Development of Self-correction Algorithms for Thermostats Using OpenAPI Capabilities

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ABSTRACT

Advanced HVAC data analytics tools such as fault detection & diagnostics (FDD) are growing in popularity in large commercial buildings, and recent research has demonstrated potential for such tools to automatically correct certain faults. However, market adoption of such technologies is very low in small- and medium-sized buildings (SMBs). Furthermore, a lack of on-site maintenance teams and limited maintenance expenses restrict rapid, effective resolution after faults occur and are identified in HVAC systems. Those factors could cause significant energy waste and downgrading system performance (e.g., decreased occupant comfort and reduced system lifetime). Considering commercial buildings under 50k square feet comprise 94% of all commercial buildings in the U.S, there is a significant need to develop cost-effective solutions for those buildings.

While much attention has been given to the benefits of basic smart thermostats, more prevalent mid-tier connected thermostats provide significant untapped opportunities to advance the state of operational practice in SMBs. These devices now offer *two-way* APIs that can be combined with everyday computing resources to open the door to continuous, automated monitoring and correction of the most common problems in HVAC control settings. Such technology presents the potential for a lightweight solution to address monitoring and control barriers.

In this paper, we present the results of a study to develop self-correction algorithms to correct common setting faults in SMBs, including inefficient HVAC setpoints, and wrong schedule setting when using thermostats. The detection and self-correction actions were achieved by employing two-way APIs embedded in thermostat products. The developed correction algorithms were evaluated in a lab environment. The results show that common thermostat setting faults can be efficiently corrected. Consequently, energy waste that commonly goes undiscovered, can be effectively avoided. We conclude with a discussion of how these solutions can be delivered to market by OEMs or as managed service offerings from thermostat installers and other service providers.

Key works

Fault correction, smart thermostat, fault detection and diagnostics, OpenAPIs

1. INTRODUCTION

In the U.S, HVAC systems in buildings are responsible for around 44% total electricity consumption (Energy Information Administration, 2016). In addition, it is reported that HVAC systems for air conditioning release 1,950 million tons of carbon dioxide, which is equal to 3.94% of global greenhouse gas emissions (*NREL*, 2022). Fault free operation of HVAC systems is critical to ensure the system operation performance and energy efficiency. However, various types of faults in HVAC systems have been widely reported in commercial buildings (Kim et al., 2021). For example, it is reported that 30% of air terminal units (e.g., variable air volume boxes) experience faults in commercial buildings (Crowe et al., 2023). Faults and malfunctions in HVAC systems can cause considerable negative impacts on system operational performance, and consequently increase energy consumption and carbon emissions, lower occupant comfort, as well as increase maintenance costs. For instance, it is estimated that 5% to 30% of energy waste are caused by various types of faults in various equipment and systems in commercial buildings (Katipamula & Brambley, 2005).

Fault detection and diagnostics (FDD) technology, which is core in the energy management and information system (EMIS) solution, employs multiple data sources such as building automation systems (BAS) operation data and interval meter data to run various advanced algorithms to identify system faults in HVAC systems (Lin et al., 2022). It is reported that the employment of FDD in EMIS tools can achieve a median 9% whole building energy savings (Lin et al., 2020).

Faults in HVAC systems can persist very long due to untimely maintenance after the FDD tool flags the faults (Crowe et al., 2023). For example, a study showed that the average maximum continuous reported fault duration for a zone temperature sensor frozen fault can be more than 70 days when the fault was detected and flagged by the FDD tool (Chen et al., 2022). It indicates that when this fault occurs and is detected, the fault tends to be neglected by the facility team. This situation causes the loss of energy saving potential even if FDD technologies are deployed in commercial buildings. To address this issue, some fault correction strategies were developed to quickly address some faults when they are detected and diagnosed by FDD tools (Fernandez et al., 2009; Lin et al., 2020; Padilla et al., 2015; Pritoni et al., 2022). Here, the faults that are correctable are some software setting faults (e.g., inefficient schedule settings) or control parameter setting faults (e.g., improper PI parameter settings). In the fault correction practice, a two-way communication technology was developed to unlock the capability of interfacing with the BAS through the EMIS tool. Using this technology, the EMIS tool cannot only query data from the BAS, but also write back signals to correct certain types of faults (Pritoni et al., 2022). Consequently, the fault correction technology can significantly reduce the maintenance response time after a fault is detected and flagged, and hence avoid energy waste due to delayed maintenance of the HVAC systems in large commercial buildings.

However, in small- and medium- sized buildings (SMBs, i.e., less than 50,000 square feet), where the BAS and EMIS tools are seldom deployed and there is a lack of professional maintenance team, HVAC system faults cannot be efficiently detected and addressed quickly (Katipamula et al., 2012). As a result, it can dramatically increase energy waste and downgrade system performance (e.g., decreased occupant comfort and reduced system lifetime) in SMBs. Considering commercial buildings under SMBs comprise 94% of all commercial buildings in the U.S (Energy Information Administration, 2016), there is a significant need to develop cost-effective solutions for those buildings.

Today, thermostats are widely used to control HVAC equipment (e.g., rooftop units and air terminal units). Smart thermostats offer programmable capabilities to allow users to more efficiently control or manage HVAC equipment to satisfy occupant comfort, as well as enhance energy efficiency (Özgür et al., 2018).

Additionally, smart thermostats can communicate with other devices or cloud-based services through the Internet. Those features provide smart thermostats with significant potential to monitor and control HVAC systems in SMBs in a cost-effective manner (Rovito et al., 2014). Moreover, more and more thermostat products provide open application programming interfaces (OpenAPIs), which allow users to read from and write to thermostats. This feature releases the possibility of continuously correcting certain software setting faults, which are commonly observed in HVAC system operation in SMBs.

This paper presents the development of the FDD and correction algorithms using OpenAPIs for smart thermostats. Tests in the lab environment demonstrate the effectiveness of the developed algorithms. The developed algorithms can be embedded into the smart thermostats to build a light-weight monitoring and control solution, which is suitable for applications in SMBs.

The remainder of the paper is organized as follows: Section 2 introduces the fault detection and correction algorithms developed for smart thermostats. Section 3 illustrates the tests that were implemented in the lab environment, and presents the results. Section 4 concludes the paper and proposes the future work.

2. METHODOLOGY

Non-optimal HVAC control software settings, such as inefficient temperature setpoint settings, and schedule settings mismatched to occupancy, are common faults in HVAC system operations caused by human errors (Torabi et al., 2022). In this Section we illustrate the FDD and correction algorithms aiming to correct three common control software setting faults in thermostat applications. They are 1) overcooling (i.e., low cooling setpoint) fault, 2) overheating (i.e., high heating setpoint) fault, and 3) schedule setting fault for smart thermostats. These faults are not difficult to detect and resolve in a single RTU using manual review. The context of this study was to consider RTU control faults that occur at scale, and which can re-occur, in buildings without dedicated operations staff. For example, an owner of many small buildings would benefit from a centralized and/or automated means of ensuring that all RTUs across the portfolio are configured in line with industry best practices, and that those RTU setting are maintained long term.

2.1 Development of Overcooling and Overheating FDD and Correction Algorithm

The setpoint setting fault includes two types of settings as the "overcooling or overheating" fault (i.e., a low cooling setpoint, or a high heating setpoint), as well as the "heating and cooling setpoints too close together" fault (i.e., there is an overly narrow thermostat dead band) (Lin et al., 2015). Here, we illustrate the development of the FDD and correction algorithms for the overcooling fault and overheating fault.

To detect both faults, the current setpoint settings in the thermostat are compared with the preferred heating and cooling setpoints, respectively. The preferred setpoints can be referred to certain criteria. For example, the subset of the ASHRAE comfort zone is defined between the heating setpoint of 68°F (20.0°C), and the cooling setpoint of 74°F (23.3°C) respectively. Consequently, if the heating setpoint is identified to be higher than 68°F, or the cooling setpoint is identified to be lower than 74°F, a setpoint setting fault (i.e., overheating or overcooling) can be flagged. Then, the correction action can be initiated to correct setpoint settings.

Figure 1 illustrates the fault detection algorithm. The algorithm first collects the setpoint settings during the occupied hours of the predefined detecting duration (e.g., two weekdays in this study). Then, the setpoint values are averaged following Equations 1 and 2.

$$average\_clg\_spt = \sum_{i}^{n} cooling\_spt_i / n \qquad \text{(Eq. 1)}$$

$$average\_htg\_spt = \sum_{i}^{n} heating\_spt_i / n \qquad \text{(Eq. 2)}$$

where, n is the number of setpoint values.

After the averaged cooling setpoint and heating setpoint are calculated, they are compared with the preferred settings. If the difference between the averaged setpoint and the preferred setting is equal or higher than the threshold (e.g., 1°F in this study), a fault is flagged. For example, if the averaged cooling setting point (average_clg_spt) during the two day operation is 72°F and the preferred cooling setpoint (pre_clg_spt) is 74°F, then the difference (pre_clg_spt minus average_clg_spt) is 2 °F, which is higher than the threshold.

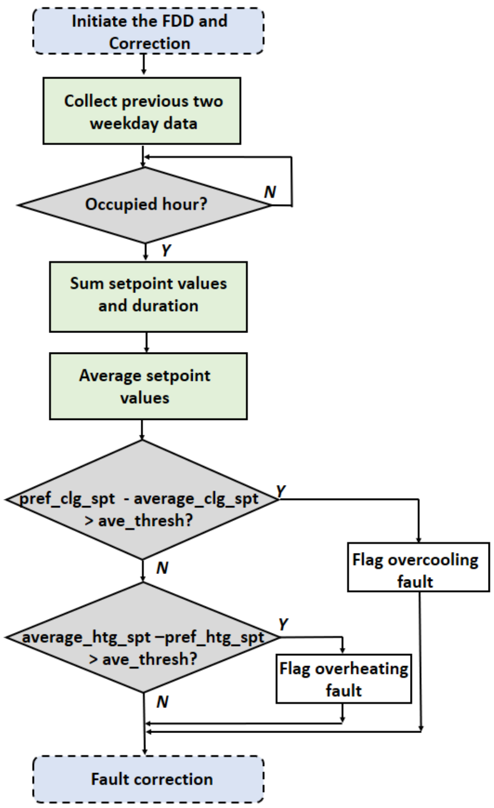

Figure 1: Fault detection algorithm.

It is noted that, the predefined detecting duration was set to two weekdays, i.e., the detection algorithm averages the setpoint settings during the occupied hours in two weekdays. This can suppress certain fault alarms and can be customized by users according to their applications.

Figure 2 illustrates the correction algorithm. The correction action is initiated by overriding the setpoint values to the preferred values after the fault detection result is received by the algorithm.

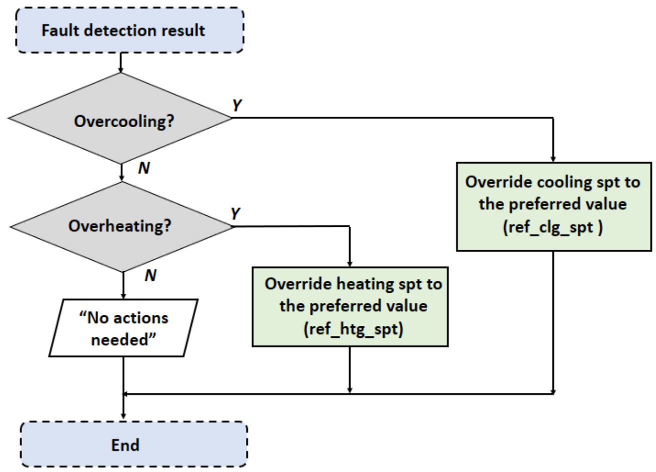

Figure 2: Fault correction algorithm.

2.2 Development of Schedule Setting FDD and Correction Algorithm

A schedule setting fault occurs when the occupants set an undesired schedule that drives the system to operate during the unoccupied period. When a schedule setting fault occurs, the HVAC system has unwanted operations, causing excessive energy consumption. The wrong schedule setting fault detection and correction includes three major scenarios as illustrated below.

Scenario 1: Operational schedule extraction

The algorithm uses the historical operation data (i.e., the cooling setpoint setting and the heating setpoint setting) to learn the operation schedule pattern, and extract the system operational schedule (i.e., the occupied start time and occupied stop time) on weekdays. This is because the thermostat does not explicitly map the occupied start time and the occupied end time to certain data points. Instead, it uses the setpoint settings under a certain time to drive the HVAC system's operation.

Step 1: A predefined number of previous weekdays (e.g., five weekdays used in this study) are collected to serve as the baseline days, when the FDD and correction algorithm is initiated.

Step 2: The timestamps of the setpoint changes are extracted. Here, the setpoint change should be higher than a threshold. This is because some setpoint changes are not intended to drive a new schedule, instead, they are overridden because the occupants may want to adjust the zone conditioning within the occupied hours. For example, if occupants need more cooling or if they need more heating, they may decrease the cooling setpoint a little or increase the heating setpoint a little. Consequently, a small setpoint change may not indicate a new schedule setting. Here, in this study, we select the cooling setpoint change threshold to be 8°F, and heating setpoint change threshold to be 6°F. The timestamps corresponding to those setpoint changes are extracted. Consequently, for each weekday, a list of timestamps when the cooling setpoint changes (from a higher value to a lower value) are higher than a threshold (i.e., 8°F), and when the heating setpoint changes (from a higher value to a lower value) higher than a threshold (i.e., 6°F), is created. Using the same scenario, the daily occupied end time can be identified as well.

Step 3: For all baseline days, daily occupied start time and occupied end time are grouped for extracting the occupied start time and occupied end time.

Figure 3 shows the operation schedule extraction algorithm.

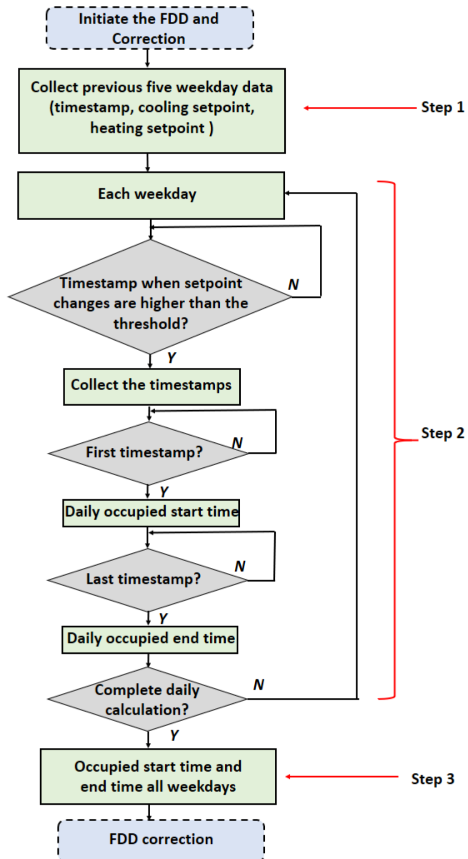

Figure 3: Schedule setting fault schedule extraction algorithm.

In the thermostat, the weekday occupied start and end time can be extracted by calculating the mean of all daily occupied start times in the list, and calculating the mean of all daily occupied end times in the list, respectively as given in Equations 3 and 4.

$$\text{weekday\_occ\_start\_time} = \text{mean}(\text{daily\_occupied\_start\_time}) \quad \text{(Eq. 3)}$$

$$\text{weekday\_occ\_end\_time} = \text{mean}(\text{daily\_occupied\_end\_time}) \quad \text{(Eq. 4)}$$

Scenario 2: Algorithm of schedule setting fault detection

The schedule setting fault was detected by comparing the occupied start time and occupied end time with the preferred settings, respectively. If the difference between the extracted schedule setting and the preferred setting is higher than a threshold, e.g., 30 minutes, then the schedule setting fault is flagged. That is, if the scheduled occupied start time is 30 minutes earlier than the preferred start time, a schedule setting fault (occupied start time too early) is flagged. Similarly, the occupied end time too late can be flagged by comparing the scheduled occupied end time and the preferred end time.

Scenario 3: Fault correction

A fault correction action is initiated by overriding the cooling setpoint and heating setpoint at a designated timestamp, which indicates the occupied start time or the occupied end time. The action is taken by using OpenAPIs to write back the new values to the thermostat. Figure 4 indicates the correction logic.

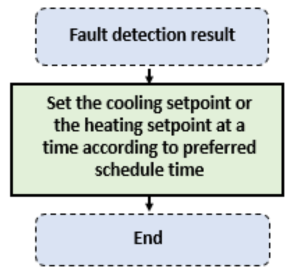

Figure 4: Schedule setting fault correction logic

2.3 Development of OpenAPIs

In this study, we selected a product, which is an example of a thermostat used in commercial building applications that has an associated OpenAPI, to demonstrate the FDD and correction algorithms in a lab setting. Table 1 lists the data points that are in the OpenAPIs to enable two-way communication between the FDD and correction algorithms (running on the local computer) and the cloud service of the thermostats.

Table 1: Data point list

No.	Point name	Property	Value entry format	Description
1	name	R/W	String	The configured name of the thermostat
2	SerialNO	R	String	The thermostat's serial number
3	dayOfWeek	R/W	String	The day of the week for this schedule set time
4	setTime	R/W	Integer	The indexed set time for this schedule entry
5	startTime	R/W	String	The time of day (24 hr format) for this schedule entry
6	system	R/W	String	The system mode
7	heatSetting	R/W	Integer	Heating setpoint
8	coolSetting	R/W	Integer	Cooling setpoint

The frequency of data query was set to be four hours, i.e., the FDD and correction algorithms query thermostat operation data from the cloud every four fours. This setting can avoid too frequent communication between the local computer and the cloud server.

3. FAULT TEST AND RESULTS

In this Section, we illustrate fault test settings, and the fault detection and correction results for two cases, i.e., wrong setpoint setting faults (including overcooling and overheating faults) and the wrong schedule setting fault.

3.1 Description of Lab Environment

The fault self-correction tests were implemented in the XR cell at the FLEXLAB at Lawrence Berkeley National Laboratory. A unitary packaged rooftop unit (RTU) conditions the zone of the testing cell, where occupant simulators are located to simulate occupants' load. The thermostat was mounted to the wall and the control signals were wired to the RTU. Figure 5 shows the testing environment and the thermostat deployment.

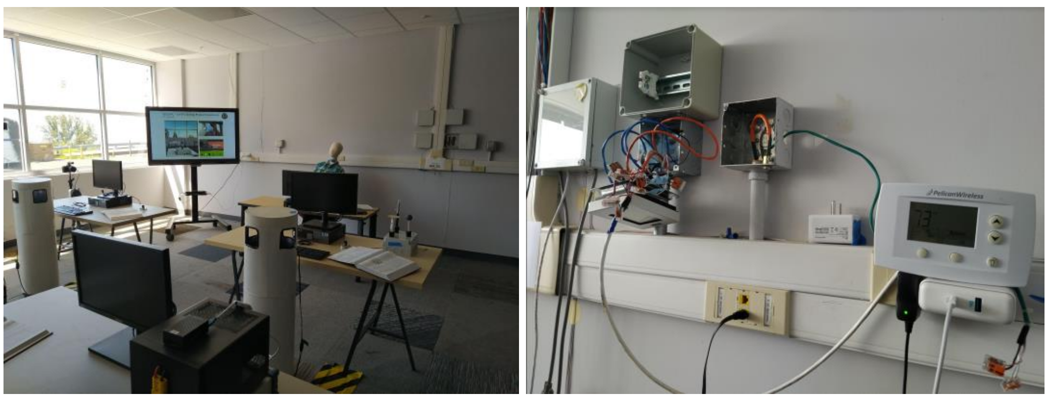

Figure 5: Test environment (Left: zone environment; Right: thermostat installation)

3.2 Control System Architecture

The control system architecture was developed as shown in Figure 6. In the architecture, a Gateway was used to build the connection between the thermostat and the internet (i.e., cloud service such as data logging). The thermostats talk to the Gateway via the IEEE 802.15 communication protocol. The Gateway communicates with the thermostat vendor's cloud service using the TCP/IP internet protocol. The FDD and correction algorithms run on the laptop locally and communicate with the cloud-based service to read and write data.

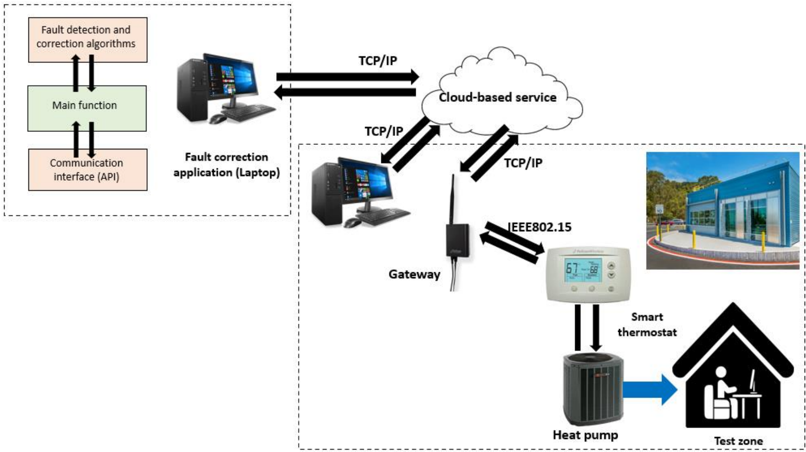

Figure 6: Control system architecture

3.3 Setpoint Wrong Setting Testing Result

In this study, we tested the FDD and correction algorithms for the overcooling and overheating faults from June 20 to June 21, 2023. To impose this fault, we adjusted the cooling setpoint to 72°F (the preferred cooling setpoint is 74°F) and heating setpoint to 69°F (the preferred heating setpoint is 68°F). The fault detection flagging threshold is set to be two days, i.e., the FDD and correction algorithm flags the fault and initiates the correction action after the fault exists for two days. When the faults were flagged, they were automatically corrected at 8:00AM on June 22. Figure 7 illustrates the fault implementation and correction result.

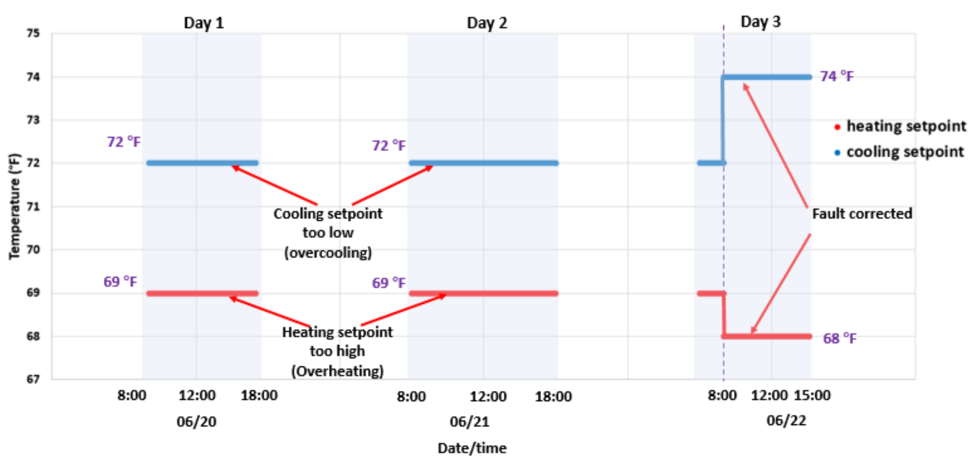

Figure 7: Fault detection and correction for the setpoint wrong setting fault

3.4 Schedule Wrong Setting Testing Result

We imposed the wrong schedule setting fault by setting a cooling setpoint value to 74°F and a heating setpoint value to 68°F at 5:00AM each weekday, indicating the occupied start time to be 5:00AM (the preferred start time is 6:00AM). At the same time, we set a cooling setpoint value to 62°F and heating setpoint values to 85°F at 8:00PM each weekday, indicating the occupied end time to be 8:00PM (the preferred end time is 6:00PM). By this way, the occupied time was extended by 3 hours.

Figure 8 shows the schedule setting fault existed and the correction action through July 3 to July 11. The FDD and correction algorithm flagged the fault at 8:00AM on July 10. Then, a correction action was initiated by overriding the cooling setpoint and the heating setpoint to 74°F and 68°F, respectively at 6:00AM, and to 85°F and 62°F, respectively at 6:00PM. The result shows that on July 10, the cooling setpoint was changed to 85°F and the heating setpoint was changed to 62°F, indicating the occupied end time took effect. On the following day, i.e., on July 11, the cooling setpoint was changed to 74°F and the heating setpoint was changed to 68°F at 6:00AM, indicating the occupied start time took effect on that day.

It can be seen that the occupied hours were decreased from 14-15 hours (when the fault existed) to 12-13 hours (when the fault was corrected).

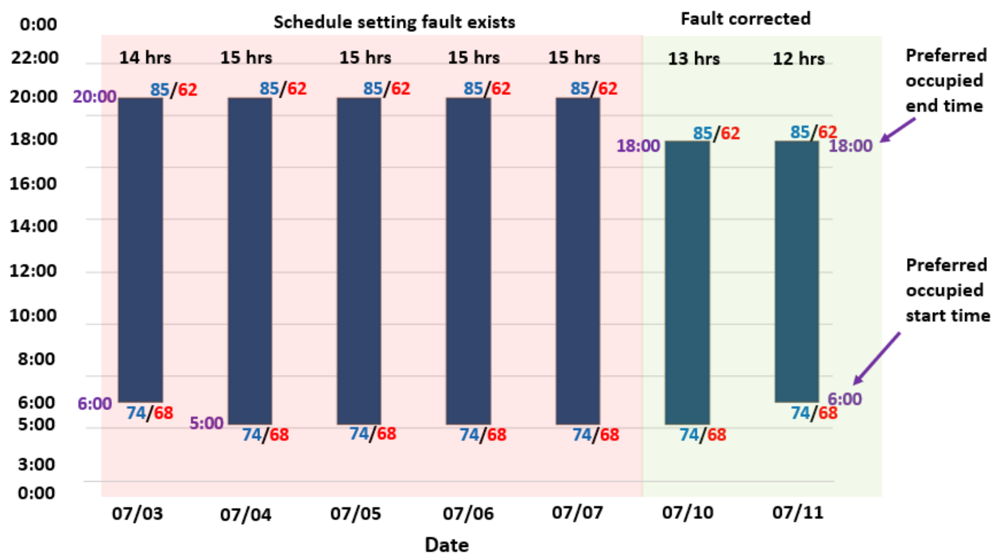

Figure 8: Schedule setting fault detection and correction

4. CONCLUSION AND FUTURE WORK

Smart thermostats offer attractive potential to enhance the monitoring and control of HVAC systems in SMBs in a cost-effective way. Furthermore, OpenAPIs provided by the smart thermostat bring the opportunity to develop lightweight control solutions in SMBs to achieve the ambitious goals of HVAC system energy efficiency and building decarbonization.

In this paper, we extend the fault self-correction family, which was successfully implemented in the EMIS and BAS solution for large commercial buildings. By using OpenAPIs in smart thermostats, we developed novel fault detection and correction algorithms to correct wrong setpoint setting faults and the schedule setting fault, which are commonly observed in the thermostat application. We implemented tests in the lab environment to demonstrate the effectiveness of FDD and correction algorithms in efficiently correcting thermostat setting faults, as well as avoiding energy waste caused by those faults.

Potential future work could include field demonstrations outside of a lab setting, to assess robustness to the variety of conditions observed in diverse building stock, and also receptiveness of building owners and operators. Such demonstrations may result in refinements and/or development of variants to the core algorithms to suit different contexts. Further research could also consider other software-based control faults with potential for self-correction. In parallel with technical research, there is also a need for broader market/qualitative research to determine the most effective means of delivering such services to the SMB market.

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