Building Technologies & Urban Systems Division
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Energy Technologies Area
November, 2022

Disclaimer:

Acknowledgements:

The authors would like to thank Christopher Weyandt and Raphael Vitti of the Sustainable Berkeley Lab for their significant contributions to this case study. This work was supported by the Assistant Secretary for Energy Efficiency and Renewable Energy, Building Technologies Office, of the U.S. Department of Energy, under Contract No. DE-AC02-05CH11231.

Integration of FDD Data to Aid HVAC System Maintenance

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ABSTRACT

Maintenance of heating, ventilation and air conditioning (HVAC) systems in building portfolios becomes increasingly challenging as systems become more complex, and as the number of systems increases across a managed portfolio. Data-driven maintenance approaches employ multiple data sources to analyze the system's operation and maintenance (O&M) status, and hence can effectively support decision making for complex systems' maintenance. Automated fault detection and diagnostics (FDD) tools are used to identify abnormal operations and resolve the types and locations of problems in HVAC systems. Data generated by FDD tools contain essential information in terms of the system's abnormal operation such as fault causes, fault location, fault occurrence, and duration. Therefore, the integration of FDD tools' output data into data-driven maintenance tools can significantly support the maintenance decision-making procedure, and streamline HVAC system's O&M processes. However, the semantic heterogeneity and the structural heterogeneity in FDD data lower data interpretability and interoperability, and hence hinder the integration of the data by other maintenance tools. In this paper, we propose a framework to organize and integrate FDD data, so that the data can be efficiently queried by or integrated into other maintenance tools. The framework includes the FDD data model, the fault taxonomy library, and organized FDD data structure. The case study demonstrates that the FDD data reorganized under the framework can be efficiently analyzed to assist HVAC system maintenance.

CCS CONCEPTS

Information systems ~ Data management systems ~ Information Integration

KEYWORDS

HVAC system, FDD, Data integration, Operation and Maintenance, Fault taxonomy

ACM Reference format:

Yimin Chen, Eliot Crowe, Guanjing Lin, Jessica Granderson, 2022. Integration of FDD Data to Aid HVAC System Maintenance. In *Proceedings of* The 9th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation. *Boston, MA,* ACM, New York, NY, USA,.4 pages https://doi.org/10.1145/3563357.3567405

BuildSys '22, November 9–10, 2022, Boston, MA, USA

ACM ISBN 978-1-4503-9890-9/22/11.
https://doi.org/10.1145/3563357.3567405

1. Introduction

Heating, ventilation and air conditioning (HVAC) systems, which are used to provide satisfactory indoor thermal comfort and air quality, have become one of the most critical facilities in commercial buildings. Therefore, it is essential to perform the efficient operation and maintenance (O&M) to ensure the system's operational performance. The adoption of building analytics tools provides insights on the system operation to building operators [1]. However, effective maintenance of HVAC systems becomes challenging because of the increasing complexity of the HVAC system, as well as the growing maintenance scale especially in building portfolios [2].

Data-driven maintenance approaches employ multiple data sources to implement advanced decision-making algorithms so that the efficient and cost-effective system O&M activities can be carried out. Examples of these data sources in commercial buildings include building automations systems (BAS), fault detection and diagnostics (FDD) tools, as well as the computerized maintenance management systems (CMMS) [3]. Each tool generates a large volume of data on a continuous basis. However, very little research investigated FDD data characteristics, and how FDD data can be used to support HVAC O&M activities.

FDD tools show promise for HVAC system maintenance [4] FDD tools employ building operational data to identify abnormal operations and resolve the types and locations of root causes of problems in HVAC systems. Today, more than 30 commercialized FDD software tools are available in the market in the U.S., commonly provided as software-as-a-service (SaaS) to building operators [5]. FDD data provide valuable information including fault occurrence, fault duration and fault impacts in HVAC systems. In building portfolios, a considerable amount of FDD data can be generated by the FDD tools due to 1) the increasing complexity of HVAC systems; 2) more comprehensive fault detection capabilities; and 3) wider deployment of FDD solutions. For example, it is reported that the average number of reported HVAC faults per building per month can reach up to 245 (buildings equipped with air handling (AHU) and air terminal unit (ATU)) in commercial buildings in the U.S [6]. This situation becomes convoluted when FDD data is continuously and automatically generated and stored in a database for a time period. For instance, Heinemeier reported that an HVAC FDD tool could generate 25 million fault messages across all Walmart buildings in one year of operation [7]. Although some fault messages, which reflect severe fault impacts, could be handled in a timely manner by building facility staff, most FDD data would be ignored due to limited facility staff resource and high maintenance costs. FDD data mining and analytics will not only uncover knowledge on fault occurrences such as fault prevalence in HVAC systems [10], but also support decision making in data-driven maintenance tools to improve maintenance activities.

However, the incompleteness, lower interpretability and lack of interoperability in FDD data may cause considerable barriers for FDD data analytics and prevent its integration from other data-driven applications for HVAC maintenance. The unstructured FDD data generated by some FDD tools miss the exact information such as component type and locations. For example, the FDD data indicates a temperature sensor fault but does not provide the sensor location information, causing the data incompleteness. Additionally, various FDD tools employ customized ways to describe HVAC faults and generate FDD data. For instance, for a damper stuck fault, one FDD tool uses “Damper position feedback lower than command”, but another FDD tool uses an abbreviation format as “OA_FULL_OPEN_HIGH_OAT”. This causes semantic heterogeneity and the structural heterogeneity in FDD data. Although some semantic models such as Brick schema [8] or other ontology-based FDD solutions [9] may contain some fault status elements, those models do not provide complete fault descriptions or the fault data model.

In this paper, we proposed a framework for integrating HVAC system FDD data into CMMS tools to support the O&M process. The framework includes a FDD data model, the fault taxonomy library, and the organized FDD data structure. We demonstrate the effectiveness of the framework to enhance the FDD data interpretability and interoperability, as well as to evaluate the maintenance status.

2. Methodology

2.1 Overall description of the framework

Figure 1 shows the integration framework of FDD data and the CMMS tool. It can be seen that apart from the maintenance cost data, maintenance work orders, staff schedule and building/equipment schedules which the CMMS tool often uses, the FDD data generated by the FDD tool can be integrated with the maintenance decision making algorithms in the CMMS tool.

2.2 FDD data model

To effectively employ FDD data in HVAC system maintenance practices, an FDD data model is developed to ensure the completeness of data as shown in Figure 2. This chain data model contains four levels: 1) the fault occurrence time (i.e., the timestamp when the fault is flagged and recorded by the FDD tool); 2) the building ID and equipment ID which are used to indicate the fault location at the building level and the equipment level; 3) the fault ID which provides a unified HVAC fault name as described in Section 2.3; and 4) additional fault information which indicates other characteristics associated an HVAC fault to support maintenance activities. It is noted that the additional information can be generated either by the FDD tool or by the CMMS tool after the first three level FDD data are post processed.

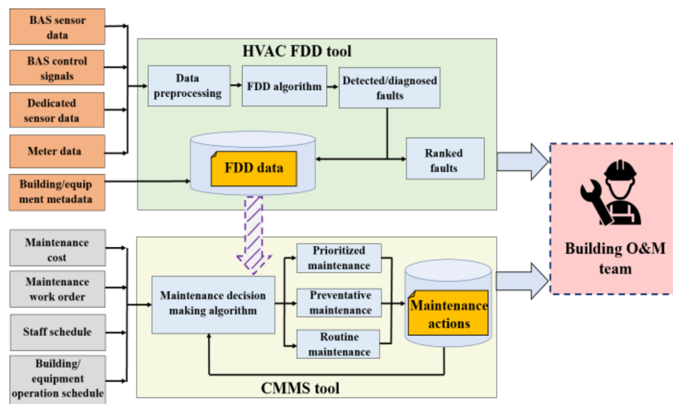

Figure 1. Data integration framework between the FDD tool and the CMMS tool

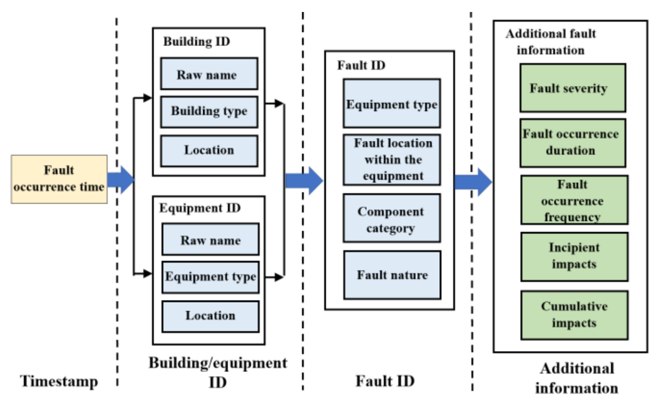

Figure 2. FDD data model

2.3 Fault taxonomy library

The previously developed HVAC fault taxonomy is used to unify the inconsistent fault naming conventions [11]. In the HVAC fault taxonomy, a four-level fault structure, which includes the equipment type, location within the equipment, the component category and fault nature, is defined to represent an HVAC fault as illustrated in [11]. Accordingly, a four-element structured fault ID is assigned to each HVAC fault. In addition, the faults reported by FDD tools were categorized into condition-based faults (CB), behavior-based faults (BB) and outcome-based faults (OB) [12].

2.4 Description of the FDD data format

Under the framework, FDD data can be restructured to generate a concise format to increase its interoperability. Table 1 shows an example of the one piece of FDD message which includes the first three levels of information in the FDD data model. Using the structured FDD data format, fault messages can be harmonized to a daily binary fault (BDF) message, i.e., for a calendar day, a fault for a piece of equipment in the building is flagged as one fault message and stored in the FDD tool database for later analysis or query.

Table 1. Structured FDD data.

Timestamp	Building ID	Equipment ID	Fault ID
20220102	15	RTU-001	RTU-Outdoor_air-Damper-Stuck

2.5 FDD data for HVAC system maintenance

Using the proposed framework, the FDD data can be efficiently post-processed to evaluate the system operation and maintenance status in the long term. For example, Figure 3 illustrates the FDD data for an HVAC fault (e.g., the ‘RTU-Outdoor_air-Damper-Stuck’ fault) in a piece of RTU under the normalized BDF format in one year. In the figure, four colors are used to indicate four operational conditions of an equipment as: 1) the red color shows the BDF messages for the true positive fault messages flagged by the FDD tool; 2) the purple color shows the BDF messages for the false positive messages reported by the FDD tool; 3) the blue color shows the false negative period in which there is a fault but the FDD tool does not detect or diagnose such a fault; and 4) the green color shows true negative operational period. It can be seen that both the red color bars and the purple color bars represent the flagged faults reported by the FDD tools. However, it is noted that the ground truth (i.e., whether it indicates a true fault or false alarms) should be validated by the building facility staff. Contrarily, the periods labeled by the green color and blue color represent there are no BDF messages flagged by the FDD tool. It is noted the ground truth should be further validated by the building facility staff.

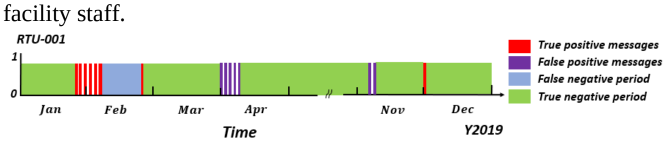

Figure 3. Reorganized FDD message (in the BDF format)

FDD data can be integrated into the decision-making algorithms in a CMMS tool to support maintenance activities. For example, if the flagged fault messages for critical components/equipment (i.e., fans and chillers) indicate severe fault impacts on the HVAC system or on the thermal comforts, the prioritized maintenance strategy can be carried out for facility staff to quickly address the issues [13]. On the contrary, if the fault messages are generated for a less critical fault for a long time, the preventative maintenance or routine maintenance strategies can be activated to optimally assign facility staff to address the issue. In addition, various metrics can be developed to evaluate a system's O&M. In such practice, cost effective maintenance can be achieved while ensuring few faults to be ignored. In this study, we proposed a metric, namely continuous reported fault duration (CRFD), which is calculated by the reorganized FDD data, to evaluate the HVAC O&M status. The CRFD is defined as for a piece of equipment, the FDD tool continuously reports faults (i.e., either a specific type of fault, or a set of faults). For example, if the FDD tool continuously reports the fault for the RTU-001 for six consecutive days in the BDF format, then the CRFD for this type of fault is six. It is noted that the CRFD may include either true positive messages (e.g., six red bars in Figure 3) or false positive messages (e.g., five purple bars in Figure 3).

For each type of fault or each piece of equipment, the maximum CRFD (i.e., MaxCRFD) can be obtained through comparing the CRFDs in a certain time range as given by:

$$\text{MaxCRFD} = \text{Maximum}\,(CRFD_1,\ CRFD_2,\ \ldots\ CRFD_n\,) \quad (1)$$

where n is the number of the CRFD counted within a time period.

The MaxCRFD reflect equipment O&M status within a time scope. For example, a higher MaxCRFD value indicates that the equipment operates under faulty conditions for a long time and need to be scheduled for maintenance works.

For a specific type of HVAC fault, the mean MaxCRFD (mean_MaxCRFD) can be obtained by averaging the MaxCRFD from multiple pieces of equipment as given by:

$$\text{mean\_MaxCRFD} = \sum_{i=1}^{n} MaxCRFD_i \quad (2)$$

3. Case Study

The FDD data from one commercial FDD tool vendor was used to demonstrate the effectiveness of the reorganized FDD data in interpreting the system's O&M. The FDD data include fault diagnostics for 2162 RTUs from 131 mercantile buildings across the U.S. from 2018 to 2019.

3.1 Fault name mapping result

Raw fault names were first extracted from the FDD data because there is not a complete fault library available. A total of 135 raw fault names were identified. The raw fault names were mapped according to the taxonomy library to ensure data interpretability and completeness as shown in Figure 4.

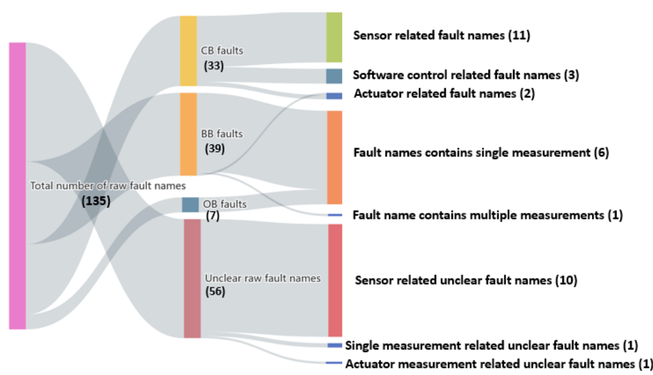

Figure 4. Taxonomy mapping results

Among the 135 raw fault names, 33 fault names were identified as the CB faults, 39 fault names were identified as the BB faults, and 7 fault names were identified as the OB faults. Some fault names represent a same fault. For example, both the “Zone Air Relative Humidity Sensor Reading is Unchanging” and the “Zone Air Relative Humidity Sensor: Stuck” were mapped to the “RTU-Zone-Relative_humidity_sensor-Frozen” fault as provided in the taxonomy library. Consequently, a total of 23 fault IDs, which included 11 sensor related faults, 3 control related faults, 2 actuator related faults, 6 single measurement related faults, and 1 multiple measurement related faults from the taxonomy library were assigned. Additionally, 56 fault names were found to lack complete information such as the component location, or the component type, or the fault types. For example, a "Stuck Carbon Dioxide C1 Sensor" raw fault name was flagged in the FDD data, but this fault message did not indicate the CO_2 sensor location. Hence, the "RTU-NA-CO2_sensor-Frozen" fault ID was mapped to those fault names. Finally, a total of 12 fault IDs, which include a "NA", were mapped.

3.2 Reorganized FDD data

A Python language-based wrapper script was developed to generate the BDF format data via translating data from multiple sources including the FDD data, the fault mapping file, and FDD metadata files (i.e., building ID and equipment ID mapping files). Consequently, the FDD data was reorganized to generate 2.8 million messages in the BDF format as given in Table 1.

3.3 FDD data for the O&M evaluation

The FDD data can be used to evaluate the system O&M status in terms of each type of the fault. Table 2 shows 10 CB faults of which the number of RTUs reporting such a fault is higher than 100. For example, the zone temperature sensor frozen fault in 75.9% of RTUs (the total number is 2162) was flagged at least once.

Table 2. Number and percentage of RTUs reporting faults

Fault ID	Num of RTUs	Pct of RTUs
RTU-Zone-Temperature_sensor-Frozen	1641	75.9%
RTU-Control-Economizer_sequence-Setting	1444	66.8%
RTU-Zone-Dewpoint_sensor-Frozen	1396	64.6%
RTU-Supply_air-Temperature_sensor-Frozen	1328	61.4%
RTU-Zone-Relative_humidity_sensor-Frozen	1276	59.0%
RTU-Outdoor_air-Temperature_sensor-Frozen	1028	47.5%
RTU-Return_air-Temperature_sensor-Frozen	952	44.0%
RTU-Control-Sequence-Setting	347	16.0%
RTU-Zone-Temperature_sensor-Drift	211	9.8%
RTU-Outdoor_air-Relative_humidity_sensor-Frozen	135	6.2%

Figure 5 shows the mean_MaxCRFD results for the 10 CB faults given in Table 2. It can be seen that the mean_MaxCRFD for the zone temperature sensor frozen fault is around 231 days in a two-year time scope. This means that when this type of fault is frequently flagged by the FDD tool, the fault tends to be ignored by the building facility team. Similarly, this mean_MaxCRFD can be used to evaluate a piece of equipment to optimize O&M activities.

4. Conclusion and future work

Data generated by FDD tools is valuable to support the maintenance process. In this paper, we propose a framework to augment FDD data interpretability and interoperability. This framework includes the FDD data model, fault taxonomy library and the organized data structure. The case study demonstrates good potential in effectively streamlining the FDD data in the HVAC O&M. The reorganized FDD data can be efficiently queried and integrated by other maintenance applications. Our on-going and future works include analyzing the HVAC fault prevalence, and investigating the HVAC fault prioritization via FDD data. Additionally, we will investigate the integration of the FDD data model with other semantic models such as Brick Schema to further enhance the interoperability of FDD data.

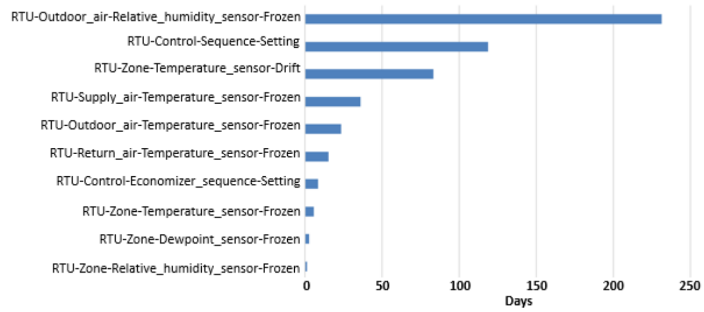

Figure 5. Result of the mean_MaxCRFD

ACKNOWLEDGMENTS

This work was supported by the Assistant Secretary for Energy Efficiency and Renewable Energy, Building Technologies Office, of the U.S. Department of Energy under Contract No. DE-AC02-05CH11231.

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