rate of energy consumption. When the flow rate value was very low, it suggests the occupants set the inlet temperature of HVAC high and HVAC was running at a low rate of energy consumption. For instance, the value of flow rate in the Easter holiday was lower than on working days. On weekends and Festival, the flow rate was around 20 l/s, which suggests that not many occupants worked in the campus. Therefore, based on sensor data, facility manager can clearly know the operation status of HVAC system and usage frequency, which is highly related to the deterioration curve of building facilities.

The sensor data of one chiller over five months were collected from the IoT network, and the temperature sensor data, pressure sensor data, and flow rate sensor data are shown in Fig. 15. Apart from sensor data, the trend of the sensor data, the number of abnormal events, and problem type are also collected for the analysis of equipment condition. For other critical equipment, such as the water supply pump and lighting system, their methods of condition monitoring and condition analysis are similar. Besides the condition monitoring, the technical inspection methods for the HVAC system includes calibrated measurement instruments, inspecting building system controls and control parameters, noise and sound tests, vibration tests, and electrical tests. These methods are used for analyzing the abnormal events and causes.

4.2.1.3. Data from the FM system. The chiller's main characteristics are collected from the FM system. Inspection records, past maintenance records and sensor data are used for prediction. The main characteristics and values of four chillers are shown in Table 3 as an example. Nine factors are used to build the prediction models, namely, (1) capacity, (2) year of installation or number of years in use, (3) minor repair times/year, (4) major repair times/year, (5) total service years, (6) abnormal times, (7) problem type 1, (8) problem type 2, and (9) current condition.

4.2.2. Condition monitoring

Each chiller is monitored using different sensors. The data of pressure sensor for chiller 1 in two weeks (03.27.2017–04.10.2017) was selected and is shown in Fig. 15. These sensor data and sensor data trends can be visualized in BIM model, as shown in Fig. 6. The facility manager can check the operation condition of each chiller based on these sensor data. In Fig. 16, the pressure of the pump suddenly increased dramatically, which indicated there was a warning signal and facility manager should inspect the chiller as soon as possible. The pressure value was fluctuant two days later and an abnormal event appeared. The condition monitoring proves that the warning signal is helpful for facility manager to keep the functionality of building facility. In the proposed predictive maintenance planning framework, the warning signal is shown in the plug-in in Fig. 6. The warning signal instantly alarms the FM team to inspect the chiller as soon as possible.

4.2.3. Condition assessment

Based on the condition monitoring, the abnormal events and warnings recorded in the FM system are used as references for condition assessment. The FM staff check the chiller condition each month, and Fig. 17 shows the monthly report on chiller conditions in April 2017. As shown in Fig. 17, FM staff observed any abnormal noise, vibration and high temperature in several condition indexes, including (1) condenser water condition, (2) chilled water condition, (3) condenser water temperature sensor, (4) chilled water temperature sensor, and so on. For example, FM staff check the inlet pressure gauge of the condenser water condition. If there is no any abnormal noise and no vibration, and the pressure and temperature are at acceptable levels, the condition of condenser water will be satisfactory.

Moreover, FM staff filled in the chiller configuration list according to field inspection, as shown in Fig. 18. Finally, facility manager evaluated the overall condition of the chiller based on Table 1. In this case, the current conditions of four chillers were 9.2, 6.7, 7.8, and 8.3 respectively.

4.2.4. Condition prediction

4.2.4.1. Model training for condition prediction. In total, 300 data sets were collected for condition prediction. Each data set includes three groups of data collected from BIM models, IoT sensor network, and FM system as aforementioned (Fig. 9). The prediction process consists of four steps: (1) training using 240 data sets (80% of total data sets), (2) cross validation using 30 datasets (10% of total data sets), (3) testing and prediction using 30 data sets (10% of total data sets), according to the prediction process algorithms, and (4) prediction. ANN and SVM are used to predict the condition of the chillers and for evaluation.

4.2.4.2. Comparison of predictive maintenance methods. The predicted conditions of chillers using the ANN and SVM algorithms are compared, and the actual condition and predicted condition for testing are shown in Table 4. 30 data sets (10% of the total data sets) are used for testing. Table 4 provides a comparison between the ANN and SVM algorithms in term of prediction results, e.g., predicted condition, prediction error, and prediction accuracy. To ensure the generality of the comparative performance analysis of these algorithms, the condition prediction was conducted using the same datasets.

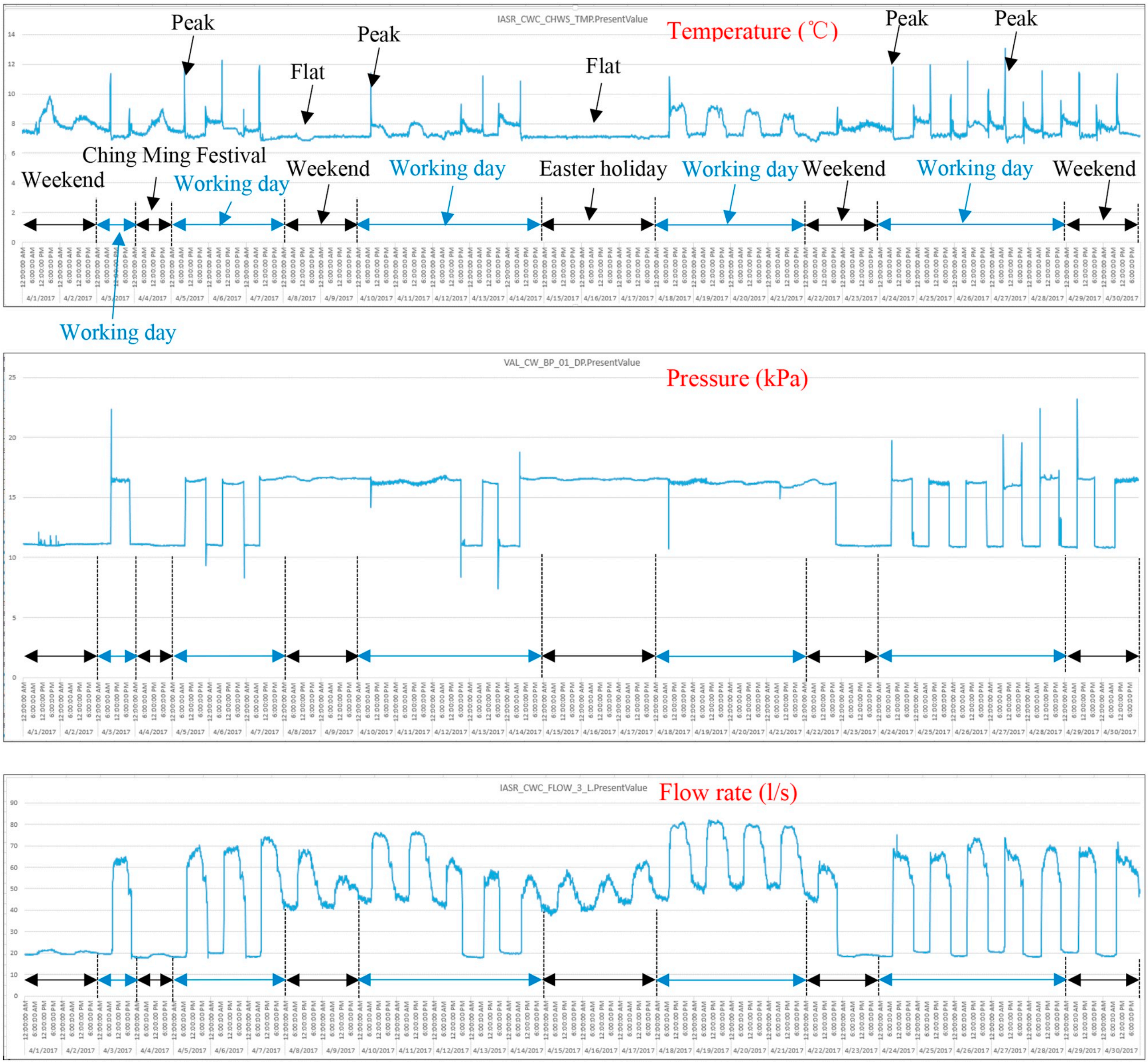


Fig. 14. The sample of past sensor data in one chiller.

Based on Table 4, the prediction accuracy of SVM is 96.547%, better than ANN (96.422%). Correspondingly, the absolute average error of ANN is 3.578%, larger than SVM (3.427%). In addition, Table 5 shows the comparison of ANN and SVM. The experimental results indicate that the prediction result of the correlation coefficient is around 0.993 in both methods. However, the error indexes indicate that SVM (0.1875 and 0.2267) shows better performance than ANN (0.1909 and 0.2282) in mean absolute error and root mean squared error, as shown in Table 5. Moreover, SVM is better than ANN in root relative squared error and in the relative absolute error, as shown in Table 5. Therefore, the prediction accuracy and error indexes of ANN and SVM suggest that SVM has better performance than ANN. On the other hand, in the aspect of the required processing time for the training and validation, ANN requires twice the time (0.21 s and 0.14 s) compared with SVM (0.09 s and 0.05 s). If there are large datasets, SVM method is more efficient than ANN. Overall, the experimental results indicate that the proposed SVM algorithm is slightly better than the ANN algorithm.

In addition, the comparison of ANN and SVM using paired *t*-test are done in order to make the results more convincing and the results are shown in Table 6. The absolute value of mean between the actual value and predicted value of ANN is 0.0327, while the absolute value of mean between the actual value and predicted value of SVM is 0.021. The performance of SVM is better than ANN. The absolute value of t in pair 1 is 0.781, while the absolute value of t in pair 2 is 0.502. The larger the value of t, the more pronounced the difference between the actual value and the predicted value, and the smaller the probability that this difference occurred by chance. It means the difference between the actual value and the predicted value using ANN is more pronounced, and the probability that this difference occurred by chance is smaller. Therefore, it means SVM is better than ANN in terms of t value.

Both of the *P* values of the two-tailed test in pair 1 and pair 2 are greater than 0.1 and it indicates that the null hypothesis (plausible statement) is accepted. It means the prediction results of ANN and SVM have no significant difference when comparing with the actual condition values, and the prediction results can be used for predictive maintenance in terms of P value of the two-tailed test. Therefore, the prediction results are statistically acceptable. Moreover, the larger *P*-value, the more convincing the predicted result. Therefore, the SVM is better than ANN in terms of P value.

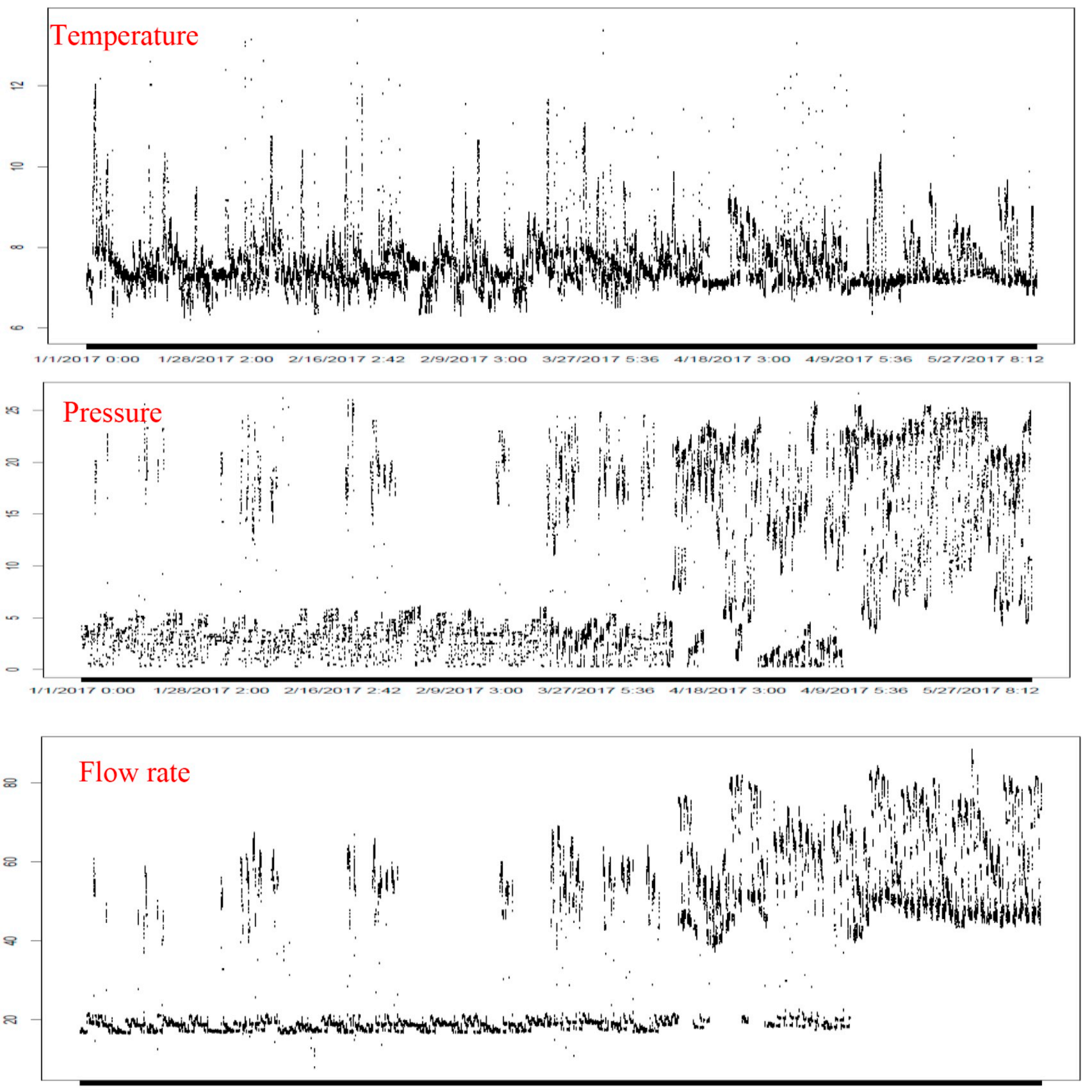


Fig. 15. Collected sensor data over five months for condition prediction.

Table 3
Collected chiller's main characteristics.

Characteristics	Chiller 1 WCC01	Chiller 2 WCC02	Chiller 3 WCC03	Chiller 4 WCC04
Chiller type	Water-cooled liquid	Water-cooled liquid	Water-cooled liquid	Water-cooled liquid
Capacity	1800 kW	1800 kW	1800 kW	350 kW
Location	IAS building	NABN building	NABS building	IAS building
Installation year	2015	2002	2006	2013
Usage age	2	15	11	4
Minor repair times	3	3	3	2
Major repair times	0	3	2	1
Total service years	25 years	25 years	25 years	25 years
Abnormal times/last year	3	3	4	2
Problem type 1	2	2	3	2
Problem type 2	1	2	1	0
Inspection times/year	12	12	12	12
Current condition	9.2	6.7	7.8	8.3

4.2.5. Maintenance planning

Based on the comparison between ANN and SVM methods, the trained SVM model is selected to predict the future condition of the four chillers. The proposed framework can predict the future condition at a certain time. We select three months later and one year later as example for future maintenance planning and show the corresponding dynamic maintenance planning. The predicted future conditions of chillers three month later and one year later are shown in Table 7. Based on the future condition, the corresponding maintenance actions and maintenance priority is generated according to the Table 1 and Fig. 8.

Traditionally, maintenance planning is designed based on the current actual condition and the order of priority in traditional maintenance strategy is Chiller 2, Chiller 3, Chiller 4 and Chiller 1. The inspection is performed regularly.

In predictive maintenance planning, the condition of Chiller 1 is the best one among the four chillers, and it will decrease from 9.2 to 9.0 in three months and will continue to decrease to 8.7 one year later. It indicates that the monthly inspection and regular maintenance action is appropriate for Chiller 1 in the coming one year. Chiller 2 has the priority of maintenance because the condition of Chiller 2 is worst and will decrease obviously from 6.7 to 6.1 in the coming year, which

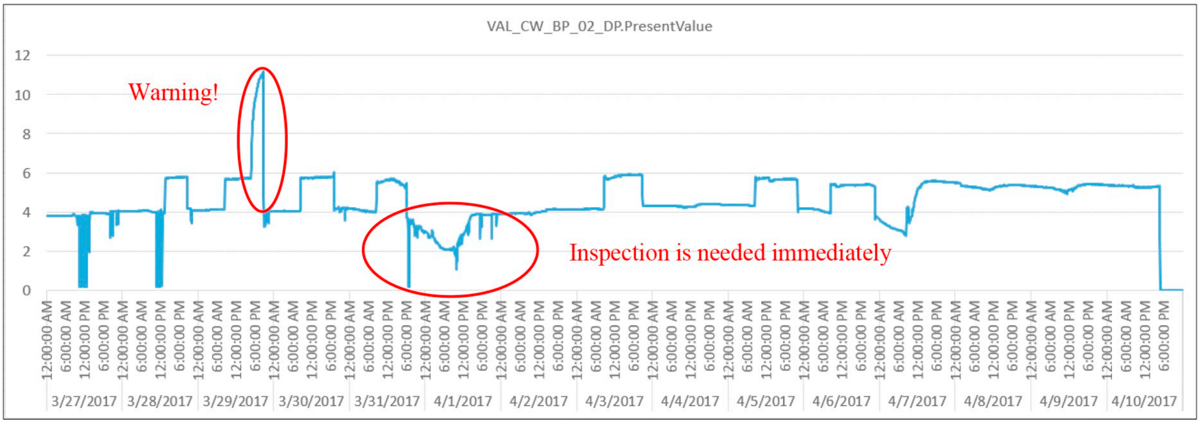


Fig. 16. Condition monitoring in one chiller with pressure sensor.

Monthly Report on Chiller Conditions

Location : *The Hong Kong University of Science & Technology*

Monthly : 04/2017

Item	*Work Done*	*Results / Recommendations*
1)	Check and clean starter panel	✓
2)	Observe any abnormal noise, vibration and high temperature	✓
	Check condenser water condition	
	a) Inlet pressure gauge	✓
	b) Outlet pressure gauge	✓
	c) Inlet temperature gauge	✓
	d) Outlet temperature gauge	✓
3)	Check chilled water condition	
	a) Inlet pressure gauge	✓
	b) Outlet pressure gauge	✓
	c) Inlet temperature gauge	✓
	d) Outlet temperature gauge	✓
4)	Check condenser water temperature sensor	
	a) Inlet temperature sensor	✓
	b) Outlet temperature sensor	✓
5)	Check chilled water temperature sensor	
	a) Inlet temperature sensor	✓
	b) Outlet temperature sensor	✓
6)	Lubrication the vane control linkage bearings, ball joint and pivot joint	✓
7)	Check and clean control panel	✓
8)	Check and clean control relays for purge unit	✓
9)	Check flow switch	
	a) Chilled water side	✓
	b) Condenser water side	✓
10)	Start chiller to observe any leakage	✓
11)	Take chiller running log	✓

Fig. 17. Part of monthly report on Chiller conditions.

MACHINE CONFIGURATION GROUP

	Menu Item	Choices	Default	Design / Actual
1	Unit Frequency :	60 HZ, 50 HZ	Refer Order	50 HZ
2	Unit Type :	CVGE, CVAE, RTHB	CVAE	Fast Pak W/C
3	Unit Tons :	100->1600 (10 Ton incr)	Refer Order	1040
4	Refrigerant Type :	R134a/R22	R134a	R123
5	Refrigerant Monitor Type :	None, 01-Analog, 02-IPC	None	None
6	Starter Type :	Undefined, Variable Speed, Y-Delta, X-Line, Solid State, Auto Xformer, Primary Reactor	Y-Delta	Y-Delta
7	Level 2 Contactor Integrity Test :	Disable, Enable	Disable or Enable	D
8	Rated Load Amps :	0->2,500 Amp	Refer to Table 3	1152
9	Motor Heating Constant :	0-100 Minutes	30 Minutes	45 min
10	Current Overload Setting #1 :	From 00 to 31	Refer to Table 4	23
11	Current Overload Setting #2 :	From 224 to 255	Refer to Table 4	232
12	Maxi Accel Timer Setpt #1 :	Y to Delta	12 seconds	12
13	Maxi Accel Timer Setpt #2 :	Y to Delta	243 seconds	243
14	Hot Water Control Option :	Heat pump mode	E or D	D
15	External Chilled Wtr Setpoint :	Installed, Not Installed	E or D	D
16	External Current Limit Setpt :		E or D	D
17	External Hot Wtr Setpoint : (Use only when Hot Wtr Cnt is 'Enabled")	Appear if "hot water control option" is validated	E or D	D
18	Acceleration Time Out Action :	Shutdown, Transition	Shutdown	Shutdown
19	Motor Winding RTD Type :	Sensor	75 Ohm at 75°F	75Ω/75F
20	High Pressure Cutout Setting :	0->3447 kPa	1390 kPa	103 kpa
21	Line Voltage Sensing Option :	Refer Order	E or D	E
22	Unit Line Voltage :	Appear of "line voltage sensing option" validated from 180 to 6600V		380
23	Auxiliary Condenser Option :	Display Temperature	Refer Order	/
24	Heat Recovery Option :	Installed, Not Installed	Not Installed	N.I.
25	Hot Gas Bypass Option :	Installed, Not Installed	Installed	N.I.
26	Condenser Press. Sensor Option :	Installed, Not Installed	Not Installed	N.I.
27	Discharge Temp Sensor Option :	with HGBP / without HGBP	Not Installed	N.I.
28	Ice Building Option :	To be set on site	On site	/
29	Diff Wtr Press Sensor Option :	Not available	Not Installed	N.I.
30	External Setpt Inputs :	4-20 ma, 2-10 vdc	On Site	4-20 mA
31	Tracer Option :	To be set on site	-	Installed
32	TCI Option :	To be set on site	-	Installed
33	Printer Option :		Not Installed / Installed	N.I.

Fig. 18. Part of the chiller configuration check list.

Table 4
The predicted condition of chillers using ANN and SVM.

Instance#	ANN			SVM		
	Actual	Predicted	Error (%)	Actual	Predicted	Error (%)
1	6.9	6.576	−4.696	6.9	6.879	−0.304
2	7.5	7.248	−3.360	7.5	7.239	−3.480
3	7.1	7.057	−0.606	7.1	7.131	0.437
4	3	2.948	−1.733	3	3	0.000
5	2.8	2.841	1.464	2.8	2.78	−0.714
6	6.8	7.057	3.779	6.8	7.185	5.662
7	7.8	7.693	−1.372	7.8	7.777	−0.295
8	5.9	5.967	1.136	5.9	6.002	1.729
9	3.5	3.41	−2.571	3.5	3.347	−4.371
10	6.1	6.204	1.705	6.1	6.189	1.459
11	5.4	5.201	−3.685	5.4	5.236	−3.037
12	6.2	6.261	0.984	6.2	6.36	2.581
13	6.7	6.414	−4.269	6.7	6.525	−2.612
14	2.6	2.811	8.115	2.6	2.734	5.154
15	5	5.22	4.400	5	5.263	5.260
16	9.3	9.219	−0.871	9.3	9.54	2.581
17	6.6	6.195	−6.136	6.6	6.193	−6.167
18	4.1	4.379	6.805	4.1	4.367	6.512
19	7.4	7.462	0.838	7.4	7.532	1.784
20	7	6.61	−5.571	7	6.69	−4.429
21	4.8	4.902	2.125	4.8	4.807	0.146
22	6.4	6.109	−4.547	6.4	6.103	−4.641
23	3.6	3.55	−1.389	3.6	3.669	1.917
24	6.6	6.196	−6.121	6.6	6.198	−6.091
25	7.7	7.66	−0.519	7.7	7.633	−0.870
26	8.7	8.887	2.149	8.7	9.041	3.920
27	4.6	4.799	4.326	4.6	4.897	6.457
28	2.8	3.236	15.571	2.8	3.189	13.893
29	5.3	5.446	2.755	5.3	5.521	4.170
30	9.1	8.76	−3.736	9.1	8.904	−2.154
Absolute average error (10%)			3.578			3.427
Prediction accuracy (10%)			96.422			96.574

indicates that significant deterioration exists and repairs or replacement of some components are necessary. Therefore, facility manager should prepare the maintenance equipment, material, tools ahead of time based on the predicted condition, rather than repair after failure. Chiller 3 will deteriorate sharply and the condition will be reduced from 7.8 to 7.3 in the coming three months. It indicates significant deterioration, and facility manager should increase the frequency of regular inspection to twice a month. The condition will decrease slowly, which means regular inspection and minor maintenance action for Chiller 3 are sufficient in the next nine months. Based on the prediction, the condition of Chiller 4 will decrease from 8.3 to 8.0 over three months, and monthly inspection and minor maintenance should be conducted based on need. However, the future condition will decrease by 0.4 in next nine months, which suggests that obvious deterioration exists. The maintenance priority of Chiller 4 is changed from 3 to 2, and maintenance action is necessary.

Overall, in a predictive maintenance strategy, facility manger can note the change of deterioration and condition clearly, and prepare the tools and time correspondingly in advance. The maintenance planning is changed according to each predicted action.

4.3. Discussion

In this study, the proposed framework is suitable for prediction maintenance of MEP components of buildings. It is not only suitable for chillers of HVAC system, but also for other components, such as electrical systems, lift/elevator systems, and plumbing systems. In the process, those selected parameters of chiller for machine learning may be not entirely appropriate for other MEP components. For example, a vibration sensor is used for monitoring the lift/elevator, and the sensor data is different from that of a chiller. Therefore, in practice, the parameters would be changed depending on different components.

In this paper, ANN and SVM methods are selected to illustrate how to perform a predictive maintenance strategy using this framework. The

Table 5
The comparison of ANN and SVM.

	Training model		Cross validation for model		Prediction result	
	ANN	SVM	ANN	SVM	ANN	SVM
Correlation coefficient	0.9952	0.9949	0.9935	0.9946	0.9935	0.9927
Mean absolute error	0.1878	0.1757	0.2034	0.1813	0.1909	0.1875
Root mean squared error	0.2289	0.2154	0.2537	0.2206	0.2282	0.2267
Relative absolute error	10.3296%	9.663%	11.1456%	9.9344%		
Root relative squared error	10.7591%	10.1263%	11.8939%	10.3403%		
Time taken (s)	0.21	0.09	0.14	0.05		
Instance no.	240	240	30	30	30	30

comparison of different prediction methods is not necessary to do every time when the facility manager uses the proposed framework in practical process. The comparison as an analysis example shows that different prediction methods will have different results in terms of accuracy and processing time. In addition, the prediction results not only depend on the quality and the number of collected datasets, but also depend on the selected algorithms. The selection of different algorithms depends on the experience of developer and repeated testing, and the selection process done by developer is time consuming. Moreover, the proposed prediction maintenance framework is sufficiently flexible to use different prediction methods, such as deep neural network (DNN), convolutional neural network (CNN) and other regression models, when the structures of methods are suitable for collected data sets and the predicted components.

In this study, the same datasets are used for prediction in ANN and SVM algorithms. However, the errors are different. It means the errors result from the fundamental structures of different algorithms. In addition, the quality and the number of collected datasets also have the influence on the prediction results. After testing the relationship between the number of data sets and the reliability of prediction results, we found that more than 100 datasets can provide the reliable results. Moreover, facility managers are responsible to determine the causes of abnormal events and assess the conditions of component, which are sometimes subjective. Therefore, the variable of facility manager personal background/experience is another reason for prediction errors.

In addition, different sensors collect data and those data is used for predictive maintenance through a framework. The data integration generates a standardization and synchronization issue. In this study, COBie and IFC extension is applied for data integration. In fact, other possible solutions can be used to address the data integration issues, such as adapting an ontology in the proposed predictive maintenance system, including different sensors, equipment, building components, etc. For example, Umiliacchi et al. [57] defined a new platform to address the data integration for predictive maintenance. They applied ontology approach and implemented in WSDL (Web Service Description Language), which provided a standard means of interoperating between different software applications. Maleki et al. [58] developed a new sensor ontology that structured the domain knowledge, covering both theoretical and experimental sensor attributes, following a Knowledge Management methodology, to reduce the time and cost of the design process of the condition-based maintenance services. For the IoT ontology approaches for data integration, Agarwal et al. [59] mentioned a number of core concepts from various mainstream ontologies and taxonomies, such as Semantic Sensor Network (SSN), M3-lite, WGS84, and IoT-lite. Therefore, in the future, ontology approach can be the possible solution for data integration of standardization and synchronization.

The proposed framework has significant implications in the following three aspects: (1) FM staff can achieve fault alarming in an early stage to avoid the failure. (2) Facility manager can predict the future condition and know the failure timing in advance, which enables FM staff to repair and replacement before failure for safe operation. (3) FM staff can prepare the maintenance materials and tools ahead of time to minimize or avoid overtime costs.

5. Conclusions

The paper discusses how BIM and IoT can facilitate the implementation of predictive maintenance and improve the feasibility of adopting a long-term and dynamic maintenance strategy in the FMM process. The architecture of the proposed framework is comprised of two layers: the information layer and the application layer. The data integration and data flow process in the information layer are represented for data transmission among the BIM models, IoT sensor network, and FM system. Four modules of application layer are applied for predictive maintenance, including (1) condition monitoring and fault alarming module, (2) condition assessment module, (3) condition prediction module, and (4) maintenance planning module. The intelligent framework makes a control loop in the building facility monitoring, prediction and maintenance. Furthermore, two machine learning algorithms (ANN and SVM) are applied for predicting the condition in order to maintain or repair the components in advance and extend the lifetime of MEP components. Some suggestions for FM manager are given to perform the maintenance planning in a scientific way.

There are three limitations in this paper: (1) The algorithm selection depends on the experience of developer and repeated testing, so that the experience of developer would be an influence variable of prediction results. However, it was not considered in this study. (2) Other prediction methods were not considered in this study, such CNN and DNN. (3) The predicted deterioration curves of different MEP components are effected by different parameters, and facility managers need to train a new model when predicting the condition of a new MEP component. In the future, the influence from the experience of FM staff

Table 6
The comparison of ANN and SVM using paired *t*-test.

		Paired differences					t	df	*P* value Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	Actual - ANN predicted	0.032733	0.229682	0.041934	−0.053031	0.118498	0.781	29	0.441
Pair 2	Actual - SVM predicted	−0.021033	0.229514	0.041903	−0.106735	0.064669	−0.502	29	0.619

Table 7
The predicted condition of chillers and corresponding maintenance actions.

	Current actual condition	Predicted future condition		Maintenance action		Maintenance priority	
		3 month later	1 year later	3 month later	1 year later	3 month later	1 year later
Chiller 1	9.2	9.0	8.7	Monthly inspection and routine maintenance	Monthly inspection and routine maintenance	4	4
Chiller 2	6.7	6.5	6.1	Repairs are needed and some deterioration exists. Replace some components if necessary.	Repairs are needed and some deterioration exists. Replace some components if necessary.	1	1
Chiller 3	7.8	7.3	7.1	Inspection and minor maintenance action is necessary. Some deterioration exists, and maintenance needs are significant	Regular inspection and minor maintenance action is necessary.	2	3
Chiller 4	8.3	8.0	7.6	Inspection and minor maintenance	Inspection and minor maintenance action is necessary. Some deterioration exists, and maintenance needs are significant	3	2

should be reduced or avoided in the proposed framework. Other machine learning methods and deep learning algorithms, such as CNN and DNN, will be applied to predict the future condition and improve the accuracy of prediction results. In addition, more MEP components would be used to test and improve the proposed framework. An ontology approach will be considered to develop a new data model to establish a standardized data integration solution among different types of sensors and different application systems for predictive maintenance.

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.

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