# Crowdsourcing Building Occupant Complaints to Aid Fault Detection and Diagnosis

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## Abstract

Numerous fault detection and diagnosis (FDD) methods for buildings have been developed but many faults are still undetectable. There are also several crowdsourcing applications developed to collect building occupants' input. However, there is no solid framework enabling building operators to make the most of the collected data and directly integrate it into FDD. To end this, a framework is proposed to transform occupant feedback into insightful technical contextual information, which supports building operators to make more informed decisions. According to the spread (e.g., multiple on a floor or zone) of problems and their severity computed from sensor readings, local and/or central rulesets are used. Through this framework, the data collected by crowdsourcing occupants' feedback applications are used more effectively for FDD purposes. The advantages of this framework are demonstrated through occupants' feedback and measured data extracted from maintenance management and building automation systems, respectively, for an academic office building in Ottawa, Canada.

## Introduction

Although various FDD methods have been developed in the literature and are currently used in buildings, there are still some problems preventing these tools from effectively diagnosing faults that detrimentally affect energy and comfort performance. Firstly, FDD tools provide an overwhelming number of alarms, many of which are inevitably ignored (Deshmukh et al., 2018). Secondly, occupant concerns are prioritized since occupants' comfort, health, and productivity are economically more significant than the cost of energy. However, where occupant complaints are addressed, it is often done on an ad hoc basis that is likely to satisfy the occupant but not necessarily improve overall performance or find the root cause of the issues. For instance, after investigating many examples, we noticed complaints often trigger superficial solutions, such as overriding temperature setpoints, without addressing underlying controls hardware and software issues. This situation intensifies when building operators' decisions neither satisfy occupants nor improve the energy efficiency of buildings.

Moreover, users' subjective feedback (complaints) has not been managed and analyzed by FDD methods. In fact, facility management (FM) organizations can integrate complaint management into FDD processes. This integration presents an opportunity to introduce a new framework that leverages new sources of information, such as occupants' input, to support operational energy decisions.

Furthermore, newly emerging concepts such as crowdsourcing and occupant voting systems (OVS) which utilize new devices smartphones and smartwatches allow FM service providers to combine high-quality subjective feedback on a large scale with sensor measurements. Many researchers have developed smartphone applications to assess the occupants' comfort (Konis et al., 2020; Lazarova-Molnar et al., 2017; Pritoni et al., 2017). Jayathissa et al. (2020) presented a methodology to collect longitudinal subjective feedback on comfort preferences through a smartwatch platform. They also aimed to predict the occupant comfort to supplement the objective environmental sensor data. Likewise, Khan et al. (2021) applied OVS to identify misalignment between the collected votes and monitored IEQ variables as well as to demonstrate its use to detect problematic IEQ conditions. Although both studies acknowledged that such data collection platforms could facilitate detecting building anomalies, their detection processes require operators' interpretations. The connection between these platforms and FDD methods has remained unclear and non-systematic. Pritoni et al. (2017) put one step ahead by integrating thermal comfort votes into the control logic of a building. Another paper assessed the impact of OVS on energy use and the energy-saving opportunities presented by trying different control strategies based on occupants' feedback (Khan & Kolarik, 2021b). They concluded that this system could save energy and improve occupant satisfaction in occupant-centric control strategies (Khan & Kolarik, 2021a).

One of the earliest frameworks that aimed to integrate mobile crowdsourcing into a cloud-based collaborative FDD system was conducted by Lazarova-Molnar and Mohamed (2017). They collected and stored both crowdsourced and metered data in the cloud to validate and label them as either correct or anomalous building functioning. Then, association rules with anomalous and

correct building behaviour were automatically extracted. However, the application of crowdsourced data was not clear in that framework, and the technical context provided by them was limited to the validation of occupancy. The criteria of the framework making a distinction between anomalous and correct behaviour must be expanded.

This study proposes a new workflow that integrates occupant-based inputs into FDD methods. To demonstrate how occupants' inputs such as thermal comfort feedback can integrate into FDD methods, a practical framework is also developed. Crowdsourcing increases the number and granularity of occupant inputs, and consequently, they provide FDD tools with more reliable data. As a result, FDD methods will generate more accurate outputs, and building operators will better understand the problems' severity and root causes. Therefore, this methodology can be an extension of crowdsourcing platforms as the studies in the literature have primarily focused on the data collection of crowdsourcing rather than employing them for FDD purposes. This paper takes crowdsourced data as input and transforms them into more technical contexts with the help of FDD tools so that building operators make more informed operational decisions. This study includes the FDD methods focused on HVAC systems. However, we aim to develop this concept and apply it to other types of occupant comfort and building systems in future. Evidently, this study only takes HVAC-related occupants' feedback as input to the framework.

This paper first describes the aforementioned workflow and framework in detail. Next, a few problems that could be more effectively responded to if this approach was employed are exemplified. This way, the impact of the framework, as well as the technical context provided by using it, will be revealed.

## Methods

This section first describes how maintenance teams utilize FDD methods and conventionally react to occupants' input. Next, a new conceptual workflow is proposed in which the sequence of activities is rearranged so that the integration of FDD tools into crowdsourcing as well as complaint management becomes feasible. Finally, a framework for HVAC-related inputs is developed to demonstrate how the proposed workflow can be implemented in practice.

### Proposed workflow

As shown in Figure 1(a), FDD tools are designed to generate alarms in a conventional workflow. Simultaneously, occupants' input is also considered ad hoc whenever they are dissatisfied with indoor qualities and report an issue. Additionally, the building operators observe some anomalies in their inspections. However, they tend to focus on system-level issues rather than local and zone-level components as the energy-saving opportunities at system-level analysis are more rewarding. Although maintenance teams take advantage of both information sources of FDD alarms and human input (occupants' complaints and operators' reports), these sources are used separately without having a clear connection with each other.

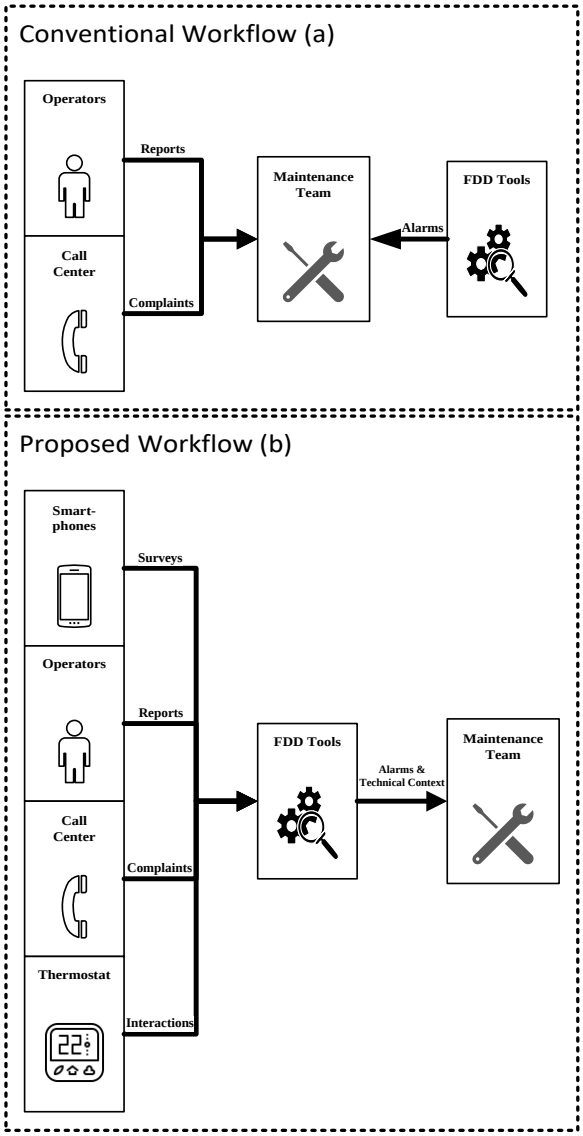


*Figure 1. Conventional (a) and proposed (b) workflows utilizing information sources (the thermostat icon was provided by 'Flaticon.com')*

We conceptualize a new workflow (Figure 1 (b)) by which FDD tools provide more technical context for maintenance teams by analyzing the crowdsourced inputs, including smartphone/smartwatch surveys or virtual thermostats, operators' reports, service calls, and thermostat interactions. In fact, the application of FDD tools is extended, and they not only independently generate alarms but also take and analyze the inputs coming from occupant-based sources. When an occupant complains, a practical framework explained later prompts FDD methods to generate contextual information by using the data available. By changing the sequence of activities, building operators can

leverage FDD tools when reacting to a report or complaint, which enhances their knowledge about the root cause of an issue. Moreover, as a result of using crowdsourcing, more granular and accurate feedback is available, allowing operators to identify and react to anomalies more effectively and quickly.

**A framework to implement the integration concept**

This framework is an additional tool where building operators deal with complaints or whenever there is an input provided by one of the crowdsourcing sources. Therefore, it is not necessarily a continuous FDD method. This process is request- and occupant-driven, but building systems' performance is almost constantly monitored thanks to the nature of crowdsourcing. As shown in Figure 2, the steps of the framework linking crowdsourcing and complaint management with FDD methods for occupant feedback are as follows:

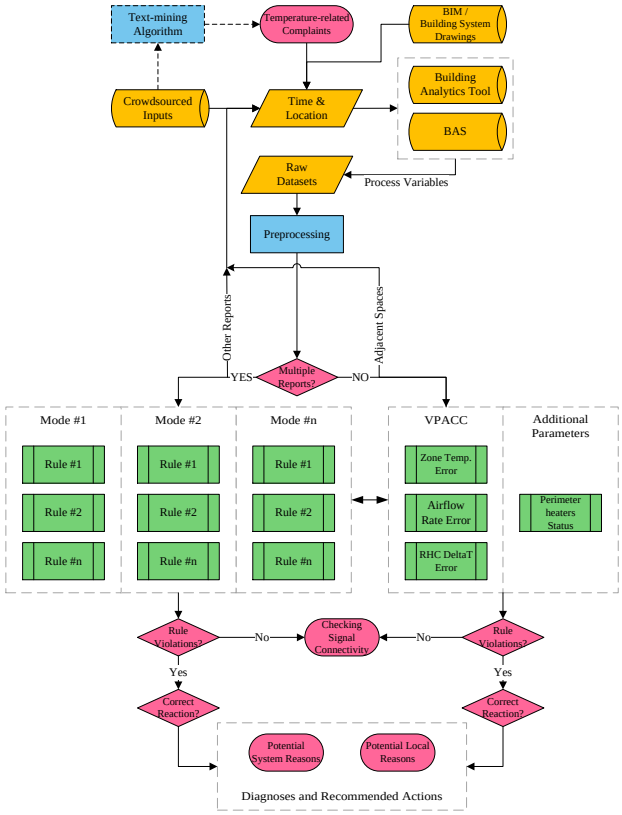


*Figure 2. A framework that applies the proposed workflow to HVAC-related issues*

1. Some data sources may be collected in verbal forms, such as traditional surveys or service calls. They may need to be analyzed and classified by text-mining algorithms. This step can simply be skipped for the tools collecting these inputs in a structured and machine-interpretable manner. In this step, occupants' input is analyzed to catch and collect the following information: time, location (building, floor, room), service trade and provider (plumbing, HVAC, control; vendor, contractor, in-house technicians etc.), nature of the report (e.g., "too hot" or "too cold"). The required text-mining techniques were developed in the previous publications (Dutta et al., 2020; Nojedehi et al., 2021; Villeneuve & O'Brien, 2020).
2. Since a part of the analysis requires information about higher-level components such as heating/cooling systems or air handling units (AHUs), the additional information such as the IDs of the thermal zone or AHU serving a particular space can be retrieved automatically from relational databases providing BIM models are in place. Otherwise, the information must be manually given from building systems drawings.
3. Based on the time and location, the datasets of associated process variables such as air and water temperature and flowrates trends (at the room, zone, and system levels), as well as the status of valves and dampers, will be retrieved from the building automation system interfaces. This step may be repeated if there are multiple reports on a floor or zone or when the adjacent spaces are being analyzed.
4. After implementing prepossessing techniques, including removing nonsensical values, matching, and merging, the framework prompts two rule-based FDD methods focused on HVAC systems. This framework, including the FDD methods, is occupant-driven and triggered by crowdsourced inputs; hence it is not necessarily used continuously. The framework applies the FDD methods to the preprocessed datasets. The FDD methods utilized herein are VPACC (VAV Box Performance Assessment Control Charts) (Schein & House, 2003) and APAR (air handling unit performance assessment rules) (Schein et al., 2006). They will be briefly explained later. Other FDD methods can be used in this framework depending on the building system or types of comfort that are meant to investigate.
5. If there are limited and scattered complaints, only VPACC is used. However, the framework also investigates the (adjacent) spaces served by shared VAVs or HVAC systems to ensure that they are working properly according to VPACC. If other spaces perform improperly or when multiple reports on a floor or zone are issued on the same day, AHU-level rules (APAR) are also checked in addition to VPACC.
6. If none of the rules proposed by these two FDD methods are violated while the occupants register an issue, the framework suggests operators check the connectivity of the associated control devices and sensors. By doing that, the building operators ensure that the measured data are reliable and the lack of errors actually implies that there is no issue at all. A similar problem will be exemplified later in Results and Discussion.

This framework leverages those aforementioned FDD methods as they are already well-established for HVAC

systems, but other methods can be replaced depending on maintenance needs.

**VPACC**

VPACC is a local zone-level fault detection tool that uses a few control charts to assess the performance of VAV boxes. The basic concept behind this approach is to accumulate the error between a process variable and the expected value of the variable. It takes the process variables of indoor air temperature, air flowrate, and reheat coil differential temperature into account. The definition of error for each process variable is given in Table 1. The process of transforming the listed errors to cumulative sum (CUSUM) along with the associated parameters are explained in detail in the literature (Schein & House, 2003). The temperature error is modified herein as the control logic was different in our case study. VPACC takes a set of constant cooling and heating setpoints when computing zone temperature error. In contrast, there is one variable setpoint in this case study. Hence, we introduce another parameter named zone temperature threshold, which is computed according to the standard deviation of zone temperature under the normal operating condition where no fault is reported ($\varepsilon_{t,z} = 0.6℃$) (Schein & House, 2003). This study assigns other statistical parameters and allowable CUSUM thresholds based on Schein's recommendations (2003). VPACC considers the occupancy of spaces, but a fixed schedule is proposed in this framework because it might be unavailable in some cases.

*Table 1. The definition of error for the process variables in VPACC (Schein & House, 2003)*

| Process Variable | Formula |
|---|---|
| Airflow rate | $Q_{error} = Q_{actual} - Q_{setpoint}$ |
| | $\lvert Q_{error}\rvert = \lvert Q_{actual} - Q_{setpoint}\rvert$ |
| Temperature | IF : $T_{zone} > T_{sp} + \varepsilon_{t,z}$<br>Then: $T_{error} = T_{zone} - T_{sp} - \varepsilon_{t,z}$ |
| | IF : $T_{zone} < T_{sp} - \varepsilon_{t,z}$<br>Then: $T_{error} = T_{zone} - T_{sp} + \varepsilon_{t,z}$ |
| | IF : $T_{sp} - \varepsilon_{t,z} \leq T_{zone} \leq T_{sp} + \varepsilon_{t,z}$<br>Then: $T_{error} = 0$ |
| Reheat coil differential temperature | IF : $u_{hc} = 0$<br>Then: $\Delta T_{error} = T_{discharge} - T_{entering}$ |
| | IF : $u_{hc} \neq 0$<br>Then: $\Delta T_{error} = 0$ |

One or more process variables may be disregarded due to data unavailability in some cases. The space may be equipped with other pieces of HVAC equipment such as perimeter heaters. Their malfunction not only wastes energy but also causes discomfort. Thus, they provide building operators with insightful contexts when a complaint is received. Hence, we also include their datasets such as valve status or temperature differential if available when conducting an investigation.

**APAR**

APAR represents an FDD method that assesses the performance of system-level units (e.g., AHUs) by using a set of rules. APAR uses control signals and occupancy information (if available) to identify: firstly, the mode of operation of the AHU, and secondly, a subset of the rules determining temperature relationships that are applicable for the mode identified in the first step. The operating modes are heating (Mode 1), cooling with outdoor air (Mode 2), mechanical cooling with 100% outdoor air (Mode 3), mechanical cooling with minimum outdoor air (Mode 4), and unknown occupied mode (Mode 5). APAR has a total of 28 rules. An excerpt of the ruleset is given in Table 2 that summarises the subrules for Mode 3 and 4 since our examples are only relevant to these modes herein. In this table, when a rule is true, that implies the existence of a fault. This paper takes the thresholds and values for process parameters and errors proposed by Schein et al. (2006). Evidently, other FDD methods complement this framework as other high-level systems may be the root cause of discomfort. However, this framework only adopts two tiers of HVAC systems investigation for simplicity.

The next section investigates a few examples where the operators did something hasty but not optimal in response to an occupant complaint (e.g., overriding setpoints). Moreover, we will show how they could react more effectively if they utilized our framework instead: the recommended actions.

*Table 2. An excerpt of APAR ruleset for modes 3 and 4 (Schein et al., 2006)*

| Mode | Rule | Rule Expression |
|---|---|---|
| Mechanical Cooling with 100% Outdoor Air (Mode 3) | 8 | $T_{oa} < T_{sa,s} - \Delta T_{sf} - \varepsilon_t$ |
| | 9 | $T_{oa} > T_{co} + \varepsilon_t$ |
| | 10 | $\lvert T_{oa} - T_{ma}\rvert > \varepsilon_t$ |
| | 11 | $T_{sa} > T_{ma} + \Delta T_{sf} + \varepsilon_t$ |
| | 12 | $T_{sa} > T_{ra} - \Delta T_{rf} + \varepsilon_t$ |
| | 13 | $\lvert u_{cc} - 1\rvert \leq \varepsilon_{cc}$ and<br>$T_{sa} - T_{sa,s} \geq \varepsilon_t$ |
| | 14 | $\lvert u_{cc} - 1\rvert \leq \varepsilon_{cc}$ |
| Mechanical Cooling with Minimum Outdoor Air (Mode 4) | 15 | $T_{oa} < T_{co} - \varepsilon_t$ |
| | 16 | $T_{sa} > T_{ma} + \Delta T_{sf} + \varepsilon_t$ |
| | 17 | $T_{sa} > T_{ra} - \Delta T_{rf} + \varepsilon_t$ |
| | 18 | For $\lvert T_{ra} - T_{oa}\rvert \geq \Delta T_{min}$:<br>$\lvert Q_{oa}/Q_{sa} - (Q_{oa}/Q_{sa})_{min}\rvert > \varepsilon_f$ |
| | 19 | $\lvert u_{cc} - 1\rvert \leq \varepsilon_{cc}$ and<br>$T_{sa} - T_{sa,s} \geq \varepsilon_t$ |
| | 20 | $\lvert u_{cc} - 1\rvert \leq \varepsilon_{cc}$ |

## Results & Discussion

We demonstrate herein how the framework developed utilizes FDD methods to manage complaints in practice and transform crowdsourced input into a more technical context when building operators deal with occupants' reports. The examples are chosen from an academic office building in Ottawa, Canada.

**Example 1: a local remedy for a central issue!**

In this example, an occupant is dissatisfied with the indoor air temperature and quality of the room they work in: "Very hot, stuffy and no airflow in room 6209". After pre-processing the associated datasets, As shown in Figure 3: the indoor air temperature of the room was beyond the comfort range (even about 28ºC) before the building operator reacted to this issue. The building operators responded to this complaint by overriding the temperature setpoints without investigating the conditions of adjacent spaces or system-level components. That reaction was not effective, and even the air temperature reached above 30 ºC later for the reason that will be explained. It is worth noting that the building operators only overrode the zone temperature setpoint in response to this issue. Further analysis provided in this section was done based on our proposed methodology.

Figure 4 also shows after the operators' reaction, the situation worsened as one of the outputs of VPACC, CUSUM error of zone air temperature, has been reached the positive threshold (=1000) multiple times, but VPACC method is not sufficient alone to identify the root cause when the system-level components play a role.

Alternatively, the building operators could go through the framework developed in which we combine VPACC with other FDD methods and information sources. First, the air temperature error of adjacent rooms, according to Table 1, is also investigated to verify that the issue is local or central. Figure 3 shows that the other spaces (e.g., room 6208) have a similar temperature trend. Therefore, the AHU supply air temperature is monitored as a system-level parameter. By doing that, the operators would realize that overriding a thermostat would not resolve the issue as the supply air temperature is also elevated during this period. Secondly, system-level investigations are necessary.

The framework successfully determines that the root cause may originate from AHU. Hence the second tier of investigation is conducted. Then, the framework first identifies the mode of operation of the AHU as cooling, but it may fluctuate between Mode 3 and Mode 4 in the shoulder seasons as the outdoor air temperature varies (Bruton et al., 2015). Mode 3 brings in the maximum outside air with cooling. The outdoor air damper is fully open to provide the lowest mixing box temperature when the outside air temperature is above the supply air temperature setpoint but below the return air temperature. It is still necessary to mechanically cool down the air stream to the supply air setpoint. On the contrary, Mode 4 takes in the minimum outdoor air with cooling. When the outdoor air temperature rises above the return air temperature, the outdoor air damper is assigned to its minimum position to supply the lowest possible mixed air temperature and simultaneously minimize mechanical cooling.

The framework checks the rulesets proposed by APAR for both modes. For instance, Rule #11 in Mode 3 and Rule #16 in Mode 4 state that supply air temperature should be less than mixed air temperature; otherwise, AHU is not functioning properly. Likewise, Rule #12 in Mode 3 and Rule #17 in Mode 4 state that supply air temperature should be less than return air temperature otherwise, there is a malfunction in the AHU.

The temperature rises across the supply and return fans (1.1 ºC), as well as temperature threshold (2 ºC), are computed based on the APAR's suggestion. After these values are applied to the equations, it is revealed that the mentioned rules are violated as the pattern of their violations is shown in Figure 5, which means the AHU does not function properly. APAR suggests a set of possible reasons cause the violations of these rules.

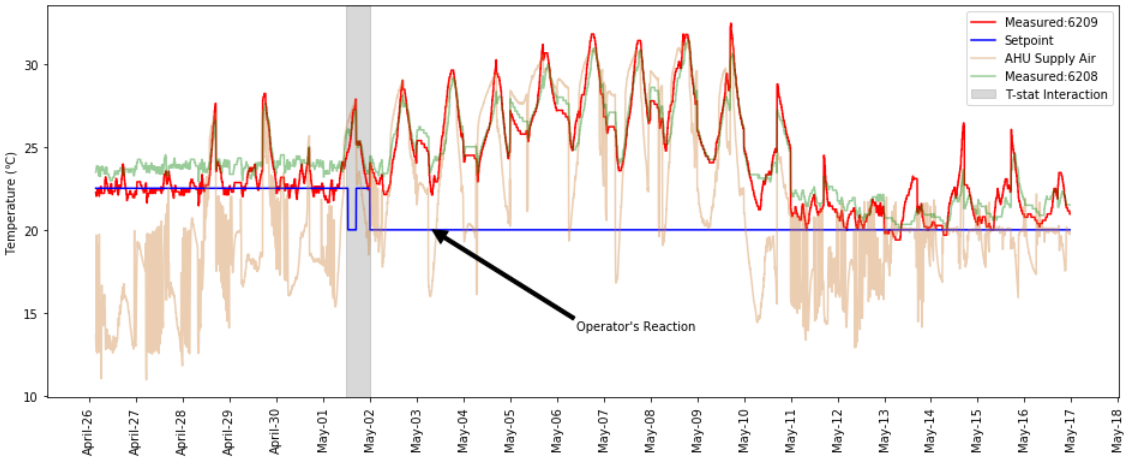


*Figure 3. Measured air temperatures and setpoint*

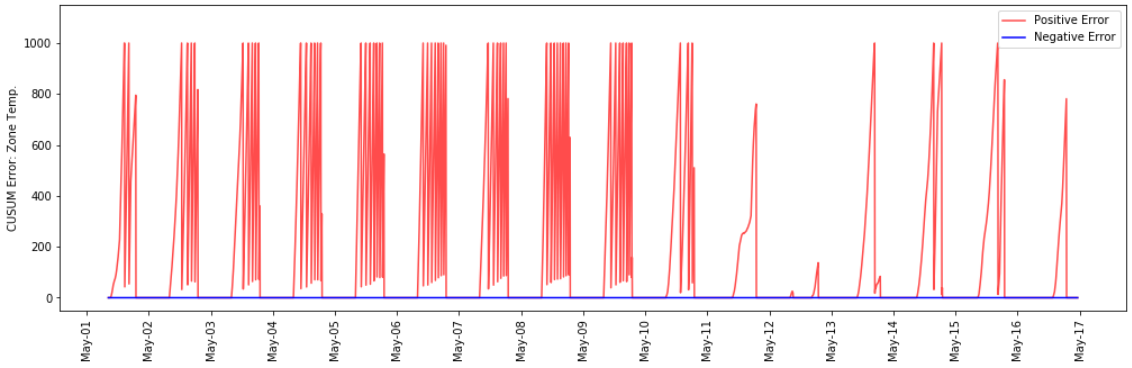


*Figure 4. CUSUM errors for zone air temperature after the* operator's reaction: example 1

Further analysis proved that no chilled water had been provided in that period while the building operator reacting to this report was not aware of this issue. This example demonstrated how occupants' feedback is transformed into a more technical context through the proposed framework so that building operators make more informed operational decisions.

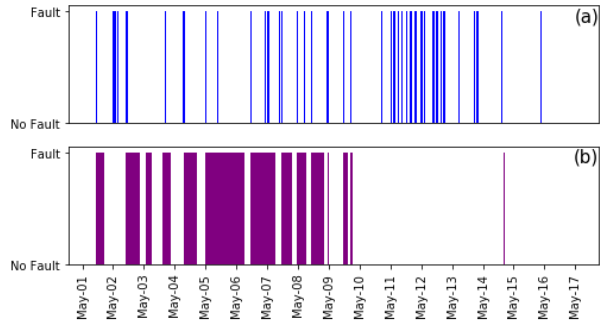


*Figure 5. The pattern of violation of Rule 11 & 16 (a) and Rule 12 & 17 (b) in Mode 3 and 4 after the operator's reaction*

**Example 2: humans-as-a-sensor verifies measurements**

In this example, the classroom occupants have complained about the indoor air temperature multiple times. Figure 6(a) shows that the indoor temperature has constantly been almost equal to the setpoint with no variation for about two weeks. The occupants interacted with the thermostat multiple times, but the temperature setpoint reverted to the default value at the beginning of each day based on the control logic defined in this building. For this reason and because the thermostat was overridden at late hours of the day when the occupancy was almost zero, no positive or negative error was computed, as shown in Figure 7. Also, the other HVAC components, either local or central, were normally reacting to changes as the local components shown in Figure 6(b-c). Thus, system-level FDD methods cannot also identify any issue as no rule was violated. As described earlier, the framework proposes to check the connectivity of sensors when occupants complain, but FDD tools report no alarm.

Our further investigations demonstrated that it also applies to this example. The indoor temperature measurements are not credible because of a device connectivity issue. After the occupant's report and fixing the connectivity issue, VPACC algorithm has managed to trigger a reasonable number of alarms. Similar issues repeated two more instances in this space and lasted each time for about one and four months. They were reported by occupants every time. Suppose crowdsourced inputs, including thermostat interactions, were integrated into FDD methods proposed in the framework. In that case, such issues would be identified more quickly. More accurate reactions could be made instead of superficial solutions such as overriding temperature setpoints.

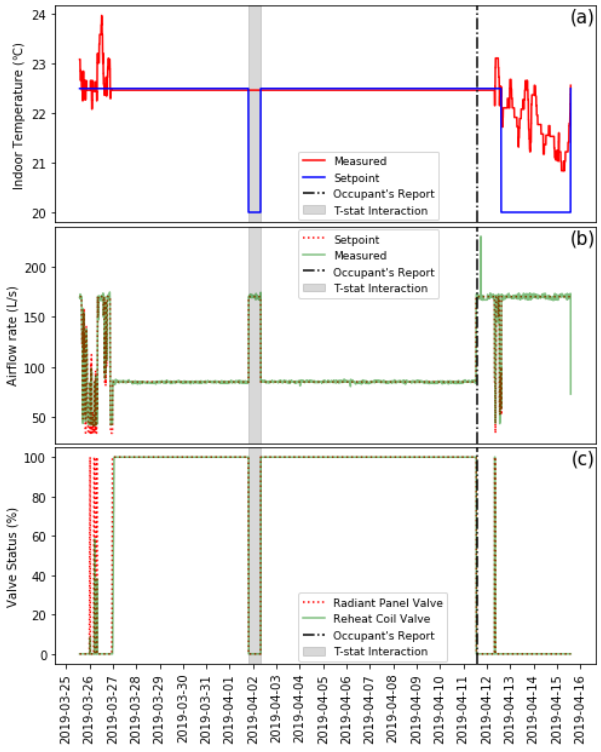


*Figure 6. humans-as-a-sensor identifies the lack of control connectivity (a) while HVAC components are performing normally (b & c)*

In fact, humans-as-a-sensor can almost continuously complement the control and FDD systems as additional living sensors. These examples demonstrated that the lack of technical context could lead to inappropriate reactions regardless of building operators' expertise and knowledge about the buildings.

In both examples, the occupants have been dissatisfied with the thermal and indoor air quality multiple times for days or weeks. Moreover, many occupants working in other spaces on the same floor or under a shared HVAC system have never complained. However, if better technologies such as crowdsourcing were employed, FM organizations could collect their feedback earlier. As a result, not only would the occupant be satisfied with their indoor qualities, but also the energy performance of the building would be improved. Other aspects of occupants' well-being were not covered in this work. This work is limited to HVAC systems and the associated occupant feedback. Yet, using crowdsourcing inputs for FDD purposes can also be applicable to them if appropriate methods are linked to this framework.

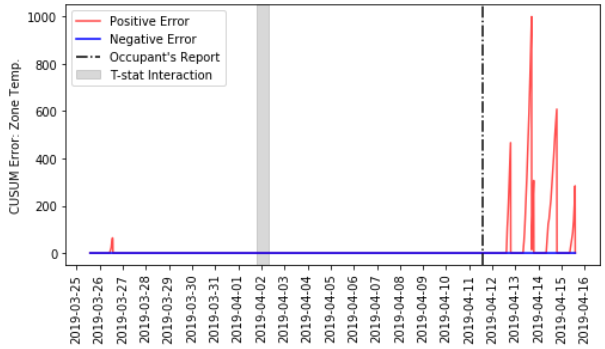


*Figure 7. CUSUM errors for zone air temperature: example 2*

## Conclusion

In this paper, we proposed a workflow that changed the sequence of activities to facilitate integrating crowdsourcing and complaint management into FDD tools. Also, the proposed workflow was demonstrated by a practical framework on the occupants' inputs. This framework focusing on HVAC systems included two tiers of investigation for either local or central issues and was based on single or multiple reports on a floor or zone. We utilized VPACC methods for local issues and APAR for central issues and where multiple negative votes were reported as FDD methods. However, other tiers of investigation may be applicable depending on the data availability and the nature of building systems. This kind of additional FDD method can extend the applicability of this framework. As a result, we only take HVAC-related occupants' feedback at this point.

The framework was demonstrated on different examples, and it is revealed that it helps building operators make more informed operational decisions by knowing the spread and severity as well as the root cause of a complaint. This certainly reduces the number of hasty but not optimal reactions, which improve the energy efficiency of buildings and occupants' satisfaction.

This work can link with the existing crowdsourcing data collection platforms as it complements their functionality because they tend to focus on assessing indoor environmental qualities rather than FDD purposes. We aim to fully link this methodology to longitudinal inputs to extend its functionality to a continuous integration rather than a request-driven connection on an on-demand basis. This way, we also assess how accurate the alarms triggered by FDD tools are. Moreover, building operators can adjust the threshold limits based on occupants' customized numbers rather than a constant number for all cases. Furthermore, smartwatches that collect occupants' physiological attributes such as heart rate or near body temperature sensors can trigger FDD tools whenever these attributes deviate from the acceptable ranges; this may reveal the relationships between the control thresholds and occupant's wellbeing.


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## Nomenclature

| | |
|---|---|
| $Q_{actual}$ | measured VAV airflow rate |
| $Q_{error}$ | VAV airflow rate error |
| $Q_{setpoint}$ | VAV airflow rate setpoint |
| $\frac{Q_{oa}}{Q_{sa}}$ | outdoor air fraction |
| $\left(\frac{Q_{oa}}{Q_{sa}}\right)_{min}$ | threshold on the minimum outdoor air fraction |
| $T_{co}$ | change-over air temperature for switching between modes 3 and 4 |
| $T_{discharge}$ | temperature of the air leaving the reheat coil |
| $T_{entering}$ | temperature of the air entering the reheat coil |
| $T_{ma}$ | mixed air temperature |
| $T_{oa}$ | outdoor air temperature |
| $T_{ra}$ | return air temperature |
| $T_{sa}$ | supply air temperature |
| $T_{sa,s}$ | supply air temperature setpoint |
| $T_{sp}$ | zone temperature setpoint |
| $T_{zone}$ | zone temperature |
| $u_{cc}$ | normalized cooling coil valve control signal |
| $u_{hc}$ | normalized reheat coil valve control signal |
| $\Delta T_{error}$ | reheat coil differential temperature error |

$\Delta T_{min}$ threshold on the minimum temperature difference between the return and outdoor air

$\Delta T_{rf}$ temperature rise across return fan

$\Delta T_{sf}$ temperature rise across supply fan

$\varepsilon_{cc}$ threshold for cooling coil valve signal control

$\varepsilon_f$ threshold parameter for errors related to airflows

$\varepsilon_t$ threshold for errors in (AHU) temperature

$\varepsilon_{t,z}$ threshold for errors in zone temperature

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