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Analysis of Automated Fault Detection and Diagnostics Records as an Indicator of HVAC Fault Prevalence: Methodology and Preliminary Results

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ABSTRACT

Faults in commercial buildings can cause energy waste and other performance problems such as reduced occupant comfort, reduced equipment longevity, and increased noise. However, it is currently unknown how commonly faults occur in different equipment types. This paper describes a method to estimate the prevalence of faults in air handling units, air terminal units, and rooftop units and the use of three metrics for summarizing results. This method was developed by the authors as part of a study which includes data from several automated fault detection and diagnostics (AFDD) data providers, providing a large sample with a wide range of building types, geographical locations, and equipment types. This dataset includes fault diagnoses from thousands of buildings throughout the United States, as well as anonymized metadata describing the building and equipment characteristics. The number of fault records is on the order of 10^6. We describe here how the data from different data providers can be processed and unified using a common taxonomy, and illustrate three metrics that can provide insights using this type of data. The methods developed for this study are illustrated here with preliminary data. This work supports a multi-year, multi-institutional project that will provide insight into the drivers of fault prevalence; for example, whether prevalence is correlated with characteristics like building type, building size, and geographical location (including related factors like local climate and utility rates). We discuss some of the challenges of harmonizing disparate outputs from multiple AFDD providers, the usefulness of applying a unifying fault taxonomy, and provide preliminary figures that illustrate three fault prevalence metrics.

1. INTRODUCTION

Commercial buildings consume approximately 18% of total energy and 37% of electrical energy in the United States (EIA, 2018). Heating, ventilation, and air-conditioning (HVAC) systems are one primary end use in these buildings. Unfortunately, these systems often operate far from their optimal efficiencies because of design, installation, and operational problems. HVAC faults, or deviation from the expected operating conditions of an HVAC system or component, can increase a building's energy consumption and operational costs; may prevent the building from receiving needed services for HVAC; may negatively affect other interconnected energy systems; and could increase equipment maintenance or replacement costs (Ebrahimifakhar *et al.*, 2020).

Automated fault detection and diagnosis (AFDD) tools use building automation system data to detect the presence of HVAC faults and support diagnosis of their root causes. Applying AFDD tools in commercial buildings and correction of the identified faults can save 9% of energy consumption (Kramer *et al.*, 2020). Faults in U.S. commercial buildings waste approximately 0.9–2.7 quads of energy annually (Frank *et al.*, 2019). However, this energy waste estimate is based on uncertain estimates of actual fault prevalence in the field. There is a lack of reliable data about which HVAC faults appear how frequently by building and system type. The purpose of this study is to fill the gap in the current state of knowledge about HVAC fault prevalence.

Researchers and AFDD providers have largely focused on evaluating AFDD performance building by building, and quantifying costs or other impacts. They often propose approaches that purport to improve the accuracy of fault detection, but by necessity will limit their investigations to simulated data (Li and O'Neill, 2019), a single building, or a small collection of buildings. A study exploring the use of automated methods for identifying "non-routine events" (possible faults) found success in streamlining measurement and verification processes, but recommended further work analyzing a larger set of buildings, including data from multiple real-world buildings and projects (Touzani *et al.*, 2019). However, no unified dataset has been published on the observed prevalence of faults that could inform future studies. An exploratory study (limited to 12 buildings) that informed the current project was the first of its kind to attempt to harmonize AFDD data from multiple buildings and identify the necessary steps and the barriers to doing so (Newman *et al.*, 2020). One key challenge was the lack of a common taxonomy across individual studies. This was addressed by Chen *et al*. (2020) presenting a standardized taxonomy for HVAC faults related to air handling unit (AHU), air terminal unit (ATU), and rooftop unit (RTU) systems, which is described in Section 2.2.

Several studies have been conducted for finding the frequency of faults in refrigeration and air conditioning systems. Stouppe and Lau (1989) examined 15,760 failure records occurring between 1980 and 1987 on different air conditioning systems by analyzing insurance claims. They found that in hermetic air conditioning systems 76.6% of faults were electrical, 18.9% of faults were mechanical, and 4.5% of faults were attributed to a malfunction in the refrigerant circuit. Breuker and Braun (1998) estimated the frequencies of occurrence and the service costs of different RTU faults by analysis of service records of a company from 1989 to 1995. They found that 60% of failures were electrical or control problems, while 40% of faults were mechanical. They also found that although compressor failures do not happen as frequently as other faults, they have the highest service costs in RTUs. Comstock *et al.* (2002) conducted a fault survey among four major American chiller manufacturers to identify the most common faults in chillers. They reported that most common faults happened in control box and starter sections. Refrigerant leakage was the second most commonly cited fault in chillers.

Felts and Bailey (2000) monitored and analyzed over 250 RTUs in northern California in various climate zones. This study showed that 40% of the RTUs were more than 25% oversized, and 10% of the RTUs were more than 50% oversized. It was also shown that economizers generally did not operate correctly. Downey and Proctor (2002) collected and analyzed performance data on over 13,000 air conditioners in residential and commercial buildings in California. Their analysis concluded that 57% of the units had improper refrigerant charge, and 21% of the units had low airflow rate through the indoor coil. Cowan (2004) investigated data from 503 RTUs at 181 commercial buildings sites in 5 states, gathered in four field studies. It was found that 46% of the units had improper refrigerant charge, 64% of the units had economizer problems, 42% of the units had airflow problems, 58% of the units had thermostat problems, and 20% of the units had sensor problems. Madani (2014) analyzed the fault reports provided to heat pump manufacturers and insurance companies in Sweden. This study showed that control and electronics faults are the most common and costliest faults in heat pump systems.

Yoshida *et al.* (1996) conducted a survey among HVAC experts in Japan to identify the ten most important faults in variable air volume (VAV) air handling systems based on their experience. The faults were ranked not only on frequency of occurrence, but also other factors such as environmental impacts, energy impacts, difficulty of detection, causing physical damage, and repair costs. The survey suggested that faults that occur in outdoor air damper and VAV box sections are fairly common. Qin and Wang (2005) conducted a site survey in a large commercial building in Hong Kong with 1,251 pressure independent VAV terminal units. Their investigation showed that zone temperature sensor error and local direct digital control error are the most common faults in VAV terminals. Gunay *et al.* (2019) developed a text-mining algorithm to extract information about fault frequency of HVAC systems from computerized maintenance management systems databases in Canada. Analyzing a central heating and cooling plant dataset showed that the average annual warning/failure rate was 4.5 for a chiller, while it was 6.5 for a boiler. From a building cluster dataset, they found that approximately 50% of the warning/failure events were related to room/zone/floor level systems.

Recently, Shoukas *et al.* (2020) analyzed the fault data collected from AFDD tools provided by four companies, representing over 28,000 RTUs, to determine the frequency of the reported faults. Since different companies use different formats, fault definitions, diagnostics, and reporting, they were not able to compare between AFDD tools, and results were presented separately for each data provider. They concluded that the frequency of the faults depends on the fault definitions and the diagnostics methods. They found that RTU faults occurred most commonly on economizer dampers, sensors, communications, and cooling systems.

This paper presents a method that is being developed to estimate the prevalence of faults in AHU, ATU, and RTU systems. It incorporates AFDD data from providers who monitor existing buildings and provide information on detected faults. The preliminary fault prevalence estimates presented in this paper are limited to commercial buildings in the U.S. whose AHU, ATU, and/or RTU systems are monitored by one of three AFDD providers. The faults are categorized using a standard taxonomy, and the results of a pilot study that provides preliminary illustrative values from analysis of a subset of data for estimated fault prevalence are presented here. Future work will analyze how the prevalence of specific faults is related to factors expected to affect the likelihood of observing faults such as building type, building size, climate, or utility costs, and will include a comparison with observed data garnered from manual inspection of individual buildings monitored by an AFDD provider. A key motivation in presenting the method in this forum is to dialogue with experts, in order to gain insight and new ideas for improving the study while it is in progress.

2. METHODOLOGY

The primary source of data for this study comes from commercial AFDD software tools. This is because commercial AFDD software outputs can be obtained for a large number of buildings and HVAC systems at a relatively low cost. Since AFDD software outputs are subject to error, i.e., they might have some level of false negative, false positive, and misdiagnosis rates, some of the AFDD software outputs will be verified in our future work using manual inspection of buildings.

2.1 Data Overview

The preliminary fault data received for this study is sourced from three commercial AFDD software tools. Data from at least four additional data providers will be added in the future. The study dataset includes at least twelve months of data for each building. The study includes three classes of system: AHU, ATU and RTU, and includes analysis of components of these systems, such as a supply air temperature sensor for an AHU. Table 1 shows the number of buildings, HVAC systems, and daily fault records for each of the data providers. A "daily fault record" constitutes the presence of a specific fault on a unique piece of equipment on a single day. A fault flagged multiple times in a single day constitutes one daily fault. For example, an RTU flagged with a stuck economizer damper fault every hour in 2019 would generate 365 daily fault records in the study dataset. During that same time period the same RTU could generate other daily fault records relating to other fault types. Tables 2 and 3 show that the sample space of data obtained from these three providers represents multiple building types and climate zones.

Table 1: AFDD data sources

Data Source	# of Buildings	# of AHUs	# of ATUs	# of RTUs	# of Daily Fault Records
Provider A	131	964	18,896	0	3,246,379
Provider B	131	0	0	2,174	2,944,853
Provider C	1103	0	0	5,843	348,911

Table 2: Number of buildings by building type

Building Type	Mercantile	Other	Office	Health Care	Food Service	Food Sales	Public Assembly	Service	Religious Worship	Education	Lodging	Warehouse and Storage
# of Buildings	840	159	82	82	66	57	36	12	11	8	7	5

Table 3: Number of buildings by Building America climate zone

Climate Zone	Cold	Marine	Mixed-Humid	Hot-Dry	Hot-Humid	Mixed-Dry	Very Cold
# of Buildings	381	328	254	238	159	3	2

Curating and analyzing data from a number of different sources is complicated by the diversity of data formats, fault naming conventions, and metadata and file structures that the AFDD software tools employ. The first, and most intensive, step is to prepare the data by cleaning and normalizing it by mapping it to a common fault taxonomy. Data preparation includes the following steps:

- Cleaning data to identify and resolve missing, mislabeled, empty fields, erroneous data, etc.
- Anonymizing data to ensure that any sensitive information that may identify buildings or partners is removed
- Normalizing data to a standard format using a common fault taxonomy

Fault data from each partner are converted to a standard format, which is called binary daily fault (BDF) data. Table 4 shows a sample of BDF data. HVAC fault prevalence metrics are calculated from the BDF data.

Table 4: Standard binary daily fault data

Fault record	**Building ID**	**Equipment ID**	**Equipment type**	**Date**	**Fault name mapped**
1	A0001	A-AHU00001	AHU	20190101	AHU-Heating-Coil_valve-Leakage
2	A0002	A-AHU00002	AHU	20190101	AHU-Cooling-Coil_valve-Stuck
3	B0001	B-ATU00001	ATU	20190101	ATU-Discharge_air-Damper-Stuck
4	B0002	B-ATU00002	ATU	20190103	ATU-Discharge_air-Airflow-Abnormal
5	C0001	C-RTU00001	RTU	20190102	RTU-Outside_air-Airflow-Abnormal
6	C0002	C-RTU00002	RTU	20190104	RTU-Mixed_airTemperature_sensor-Frozen

2.2 Standardized Taxonomy for HVAC Faults

Each AFDD tool uses different fault names to refer to the same fault in an HVAC system. For example, in one commercial AFDD tool, an “economizer damper hunting” fault is reported to show a malfunctioning damper control, but in another tool, this fault may be reported as an “economizer damper short cycling” fault or an “unstable economizer damper” fault. Therefore, a unifying taxonomy for HVAC faults in AHUs, ATUs, and RTUs in commercial buildings was developed (Chen *et al.*, 2020). The developed fault taxonomy contains 134, 39, and 115 unique fault names for AHUs, ATUs, and RTUs, respectively. Mapping functions were created for each AFDD tool to convert their fault reports to this unifying taxonomy. Table 5 shows a selection of some of the HVAC faults in the taxonomy.

There are three different fault categories based on how the faults are presented: condition-based, behavior-based, and outcome-based (Frank *et al.*, 2019). Condition-based faults are improper or undesired physical conditions in HVAC systems such as stuck dampers, leaky valves, and biased sensors. Behavior-based faults present improper or undesired behavior during the operation of HVAC systems. Examples of behavior-based faults are economizer damper hunting, and simultaneous heating and cooling. Outcome-based faults are states in which an outcome or performance of the HVAC systems deviates from expected values, such as excessive energy consumption or insufficient ventilation rate. The HVAC fault taxonomy applied in the current project only includes condition-based and behavior-based faults, since they are most commonly used in AFDD software tools.

An important feature of the taxonomy is that it supports flexible analysis based upon multiple levels of equipment class. For example, prevalence can be calculated for specific faults related to RTU supply air temperature sensors, supply air temperature sensors in general, temperature sensors in general, or sensors in general. Similarly, prevalence could be calculated for all heating faults, all damper faults, all stuck damper faults, and so on.

Table 5: Example list of the HVAC faults in the developed taxonomy

Equipment	Component	Fault Name	Fault ID	Fault Type*
AHU	Air economizer	Economizer damper hunting	AHU-Economizer-Damper_control-Hunting	BB
	Cooling coil valve	Cooling coil valve stuck	AHU-Cooling-Coil_valve-Stuck	CB
	Outside air temperature sensor	Outside air temperature sensor bias	AHU-Outside_air-Temperature_sensor-Bias	CB
ATU	Reheat coil valve	Reheat coil valve leakage	ATU-Reheat-Coil_valve-Leakage	CB
	Discharge air damper	Discharge air damper hunting	ATU-Discharge_air-Damper_control-Hunting	BB
	Discharge air temperature sensor	Discharge air temperature sensor drift	ATU-Discharge_air-Temperature_sensor-Drift	CB
RTU	Air economizer	Economizer damper stuck	RTU-Economizer-Damper-Stuck	CB
	Supply air temperature sensor	Supply air temperature sensor frozen	RTU-Supply_air-Temperature_sensor-Frozen	CB
	Compressor	Compressor short cycling	RTU-Compressor-Unassigned-Short_cycling	BB

*BB = Behavior-based, CB = Condition-based

2.3 Metric Definitions

There are many different ways to express fault prevalence. To determine the priority HVAC fault prevalence metrics to be calculated in this study, we identified several questions that we expect to be of most interest to the study's target audience of AFDD providers, users, regulators, and researchers. These questions include:

1. What percentage of units are observed to be faulted at any given point in time?
2. Which faults are most often observed to be present?
3. How many faults are observed to be present each month for a given building?

To quantitatively characterize the HVAC fault prevalence, the following metrics are defined.

2.3.1 Metric 1 (Monthly Fault Presence) This metric gives the percentage of equipment that experiences the presence of fault type ‘x’ on one or more days, for each month of the year, and is expressed as a percentage of all equipment. For a given piece of equipment, if fault ‘x’ is present for at least one day in a given month, that month is denoted as a “1” binary value, and considered one “fault_month”. If the fault is observed to be present in multiple years for a given piece of equipment (e.g., present in February 2018 and in February 2019), each case will be considered a distinct value for this metric (e.g., February 2018 = 1, and February 2019 =1, a total of two “fault_months” for February).

This metric is calculated by:

$$monthly\_fault\_presence = \frac{fault\_months}{equipment\_months} \tag{1}$$

where $fault\_months$ is the accumulated number of monthly fault occurrences for one type of fault in a calendar month across different years, and $equipment\_months$ is the number of monitored pieces of a specific type of equipment in one calendar month, or in a calendar month over a range of years. For example, if 100 dampers are monitored for two full years, the damper $equipment\_months$ count for June would be 200.

The $fault\_months$ is calculated by:

$$fault\_months = \sum_{i=1}^{num\_calender\_year} \sum_{j=1}^{equipment\_months} Fault\_OC_{month} \tag{2}$$

where $Fault\_OC_{month}$ is the monthly fault occurrence. If there is at least one fault record in the AFDD report within the month, then $Fault\_OC_{month} = 1$. The $num\_calender\_year$ is the number of all years that may cover the time range of interest (e.g., the month of January appears in our dataset for a piece of equipment across two years, hence $num\_calender\_year$ would equal 2.

Figure 1 illustrates the calculation of $Fault\_OC_{month}$ and $fault\_months$ under a selected time period. There are three AHUs, each monitored for two years. In January three out of six pieces of equipment had a fault flagged at least once during the month (so that $Fault\_OC_{month} = 1$ for these three), hence there is a total of three $fault\_months$ for January of six possible. This represents a monthly fault presence of 50 percent for January

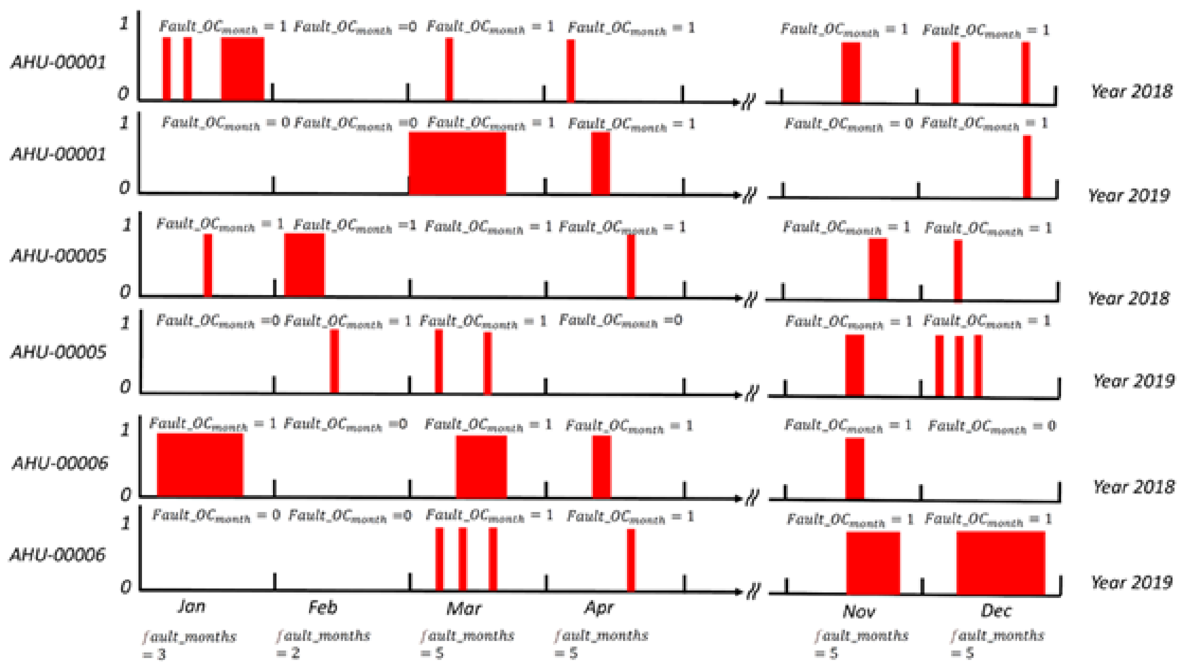


Figure 1: Graphical depiction of Metric 1 (Monthly Fault Presence)

2.3.2 Metric 2 (Average Monthly Fault Presence) Metric 2 is closely related to Metric 1, and shows the percentage of equipment that experiences the presence of a given fault type on one or more days in a month, averaged across all months (whereas Metric 1 presents a different fault presence value for each month). This metric shows which fault types are most often present in the data.

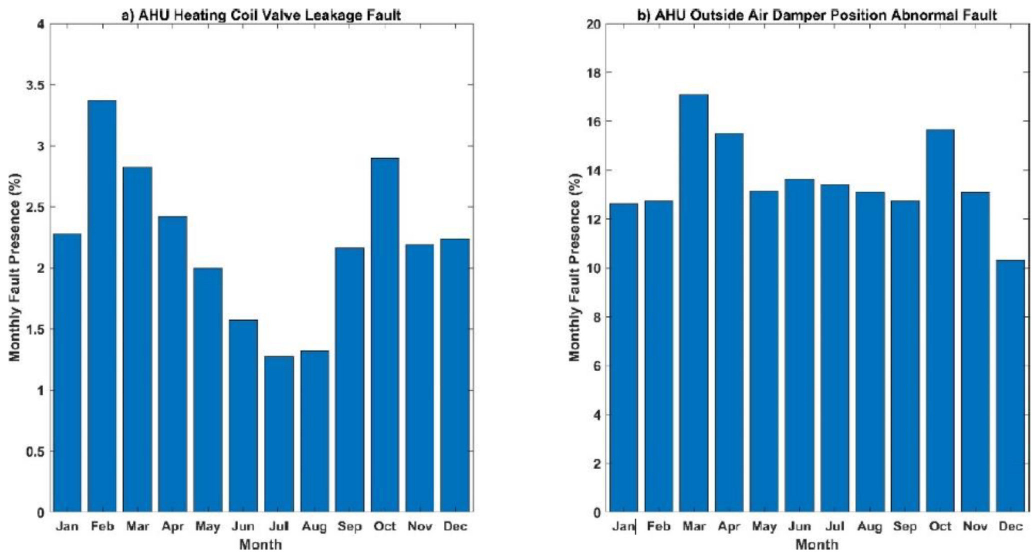
2.3.3 Metric 3 (Mean Number of Faults per Building per Month) This metric shows how many faults are observed to be present (at the building level) each month, among the set of faults considered in this study. The calculation steps of this metric are:

1. Establish total unique faults for each month, for one building
2. Calculate mean value across all months for that building
3. Repeat for all buildings
4. Calculate mean of all building-specific mean values

3. PRELIMINARY RESULTS AND DISCUSSION

A total of 6,540,143 daily fault records of AHUs, ATUs, and RTUs were analyzed from the three AFDD providers. Values for metrics 1 to 3 have been generated. There are several questions that will be explored by further analysis of the results in future work. For example: does fault prevalence vary with climate zone (perhaps correlated to energy costs, for example)? Does fault prevalence vary with building type, season, building size, building type, or other factors? Do different AFDD providers detection rates vary significantly? It is possible that the sample size will be too small, in many cases, to provide statistically significant answers to these types of questions.

Figures 2a and 2b show the monthly fault presence (Metric 1) for two AHU fault types: "heating coil valve leakage" (condition-based) and "outside air damper position abnormal" (behavior-based). The analysis will explore, for example, whether the apparent seasonal trend in Figure 2a does represent a genuine trend. There could be competing factors driving this trend: reduced usage of heating systems in summer; and difficulty diagnosing a leak in winter (when there *should* be flow much of the time). The fault in Figure 2b has higher overall rates, and also is likely to be correlated to season, but there is less apparent seasonal trend. Interestingly, the shoulder months for both fault types have the highest prevalence values. These preliminary results illustrate the potential use of this metric and further analysis to be done.



Figures 3a and 3b show the monthly fault presence (Metric 1) for two different ATU faults. “Discharge air damper stuck” is a condition-based fault and “reheat coil valve hunting” is behavior-based. Figure 3a shows that somewhat fewer ATU dampers were diagnosed as being stuck in summer months, but with a range of 0.5% to 2.5%, these differences from month to month may not be significant. 8% to 9% of reheat coil valves were diagnosed to be hunting each month, but with no obvious seasonal trend.

Figures 4a and 4b show the 10 most common AHU and ATU faults. These faults are selected out of 34 AHU faults and 13 ATU faults that were successfully mapped to the fault taxonomy. Average monthly fault presence is a useful way to sort the relative prevalence of all individual fault types, and can also help in understanding the most problematic system components (e.g., dampers, sensors) or functional elements (e.g., cooling, heating). Five AHU and six ATU faults in the 10 most common faults lists are behavior-based.

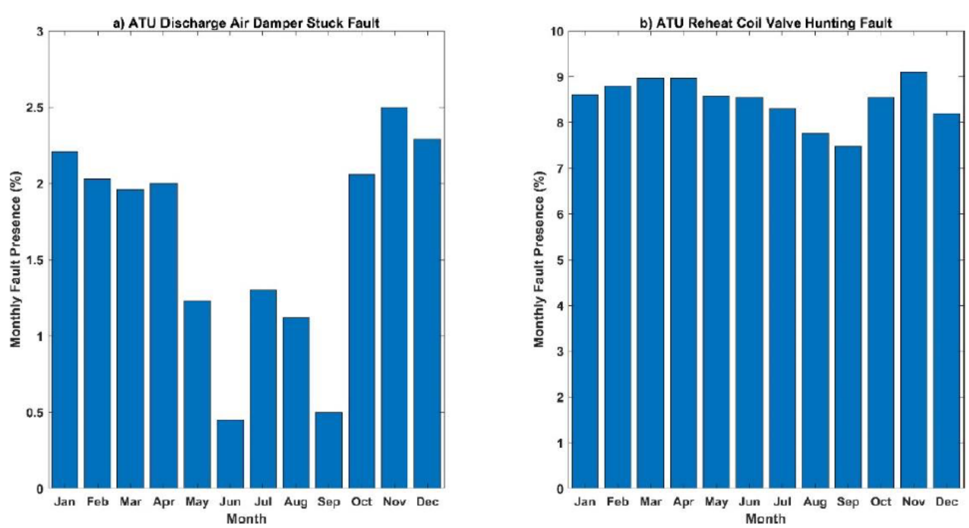


Figure 3: Monthly fault presence (Metric 1) for two ATU faults (preliminary illustrative result)

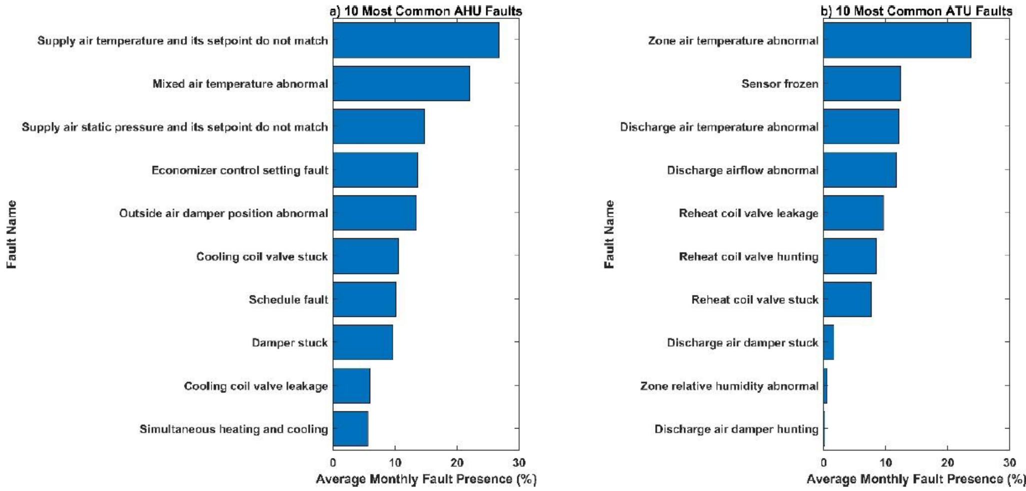


Figure 4: Average monthly fault presence (Metric 2) for 10 most common AHU (left) and ATU (right) faults

Figure 5 shows the distribution of the mean number of faults per building per month. As can be seen, 77.4% of the buildings were in the range of 0-50 faults per month, 10.8% were in the range of 50-100, 5.6% were in the range of 100-150, 2.0% were in the range of 150-200, and 4.2% had higher than 200 faults per month. It should be noted that the number of faults in each building includes all the AHU, ATU, and RTU faults. As we expected, buildings with higher quantities of equipment had higher quantities of faults. One health care (inpatient) building in a hot-dry climate zone with 38 AHUs and 834 ATUs had 1071 faults per month which was the highest number among all the buildings. This is an example of a metric where it could make more sense to normalize, and the study will consider normalizing factors such as the number of pieces of equipment in the building and the number of fault detection rules programmed into the AFDD tool, or other related factors affecting the number of reported faults.

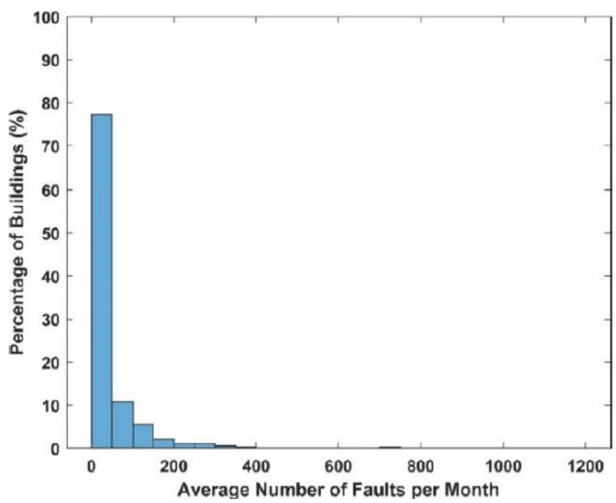


Figure 5: Mean number of faults per building per month distribution

3.1 Ongoing Challenges and Questions

A key element of the work in this project is development of fault prevalence concepts and systematic methods for quantifying and communicating prevalence. To illustrate: one challenge in fault prevalence is that for a given condition-based fault, a number of behavioral symptoms could arise. Conversely, a behavior-based fault may arise from multiple condition-based faults. For example, behavior-based faults, such as “supply air temperature and its setpoint do not match” and “simultaneous heating and cooling” may each be caused by the “cooling coil valve stuck" condition-based fault. This study acquires data generated by several AFDD software tools, that contain a mixture of condition-based and behavior-based faults. Therefore, it is important to address any potential overlap or duplication with a well-designed taxonomy and careful mapping to this taxonomy from the AFDD.

Another question concerns the relationship between fault presence and fault detection. In a temporal sense, a fault that is not addressed could be flagged by an AFDD tool intermittently over time. A stuck economizer damper fault might be undiagnosable with some diagnostic approaches when the system is not calling for economizing; a valve leak may only be detected when a threshold of flow leakage is exceeded; etc. AFDD approaches also may deliberately or inadvertently miss faults that have a small severity. The planned field verification portion of the project is one approach that will help to address this challenge, but other data-driven approaches also will be needed.

Preliminary data review and analysis is proving insightful as we gain a more granular understanding of HVAC fault prevalence. The study team is also working to address many data-related challenges, with one in particular being the interpretation of fault absence. For instance, the absence of a fault record may indicate fault-free operation but could potentially be due to the lack of a specific component type (e.g., an AHU without a heating coil cannot have a heating coil valve leakage fault), or an AFDD software tool was not programmed to identify that fault. Each AFDD dataset is being validated separately, in collaboration with the data provider, to address these types of issues.

4. CONCLUSIONS

The results presented here are preliminary and illustrate how fault prevalence can be assessed in various dimensions. These results are not intended to indicate the final representative fault prevalence for any specific fault type. The team continues to add new data, quality check the data, and validate the data in partnership with the AFDD providers. The process for unifying data from disparate AFDD tools is labor-intensive. The authors have developed a method for mapping this data to a common taxonomy of HVAC faults that facilitates unification and comparison of the data and has the ability to allow related faults to be aggregated together.

Preliminary metrics have also been developed to provide information related to specific questions that we believe that the study's audience will find useful. As the study proceeds, we will analyze data by fault type, by building type, and by HVAC system type. We will gather additional data, including data from new data providers; perform statistical analyses to assess national representativeness, precision and confidence, and drivers of prevalence; and validate a subset of results using field study data from manual site inspections. We are also implementing additional metrics that can provide new insights about the data.

This study will conclude in 2022 and is on track to generate the largest empirical study to date on HVAC fault occurrence rates in existing commercial buildings. Future work could potentially apply the same methods to other equipment types (e.g., chillers); evaluate the persistence of fault resolution; analyze longer term fault trends; and assess the relationship between fault rates, false positives and negatives, and the use of different fault detection algorithms.

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