AUTOMATED ANOMALY MONITORING AND DETECTION SYSTEM FOR FCU SYSTEM

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Abstract

Implementing and integrating new technologies such as the Internet of Things (IoT), smart sensors, and information and communication technology (ICT) into building facilities generates a large amount of data that will be utilized to better manage building facilities specifically FCU. Automated fault detection and diagnostics(AFDD) systems assist facility managers in informing operators to perform scheduled maintenance and visualizing facility anomalies on building information models (BIM). This study proposes a AFDD system for FCU system using an IoT sensors and by visualizing faults in a BIM model. The proposed system shows the data management and anomaly detection and monitoring technique on the BIM. The experiment results demonstrated the framework's competence to detect anomalies in the FCU system. Furthermore, data collected from various simulated conditions of the building facilities was utilized to monitor and detect anomalies in the 3D model of the fan coil. The automated detection FCU anomalies on the BIM model and preliminary results of the system are demonstrated.

Introduction

Recent technological advances such as Internet of Things (IoT) Platforms, Big Data Management, and new approaches of AFDD systems, are enabling novel possibilities in terms of cognitive and decision-making processes relevant to building facility management (Pourarian et al., 2017).

FMs rely on real-time reliable data to perform maintenance operations and present accurate information to senior managers (Matarneh et al., 2019). However, building inspections, maintenance analysis, and data collection are time-consuming and labor-intensive (Naticchia et al., 2020). Furthermore, building maintenance budgets and resources are limited, and maintenance personnel complain that their budgets and resources are insufficient and fall short of their needs (Zhan et al., 2019). This trade-off has an impact on the quality and relevancy of maintenance operations and inspections, resulting in insufficient facility maintenance and quality management policies (Pitt et al., 1997). By generating real-time building facility data, the dynamical monitoring platform provides enhanced HVAC operation, controls, and AFDD procedures. Faulty HVAC system operation can be caused by component degradation, failure, or incorrect control methods, resulting in wasted energy and poor thermal comfort for building occupants. However, establishing AFDD techniques utilizing real building data requires the implementation of faults in these buildings, which is sometimes difficult.

Recent studies in the area of AFDD of FCU provided by authors (Zhao et al., 2019), (Kim et al., 2018), (Schwabacher et al., 2007), (Katipamula et al., 2001) demonstrate that statistical bands, including the control chart approach, pattern recognition techniques, and hypothesis testing on physical models, are typically used to detect faults (Villa et al., 2021). To isolate defects, information flow charts, expert systems, semantic networks, machine learning approaches (Villa et al., 2022), and parameter estimate methods are often applied. To assess faults, heuristic criteria and probabilistic methodologies are applied. Based on the study, a number of AFDD products, including software and hardware, have been developed (Aliev et al., 2021). However, properly analyzing various AFDD technologies and products is a difficult task that is highly valued by experts in this field.

Furthermore, there are relatively few AFDD design and assessment tools available for other common secondary systems of HVAC, such as FCU. There are also very few experimental data sets available for the development of these technologies. FCUs are simple and low-cost systems that are widely employed in commercial, institutional, industrial and residential buildings.

Authors of (Chu et al., 2005) and (Ke et al., 2007) propose fuzzy logic control to analyze a certain type faults of FCUs, but no prior publication addresses the dynamic fault detection system of FCUs, particularly when failures occur.

A FCU is composed of a fan and at least one air-water heat exchanger coil that heats or cools the airflow. Hot or cold water is pumped through the FCU coil to add or remove heat from the airstream released into the space by the fan to condition the space. The amount of heating or cooling is mainly controlled by regulating the water flow and partially by adjusting the fan speed. FCUs can be mounted horizontally or vertically. In addition, there are two separate arrangements on the water side. A two-pipe FCU has one supply pipe that delivers hot or cold water to the coil depending on the season, and one return pipe. FCUs with four pipes have two supply pipes and two return pipes. This enables both hot and cold water to enter the unit at the same time. The four-pipe fan coil unit is the most widely utilized since it is often essential to heat and cool different areas of a building at the same time due to variances in internal heat loss and heat gain (Golestan et al., 1996). The imbalanced condition of the FCU motors produces noise (acoustic discomfort), and motor vibrations might influence the comfortability of the room. Furthermore, continuous vibrations can cause unexpected FCU failures. As a result, the imbalanced conditions of the FCU motors must be monitored dynamically in order

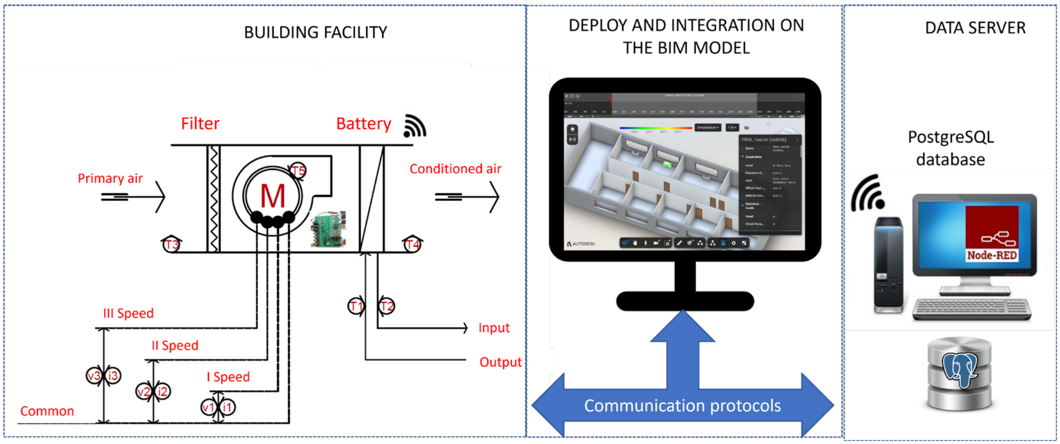

Figure 1: Experimental case study framework

to prevent further failures, particularly inside the hotel rooms and offices, but not necessarily in crowded bars. The noise produced by imbalanced conditions has no effect on heating performance, but it does have an impact on indoor comfortability.

The proposed AFDD system and monitoring in BIM model fills a gap in maintenance processes by supporting FM teams in taking early action and preventing unanticipated failures without the need for expensive lengthy inspection of the installations. The proposed AFDD methodology is made up of three major parts: an IoT architecture for collecting real-time data from the building; an AFDD algorithm and methodology for analyzing the data and supporting the maintenance activity; and a BIM for providing a virtual representation of the building and visualizing the maintenance activity.

Methodology

FCU systems are commonly used to heat and cool rooms particularly in office buildings, hospitals, and schools. In the proposed anomaly monitoring and detection methodology, sensors are installed in the various components of the FCU in order to monitor its operation. The selection of which elements to monitor is based on the detection of anomalies in collected data. The most typical FCU system anomalies include a blocked motor, inadequate air flow, filthy filters, capacitor failure, insufficient water flow, and so on. Each of these anomalies requires a certain action. Operators must do maintenance tasks such as cleaning the filter and battery, changing bearings, replacing capacitors, and checking valve adjustment and the presence of pipe particles. As a result, an FC condition monitoring system is created based on the sorts of anomalies and data acquired by sensors. Furthermore, centralized collected data may be utilized to notify facility managers about the condition of any FCU and, if necessary, perform preventative maintenance services.

The framework of the automated anomaly prediction system for building facilities specifically FCU is depicted in Figure 1. The framework composed of several interconnected sections. On the framework, the building facility FCU a model FC83M-2014/1 is utilized and is equipped with sensors and sensor board RPIZCT4V3T2 that is communicated with the local server through TCP/IP, acquiring and storing important data for anomaly detection model. Node-Red is installed on the sensor board to provide access to the sensors' variables through serial protocols and display them on its own local dashboard. The RPIZCT4V3T2 board's MQTT protocol flow is in charge of sending (Publishing) a message to the cloud server, which will operate as a receiver (Subscriber) through the Message Queue Telemetry Transport (MQTT) protocol. The MQTT protocol is an OASIS standard for IoT messaging. It is intended to be a very lightweight publish/subscribe message transport for connecting remote devices with a minimal code footprint and low network bandwidth (Hue et al., 2021). Afterwards, acquired data has been preprocessed to extract significant information from a dataset and transferred to check unblanaced condition of the FCU. Unbalanced condition of the FCU are detected using developed models on the software and hardware level. The application layer of the framework shows sensor data and detected model results, as well as integrating the BIM model, to enable facility managers and operators to perform on-time building facility maintenance.

The proposed framework allows the maintenance department to receive anomaly alerts and remotely monitor the position of building facilities through the customized interface.

The subsection which follows describes the experimental setup for collecting data from FC as well as how to organize acquired data for passing to anomalies detection model.

Case study

The experiment was carried out at the Politecnico di Torino's DIGEP laboratory to demonstrate the framework's applicability. The experimental laboratory is located in the basement of the building. The heating, ventilation, and air conditioning (HVAC) system includes the fan coil unit (FCU). It is considered an essential building facility since it combines a coil and a fan to heat or cool the building's rooms. FC83M - 2014/1 FC with four speeds was used for this experiment. The FC's motor operates at 1100 RPM in an anti-clockwise motion. FC also includes a cooling and heating batteries, as well as filters that must be maintained on a regular basis. In order to monitor and detect anomalies of the FCU sensors listed in Table 1 is mounted on the FCU.

Table 1: List of sensors mounted on the FCU

Sensor name	Variable	Operating Range	Acc.	Unit	Sensor allocation
Current SCT-013-000	i1, i2, i3	0-100A	±3	A	Motor current
Voltage 77DE-06-09	v1, v2, v3	0-230 (50Hz)	±5	V	motor voltage
Temperature DS18B20	T1	0°– 90°C	±0.5	°C	Delivery pipe
Temperature DS18B20	T2	0°– 90°C	±0.5	°C	Return pipe
Temperature DS18B20	T3	0°– 90°C	±0.5	°C	Air intake
Temperature DS18B20	T4	0°– 90°C	±0.5	°C	Air outlet
Temperature RTD(PT100)	T5	-200°-550°C	±0.05	°C	Motor case

Temperature sensors T1, T2, and T4 on the FCU monitor the temperature of the deliver and return pipes, as well as the air intake condition temperature, which should be between 0° and 90° C. T3 is in charge of monitoring the air temperature in the 0°– 50°C range, whereas T5 is attached to the motor casing and measures in the 0°–200°C range. Figure 2 shows voltage, current and temperature sensors attached to the FCU to monitor the motor's operation at three speeds.

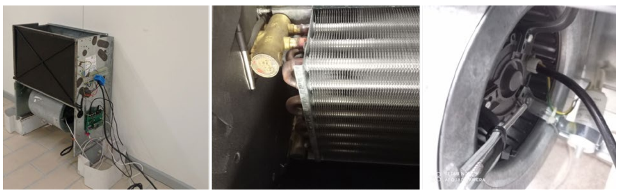

Figure 2: Positioning of sensors on the FC.

Figure 3 depicts anomaly detection algorithm and alert system implemented on the RPIZCT4V3T2 sensor board. The maintenance alerting system is divided into following parts: sensors installed on the FC, a management and monitoring system for the FC components, and an alarming system that warns FMs or end-users when an anomaly occurs. Simultaneously, sensor data and detected anomalies of the FCU visualizes on the BIM.

The temperatures of the delivery pipe, return pipe, air inlet, and air outlet components on the RPIZCT4V3T2 board are monitored every 30 minutes by sending average values when the voltage is at least 200 V, while the current and temperature of the motor must be monitored every 10 seconds and sent to the server as average values every 30 minutes.

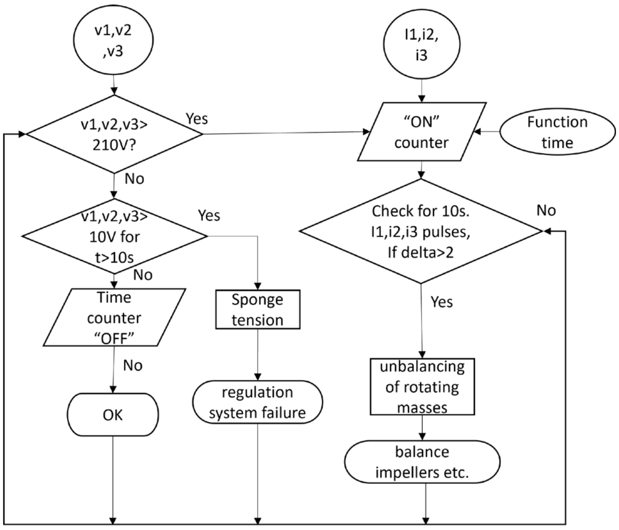

Figure 3: Implemented anomaly detection algorithm and alert system.

The focus of this alarming system is to monitor FCU motor impeller that is the voltage between 0 and 200 V. For this reason, the motor voltage must be checked more often, and the sensor board must send average readings to the server every time when the FCU is started or changed the speed. On the proposed anomaly detection system, electric power (current) must be monitored in the first 10 seconds when the voltage exceeds 200V. The supplied measure ranges are implemented on the RPIZCT4V3T2 board using Node-Red flows functions. To acquire building facility sensor data in real time via WiFi to a PostgreSQL database, a customized node-red flow function is developed.

To illustrate the system's reliability, the following experiments were carried out: the first was to gather balanced (normal) conditional data from the FC motor, and the second was to create an imbalanced scenario by adding 15g of mass to one of the FC motor's blades. The experiment was repeated three times, each at a different speed. Throughout the experiment, all relevant raw data was collected and stored to a database for later analysis. The detected anomaly results, such as balanced and unbalanced FC situations, are displayed on the construction's BIM model. The next section introduces the findings of the experiment and building facility sensor data results integrated into the BIM model.

Results

The FCU data shows both balanced and unbalanced conditions of the motor impeller. Figure 4 depicts the real power data of the motor impeller under balanced and unbalanced situations.

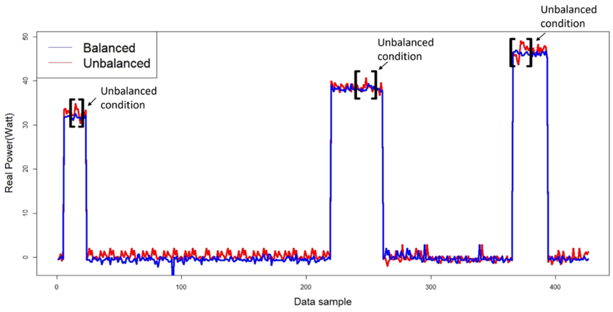

Figure 4: Balanced and unbalanced real power data.

As illustrated in Figure 4, when an unbalanced condition occurs, the motor consumes a large amount of power, demonstrating the imbalanced condition that provides a threshold between balanced and unbalanced scenarios. According to the proposed monitoring algorithm, if the real power is within the threshold, the motor impeller is balanced; otherwise, the motor is imbalanced.

For the proposed algorithm 10 seconds is enough to check the impeller because high power consumption $I_{ub} > I_b$ occures when the impeller starts to rotate as explained in Figure 5.

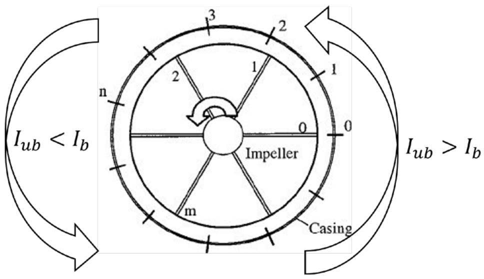

Figure 5: FCU impeller balanced and unbalanced condition.

Thus, the difference between I_{ub} and I_b identifies the threshold where occures imbalanced condtions. In this case the threshold is ± 2.4 for the balanced condition if the more than ± 2.4 there is anomaly.

Data acquired from the experiment used to demonstrate balanced and unbalanced conditions of the FCU motor impeller. To demostrate detected unbalanced condition it is enough to observe the first 10 seconds when the motor rotation is occurred. Since the data acquisition sampling frequency is 2 Hz, the first 10 seconds (20 sampling) data of balanced and imbalanced conditions are enough to demonstarte condition of the FCU as shown in Figure 6. In the Figure 6, detected unblanaced condition of the motor impeller is demonstrated and marked with red dots.

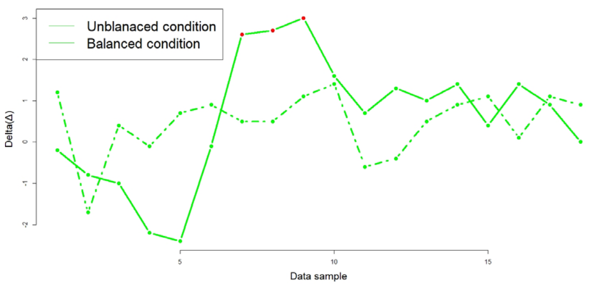

Figure 6: FCU impeller balanced and unbalanced condition.

Anomaly detected during the simulated experiment within the full acquired data is shown in Figure 7.

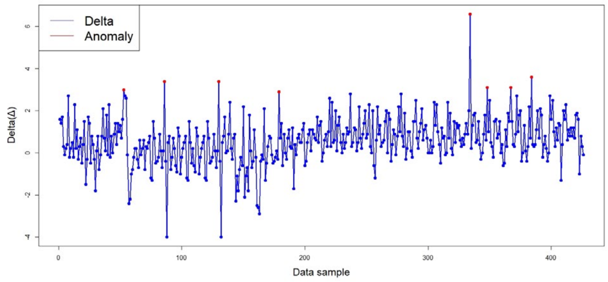

Figure 7: FCU impeller balanced and unbalanced condition.

Finally, the FCU condition results and sensors data are uploaded to the BIM using Autodesk Navisworks software by creating the PostgreSQL database using Data tools settings. Following detecting anomalies on the FCU, the system visualizes detected anomalies and sensor data on the BIM model as shown in Figure 9. When the anomaly is detected on the BIM model the fan coil becomes “red” color, otherways “grey”.

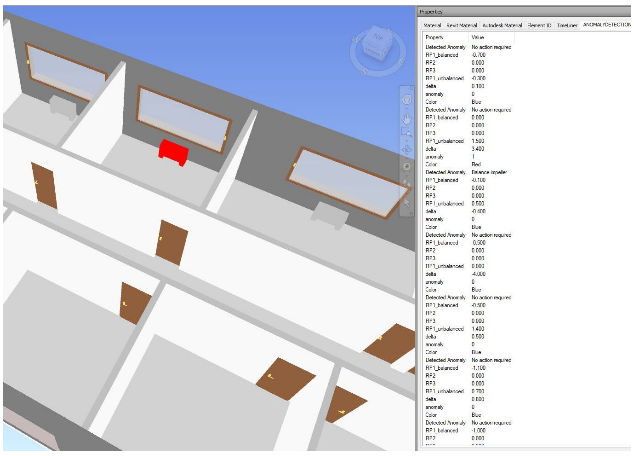

Figure 8: Detected anomaly visualization on the BIM model.

Conclusions

This study describes an automated anomaly monitoring and detection methodology for FCU maintenance using IoT technology. The sensor node and wireless sensor network on the framework continuously send received data to the BIM model via the local servers at the set sample frequencies. The proposed fault detection method was implemented on the application layer and sends alarms to end users or managers when any anomaly happens in order for it to be efficiently repaired. BIM was used to visualize the monitored FCU condition. An experimental case study was utilized to assess the reliability and applicability of the proposed framework. In comparison to other approaches, such as anomaly detection using acceleration sensors or ultrasonic sensors, the presented current sensor data-based anomaly detection is more efficient and reliable.

The introduction of the FCU anomaly monitoring system into the BIM model would increase the building's maintenance plan by assisting facility managers in inspecting the monitored building environments inside the BIM model. As a result, facility managers may benefit from the proposed methodology to handle maintenance issues in the following areas: Facility managers may plan and schedule maintenance work in advance by using anomaly or failure signals from building facilities; conditional and real-time data from sensors allows for more accurate maintenance. IoT sensor data for building components within the BIM model makes maintenance work more convenient; for example, finding the location of the failure component in the real-time BIM model would be simple.

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