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Not I But Christ.

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How HE has blessed me, tongues can never tell.
On the cross HE suffered, shared HIS blood and died.
That I might ever in HIS love confide.
Following Jesus, ever day by day;
Nothing can harm me when Jesus leads the way!
Darkness or sunshine, what’er befall;
Jesus, the Shepherd is my ALL in ALL.”*

Leonard Weaver (1984)

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Abstract

This dissertation presents an investigation of two strategies for evaluating the performance of smart thermostat-driven fault detection and diagnosis (FDD) methods that are intended for vapor compression air conditioning (AC) systems in residential homes. Though there have been some research efforts within the last decade on smart thermostat-driven FDD, there are several challenges which have limited the advancement of the concept into a marketable technology. Therefore, the investigation in this dissertation is to explore some of the ways these challenges can be addressed.

For the first strategy, a novel dynamic co-simulation model is developed using EnergyPlus and Modelica to gain a fundamental understanding of the coupling between building thermal response and AC system. The model is then validated and used to investigate the effectiveness of using smart thermostats for low-cost FDD in residential AC systems.

Smart thermostats measures indoor air conditions which reflect the indoor air responses to both AC operations and other factors like weather and building gains. As these other factors are typically unmeasurable by smart thermostats and yet prone to variability, they pose potential disturbances which can affect AC operation. This makes estimating the impact of these disturbances (referred to as uncontrollable building load disturbances (UBLDs)) on AC operation in buildings and the performance of FDD methods critical. Therefore, in this study, it is essential to couple the dynamics of AC operation and building response in the development of the co-simulation model. Additionally, a novel automated calibration framework is also developed in this research to validate the coupled model. The validated model was then used to simulate seven UBLD cases and two prevalent faults with different severities.

The study also proposed a set of metrics for evaluating the performance of FDD methods. With the simulation results and the proposed metrics, impact analysis on AC duty factor and enthalpy change were carried out. Results of the analyses showed that severe UBLDs can cause almost 9% increase in energy consumption. The results also showed that these UBLDs can cause false alarm rates in FDD up to 70% if appropriate thresholds and post-processing strategies are not used. Meanwhile, results on the impact of faults showed that with the simultaneous impact of UBLDs, only low charge faults up to 30% severity and low indoor airflow fault up to 60% severity can be confidently detected using duty factor as FDD feature. Meanwhile, the analyses and results also led to the proposal of another FDD feature (enthalpy change) which offers better sensitivity and a potential for diagnosis which the duty factor feature lacks. With this new feature, an automated FDD algorithm was developed, validated and successfully deployed in four test-homes where it was able to detect 30% undercharge fault and 30% low indoor airflow, as well as installation mismatch. Overall, this research work creates a new pathway for promoting smart thermostat FDD technology in the residential market within the US and beyond.

Chapter 1: Introduction

This chapter provides the background for smart thermostat-based FDD. It then discusses the state-of-the-art of smart thermostat-based FDD, reviews the different techniques that have been explored, and highlights the research gaps. It concludes with the research questions and hypotheses proposed in this study.

1.1 History and Background of Smart thermostat-based FDD for Residential AC Systems

Heating, ventilating, and air-conditioning (HVAC) systems, which account for approximately 48% of the total residential energy use in the US [1], are critical for maintaining indoor comfort, demand response, building decarbonization, etc. if operated efficiently. However, these systems are prone to various faults such as refrigerant leaks and low indoor airflow. [2]. This makes fault detection and diagnosis (FDD) an effective strategy for ensuring the efficient operation of HVAC systems. However, most FDD studies have focused on commercial HVAC systems, whereas less attention has been given to FDD in residential HVAC systems [3]. FDD studies on residential systems have been reported to be less than 16% of those on HVAC systems [4]. This is because unlike commercial systems that have platforms such as the Building Automation System (BAS), which can be leveraged for FDD, residential HVAC systems do not have such platforms. Meanwhile, because residential HVAC systems are small-scale products compared to commercial HVAC systems, it was not very appealing to homeowners and manufacturers to invest considerably in FDD in residential HVAC systems.

However, with more research, it has been found that faults like low refrigerant charge, low airflow rates, and duct leakage, which frequently occur in most residential HVAC systems [11,12], can

result in increased annual energy usage by 9-23% [13,14], costing homeowners across the US an additional \$2.5 billion annually [2]. FDD also has several benefits for residential HVAC systems, as summarized in Figure 1.1. Thus, there has been growing interest in the research and development of FDD tools for residential HVAC systems.

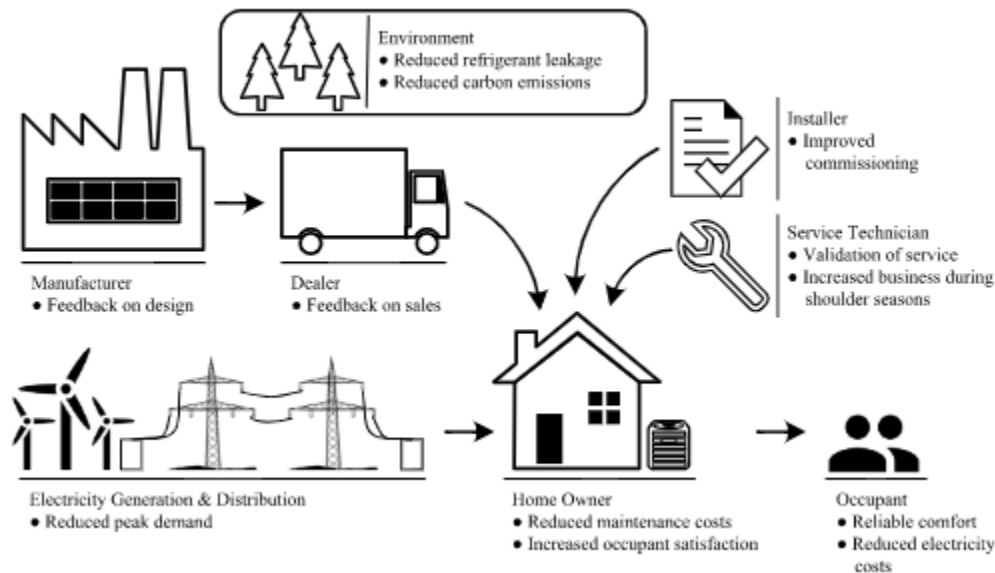


Figure 1.1: Benefits of FDD for residential HVAC systems [3]

A major contributor to the cost of FDD in residential HVAC systems is the required sensors. Therefore, most FDD studies are aimed at reducing the number of additional sensors required for an accurate FDD. Some of the methods explored include rule-based methods [5–7], the development and use of virtual sensors [8–13], and the application of deep learning techniques [14,15] and so on. However, most of these studies involved the use of several additional sensors.

Currently, some commercial Automated Fault Detection and Diagnosis (AFDD) tools are available for residential HVAC in the market. AFDD is a technology or tool that implements the FDD process and alerts users to the presence of a fault [16]. An AFDD tool essentially integrates the FDD algorithm into a hardware device that enables real-time, automated, and continuous

monitoring of a system's behavior, and communicates the outcome of such monitoring, especially of a detected fault, to the user. Examples of commercial AFDD tools include Sensi Predict, which uses 10 additional sensors (four temperature sensors, two current sensors, two voltage sensors, and two control signal sensors) [17], ComfortAlert diagnostics that use data from Copeland scroll compressors for AFDD [18], and ComfortGuard, which also requires 10 additional sensors (similar to those for Sensi Predict) to be installed [19]. Although innovative and efficient, these products incur additional costs (installation costs, sensor costs, and subscription fees). In addition, some HVAC manufacturers have embedded AFDD in their residential equipment, but such features exist only in high-end, variable-speed units, specifically for the purpose of equipment reliability. Furthermore, the industry is yet to standardize the domain of residential AFDD or identify which types of faults should be consistently reported, how to report them, and which stakeholders are intended to receive what information [20].

With the advent of smart thermostats and their growing market penetration [21] owing to their attractive features such as cloud storage and IoT-capability, which make their data accessible for machine learning and FDD purposes, researchers have started exploring the possibility of utilizing the data from these devices to develop low-cost FDD methods for residential HVAC systems that require very few or no additional sensors. Data such as indoor temperature, T_{in} , and indoor relative humidity, ϕ_{in} , indoor temperature setpoint, T_{set} , runtime, t_{ac} , and outdoor temperature, T_{oa} , which relate to the HVAC system operation, can be accessed and processed into meaningful quantities (called features) and used for FDD in HVAC systems with little or no additional sensors, no additional hardware, less technicalities, and thus, little or no added cost. Therefore, these advantages have increased research interest in Smart thermostat-based FDD for residential HVAC systems [2,3].

Smart thermostat (ST) FDD methods use performance features (which serve as FDD indices) because they cannot measure state properties, such as refrigerant temperature. Although only a few studies have been conducted on Smart thermostat-based FDD and this area of research is still relatively new, it is gaining increasing attention in the research community. Owing to the potential benefits, especially cost-wise, Smart thermostat-based FDD could break the market barrier facing FDD for residential HVAC systems. However, methods to improve the performance of Smart thermostat-based FDD for residential HVAC systems remain a concern.

1.2 State-of-the-Arts of Smart thermostat-based FDD

1.2.1 System Identification Methods

In [22], a system identification approach was used in which the authors proposed a black-box model that takes only two inputs: T_{in} and T_{oa} . The model parameters were obtained using the recursive least-squares (RLS) method. Using the RLS method, these parameters were then constantly updated and compared with the original parameters, and the deviations were classified as faults. Although the method is simple, easy to implement, and appears scalable, the building/HVAC dynamics are not well captured. Factors such as the internal heat gain, $\dot{Q}_{int}$, solar gain, $\dot{Q}_{sol}$, infiltration heat load, $\dot{Q}_{inf}$ and HVAC heating/cooling output, $\dot{Q}_{hvac}$ which affects the operations of the HVAC were not considered in the model. Thus, a change in the parameter(s) used as FDD features could be due to either of these neglected factors rather than an actual fault. Meanwhile, no threshold was specified, and simulation data were used to test the method for the detection of component-level faults, such as compressor failure and total cooling system failure. In addition, the accuracy of this method has not been reported. In [23] a 3R2C model was trained using an Extended Kalman Filter and was used for prediction of T_{in} . Using the predicted T_{in} and

T_{set} , the expected time-to-cool setpoint, t_{coolsp} was compared with the actual t_{coolsp} . A fault alarm is raised when for 70% of the total AC ‘on’ cycles, measured $t_{coolsp} > 1.2 \times \text{predicted } t_{coolsp}$, where 1.2 signifies a deviation threshold of 20%. Simulation data were used to test the method, and detection accuracies of 70%, 77%, and 82% were reported for a 40% undercharge (UC), 40% low indoor airflow (LIAF), and duct leak faults, respectively. However, $\dot{Q}_{int}$ was considered negligible, Also, $\dot{Q}_{inf}$ s not well modeled [24]. While $\dot{Q}_{hvac}$ was gotten from a cooling capacity model which uses data provided by the HVAC manufacturer, called the expanded performance table or EPT data, the reliability of the EPT data and accessibility for several brands is still a concern [25]. Due to this concern, $\dot{Q}_{hvac}$ estimated from the EPT data was assumed to be overestimated by 20%, hence the 20% deviation threshold. However, the accuracy of this assumption was not substantiated, and the possibility of such an assumption leading to false negatives was not investigated i.e., in cases where $\dot{Q}_{hvac}$ becomes underestimated due to the 20% factor of safety being too large or unnecessary, thus causing $\hat{\tau}_{nf} > \tau_{mea}$. Meanwhile, EnergyPlus simulation data was used for testing this method, which though widely accepted for building energy modeling, is not suitable for modeling the dynamics of vapor compression (VC) cycle AC systems which are typical in residential AC units. This is evident from the nonrealistic T_{in} profiles shown in Figure 1.2. The clean steady state T_{in} maintained even when the AC is off (Figure 1.2b) and T_{oa} is high (Figure 1.2a) is non-typical. In addition, smooth profiles suggest noiseless data that are not representative of real-life cases. A further concern is that the proposed algorithm for identifying 3R2C model parameters is highly nonconvex and leads to several local optimal solutions. To address this non-convexity issue, the same authors proposed a method for selecting the best model from a list of optimal solutions [26]. The selection was based on the resultant model that gives the least mean squared error (MSE). For this study, real-world data from a laboratory

home at the Florida Solar Energy Center were used. The algorithm successfully detected 30% UC, 11% duct leak, and simultaneous 30% UC and 11% duct leak, with accuracies of 70.6%, 69.1%, and 85.2%, respectively. Runtime fraction (RTF) was used as the FDD feature for this study. However, in this study, $\dot{Q}_{int}$, $\dot{Q}_{inf}$, and $\dot{Q}_{sol}$ are also not properly modeled. To address this, the authors used a deviation threshold of 40% and a fault alarm is raised when 65% of the total AC ‘on’ cycles record deviation in $RTF > 40\%$ (the deviation threshold), thus raising the same concern with the previous study about false negatives caused by the deviation threshold being too large.

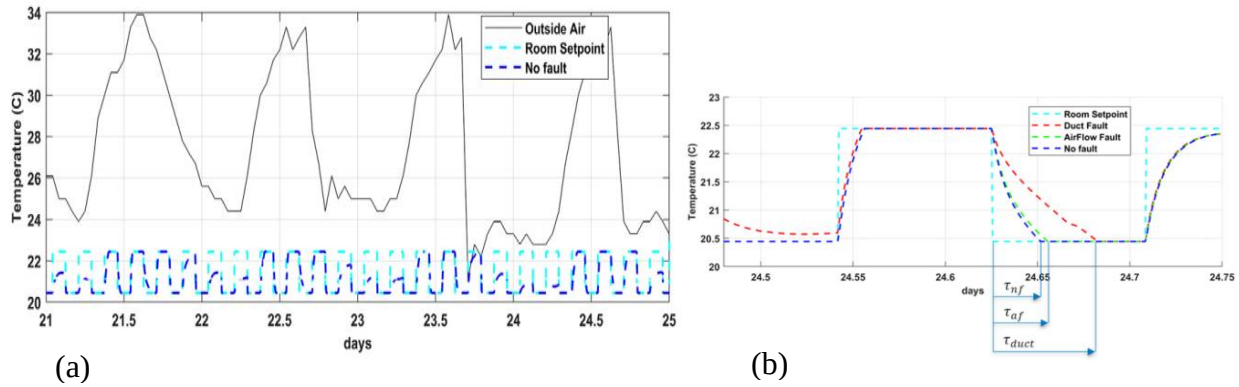


Figure 1.2: EnergyPlus data used in [23] (a) thermostat drive cycles (b) a single cycle

In [27], a leak detection algorithm was developed based on smart thermostat data. However, as the study was originally on cold rooms rather than HVAC systems, the authors proposed an adaptation of the algorithm used for cold rooms to HVAC systems. Essentially, the proposed thermal model attempts to split the conditioned space into multiple thermal zones demarcated by a thin layer of air with a negligible thermal mass. While the demarcations help to capture the stratification of the room air, it makes the resulting models very complex and raises curiosity about how, with just three smart thermostat data inputs (occupancy data, T_{in} and T_{oa}), 18 model parameters can be learned. Unfortunately, there were no reported tests that were conducted, nor the results provided,

and there has so far been no follow-up on the proposed method, possibly because of its complexities vis-à-vis the limited data from smart thermostats.

Owing to the concern that smart thermostat data are insufficient for FDD, in [28], the authors proposed adding a Home Energy Monitoring System (HEMS) and an outdoor weather monitor to the smart thermostat data for FDD. They then used indoor and outdoor temperatures from these sources, power data, and a trained black-box model to monitor energy usage in approximately 150 homes in Austin, Texas, USA. They tested the proposed method on an outdoor airflow reduction fault and found that the proposed method could only detect faults with a severity above 50%, making the method less attractive in terms of cost increment. In a similar study [29], the authors proposed adding a smart power meter to a smart thermostat as well as building assessor's data to perform FDD on residential HVAC systems. Then, a gray-box model was trained with these data, validated by an AC modelling tool called ACHP [30], and used to predict $\dot{P}$ (power consumed by the AC). If measured $\dot{P} > \text{predicted } \dot{P}$, then a fault is signaled. The proposed method was tested on 39 residential HVAC systems located in Austin, Texas, and six units were classified as inefficient or faulty. However, the fault types and severity have not been reported.

1.2.2 Statistical Methods

Considering the insufficiency of smart thermostat data for FDD, Rogers et. al. [31] proposed using a moving data window and the statistical t-test (which is suitable for studies where little data are available for estimating the nominal operating behavior) to detect changes in the duty cycle or duty factor (i.e., fractional runtime of AC in a period) of an AC. A Monte Carlo method was used with Kernel Density Estimation (KDE) to ascertain appropriate thresholds for various sample sizes in this study. The method was tested in six homes in Texas, and the same threshold and sample size were used for all homes. While duty factor changes were detected for some homes, a challenge for

real-life applications is that such changes could be due to other factors such as homeowners leaving windows/doors open or changing setpoints, and not necessarily due to a fault. Rogers et. al [32] attempted to address this challenge by proposing a mode labeling technique in which smart thermostat data are sorted into tracking, regulating, and free response modes. The tracking mode involves transient periods during which AC attempts to cool the space to T_{set} . The regulating mode is the period during which the AC attempts to maintain T_{in} at the attained T_{set} . The free response mode usually occurs when AC is off and T_{in} is driven by weather or space conditions. Two case studies were considered: single-system degradation detection and multi-system performance comparison. For the single system, changes in the duty factor during the cool-regulating mode at the same ΔT_{oi} (difference between T_{in} and T_{oa}) was used to detect performance degradation in the system. For the multi-system performance comparison, the relationship between ΔT_i (indoor temperature increase) and ΔT_{oi} during free-response modes for two different systems was used to characterize each building based on their different response to T_{oa} . Therefore, a building that shows a quicker rise in T_{in} likely has poorer envelopes than one with a slower rise. While this is not directly related to an HVAC fault, they proposed combining such an analysis with cool-regulating mode analysis to ensure that the fault detected in the latter is not due to homeowners leaving a window/door open. However, the study did not specify which fault types and severities were detected, as they detected system degradation.

1.2.3 Data Clustering Methods

Another strategy used by some studies is to use cloud-based data from a large pool of smart thermostats. In [33], a statistics-based FDD method that utilized cloud-based thermostat data from multiple residences was proposed. The method that leverages the mode-labeling technique proposed in [32] involves isolating systems with poor cool-tracking periods from a pool of

systems. A system is said to exhibit poor cool tracking if, during a cooling cycle, T_{in} , instead of dropping, rises over 5 °C above T_{set} over a significant period, and such behavior is observed for at least fifteen days in a summer season. Next, the isolated systems are further examined with two features, namely: average degree hour above setpoint, $\overline{DH}$, and average maximum indoor temperature, $\bar{T}_{i,max}$. $\overline{DH}$ was defined as the average $\Delta T_{in,sp}$ (difference between T_{in} and T_{set}) during poor transient periods (when AC fails to maintain T_{in} around T_{set}) in an entire cooling season. Thresholds were set for $\overline{DH}$ and $\bar{T}_{i,max}$ at $6.9\text{ }^{\circ}\text{C} \cdot \text{hr}$ and $26.7\text{ }^{\circ}\text{C}$ based on the KDE of the isolated systems. Systems with both features above these thresholds are then flagged as faulty. The method was tested on about 10,000 AC units in Florida, 68 of which were tagged faulty. In addition, the faulty systems exhibited long periods of poor tracking, spanning from sunrise to sunset every day. While their study demonstrated the potential of using cloud-based thermostat data for FDD on multiple HVAC systems, the hard thresholds make the detected faults obvious and perceptible to homeowners, even without any FDD algorithm. Such faults are classified as hard faults and do not require the detection of an FDD algorithm. Moreover, the method can only identify a cooling capacity degradation or undersized unit but does not detect the cause of such degradation. In [34], clustered smart thermostat data from multiple residential HVAC units were proposed for identifying faulty systems from multiple units using outliers. Five features were used, namely: ΔT_{oi} , $\Delta \omega_{oi}$ (difference between indoor and outdoor humidity ratio), E_c (cooling effort), F (cycle frequency), and T_{spe} (cooling setpoint error). ΔT_{oi} and $\Delta \omega_{oi}$ specifies the operating conditions while E_c , F , and T_{spe} characterizes the operational behavior of the system and were used for identifying faulty systems. E_c is a measure of how hard the system runs, which for a single speed system is the same as duty factor. T_{spe} shows how off T_{in} is from T_{set} during cycling on & off. So, for instance, a high E_c under mild weather conditions might suggest an undersized or faulty

system. Then, statistical univariate tests of each feature were used to identify outliers (extreme cases) from a distribution. While multivariate test of multiple features was used to identify outliers (mild cases) from a distribution. With thresholds of 1% for E_c , F , and T_{spe} each in the case of univariate tests, and 5% for different combinations of E_c , F , and T_{spe} for multivariate tests, outliers that fall below this threshold are labelled faulty. The thresholds represent weighted average, $\bar{\alpha}$, of systems within a subset that show poor performance. So, if $\bar{\alpha}$ for T_{spe} test of a system is 0.5%, it means that on average, only 0.5% of other systems have higher T_{spe} than such system, thus suggesting that such system is faulty. With the proposed method, about 9000 residential cooling systems were tested in [35] out of which 257 systems were flagged as faulty (either due to control problems, inadequate capacity or oversizing). However, most of the clustered systems were assumed fault-free. In [36], a baseline characteristic curve, generated from steady state duty factor computation for multiple AC systems using their respective smart thermostat data was proposed. Similar curves were obtained for each AC and were all plotted against ΔT_{oi} . Then faults were detected if an AC curve deviated from the baseline characteristic curve. Still, a concern remains about how to verify that the baseline characteristic curve is generated from fault-free data. Meanwhile, the clustered smart thermostat data may be influenced by occupant activities like mistakenly leaving windows open or exhaust fan on, and these can affect a system's performance. In [37], partial Mann-Kendall with moving block bootstrap (PMK-MBBS) statistical test method was used to detect increase in E_c , but with consideration of the impacts of T_{set} . E_c was computed from the steady state energy balance equation for a building:

$$E_c S = UA\Delta T_{oi} + \dot{Q}_{sol} + \dot{Q}_{int} \quad (1.1)$$

where S is the AC size (in tons), U is the overall heat transfer coefficient, A is the total surface area of the building envelope. Smart thermostat data from 10,000 residential ACs was used for the test. An hourly analysis using steady state E_c detected 69 ACs as faulty. While with the daily E_c , 99 ACs were detected as faulty. Both hourly and daily analysis also helped prioritize faults based on their severity which was estimated from the calculated magnitude of observed rising trends in E_c . However, $\dot{Q}_{sol}$ was considered already captured in ΔT_{oi} and so was neglected, a constant $\dot{Q}_{int}$ was assumed for each home which is not typical in residential homes.

1.3 Research Gaps and Research Questions

1.3.1 Research Gaps

Based on the reviews in Section 1.2, the following are the identified research gaps in the current state-of-the-art of Smart thermostat-based FDD

1.3.1.1 Lack of Studies Evaluating the Impact of UBLDs

Most of the previous studies do not consider variables like $\dot{Q}_{int}$, $\dot{Q}_{inf}$, and $\dot{Q}_{sol}$ [22] or made simplifying assumptions [23,26] for them. While this is understandable due to the unavailability of such data from smart thermostats, it however raises concerns about the reliability of such FDD methods considering the uncertainties associated with these variables especially with regards to occupant activities (which is very dynamic and unpredictable [38]) or weather fluctuations. Though several occupancy detection models have been developed, these models mainly rely on deterministic approaches which may not fully capture stochastic variations in occupant behavior and environmental interactions [38]. Hence, proper capturing of occupancy dynamics is still an open problem [39,40].

Also, because smart thermostats are not primarily measuring devices but control devices with built in sensors, they have certain features that can introduce additional noise to smart thermostat data. Features like data processing algorithms, lack of synchronization of thermostat data with AC dynamics due to thermal delays, proprietary limitations from some third-party smart thermostat manufacturers, communication restrictions [16], etc. The added noise could also be due to poor installation of smart thermostats in buildings. For instance, a thermostat that is wrongly located in a building could generate data that is not well representative and suitable for FDD purposes. In [33], thermostat misplacement was considered as a fault. This suggests that the position of the smart thermostat in the home can significantly affect the reliability and accuracy of a Smart thermostat-based FDD algorithm. So far, there is no known study that has attempted to address this concern. In [27], the authors installed the thermostat close to the blower fan of the refrigeration unit (RU) so as to focus more on the RU output and less on the thermal noise in the environment. However, the study was for a cold room rather than a building. In addition, as smart thermostats rely on internet connectivity, limitations could arise from internet disruption, power outages, which can lead to missing data [28,32].

Studies on the impact of disturbances arising from the above variables/features (referred to as uncontrollable building load disturbances (UBLDs)) in residential HVAC operations can encourage research efforts in predictive models of these variables and integration of such models into HVAC systems. Such models can help to detect these UBLDs, and alert homeowners, for example, about someone mistakenly leaving a window/door open (using infiltration increase). Such models can also help prevent false positives in FDD methods. However, there is a paucity of comprehensive impact studies in this area. Most existing studies focus on such occupancy based

disturbances and are for commercial buildings [41–46], which have different load profiles and occupancy patterns compared to residential buildings.

Some early results of this work were presented in [47–49] which attempted to investigate the impact of UBLD on Smart thermostat-based FDD methods. However, in these preliminary investigations, the co-simulation model used was not well representative and properly validated. In [47,48], just three days were simulated which is not sufficient to capture the variations especially with weather. Therefore, the lack of thorough investigation on the impact of UBLDs on HVAC operations remains a research gap.

1.3.1.2 Lack of Standardized Evaluation Methods/Metrics

Lack of standardized methods for evaluating the performance of FDD methods/tools has been identified as a barrier to the advancement of FDD technology in the residential sector [16,50]. Such evaluation methods essentially tell how well an FDD tool performs and whether it meets a code requirement. A standard evaluation method will help end-users to make informed decisions about what FDD tool to go for during purchase. It will also be a useful guide for researchers/manufacturers in developing the technology and help regulatory bodies like the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) in establishing standards and guidelines for residential FDD tools.

Few studies have been conducted on evaluating the performance of FDD for AC systems. In [51], the evaluation method proposed involves feeding data from a library of experimental results into an FDD method and comparing the outputs with reference values. The data library contains data from fault-free experiments and from experiments with one of seven fault types imposed (evaporator airflow, condenser airflow, undercharge, overcharge, liquid-line restriction, presence

of non-condensable gas(es), and compressor valve fault). Five evaluation metrics were used as follows:

- i. **no response:** which means FDD cannot be applied or cannot perform diagnosis;
- ii. **correct:** meaning FDD method gives the right result;
- iii. **false alarm:** which means a fault is indicated when no fault is present;
- iv. **misdiagnosis:** which means the wrong fault is diagnosed; and
- v. **missed detection:** which means FDD indicates no fault when a fault is present.

The evaluation method was tested on the RCA protocol, described in the Appendix RA of Title 24 – 2008 [52] - California building energy code. RCA stands for Refrigerant Charge and Airflow and is used to check for EA, UC or OC faults in cooling-mode ACs. The evaluation which was done with a data library of 725 tests from 13 systems reportedly showed that the RCA performed poorly. The above metrics were then evaluated for different fault intensities, *FI*, defined as follows:

$$FI = \frac{\text{Actual FDD feature} - \text{predicted FDD feature}}{\text{predicted FDD feature}} \quad (1.2)$$

In [50], a similar study was conducted but in this case fault impact ratio (*FIR*) was used instead of *FI* for characterizing the FDD performance. The *FIR* is defined as follows:

$$FIR = \frac{\text{FDD Feature under faulty condition}}{\text{FDD Feature under fault-free condition}} \quad (1.3)$$

Also, different *IR thresholds* were used to assess FDD performance. Using this method, they tested the RCA protocol and reported a 51% false alarm rate, a 26% misdiagnosis rate, and a 32% missed detection rate. In another similar study [53], simulation data was used instead of experimental data to develop the data library used for the evaluation. The use of simulation data was prompted by the advantage of generating larger amount of data for different operating conditions, fault types,

FIs, and AC systems. However, a critical requirement for the use of simulation data is model reliability, especially for simulating faults. Gray-box models proposed in [54] were used. These models are physics-based models that require training with experimental data e.g., the polytropic compression model, heat transfer and pressure drop correlations, heat exchanger effectiveness models, etc. The gray-box models were used to generate data for training Automated Neural Network (ANN) models which were in turn used to generate data for the FDD evaluator. The purpose of using ANN models was to improve the speed of the evaluator. This method was tested on 3 different FDD methods: the RCA protocol, a commercial FDD tool, and an FDD protocol developed for use in utility-sponsored maintenance programs. A comparison between simulation-based and experiment-based evaluator was also done. The results showed that the commercial FDD tool was better for both experimental data and simulation data. However, a significant disparity between results from simulation and results from experiments was observed. While the evaluation methods reviewed in this section look promising, they were all based on traditional FDD methods which use system-level inputs like subcool, superheat, condensing temperature, evaporating temperature, etc. For Smart thermostat-based FDD methods, there are no such evaluation methods that have been developed or proposed in literature.

1.3.1.3 Lack of Smart thermostat-based Studies on Fault Diagnosis

Another gap identified in the current state-of-the-art of Smart thermostat-based FDD is that all the studies focused on just fault detection without diagnosis. Meanwhile, the reason for this is not reported in any of the existing literatures. But for fault detection to be more meaningful, it needs to be accompanied by some diagnosis to advance the technology and encourage market adoption.

1.3.2 Research Questions (RQs)

Based on the identified gaps in Section 1.3.1, the following research questions (RQs) are formulated:

- RQ1.** How much impact do UBLDs have on AC operations?
- RQ2.** With reference to RQ1, to what extent do UBLDs affect Smart thermostat-based FDD performance? Can we differentiate their impact from actual faults?
- RQ3.** What standard metrics can be used to assess the performance of Smart thermostat-based FDD methods?
- RQ4.** Can smart thermostat data be used for both fault detection and diagnosis?

RQs 1 and 2 are drawn from Section 1.3.1.1. RQs 3 and 4 are drawn from Sections 1.3.1.2 and 1.3.1.3, respectively.

1.4 Research Hypotheses (RH) and Research Objective

To address the research questions identified in Section 1.3.2, the following research hypotheses are proposed in this study:

- RH1.** The use of well-representative models that properly capture dynamics like infiltration, occupancy behavior, thermostat features, etc., can be used to study the impact of UBLDs on AC operations. This will address research questions 1 and 2.
- RH2.** In addition to RH1, coupling the building dynamics and the AC dynamics together can ensure a proper investigation of UBLD impact on AC operations. This is because as depicted in Figure 1.3, traditional FDD methods use state variables like refrigerant pressure, mass flowrate, refrigerant saturation temperatures, power consumption, which are mainly affected by the AC dynamics and decoupled from the building dynamics [2].

However, smart thermostat data like indoor temperature, indoor relative humidity, AC runtime, etc., are affected by the interaction between the AC dynamics and the building dynamics. Thus, to properly study the impact of UBLDs on Smart thermostat-based FDD, the coupling of the AC dynamics and building dynamics is required.

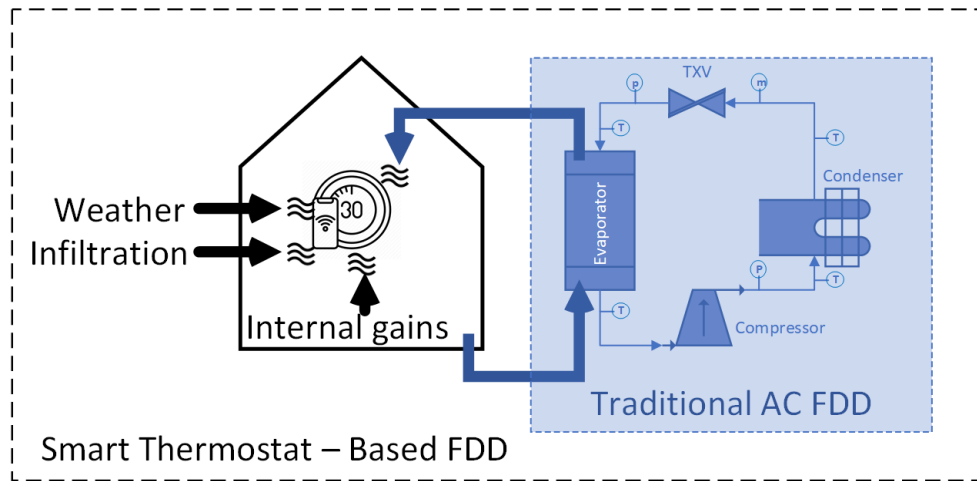


Figure 1.3: Interaction between AC dynamics and building dynamics in residential buildings.

- RH3.** By using the results from RH1 and RH2, quantities like thresholds, FIR, FPR, FNR, and signal-to-noise (SNR) ratio can be used as standard metrics for evaluating the performance of Smart thermostat-based FDD methods. This will help to address RQ3.
- RH4.** Enthalpy change (Δi) across the evaporator of an AC system is positive for LIAF and negative for UC. If this is true, then Δi can be used for both fault detection and diagnosis. This will help to address RQ4.
- RH5.** By using real-life data to test RH3 instead of simulation data or controlled experimental data which may not fully capture all the dynamics in real-life data, more reliable conclusions can be made.

Testing these RHs would help to achieve the research objective of this work which is to propose possible strategies for improving the performance of smart thermostat-based FDD.

1.5 Research Overview and Scope of the Study

Figure 1.4 shows the research flowchart followed in this study to investigate the propounded research hypotheses in this work.

The scope of this study is limited to AC systems operating in wet climate regions. The outline of the studies is as follows:

- **Chapter 1** provides an introduction and gap analysis of this study.
- **Chapter 2** gives a layout of the methodology adopted in this study.
- **Chapter 3** is on the investigation of the impact of UBLDs on AC operations.
- **Chapter 4** is on performance evaluation of FDD methods
- **Chapter 5** is on the investigation of a smart thermostat-based approach for automated FDD in residential AC systems, using enthalpy change as FDD feature
- **Chapter 6** gives the conclusions for the study and recommendations for future work.

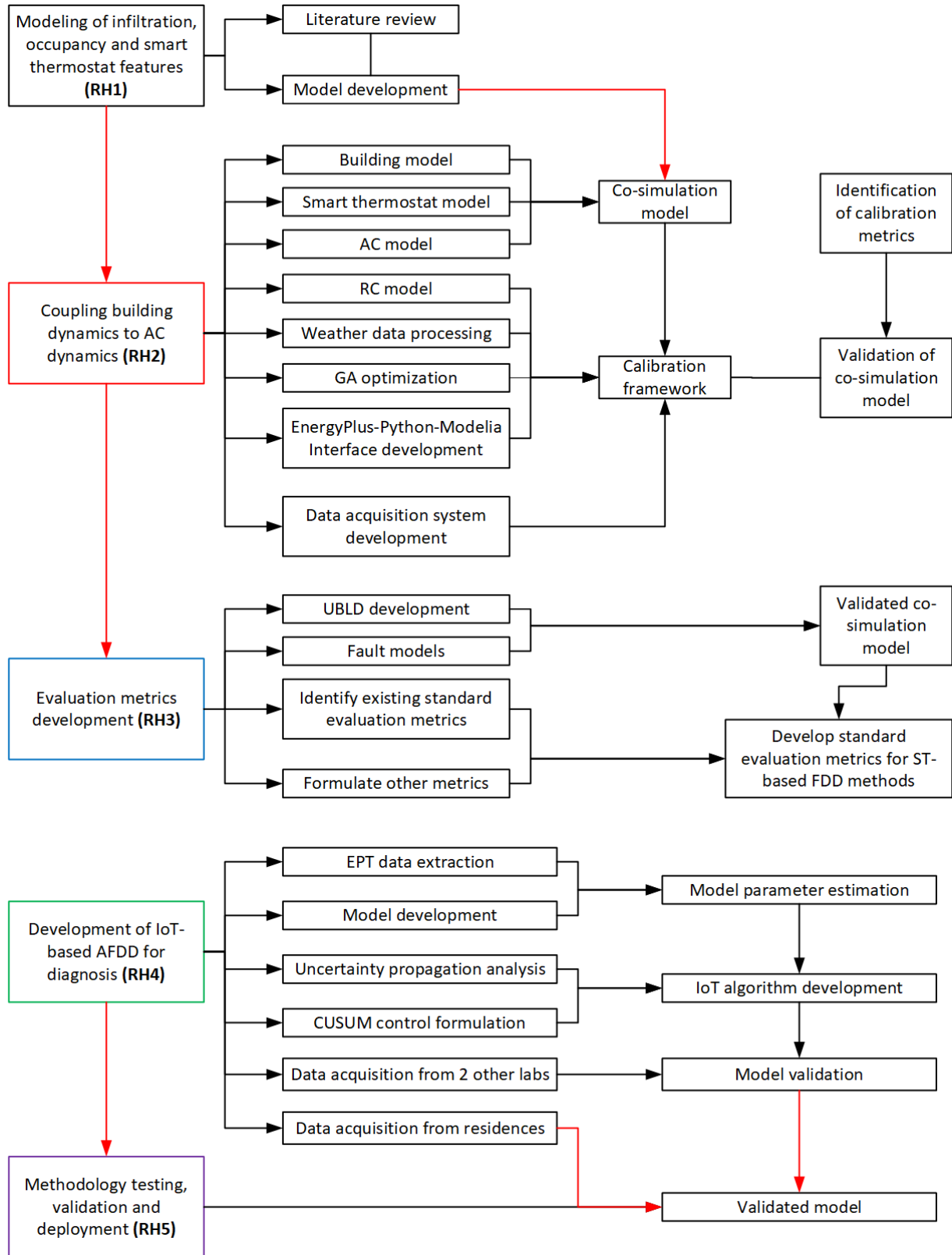


Figure 1.4: Research flowchart

1.6 Thesis Contributions

The intellectual contributions of this work include:

1. Development of a novel co-simulation testbed that couples the AC dynamics to the building dynamics in a more representative way to real-life systems.
2. Development of a novel automated framework for calibrating residential buildings and AC system.
3. Development of standard metrics for evaluating the performance of smart thermostat-based FDD methods.
4. Quantification of the impact of UBLDs on HVAC operations in residential buildings.
5. Development of a smart thermostat-based automated FDD technique with detection and diagnostic capabilities for residential applications.

Chapter 2: Methodology

This chapter discusses relevant data and features used for this study; the system developed to acquire this data as well as the research methodology employed. It also describes the faults considered in this study and concludes by stating the strategies proposed to achieve the research objective.

2.1 Identification of Relevant Variables and smart thermostat Data Needed

Based on a modified version of the general FDD sequence reported in [55] and [23], a critical element of the FDD process is the feature, f , as shown in Figure 2.1. This is because the feature usually has characteristics that can help to determine the condition of an AC system. Therefore, a critical aspect of this work is identifying relevant features to use for this study.

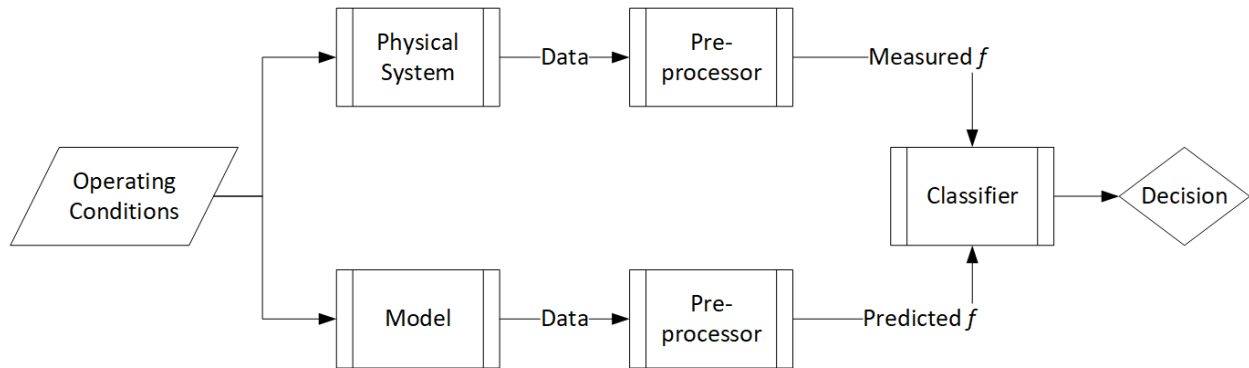


Figure 2.1: General FDD Sequence

From the literature review conducted in this work, two features were selected, namely: duty factor and enthalpy. These two features were selected based on the feature selection criteria recommended in [23]. The criteria are:

1. that the feature is easy to measure with widely available and inexpensive sensors; or easy to compute from readily available data;

2. that there is an appropriate model with high accuracy, which can be used to predict the feature;
3. that the training or development of the model can be done with readily available data;
4. that the feature shows significant sensitivity to faults at different severities.

2.1.1 Duty Factor

The duty factor feature (DF) was used in [31–37], as the FDD feature. This is perhaps because of the ease of computation of the feature from readily available smart thermostat data, as required in the feature selection criteria given in Section Chapter 2:. For the computation of the duty factor, the main smart thermostat data required is the AC runtime (t_{ac}). This feature was chosen for this study because it is the most used feature in the existing literature on Smart thermostat-based FDD. Out of twelve studies reviewed in this work, seven of them used duty factor as the FDD feature. In [26], though AC runtime fraction was used, it has similar definition as duty factor. So, duty factor can be said to have been used in about 67% of Smart thermostat-based FDD studies.

For the studies where duty factors have been used, two types of analysis have been considered, namely: hourly analysis and daily analysis. The differences between both are:

1. For the hourly analysis, the duty factor is defined as the fraction of time within a given number of hours during which an AC runs, while for the daily analysis the duty factor is the AC runtime fraction in a day.
2. For the hourly analysis, previous studies [26,37] considered just the regulating period to ensure that only steady state data is used. But the daily analysis considered both transient and steady state data.

For this work, the daily analysis approach was adopted over the hourly analysis based on the following considerations:

1. The daily analysis is more suitable for all operating conditions. Conversely, the hourly analysis is more suitable for systems with relatively constant cooling setpoints and as such gives more steady state data. To study the impact of UBLDs related to irregular or frequent setpoint changes, the hourly analysis would therefore not be suitable [37].
2. In [37], the daily analysis was reported to detect thirty more faulty AC systems than the hourly analysis, mainly because those thirty systems did not have sufficient data in the regulating mode for hourly analysis.
3. The hourly analysis has a higher computation cost than the daily analysis mainly because the former uses smaller periods.

2.1.2 Enthalpy Change

Enthalpy is a thermodynamic property that represents the total energy of a system including both internal energy and flow work. In HVAC, enthalpy captures both the sensible and latent heat in moist air. During cooling in AC systems, moist air flowing across the evaporator has both sensible and latent heat, making enthalpy a suitable variable for representing the heat transfer mechanism in the evaporator. As air flows across an evaporator during cooling, the enthalpy of the air changes. This enthalpy change (Δi) relates to the cooling capacity (q_{cc}) of the AC, based on Equation (2.1)

$$q_{cc} = \dot{m}_{sa}(i_{ra} - i_{sa}) = \dot{m}_{sa}\Delta i \quad (2.1)$$

where $\dot{m}_{sa}$ is the supply airflow rate, i_{ra} is the enthalpy of the return air (i.e., the air entering the evaporator), and i_{sa} is the enthalpy of the supply air (i.e., the air leaving the evaporator). Cooling capacity has been used in several fault impact studies. In [33], detection of cooling capacity

degradation was considered. This is because, most faults that occur in residential AC systems (such as those in Table 2.6) affects q_{cc} . Prominent faults such as undercharge and low indoor airflow cause a reduction in q_{cc} , making q_{cc} a potential FDD feature. However, using q_{cc} as a feature would require the use of an airflow sensor (which is relatively costly) as shown in Equation (2.1). Alternatively, Δi in Equation (2.1) can be used as an FDD feature too, if it can show significant changes due to a fault. This can be demonstrated from a simple sensitivity analysis as shown below.

2.1.2.1 Sensitivity Analysis for Δi , q_{cc} , and duty factor

The steady state heat balance equation in a building can be expressed as:

$$q_{gain} = q_{ac} \quad (2.2)$$

where q_{gain} (W) represents the total heat gain in the building which constitutes the building load, while q_{ac} (W) is the cooling output from the AC and is equivalent to the cooling capacity of the AC, q_{cc} . In kWh, Equation (2.2) can be expressed as:

$$\sum_{k=1}^N [q_{gain}(k) \times t] = \sum_{k=1}^N [q_{cc}(k) \times t] \quad (2.3)$$

where t represents time (in hours) and k represents timestep. Considering a day, for periods when the AC is on (during which q_{cc} is non-zero), if q_{cc} is assumed to be constant and an hourly time interval is used, Equation (2.3) can be further expressed as:

$$\sum_{k=1}^N q_{gain}(k) = q_{cc} \times \sum_{k=1}^N t(k) \quad (2.4)$$

$\sum_{k=1}^N t(k)$ represents the AC daily runtime, t_{ac} (in hours) in Equation (2.4). By dividing both sides of Equation (2.4) by 24 (i.e., total number of hours in a day), Equation (2.4) can be expressed in terms of duty factor (based on Section 2.1.1) as shown in Equation (2.5)

$$\sum_{k=1}^N q_{gain}(k) = 24 \times q_{cc} \times DF \quad (2.5)$$

Typically, AC systems run for a period (i.e., t_{ac}) to match the building gain (as depicted in Equation (2.5)), and thereby achieve desired thermal comfort in buildings. This makes the building gain an independent variable. Thus, the total daily building gain in Equation (2.5) is not affected by faults in the AC system. Therefore, from Equation (2.1) and (2.5), Table 2.1 shows results for the sensitivity analysis of duty factor, q_{cc} , and Δi to a 30% low indoor airflow fault (AF70) and a 30% undercharge fault (RC70). The results show significant changes in Δi due to these prevalent faults and suggests that Δi is far more sensitive than duty factor or q_{cc} for AF70. For RC70, Δi shows equal sensitivity with q_{cc} , but slightly less sensitivity than duty factor. Based on this analysis, Δi shows a good prospect as an alternative for detecting faults instead of q_{cc} .

Table 2.1: Results of Theoretical Sensitivity Analysis for Selected FDD Features

Hypothetical Degree of change in DF (%)	Corresponding Degree of change in q_{cc} (%)	Corresponding Degree of change in Δi (%)	
		AF70	RC70
4	-3.85	37.36	-3.85
8	-7.41	32.27	-7.41
12	-10.71	27.55	-10.71
16	-13.79	23.15	-13.79

2.1.2.2 Diagnostic Potential of Δi

Furthermore, as hypothesized in Section 1.4 (RH4), Δi can be used to diagnose between indoor airflow faults and refrigerant charge faults based on the physics of the vapor compression cycle:

where for low charge, Δi across the evaporator reduces but increases for low indoor airflow fault. Meanwhile, unlike q_{cc} , Δi does not require the use of an airflow sensor, as it is a function of just i_{ra} and i_{sa} . From psychrometry, i_{ra} and i_{sa} for moist air can be determined from any three thermodynamic properties of moist air. Pressure, which is one of the three properties, is typically the standard atmospheric pressure with variations based on location. Therefore, for the same location, pressure can be treated as constant, leaving two more properties left to determine enthalpy. Smart thermostats provide indoor air temperature, T_{in} , and indoor air relative humidity, ϕ_{in} . Since there is no outdoor air intake in residential AC systems except for the minute impact of infiltration, the indoor air can be assumed to have the same conditions as the return air as depicted in Figure 1.3. Thus, T_{in} and ϕ_{in} can be used to estimate i_{ra} . For i_{sa} , the supply air temperature and any other thermodynamic property of the supply air can be used. This study proposed using the free node sensor which usually comes with smart thermostats for obtaining i_{sa} . Figure 2.2n shows a picture of a node sensor placed on top of a diffuser. Details of how the node sensor is used to estimate i_{sa} is provided in Section 5.3 and 5.3.1.

Based on the preceding discussion, Δi has more potential as an FDD feature than q_{cc} in terms of cost, capability, and even technicality. Compared to other features that have been previously used such as duty factor, time-to-cool, etc., it shows better capabilities especially in terms of diagnosis (which the other features cannot be used for). In addition, Δi meets the criteria specified in Section Chapter 2: such as being computable, modellable, and sensitive to different fault severities. More details on this would be given in Section 5.3. Though Δi is not suitable for studying UBLD impacts, it addresses RQ4 and so is chosen as an FDD feature in this study.

2.1.2.3 Less Susceptibility to UBLDs

In addition to the advantages of using Δi , as discussed above, another advantage of using Δi is that it is unaffected by UBLDs, unlike duty factor. This is because just like traditional FDD features which are system level features, Δi is also a system level feature as it measures the space air condition across the evaporator. Duty factor on the other hand measures the AC performance within the building and is thus susceptible to UBLDs. Thus, Δi combines some of the advantages of operation-based features such as better accuracy, and some of the advantages of performance-based features such as lower cost [23].

2.2 Data Sources

As shown in Figure 2.1, there are typically two sources of data in most FDD studies. The data source can be from a physical system or from a model. The physical system can be a laboratory or an actual building. Thus, there are three broad categories of data, namely: experimental data; field-data; and simulation data. All three data sources are used in this study to make it more robust. Each of these data sources is discussed in the subsequent sections.

2.2.1 Experimental Data

These are data collected from controlled environments. Such control could be partial or total. For instance, for a totally controlled environment, the outdoor conditions can be controlled to give desired outdoor temperatures, humidity, etc. Totally controlled environments are usually possible in a test chamber rather than a physical building. For partially controlled environments, certain variables (especially outdoor conditions) cannot be controlled. This is because real buildings, primarily used for experiments, are used to provide the data. Such buildings are called laboratories. They are usually unoccupied, with several sensors installed in them for collecting real-life data.

Experimental data from partially controlled environments are more suitable than those from totally controlled environments because the former provide real-life data under natural conditions, though the latter offers more flexibility. Most traditional FDD studies use such laboratory data as reported in [3]. For the Smart thermostat-based FDD study in [26], laboratory data was also used, together with simulation data.

Laboratory data is important because they serve as real-life data that can be used not just for testing purposes, but also for calibration and validation of computer models in the case of simulation-based studies. Therefore, laboratory data was used in this study.

For this study, two laboratories were used. The first is located on the University of Oklahoma (OU) campus in Norman, OK, and is used as the main testbed for this study. It is called the OU lab-house subsequently. The second is in Miami, FL, and is called the Miami Lab-house.

2.2.1.1 OU Lab-house

Figure 2.2 shows the OU lab-house with some of the devices installed and used to develop the data acquisition system. It is a single-family, one-story unoccupied house with a floor area of 1,658 ft² (154 m²), built in 1940. The house is equipped with a dual-mode air-source heat pump (ASHP) that has a 3.5-ton outdoor unit (Figure 2.2b) and a 4-ton indoor unit (Figure 2.2c). The house has three bedrooms, one living room and two bathrooms. The house also has an Ecobee smart thermostat installed in the living room, an Ecobee smart node sensor installed in the diffuser closest to the indoor unit, and a smart power meter. The node sensor is linked to the smart thermostat, making it possible to access its data via the thermostat. An IoT-based data acquisition system was installed in the house to measure the relevant variables used in this study. The system was developed by calibrating relevant sensors like t-type thermocouples. These sensors were then carefully installed in the lab-house and connected to Raspberry Pis (Figure 2.2j).



Figure 2.2: OU Lab-house overview (a) front view (b) Outdoor unit (c) Indoor unit (d) Thermocouple calibration (e) Tie Thermocouples (f) Indoor air velocity sensor (g) Hobo logger for SAT (h) condenser outlet temperature thermocouple (i) condenser saturation temperature thermocouple (j) Raspberry pi with mounted hat (k) Smart thermostat (l) Power meters (m) Smart power meter (n) Diffuser with a node sensor above it

Measured data were logged using the Raspberry Pi and its associated thermocouple hat. For the IoT feature, the Raspberry Pis are connected to an open-source and secure execution and communications IoT platform called VOLTTRON [56] developed and maintained by PNNL, making it possible to access and retrieve data from the lab-house remotely. Figure 2.3 shows the floorplan of the OU lab-house, with the locations and description of each sensor and Raspberry Pi.

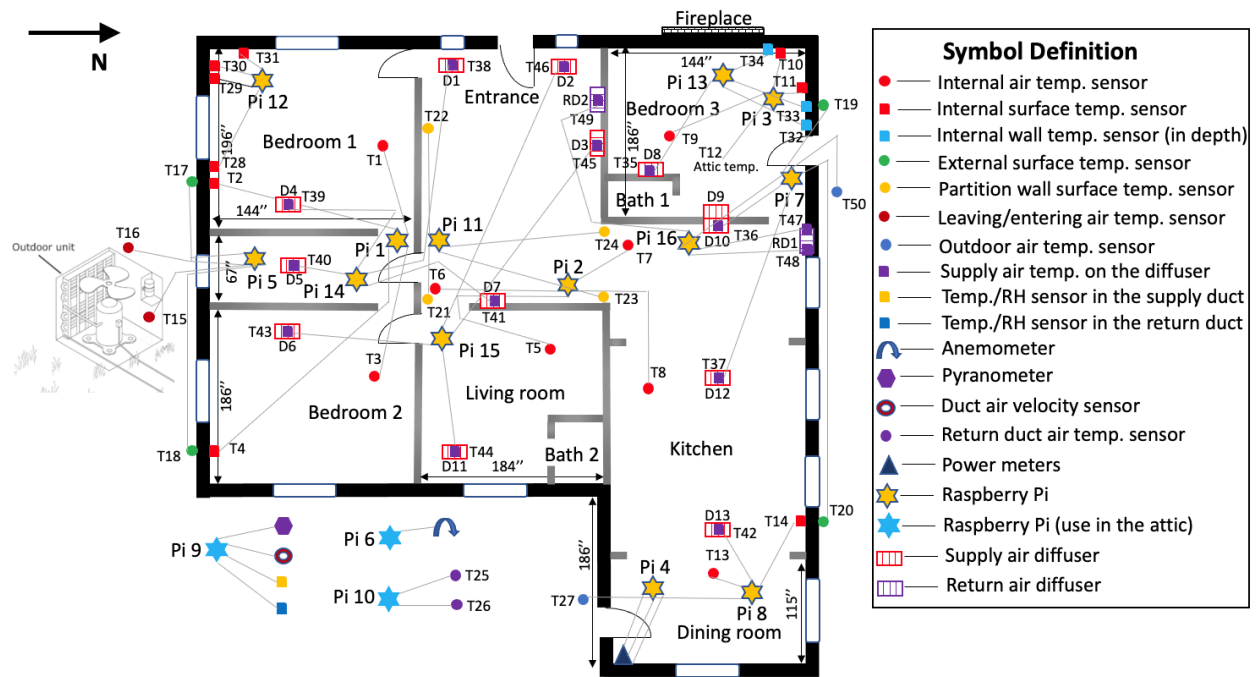


Figure 2.3: OU Lab-house Floorplan with sensor locations

Figure 2.4 illustrates the connection to VOLTTRON – a communication protocol designed for managing energy systems, integrating IoT devices, and enabling intelligent control in smart buildings. It offers a modular, agent-based architecture that facilitates data acquisition, control, and optimization of energy resources. For the OU lab-house data acquisition system, VOLTTRON is used to publish data stored locally on the Raspberry Pis into an online database called PostgreSQL [57].

Another online database used for some part (Section 5.5) of this study is the InfluxDB database [58]. This database was used for this study because, unlike the PostgreSQL database which is a relational database management system (RDMS), the InfluxDB database is a time-series database (TSDB). RDMS is a type of database that organizes data into structured tables with rows and columns and uses structured query language (SQL) for querying and managing data from the database. TSDB on the other hand is optimized for time-stamped data and is more suitable for real-time monitoring. This database was primarily used to store the data from the smart devices installed in the lab-house by means of a python code that accesses the APIs of the smart thermostat and the smart power meter and thereby extracts data from these devices and upload the data to InfluxDB.

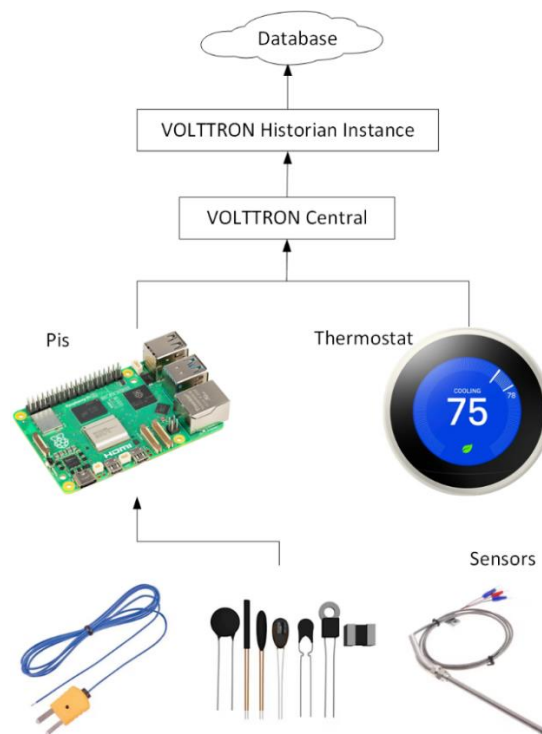


Figure 2.4: Overview of Test-house IoT-Based Data Acquisition System

For the visualization of the collected data and the FDD outputs, Grafana – an open-source online platform for visualization and monitoring data from multiple sources in real-time was used [59].

Grafana connects to several databases like InfluxDB, PostgreSQL, etc., retrieves data from these databases and then displays the data on panels/dashboards in real-time.

The relevant data retrieved and used for the study are shown in Table 2.2. The data are categorized into inputs and outputs based on the application during this study. Further details on this are provided in subsequent chapters of this work.

Table 2.2: Data Extracted using the Data Acquisition System and used in this Study

Variable	Unit	Source(s)
Inputs		
Indoor air temperature, T_{in}	K	Smart thermostat, Thermocouple, Hobo data logger
Indoor air relative humidity, ϕ_{in}	%	Smart thermostat, Hobo data logger
Interior wall surface temperature, T_{ie}	K	Thermocouple
Outdoor air temperature, T_{oa}	K	Oklahoma Mesonet data [60,61]
Solar irradiation, G	W/m ²	
Windspeed, w	m/s	
Indoor airflow rate, Q_{sa}	m ³ /s	Air velocity sensor
Compressor speed, n	Hz	Based on system specifications
Outdoor airflow rate, Q_{oa}	m ³ /s	Based on system specifications
Outputs		
Supply air temperature, T_{sa}	K	Hobo data logger, Node sensor
Condenser saturation temperature, T_{cond}^{sat}	K	Thermocouples
Condenser outlet temperature, T_{cond}^{out}	K	Thermocouples
Compressor power usage, P_{comp}	W	Power meter
Indoor fan power usage, P_{fan}^{in}	W	Power meter
Outdoor fan power usage, P_{fan}^{out}	W	Power meter
Evaporator cooling capacity, q_{cc}^{Evap}	W	Based on ratings
Condenser cooling capacity, q_{cc}^{Cond}	W	Based on ratings

2.2.1.2 Miami Lab-house

The Miami lab-house is shown in Figure 2.5. It is a single-family, two-story building with a floor area of 2,757 ft², built in 2002. The first floor is equipped with a 4-ton AC system while the second floor has a 3-ton AC system. On the first floor, there is a bedroom, a living room, a family room, a dining room and a kitchen. The second floor has three bedrooms. A thermostat is in the hallway on each floor. Hobo data loggers were installed in the house, which measured the temperature and relative humidity of the indoor air, outdoor air, supply air from a diffuser and return air inside the AC cabinet. A power meter was installed to measure the power of the indoor unit and outdoor unit of both AC systems. One-time airflow rate measurement was taken at each diffuser and summed up to obtain the total indoor airflow rate of both AC systems. An irradiation sensor was installed outside one southside window on the second floor to measure the solar irradiation. The locations of the sensors and power meters are shown in Figure 2.5. The measurements were taken at one-minute intervals.

To further illustrate the sensor locations in the house, floor plans were drawn and are shown in Figure 2.6.

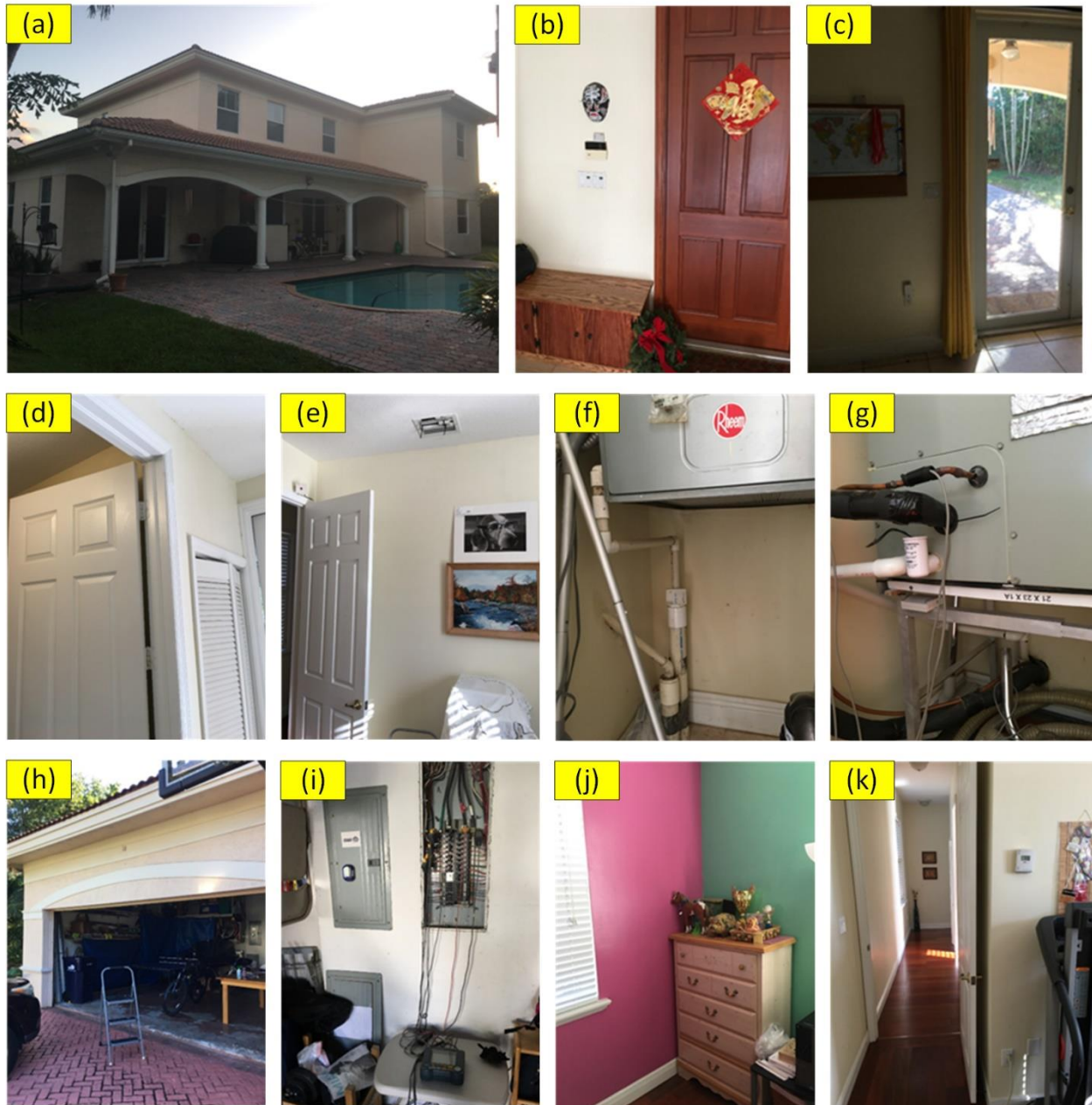


Figure 2.5: Back view of Miami lab-house; (b) T_{in} measurement in the living room (entrance); (c) T_{in} measurement in the family room; (d) T_{sa} measurement at a diffuser on the first floor; (e) T_{sa} measurement at a diffuser on the second floor; (f) T_{in} measurement in the return cabinet on the second floor; (g) T_{oa} measurement in front; (h) power meters for the indoor and outdoor units of both AC systems; (i) T_{in} measurement in a bedroom on the second floor; (j) T_{in} measurement in the master bedroom on the second floor.

2.2.2.1 Residential Homes in Norman

Field data from three residential homes located in Norman, OK were used. An Ecobee smart thermostat and a node sensor linked to it, and a smart power meter were installed in each of these homes for data collection. The diffuser closest to the indoor unit in each of these homes was identified and the node sensor was placed on the diffuser to collect supply air temperature measurements, like what was done for the OU lab-house. The data was then retrieved using a python code that accesses the APIs of the smart devices remotely, extract the data and upload the data to InfluxDB. Table 2.3 shows a brief description of the residential homes used for field testing in this study, specifically for the deployment of the performance enhancement strategy discussed in Section 5.5.

Table 2.3: Specifications of Residential Homes in Norman

Home	Square footage	Tonnage		AC age	Test period
		Outdoor unit	Indoor unit		
Home A	2100	5	5	4 years	May 14 – Sept. 26
Home I	2450	5	5	8 – 15 years	May 14 – Sept. 26
Home J	2150	2.5	3	8 – 15 years	July 14 – Sept. 26

2.2.2.2 American Time-of-Use Survey (ATUS) Data

The American Time-of-Use Survey (ATUS) data was used to estimate the times when US residents engage in various activities and their frequency. The ATUS dataset is based on a survey, supported by the US Bureau of Labor Statistics (BLS), and conducted by the US Census Bureau [62]. The survey provides nationally representative estimates of how US residents spend their time and is the only federal survey providing data on the full range of activities such as sleeping, working,

eating, socializing, etc. From 2003 to 2023, nearly 245,000 interviews have been conducted and used to develop the ATUS dataset. Table 2.4 shows an illustration of what the ATUS data looks like. TUCASEID is a unique ID for each resident. TUACTIONITY_N shows the activity number while TUTIER1CODE indicates the activity type. TUSTARTTIM and TUSTOPTIME records the start and stop times of each activity, while TUACTIONDUR24 records the duration of the activity in minutes.

Table 2.4: Sample data from ATUS Survey [63]

TUCASEID	TUACTIONITY_N	TEWHERE	TUACTIONDUR24	TUSTARTTIM	TUSTOPTIME
2017010117002	1	-1	90	4:00:00 AM	5:30:00 AM
2017010117002	2	-1	30	5:30:00 AM	6:00:00 AM
2017010117002	3	12	15	6:00:00 AM	6:15:00 AM
2017010117002	4	2	15	6:15:00 AM	6:30:00 AM
2017010117002	5	2	150	6:30:00 AM	9:00:00 AM
2017010117002	6	2	30	9:00:00 AM	9:30:00 AM
2017010117002	7	2	300	9:30:00 AM	2:30:00 PM
2017010117002	8	2	30	2:30:00 PM	3:00:00 PM
2017010117002	9	12	15	3:00:00 PM	3:15:00 PM
2017010117002	10	3	3	3:15:00 PM	3:18:00 PM
2017010117002	11	12	3	3:18:00 PM	3:21:00 PM
2017010117002	12	1	45	3:21:00 PM	4:06:00 PM
2017010117002	13	1	30	4:06:00 PM	4:36:00 PM
2017010117002	14	1	10	4:36:00 PM	4:46:00 PM
2017010117002	15	-1	15	4:46:00 PM	5:01:00 PM
2017010117002	16	1	14	5:01:00 PM	5:15:00 PM
2017010117002	17	-1	405	5:15:00 PM	12:00:00 AM
2017010117002	18	-1	7	12:00:00 AM	12:07:00 AM
2017010117002	19	-1	233	12:07:00 AM	5:30:00 AM
2017010117012	1	-1	180	4:00:00 AM	7:00:00 AM
2017010117022	2	1	60	7:00:00 AM	8:00:00 AM

The ATUS dataset was used in [64] to study various typical occupancy schedules in residential buildings within the US. Using this data, they developed occupancy schedules for residential homes. The schedules included those for one-member households to four-member households. Also, there were schedules for different age groups, ranging from under 25 years to over 75 years. Meanwhile, these schedules were sorted into weekdays schedule and weekend schedules.

Furthermore, for the different categories above, the study showed the spatial distribution of occupants within residential buildings in the US i.e., where most occupants spend most of their time in a home in a day, and the associated time of the day. The study demonstrated the suitability of the ATUS dataset for understanding occupancy behaviors in residential buildings. The study, together with other studies [63,65] also demonstrated that the default occupancy schedule in EnergyPlus is not well representative.

Based on the foregoing, the ATUS data was used in this study for developing occupancy schedules and infiltration schedules which were used in the performance enhancement strategies proposed in Section 2.5.1. The ATUS data used is from 2003 – 2019 and covers 219,368 homes across the US. This period was chosen to avoid covid periods (from 2020) which could significantly affect occupant behavior. Details of this strategy are provided in Sections 2.5.1 and chapter 3 of this study.

2.2.2.3 Ecobee DYD Program

The Ecobee DYD (Donate Your Data) program is an initiative designed to collect anonymized thermostat data from users to support energy efficiency research and improve smart home technology [66]. This allows researchers to use aggregated field data from multiple smart thermostats to conduct studies that can improve the performance of smart thermostats.

The DYD dataset contains operational data such as indoor temperature, indoor humidity, outdoor temperature, occupancy signals, temperature setpoints, etc. A metadata associated with the DYD dataset provides details of each anonymized user such as house type, location (i.e., province/state and city), the floor area, the maximum number of residents, etc. The DYD program comprise of over 200,000 users across the US and Canada.

In [65], this dataset was used to generate representative occupancy schedules for residential buildings in the US. However, the study in [64] which used the ATUS data is more detailed than the study in [65], likely because of the limitation in smart thermostat occupancy data as pointed out in Section 1.3.1.1.

Therefore, the ATUS dataset was chosen over the Ecobee DYD dataset for the occupancy schedules and the infiltration schedules in this study. Instead, the Ecobee DYD dataset was used to generate the setpoint schedules used in the performance enhancement strategy proposed in Section 2.5.2, since the setpoint data is more reliable and representative than the occupancy data from smart thermostats. Details of this strategy and the use of the DYD dataset are provided in Section 2.5.2 and chapter 3.

2.2.3 Simulation Data

In simulation-based approach, computer models of a physical system are usually developed, calibrated and validated. Then the validated models are used to generate the required data.

A simulation-based approach was adopted for this study based on the following advantages:

1. Cost-effectiveness, when compared to experimental or field study; especially when there are several cases to consider.
2. Flexibility, in terms of being able to conduct tests under different conditions and cases that may not be feasible in field studies or difficult to replicate in experimental studies.
3. Speed, in terms of providing results quickly. For instance, while field study could take weeks or even months to simulate a cooling season, and experiments might take slightly less, with simulation, this can be done in a matter of minutes or a few hours.

4. Simulation is suitable for cases where available data is inadequate, which is one of the challenges identified with Smart thermostat-based FDD.
5. Simulation studies allow for better understanding of how a system works and is expected to perform in real life.
6. Simulation studies can help in identifying constraints in a system that should be considered.
7. Modelling and simulation is one of the most powerful techniques for integrated approach to building studies [67,68].

While simulation offers several advantages as listed above, there are some disadvantages with simulation studies, such as:

1. Model limitations: Simulation studies are mainly based on mathematical models that are solved by mathematical methods. These mathematical methods are usually built into solvers which may impose limitations that are either based on assumptions made in the model or computational requirements of these solvers.
2. Model complexity: HVAC systems are complex dynamic systems, and creating accurate models that capture all the relevant physics and behaviors can be challenging.
3. Parameterization: Simulation studies require accurate input data such as design parameters, operating conditions, and environmental factors. Obtaining this data can sometimes be time-consuming, expensive, inaccurate, or incomplete, thus affecting the accuracy of simulation results.
4. User expertise: Simulation software can be complex and require specialized expertise to use effectively. Users must have a thorough understanding of the software, as well as the underlying physics or principles of the simulated system, to accurately model the system and interpret simulation results.

5. Verification and validation: This is very critical for simulation studies. However, it requires additional time and effort to conduct experiments or collect data. Meanwhile errors can still occur due to differences between simulation and field or experimental conditions.

Despite these disadvantages, the advancement of computational studies and simulation tools have made simulation-based approach more robust and widely accepted. Some Smart thermostat-based studies have adopted this approach. For instance, in [22,23,26], simulation data was used. But for this study, a co-simulation approach was adopted. The next section introduces the co-simulation testbed used in this study.

2.2.3.1 Co-Simulation Testbed

Co-simulation is a powerful technique that involves the combination of different simulation tools, run simultaneously with data exchange between them, to study interactions between systems [69]. Co-simulation gives the advantage of being able to use the best tools to model specific components of an integrated system [70] and is considered more robust than a monolithic simulation where one tool is used to simulate both AC and building models [67,68,71–73]. There have been a few studies involving co-simulation of AC and building models. Some of such studies were to investigate airflow or indoor air quality or building energy use in non-residential buildings [70,74–77]. In [78], co-simulation of a room model and a control system model was demonstrated. In [69], co-simulation of an AC system developed in Modelica and linked to a room model in EnergyPlus was demonstrated. However, the AC system was an ideal heater model which is not capable of simulating refrigeration charge faults of a vapor compression (VC) cycle which is typical in residential AC systems. While there have been several co-simulation studies, there is a lack of such studies conducted for typical VC cycle based residential AC systems, and for FDD purposes.

Presently, there are several simulation tools like TRNSYS, HVACSIM+, ResStock, REGCAP, OpenStudio, EnergyPlus, Dymola, etc., which have been used in FDD studies in general. For Smart thermostat-based studies, REGCAP was used in [22], EnergyPlus was used in [23,26]. However, for the co-simulation-based approach adopted in this work, EnergyPlus and Dymola were used. EnergyPlus is a whole building energy modeling (BEM) tool suitable for computing building loads and simulating building thermal dynamics [79]. It is widely accepted both in the industry and research community for BEM applications. Dymola (Dynamic Modeling Laboratory) is a modelica-based simulation tool mostly used for modeling and simulating complex and integrated systems as well as processes involving fast dynamics like HVAC operations [80]. Modelica is an object-oriented language for modeling physical systems using an acausal modeling approach. A major advantage of modeling in Modelica is the concept of acausal modeling where equations define relationships between variables without specifying a fixed computational sequence. This makes models to be more flexible and modeled based on equations that resemble real-world physics instead of software logic. It also increases the reusability of models, thus encouraging the development of libraries which provide pre-built components, models and functions for simulating multi-domain physical systems. Based on reviews of different software [81], Modelica was used to model the AC system and the air dynamics within the building; while EnergyPlus was used to compute the building loads. For the modeling of the building, EnergyPlus was used together with components from Modelica-based libraries like Buildings Library [82] and Modelica Standard Library [83] which are very suitable for modeling building controls and dynamics. While for the modeling of the AC system, components from another Modelica-based library, TIL [84], were used based on its suitability for modeling vapor compression cycle AC systems. More details on the co-simulation model are provided in Section 3.2.

Though the computation of the building load can also be achieved in Modelica using models like the MixedAir model in the Modelica Buildings Library (MBL), EnergyPlus was preferred because apart from being more widely accepted for building modeling, it is more user-friendly based on the GUI (Graphical User Interface) which OpenStudio offers. This GUI, together with already built-in schedules, construction materials and their properties, makes it easier to develop a building model. Whereas, for the MixedAir model, schedules and construction materials and properties have to be entered manually, making it more tedious.

2.2.3.2 Calibration of the Co-Simulation Testbed

As noted in Section 2.2.3.1, a crucial requirement for using simulation data is proper calibration and validation of the computer models used to generate the data. Therefore, this section discusses the calibration methods adopted in this research and the metrics identified and used in this study to ensure that the co-simulation testbed was well calibrated based on acceptable standards. Details on the calibration of the co-simulation testbed are provided in Section 3.3.

2.2.3.2.1 *Review of Calibration Methods*

Calibration methods can be classified into four types: manual, graphical, analytical, and automated calibration [85]. While all four categories could offer high model accuracy if the calibration is properly done, automated calibration reduces time and expert knowledge requirement.

Therefore, several studies have been conducted on automated calibration methods using different algorithms. In [86], a Bayesian Optimization (BO) algorithm was used to calibrate 17 parameters of a coupled building/HVAC based model. The method involves learning the calibration-cost map (the relationship between parameter settings and the resulting cost function) instead of simulating the full system dynamics, in a bid to reduce computational cost. Calibrated parameters over 90%

accuracy with less than 1000 model simulations were reported. However, an idealized scenario was considered where the Modelica model structure perfectly represents the physical system. Also, this study was for a commercial building. In [87], a batch-wise BO method that leverages Attentive Neural Processes (ANPs) was proposed for largescale calibration of industrial digital twins. The digital twin was modeled in Modelica. Coefficient-of-Variation Root-Mean-Squared Error (CVRMSE) less than 1% was reported for all the compared outputs with most parameters having over 90% relative accuracy. Risch et al. [88] studied the impact of data availability on Bayesian calibration of urban Building Energy Models (BEMs). Archetype BEMs for 3 research buildings were used for this study. Individual Bayesian calibration of the archetype BEMs was then performed at 3 levels of data availability. In level 1, the orientation and façade area as well as the window-to-wall ratio was added to the BEMs. In level 2, structural properties of the building elements were further added. While in level 3, heating schedule for the system operation was additionally introduced. Level 3 reportedly showed better results for all buildings, with level 2 having the most significant impact. This study was, however, also for a commercial building and for heating application. In [89], Heteroscedastic Evolutionary BO algorithm was used to calibrate 45 parameters of an air handling unit (AHU) coupled to a commercial building. CVRMSE of 0.38% and a maximum absolute error (MAE) below 1 °C was reported in this study. However, this study only considered heating operations. Meanwhile, the dynamics of AHU are different from that of vapor compression cycle found in residential HVAC units. In [85], a framework that recursively calibrates simulation models was proposed and applied to a heat pump digital twin model. Differential Evolution (DE) optimization method was used. The heat pump model was developed in Modelica with the AixLib Modelica library. An RMSE (Root Mean Squared Error) consistently below 1 K was reported. However, the calibration was just for the digital twin HVAC

system, which was a heat pump – and has different dynamics from an AC system. Slime Mold Optimization (SMO) algorithm was used in [90] to calibrate an office building. The method involved optimizing occupant-related variables to minimize differences between measured and simulated building energy consumption. Apart from also being on commercial buildings, the proposed method here could highly be affected by occupant-related uncertainties. Energym – an open-source building model library for benchmarking controllers was proposed in [91]. The functionality of the library was demonstrated in the calibration of 11 models – with envelope and equipment calibrated for 4, while for the others only parts of the equipment were calibrated. For both envelope and equipment calibration, the Non dominated and crowded Sorting Genetic Algorithm 2 (NSGA-II) was used. However, all the 8 different building models calibrated in this study were commercial buildings. The NSGA-II was also used in [92] for calibrating an AHU. A similar open-source package known as AixCaliBuHa has also been developed [93]. The package enables automated calibration of dynamic building and HVAC simulation models. The package which was built in Python is reported to support the calibration of Functional Mock-up Units (FMUs) and Modelica models. Also, the package is said to have the capability to perform automated sensitivity analysis. Application of the package for automated calibration requires users to first formulate the optimization problem. The formulated optimization problem is then linked to relevant python data types based on the definition of data types (a core part of AixCaLiBuHa). Also, a standardized interface for coupling Modelica models to the calibration toolchain of the AixCaLiBuHa package has reportedly been developed [94]. Details of this and steps for using this package can be found in [95]. While the package shows good prospects with attractive features like automated sensitivity analysis, the optimization leverages existing libraries like Scipy, Dlib-ml, and Pymoo (a multi-objective optimization framework). For complex systems with lots of

parameters, convergence to local optima particularly in complex parameter spaces could lead to convergence issues, as is typical with search-based optimization algorithms.

So far, the above review reveals a paucity of studies on automated calibration of building/AC systems in the residential sector. Also, in most of the studies reviewed, simplified models were used likely due to the complexity of commercial systems and the high computation cost it could incur if co-simulation-based models were used. For instance, in most of the above studies, Modelica with libraries like the Modelica Buildings Library (MBL) and AixLib were used. While these libraries are very resourceful for building modeling, they are not very robust for modeling AC systems especially in residential applications, when compared to libraries like the TIL library [84] developed by the TLK-Thermo Group or the Modelon AC library [96] developed by Modelon Impact. Several studies [47,48,97,98] have demonstrated the robustness of the TIL library for modeling vapor-compression based AC systems. Additionally, studies [47,48,70–73,76,78,99,100] have shown the usefulness of co-simulation which makes it possible to combine different simulation tools like EnergyPlus which is more suitable for building modeling and Dymola/Modelica which is more suitable for AC and control system modeling. Lastly, in most of the studies reviewed above, advanced search-based optimization methods were used e.g., population-based or evolutionary search methods [85,90–92], probabilistic learning algorithms like the Bayesian algorithms [86–89]. However, these algorithms perform better with fewer calibration parameters. As noted earlier, large number of calibration parameters could potentially lead to convergence to local optima or make convergence difficult. Also, convergence might be a challenge especially if the model parameter map present spaces that are nonlinear, non-differentiable, or non-convex – which is usually the case [89]. Thus, for the calibration of the co-

simulation testbed in this research, a two-phase automated calibration framework was developed which uses:

- A genetic algorithm (GA) optimization for calibrating the AC model in Phase 1. A GA optimization was used because it is a very popular and widely used method for calibration of models. However, because GA performs poorly when the number of calibration parameters are much, the GA optimization was applied to just the calibration of the AC model, thereby reducing the number of calibration parameters.
- A Resistance – Capacitance (RC) model optimization was used for calibrating the building model in Phase 2. The calibrated AC model from Phase 1 was coupled to the building model through the co-simulation setup. The RC model is a simplified 2R2C model which significantly reduces the number of calibration parameters required by lumping the numerous parameters in building models (e.g., geometric/structural parameters, thermal parameters, etc) into just 2 parameters: thermal resistance (R) and thermal capacitance (C). This was used to calibrate the building model.

Unlike most calibration studies, which primarily focus on energy performance, the proposed automated framework performs a more comprehensive calibration of both the building and AC system to match the dynamics of AC operation in buildings. Discussion on the RC calibration method is presented in the following section.

2.2.3.2.2 RC Model Calibration Method

Due to the accuracy of building thermal network models (also known as resistance-capacitance or simply RC models) in indoor air prediction and building envelope evaluation, coupled with the advantage of lumping several model parameters into just R and C [101], an RC model is adopted

for this study. RC models are data-driven models which capture the thermal properties of a building without the need for physical building information. These models describe the heat transfer through building envelopes in terms of the thermal resistance ($R = \frac{\Delta x}{kA}$, in K/W, for solid media) and thermal capacitance ($C = \rho Vc$, in J/K); where Δx is the thickness (m), k is the thermal conductivity (W/m-K), A is the surface area (m²), ρ is the density (kg/m³), V is the volume, and c is the specific heat capacity (J/kg-K).

To calculate the total resistance (R_{total}) of the whole envelope of a building, the resistances of walls (R_w), windows (R_{win}) and doors (R_d) can be treated as parallel connections while the resistances of roof (R_{roof}) and ceiling (R_{ceil} , in the existence of an attic) can be treated as series connection. Thus, the total resistance can be expressed as:

$$R_{total} = \frac{1}{\frac{1}{R_{t,w}} + \frac{1}{R_{win}} + \frac{1}{R_d} + \frac{1}{R_{roof} + R_{ceil}}} \quad (2.6)$$

$$R_{t,w} = \frac{1}{h_i A_i} + R_w + \frac{1}{h_o A_o} \quad (2.7)$$

where $R_{t,w}$ is the overall resistance of the walls (K/W); h_i and h_o are the convective heat transfer coefficients (in W/m²K) from interior wall surface and from exterior wall surface, respectively; and A_i and A_o are the surface areas of the interior and exterior walls, respectively.

Similarly, with the density, volume and specific heat of each component, the total capacitance, C_{tot} , of the whole envelope can be gotten from

$$C_{tot} = C_w + C_{win} + C_d + C_{roof} + C_{ceil} \quad (2.8)$$

RC models have been developed in different forms, e.g., 1R1C [101], 2R2C [102], 3R2C plus 2R2C [103], and have been used in optimal precooling studies [104,105], MPC studies [106], and

envelope performance evaluation [107,108]. A detailed review of the different RC models can be found in [109].

For residential building models, the 2R2C model has been shown to be accurate [102,106], and is considered sufficient and appropriate for this study because of its simplicity. Figure 2.7 shows a schematic of the 2R2C model.

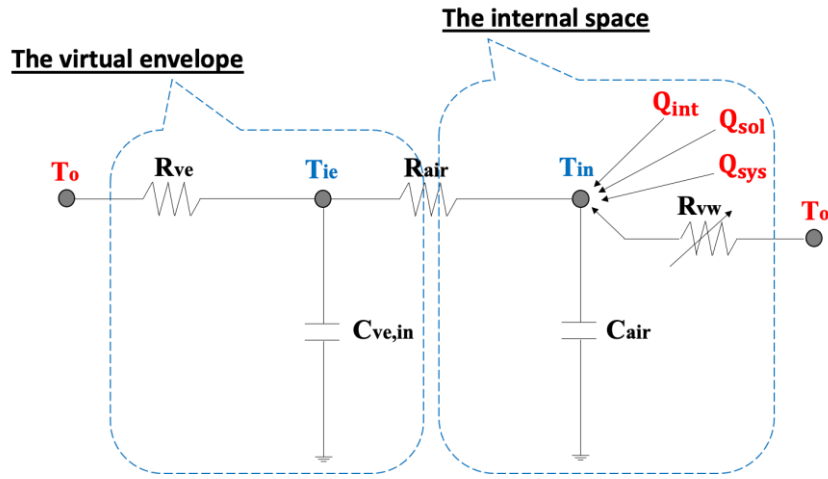


Figure 2.7: Schematic of the 2R2C model [106]

A simplified 2R2C model was defined in [102,106] by Equations (2.9) and (2.10)

$$\frac{dT_{ie}(t)}{dt} = \frac{1}{\tau_1} [T_o(t) - T_{ie}(t)] + \frac{1}{\tau_2} [T_{in}(t) - T_{ie}(t)] \quad (2.9)$$

$$\begin{aligned} \frac{dT_{in}(t)}{dt} = & \frac{1}{\tau_3} [T_{ie}(t) - T_{in}(t)] + \frac{1}{\tau_3} [(T_o(t) - T_{in}(t))(b_1 W(t) + b_2 W^2(t)) + a_1 G(t) + \\ & a_2 G^2(t) + a_3 G^3(t) + Q_i u_i(t) + Q_{sys} u_{sys}(t)] \end{aligned} \quad (2.10)$$

where T_{ie} , T_{in} , and T_o , are temperatures for the interior wall, indoor air, and outdoor air, respectively. G is the global horizontal irradiation (GHI); W is the windspeed; Q_i and Q_{sys} are the internal gains and AC output into the conditioned space (i.e., cooling capacity), respectively. $\tau_1 =$

$R_{ve}C_{ve,in}, \tau_3 = R_{air}C_{air}$ are time constants of the virtual envelope and space air. $\tau_2 = R_{air}C_{ve,in}$ is a parameter scaled by the space air. $\tau_1, \tau_2, \tau_3, a_1, a_2, a_3, b_1, b_2,$ and Q_{sys} are the parameters of the model and can be identified using a parameter estimation method [102,106]. From the above definitions, τ_1 represents the thermal properties of the entire envelope of a residential building, where R_{ve} and C_{ve} represents R_{total} and C_{total} in Equations (2.6) and (2.8). Thus, it was used as the calibration index for the residential building model. The parameter estimation method used in this study is the least squares method. Q_i in Equation (2.10) can be assumed to be mainly from heat generated by occupants. But since the building used for the experiment is unoccupied, Q_i is therefore eliminated from the equation.

The advantage of using the RC model calibration is that it helps consolidate the different envelope parameters into just two parameters, R and C . For instance, there are about 60 parameters in the EnergyPlus building model which contribute to the thermal dynamics of the building [110]. By using the 2R2C model described above, these 60 parameters can be lumped into just two parameters, R and C . This consolidation significantly reduces the number of parameters that need to be tuned during the calibration process, thus making it easier to automate the process. Further discussion on the tuning process is provided in Section 2.2.3.2.3.

2.2.3.2.3 Overview of the Automated Calibration Framework

The automated calibration framework used to calibrate the building model was developed using Python, Dymola, and EnergyPlus. To set up the framework, an interface between Python, Dymola and EnergyPlus was first developed as shown in Figure 2.8.

Several Python interfaces to Dymola have been developed. These interfaces allow direct interaction between Dymola and Python scripts. This makes it possible to use Python scripts to

load and simulate Modelica models, extract simulation results, automate tasks like parameter sweeps and calibration. Example of such interfaces include the built-in Dymola-Python interface [111], DymPy [112] and BuildingsPy [113]. After reviewing the different interfaces available, the BuildingsPy interface was chosen as it was found to be more robust. Also, it is more suitable for workflows involving building energy models [114].

For interaction between Python and EnergyPlus, Eppy – a Python library for establishing access to EnergyPlus IDF files [115], was used. Such access makes it possible to modify IDF files using a Python script. It also makes it possible to make large changes to single or multiple IDF files.

Figure 2.9 shows the flow chart of the automated calibration process used in this study. The process begins with (i) extracting the relevant data in Equations (2.9) and (2.10) from the data acquisition system (discussed in Section 2.2.1.1); (ii) least square estimation of the parameters in Equations (2.9) and (2.10); (iii) steps (i) and (ii) is then repeated using data from the co-simulation; (iv) τ_1 estimated with measured data and simulated data are compared in the Cost Function; (v) If the difference satisfies the specified criteria, the process is stopped. But if not, the IDF file and building model are auto-tuned using a simple algorithm (that adjusts relevant parameters that affect τ_1 and infiltration e.g., thermal conductivity, thermal resistance, and specific capacity for the IDF file and the effective leakage area for the building model in Modelica) until a good match is found.

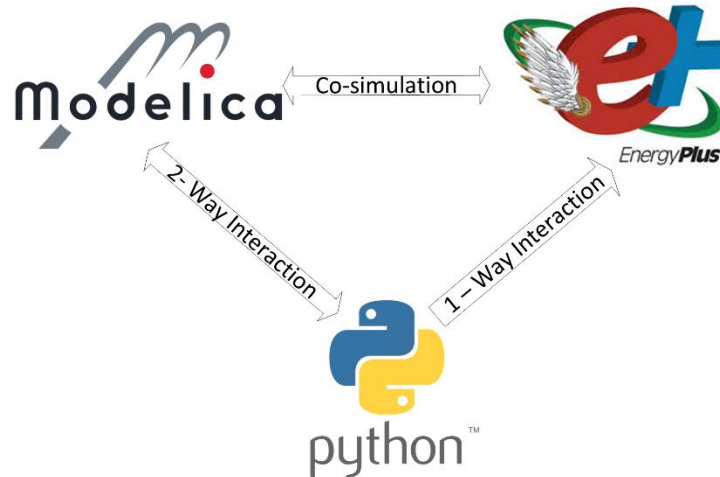


Figure 2.8: Python-Modelica-EnergyPlus Interface used in the Automated Calibration Framework

As discussed in Section 2.2.3.2.2, the envelope thermal properties of the EnergyPlus building model (referred to as IDF file) were reduced to just two parameters, R and C . Both parameters are a function of k , ρ , and c which are each provided for the different construction materials used in the EnergyPlus building model. Thus, the tuning of the IDF is simplified to just the tuning of these three parameters. From the building model components developed in Modelica such as those modeling the air dynamics of the building, three parameters were added to the tuned parameters, namely: the infiltration airflow rates and the air mass in the zone. This brings the total number of parameters that need to be tuned for the building model calibration to just five.

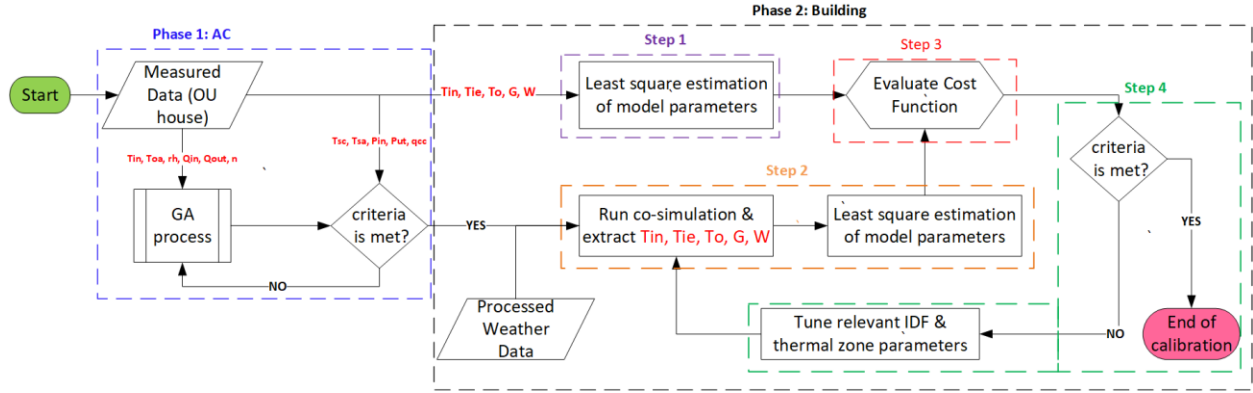


Figure 2.9: Flow Chart of the Automated Calibration Process

2.2.3.2.4 Metrics for Calibration of Co-Simulation Testbed

To calibrate the AC model and the building model, there are several error metrics that can be used. Based on the recommendations of well reputed agencies like ASHRAE, the International Performance Measurement and Verification Protocol (IPMVP) and the Federal Energy Management Program (FEMP), CVRMSE and Normalized Mean Bias Error (NMBE) were used. Studies have also shown these to be the standard and more commonly used metrics [89,116]. Equations (2.11) and (2.12) gives expressions for NMBE and CVRMSE, respectively.

$$NMBE (\%) = 100 \times \frac{1}{\bar{y}} \frac{\sum_{i=1}^n (y_i - \hat{y}_i)}{n} \quad (2.11)$$

$$CVRMSE (\%) = 100 \times \frac{1}{\bar{y}} \sqrt{\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}} \quad (2.12)$$

where y_i is the measured variable, $\hat{y}_i$ is the simulated variable, n is the number of samples and $\bar{y}$ is the mean of the measured values.

While NMBE and CVRMSE have been recognized by agencies like IPMVP, FEMP and ASHRAE as standard metrics for evaluating model accuracy, these metrics are based on energy performance indicators like power consumption and cooling capacity. For calibration of building energy

simulation models, Table 2.5 gives a summary of acceptable thresholds for model calibration for energy consumption based on different guidelines. However, there are no such formal guidelines or criteria specified by the above agencies for calibration of simulation models for monitored temperature data. Though from previous studies, the acceptable metric for temperature data is mean absolute error (MAE) with a range of $\pm 1 - 2\text{ }^{\circ}\text{C}$ [117].

Table 2.5: Summary of Acceptable Calibration Criteria for Energy Consumption based on Different Guidelines [98]

Guideline	Data type	Metrics	Criteria
ASHRAE [118]	Hourly	NMBE	$\pm 10\%$
		CVRMSE	30%
	Monthly	NMBE	$\pm 5\%$
		CVRMSE	15%
IPMVP [119]	Hourly	NMBE	$\pm 5\%$
		CVRMSE	20%
	Monthly	NMBE	$\pm 20\%$
		CVRMSE	20%
FEMP [120]	Hourly	NMBE	$\pm 10\%$
		CVRMSE	30%
	Monthly	NMBE	$\pm 5\%$
		CVRMSE	15%

2.2.4 Weather Data

As indicated Table 2.2, Oklahoma Mesonet data [60,61] was used for to provide the weather data. The Mesonet data has been shown to be reliable [101] and thus has been used in several studies [101–104,121,122]. Moreover, the Mesonet data provides other relevant weather data like solar irradiation and windspeed which smart thermostats do not provide. Therefore, the Mesonet data was used in this research.

To retrieve the data from the Mesonet website, MATLAB code was developed and used. The code retrieves the data from the website and processes it into the desired format in terms of time interval and the local time zone. This is because the data from the Mesonet website is provided in 5-minutes interval, and in UTC time zone. But to simulate the fast dynamics of AC systems, a 1-minute interval is needed.

However, for the implementation of the Mesonet weather data in the co-simulation done in this research, a conversion of the data into a suitable format had to be done. This is because both EnergyPlus and the Weather Reader in MBL each requires the input weather file to be in the Typical Meteorological Year 3 (TMY3) format. Although EnergyPlus provides TMY3 data for several locations around the world, it does not have data for Norman, Oklahoma. The closest location is Oklahoma City-Tinker AFB. So, a conversion of the collected Mesonet data had to be done.

The local weather data extracted from the Mesonet website includes dry-bulb temperature, relative humidity, global horizontal irradiation (GHI) and windspeed. But to convert to the TMY format, wet-bulb temperature, dew-point temperature, atmospheric pressure, normal direct irradiation

(G_{ND}), and diffuse horizontal irradiation (G_{dH}) are also required. However, these are not available from the Mesonet website. So, to acquire the other relevant data, other tools had to be employed.

For G_{ND} and G_{dH} , these were calculated using the ASHRAE Clear Sky Model [123] defined by Equations (2.13) - (2.15)

$$G_{ND} = \frac{A}{\exp\left(\frac{B}{\sin \beta}\right)} C_N \quad (2.13)$$

$$G_{DH} = G_{ND} \sin \beta \quad (2.14)$$

$$G_{dH} = C(G_{ND}) \quad (2.15)$$

where A is the apparent solar irradiation at air mass of zero, B is the atmospheric extinction coefficient, C is the ratio of diffuse irradiation on horizontal surface to direct normal irradiation, β is the solar altitude and C_N is the Clearness number. Parameters A , B , C , and C_N are obtained from [123]. While for β , it is obtained from Equation (2.16)

$$\sin \beta = \cos(L) \cos(H) \cos(\delta) + \sin(L) \sin(\delta) \quad (2.16)$$

where L is the latitude of the location. To obtain the remaining parameters in Equation (2.16), Equations (2.17) - (2.21) [123] are used.

$$EOT = 2.29[0.007 + 0.19 \cos(N) - 3.21 \sin(N) - 1.46 \cos(2N) - 4.09 \sin(2N)] \quad (2.17)$$

$$N = \frac{n-1}{365} \times 360; \quad n = 1 \leq n \leq 365 \quad (2.18)$$

$$\delta = 23.45 \sin\left(360 \times \frac{n+284}{365}\right) \quad (2.19)$$

$$AST = LST + \frac{EOT}{60} + \frac{(L_L - L_S)}{15} \quad (2.20)$$

$$H = (AST - 12) \times 15 \quad (2.21)$$

where n is the day of the year, δ is the angle of declination, AST is the apparent solar time (in hours), LST is the local standard time (in hours), EOT is the Equation of time (in minutes) and H is the Hour angle (in degrees).

After obtaining all the required data, the conversion was done using the EnergyPlus Weather Converter tool. After running the converter, it generates a TMY file (.epw) which can then be used in EnergyPlus. To use the converted weather data in Dymola, further conversion of the .epw file into .mos file is required. The converter provided by MBL was used for this.

2.3 Faults Considered in this Study

In residential HVACs, there are various faults which occur. These faults occur at different stages and have varying degrees of impact on the system. Hence an understanding of the different classes of faults and their impact levels is important for FDD.

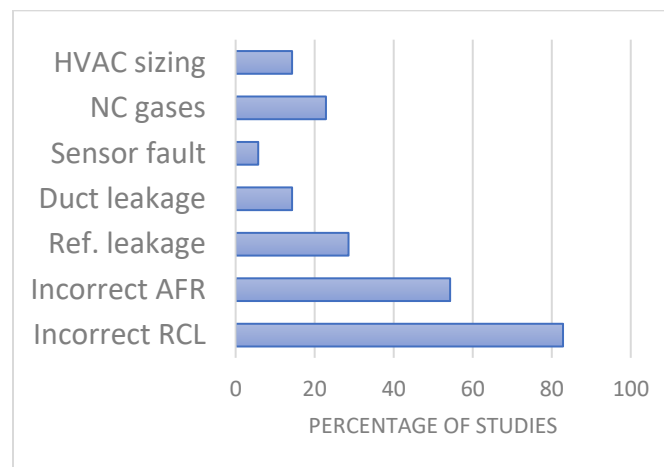
Based on the nature, HVAC faults are broadly classified into design faults, installation faults, gradual faults, and sudden/abrupt faults [124]. Design faults result mainly from poor decisions or wrong analysis during the design, e.g., oversizing/undersizing of an HVAC system component. Installation faults occur during the installation of an HVAC system, e.g., the presence of non-condensable gases like air in the system. Gradual faults are faults that arise from deterioration of the system or system components overtime e.g., refrigerant leakage which leads to low refrigerant charge, duct leakage leading to low airflow rate, sensor faults, condenser/evaporator fouling, etc. As they occur gradually, they are often imperceptible until they become severe and thus are also called soft faults. Sudden faults are faults that occur abruptly and are thus easy to detect. Such faults are called hard faults.

Studies have shown that air conditioners (ACs) and air-source heat pumps (ASHPs) suffer significantly from any of the above faults which result in degradation and reduction of system performance and in turn negatively impact thermal comfort and energy usage in buildings. The majority of these faults have been identified as improper HVAC sizing, incorrect duct sizing, duct leakage, incorrect refrigerant charge, and incorrect airflow rate [125–128]. Table 2.6 shows the various faults and the associated references. Based on the citations in Table 2.6, a total of thirty-five literatures related to studies on faults in residential HVAC systems were surveyed in the course of this review. Figure 2.10 shows the percentage of the thirty-five literatures found which focused on different faults. As can be seen from the chart, incorrect refrigerant charge levels (RCL) and incorrect airflow rate (AFR) are the most researched as noted also in [28,129]. Refrigerant leakage which is the third place can be classified with low RCL. Duct leakage is included as a common fault in [3,23], but can be considered under incorrect airflow as it leads to low airflow.

Thus, RCL and AFR can be considered as the most significant. Also, from the chart, sensor fault is least studied for residential HVAC. This is because residential HVAC typically have much fewer sensors compared to commercial HVAC.

Table 2.6: Common Fault Types in Residential HVAC and their Related Studies

S/N	Fault Type	Studies
1	HVAC sizing	[55,125–127,130]
2	Presence of NC gases	[6,125,130–135]
3	Sensor fault	[3,136]
4	Duct leakage	[125–127,130,137]
5	Refrigerant leakage	[5,6,15,131,133,136,138–141]
6	Incorrect airflow rate	[13,20,130,131,133–135,137,139,140,142,22,23,55,125–129]
7	Incorrect charge	[6,8,13,20,22,23,55,125–131,133,134,136–140,142–150] [6,8,128–131,133,134,136–139,13,140,142–150,20,22,23,55,125–127]

**Figure 2.10: Level of Studies on Typical Faults in Residential HVAC Systems**

A review on this has been published in [2]. Based on the above survey, AFR and RCL faults were considered in this study.

2.4 The Cumulative Sum (CUSUM) Control Strategy

The Cumulative Sum (CUSUM) control strategy is a widely used statistical method for monitoring changes in a process [151]. Since 1954, when it was first introduced by E. S. Page [152], it has been widely used in various fields, including data quality control.

As its name implies, CUSUM involves the calculation of a cumulative sum. Samples from a process x_n are assigned weights ω_n , and summed as follows:

$$S_0 = 0 \quad (2.22)$$

$$S_{n+1} = \max(0, S_n + x_{n+1} \pm \omega_n) \quad (2.23)$$

When the value of S exceeds a certain threshold value (referred to as CUSUM threshold), a change in value has been found.

For the FDD applications, the CUSUM control strategy is very useful in preventing false fault alarms. In [27], CUSUM was applied to the proposed FDD method with a slight modification to the definition above as follows:

$$S_0 = 0 \quad (2.24)$$

$$S_{n+1} = \max\left(0, S_n + \begin{cases} 1, & \text{if } x_{n+1} \geq \bar{x} \\ -1, & \text{if } x_{n+1} < \bar{x} \end{cases}\right) \quad (2.25)$$

indicating that if a sample deviation (x_n) exceeds a specified deviation threshold ($\bar{x}$), 1 is added to the S . If not, 1 is removed.

Figure 2.11 illustrates how the CUSUM control strategy works. The first subplot shows the individual deviations in real-time. As seen from the subplot, some deviations abruptly exceed Dev_thresh (the deviation threshold) while subsequent deviations fall below the threshold. To

ensure that such deviations are induced by a fault, the second subplot shows how these deviations are monitored using the CUSUM control strategy. With this technique, a fault is only detected at the 22nd hour instead of at the 1st hour, which might be misleading.

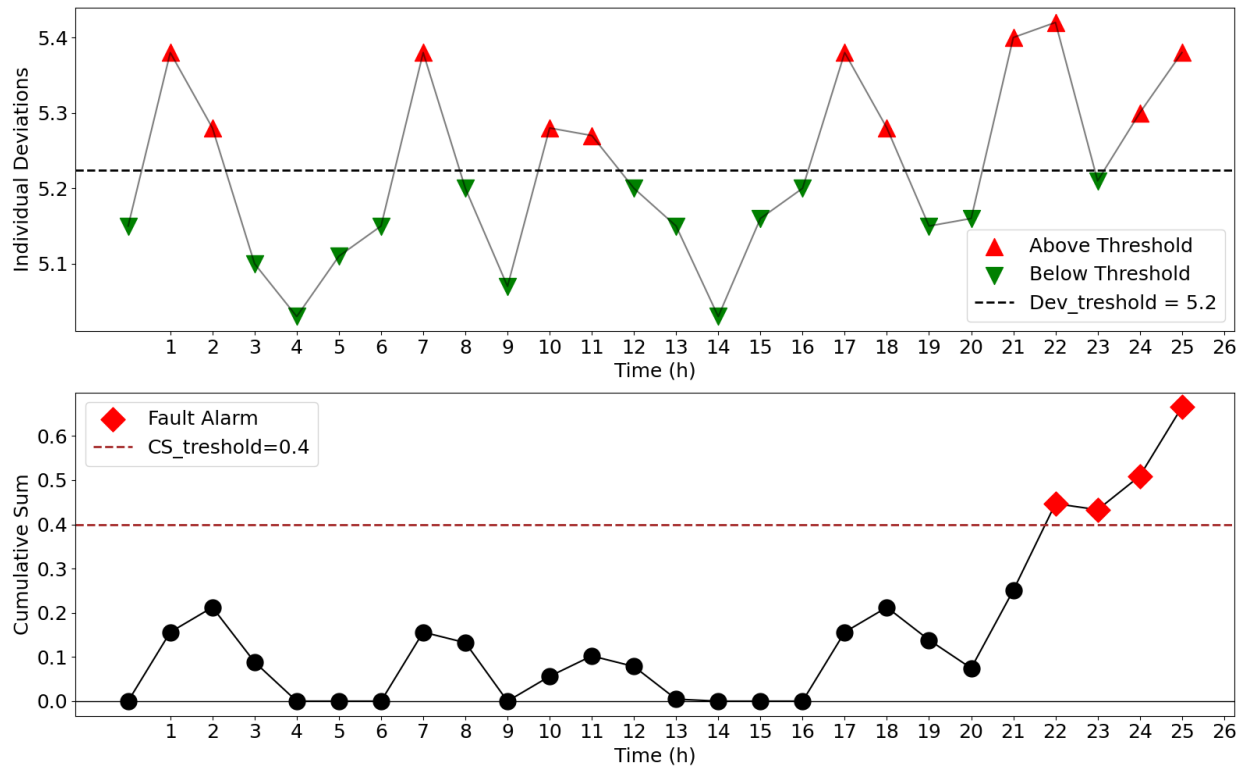


Figure 2.11: Illustration of the CUSUM Control Strategy

While this approach may result in delayed detection or high false negative rate (FNR), reducing the false positive rate (FPR) of FDD methods is more critical as earlier pointed out in Section 2.5.1. Meanwhile the likelihood of the CUSUM control strategy resulting in higher FNR is lower. The major concern is that such a reduction of the FPR might be at the expense of early detection, but that is a justified tradeoff. Based on these considerations, the CUSUM control strategy is adopted in this study for both proposed performance enhancement strategies in Section 2.5.

2.5 Strategies for Improving the Performance of Smart thermostat-based FDD

Methods

Based on the research hypotheses propounded in this study, two strategies were explored to address the objective of this work which is to improve the performance of smart thermostat-based FDD methods.

Figure 2.12 shows an overview of the methodology adopted for this research, depicting the two strategies proposed and the connection between them. The figure also shows the relevant components discussed so far from Section Chapter 2: to Section 2.4.

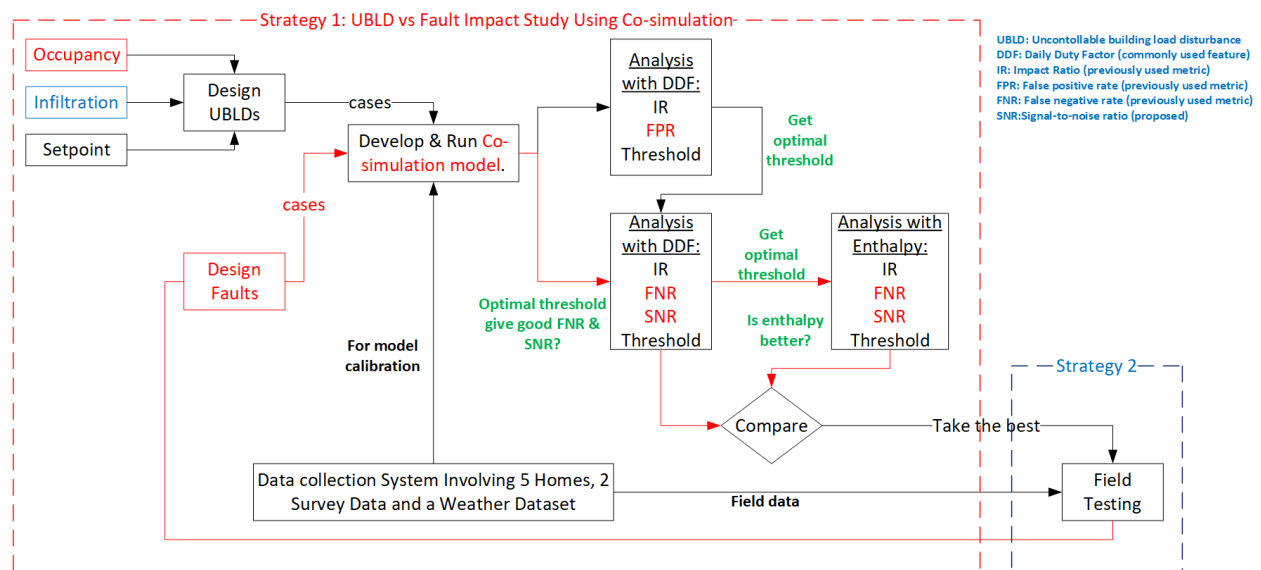


Figure 2.12: Methodology Overview

Strategy 1 adopts a co-simulation-based approach to investigate the impact of Uncontrollable Building Load Disturbances (UBLD) on AC operation and faults. Strategy 2 then uses a field-based approach to investigate a novel approach for performing both detection and diagnosis of faults using a new FDD feature – enthalpy change. This novel concept extends the capability of

smart thermostat data beyond fault detection to achieving fault diagnosis. These strategies are discussed further in Sections 2.5.1 and 2.5.2.

2.5.1 Investigation of the Impact of Uncontrollable Building Load Disturbances (UBLD) on Smart thermostat-based Fault Detection Methods

This strategy involves using analysis of UBLD impacts on Smart thermostat-based fault detection methods to come up with suitable thresholds and techniques which researchers can use in developing their fault detection methods to avoid both false positives (especially) and false negatives. This will improve the performance of Smart thermostat-based FDD methods by making them more resilient, adaptive and accurate.

For this strategy, the duty factor feature (Section 2.1.1) and the enthalpy change feature (Section 2.1.2) were used. Also, this strategy uses both experiments and simulation, where the experiments were primarily used to validate the simulation results. A simulation period of 70 days was used, from June 21 – August 31. These days were chosen to give sufficient and representative summer days. Further details on this strategy are presented in chapters three and four.

As mentioned in Section 1.3.1.1, UBLDs are disturbances that arise from irregularities in variables such as weather conditions, internal gains, thermostat features, etc., which smart thermostats cannot capture. However, these variables contribute to the dynamics of buildings as shown in Figure 1.3, making it critical to understand how their irregularities impact AC operation. To study these impacts, the first step is to formulate representative patterns for each of these UBLDs. This is the focus of this section.

2.5.1.1 Definition of UBLD from Internal Gains

Internal gains in buildings refer to the heat generated usually from three sources: occupants (people), lighting, and equipment (appliances and devices). For this study, only heat gain from people was considered because:

1. All three sources are correlated to building occupancy.
2. Heat gain from people is believed to be more variable and unpredictable. While lighting and equipment loads are often scheduled or automated, occupancy patterns can fluctuate significantly due to irregular visits, events, and diverse occupant behaviors.
3. Lighting and equipment heat gains can be easily estimated with high accuracy, from known specifications and schedules. However, heat gain from people depends on factors such as activity level, clothing insulation, and metabolic rate, which are unpredictable.

The above reasons explain why there have been several research efforts on occupancy prediction. However, this research area remains an open problem [39,40]. Therefore, only UBLD from occupancy gains is considered with respect to internal gain. Discussions on the design of the UBLD from occupancy variations will be presented in Section 3.1.1.

2.5.1.2 Definition of UBLD from Infiltration Gains

Irregular weather patterns can lead to UBLDs associated with variables like solar irradiation and wind speed, outdoor temperature (T_{oa}), etc. These variables affect building dynamics either through solar heat gain (mainly from solar irradiation) or infiltration gains (mainly from wind speed and T_{oa}). Though solar irradiation data cannot be obtained directly from smart thermostats, fair estimates can be obtained from the global horizontal irradiance (GHI) which can be obtained from a nearby weather station. With GHI, solar heat gain can be estimated. Conversely, though

wind speed and T_{oa} data can be gotten from a weather station and smart thermostat, respectively, it is more difficult to estimate the infiltration gain. This is because infiltration depends on several other factors such as air exchange rate, envelope air leakage, pressure difference (across envelope leaks) induced by wind, inside-outside temperature differences, and the operation of mechanical equipment in a building [24]. Thus, UBLD from infiltration gain is more critical than UBLD from solar heat gain.

Infiltration refers to the unintended inflow of outside air into a building through cracks, gaps, and other unintentional openings and through the normal use of windows, exterior doors and egress [24]. It occurs mainly from pressure difference between indoors and outdoors, causing air movement from the high-pressure areas to the low-pressure areas. While infiltration can be beneficial in providing natural ventilation, reducing indoor air pollutants, and maintaining indoor air quality, it can be detrimental in terms of energy loss, increased load on AC systems, and increased AC runtime. Hence there is need to study how this might affect FDD features like duty factor. This is necessary for FDD studies because with the unavailability of data for estimating infiltration load, most Smart thermostat-based FDD studies [22,31–37] do not take this into account. Others [23,26] use unrealistic assumptions which can be invalidated by erratic occupant behavior. For example, an occupant might mistakenly leave a window or a door open during AC operation or forget to turn off bathroom/kitchen exhaust fans, and these can add more infiltration load to the AC system. So, how does one ensure that an increase in duty factor detected by an FDD method is probably not due to this mistake by the homeowner, since the FDD algorithm does not have real-time data on this? Discussions on the design of the UBLD from infiltration will be presented in Section 3.1.2.

2.5.1.3 Definition of UBLD from Thermostat Setpoint

Thermostat setpoint, T_{set} , defines the temperature range within which an AC system operates. T_{set} plays a crucial role in building energy efficiency, optimization and control. It contributes to achieving occupant comfort, energy savings, efficient operation and durability of AC systems, etc. Several studies have been conducted on the energy savings potential of smart thermostats [153–155]. For instance, a study conducted by the National Renewable Energy Laboratory (NREL) reported an annual cost reduction of about \$100 from adjusting thermostat setpoints [153]. According to the US Department of Energy (DOE), adjusting the thermostat by 7-10 °F for 8 hours per day can result in energy savings of up to 10% per year on heating and cooling costs [154].

Additionally, several smart thermostat manufacturers like Nest and Ecobee [156] now build algorithms into their smart thermostats that adaptively changes T_{set} to achieve energy savings for homeowners.

While the changing of T_{set} (manually or adaptively) can lead to energy and cost savings, such savings come from changes in the operation of the AC systems e.g., changes in the cycling times, cycling frequencies, AC runtime and by extension duty factor. Such changes to the AC operation can affect the performance of FDD methods that do not capture T_{set} . For instance, irregular or abrupt changes in T_{set} can result in false alarms; while cost-savings T_{set} overrides built into smart thermostats could interfere with third-party FDD algorithms and impede detection of existing faults. Furthermore, irregularities in T_{set} schedules can introduce noise into smart thermostat data [49] which can also make it difficult to distinguish between normal operational variations and actual faults.

Therefore, it is important to study how irregularities in T_{set} can affect the performance of Smart thermostat-based FDD methods. T_{set} has been used in several Smart thermostat-based FDD methods. In [33], T_{set} was used to cluster AC systems that show poor transient behavior which were then further analyzed using other variables to identify faulty systems from the cluster. In [23], T_{set} was used to compute the time-to-cool setpoint used as FDD feature. However, these studies did not investigate how irregular changes in T_{set} can affect the performance of Smart thermostat-based FDD methods. Therefore, irregularities in T_{set} is considered in this study as source of UBLD that can affect the performance of Smart thermostat-based FDD methods.

2.5.1.4 Evaluation Metrics used for Impact Analysis

For the impact analysis, two cases are considered: an ideal scenario and a real scenario. For the ideal scenario, the same weather conditions are used for all the cases (including the baseline case). This was achieved by using the same day and the same year for all cases. Hence, for this case, a baseline estimation is not required as the actual baseline duty factor is used. However, this is not achievable in real life, hence it is classified as an ideal scenario. For the real scenario, a different year was co-simulated to generate data for estimating the baseline duty factor.

As depicted in Figure 2.1, the general FDD sequence requires a reference (baseline) for comparative analysis to detect and diagnosis faulty system behavior. This baseline is typically estimated with the help of a suitable model. Different models have been used for estimating this baseline in previous studies. In [22], a black-box model was used which was very unrepresentative of the building/AC dynamics. In [23,26,27], different gray-box models were used which had several shortcomings discussed in Section 1.2.1. In [31–37], different statistical models were used to estimate the baseline, with several being regression-based statistical models.

For this research, a linear regression model was adopted for the duty factor baseline estimation. Linear regression-based modeling is a fundamental statistical method that is widely used in various fields [157]. It helps in prediction, trend analysis, and quantifying the strength of relationships between variables. The simplicity and interpretability, as well as predictive power of linear regression, made it a good choice for the impact analysis done in this research.

In the application of linear regression-based modeling, the duty factor was considered as the dependent variable while the outdoor air temperature (T_{oa}) was considered as the independent variable. The regression was then extracted from the plot of duty factor against T_{oa} . More details on the application of this method are given in Section 3.6.

For the enthalpy change baseline estimation, a quadratic regression model was used. The model is a modified version of the cooling capacity model in [25]. The cooling capacity model was adapted for Δi prediction because as Equation (2.1) shows, cooling capacity is a function of Δi . The quadratic regression model is shown in Equation (2.26)

$$\Delta \hat{i} = a_o + a_1 T_{ewb} + a_2 T_{ewb}^2 + a_3 T_{odb} + a_4 T_{odb}^2 + a_5 T_{ewb} T_{odb} \quad (2.26)$$

where $\Delta \hat{i}$ is the predicted enthalpy change (differentiated from Δi with a ‘hat’ symbol above it), T_{ewb} is the entering wet bulb temperature into the evaporator, T_{odb} is the outdoor dry bulb temperature, while $a_o, a_1, a_2, a_3, a_4, a_5$ are the model parameters.

The following sections discuss the different performance metrics used for evaluating the impact of the various UBLDs investigated in this research.

2.5.1.4.1 Impact Ratio (IR)

In the context of FDD in AC systems, impact ratio serves as a pivotal metric that quantifies the practical significance of a variable's effect on a feature relative to the feature's acceptance limit. In [50,158], fault impact ratio (FIR) was used as a performance evaluation metric for FDD protocols with COP and cooling capacity as the monitored features. Yuill et al. [50] reported that FIR is well suited for performance evaluation as it allows potential FDD users to understand the performance of an FDD protocol for a fault impact level that is appropriate to their application. Therefore, IR is used for investigations on both UBLD impacts and faults impact on the FDD features discussed in Section Chapter 2:.

Equation (1.3) gives the definition of IR adopted in this research:

$$IR = \frac{\text{Actual FDD Feature}}{\text{Actual FDD Feature}} \quad (2.27)$$

2.5.1.4.2 Impact Ratio Threshold

The importance of thresholds was highlighted in Section 1.2.1. Summarily, thresholds help to draw the distinction between faulty and faultless conditions, thereby preventing false alarms in FDD tools [50]. This makes thresholds very critical, and the choice of thresholds determines the performance level of an FDD tool. Therefore, a threshold is necessary for evaluating the impact ratios obtained from Section 2.5.1.4.1, and by extension the performance of FDD methods. The IR threshold corresponds to the deviation threshold used in studies where FDD is based on deviation from a baseline as discussed in Section 1.2.1.

2.5.1.4.3 False Positive Rate, False Negative Rate, and Fault Probability

False positive rate (FPR) and false negative rate (FNR) are two important evaluation metrics which have been used in previous studies [50,51,53,135,158,159]. FPR refers to the rate at which an FDD

method generates false positives/alarms. Mathematically, false positives are generated if the IR due to disturbances or uncertainties exceeds the specified IR threshold, thereby wrongly suggesting a fault when there is no fault. Equations (2.28) and (2.29) show the expressions used to compute the FPRs without and with the CUSUM control strategy, respectively:

$$FPR_{No\ CUSUM} (\%) = \frac{\text{Number of } IR > IR\ Threshold\ in\ N\ samples}{\text{Total Size of } N\ samples} \times 100 \quad (2.28)$$

$$FPR_{CUSUM} (\%) = \frac{\text{CUSUM of } IR > IR\ Threshold\ in\ N\ samples}{\text{Total Size of } N\ samples} \times 100 \quad (2.29)$$

On the other hand, FNR refers to the rate at which an FDD method generates false negatives. Mathematically, false negatives are generated if the IR (when there is a fault) is below the specified deviation threshold, thereby suggesting no fault when there is a fault. Equations (2.30) and (2.31) show the expressions used to compute the FPRs without and with the CUSUM control strategy, respectively:

$$FNR_{No\ CUSUM} (\%) = \frac{\text{Number of } IR < IR\ Threshold\ in\ N\ samples}{\text{Total Size of } N\ samples} \times 100 \quad (2.30)$$

$$FNR_{CUSUM} (\%) = \frac{\text{CUSUM of } IR < IR\ Threshold\ in\ N\ samples}{\text{Total Size of } N\ samples} \times 100 \quad (2.31)$$

The FPRs are defined in terms of disturbance induced IRs because false positives are based on disturbance signals which are not fault signals. Likewise, the FNRs are defined in terms of fault-induced IR because false negatives are based on fault signals which are misclassified as ‘no fault’ signals.

In cases where IR exceeds the threshold due to an actual fault, FPR is called Fault Probability (FP) instead because deviations caused by faults cannot be described as false positives.

2.5.1.4.4 Signal-to-Noise Ratio (SNR)

Signal-to-Noise Ratio (SNR) is a measurement of how much signal there is compared to how much noise there is in a data [160]. SNR has been used in many fields including engineering, communications, image processing, etc., for performance evaluation. Originally, SNR is defined in the context of sound as [161]:

$$SNR_{dB} = 20 \log \left(\frac{signal}{noise} \right) \text{ in } dB \quad (2.32)$$

which can be formatted into Equation (2.33)

$$SNR = \frac{signal}{noise} = 10^{\frac{dB}{20}} \quad (2.33)$$

From the above definitions, an $SNR > 0$ dB implies more signal. While an $SNR < 0$ dB means more noise. Generally, a higher SNR is better as illustrated by the following classification [161]:

- SNR of +10 dB = 3.16 is considered excellent
- SNR of +3 dB = 1.41 is considered good
- SNR of +0 dB = 1.00 is considered bad
- SNR < +0 dB is classified as very bad

Different fields use other approaches for classifying SNR. For instance, in the field of image processing, industry standards recommend a SNR of 40:1 for excellent image quality, and 10:1 for acceptable image quality. Also in the same field, there is the Rose Criterion [160] which recommends an $SNR \geq 5$ to distinguish image features with certainty. In fields like communication and sound, there are other criteria like the Shannon-Hartley theorem and the Neyman-Pearson criterion.

However, for FDD applications, there is really no theory for classifying SNR. The closest alternative is to use typical values for machine learning applications. Meanwhile, other forms of SNR have been adopted for FDD applications. For example, in [31,37], SNR was defined in terms of the mean (μ) and standard deviation (σ) as

$$SNR = \frac{\mu}{\sigma} \quad (2.34)$$

For the classification, in [31] and $SNR \leq 1$ is classified as low while an $SNR > 3$ is classified as high. In [37], an $SNR = 5$ is classified as high.

In general practice, SNR is classified as:

- SNR of 0 - 10 dB = 1 - 3.16, is low, making it difficult to distinguish signal from noise.
- SNR of 10 - 20 dB = 3.16 - 10 is moderate. Signal is detectable but performance may vary.
- SNR > 20 dB i.e., > 10 is excellent.

Based on the foregoing, there seems to be no standard for SNR classification in the field of FDD studies. Though the classification depends on several factors such as the context of the data, the type of machine learning task, performance metrics, sample size, dimensionality of data, etc. Therefore, for this research, the following classification is adopted:

- SNR < 4: low
- SNR $\leq$ 10: moderate
- SNR > 10: high

and the definition of SNR adopted for this research is expressed in Equation (2.35)

$$SNR = \frac{Signal}{Noise} = \frac{[100 - FNR]_{fault}}{FPR_{UBLD \text{ or } uncertainties}} \quad (2.35)$$

2.5.1.4.5 Energy Consumption and Cost Analysis

In real-world building operation, energy performance is rarely static. UBLDs such as occupancy variations, varying infiltration, and thermostat setpoint variations – all arising from unpredictable occupant's activities, introduce deviations from ideal performance. Such deviations lead to excess energy use and increase operation costs. Understanding these impacts is crucial for designing robust energy-efficient strategies. Therefore, energy consumption and cost analysis were also carried out in this research, particularly for the investigation of the impact of UBLDs on AC operation covered in chapter 3.

To make this analysis more meaningful, the ideal scenario discussed in Section 2.5.1.4 was used. The analysis was done in terms of the total energy consumption for the entire simulation period, and the associated cost. For the total energy consumption and the corresponding operating cost, Equations (2.36) and (2.37) are used, respectively:

$$Total\ kWh = \sum_{k=1}^N [P_{comp}(k) + P_{in}(k) + P_{out}(k)]_{ON\ cycle\ only} \quad (2.36)$$

$$Total\ cost = \sum_{k=1}^N \left[(P_{comp}(k) + P_{in}(k) + P_{out}(k)) \times utility\ rate \right]_{ON\ cycle\ only} \quad (2.37)$$

where P_{comp} , P_{in} , P_{out} are the power consumed by the compressor, indoor fan and outdoor fan, respectively.

2.5.2 Investigation of a Smart thermostat-based Automated Fault Detection and Diagnosis Method That Monitors Evaporator Enthalpy Change

This strategy focuses on enhancing the performance of Smart thermostat-based FDD methods by addressing the lack of diagnostic capability with current Smart thermostat-based FDD methods (Section 1.3.1.3). It does this by using a novel FDD feature (enthalpy change) which can

thermodynamically be used to differentiate between two prevalent faults (low indoor airflow and low charge) in residential AC systems. Section 2.1.2 describes the enthalpy change feature. Details of this strategy are covered in chapter 5.

Chapter 3: Investigation of the Impact of Uncontrollable Building Load Disturbances on AC Operation

This chapter begins with the formulation of the uncontrollable building load disturbances (UBLDs) considered in this study. It then provides details on the co-simulation testbed used and the calibration of the testbed. Thereafter, results on the validation of the testbed were given. The chapter concludes with a presentation of the simulation results of the different UBLDs and analyses of their respective impact on AC operations.

3.1 Design of UBLDs

3.1.1 UBLD from People Gains

To design the occupancy-based UBLD adopted in this study, two assumptions were made:

1. Changes in occupancy profile occasionally happen during the simulation period.
2. Changes in number of occupants occasionally happen during the simulation period.

Next, representative occupancy profiles/schedules were developed. These are usually needed in most building modeling tools like EnergyPlus which was used in this study. However, the default occupancy schedule in EnergyPlus has been shown to be non-representative [63–65]. From the typical occupancy schedules developed in [64] using the ATUS data introduced in Section 2.2.2.2, a four-member household occupancy schedule was chosen for this study because the four-member schedule reportedly covers more age ranges and percentage of homes within the US [64].

Figure 3.1 shows the different occupancy schedules used in this study. The first subplot shows the schedule in fraction, used as inputs in EnergyPlus. The second subplot shows the corresponding number of occupants throughout a day based on the schedule in the first subplot. The

Normal_Weekday and Normal_Weekend schedules are based on the original weekdays and weekend schedule from [64], and were used for the baseline case. The Home_All_Day schedule typifies a case where occupants stay at home all day. The abnormal schedule typifies a case where there is a change from the normal schedule. For example, an occupant falling sick and remaining at home with an additional occupant to take care of the sick person. These different schedules relate to the first assumption stated above.

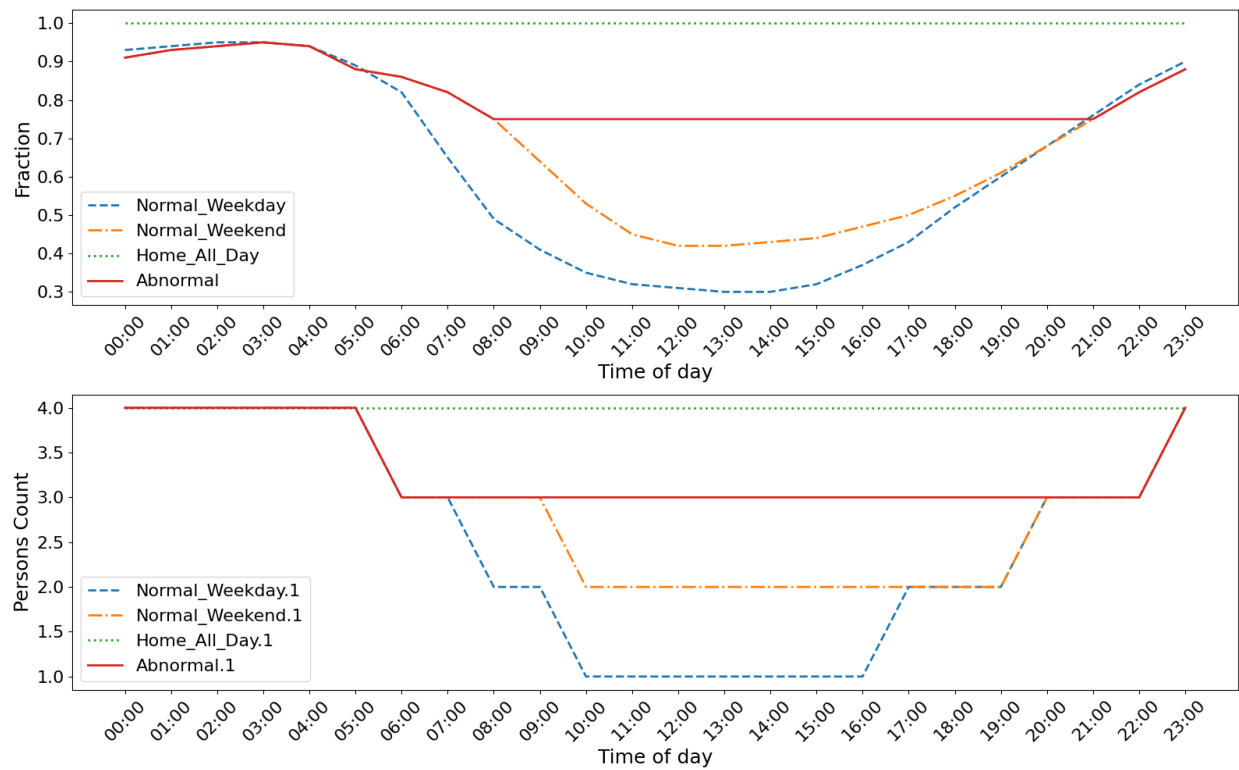


Figure 3.1: Occupancy Schedules used in the Study

With respect to the second assumption, changes in the number of occupants could happen due to several factors such as visits, events, etc. For example, residents can occasionally have a short-term or long-term visitor; or there can be a social or religious event in the home with invited guests

in attendance. In addition to increasing the number of occupants, such activities can also increase metabolism and thus the heat generation rate ($\dot{Q}_{peo}$) of occupants.

According to [24], there are different heat generation rates associated with various activities. By default, EnergyPlus uses a constant $\dot{Q}_{peo}$ of 131.25 W (for both sensible and latent heat) which corresponds to moderate activities in a home [24]. Other activities like dancing, walking, etc., have higher values. For the baseline case, a constant $\dot{Q}_{peo}$ of 131.25 W was specified in EnergyPlus for each occupant. Then for the occupancy-based UBLD case, $\dot{Q}_{peo}$ is alternated between 131.25 W, 164.0625 W, and 625 W. The latter two values were estimated due to a constraint in the computation of the total $\dot{Q}_{peo}$ in EnergyPlus. The total $\dot{Q}_{peo}$ in EnergyPlus is computed from the expression:

$$Total \dot{Q}_{peo}(k) = N_{peo} \times F_{sched}(k) \times \dot{Q}_{peo}(k) \quad (3.1)$$

where N_{peo} is the number of people – this remains constant for every timestep, k , and is usually specified in EnergyPlus as a single integer, since the number of occupants cannot be a fraction. F_{sched} is the occupancy schedule, used to compute the real-time occupancy as shown in the second subplot in Figure 3.1. Since F_{sched} ranges from 0 and 1, as shown in the first subplot in Figure 3.1, the real-time occupancy cannot exceed N_{peo} during a simulation. This imposes a constraint on introducing an increase in occupancy during a simulation that typifies the UBLDs discussed above. To address this, the following expression is used:

$$\dot{Q}_{peo}^{ubld}(k) = \frac{N_{peo}^{ubld} \times \dot{Q}_{peo}(k)}{N_{peo}} \quad (3.2)$$

where $\dot{Q}_{peo}^{ubld}$ is the estimated heat generation rate which can be multiplied with the predefined N_{peo} to obtain the same total $\dot{Q}_{peo}$ that an increased number of occupants (N_{peo}^{ubld}) will generate. So, a

164.0625 W typifies a case where the maximum number of occupants increased to five, perhaps due to a short-term or long-term visit. While a 625 W heat generation rate is for a case where there is a social event (like a party), leading to an increase in occupancy to ten. Additionally, for such social events, a higher degree of activity is assumed e.g., dancing. So, a higher heat generation rate of 250 W was used for each occupant based on the specified value for moderate dancing in [24].

To further make the above analysis more representative, the times when these activities occur, and the frequency of their occurrence had to be determined. This is because these activities deviate from the normal routine of residents and so are expected to occur less frequently. To ascertain the times when different activities occur in a day in US homes, the following steps were taken:

1. With the ATUS data described in Section 2.2.2.2, different activities were extracted from the data using the associated ATUS codes.
2. Outliers were removed from the extracted data based on activity durations. To do this, a duration threshold was ascertained from Tukey's method as stated below:

$$duration\ threshold = q3 + 1.5 \times iqr \quad (3.3)$$

where $q3$ represents the third quartile and iqr is the interquartile range. This step was taken to filter out data which had unreasonable durations for certain activity. For example, data showing 24-hour duration for an activity would likely be an error.

3. Next, k-means clustering was used to cluster the filtered data based on activity start times and stop times.
4. The data was further sorted into weekdays and weekends using the variable 'TUDIARY' in the ATUS dataset.

5. Lastly, weights, w , were generated for each activity, i , within a given time interval, k , using the following expression:

$$w_{i,k} = \frac{n_{i,k}}{N_k} \quad (3.4)$$

where n is the number of homes involved in activity i at the k interval, and N is the total number of homes within k .

Based on the above steps, profiles for different activities were generated as shown in Figure 3.2. In the figure, religious/social activities is a sum of the following activities in the ATUS dataset: religious practices, spiritual activities, religious education activities, social events, socializing and communicating. The profiles show that sleeping has a high fraction between midnight and 5:00 am, as expected. It also shows that social activities are less frequent during the day, with weights not exceeding 0.1. This is in line with the consideration that such activities are expected to happen less frequently.

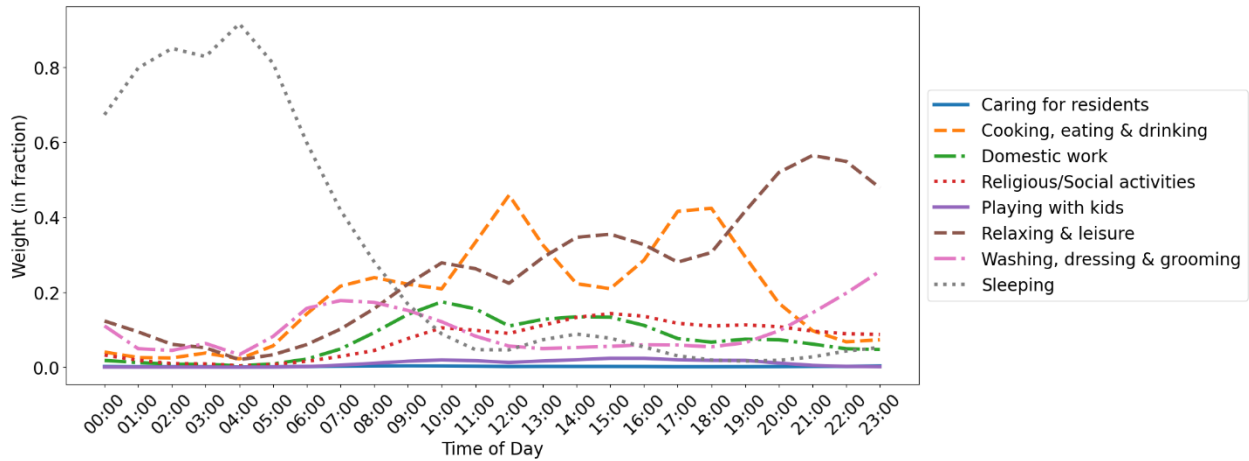


Figure 3.2: Activity Profiles Generated from ATUS data

For the frequency of social events in a period, e.g., a month, the following analysis was done:

1. From the weekend profile, the hourly weights for just social events were multiplied by 8, where 8 represents the number of weekend days in a month. According to the ATUS data, Mondays to Fridays are classified as weekdays while Saturdays and Sundays are classified as weekend days. Therefore, in a month, there are expected to be 8 weekend days. Based on the foregoing, the weights (in days) become:

$$w_{SE,k}^{days} = w_{SE,k} \times 8 \quad (3.5)$$

where $w_{SE,k}$ is the weight for social events (SE) obtained from Equation (3.4).

2. Next, the average weight (in days) within a 24-hour period was taken and converted into hours using the following expression:

$$w_{SE}^{hours} = [average(w_{SE,k}^{days}) \forall k = 0,1, \dots, 23] \times 24 \quad (3.6)$$

From Equation (3.6), it was deduced that the approximate number of hours in a month (during just weekends) where social events may occur is approximately 2 hours. The above analysis was repeated with the weekdays profile from which a similar deduction of approximately 2 hours was obtained.

To get the times of the day when such social events are likely to happen, the k interval at which $w_{SE,k}^{days}$ is maximum was identified and used to ascertain the likely start time of such social events. Then the stop time becomes 2 hours from the start time based on the earlier deductions. Based on these analyses, for the weekend profiles the period for social events were obtained as 7pm – 9pm. While for the weekday profiles, it was 2/3pm – 4/5pm.

Summarily, for the UBLD arising from occasional activities such as social events, two days are randomly selected within a month, where the heat generation rate is increased from the baseline

value (525 W) to 2500 W during the deduced periods above. This depicts a change in the number of occupants from four (at moderate activity level [24]) to ten (at a higher activity level [24]) during the social activity.

3.1.2 UBLD from Infiltration Gain

In EnergyPlus, there are three major infiltration models [162]. From the least advanced to the most advanced, they are the design flow rate model; effective leakage area (ELA) model; and the flow coefficient model. Essentially, all three models show that infiltration is a function of ΔT_{oi} , w_{spd} , and the use of windows, exterior doors and egress, in line with the definition in [24]. Though the flow coefficient model is more advanced, getting all the required parameters is a challenge. So, the ELA model was used in this study because it gives a good balance between simplicity and accuracy [24].

To compute the airflow rate ($\dot{m}_{inf}$, in kg/s) into the building due to infiltration through cracks and openings in the building envelope, a modified version of the ELA model (Equation (3.7)) was used

$$\dot{m}_{inf} = \frac{\rho_{air}(A_L + A_{win}u_{win})}{1000} \sqrt{C_s \Delta T_{oi} + C_w w_{spd}^2 + Q_{fan} u_{fan}} \quad (3.7)$$

where ρ_{air} is the density of air (kg/m³), A_L is the effective leakage area (cm²), A_{win} (cm²) is the area of window opening, u_{win} is a window opening schedule, u_{fan} is a schedule for exhaust fans, Q_{fan} (kg/s) is the exhaust fan design airflow rate, C_s is the stack coefficient ((L/s)²/cm⁴K), and C_w is the wind coefficient ((L/s)²/[cm⁴(m/s)²]). Reported typical values for C_s and C_w in [24] for a one-story, single family residence were used. A_L was optimally determined from the calibration process discussed in Section 3.3. Based on the actual specifications of the OU lab-house used in this study, A_{win} was computed as half of the area of one of the windows in the house. Also, the

house has a kitchen exhaust fan, and a bathroom exhaust fan whose typical ratings were used to obtain Q_{fan} . Table 3.1 shows the values used for the infiltration model parameters.

Table 3.1: Infiltration model parameters

Parameter	Value	Unit	Source(s)
Density of air, ρ_{air}	1.2	kg/m ³	
Effective leakage area, A_L	2800	cm ²	Through calibration
Window opening area, A_{win}	10500	cm ²	OU lab-house
Exhaust fan (kitchen and bathroom) airflow rates, Q_{fan}	0.085	kg/s	OU lab-house and ASHRAE handbook [24]
Stack coefficient, C_s	0.000145	(L/s) ² /cm ⁴ K	ASHRAE handbook [24]
Wind coefficient, C_w	0.000319	(L/s) ² /[cm ⁴ (m/s) ²]	

For the baseline case, u_{win} is always set to 0 to signify that all the windows in the house are closed throughout the simulation, as is expected in a normal setting. For u_{fan} , a typical regular schedule was developed using the ATUS data. Cooking-related activities and bathing-related activities from the ATUS data were mapped to the operating times for the kitchen exhaust fan and bathroom exhaust fan, respectively. These activities were specifically extracted from the ATUS data. Probability density function was then applied to the data and normalized to get representative schedule.

The US DOE prototype EnergyPlus models provide schedules for cooking (tagged “CookingRangeDay” in the IDF file), bath (tagged “BathsWeekday” and “BathsWeekend” in the IDF file) and shower (tagged “ShowerWeekday” and “ShowerWeekend” in the IDF file). These

schedules are believed to be based on the standards (like ASHRAE 90.2 or IECC) used for developing these prototype models. Therefore, the cooking and bathroom schedules derived from the ATUS data were compared with the EnergyPlus schedules from a DOE prototype building modeled based on the IECC 2006 standard as shown in Figure 3.3. As seen from the figure, for both weekdays and weekend, the ATUS schedule closely matches the EnergyPlus shower schedule (EP_shower). The EnergyPlus bath schedule (EP_Bath) however, shows more disparity. Both the bath and shower schedule, however, show two peaks: one in the morning (for shower) and the other in the evening (for bath). The ATUS schedule also shows two peaks, but the evening peak was smaller. For the kitchen, the ATUS weekday schedule shows a closer match with the EnergyPlus schedule. Though, both the weekday and weekend ATUS schedules had a good match with the EnergyPlus schedule during the evening period. The fourth subplot shows the ATUS profile combining the bathroom schedule and kitchen schedule.

From the above analyses, a u_{fan} schedule was generated which shows a peak in the morning and another in the evening. The schedule was, however, modified into binary format i.e., 0 and 1 since exhaust fans in residential buildings typically operate in a on/off mode. This schedule was used each day for the baseline case.

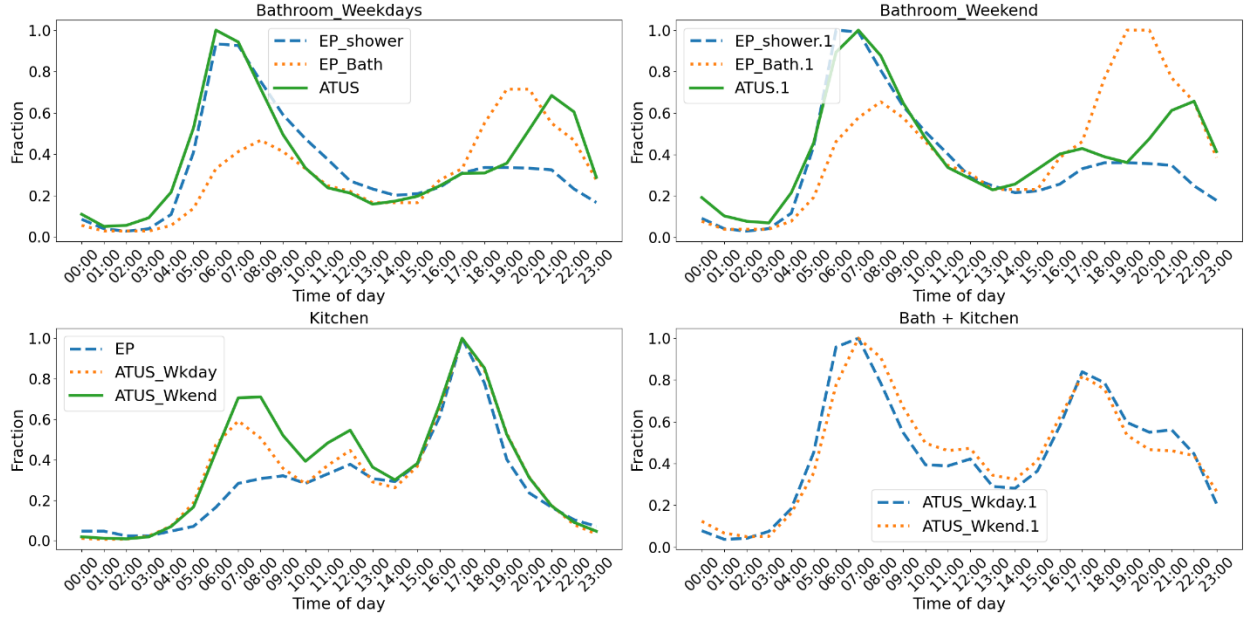


Figure 3.3: Kitchen and Bathroom Schedules from EnergyPlus (EP) and ATUS

To depict the UBLDs due to irregular changes in the infiltration airflow rate which may be caused by an occupant mistakenly leaving a window open or mistakenly leaving an exhaust fan on, the following modifications were made:

1. A 24-hour hourly schedule was designed for u_{win} which changes from 0 to 1 at a given time of the day, where 0 signifies that the window is closed and 1 signifies that the window is open. Since in real-life such act of leaving a window open opens accidentally, only 4 out of the 70 days simulation period was used for this occurrence, with the window scheduled to be open for just 6 hours in each of the 4 days.
2. The u_{fan} schedule for the baseline case was modified to occasionally have days when the exhaust is turned at the regular time in the morning and mistakenly left on until evening. However, fewer days were considered when this happens.

3.1.3 UBLD from Thermostat Setpoint

For the design of the thermostat setpoint (T_{set}) schedules used in this study, the Ecobee DYD data introduced in Section 2.2.2.3 was used. Codes written in SQL (structured query language) were used to extract and process T_{set} data from all the users across the US. Only T_{set} data between 65 F (18.33 C) and 90 F (32.22 C) were considered. The processed data covers 184,553 smart thermostat users across the US, collected between January 1st, 2017, and February 12, 2024.

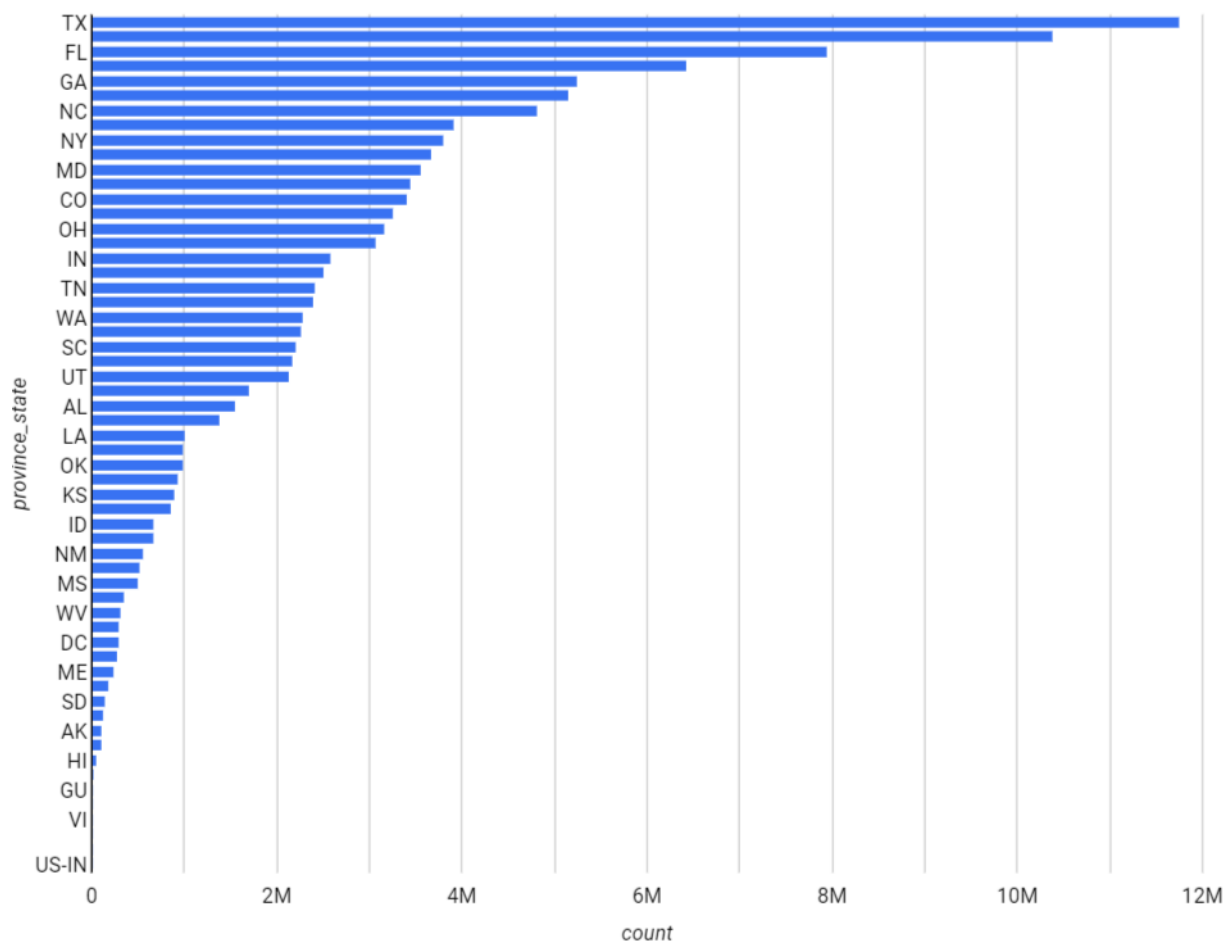


Figure 3.4: Distribution of Smart thermostat data across the US based on Ecobee DYD data.

Figure 3.4 shows the distribution of smart thermostat data donated to the Ecobee DYD program across the US. The figure reveals that Texas donated the largest amount of data. Florida had the third largest amount of donated data with about 8 million datapoints. Oklahoma, which was one of the locations used for this research, had one of the smallest amounts of donated data at about 1 million datapoints. Since Miami, Florida is one of the locations considered for this research and Florida is among the top three of the most donated datapoints, the extracted T_{set} data for users across the US was further processed to contain just single-family homes in Miami. A distribution of this data was obtained and used as the setpoint schedules used for this research.

3.1.4 Representative Profiles for the UBLDs

Based on the considerations discussed in the preceding sections for the UBLDs related to occupancy, infiltration and setpoint, respective profiles were generated as shown in Figure 3.5.

The first subplot shows the heat generation rate based on the occupancy profile. The five spikes represent the two-hour periods of social events in which the number of occupants increased from four to ten, each with increased activity levels as discussed in Section 3.1.1. The eight profiles between day 188 and day 195 represent the days with an additional resident. The five profiles with a short horizontal portion signify days with constant occupancy, perhaps due to bad weather, etc. While the rest are normal weekday and weekend profiles. Only these normal profiles were used in the baseline cases in Section 3.4.

The second subplot shows the assignment of the thermostat temperature setpoint profile developed from Section 3.1.3. The setpoints are in four groups: group 1 is for the normal profile and is maintained for all the days in the baseline case; group 2 had setpoints as low as 22 C; while group

3 has setpoint dropping below 20 C. The following additional considerations were made in the assignment of the setpoint profiles to each day of the simulation period:

1. Days with group 3 setpoints are few (just 4 days out of the 70-day simulation period). This is to ensure that those very low setpoint days are minimized.
2. Group 2 profiles were assigned to 8 days out of the 70-day simulation period.
3. Group 1 profiles were assigned to the rest of the days in the simulation period.

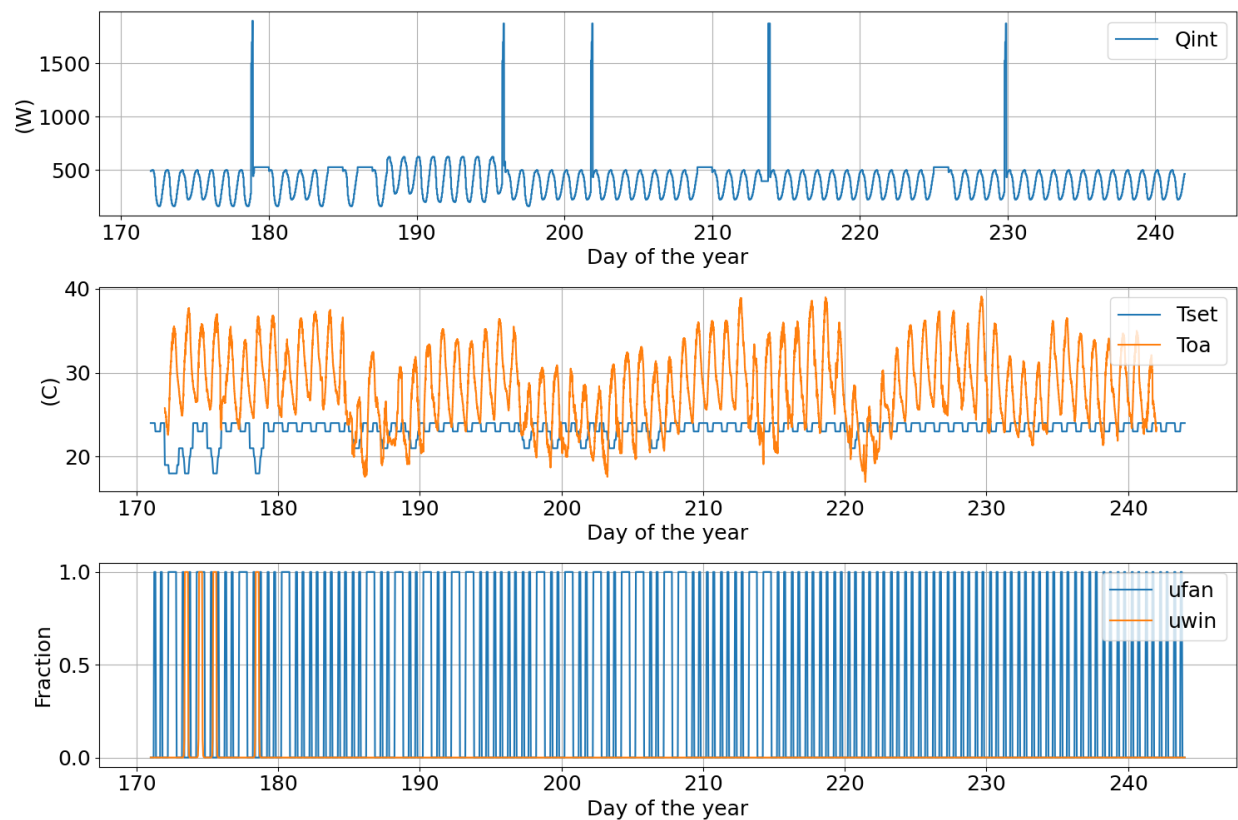


Figure 3.5: Representative Profiles for the UBLDs

The third subplot shows the schedule for the fan and window opening. A fraction of 1.0 means the fan is on or the window is open. Zero means the reverse. To minimize the UBLD impact, only 4

out of 70 days had instances of window mistakenly opened by homeowner. Also, days with fans mistakenly left on were limited while days with regular fan schedule were more.

Though the frequency of occurrence of the UBLDs would vary in real-life from one home to another, the assignments done for this research are considered sufficient for demonstrating the proposed concept.

3.2 Development of Co-simulation Testbed

As noted in Section 2.2.3.1, a co-simulation testbed was used for investigation in this and the next chapter. The testbed consists mainly of a building model (which captures the building dynamics) and an AC model (which captures the AC dynamics) coupled together to simulate the interaction of both dynamics. Figure 3.6 gives a pictorial overview of the co-simulation testbed built on Dymola 2024x. The building model (Figure 3.6b) is made up of a smart thermostat sub-model (Figure 3.6d), a thermal zone sub-model (labelled ‘zon’ in the figure) which handles the air heat and mass balancing from different sources like infiltration and forced ventilation. Envelope load and internal gains from people, lights, equipment were captured in an IDF file specified within the component labelled ‘building’ in the figure. The weather file is also specified in the ‘building’ component. The building model and AC model are coupled together through the fluid ports (SA port and RA port) and the relevant output-input connectors (the triangle-like components in Figure 3.6b and c). Then, within the ‘zon’ component is contained a sub-component which initiates the EnergyPlus Spawn package for generating an FMU of the building model to establish the co-simulation process.

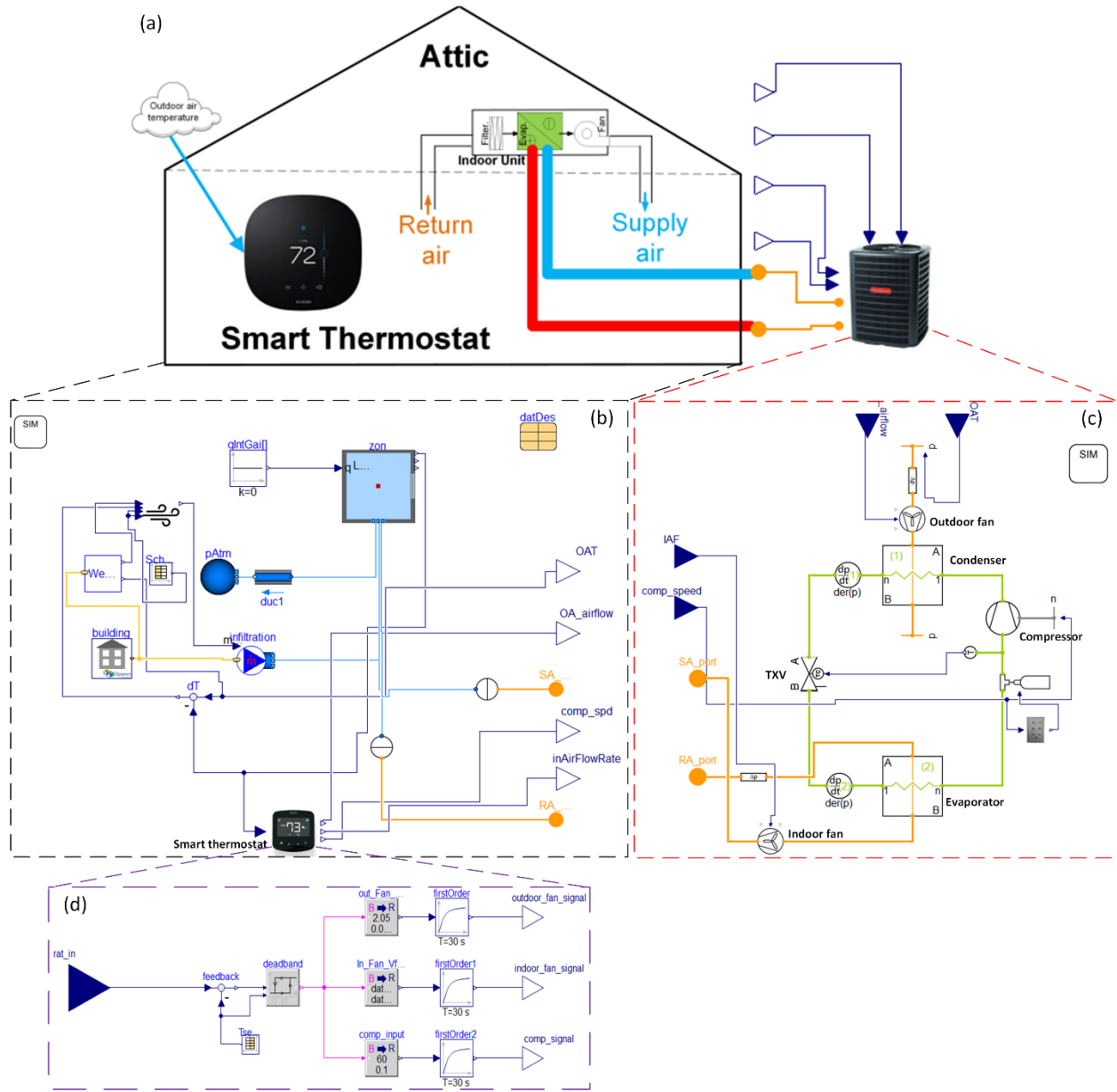


Figure 3.6: Picture of the Co-simulation testbed (a) Coupled model (b) Building Sub-model (c) AC sub-model (d) Smart thermostat sub-model

To achieve thermal comfort in buildings, the AC dynamics and building dynamics interact with each other to control the indoor temperature, T_{in} (C), and indoor humidity ratio, W_{in} (kg/kg), within a space. This interaction can be expressed by the transient heat balance equation (Equation

(3.8)) which controls T_{in} and the transient moisture balance equation (Equation (3.9)) which controls W_{in} :

$$\frac{dT_{in}}{dt} = \frac{1}{C_{air}} (q_{gain} - q_{ac}) \quad (3.8)$$

$$\frac{dW_{in}}{dt} = \frac{1}{m_{air}} (\dot{m}_{mois} - \dot{m}_{ac}) \quad (3.9)$$

where C_{air} (J/K) is the thermal capacitance of the space air, q_{ac} (W) is the AC output into the space, m_{air} (kg) is the mass of air in the space, $\dot{m}_{mois}$ (kg/s) is the total moisture generation rate in the space, and $\dot{m}_{ac}$ (kg/s) is the moisture removal rate by the AC. q_{gain} (W) is the total heat gain in the building which can be expressed as

$$q_{gain} = q_{env} + q_{int} + q_{inf} \quad (3.10)$$

where q_{env} is the heat gain by conduction through the building envelope and solar radiation through the windows, q_{int} is the sensible internal heat gain from occupants, lights and equipment (devices and appliances) in the building, and q_{inf} is the heat gain through infiltration.

Meanwhile, $\dot{m}_{mois}$ and $\dot{m}_{ac}$ can further be expressed as:

$$\dot{m}_{mois} = \dot{m}_{peop} + \dot{m}_{inf} + \dot{m}_{other} \quad (3.11)$$

$$\dot{m}_{ac} = \dot{m}_{sa}(W_{in} - W_{sa}) \quad (3.12)$$

where $\dot{m}_{peo}$ is the moisture generation rate from occupants through breathing, sweating, etc., $\dot{m}_{inf}$ is the moisture generation rate from infiltration, and $\dot{m}_{other}$ is the moisture generation rate from other sources like cooking, showering, etc., $\dot{m}_{sa}$ (kg/s) is the supply air mass flow rate, and W_{sa} is the supply air humidity ratio.

The computation of q_{env} and q_{int} were done in EnergyPlus while q_{inf} is computed in Modelica. Also, the modeling of Equations (3.8) and (3.9) were done in Modelica.

Description of the different components of the co-simulation testbed are provided in the subsequent sections.

3.2.1 The Building Model

3.2.1.1 The EnergyPlus Component

The OU lab-house described in Section 2.2.1.1 was modeled and simulated with EnergyPlus 9.6.0 which is the same EnergyPlus version the Thermal Zone model (discussed in Section 3.2.1.2) in Modelica requires for co-simulation. The EnergyPlus building model was developed in [110] first by using OpenStudio to create a 3D model of the lab-house which was then modified in SketchUp. Figure 3.7 shows a side-view of the lab-house (a), and the same view of the 3-D model (b).



(a) Side view of the lab-house



(b) 3-D model of the lab-house

Figure 3.7: Side view of Physical house and its Building model developed in EnergyPlus [110]

Actual dimensions of the lab-house were used to generate the 3D model. But as the house was built in 1940, the actual thermal properties of the construction materials are unavailable. So, default values of these thermal properties were adopted based on the available ‘typical’ values in the built year of 1940 and default values in the EnergyPlus library [110].

The building model was treated as a single thermal zone, since the lab-house has just a single thermostat. This is also typical with most residential buildings.

The four-people occupancy schedules developed in Section 3.1.1 was incorporated into the EnergyPlus IDF file. Also, the different activity schedules developed in Section 3.1.1 for the baseline and UBLD cases were incorporated into the EnergyPlus IDF file. A concise description of the EnergyPlus building model is given in Table 3.2. Detailed description of the relevant algorithms used in the model can be found in [162].

Table 3.2: EnergyPlus Building Model Configuration

OBJECT	FIELD/VALUE	DESCRIPTION/REMARK
Shading Calculation Method	PolygonClipping	Shading calculation method to determine how shadows are processed.
Shading Calculation Update Frequency Method	Periodic	Determines how often shading calculations are updated.
Shading Calculation Update Frequency	20	Frequency of shading updates (number of timesteps).
Maximum Figures in Shadow Overlap Calculations	15000	Maximum number of figures considered in shadow overlap calculations.
Polygon Clipping Algorithm	SutherlandHodgman	Algorithm used for polygon clipping in shadow calculations.
Pixel Counting Resolution	512	Resolution for pixel-based shadow calculations.
Sky Diffuse Modeling Algorithm	SimpleSkyDiffuseModeling	Algorithm used to model diffuse sky shading.

Inside Surface Convection Algorithm	TARP	Algorithm used for inside surface convection calculations.
Outside Surface Convection Algorithm	DOE-2	Algorithm used for outside surface convection calculations.
Heat Balance Algorithm	ConductionTransferFunction	Algorithm used for heat balance calculations.
Zone Air Heat Balance Algorithm	ThirdOrderBackwardDifference	Algorithm used for zone air heat balance calculations.
Zone Air Contaminant Balance	No	Indicates whether CO ₂ concentration is modeled.
Number of people	4	Based on four-member occupancy schedule used.
Lighting level (W)	300	Estimated from actual building
Dish washer power (W)	6.56987875E+01	*FLT = 0.15, **FR = 0.6, ***FL = 0.25
Refrigerator power (W)	9.10575745E+01	*FLT = 0.0, **FR = 1.0, ***FL = 0.0
Clothes washer power (W)	2.84784378E+01	*FLT = 0.0, **FR = 0.8, ***FL = 0.2
Clothes dryer power (W)	2.13064557E+02	*FLT = 0.05, **FR = 0.15, ***FL = 0.8
Plug load (W)	5.67464238E+02	*FLT = 0.06, **FR = 0.69, ***FL = 0.25
Timestep	60	Number of timesteps per hour in the simulation.
Site: Location	Norman	Location name.
	35.25	Latitude of the site (°).
	-97.47	Longitude of the site (°).
	-6	Time zone offset from UTC (hours).

*FLT: Fraction Latent, **FR: Fraction Radiant, ***FL: Fraction Loss

3.2.1.2 The Modelica Component

The Modelica components of the building model in Figure 3.6b comprises of an infiltration sub-model, a thermal zone sub-model, and a smart thermostat sub-model. The infiltration sub-model was discussed in Section 2.5.1.2 and incorporated into the building model using components from MBL and MSL (Modelica Standard Library). The infiltration schedules discussed in Sections 3.1.2 and shown in Figure 3.5 were used as inputs to the infiltration sub-model. The smart thermostat model is discussed in Section 3.2.2. This section focuses on describing the thermal zone model.

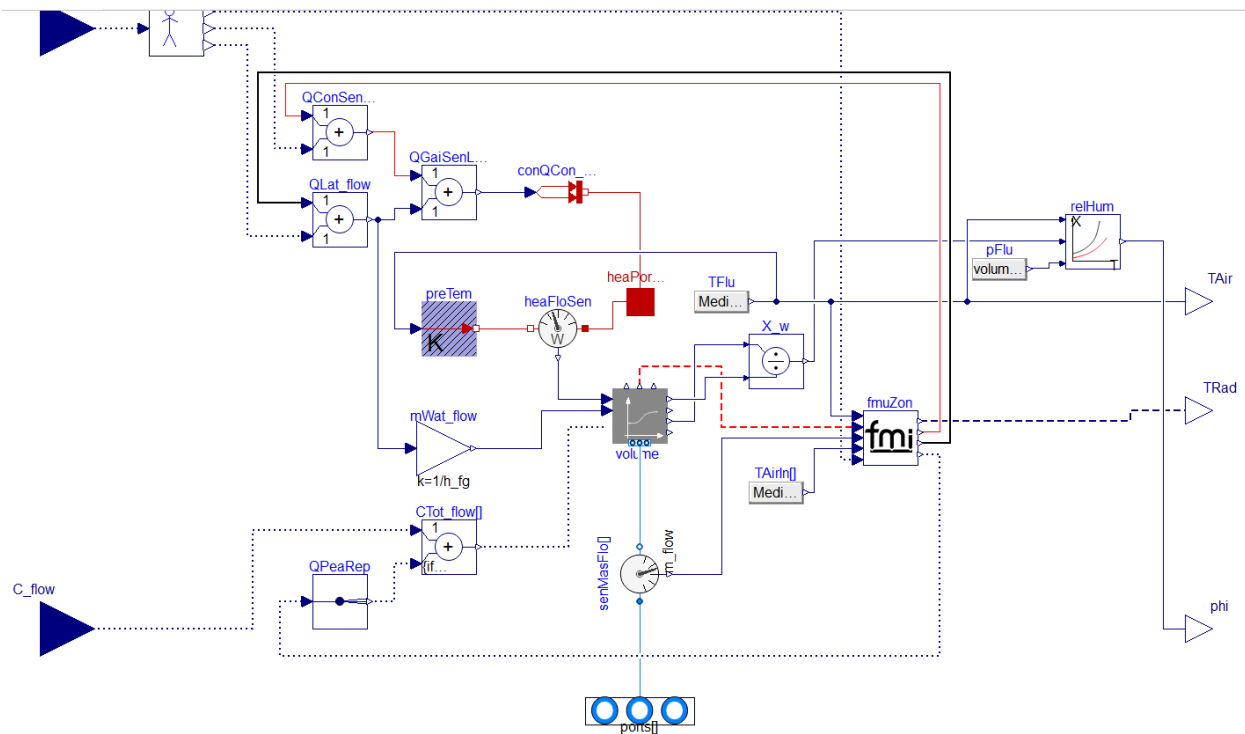


Figure 3.8: The MBL Thermal Zone Model Implemented in EnergyPlus

The thermal zone model was used to handle the air heat and mass balance within the building. MBL contains a thermal zone model (Buildings.ThermalZones.EnergyPlus_9_6_0.ThermalZone) which has been validated. The model is written in Modelica but implemented in EnergyPlus thus making co-simulation with EnergyPlus and Dymola possible. The model instantiates an FMU

(Functional Mockup Unit, labelled as ‘fmi’ in Figure 3.8) with the EnergyPlus IDF specified and connects to the specified thermal zone in the IDF file.

The zone uses a volume of air that is fully mixed. The size of the zone volume and its floor area are extracted from the EnergyPlus model. The grey square block contains the relevant conservation equations used for the air heat and mass balance as well as for computing transient T_{in} and W_{in} values in the zone. The three blue circles at the bottom of the Figure 3.8 represents fluid ports where the infiltrated air, exhaust air, supply air and return air from the AC, all mix before being channeled to the ‘fmi’ block and the ‘ConservationEquation’. The mixed air supplied to the ‘fmi’ enables dynamic air interaction with the EnergyPlus model which then computes the total sensible heat gain (q_{sen}), the total latent heat gain (q_{lat}) and the people heat gain (q_{peo}). q_{peo} was extracted from q_{sen} to be used to compute the amount of trace substance (e.g. CO₂) added to the space. But this was deactivated in the simulation as well as other variables indicated by dotted lines. The red solid line shows the q_{sen} from EnergyPlus while the thick black solid line represents the q_{lat} from EnergyPlus. The solid dash line from the ‘fmi’ component is the average interior wall surface temperature labelled as TRad. From Equation (3.13), the water mass flow rate (mWat_flow in the figure) in the air is calculated

$$\dot{m}_{wat,flow} = \frac{q_{lat}}{h_{fg}} \quad (3.13)$$

where h_{fg} (J/kg) is the latent heat of vaporization. $\dot{m}_{wat,flow}$ and $\dot{Q}_{flow}$ (combined sensible and latent heat gain from EnergyPlus) are then supplied as inputs to the ‘volume’ block.

For the air heat and mass balance in the ‘volume’ block, the mass balance equation i.e., Equation (3.11) was used. Then, Equation (3.14) is used to calculate the internal energy in the space.

$$\frac{dU}{dt} = H_{flow,b} + \dot{Q}_{flow} \quad (3.14)$$

where U is the internal energy of the space air, $H_{flow,b}$ is the enthalpy flow across boundaries, $\dot{Q}_{flow}$ is the sensible plus latent heat flow rate transferred into the space air from the EnergyPlus building model.

From the ‘volume’ block, the humidity ratio of the air (red dash line) is outputted as input to the EnergyPlus model via the ‘fmi’ block. The computed humidity ratio (X_w in the figure) was also used together with the pressure of the air and T_{in} to compute the relative humidity of the air, ϕ_{air} .

3.2.2 The Smart Thermostat Model

A smart thermostat is a control device for regulating indoor temperature (T_{in}) in a building. It consists of a temperature sensor and a closed-loop controller that compares the sensed T_{in} to the desired temperature (T_{set}) and thereby accordingly control AC operation to regulate T_{in} to T_{set} . For most smart thermostats, the closed controller also has a deadband (or differential) setting intentionally built into it to prevent AC short cycling (i.e., excessive AC cycling) which can reduce the AC lifespan. This feature forces an AC to stay on/off beyond a specified T_{set} , thereby making the AC cycle less frequently.

Figure 3.6d shows a picture of the smart thermostat model developed in Modelica for this research. The model consists of a feedback mechanism, a hysteresis block used to introduce the deadband into the controller and achieve typical on/off control in the AC based on the feedback from the room. The model also contains three conversion blocks used to convert the Boolean signal from the hysteresis block into the corresponding inputs for the outdoor fan, indoor fan, and the compressor. The input for the fans is their respective airflow rates, while the input for the compressor is the compressor speed. First order transfer function blocks were then used for each

controlled AC component to ensure numerical stability in the entire building/AC model during co-simulation. A deadband value of 1 F (0.6 C) was used for the co-simulation based on the default value in most smart thermostats.

3.2.3 The AC Model

The AC model is based on the vapor compression cycle as illustrated in Figure 3.6c. The models for each of the major components are described in the subsections below.

3.2.3.1 Description of the Compressor

The efficiency based compressor model from the Modelica TIL library was used for the AC. Path to this model can be found in *TIL.VLEFluidComponents.Compressors.EffCompressor* in the TIL library. The model is defined by the rotational speed (n), the actual displacement (V_{disp}) and three specified efficiencies, namely: volumetric efficiency (η_{vol}), isentropic efficiency (η_{isen}), and effective isentropic efficiency ($\eta_{isenEff}$) computed using the following equations:

$$\eta_{vol} = \frac{\dot{m}_{ref}}{V_{disp} \times n \times \rho_{suc}} \quad (3.15)$$

$$\eta_{isen} = \frac{h_{isen,dis} - h_{suc}}{h_{actual,dis} - h_{suc}} \quad (3.16)$$

$$\eta_{isenEff} = \frac{\dot{m}_{ref} (h_{isen,dis} - h_{suc})}{P_{shaft}} \quad (3.17)$$

where $\dot{m}_{ref}$ is the mass flow rate of the refrigerant, ρ_{suc} and h_{suc} is the respective density and enthalpy of the refrigerant at suction (i.e., compressor inlet), $h_{isen,dis}$ and $h_{actual,dis}$ is the respective isentropic enthalpy and actual enthalpy of the refrigerant at discharge (i.e., compressor outlet), P_{shaft} is the shaft power which represents the mechanical power needed to drive the

compressor. With these equations, the compressor model properly captures the physics of the compression process, taking into account deviations from an ideal compression as well as friction losses due to irreversibilities in the actual compression process. Table 3.3 gives some a summary of the compressor specifications used for the AC model.

Table 3.3: Compressor Specifications

Variable	Unit	Value	Source
Volumetric Efficiency	%	0.78	Gotten through the GA calibration discussed in Section 3.3.1
Isentropic Efficiency	%	0.79	
Effective Isentropic Efficiency	%	0.75	
Volumetric displacement	m ³	37e-6	
Compressor speed	Hz	60	From system specifications

3.2.3.2 Description of the Condenser and Evaporator

The cross flow fin-and-tube heat exchanger model from the Modelica TIL library was used for both the condenser and the evaporator components of the AC. Path to the model can be found in *TIL.HeatExchangers.FinAndTube.MoistAirVLEFluid.CrossFlowHX* in the TIL library. The model contains the following elements:

- **Geometry:** This element is used to specify the relevant dimensions and geometry of the heat exchanger e.g., number of tubes, the diameter of the tubes, the number of fins, etc. Based on the specified geometry, the heat exchange area and the hydraulic dimensions are calculated and forwarded to the pressure drop and heat drop models.

- Pressure drop:** This element contains pressure-drop models used to compute the pressure drop in the refrigerant and in the air. These pressure-drop models are based on existing correlations. For this research, the Swamee-Jain correlation [163] was used for the refrigerants while the Haaf correlation for pressure drop [164] was used for air. The Swamee Jain correlation calculates the pressure drop for circular flows, considering the roughness of the tube and its geometry. The Haaf correlation describes the air side pressure drop of heat exchangers with finned bundled tubes. The correlation is developed for both dry and moist air.
- Heat transfer:** The convective heat transfer of the refrigerant flow and air flow, as well as the heat conductance through the wall are calculated by correlation-based heat transfer models. For the refrigerant, the Steiner-Shah-Gnielinski-Dittus-Boelter model was used. This model calculates the heat transfer during evaporation, condensation or single-phase, using three different equations. The Steiner correlation [165] is used for evaporation, while Shah's correlation [166] is used for condensation. Then the Gnielinski-Dittus-Boelter correlation [167] is used for the single phase heat transfer calculations. For the air, the Haaf correlation for heat transfer [164] was used. The Haaf correlation describes the air side heat transfer in heat exchangers with finned bundled tubes. The correlation is developed for both dry and moist air.
- Finite Volume Element:** The heat exchanger is discretized into finite volume cells, each containing a differential state. The discretization is done for the media (refrigerant and air) and the wall. Because of the differential state of each cell, the size of the non-linear system of equations is not increased by the heat exchanger models. This makes the finite volume approach very suitable for fast, dynamic system simulations.

Table 3.4: Specifications for Condenser and Evaporator Models

Parameter	Unit	Value		Remark
		Cond.	Evap.	
Fin tube length	m	0.89	0.8	Gotten through the GA calibration in Section 3.3.1
Number of parallel tubes	-	36	32	
Distance between serial tubes	m	22e-3	22e-3	Based on TIL specification
Distance between parallel tubes	m	25.4e-3	25.4e-3	
Number of serial tubes	-	2	3	From product specifications
Fin thickness	m	0.15e-3	0.15e-3	
Distance between fins	m	1.15e-3	1.7e-3	
Inner diameter of tube	m	8e-3	8e-3	
Thickness of tube walls	m	1.2e-3	1.2e-3	
Number of parallel tube flows	-	4	4	
Number of cells	-	10	10	

3.2.3.3 Description of the Thermal Expansion Valve

A thermostatic expansion valve (TXV) which is common in residential AC units was used. The TXV in TIL (*TIL.VLEFluidComponents.Valves.TXV*) was modeled based on two curves: an opening curve and a flowrate curve. The opening curve is based on the working principle of the TXV where a sensing bulb is attached to the surface of the evaporator outlet. The refrigerant contained inside the sensing bulb expands when the superheat becomes too high, and this expansion causes the TXV to open more thus allowing more refrigerant into the evaporator. This in effect then reduces the superheat. On the other hand, when the superheat becomes too low, the

refrigerant in the bulb contracts and causes the valve opening to become smaller, leading to reduction in the amount of refrigerant released into the evaporator and by effect increasing the superheat. The opening curve in the TIL TXV model is obtained using the following equation:

$$p_{open} = \begin{cases} e^{-\frac{a}{T_{bulb}}+b}, & \text{if } T_{bulb} < MOT \\ cT_{bulb} + d, & \text{if } T_{bulb} > MOT \end{cases} \quad (3.18)$$

where a, b, c, d are constants obtained by specifying three reference temperatures and three reference pressures. MOT is the maximum operating temperature. T_{bulb} is the sensing bulb temperature.

The flowrate curve on the other hand is obtained using Equations (3.19) to (3.27)

$$p_{open}^{nom} = e^{-\frac{a}{T_{bulb}^{nom}}+b} \quad (3.19)$$

$$p_{open}^{nom} = cT_{bulb}^{nom} + D \quad (3.20)$$

$$A_{nom} = \frac{m_{nom}}{\sqrt{2\rho_{nom}(p_{high}^{nom} - p_{low}^{nom})}} \quad (3.21)$$

$$\beta = \frac{A_{nom}}{p_{open}^{nom} - p_{low}^{low}} \quad (3.22)$$

$$A_{max} = \frac{m_{max}A_{nom}}{m_{nom}} \quad (3.23)$$

$$\frac{dT_{bulb}}{dt} = \frac{1}{\tau_p}(T_{sensor} - T_{bulb}) \quad (3.24)$$

$$\frac{d(\Delta p_{eff})}{dt} = \frac{p_{open} - p_{sensor}}{\tau_p} - \Delta p_{eff} \quad (3.25)$$

$$A_{eff,lin}^n = \max[0, \beta \Delta p_{eff}] \quad (3.26)$$

$$A_{eff} = A_{eff,lin}^n + A_{max} - (A_{eff,lin}^n + A_{max}^n)^{\frac{1}{n}} \quad (3.27)$$

The relevant parameters for the TXV are given in Table 3.5.

Table 3.5: TXV Specifications

Parameter	Unit	Value	Remarks
First reference temperature, T_{ref1}	C	0	From opening curve and flowrate curve simulated in MATLAB
Opening pressure at T_{ref1}	bar	9	
Second reference temperature, T_{ref2}	C	10	
Opening pressure at T_{ref2}	bar	12	
Second reference temperature, T_{ref3}	C	40	
Opening pressure at T_{ref3}	bar	20	
Maximum Operating Temperature	C	25	Data gotten from manufacturer datasheet
Nominal high pressure, p_{high}^{nom}	bar	28	
Nominal low pressure, p_{low}^{nom}	bar	11	
Nominal sensing bulb temperature, T_{bulb}^{nom}	C	9*	See below
Nominal mass flow rate	kg/s	0.8	Gotten through the GA calibration discussed in Section 3.3.1
Maximum mass flow rate	kg/s	0.065	
Curvature exponent, n	-	2.5	Default specification in TIL

* Based on the TXV model in TIL, T_{bulb}^{nom} must be greater than the temperature corresponding to p_{low}^{nom} to avoid oscillations in the opening and closing of the TXV

3.2.3.4 The Filling Station Model

Though this is not a typical component of the VC cycle, it was used to ensure that the desired refrigerant charge (i.e., mass) is maintained in the AC system. The filling station model was obtained from the TIL library (*TIL.VLEFluidComponents.FillingStations.FillingStation*). This model enables the user to control the refrigerant mass within the VC cycle by adding/removing refrigerant mass until the total refrigerant mass matches the specified value, either by a fixed parameter or a time-varying input signal connected to the filling station's total mass input. This makes it possible to simulate refrigerant charging (i.e., addition) and discharging (i.e., removal). The model also allows the start and stop time of the charging/discharging process to be predefined, as well as the rate of charging/discharging. A negative rate signifies discharging while a positive rate means charging.

3.2.4 Coupling of the Building Model and AC Model Using Spawn of EnergyPlus

The coupling of the building model developed in EnergyPlus and the building model components as well as AC model developed in Modelica was achieved by an interface known as Spawn. Spawn leverages on the Modelica language and the Functional Mockup Interface (FMI) [168] for co-simulation and model-exchange. Figure 3.9 shows the architecture of Spawn.

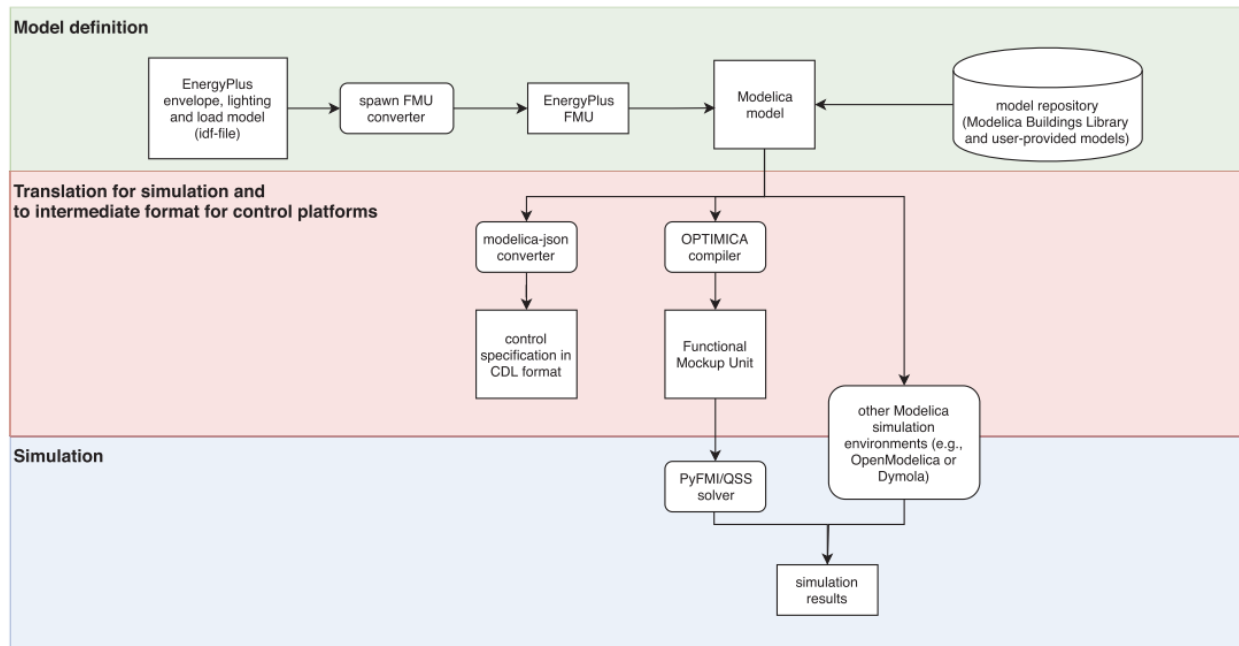


Figure 3.9: Architecture of Spawn [169]

During co-simulation, the EnergyPlus building model is run by Spawn, to obtain the internal loads, envelope heat transmission, electric and lighting loads, solar heat gains, surface conduction and radiative heat transfer. While the space air heat and mass balance including inter-zone air-exchange, AC operation and control are simulated in Modelica [169]. Figure 3.10 gives an overview of the interaction between EnergyPlus and Modelica during co-simulation, showing the variables from each of these tools.

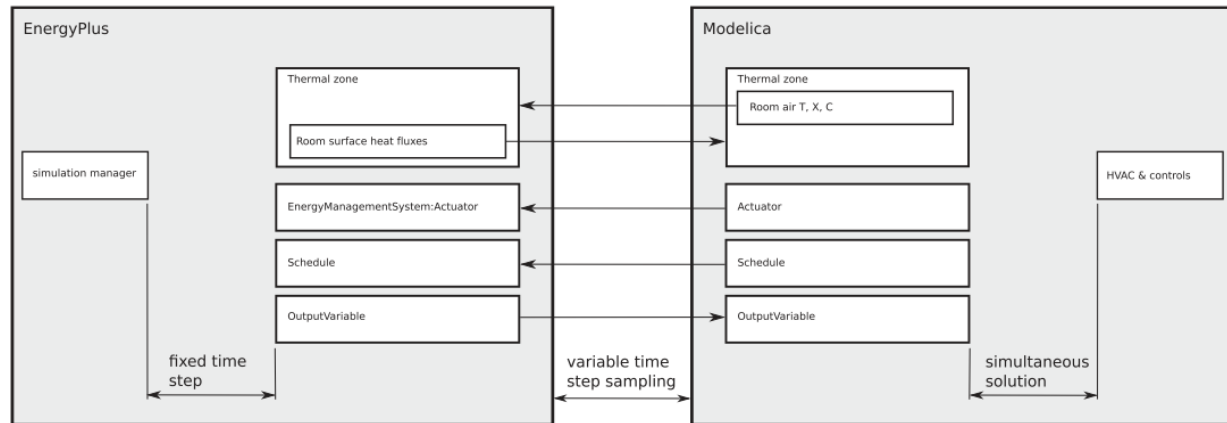


Figure 3.10: Interaction between EnergyPlus and Modelica during co-simulation [169]

3.3 Automated Calibration of the Co-Simulation Testbed

The relevant input and output data used for calibration are presented in Table 2.2. The AC unit in the lab-house was operated from June 14 – 19, 2024, under normal conditions to generate the data needed for the calibration. The output data were used mainly to validate the AC model calibration and are chosen based on the acceptable calibration metrics discussed in Section 2.2.3.2.4. The building model calibration was validated mainly with a lumped parameter which is a function of the building envelope's thermal resistance and thermal capacitance. Discussion on this parameter is provided in Section 2.2.3.2.2.

The calibration of the co-simulation testbed is done in two phases. In Phase 1, the AC model alone is calibrated. In Phase 2, the calibrated AC model is coupled to the uncalibrated building model and calibration of the building model is then performed, thus leading to the calibration of the entire co-simulation testbed. Discussion of each of these phases is provided in Sections 3.3.1 and 3.3.2.

3.3.1 Phase 1: Automated Calibration of the AC model

The calibration of the AC model was performed using the Genetic Algorithm (GA) optimization method. The GA was used to find optimal values for sizing relevant components of the AC model developed in TIL such as the compressor, condenser and evaporator. Also, optimal charge values for the AC were tuned with the GA. These components were intuitively selected as the most critical components in the AC model. Furthermore, as some components like the condenser and evaporator had several parameters used in the modeling, the most critical were identified by doing some manual sensitivity analysis. Table 3.6 gives the relevant configuration used in the GA optimization. The configuration was selected based on settings recommended in literature [170–173] to achieve a good compromise between diversity, computation cost and optimization performance. Table 3.7 then shows the gene space specified for each of the tuned parameters for the AC model. The gene space was intuitively designed based on observed impacts of each tuned parameter on the output variables listed in Table 2.2.

Table 3.6: GA Configuration

S/N	Parameters	Value/Selection
1.	Number of parents mating	4
2.	Number of parents to keep	2
3.	Number of generations	100
4.	Solutions per population	20
5.	Crossover probability	0.9
6.	Mutation probability	0.3
7.	Parent selection type	Tournament

8.	Crossover type	Single point
9.	Mutation type	random

Table 3.7: Gene Space for Tuned Parameters of AC Model in GA

S/N	Tuned Parameters	Lower bound	Upper bound	Stepsize
1.	Condenser finned tube length	0.8	0.9	0.01
2.	Number of parallel tubes in condenser	34	38	2
3.	Evaporator finned tube length	0.8	1.0	0.01
4.	Number of parallel tubes in evaporator	32	36	2
5.	Compressor displacement	33e-6	38e-6	1e-6
6.	Compressor volumetric efficiency	0.7	0.8	0.01
7.	Compressor isentropic efficiency	0.7	0.8	0.01
8.	Compressor effective isentropic efficiency	0.7	0.8	0.01
9.	Target charge	1.4	1.6	0.01

Figure 3.11 shows the measured input data which was used for the calibration of the AC model.

The data covered a 5-hour period, spanning three AC on-cycles and two AC off-cycles.

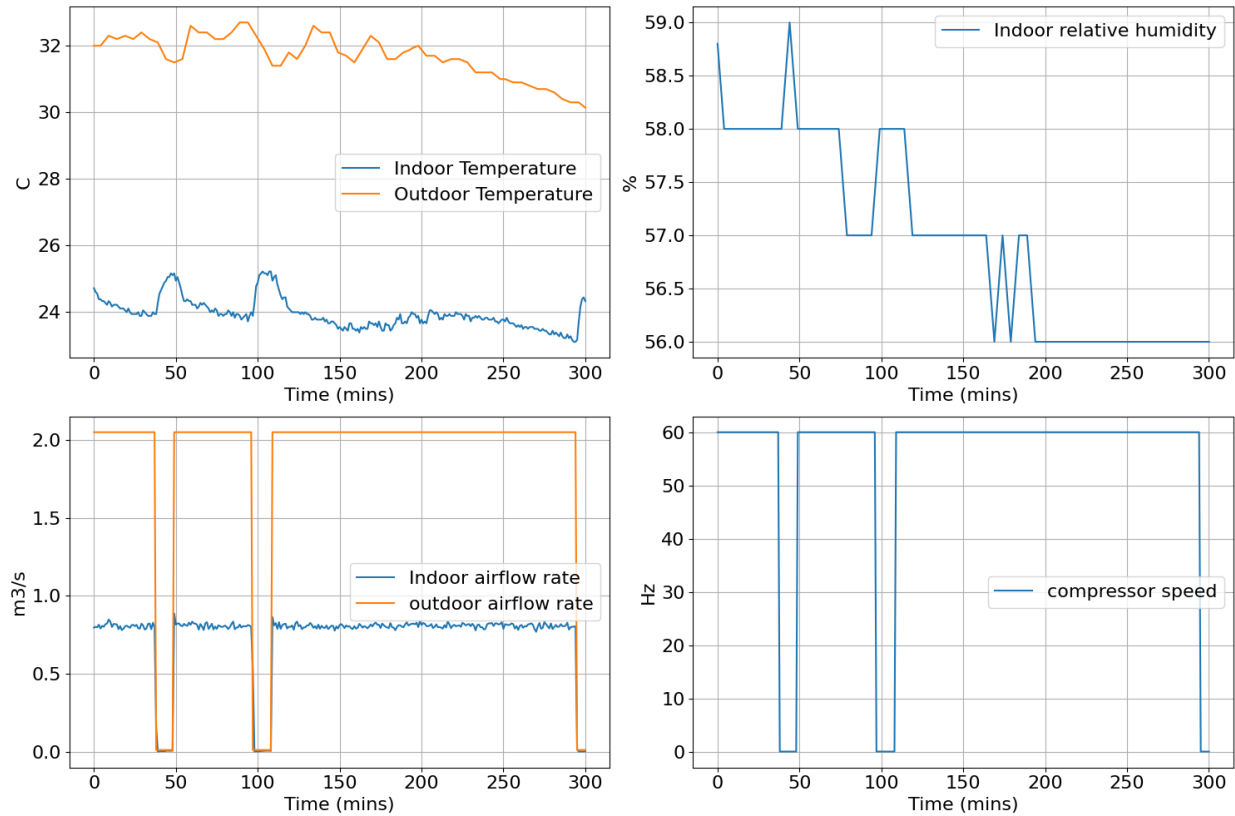


Figure 3.11: Input Variables used for Calibration

3.3.2 Phase 2: Automated Calibration of the Building Model

Although the EnergyPlus building model obtained from [110] was validated. The validation was done with AC off data, thus ignoring the AC dynamics in the calibration process. But to have a properly validated co-simulation model that couples the AC dynamics and building dynamics together, the AC dynamics must be incorporated into the calibration process by using both AC on/off data. Therefore, the EnergyPlus model had to be recalibrated.

The recalibration of the building model was done using the automated calibration framework discussed in Sections 2.2.3.2.2 and 2.2.3.2.3.

First, the accuracy of the ASHRAE Clear Sky Model used to compute relevant data (like G_{DH} and G_{dH}) needed for the conversion to TMY format but unavailable from Mesonet was examined. This was done by calculating GHI from Equation (3.28), and then comparing it with GHI from Mesonet as shown in Figure 3.12.

$$GHI = G_{DH} + G_{dH} \quad (3.28)$$

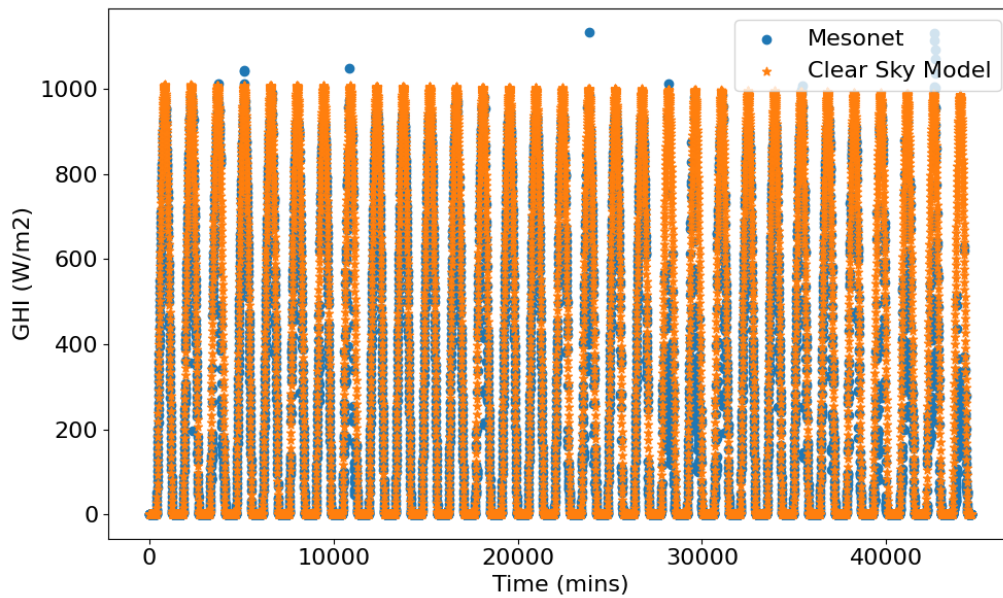


Figure 3.12: Comparison between GHI from Mesonet and GHI calculated with ASHRAE Clear Sky Model for July 2022

The comparison shows a good match between the two data. Figure 3.13 then presents the relevant input data used in the least square estimation of the 2R2C model parameters.

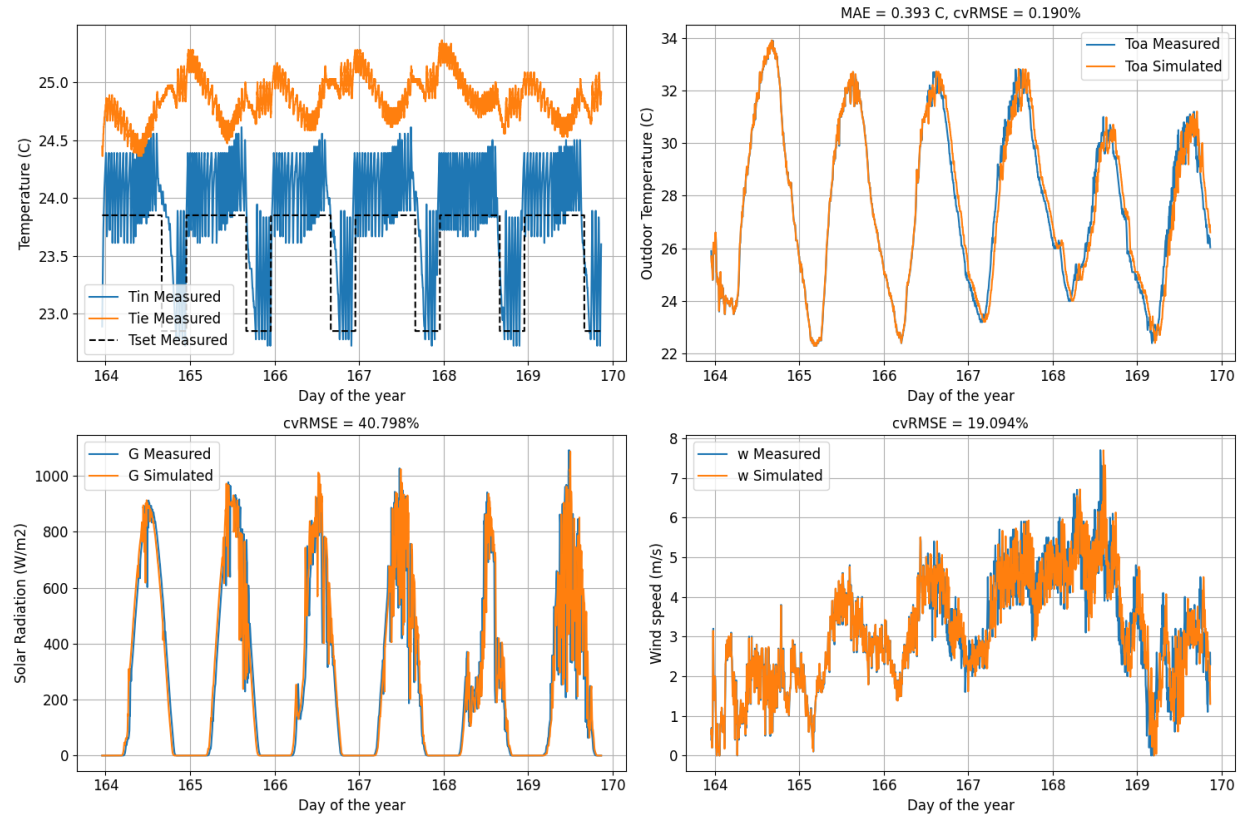


Figure 3.13: Input Dataset1 used for Co-simulation

Subplot 1 of Figure 3.13 shows the measured T_{in} and T_{ie} as well as the setpoint (T_{set}) schedule used during the experiment and which was implemented in the co-simulation. The data was collected over a period of six days. Subplot 2 - 4 compares the experimental weather data to the converted TMY data used in the co-simulation to evaluate the accuracy of the weather conversion process. The results show that the weather data conversion is reasonably accurate, especially for T_{oa} which had MAE of 0.396 C and CVRMSE of 0.191%. For windspeed, the CVRMSE was 19.203% likely because of some missing timestamps in the experimental data which is not applicable to the co-simulation. Then, in addition to the missing timestamps issue, the slight inaccuracies in the ASHRAE Clear Sky Model used to compute G likely led to even higher CVRMSE in G . Still, the comparison shows a good match overall.

3.4 Case Studies and Simulation Setup

Based on the UBLDs described in Sections 2.5.1 and 3.1, a total of eight case studies were investigated. The case studies were selected to cover a range of severity ranging from mild to worst case scenario. Three categories of UBLDs were thus considered, namely: UBLD1, UBLD2, and UBLD3. UBLD1 represents mild cases where just a single UBLD is considered for occupancy, infiltration, or setpoint irregularities. UBLD2 represents less severe cases where occupancy, infiltration, and setpoint, are grouped into alternate pairs. While UBLD3 shows the case where UBLD from all three variables (occupancy, infiltration and setpoint) are considered. Table 3.8 lists out the different case studies considered in this study. Then for the co-simulation, Table 3.9 shows the setup used

Table 3.8: List of Case Studies

S/N	CASES	LABELS	DESCRIPTION
1.	Normal	Normal	Normal operation with no fault or imposed disturbance, used as baseline
2.	UBLD1	Occ	Only Occupancy induced disturbance
3.		Inf	Only infiltration induced disturbance
4.		Tset	Only setpoint induced disturbance
5.	UBLD2	OccInf	Combination of occupancy and infiltration
6.		OccTset	Combination of occupancy and setpoint
7.		InfTset	Combination of infiltration and setpoint
8.	UBLD3	UBLD3	Combination of all UBLDs i.e., occupancy, infiltration and Tset

Table 3.9: Simulation Configuration

Parameters	Unit	Value/Selection	Remarks
Master software	-	Dymola 2024x	Environment that manages the co-simulation process
Slave software	-	EnergyPlus 9.6.0	Instantiated from the Master software
Setup in Dymola 2024x			
Mode	-	Transient	Suitable for simulating AC and building dynamics
Compiler	-	Visual studio	
Solver	-	Dassl	Suitable for handling stiff models
Tolerance	-	0.001	
Interval length	s	60	Same timestep was used in EnergyPlus
Start time	day	172	Corresponds to June 21 which was used in EnergyPlus
Stop time	day	242	Corresponds to August 31 which was used in EnergyPlus

3.5 Validation of the Co-simulation Testbed

3.5.1 Validation of the Calibrated AC Model

Figure 3.14 shows comparison of the measured AC outputs (as listed in Table 2.2) with the simulated outputs from the AC unit before the calibration. A comparison for q_{cc}^{Evap} and q_{cc}^{Cond} could not be made because of unavailability of measured values. For comparison, NMBE, CVRMSE and MAE were used as discussed in Section 2.2.3.2.4. The uncalibrated AC unit was parameterized based on visual inspection of the physical AC, manufacturer data, and default values from the TIL library for parameters that were unavailable. But, due to the gap between physical AC system and the model representation, the results in Figure 3.14 show that the uncalibrated model does not accurately represent the physical system. This can be seen more clearly from the

T_{sc} , P_{comp} , q_{cc}^{Evap} and q_{cc}^{Cond} . The uncalibrated AC model shows a zero T_{sc} and gives a MAE of 4.360 C, an NMBE of 88.135%, and a CVRMSE of 110.462%. The SAT shows slightly better results with an MAE of 1.119 C, NMBE of 0.281%, a CVRMSE of 0.487%, which falls within acceptable thresholds. For P_{comp} , an NMBE of -26.439% and a CVRMSE of 29.154% were gotten. Both P_{fan}^{in} and P_{fan}^{out} were within acceptable thresholds: P_{fan}^{in} had NMBE of -8.386% and CVRMSE of 11.983%; while P_{fan}^{out} had NMBE of 7.798% and CVRMSE of 10.08%. The q_{cc}^{Evap} and q_{cc}^{Cond} were 13.326 kW (~3.8-ton) and 15.94 kW (~4.5-ton) and showed that the uncalibrated AC unit was slightly larger than the physical system which is 3.5-ton/4-ton (outdoor/indoor). These results further highlight the need for calibration.

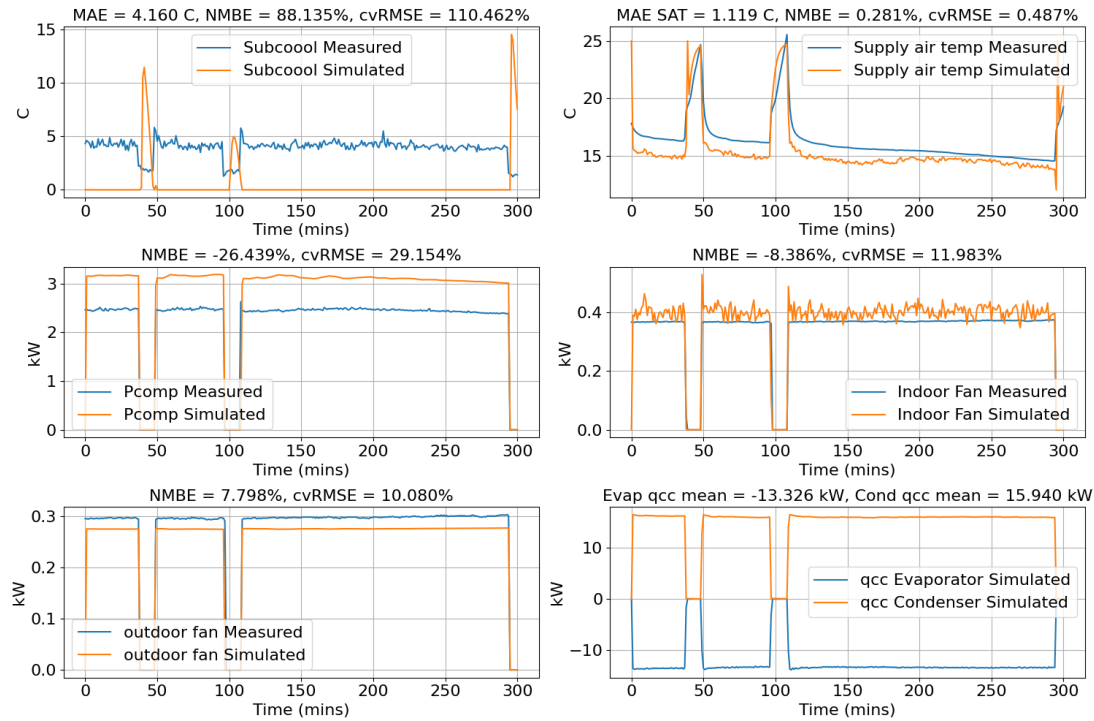


Figure 3.14: Result Before Calibration

Using the best solutions from the GA optimization that satisfied the fitness function, new simulation results were obtained as presented in Figure 3.15. The new simulation results were

based on a different dataset from the one used to train the GA. The testing dataset spanned over 9 hours with 5 AC on cycles and 5 AC off cycles. Results of the calibrated AC model (Figure 3.15) show significant improvements. For T_{sc} : MAE, NMBE and CVRMSE of 0.581 C, 5.386%, and 26.006%, respectively, were obtained. Then for SAT: MAE, NMBE and CVRMSE of 0.725 C, -0.155%, and 0.450%, respectively, were obtained. For P_{comp} : NMBE and CVRMSE of 1.878% and 11.403%, respectively, were obtained. For P_{fan}^{in} : NMBE and CVRMSE of -1.242% and 9.112%, respectively, were obtained. For P_{fan}^{out} : NMBE and CVRMSE of 0.482% and 7.394%, respectively, were obtained. Meanwhile, q_{cc}^{Evap} and q_{cc}^{Cond} were 10.887 kW (~3.1-ton) and 13.176 kW (~3.7-ton) respectively. This matches closely with the physical AC unit described in Section 2.2.1.1, especially with respect to the outdoor unit. Though, for the physical AC, a 4-ton indoor unit was used with a 3.5-ton outdoor unit. This is however not standard practice as shown in [106,174]. In the case of the AC model, the condenser (which closely matches the physical outdoor unit) is bigger than the evaporator. This is likely because from an energy balance perspective, the heat dispensed at the condenser is the sum of the heat absorbed by the evaporator and the heat generated by the compressor.

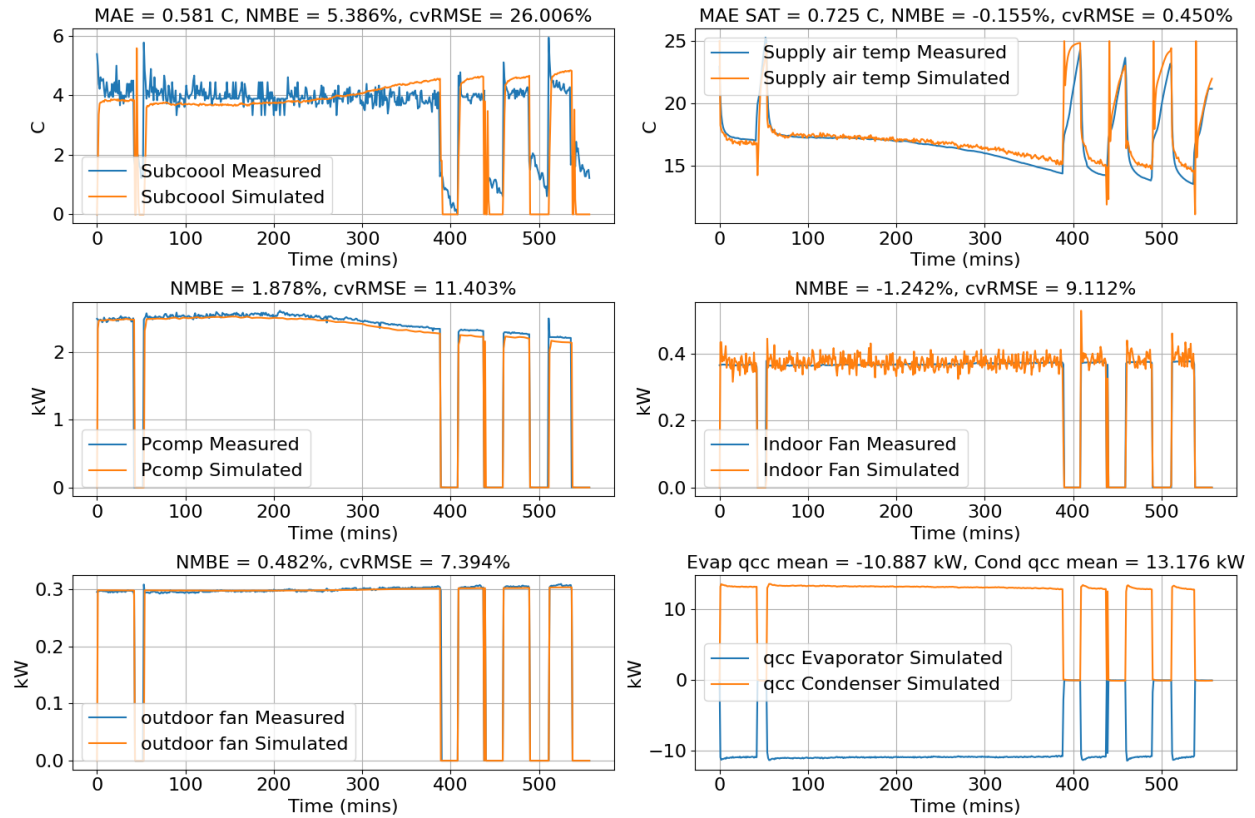


Figure 3.15: Results after Calibration of AC Model Using Genetic Algorithm.

3.5.2 Validation of the Building Model using the Calibrated AC Model

Two datasets were used for the validation of the co-simulation testbed. Dataset1 is the training data which was collected from day 164 (i.e., June 14) to day 169 (i.e., June 19). Dataset2 is the testing data and was collected from day 197 (i.e., July 17) to day 204 (i.e., July 23). The results for both dataset showed good performance of the calibration method, with dataset1 showing better performance since it is the training data.

Figure 3.16 shows the uncalibrated and calibrated result for the entire co-simulation testbed in three subplots. The first subplot shows results for the uncalibrated testbed. The second subplot shows results for the calibrated testbed using dataset1. The third subplot shows result for the calibrated testbed using dataset2.

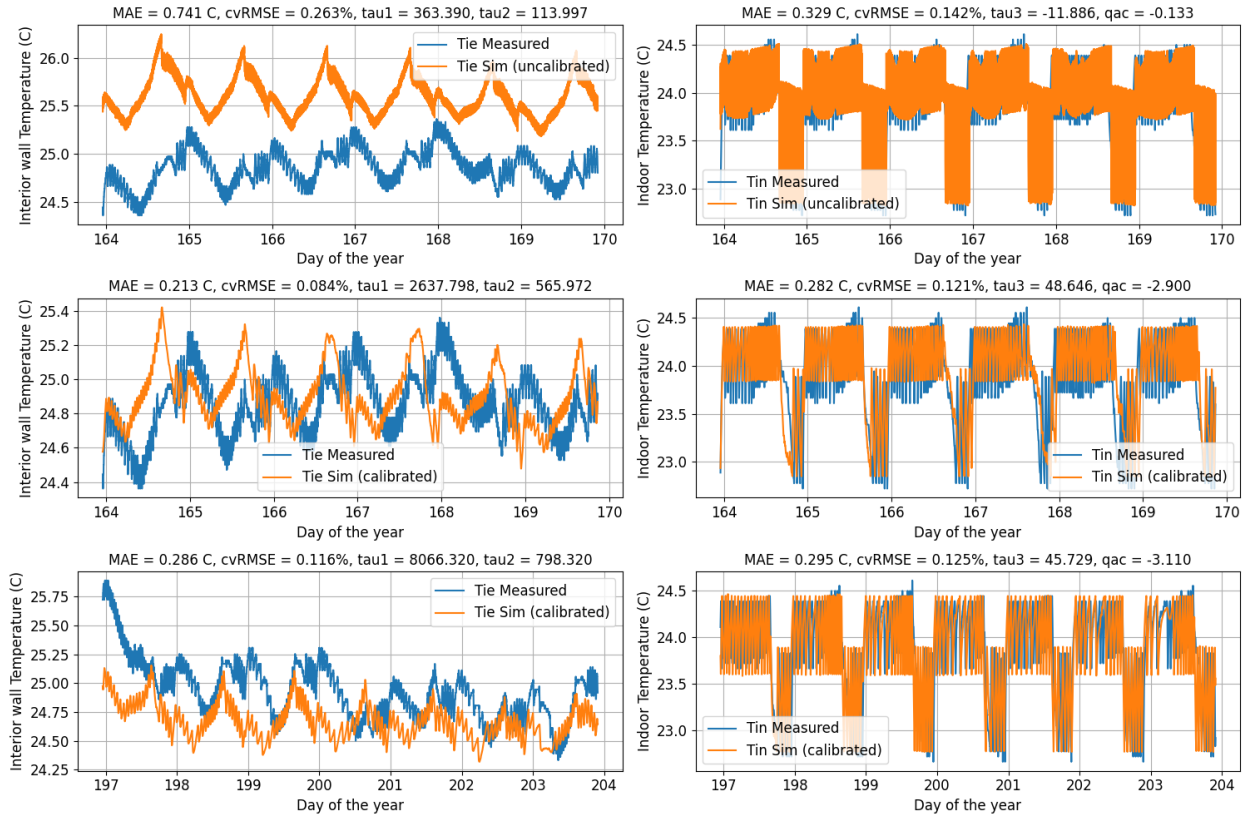


Figure 3.16: Uncalibrated (subplots 1, 2) and Calibrated (subplots 3, 4) results for the Co-simulation model

The uncalibrated co-simulation testbed consists of the calibrated AC model and the uncalibrated building model. While the calibrated co-simulation testbed consists of the calibrated AC model and calibrated building model based on the thermal model automated calibration framework described in Section 2.2.3.2.3. Based on the MAE and CVRMSE, results for both cases look acceptable. However, by visual inspection and most importantly by comparing the taus (especially tau1 which is more related to the building envelope based on its definition) with the experimental taus (see Table 3.10), the result for the uncalibrated model is unacceptable. More unacceptably is the observation of a negative τ_3 from the uncalibrated simulation results which is unrealistic based on the definition of τ_3 in Section 2.2.3.2.2. On the other hand, Table 3.10 reveals good match

between the calibrated taus and experimental taus. With dataset1, the discrepancy between the taus (i.e., tau1) was 2.5%. With dataset2, the discrepancy slightly increased to 6.298%. Also, the calibrated model shows slight improvement in the MAE and CVRMSE.

Table 3.10: Evaluation of the Automated Calibration of the Co-simulation Testbed

Model	Uncalibrated			Calibrated		
Parameter	Measured	Simulated	Difference (%)	Measured	Simulated	Difference (%)
Dataset 1 (Day 164 – 169 for training)						
tau1 (τ_1)	2573.384	363.390	-85.879	2573.384	2637.799	2.500
tau2, τ_2	472.536	113.997	-75.875	472.536	565.973	19.773
tau3, τ_3	65.853	-11.886	-118.049	65.853	48.646	-26.129
Dataset 2 (Day 197 – 204 for testing)						
tau1 (τ_1)	7588.364	765.314	-89.915	7588.364	8066.320	6.298
tau2, τ_2	890.734	60.912	-93.161	890.734	798.320	-10.375
tau3, τ_3	59.814	-12.089	-120.211	59.814	45.729	-23.548

3.6 Results and Discussion

Results for impact ratios (IR) and false positive rate (FPR) at different IR thresholds are presented and discussed in this section for all case studies under the two scenarios discussed in Section 2.5.1.4, namely: ideal scenario and real scenario. False negative rate and fault probability are not considered here since the case studies are fault free. Signal-to-noise ratio was also not considered based on the definition given in Section 2.5.1.4.4. Energy consumption and cost analysis was

considered for the ideal scenario only because the objective for this analysis is to see how these UBLDs can affect the energy consumption of AC systems in residential buildings.

The UBLDs investigated in this research fall under three categories, namely: UBLD1, UBLD2, UBLD3 as described in Table 3.8.

For the IR thresholds, values ranging from 1.00 to a maximum value were used for the impact analysis. The 1.00 IR threshold corresponds to a 0% threshold and implies that no threshold is used. The maximum IR threshold for each scenario is estimated to be the largest mean IR across all cases. Only plots for the ‘no threshold’ case and the maximum threshold were presented for the sake of brevity. Plots for other thresholds can be found in Appendix A.

3.6.1 Regression Analysis

As mentioned in Section 2.5.1.4, for the real scenario, baseline estimation is required. Therefore, the linear regression-based modeling approach was used for estimating the baseline duty factor.

Figure 3.17 shows the result for the regression obtained from the plot of daily duty factor against the daily average outdoor air temperature. The daily duty factor was computed using co-simulation data from June 21 – August 31, 2023. The regression line shows a good fit for the calculated daily duty factor based on the R-square value of 0.8575. Therefore, the regression equation was used to generate the baseline data used for the impact analysis.

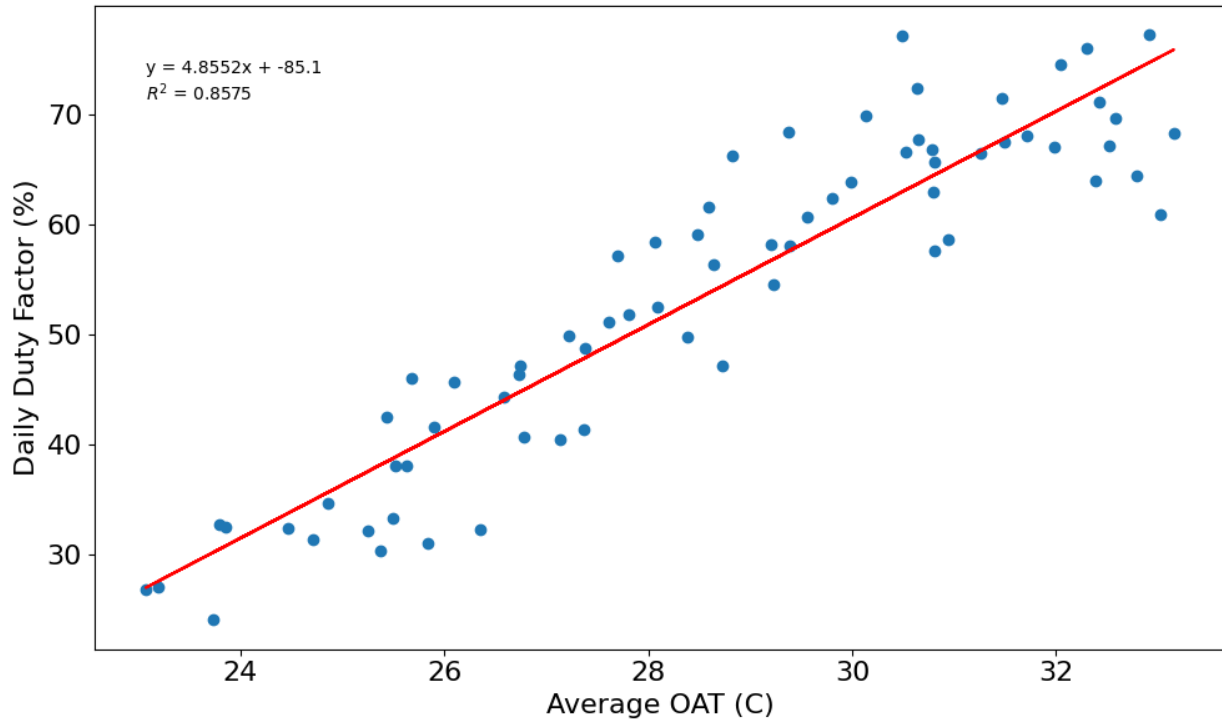


Figure 3.17: Regression for Duty Factor Estimation for the Real Scenario

3.6.2 Impact Ratio (DIR)

3.6.2.1 Ideal Scenario

Figure 3.18 shows the IR (under the ideal scenario) for the different UBLDs simulated when an IR threshold of 1.0 was used. The first subplot shows the IR for each day while the second subplot shows the impact when the CUSUM control strategy was applied.

The first subplot shows that the IR for various UBLDs fluctuate around the IR threshold of 1.0. The spread of the IR highlights the different levels of variability in the IR across the different UBLDs. For the Normal case, there were no fluctuations in the IR because the exact values under normal condition were used. Occ and Inf showed the least fluctuations, with Occ being the smallest. Tset on the other hand, showed large fluctuations even comparable to the UBLD2s and

UBLD3, thereby highlighting the dominant impact of Tset on the fluctuations in IR for the UBLD2s and UBLD3.

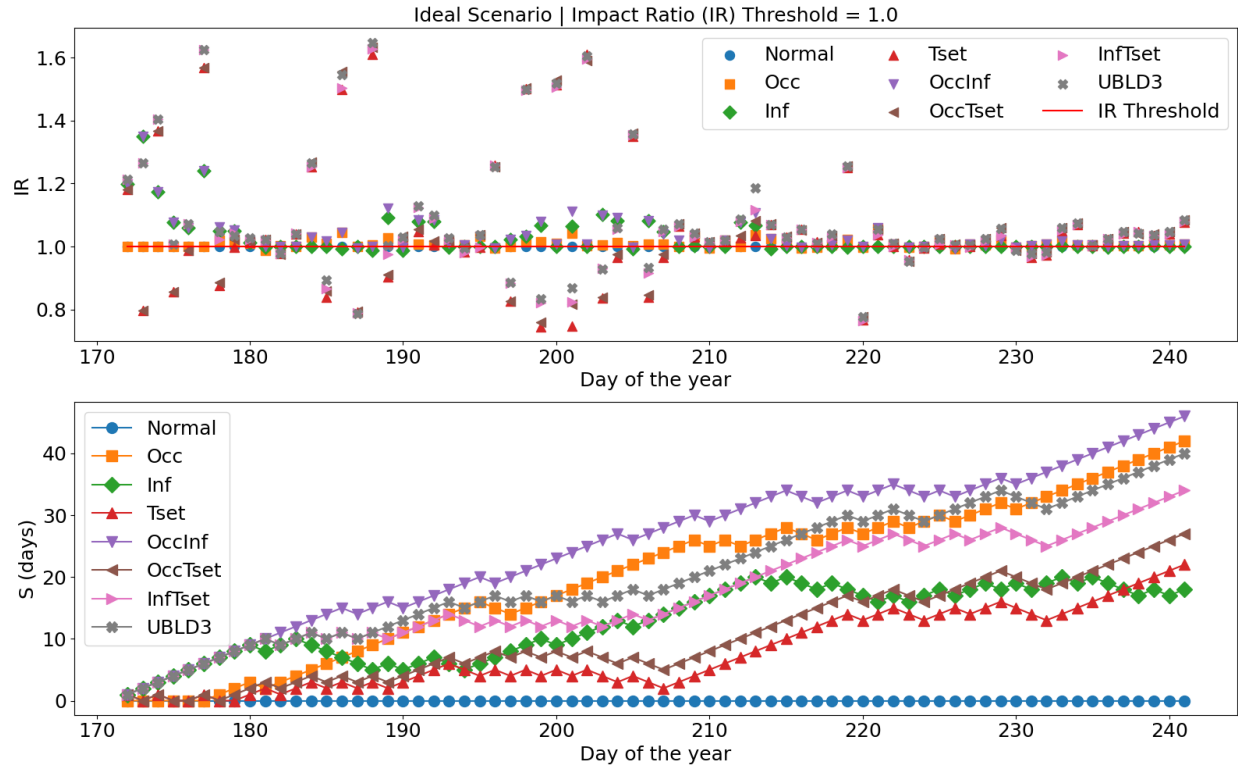


Figure 3.18: IR (from UBLDs) for Ideal Scenario with a threshold of 1.0 using Duty Factor

The second subplot quantifies the fluctuations in the first subplot by showing the evolution of S (the CUSUM control variable) due to these fluctuations. For the Normal case, the S showed no evolution because ideal data was used. Occ and OccInf showed larger upward rise in S than UBLD3, Tset and OccTset which had the largest fluctuations in the first subplot. This is because although Occ and OccInf had relatively small fluctuations, the fluctuations were above the IR threshold for the most part. Conversely, the other cases had significant fluctuations on both sides of the threshold. Tset, OccTset and Inf had the least rise in S due to their corresponding fluctuations alternating above and below the threshold. This is because while a lowered Tset or an increased

infiltration would cause an AC to run harder and longer during the day, lower outdoor temperatures can simultaneously result in a precooling effect which would thus make the AC run lesser the next day. Conversely, Occ increase only has a positive impact on the building gains.

Figure 3.19 shows the same scenario, cases, and analysis as Figure 3.18 but with a higher IR threshold of 1.09. The first subplot in both figures is the same except for the different IR thresholds. Mathematically, an IR threshold of 1.09 means a 9% IR threshold. The 9% IR threshold is the mean IR for UBLD3 which has the largest IRs. The 9% IR threshold significantly prevented the progressive rise of S leading to final S values of zero for all cases.

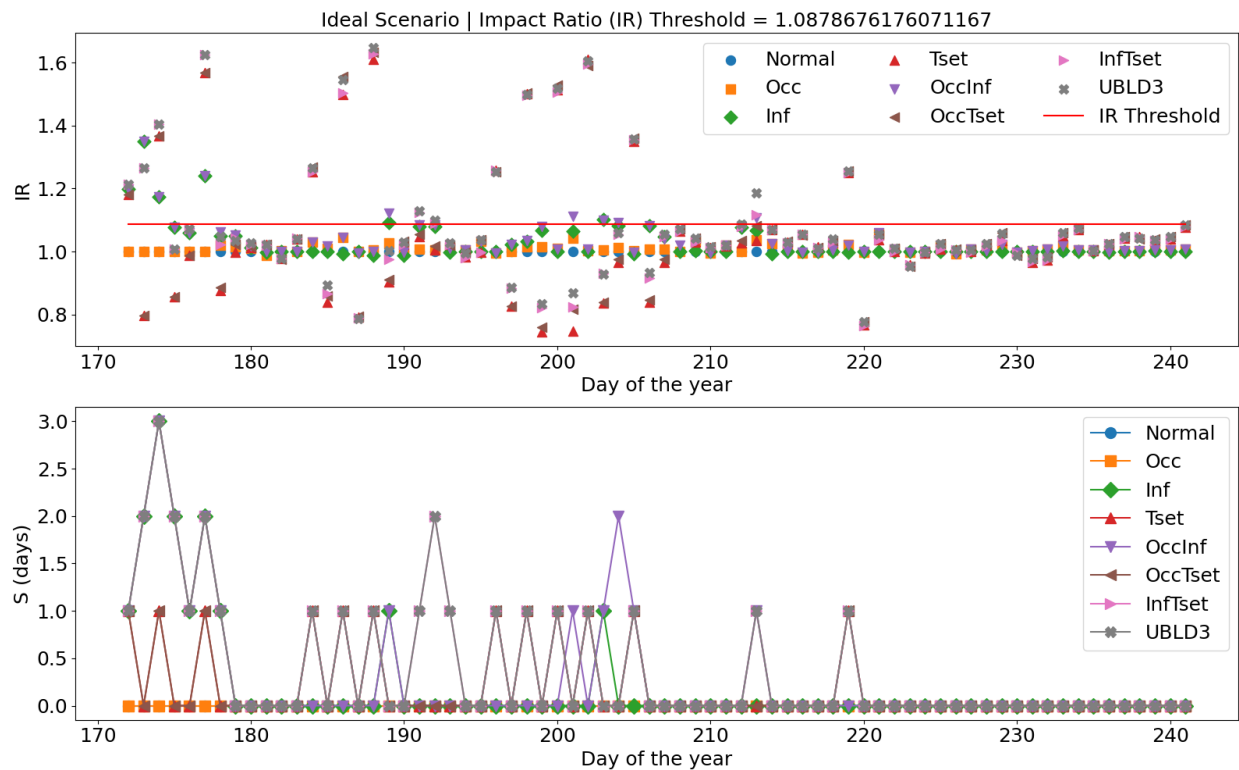


Figure 3.19: IR (from UBLDs) for Ideal Scenario with a threshold of 1.09 using Duty Factor

3.6.2.2 Real Scenario

For the real scenario, Figure 3.20 shows the IR for all cases when an IR threshold of 1.00 was used. The first subplot shows the IR for each day while the second subplot shows the impact when the CUSUM control strategy was applied.

The first subplot shows that the IR for all cases fluctuates around the IR threshold of 1.0. The spread of the IR highlights the different levels of variability in the IR across different cases. Unlike for the ideal scenario, for the real scenario, some level of variability is seen even for the Normal case. This variability is caused by the uncertainties from the regression used to estimate the baseline data used for the Normal case. So, even when there are no external disturbances, such uncertainties should be accounted for to avoid false alarms. However, the Normal case shows the smallest spread. UBLD3, InfTset and Tset show the largest fluctuations on both sides of the threshold, while Inf shows larger fluctuations below the threshold.

The second subplot quantifies the fluctuations in the first subplot by showing the evolution of S (the CUSUM control variable) due to these fluctuations. UBLD3 shows the largest trend while Normal and Occ shows the lowest trend with Occ initially rising above several other UBLDs before consistently dropping below all.

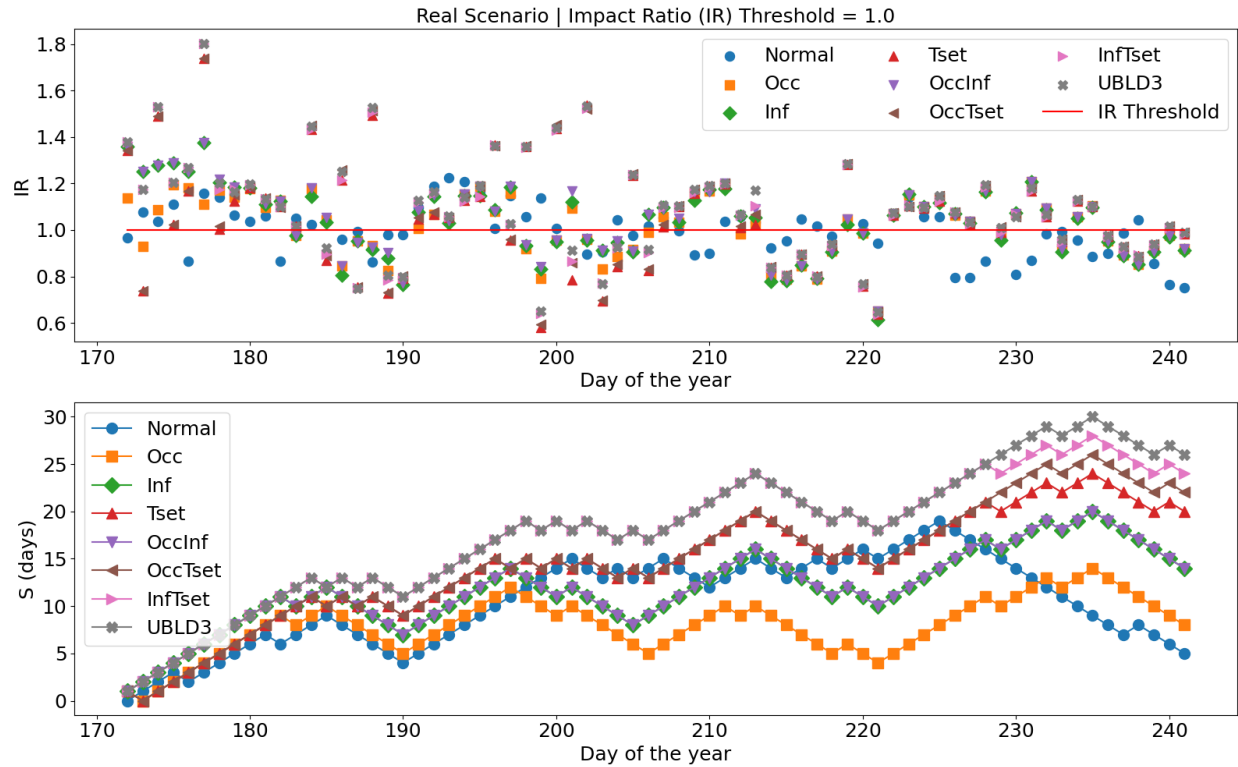


Figure 3.20: IR (from UBLDs) for Real Scenario with a threshold of 1.0

Figure 3.21 shows the same scenario, cases, and analysis as Figure 3.20 but with a higher IR threshold of 1.15 (i.e., 15%). The first subplot in both figures is the same except for the different IR thresholds. As was done for the ideal scenario, the 15% IR threshold is the mean IR for UBLD3 which has the largest IRs and is considered as the minimum IR threshold to ensure the FPR is significantly reduced for the most extreme UBLD impact. Like with the ideal scenario, the 15% IR threshold significantly prevented the progressive rise of S leading to final S values of zero for all cases.

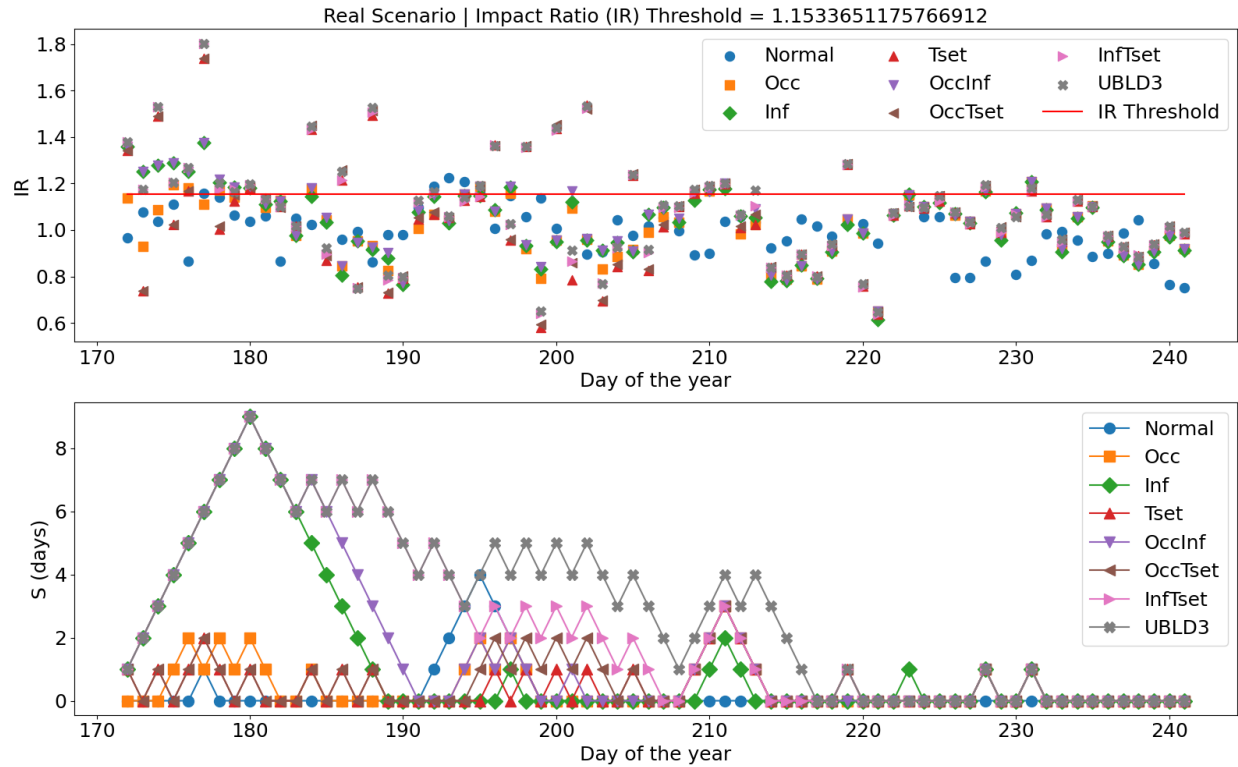


Figure 3.21: IR (from UBLDs) for Real Scenario with a threshold of 1.15 using Duty Factor

3.6.3 False Positive Rate (FPR)

To make further sense of the IR results, the IR without and with CUSUM were used to compute the associated FPRs for each case using Equations (2.28) and (2.29), respectively. IR with CUSUM is represented by the final S values in the IR second subplots. The final S values correspond to the CUSUM IR in Equation (2.29).

3.6.3.1 Ideal Scenario

For the ideal scenario, Figure 3.22 shows results for the impact of IR threshold on the FPRs when there is no CUSUM control (a) and when there is CUSUM control (b). Both subplots show a downward trend in the FPRs as the IR threshold increases. The FPRs for all cases and for all IR

thresholds were reduced as the CUSUM control strategy was imposed, with all FPRs reduced to zero at an IR threshold of 1.05 (5%) before the maximum IR threshold of 1.09 was reached.

As expected, the FPR for the Normal case was zero with and without CUSUM control because the duty factor was compared with itself for this case. Figure 3.22a shows that OccInf which had the highest FPR with a 1.00 (i.e., 0%) threshold, drops below other cases except Inf and Occ when an IR threshold of 1% was imposed. Similarly, Occ which had a large FPR of about 75% with a 1.00 threshold sharply drops to about 30% with a 1.01 (i.e., 1%) threshold and progressively drops to zero at approximately 1.06 IR threshold, while consistently below all other cases aside the Normal case. Inf shows almost similar trend, with a sharp drop from about 61% FPR to about 30% FPR but becomes fairly steady until the IR threshold increases to almost 1.06, beyond which it steadily drops to about 10% FPR. UBLD3 on the other hand was consistently above all other cases.

In Figure 3.22b, Occ and OccInf showed the largest FPR at 1.00 threshold due to the observed evolution in S , in both cases as discussed in Section 3.6.2. However, the FPR for both cases sharply drops to zero as even a small IR threshold of 1.01 (i.e., 1%) was applied. The same was observed for Inf. Again, UBLD3 was consistently above all other cases.

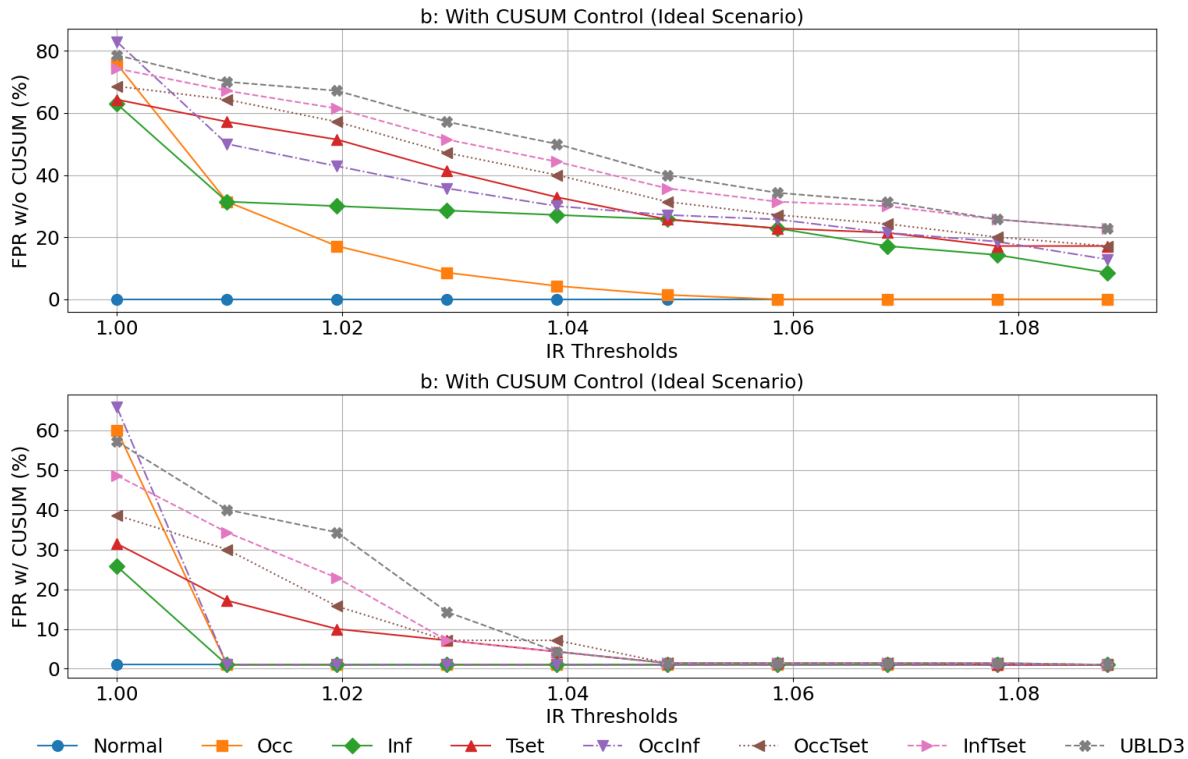


Figure 3.22: FPR vs IR threshold for the Ideal Scenario using Duty Factor (a) Without CUSUM Control, and (b) With CUSUM Control.

3.6.3.2 Real Scenario

For the real scenario, Figure 3.23 shows results for the impact of IR threshold on the FPRs when there is no CUSUM control and when there is CUSUM control. Both subplots also show a downward trend in the FPRs as the IR threshold increases. The FPRs for all cases and for all IR thresholds were reduced as the CUSUM control strategy was imposed, with all FPRs reduced to zero at an IR threshold of 1.10 (10%) before the maximum IR threshold of 1.15 was reached. Apart from UBLD3 and InfTset, the FPR for all other cases dropped to zero at a 7% IR threshold.

Unlike in the ideal scenario (Figure 3.22), Figure 3.23 shows that the FPR for the Normal case was non-zero with and without CUSUM control because the duty factor (Normal case) was compared with estimated duty factor (used as baseline). Though the FPR for the Normal case was still the

least for all cases as it was for the ideal scenario. Also, Figure 3.23 shows a very similar trend in terms of the FPR order both with and without CUSUM control. Occ maintained lower FPRs at all IR thresholds both with and without CUSUM control. Inf had the next smallest impact. Tset which had a larger FPR than even OccInf at a 0% IR threshold, dropped even below the FPR for Inf as the IR threshold increased beyond 1%. Beyond the 3% IR threshold, FPR for OccInf stayed above the FPR for all other cases aside InfTset and UBLD3.

Furthermore, the FPR at a 0% IR threshold with CUSUM control is almost equal to the FPR at a 15% IR threshold without CUSUM control and is even smaller than the FPR at IR thresholds less than 15% without CUSUM control. These observations show the superiority of the CUSUM control strategy to even the use of IR thresholds. The results further show the benefit of using both thresholds and the CUSUM control strategy. However, the results also raise the question of what an optimal IR threshold should be to balance FPR with FNR, since reducing FPR simultaneously increases FNR which is also not desired. Though a low FPR is preferred to a low FNR, as the former bothers on accuracy and reliability of an FDD tool and prevents wastage of time and resources [50], a low FNR will ensure early detection of faults. Therefore, a good compromise between FPR and FNR is important. This will be addressed in chapter four.

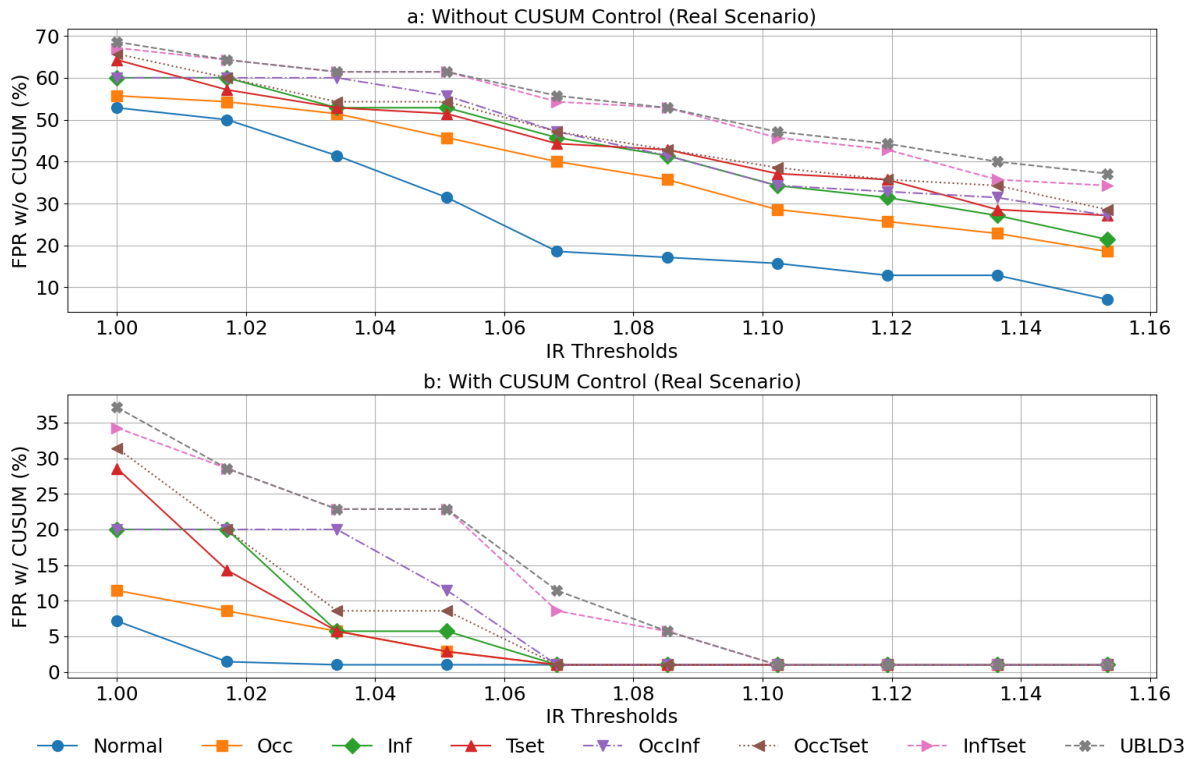


Figure 3.23: FPR vs IR threshold for the Real Scenario using Duty Factor (a) Without CUSUM Control, and (b) With CUSUM Control.

3.6.4 Energy Consumption and Cost Analysis

Table 3.11 shows results for energy consumption and cost analysis. The calculations were done from Equations (2.36) and (2.37). For the utility rate in Equation (2.37), \$0.20/kWh was used based on the national average reported in [175]. The analysis is based on the results for the ideal scenario because the objective for this analysis is to see how these UBLDs can affect the energy consumption of AC systems in residential buildings.

Therefore, for the Normal case, there was no energy consumption increase or increase in cost since that is the ideal reference. Also, the normal case shows a total energy consumption of 2417.061 kWh and a corresponding cost of \$217.54. Any deviation from this baseline quantifies the penalty imposed by UBLDs.

For the single UBLD effects (i.e., UBLD1 category), Occ had an insignificant impact on energy consumption with less than 1% increase which amounts to just \$3.85 increase. Inf had a slightly higher increase in energy consumption of 3.57%, leading to an additional cost of \$17.25. Tset driven UBLD had the largest impact in the UBLD1 category with a 4.75% increase in energy consumption and an extra \$22.98 cost.

For the dual UBLDs, the results reveal that the combined effect of UBLDs is almost additive. OccInf showed a 4.32% increase in energy consumption and a \$20.91 cost increase, which is slightly less than the sum of the individual impacts. This suggests that there is some interplay between internal heat gains and infiltration, like the precooling effect from infiltration discussed earlier. InfTset had a more severe impact with an 8.09% increase in energy consumption and a \$39.11 cost increase. This result suggests that the impact from infiltration-based UBLD is exacerbated when coupled with UBLDs from varied Tset. OccTset also showed an increase (though less severe) in both energy consumption and operation cost of about 5.47% and \$26.45, respectively.

For UBLD3, which represents the worse case scenario with all UBLDs combined, the energy use spikes by 8.79%, reaching 2629.412 kWh. The operation cost increased by \$42.47, which is a significant penalty over baseline conditions. Meanwhile, the energy increase of 8.79% is almost equal to the reported 9% energy increase caused by low charge and low indoor airflow faults [129,130,176]

Table 3.11: Energy Usage and Cost Analysis

Case	Total kWh	Total cost (\$)	Energy increase (%)	Cost increase (\$)
Normal	2417.062	483.41	0.0	0.0
Occ	2436.311	487.26	0.8	3.85
Inf	2503.305	500.66	3.57	17.25
Tset	2531.97	506.39	4.75	22.98
OccInf	2521.589	504.32	4.32	20.91
InfTset	2612.621	522.52	8.09	39.11
OccTset	2549.29	509.86	5.47	26.45
UBLD3	2629.41	525.88	8.79	42.47

These results demonstrate the need for FDD developers to come up with and incorporate algorithms into their tools that can detect not just faults, but also irregularities in the dynamics of buildings thereby potentially saving homeowners significant operation cost, especially if rates increase in the future.

3.7 Summary

In this chapter, different UBLDs that can affect AC operation were formulated. Then a co-simulation testbed was designed and developed. An automated calibration framework was then developed and used to calibrate the co-simulation testbed. Afterwards, the testbed was validated and used to run several simulations. Data from these simulations was then used for impact analysis under two scenarios: ideal scenario and real scenario. Finally, for the ideal scenario, the increase

in energy consumption and the increase in operation cost was computed for the different UBLDs investigated. From these, the key takeaways are:

1. Both the ideal and real scenario show different levels of variability in the DIR, caused by the variabilities from each UBLD.
2. These variabilities can lead to FPRs as high as 80% (for the ideal scenario) and 70% (for the real scenario) if thresholds are not used.
3. For the ideal scenario, by using thresholds up to 9%, the FPR can be reduced from 80% to about 25%. This shows the importance of using thresholds.
4. For the real scenario, at a 9% threshold, the FPR can be reduced from 70% to about 50%. This shows the importance of factoring in the uncertainties associated with models used for baseline estimation to make proper threshold selection.
5. With the CUSUM control strategy implemented in the real scenario, the FPR can be reduced from 50% to 5% at a threshold of 9%.
6. Without the CUSUM control strategy, increasing the threshold from 9% to 15% for the real scenario, can only reduce FPR from 50% to 40%. This and #5 show the greater benefit which the CUSUM control strategy offers in improving the performance of FDD methods. This will be discussed further in chapter 4.
7. Energy consumption and cost analysis show that UBLD impact can cause energy increase almost comparable to that caused by faults and can lead to additional operation cost of \$42.47 per homeowner.

Overall, the investigation reported in this chapter shows that UBLDs can have significant impact on AC operations in residential buildings. It therefore demonstrates the need for FDD algorithms that not only detect faults but can also detect these UBLDs. While the realization of such

algorithms might still be in the distant future, the investigation here also demonstrates the importance of thresholds and the potential of the CUSUM control strategy in improving the performance of current FDD methods. This will be discussed further in the next chapter, especially as it relates to optimal selection of threshold to strike a good balance between FPR and FNR in FDD methods, to achieve accurate, reliable and yet timely detection of faults.

Chapter 4: Performance Evaluation of Fault Detection Methods

This chapter presents results on impact analysis performed for two prevalent faults in residential homes across the US. The impact analysis was done for the two FDD features introduced in Section Chapter 2:. The metrics discussed in Section 2.5.1.4 were then used to evaluate the performance of smart thermostat based FDD methods that use either of the two features for detection and/or diagnosis. The chapter concludes with a comparative analysis of the performance using both features.

4.1 Case Studies and Simulation Setup

As mentioned in Section 2.3, two prevalent faults in residential AC systems across the US were considered in this research, namely: refrigerant charge (RC) fault and indoor airflow rate (AF) fault. Both faults are considered at three levels.

For the RC cases, undercharge faults at 15% severity (mild case) and 30% severity (severe case) were considered. Additionally, a slow refrigerant leak fault was simulated. The undercharge faults fall under the category of installation faults while the refrigerant leak fault typifies a slow degradation fault. As noted earlier, such faults are called soft faults because they are not readily perceptible.

The simulation of the RC faults was achieved with the filling station model described in Section 3.2.3.4. To simulate undercharge faults at a given severity, the total mass based on the undercharge severity was specified in the filling station model. For the refrigerant leak fault, a time-varying charge (i.e., mass) was specified in the filling station model. The leak was designed to start on day 177 and lead to a rapid drop in the charge level from 100% on day 177 to 70% on day 197, and

then steadily dropped to 60% at the end of the simulation period (day 242). Consequently, the refrigerant leak fault is also considered as a severe fault in this research.

The progression in the charge-drop typifies a real-life scenario where at the beginning of the leak, the discharge rate is higher because of the larger difference in pressure of the refrigerant in the system and the environment. Then as the charge in the AC system reduces, the pressure difference also reduces and so the discharge rate is reduced as well.

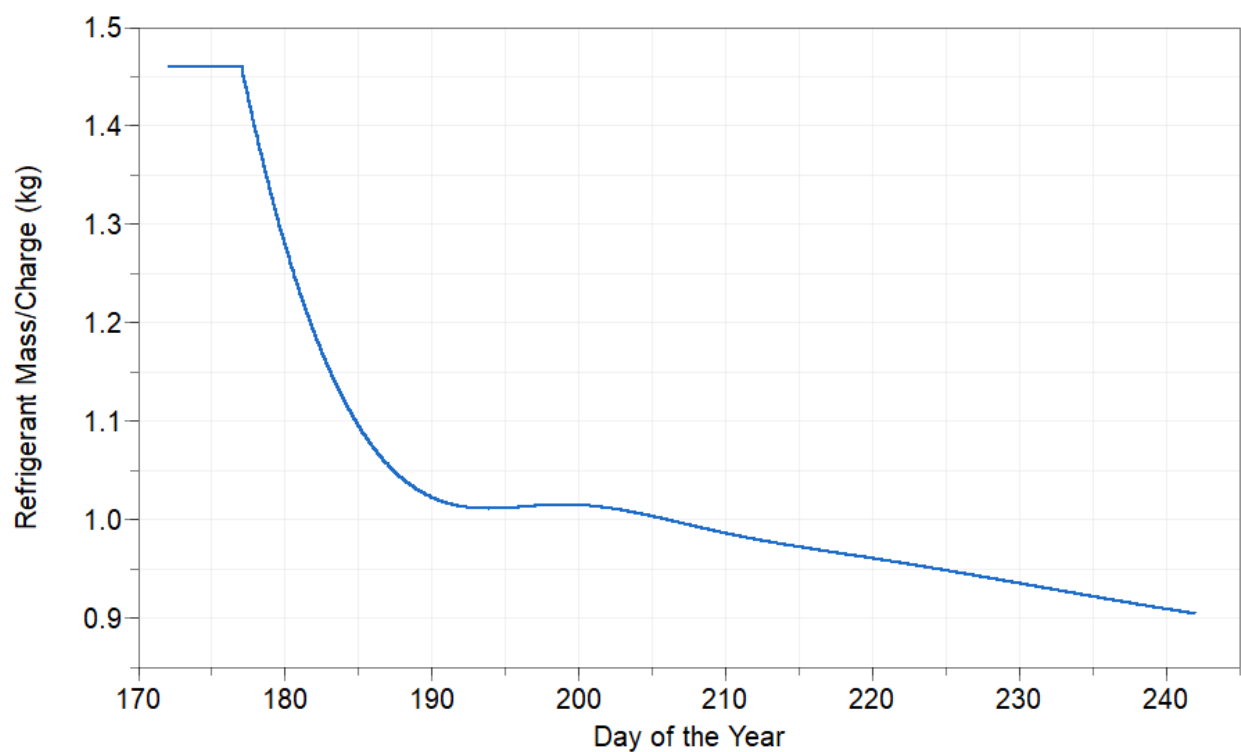


Figure 4.1: Time-Varying Refrigerant Charge for Refrigerant Leak Simulation

For the AF cases, low indoor airflow faults at 15% severity (mild case), 30% severity (severe case) and 60% severity (extreme case) were considered. These faults all fall under the category of installation faults. Simulation of these faults were achieved by simply specifying the airflow rate used as indoor fan signal output from the smart thermostat component in Figure 3.6d.

Based on the foregoing, a total of eight cases were considered as shown in Table 4.1. Based on the observations in Section 3.6 which showed UBLD3 to have the largest impact on AC operation, FPR and FNR (especially for the real scenario), UBLD3 was also considered to compare the impact with those from the different faults and fault severities. The color codes are used to represent the AC condition based on the fault severity with green signifying good and red signifying worse/extreme. Then for the co-simulation, the same configuration in Table 3.9 was used.

Table 4.1: List of Case Studies

S/N	CASES	LABELS	DESCRIPTION
1.	Normal	Normal	Normal operation with no fault or disturbance. Used as baseline
2.	RC Faults	RC85	RC level of 85% which corresponds to a 15% undercharge fault
3.		RC70	RC level of 70% which corresponds to a 30% undercharge fault
4.		RcLeak	Slow leak from RC level at 100% to 60%
5.	AF faults	AF85	AF level of 85% typifying low indoor airflow with 15% severity
6.		AF70	AF level of 70% typifying low indoor airflow with 30% severity
7.		AF40	AF level of 40% typifying low indoor airflow with 60% severity
8.		AF85RC85	Dual fault combining AF85 and RC85
9.	UBLD3	UBLD3	Combination of all UBLDs i.e., occupancy, infiltration and Tset

4.2 Results and Discussion for Duty Factor

Results for the impact ratio (IR) due to faults, false negative rate (FNR), fault probability (FP) and signal-to-noise ratio (SNR) for all case studies under the ideal scenario and real scenario discussed in Section 2.5.1.4 are presented in this section. The analysis was done using daily duty factor as

the FDD feature. FPR was not considered here since the case studies have faults. Energy consumption and cost analysis was also not considered because there is already a lot of literature on this.

For comparison, the UBLD with the largest impact was included as one of the case studies as shown in Table 4.1. From Section 3.6, this was found to be UBLD3.

For the IR thresholds, similar consideration to that made in Section 3.6 was made here with threshold values ranging from 1.00 to a maximum value (the largest mean IR from Section 3.6 which is 1.09 or 9% for the ideal scenario, and 1.15 or 15% for the real scenario). Also, only plots for the ‘no threshold’ case and the maximum threshold were presented for the sake of brevity. Plots for other thresholds can be found in the appendix section.

4.2.1 Impact Ratio

4.2.1.1 Ideal Scenario

For the ideal scenario, Figure 4.2 shows the IR for the different fault cases simulated when an IR threshold of 1.00 (i.e., 0% threshold) was used. The first subplot shows the IR for each day without the CUSUM control strategy while the second subplot shows the IR when CUSUM control strategy was applied. The means of the IRs for each case were computed and displayed above the first subplot. The same markers were used for both the first and second subplot, as indicated by the legend. The solid red line in the first subplot represents the IR threshold.

In the first subplot, the IR for all fault cases were above the threshold. Only UBLD3 had some IR below the threshold as similarly observed in Figure 3.18. For the Normal case, there were no fluctuations in the IR because there is no fault in this case and ideal baseline data was used. Hence, the mean IR is 1.00 (i.e., 0% increase). Also, for several days, the IR due to UBLD3 was higher

than all fault cases. For such days, though there is a fault in the system, there is larger uncertainty diagnosing a fault signal from UBLD3 signal. Additionally, the IRMeans show that a 2%, 4%, 4%, 6%, 9%, 16%, 17%, 17% average rise in the daily duty factor was observed for AF85, AF70, RC85, AF85RC85, UBLD3, RC70, RcLeak and AF40, respectively. This suggests that AF85 had the least impact while AF40 and RcLeak had the most impact on the duty factor. It also suggests that only RC70, RcLeak and AF40 had an average impact above that of UBLD3, and that AF85, AF70, RC85 and AF85RC85 might be difficult to diagnose from UBLDs.

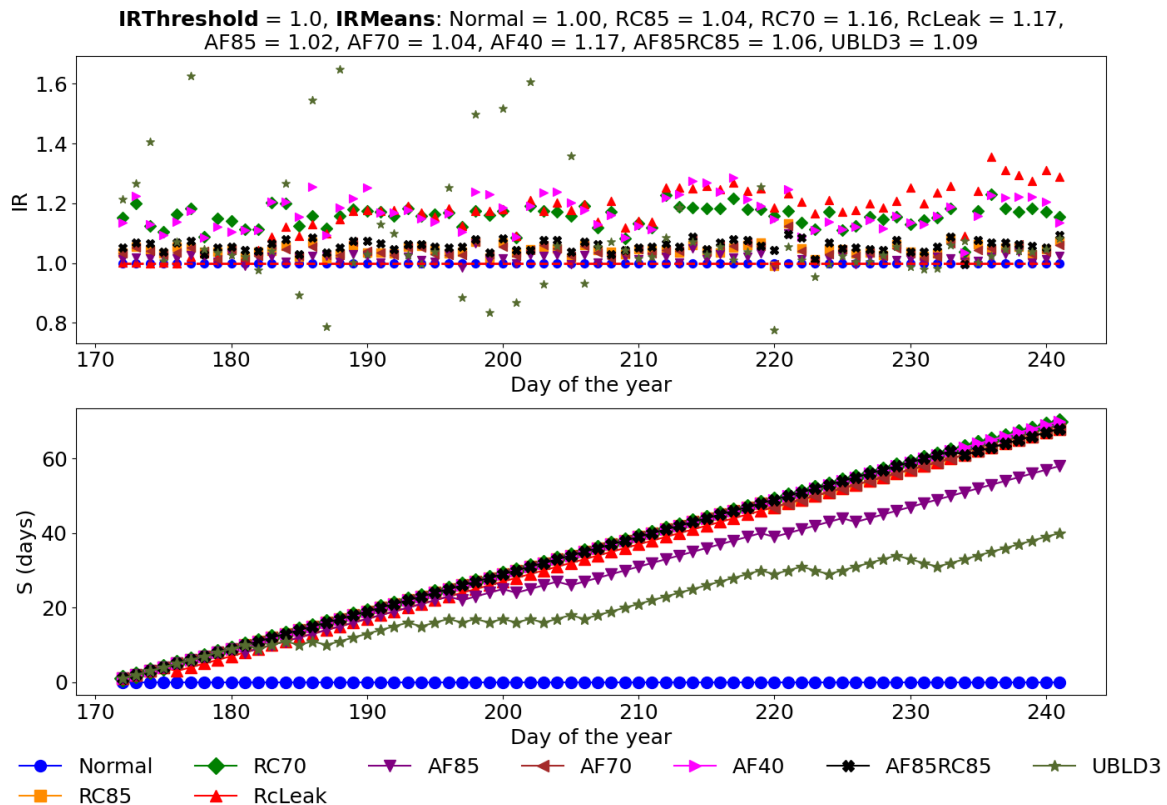


Figure 4.2: IR (due to faults) for Ideal Scenario with a threshold of 1.00 using Duty Factor

The second subplot in Figure 4.2 quantifies the IRs in the first subplot by showing the evolution of S (the CUSUM control variable) due to these IRs. For the normal case, S showed no evolution because ideal baseline data was used. All fault cases showed higher rise in S than UBLD3, showing

that with the CUSUM control, the fault impact can be diagnosed from the UBLD3 impact at all fault severities. However, to make sense of the trends in the second subplot, the final S values were converted into fault probabilities. This would be discussed further in Section 4.2.2.

Figure 4.3 shows the same scenario, cases, and analysis as Figure 4.2 but with a higher IR threshold of 1.09. The first subplot in both figures is the same except for the different IR thresholds. For the second subplot in Figure 4.3, the S values for RC70, RcLeak, and AF40 showed slightly lower values than those in Figure 4.2. The S values for the other cases reduced to approximately zero. The impact of this is explained further in Section 4.2.2.

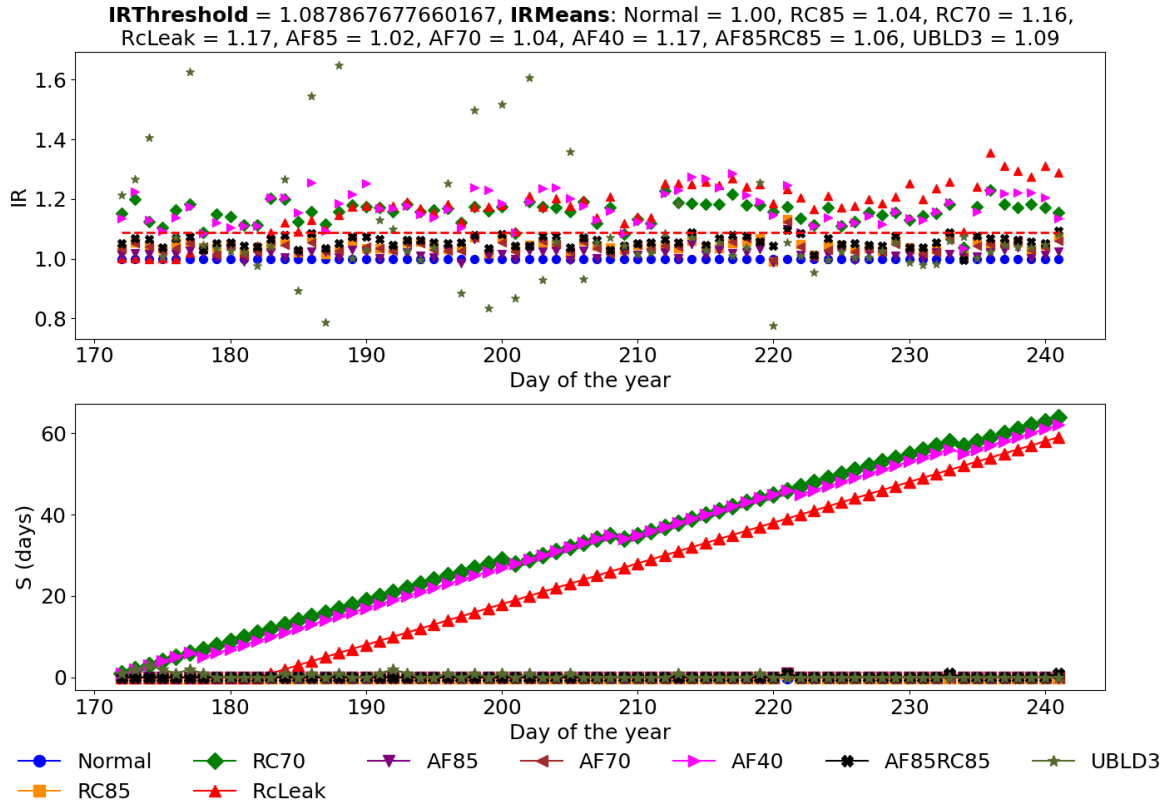


Figure 4.3: IR (due to faults) for Ideal Scenario with a threshold of 1.09 using Duty Factor

4.2.1.2 Real Scenario

For the real scenario, Figure 4.4 shows the IR plots under a 1.00 threshold. The first subplot shows the IR for each day without the CUSUM control strategy while the second subplot shows the IR when CUSUM control strategy was applied. The means of the IRs for each case were computed and displayed above the first subplot. The same markers were used for both the first and second subplot, as indicated by the legend. The solid red line in the first subplot represents the IR threshold.

Unlike for the ideal scenario, the first subplot for the real scenario in Figure 4.4 shows larger fluctuations around the IR threshold for all cases. As noted in Section 3.6.2, the fluctuations in the Normal case are due to the uncertainties embedded in the regression used to estimate the baseline

data applied in the Normal case. These uncertainties in the baseline data also affect the IR for other cases and lead to S values (second subplot) which are smaller than those shown in Figure 4.2 for the ideal scenario. Also, due to these uncertainties in the baseline data, the S values for the Normal case show some evolution unlike the observation for the ideal scenario. However, the mean IR for the Normal case was 1.0 (i.e., 0%) and the final S value for the Normal case was the least. Additionally, the IRMeans show that an 8%, 10%, 10%, 12%, 15%, 22%, 22%, 23% average rise in the daily duty factor was observed for AF85, AF70, RC85, AF85RC85, UBLD3, RC70, RcLeak and AF40, respectively. This sequence follows the same sequence for the ideal scenario but with higher averages. Though the higher averages suggest better performance in the real scenario, by applying the CUSUM control, smaller S values than those in the ideal scenario, are obtained. Thus showing that the ideal scenario still gives better performance which is expected since ideal baseline data is used.

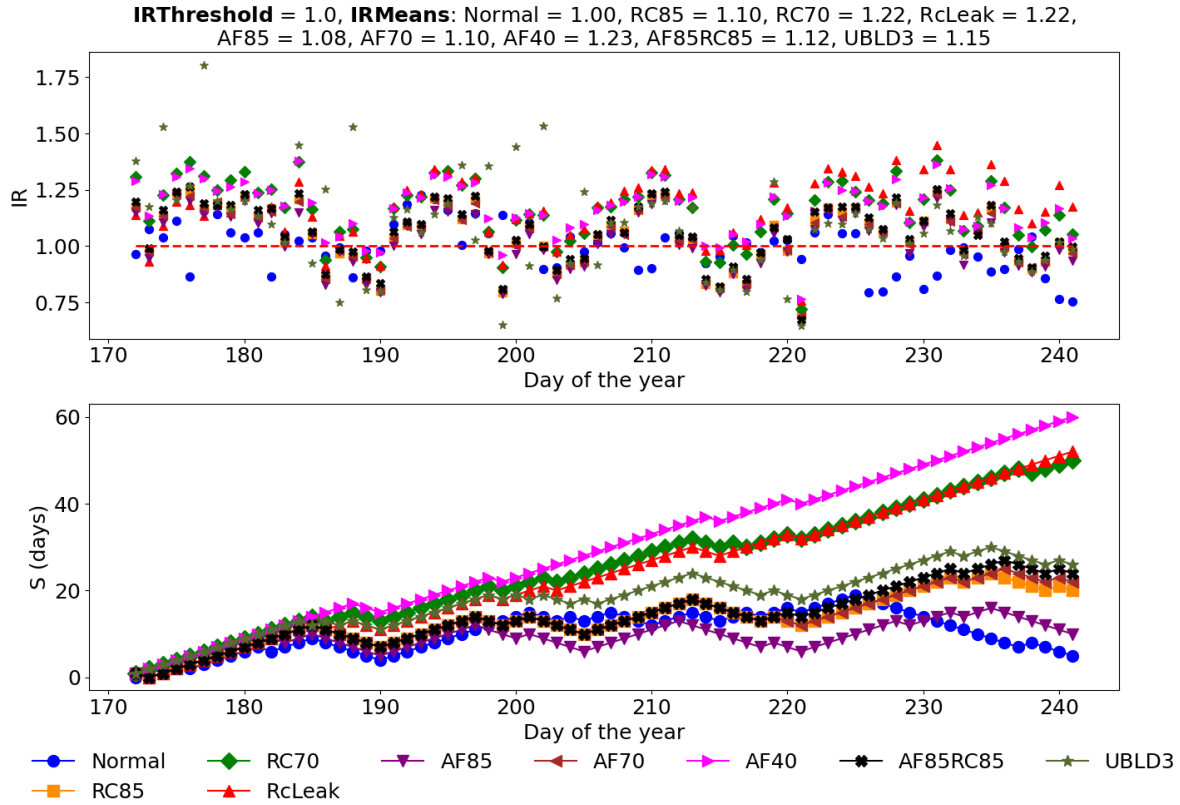


Figure 4.4: IR (due to faults) for Real Scenario with a threshold of 1.00 using Duty Factor

Figure 4.5 shows the same scenario, cases, and analysis as Figure 4.4 but under the maximum IR threshold of 1.15. The first subplot in both figures is the same except for the different IR thresholds. For the second subplot in Figure 4.5, the S values for all cases showed significantly lower values than those in Figure 4.4. The final S values for RC70, RcLeak and AF40 remained significantly higher than those for the other cases whose S values reduced to zero. Meanwhile, due to the large IR fluctuations in this case, the predominant monotonic rise was replaced with non-monotonic evolution in most of the cases. The impact of this is explained further in Section 4.2.2.

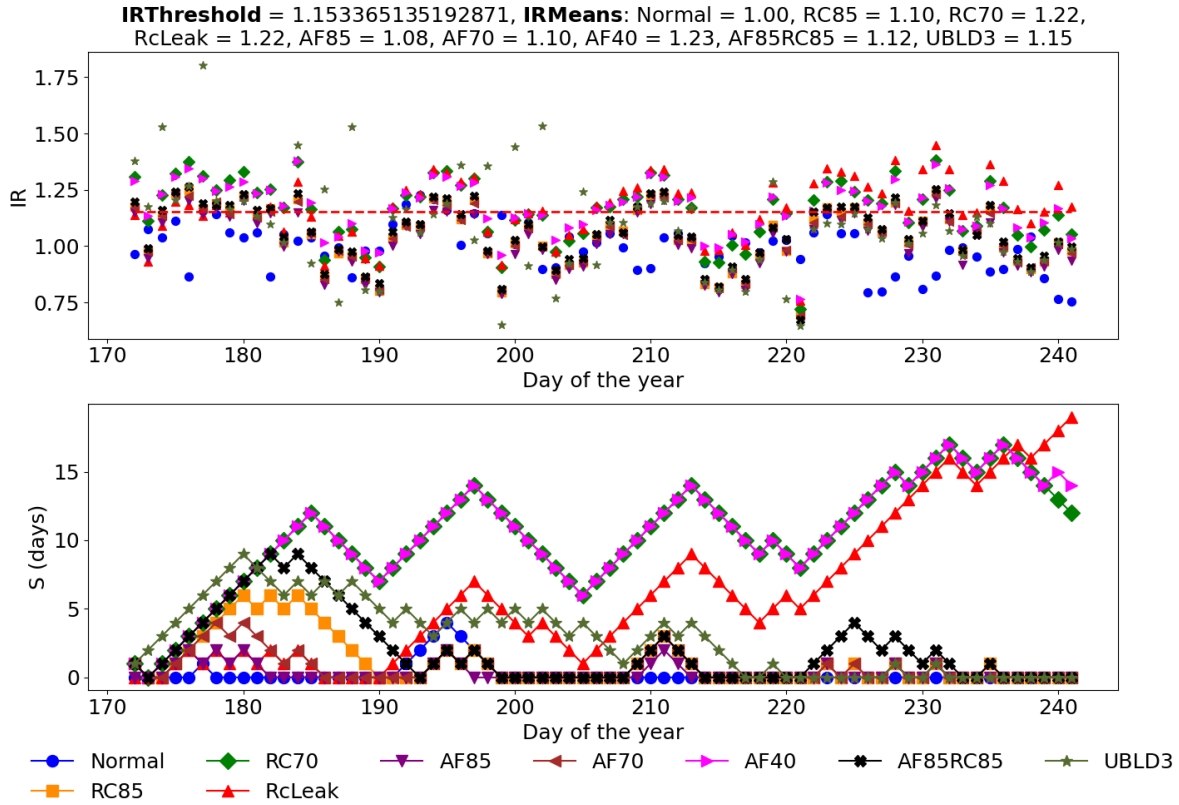


Figure 4.5: IR (due to faults) for Real Scenario with a threshold of 1.15 using Duty Factor

4.2.2 Fault Probabilities (FPs)

Equations (2.28) and (2.29) are used to compute the FPs for all cases without and with CUSUM, respectively. Though these equations are the same equations used for the FPRs, as noted earlier, FPRs are referred to as FPs in cases where there is actually a fault which causes the FIRs.

4.2.2.1 Ideal Scenario

For the ideal scenario, Figure 4.6(a) and (b) shows results of the FPs at various IR thresholds without and with CUSUM, respectively.

Both subplots show that RC70, AF40, and RcLeak had FPs above 80% for all IR thresholds. For the other cases, both subplots show a decrease in FPs as the IR threshold increases. For IR

thresholds at 2% (1.02) or less, RC85, AF70, and AF85RC85 also had FPs greater than 80%. The FPs for the Normal case was zero for all IR thresholds, since ideal baseline data was used. Also, for the most part, the FPs for the different cases follow almost the same sequence in both subplots, which in decreasing order is RC70, AF40, RcLeak, AF85RC85, RC85, AF70, UBLD3, AF85, and Normal. RC70 and AF40 had the same FPs for all IR thresholds. But at the maximum threshold, AF40 slightly drops below RC70, hence it comes in second place. Overall, the order reveals that the daily duty factor feature is more sensitive to RC faults than to low indoor airflow. For instance, it takes a low airflow at 60% severity to match a 30% undercharge fault. Also, a 15% low charge fault has a bigger FP than a 30% low indoor airflow fault. In addition, the order reveals that 15% low indoor airflow faults cannot be reliably detected because in both subplots, the UBLD3 FPs were above the AF85 FPs for the most part.

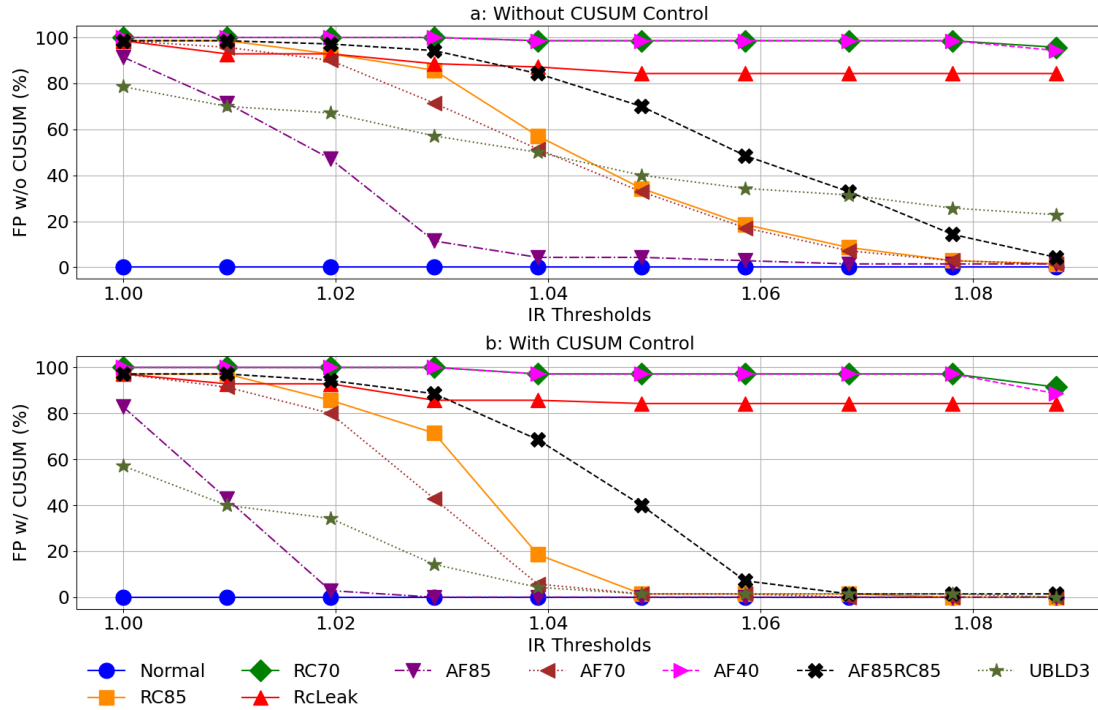


Figure 4.6: FPs vs IR threshold for the Ideal Scenario using Duty Factor (a) Without CUSUM Control, and (b) With CUSUM Control.

Comparatively, the first subplot in Figure 4.6 shows higher FPs for all cases and at all IR thresholds than the second subplot. For RC70, AF40, and RcLeak, the difference between FPs in the top and second subplot is small. For other cases, the difference is significant. For instance, at a 1% threshold (i.e., 1.01), the FP for AF85 is about 70% in the first subplot and 40% in the second subplot. FP for AF85 drops to approximately zero at the 2% threshold in the second subplot while for the first subplot, it is non-zero up to about 4% threshold. For RC85, at IR threshold of 4%, the FP is between 50% and 60% in the first subplot, while in the second subplot the FP is less than 20%. For AF85RC85, the FP is approximately 50% at a 6% threshold in the first subplot but is approximately zero in the second subplot. These observations suggest that the CUSUM reduces the prospect of detecting faults. While this is true, the use of the CUSUM control strategy is

justified by comparing the FPs from faults with the FPs from UBLD3. This justification is further demonstrated by converting the FPs into signal-to-noise ratios, which is discussed in Section 0. Also, the second subplot shows a faster reduction than the first subplot for most of the cases.

4.2.2.2 Real Scenario

For the real scenario, Figure 4.7(a) and (b) shows results of the FPs at various IR thresholds without and with CUSUM, respectively.

Compared to the ideal scenario depicted in Figure 4.6, smaller FPs are observed for this case because a realistic baseline estimate is used in this case. For instance, the ideal scenario shows FPs of 95 – 100% for RC70 and AF40 for all IR thresholds. But for the real scenario, the maximum FP was about 90% without CUSUM and without threshold. With CUSUM and no threshold, the maximum FP is about 85%. Also, the ideal scenario shows that RC70 had equal or slightly higher FPs than AF40 and significantly higher FP than RcLeak. But the real scenario shows a reversed order with AF40 having larger FPs than RC70 and RcLeak. Notwithstanding, this reversed order does not change the conclusion that duty factor is more sensitive to the RC faults than to low airflow considering that the severity of the low indoor airflow is twice the severity of the RC faults.

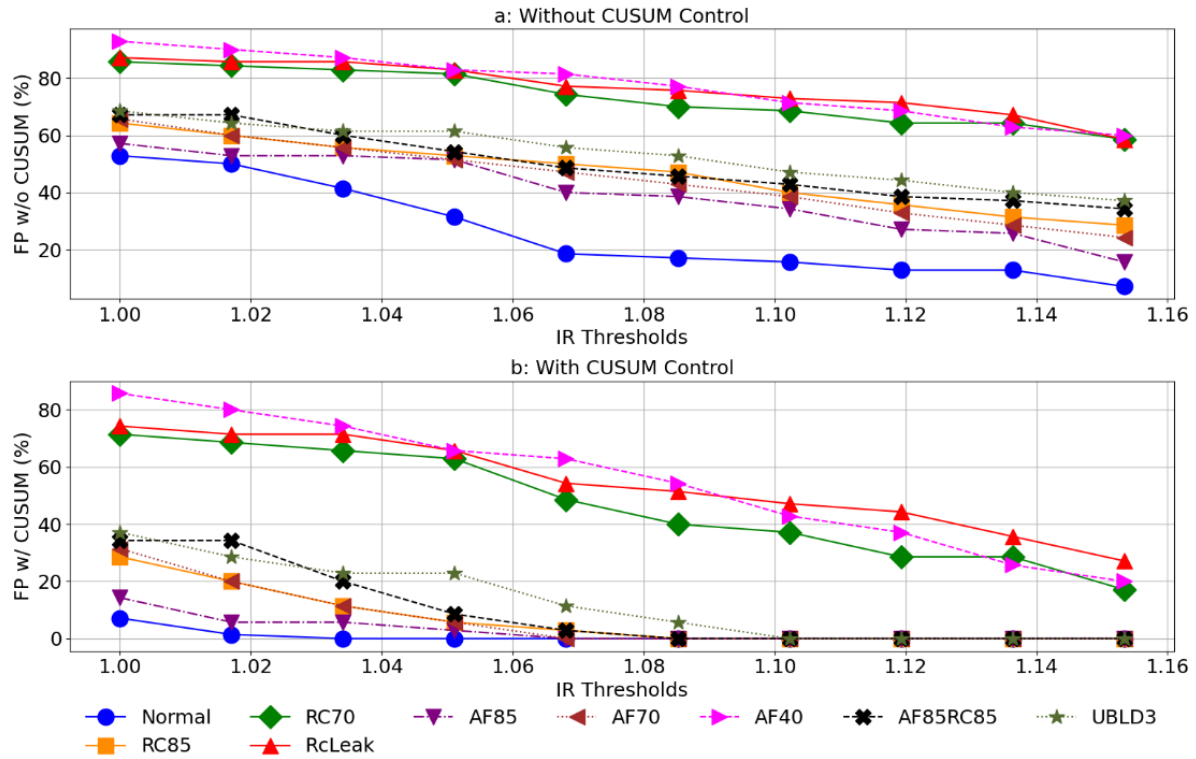


Figure 4.7: FPs vs IR threshold for the Real Scenario using Duty Factor (a) Without CUSUM Control, and (b) With CUSUM Control.

Both subplots in Figure 4.7 show a monotonic decrease in FP for all cases with increasing IR threshold. Also, as with other evaluation metrics, both subplots show non-zero FPs for the Normal case due to the regression uncertainties. However, the FPs for the Normal case was the least in all cases and for all IR thresholds as expected. Additionally, both subplots show a slightly different sequence from the sequence in the ideal scenario. The real scenario shows a sequence, in decreasing order, of FPs to be AF40, RcLeak, RC70, UBLD3, AF85RC85, RC85, AF70, and AF85 (for most of the IR thresholds). Furthermore, both subplots show that the UBLD3 FPs are larger than the FPs for all cases except AF40, RC70 and RcLeak. This suggests that only these three faults can be reliably detected using the duty factor FDD feature.

The certainty with which the three most severe faults can be detected is increased by the introduction of the CUSUM control algorithm as depicted in Figure 4.7(b). As seen from the figure, the CUSUM control brings a clearer distinction between the three faults and all other cases. For instance, with the CUSUM algorithm and at 0% threshold, the UBLD3 FP is reduced below 40% from the 70% FP observed in the first subplot. The significance of this is discussed further in Section 0. Also, the FP values for the different cases (except AF40, RC70 and RcLeak) at 0% IR threshold is about the same FP values for the same cases at the maximum IR threshold. This further demonstrates that the CUSUM strategy is more effective than thresholds.

4.2.3 False Negative Rate (FNR)

As noted earlier, the false negative rate (FNR) measures the extent to which a fault might be undetected. So, a high FNR implies that the associated fault has a high tendency of not being detected and vice versa. The FNRs without and with CUSUM are computed from Equations (2.30) and (2.31), respectively.

4.2.3.1 Ideal Scenario

For the ideal scenario, Figure 4.8 shows the FNRs without and with CUSUM for the simulated fault cases. Expectedly, the FNRs for each case in both subplots is an inversion of the corresponding FPs in Figure 4.6. Meaning the higher the FP, the lower the FNR and vice versa. Also, the sequence (in decreasing order) in Figure 4.6 was reversed in Figure 4.8. Additionally, the inversion is also in terms of the CUSUM impact as for this case, the CUSUM slightly increased the FNRs; while in Figure 4.6, CUSUM slightly increased the FPs. Furthermore, the monotonic decrease in Figure 4.6 was reversed in Figure 4.8.

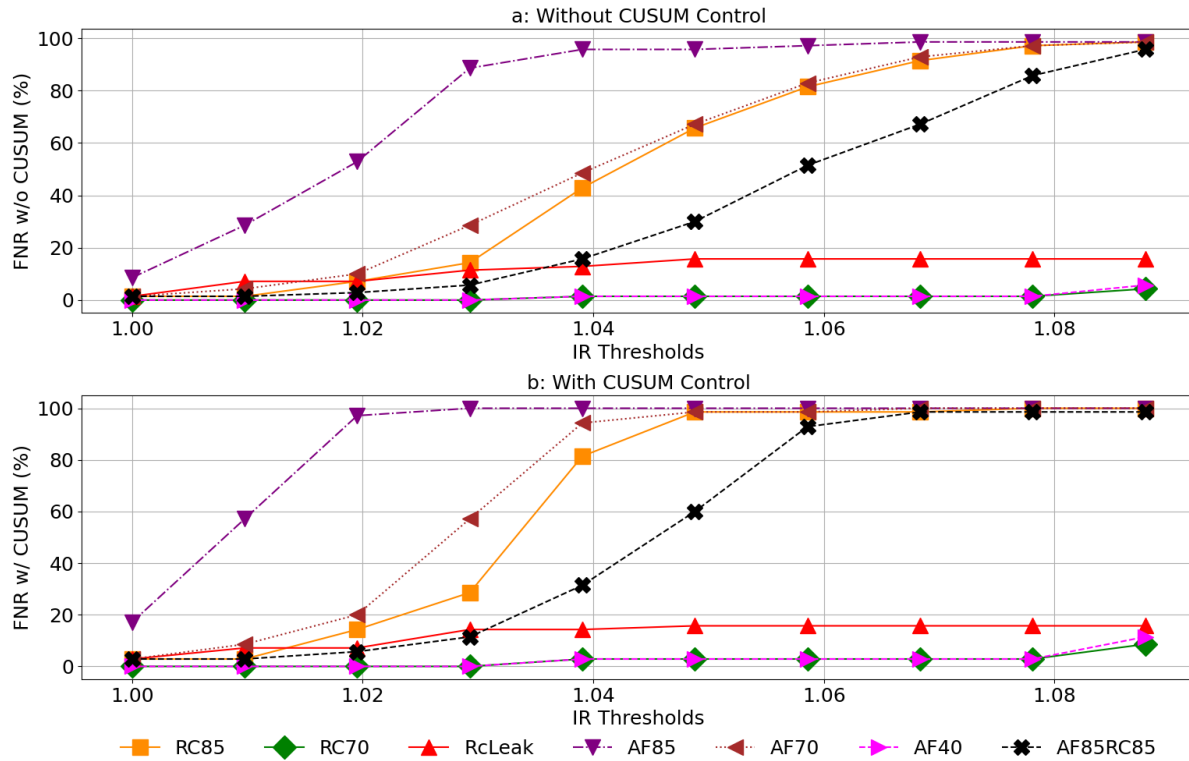


Figure 4.8: FNRs vs IR threshold for the Ideal Scenario using Duty Factor (a) Without CUSUM Control, and (b) With CUSUM Control.

In both subplots, the FNR for RC70, RcLeak and AF40 are below 20% for all IR thresholds with RC70 and AF40 having FNR of almost 0% for the most part. The FNR for RcLeak rises from 0% to about 18% beyond the 1.02 IR threshold. AF85 had the largest FNRs reaching 95 - 100% for higher IR thresholds (beyond 1.04 in the first subplot and beyond 1.02 in the second subplot). In the second subplot, RC85, AF70 and AF85RC85 also reach 90 – 100% FNR at IR threshold of 1.06 and above.

4.2.3.2 Real Scenario

The real scenario presented in Figure 4.9 shows similar observation made for the ideal scenario in terms of the inverted trends discussed in Section 4.2.3.1. Also, it shows a similar sequence with the ideal scenario in terms of decreasing order of FNRs.

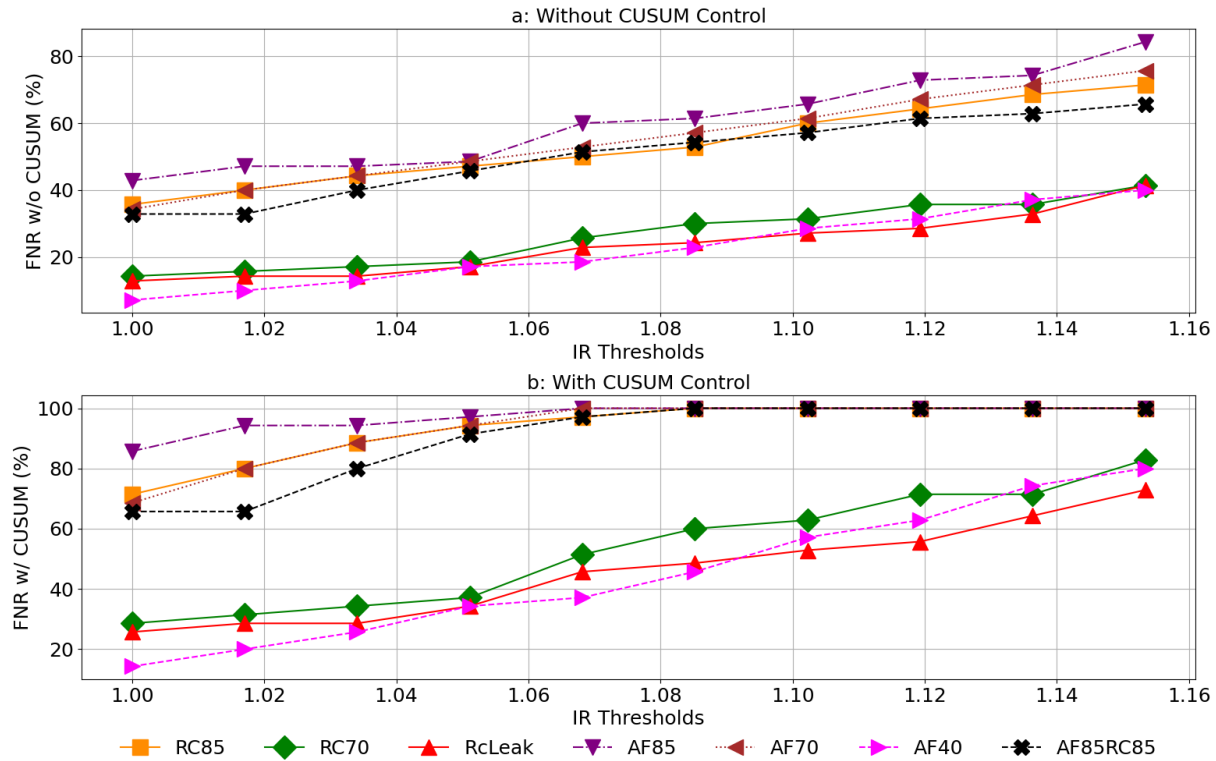


Figure 4.9: FNRs vs IR threshold for the Real Scenario using Duty Factor (a) Without CUSUM Control, and (b) With CUSUM Control.

However, unlike the ideal scenario without CUSUM, the real scenario without CUSUM shows lesser FNRs for AF85, AF70, RC85, and AF85RC85. The FNRs for RC70, RcLeak and AF40 in the real scenario without CUSUM were however higher than the FNRs for same cases under ideal scenario without CUSUM. With CUSUM control, the FNRs became higher for all cases, resulting in FNRs reaching 100% for AF85, AF70, RC85, and AF85RC85 beyond IR thresholds of 1.08. Without CUSUM control, the maximum FNR for AF85, AF70, RC85, and AF85RC85 ranged from about 65% to 82% at a 1.15 IR threshold.

4.2.4 Signal-to-Noise Ratio (SNR)

From the results and discussions so far, it is difficult to ascertain what optimal thresholds should be used in assessing the performance of FDD methods over the two prevalent faults considered in

this research and their different severities. The SNR introduced in Section 2.5.1.4.4 helps to give better insight and is discussed in this section.

The SNRs for all cases, without and with CUSUM, are generated from Equation (2.33) where the signals are the respective FIRs, and the noise is the DIR from UBLD3.

4.2.4.1 Ideal Scenario

For the ideal scenario, Figure 4.10(a) and (b) shows the SNRs without and with CUSUM, respectively. Both subplots show that the SNRs of RC70, RcLeak and AF40 were significantly higher than the SNRs for all other cases. Also, UBLD3 had an SNR of 1 for both subplots because UBLD3 FP is both the signal and the noise for this case. The SNR for the Normal case is zero at all thresholds.

In the first subplot, RC70, RcLeak and AF40 shows a monotonic increase in SNR as the threshold increased. Other cases show a non-monotonic trend which ended at SNRs close to zero. In Section 2.5.1.4.4, the following classification was made:

- $\text{SNR} < 4$ is low and poses difficulty in distinguishing signal from noise;
- $\text{SNR} \leq 10$ is moderate and suggests that signal is detectable but with uncertainty;
- $\text{SNR} > 10$ is high and means signal can be reliably detected.

Based on the above classification, the SNRs for all the cases in Figure 4.10(a) are low. Only at IR thresholds of approximately 1.09 does the SNR for RC70 and AF40 become moderate. The implication of this is that without the CUSUM control, none of the simulated faults and fault severities can be reliably detected even with the use of IR thresholds.

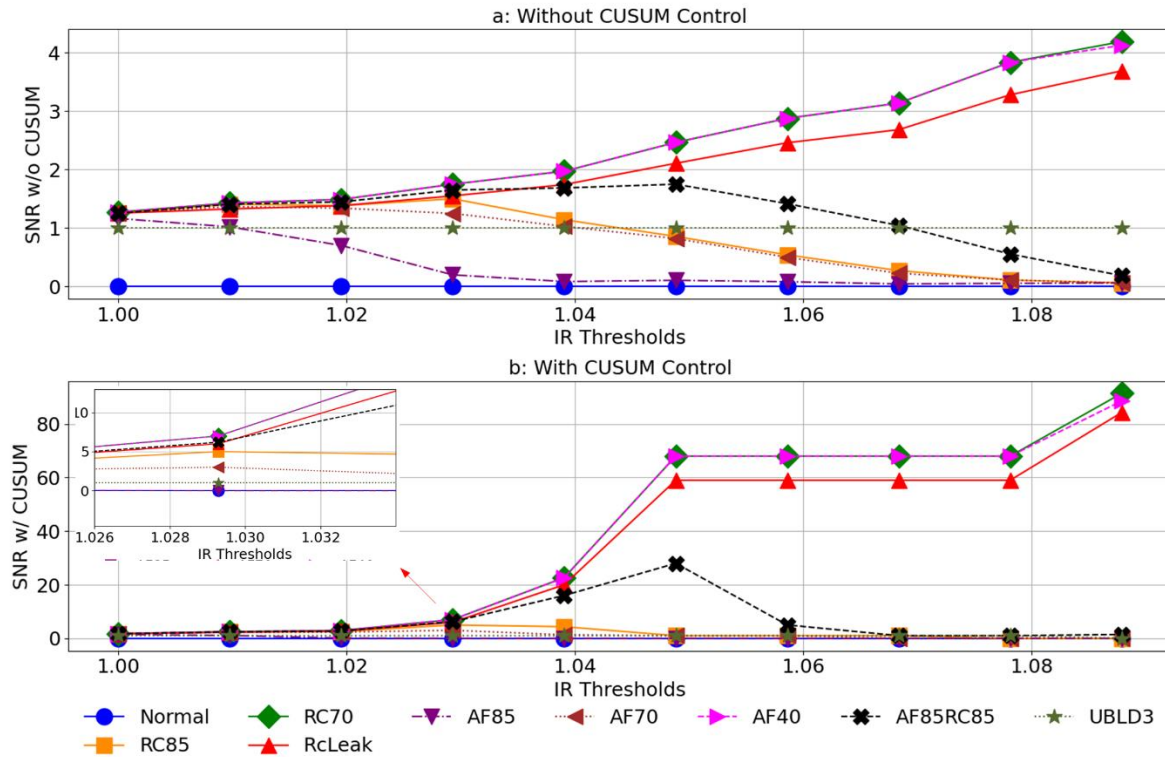


Figure 4.10: SNRs vs IR threshold for the Ideal Scenario using Duty Factor (a) Without CUSUM Control, and (b) With CUSUM Control.

In the second subplot, RC70, RcLeak and AF40 also shows a monotonic increase in SNR as the threshold increased, while other cases show a non-monotonic trend which also ended at SNRs close to zero. Based on the SNR classification, RC70, RcLeak, AF40, and AF85RC85, each have high SNRs at IR thresholds of 1.04 and above. RC85 had low SNRs for the most part. But the zoomed-in-view of the lower threshold region shown on the top left corner of the second subplot reveals that at thresholds of 1.03 (3%) and 1.04 (4%), the SNR is moderate for RC85 as well as RC70, RcLeak, AF40, and AF85RC85. All other cases had low SNRs at all IR thresholds. The implication of these results is that apart from RC70, RcLeak, AF40, and AF85RC85, the other simulated faults may not be detected using duty factor. RC70, RcLeak, AF40, and AF85RC85, on the other hand can be reliably detected at thresholds as low as 4%.

By combining the FNR results in Figure 4.8 with the SNR results in Figure 4.10, more informed conclusions can be reached. For instance, at the 3% threshold where moderate SNR was obtained for RC85, the FNR is less than 30%. This suggests that RC85 may be detected at a threshold of 3%, but with less certainty. However, at 4% threshold where the SNR is also moderate, the FNR is over 80% which suggests that RC85 cannot be detected at this threshold. This suggests that an optimum threshold for detecting RC85 is 3%. Also, though the results in Figure 4.10(b) suggest that higher SNRs can be obtained by increasing the IR threshold, this simultaneously increases FNR which is undesirable. For instance, at 4% threshold, the FNR for AF85RC85 is slightly above 30%. But at 5% threshold where the SNR is almost 30, the FNR is 60% which is high. Beyond this threshold, the SNR for AF85RC85 drops while the FNR increases significantly. For RC70 and AF40, at 3% threshold where their respective SNR is moderate, their respective FNRs is 0 which means both faults can be reliably detected at this threshold. For RcLeak and AF85RC85 which also have moderate SNRs at the 3% threshold, the respective FNRs are approximately 15% which is relatively low. This means that both faults can also be reliably detected at a threshold as low as 3%, though with less certainty compared to RC70 and AF40. Furthermore, though the FNR for RC70, RcLeak and AF40 remains fairly constant beyond the 3% threshold, increasing the threshold offers little or no benefit. For instance, as noted earlier, beyond 5% the SNR for AF85RC85 drops. For RC70, RcLeak and AF40, the SNR remains constant until a threshold of almost 8%, before increasing further. Therefore, to reach a compromise between reliability, early detection, and detection of less severe faults, the foregoing suggests an optimum threshold of 3%, which together with the CUSUM control can lead to a reliable detection of RC85, AF85RC85, RcLeak, AF40 and RC70.

4.2.4.2 Real Scenario

For the real scenario, Figure 4.11(a) and (b) shows the SNRs without and with CUSUM, respectively. Both subplots show that the SNRs for all cases reduced from their corresponding values under the ideal scenario. Also, both subplots show non-monotonic trends for almost all cases. Also, UBLD3 had an SNR of 1 for both subplots as observed in the ideal scenario.

In the first subplot, the SNR for RC70, RcLeak and AF40 were consistently greater than 1 and increased slowly but non-monotonically. While for all other cases, the SNR was less than 1 for the most part and decreased non-monotonically. An SNR less than 1 implies that the noise (UBLD3) is more dominant than the signal (faults) and suggests that these faults cannot be detected without CUSUM control. As was observed under the real scenario for other evaluation metrics, the SNR for the Normal case was non-zero, but was also the smallest with the quickest decline as the threshold increased. Based on the SNR classification in Section 2.5.1.4.4, the real scenario shows that the SNR for all the cases considered is low. The implication of this is that without the CUSUM control, none of the simulated faults and fault severities can be reliably detected even with the use of IR thresholds.

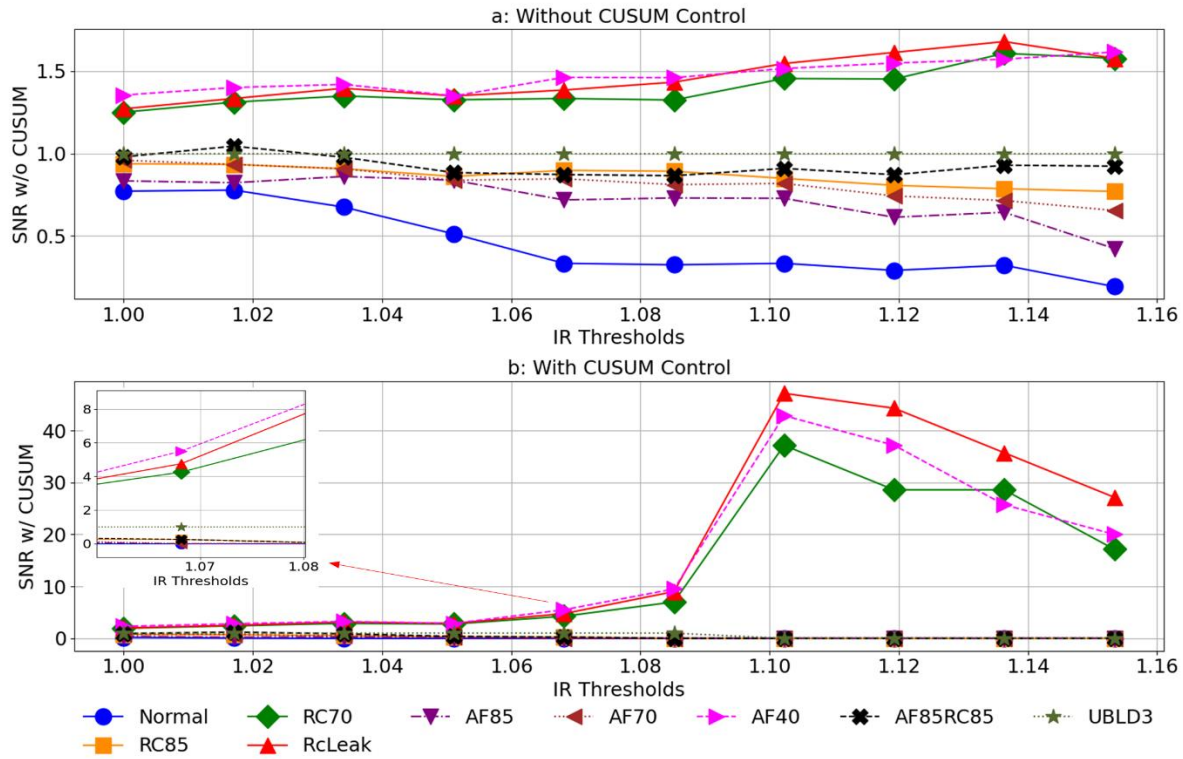


Figure 4.11: SNRs vs IR threshold for the Real Scenario using Duty Factor (a) Without CUSUM Control, and (b) With CUSUM Control.

The second subplot shows that even with the introduction of CUSUM Control, the SNR for all the cases remains low at all IR thresholds, except for RC70, RcLeak and AF40. For these three faults, the SNR first increases slowly and monotonically to an SNR of almost 10 at a threshold of about 8.5%. Beyond this threshold, the SNRs increased rapidly but still monotonically, to higher values at 10% threshold, and monotonically decreased afterwards. Thus, the 10% threshold appears to be an optimum value for these three faults. However, by considering Figure 4.9(b) alongside, the FNR for RC70, RcLeak and AF40 ranges from 50% to slightly above 60% which is high. This suggests that though high SNRs are obtained at this threshold, these faults may not be readily or quickly detected at this threshold considering the high FNRs at this threshold. At a 7% threshold where moderate SNRs are obtained for these three faults (as shown in the zoomed-in-view on the top left corner of the second subplot), the FNRs are relatively lower with values between 30% and 50%.

This suggests that at a threshold of 7%, RC70, RcLeak and AF40 may be detected but with some level of uncertainty. AF40 had an FNR below 40%, while the FNR for RcLeak was below 50%, and the FNR for RC70 was approximately 50%. These further suggests more certainty in detecting AF40 than RC70 with RcLeak in between. However, since the fault type and severities are same for both the 7% and 10% IR thresholds, the 10% threshold is considered a better choice as it gives a high SNR.

4.2.5 Summary of Results for Duty Factor

In this section, the performance of Smart thermostat-based fault detection methods using duty factor as the detection feature was investigated. Two prevalent faults at different severities were used to develop a total of eight case studies, including a baseline and the most impactful UBLD case from Chapter 3. The validated co-simulation testbed from Chapter 3 was also used for this investigation to simulate the eight cases considered and generate data which was used to conduct impact analysis under ideal scenario and real scenario. From these, the key takeaways are:

1. The ideal scenario suggests better performance of FDD methods that use duty factor as feature, than the real scenario. This is understandable because ideal baseline data was used in the ideal scenario.
2. The CUSUM control strategy is more effective than the use of threshold, in improving the reliability of FDD methods that use duty factor, especially in the presence of UBLDs.
3. The investigation reveals that only severe faults like a 30% undercharge (RC70), refrigerant leak reaching 40% severity (RcLeak), and 60% low indoor airflow (AF40), can be detected with FDD methods that use duty factor.
4. To balance reliability with effectiveness, optimal thresholds are required. To obtain such optimal thresholds, the FP, FNR, and SNR evaluation metrics need to be combined. For

the ideal scenario, an IR threshold of 3% was found to be optimum. For the real scenario, the optimum IR threshold is 10%, which gives a high SNR. Though the FNR is also significantly high.

5. Under an ideal scenario where a 100% baseline prediction is possible, a 3% IR threshold is required. With this threshold, moderate SNRs can be achieved for RC85, RC70, AF40, RcLeak and AF85RC85 with FNRs below 30%, 0%, 0%, 15% and 15% respectively. These results look promising. But under the real scenario and at the 10% threshold, only RC70, RcLeak and AF40 have moderate SNRs with FNRs of approximately 60%, 50% and 55% respectively, which is not very impressive.

Overall, the investigation reported in this section shows that FP, FNR and SNR are important metrics which should be combined with the FPR metric investigated in Chapter 3, to evaluate the performance of Smart thermostat-based FDD methods that use duty factor. The investigation also shows that the duty factor feature performs poorly in detecting prevalent faults such as low charge and low indoor airflow fault. The next section reports the findings of similar investigations done in this section but with the enthalpy change, Δi , feature.

4.3 Results and Discussion for Enthalpy Change

Results for IR, FP and FNR for the same case studies using enthalpy change, Δi , as the FDD feature is presented in this section. FPR and SNR were not considered because they are both functions of UBLDs and as noted in Section 2.1.2.3, Δi is unaffected by UBLDs. Ideal scenario and real scenario were also considered.

For the IR thresholds, an arbitrary range was chosen and used. Also, only plots for the ‘no threshold’ case and the maximum threshold were presented for the sake of brevity. Plots for other thresholds can be found in Appendix C.

For the comparison of the evaluation metrics for the different cases, this was done based on T_{oa} rather than days. Days could not be used for the comparison in this case because unlike duty factor, which is time-based, the enthalpy change variable is a state-variable.

For the real scenario, the quadratic regression (Equation (2.26)) introduced in Section 2.5.1.4 was used. The co-simulation data from June 21 – August 31, 2023, was used for training the regression model and obtaining the model parameters. The trained model was then used to predict Δi . A comparison between the predicted Δi and the actual Δi is shown in Figure 4.12.

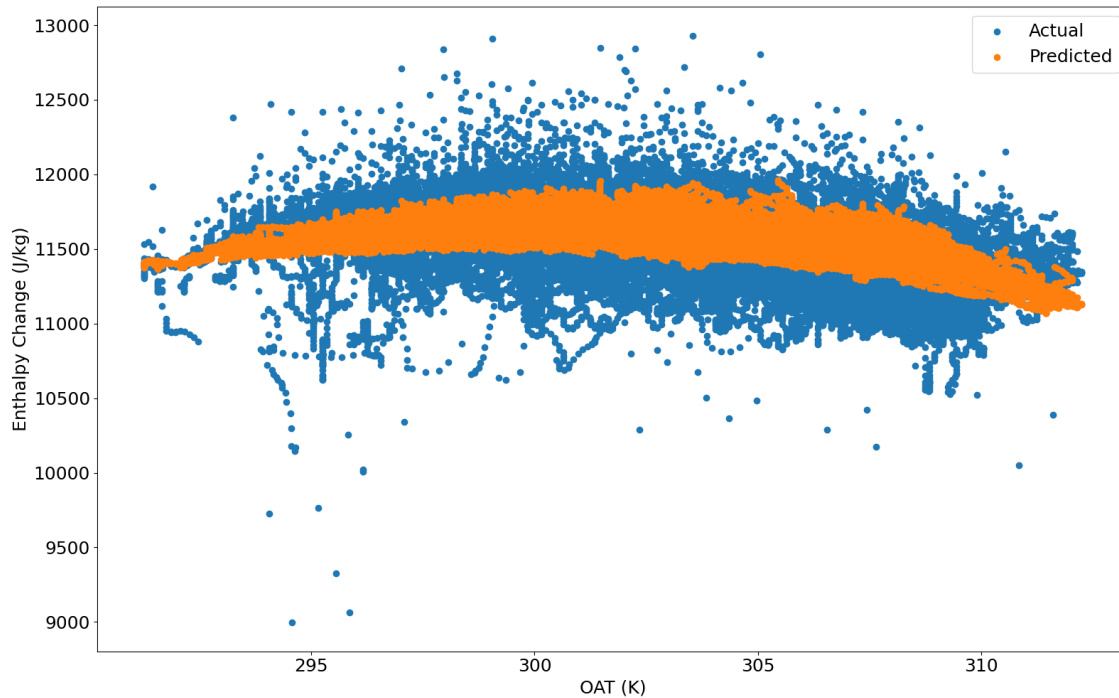


Figure 4.12: Regression for Δi Estimation for the Real Scenario

The comparison shows a good match between the predicted and the actual Δi , suggesting that the model has good accuracy and is thus suitable for this research.

4.3.1 Impact Ratio

4.3.1.1 Ideal Scenario

For the ideal scenario, Figure 4.13 shows the results at various T_{oa} , for the different cases using Δi as the FDD feature, and without threshold. The first subplot shows the IR for each case. The second and third subplot shows the S evolution for low indoor airflow and refrigerant charge faults, respectively.

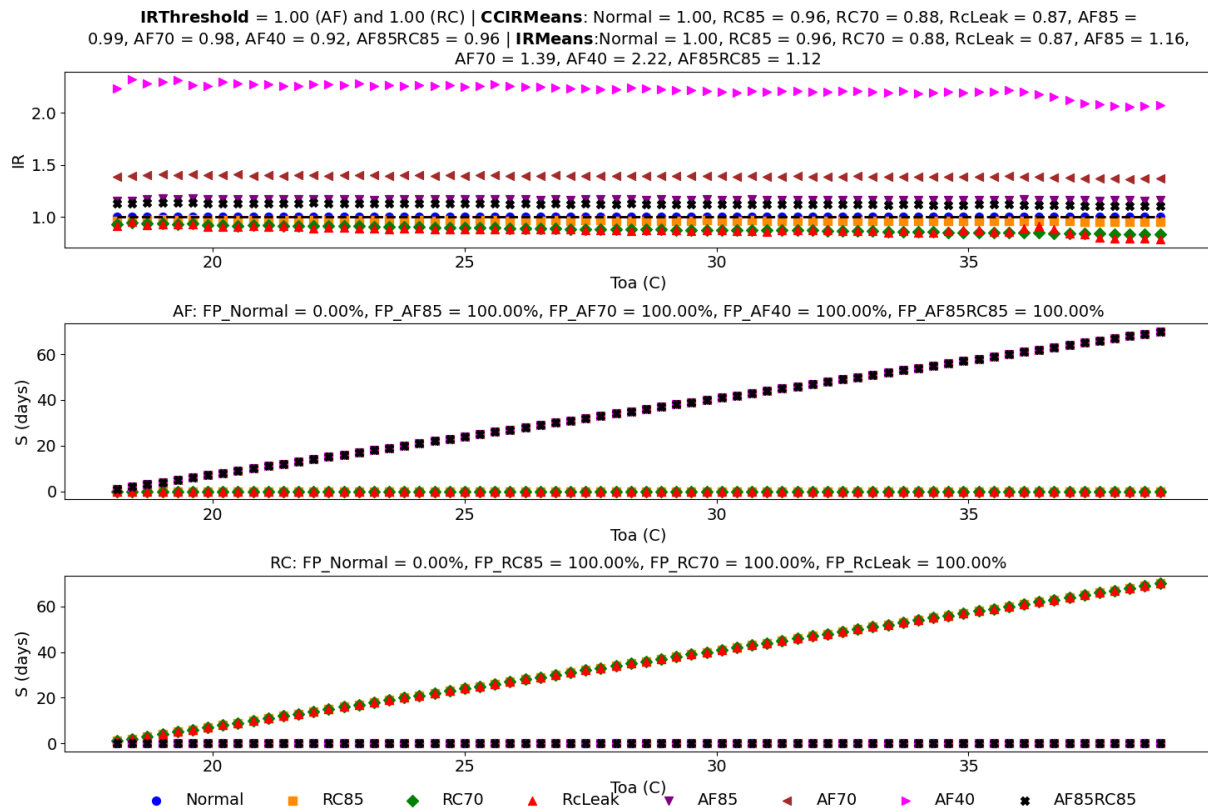


Figure 4.13: IR (due to faults) using Δi , with a 0% threshold and under Ideal Scenario

The first subplot in Figure 4.13 shows that Δi is largely independent of T_{oa} considering that the IRs are fairly constant for the entire T_{oa} range. Also, the IRs for all low indoor airflow cases were greater than 1.0 while for all the low charge related cases, the IRs were lesser than 1.0. This characteristic of Δi makes it possible to diagnose low indoor airflow from low charge faults. Also, in the first subplot, the mean IR and the mean cooling capacity impact ratio were computed and displayed above the subplot as IRMeans and CCIRMeans, respectively. The CCIRMeans were added to demonstrate the superiority of Δi over cooling capacity as an FDD feature (Section 2.1.2). For instance, CCIRMeans was less than 1.0 for all cases (except the Normal case because ideal baseline data was used), making it difficult to tell whether it is low indoor airflow or a low charge fault. Conversely, IRMeans had values less than 1.0 and greater than 1.0 for low indoor airflow and low charge faults, respectively. Also, the results show that CCIRMeans and IRMeans were the same for RC faults. This is because since the airflow rate ($\dot{m}_{sa}$) in Equation (2.1) remains constant for an RC fault, the cooling capacity changes by the same proportion as Δi . For the low airflow faults, while a 1%, 2% and 8% decrease in the average cooling capacity were observed for AF85, AF70 and AF40, respectively, a 16%, 39% and 122% increase in Δi were observed for the same faults. For AF85RC85, while a 4% decrease in the average cooling capacity was observed, a 12% increase in Δi was observed. This shows that Δi is more sensitive than cooling capacity. Furthermore, the 16% increase in Δi for AF85 was reduced to 12% in AF85RC85, showing a counteracting effect on Δi when both AF85 and RC85 are present in an AC system. However, the low indoor airflow had a more dominant impact and shows that Δi is more sensitive to airflow reduction than to refrigerant charge reduction.

The second subplot shows a steady increase in S due to the high sensitivity of Δi to low indoor airflow. Thus 100% fault probabilities were observed for all severities of low indoor airflow and

AF85RC85. A similar observation was made for the low charge faults in the third subplot, where all the low charge faults also had 100% fault probabilities. The Normal case had a 0% FP in both subplots because of the ideal baseline data used. However, these results are for a case with no threshold which is not recommended.

Figure 4.14 shows the results when a threshold of 40% is used. The 40% threshold translates to a ratio of 1.40 (depicted by the red dash line) for the low airflow faults and 0.60 (depicted by the black dash line) for the low charge faults. Based on this new threshold, the values of S for the low indoor airflow and the low charge faults were recomputed, and with that, new FPs were obtained for all the cases considered. With this threshold, only the extreme case of low indoor airflow fault was detectable, still with 100% accuracy. All the other faults were not detectable. However, this is likely because the 40% threshold is too high. Section 4.3.2 shows the FPs for other thresholds to give a more holistic assessment.

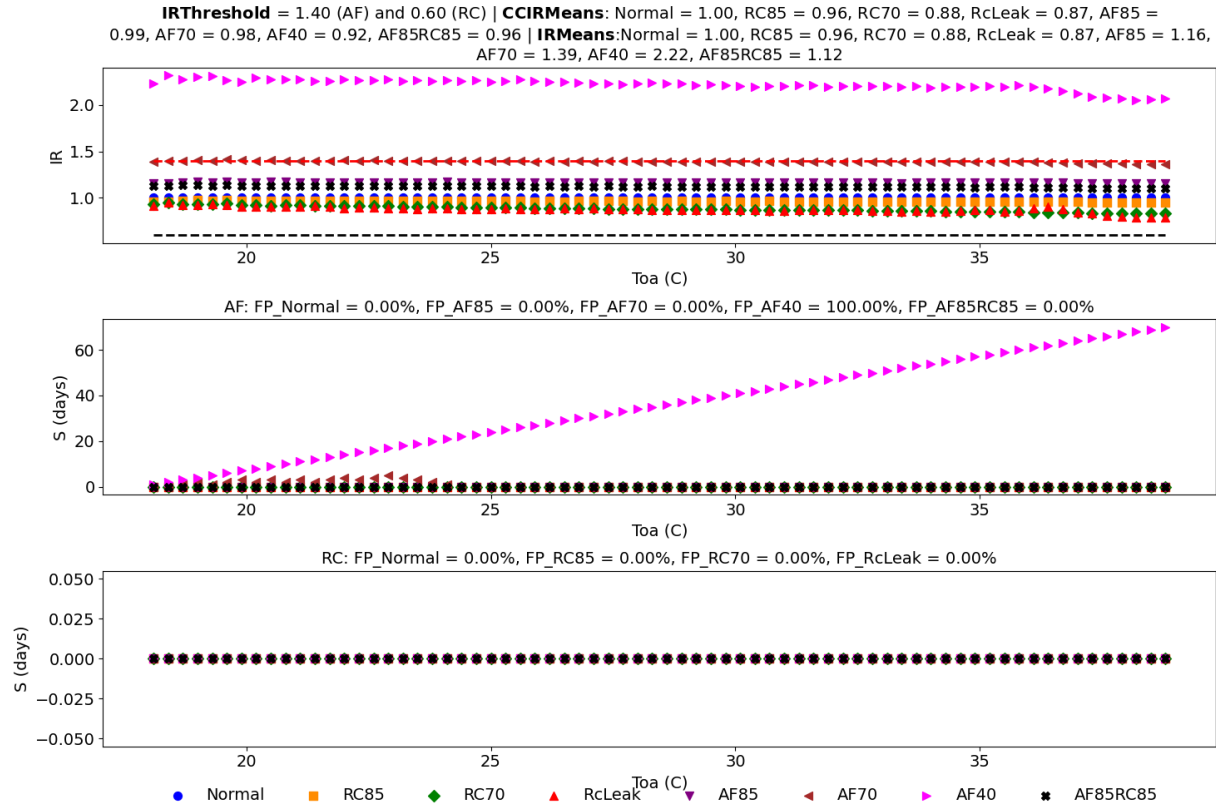


Figure 4.14: IR (due to faults) using Δi , with a 40% threshold and under Ideal Scenario

4.3.1.2 Real Scenario

For the real scenario, Figure 4.15 shows the results at various T_{oa} , for the different cases using Δi as the FDD feature, and without threshold. The first subplot shows the IR for each case. The second and third subplot shows the evolution of the CUSUM parameter S , for low indoor airflow and refrigerant charge faults, respectively.

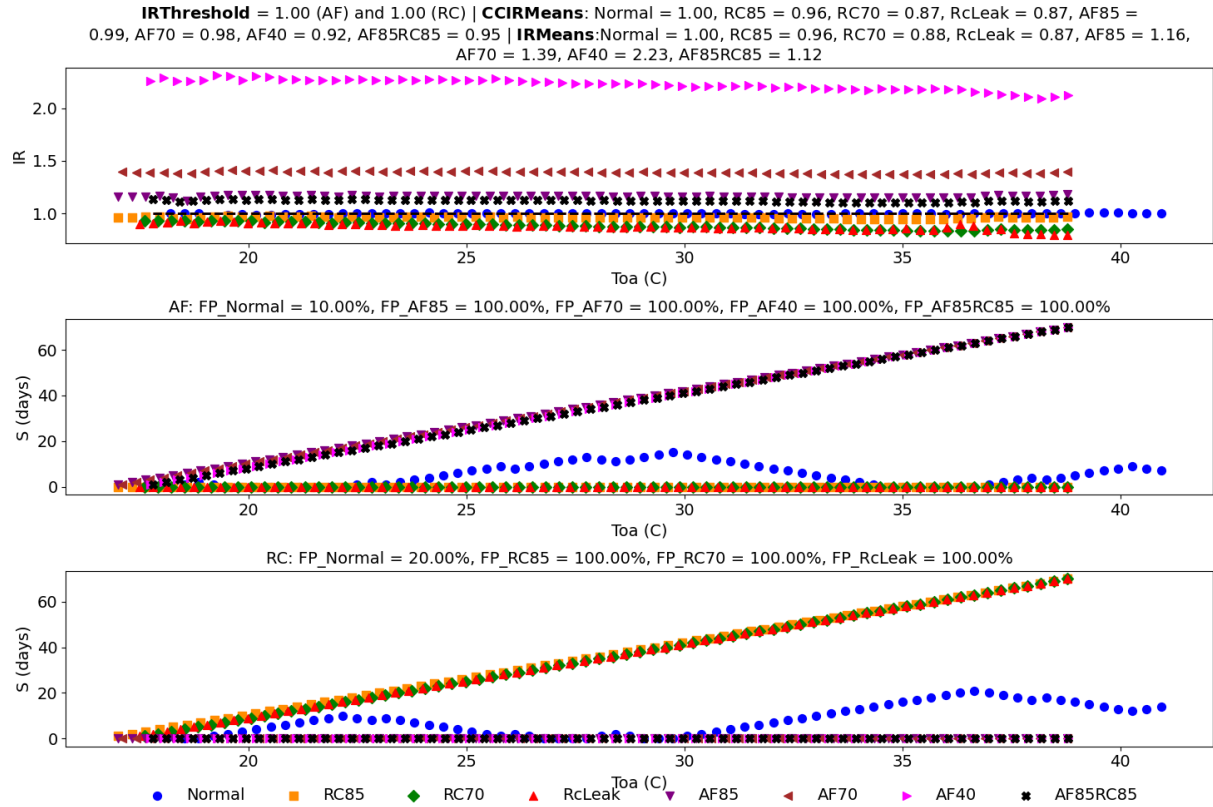


Figure 4.15: IR (due to faults) using Δi , with a 0% threshold and under Real Scenario

The first subplot in Figure 4.15 also shows that Δi is largely independent of T_{oa} as observed under the ideal scenario. Also, the CCIRMeans and IRMeans for this case are similar to those under the ideal scenario.

The second subplot shows similar trends in S to the trend observed under the ideal scenario, for the low indoor airflow cases. Except that, unlike the ideal scenario where there were no changes in S for the Normal case, a non-monotonic trend is observed here. This suggests that there were some changes in the IR for the Normal case due to the regression model. But these changes were minimal as seen from the means (CCIRMeans and IRMeans) which were 1.00 and the FP of 10.00% for the Normal case. The FPs for all the low airflow cases were the same as those under the ideal scenario, with 100% FPs for all cases.

The third subplot also shows similar trends in S to the trend observed under the ideal scenario, for the low charge cases. Similar to the second subplot, a non-monotonic trend is observed for the Normal case with an FP of 20.00%. FP_Normal in the second subplot shows that a cumulative 10% of the sampled data had IR greater than 1.00 while FP_Normal in the third subplot shows that a cumulative 20% of the sampled data had IR less than 1.00. The FPs for all the low charge cases were the same as those under the ideal scenario, with 100% FPs for all cases.

Figure 4.16 shows the results when a threshold of 40% is used. The results give similar observations to those under the ideal scenario, which is mainly that with this threshold, only the extreme case of low indoor airflow fault was detectable, still with 100% accuracy. All the other faults were not detectable.

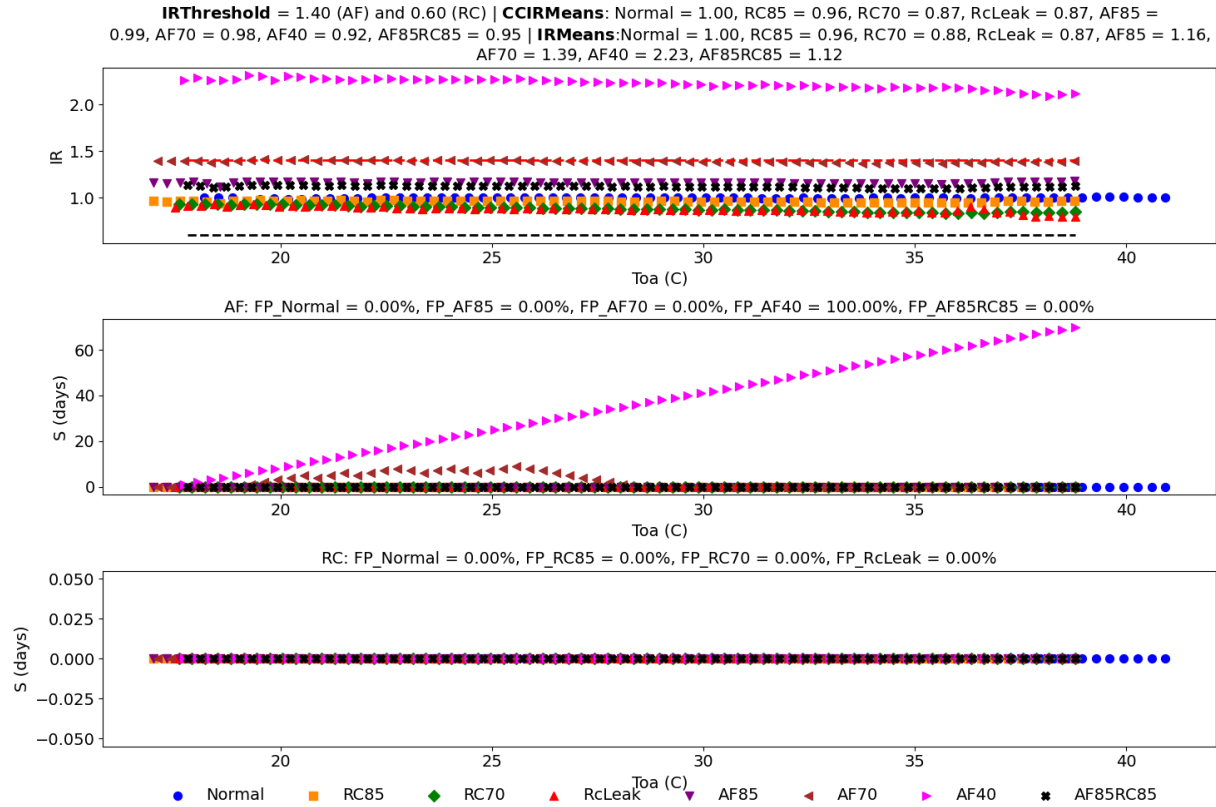


Figure 4.16: IR (due to faults) using Δi , with a 40% threshold and under Real Scenario

4.3.2 Fault Probabilities (FPs)

4.3.2.1 Ideal Scenario

Figure 4.17 shows the FPs for all cases without and with CUSUM, respectively. Both subplots look very similar with just a few slight variations, because of the negligible fluctuations in the IRs as discussed in Section 4.3.1.

The results show that the worse low airflow faults, AF70 and AF40, had 100% FPs for all thresholds up to 35%. Beyond 35%, only AF40 maintained a 100% FP. While at the 40% threshold, the FP for AF70 dropped below 20% without CUSUM, and to 0% with CUSUM. The FP for AF85

dropped from 100% to 0% at the 18% threshold. Without CUSUM, the FP for AF85RC85 also dropped to 0% at the 18% threshold but with CUSUM, it dropped to 0% at the 13% threshold.

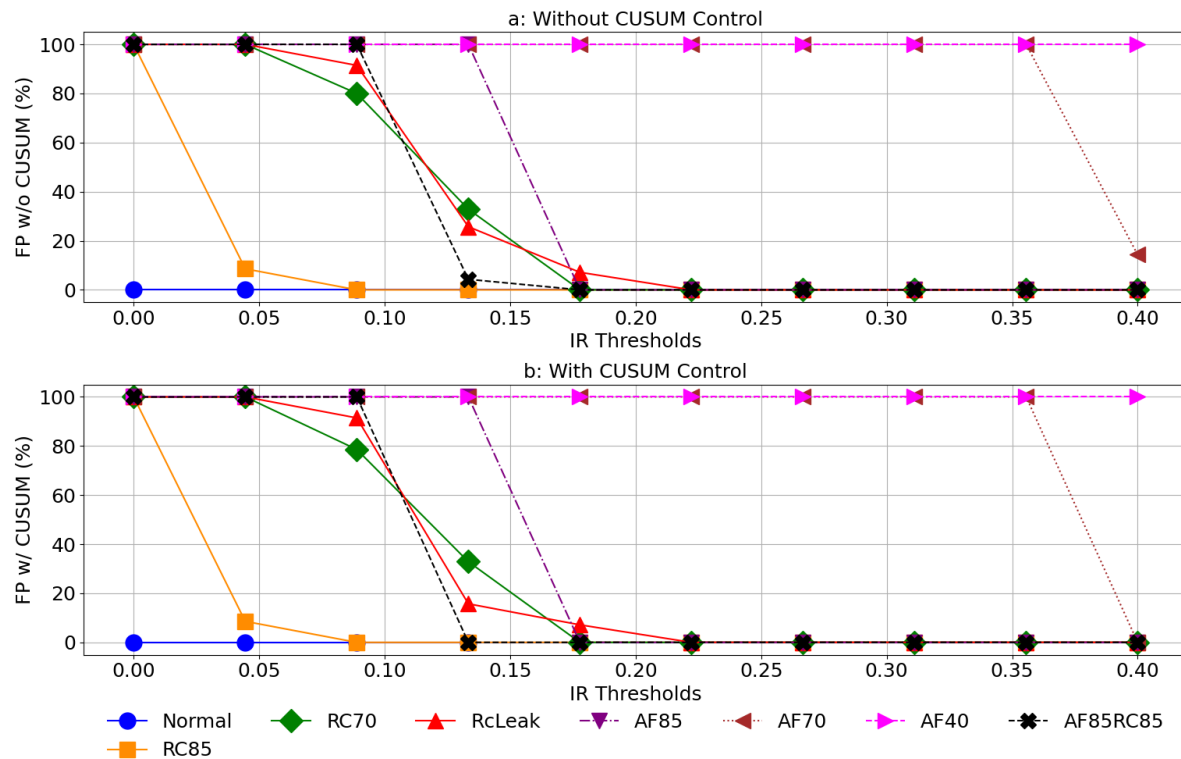


Figure 4.17: FPs vs IR threshold for the Ideal Scenario using Δi (a) Without CUSUM Control, and (b) With CUSUM Control.

RC85 showed the least detectability, with about 10% FP at a 4% threshold which dropped to 0% at approximately 9% threshold. The FP for RC70 dropped from 100% at the 4% threshold to 80% at the 9% threshold, and then to about 30% at the 13% threshold before reaching 0% at the 18% threshold. RcLeak had almost the same result as RC70, with the FP dropping from 100% at the 4% threshold to 90% at the 9% threshold. At the 13% threshold, without CUSUM, the FP for RcLeak was slightly above 20% but slightly below 20% with CUSUM. The FP then drops to approximately 10% at the 18% threshold, and to 0% at the 22% threshold.

4.3.2.2 Real Scenario

Figure 4.18 shows the FPs for all cases without and with CUSUM, respectively. The results look very similar to those for the ideal scenario with slight variations.

For the ideal scenario, 0% FPs was observed for the Normal case, with and without CUSUM. But for the real scenario, about 60% FP is observed for the Normal case without threshold and without CUSUM. With the use of CUSUM control or a threshold of approximately 5%, the FP is reduced to 20% or 0%, respectively. This highlights the need for CUSUM control and/or threshold even when the FDD feature is unaffected by UBLDs. Because without the CUSUM and threshold, such 60% FP could result in a false fault alarm which is undesirable.

Like the ideal scenario, the real scenario shows that the worse low airflow faults, AF70 and AF40, had 100% FPs for all thresholds up to 35%. Beyond 35%, only AF40 maintained a 100% FP. While the FP for AF70 dropped to 20% at the 40% threshold without CUSUM, and to 0% with CUSUM. The FP for AF85 dropped from 100% to 0% at the 18% threshold. Without CUSUM, the FP for AF85RC85 also dropped to 0% at the 18% threshold but with CUSUM, it dropped to 0% at the 13% threshold.

RC85 showed the least detectability, with about 10% and 20% FP (without and with CUSUM, respectively) at a 5% threshold which dropped to 0% at approximately 9% threshold. The FP for RC70 dropped from 100% at the 4% threshold to 80% at the 9% threshold, and then to about 30% at the 13% threshold before reaching 0% at the 18% threshold. RcLeak had almost the same result as RC70, with the FP dropping from 100% at the 4% threshold to 90% at the 9% threshold. At the 13% threshold, without CUSUM, the FP for RcLeak was approximately 40%, and 30% with CUSUM. The FP then drops to approximately 10% at the 18% threshold, and to 0% at the 22% threshold.

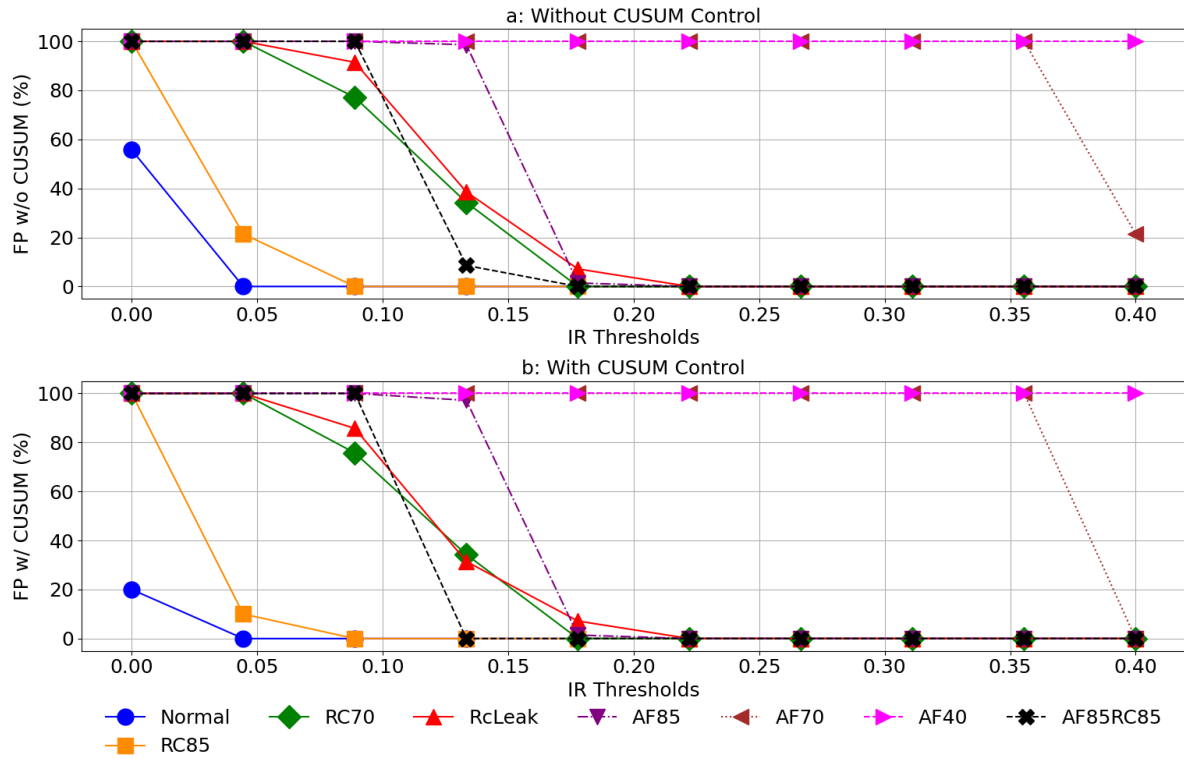


Figure 4.18: FPs vs IR threshold for the Real Scenario using Δi (a) Without CUSUM Control, and (b) With CUSUM Control.

4.3.3 False Negative Rate (FNR)

4.3.3.1 Ideal Scenario

Figure 4.19 shows the FNRs for all cases without and with CUSUM, respectively. Like with the FPs, both subplots look very similar since the FNR is simply an inversion of FP.

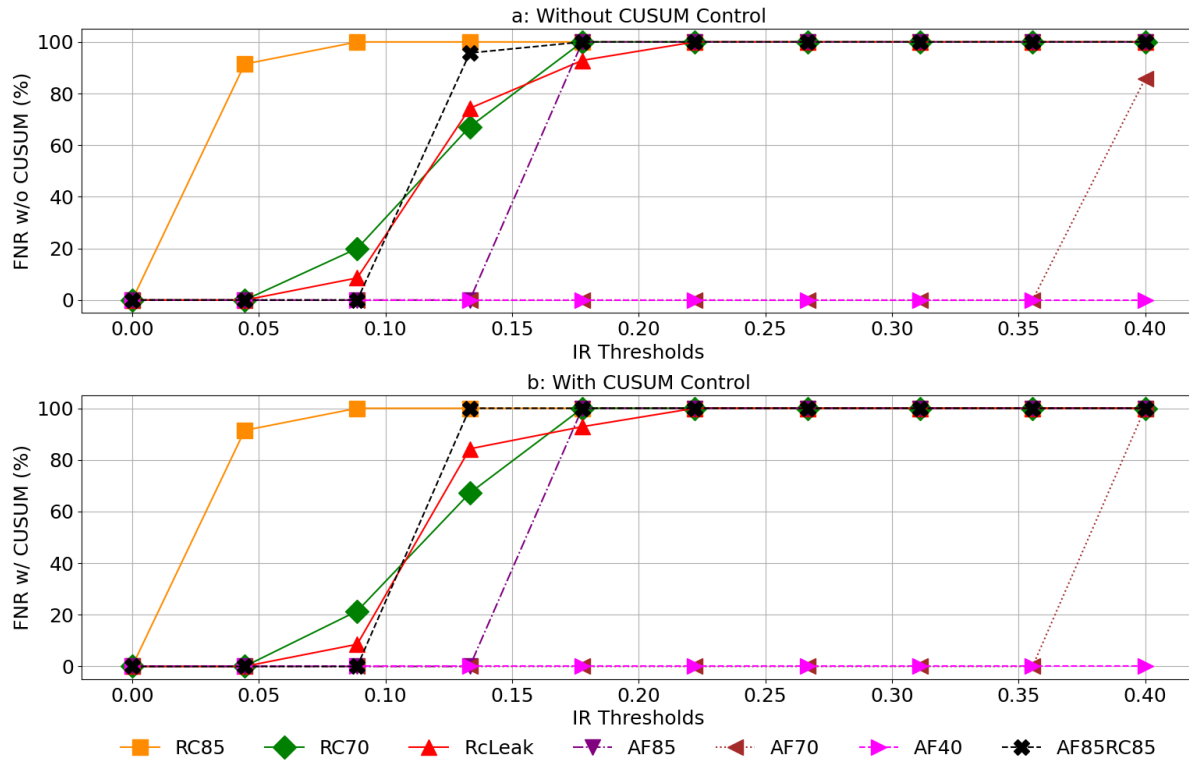


Figure 4.19: FNRs vs IR threshold for the Ideal Scenario using Δi (a) Without CUSUM Control, and (b) With CUSUM Control.

As expected, both subplots show that AF70 and AF40 had 0% FNRs for all thresholds up to 35%. Beyond 35%, only AF40 maintained a 0% FNR. The FNR for AF85 rose from 0% to 100% at the 18% threshold. Without CUSUM, the FNR for AF85RC85 also rose to 100% at the 18% threshold but with CUSUM, it rose to 100% at the 13% threshold.

RC85 showed the largest FNR of 90% at the 4% threshold which rose to 100% at the 9% threshold. The FNR for RC70 rose from 0% at the 4% threshold to 20% at the 9% threshold, and then to about 70% at the 13% threshold before reaching 100% at the 18% threshold. RcLeak had almost the same result as RC70, with the FNR rising from 0% at the 4% threshold to 10% at the 9% threshold. At the 13% threshold, without CUSUM, the FNR for RcLeak was slightly below 80%

but slightly above 80% with CUSUM. The FNR then rises to approximately 90% at the 18% threshold, and to 100% at the 22% threshold.

4.3.3.2 Real Scenario

Figure 4.20 shows that the FNRs for the real scenario is also very similar to those under the ideal scenario.

As expected, both subplots show that AF70 and AF40 had 0% FNRs for all thresholds up to 35%. Beyond 35%, only AF40 maintained a 0% FNR. The FNR for AF85 rose from 0% to 100% at the 18% threshold. Without CUSUM, the FNR for AF85RC85 also rose to 100% at the 18% threshold but with CUSUM, it rose to 100% at the 13% threshold.

RC85 showed the largest FNR of 80% and 90% (without and with CUSUM) at the 4% threshold which rose to 100% at the 9% threshold. The FNR for RC70 rose from 0% at the 4% threshold to 20% at the 9% threshold, and then to about 65% at the 13% threshold before reaching 100% at the 18% threshold. RcLeak had almost the same result as RC70, with the FNR rising from 0% at the 4% threshold to 10% at the 9% threshold. At the 13% threshold, without CUSUM, the FNR for RcLeak was approximately 60% and approximately 70% with CUSUM. The FNR then rises to approximately 90% at the 18% threshold, and to 100% at the 22% threshold.

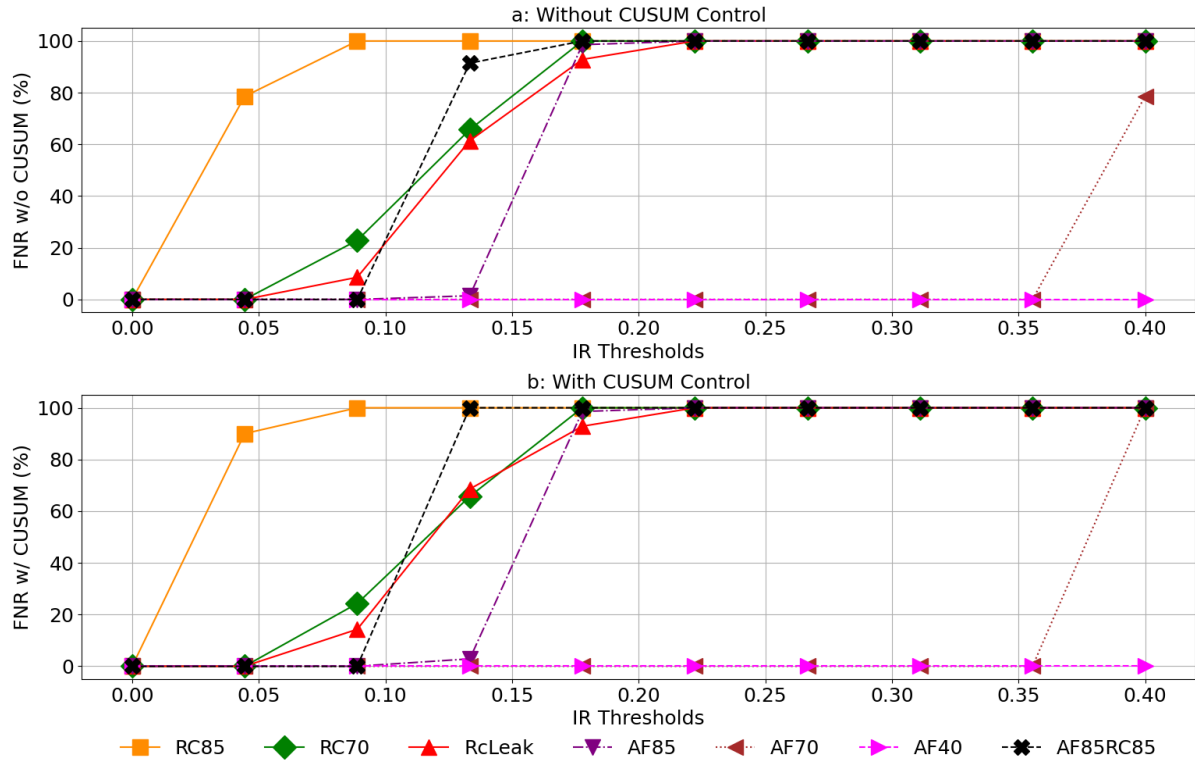


Figure 4.20: FNRs vs IR threshold for the Real Scenario using Δi (a) Without CUSUM Control, and (b) With CUSUM Control.

4.3.4 Signal-to-Noise Ratio (SNR)

Though UBLDs are not considered for the FDD method with Δi , false positives can still arise from the estimated baseline if a proper threshold is not used as found in the 0% thresholds in Figure 4.18. Therefore, the FP for the regressed Normal case is used as noise in Equation (2.33) to generate SNR when Δi is used.

Figure 4.21 shows the SNRs for Δi , at the different thresholds. The plots show that at the 4% threshold, except for RC85 which has a moderate SNR of 10 with CUSUM, all other cases have a high SNR of 100. At the 9% threshold, the SNR for RC85 becomes 0 while other cases still had high SNRs until the 13% threshold where the SNR for AF85RC85 also becomes low. At the 18% threshold, RcLeak drops to the moderate level, while others dropped to low SNRs except for AF40

and AF70 whose SNRs remained high until the 35% threshold. By comparing these SNRs with those obtained for duty factor, these results suggest that FDD methods which use Δi can achieve better performance than those that use duty factor.

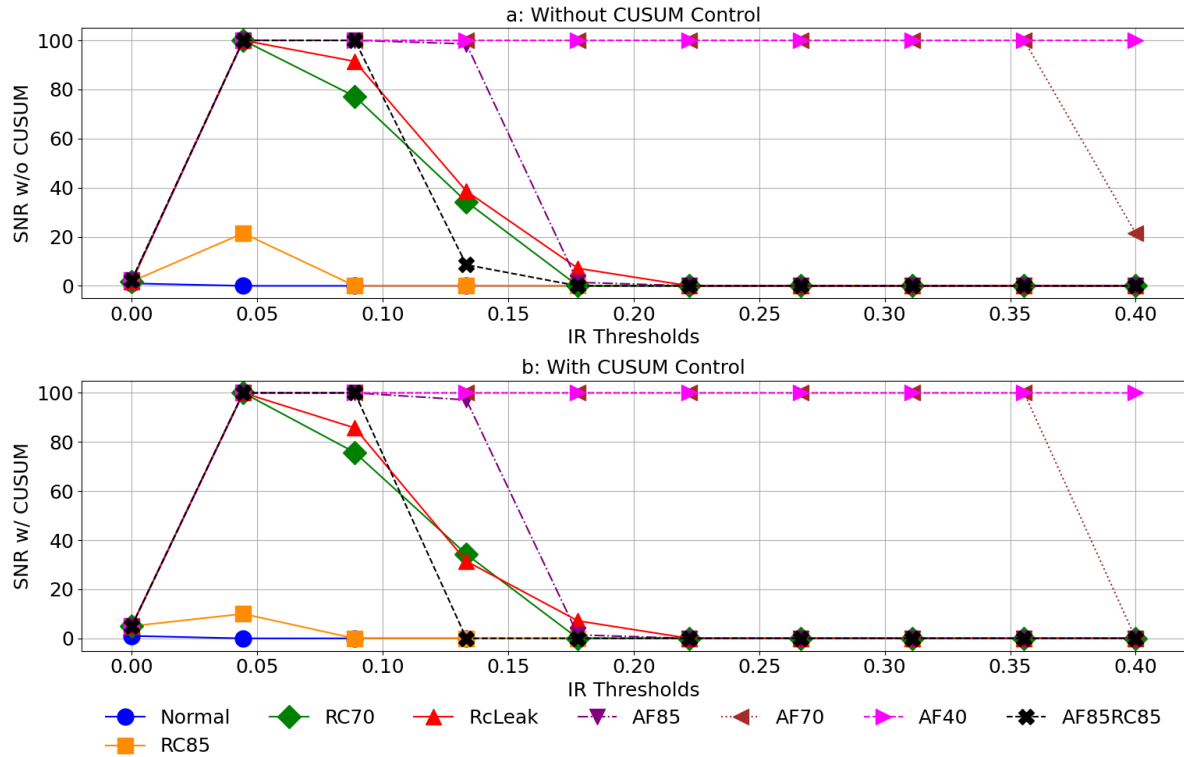


Figure 4.21: SNRs vs IR threshold for the Real Scenario using Δi (a) Without CUSUM Control, and (b) With CUSUM Control.

4.3.5 Summary of Results for Enthalpy Change

In this section, the performance of Smart thermostat-based fault detection methods using enthalpy change, Δi , as the detection feature was investigated. The case studies in Section Chapter 4: were also considered, excluding UBLD3. The simulated Δi for each case was used to generate IRs from Equation (1.3) which was then used for performance evaluation under the ideal scenario and real scenario. From these, the key takeaways are:

1. The changes in IR with outdoor temperature were insignificant for all cases, and in both ideal and real scenario.
2. Δi was more sensitive to low indoor airflow than to low charge faults.
3. The use of Δi introduced diagnostic potential into the FDD method, based on the two fault types considered in this research.
4. The use of Δi also improved the performance of the Smart thermostat-based method in terms of detectability

4.4 Final Deductions

From the investigation conducted so far using duty factor and Δi as FDD feature, Δi shows better performance than duty factor as can be seen from the comparative analysis between both features in Table 4.2. The 10% IR threshold used for the comparison is based on the analysis done in Section 4.2.4.2 which revealed 10% to be the optimum IR threshold when UBLDs are considered.

Table 4.2: Comparative Analysis Between Duty Factor and Enthalpy

Indices	Duty Factor	Enthalpy Change
Diagnosis	No	Yes
Faults detectable at a 10% IR threshold	RC70, RcLeak and AF40	RC70, RcLeak, AF85, AF70, AF40 and AF85RC85
Detectability at the 10% IR threshold in terms of SNR	High	High
Detectability at the 10% IR threshold in terms of FNR	60%, 55% and 50% for RC70, RcLeak and AF40 respectively	Below 20% for RC70, RcLeak, AF85, AF70, AF40 and AF85RC85

While the comparative analysis between duty factor and enthalpy change shows the latter to be better, the following questions remain:

1. How can enthalpy change be extracted from smart thermostat data?
2. How effective is the enthalpy change method in real-life applications.

These questions will be investigated in the next chapter.

Chapter 5: Investigation of a Smart Thermostat-Based Automated Fault Detection and Diagnosis Method Using Field Data

This chapter demonstrates the prospect of the smart thermostat (ST) method using enthalpy change as FDD feature, for field applications. It begins by giving an overview of the method and then discussing in more detail the development of the method. It then presents results on the validation of the proposed method and afterwards results from field tests. It concludes with a summary of the chapter, highlighting the limitations of the proposed method and giving recommendations for future work.

5.1 Overview of the Smart thermostat-based Method Using Enthalpy Change

The method involves two phases. Phase 1 focuses on checking the AC system for installation faults while Phase 2 checks the AC system for degradation faults. The method is based on the following sequence:

1. To get fault-free data for training the model in Phase 1, rated data collected from the expanded performance table (EPT) data of the AC system was used. More details on the EPT data are provided in Section 5.2.
2. T_{ra}, T_{sa}, T_{oa} data for the temperature of the return (or indoor) air, supply air, and outdoor air, respectively, and ϕ_{ra} data for the return air relative humidity, are collected from the smart thermostat and a connected node sensor. The collected data is then used to compute the measured enthalpy change, Δi , with the help of the CoolProp package in Python. More details on this are provided in Section 5.3.
3. The trained model is then used to predict the enthalpy change as $\Delta \hat{i}$. More details on this is provided in Section 5.3.

4. IRs are generated from Equation (1.3) with $\Delta\hat{t}$ as the FDD feature under fault-free condition. These IRs are compared to preset thresholds: IR_{lb} and IR^{ub} which is the IR lower bound (for low charge) and IR upper bound (for low indoor airflow), respectively. If an IR exceeds or drops below these bounds, the CUSUM parameter (S) is increased but decreased for the reverse.
5. If S increases beyond a specified CUSUM threshold (S_{bar}), then the corresponding installation fault is declared, and the algorithm is stopped for the homeowner to contact a technician or fix the fault, if possible. But if not, step #2 to #4 is repeated until S exceeds the CUSUM threshold OR until a specified number of days (N^{Ph1}) is reached.
6. When N^{Ph1} is exceeded, Phase 1 is discontinued, and Phase 2 begins. For Phase 2, the operation data collected during the N^{Ph1} days is used to retrain the model and then step #2 to #5 is repeated until a degradation fault is detected.

Because the quadratic model is highly sensitive to the range of operating conditions covered by the training dataset, the algorithm filters out monitored data that falls outside the operating conditions covered by the training dataset.

Figure 5.1 shows a flow chart which illustrates how the Smart thermostat-based method using enthalpy change was implemented in real life with field data. The blue dash lines show the flow path for just Phase 1. The red dash lines show the flow path for just Phase 2. The blue solid lines show the flow path for Phase 1 and Phase 2. The dash lines represent flow paths that become inactive after the first instance. For example, the model training was done just once in each phase.

The field data used for testing this method were obtained from the residential buildings described in Sections 2.2.1 and 2.2.2.1.

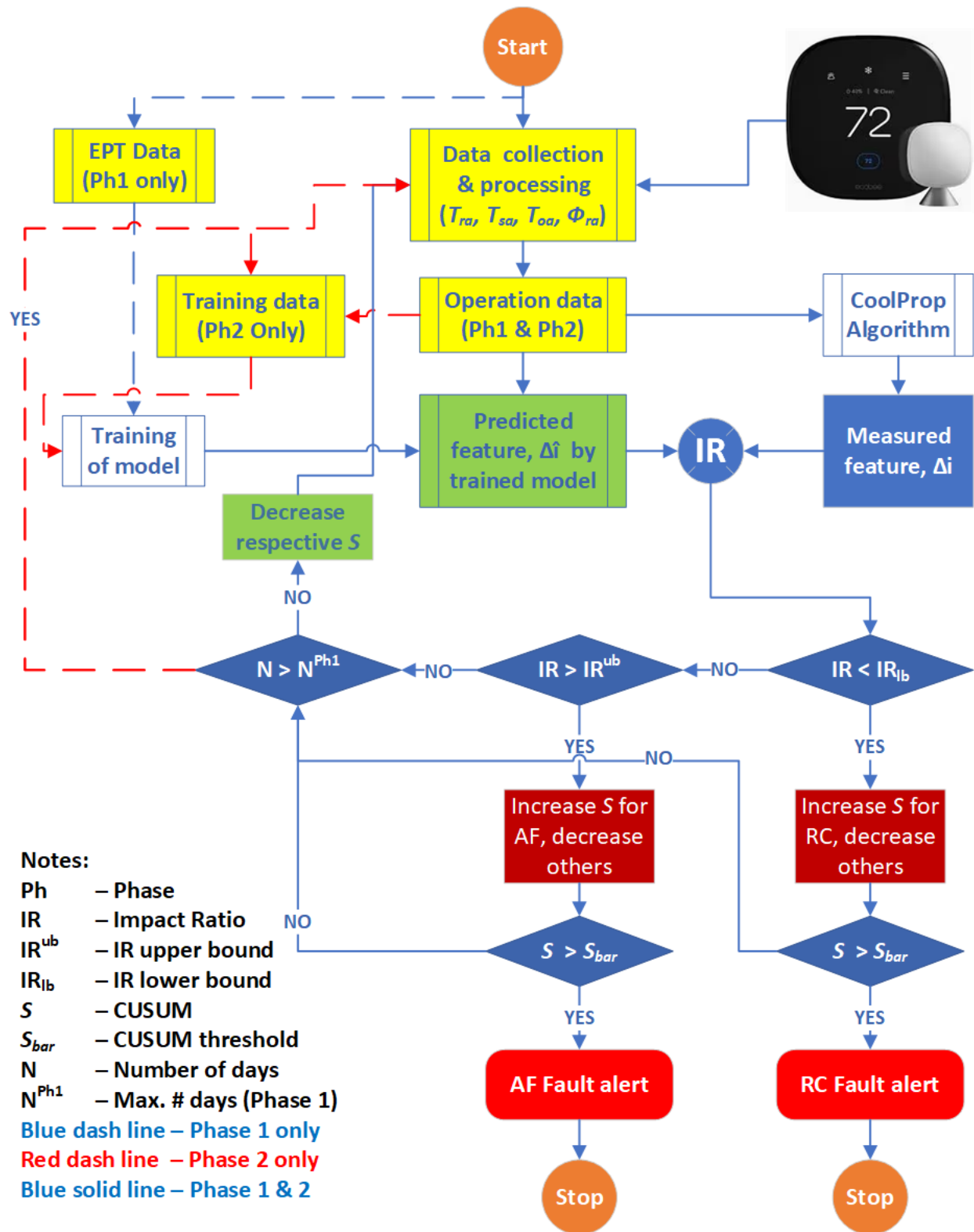


Figure 5.1: Overview of the FDD Method Implemented with Field Data

5.2 Expanded Performance Table (EPT) Data

The EPT data is typically provided by AC manufacturers and contains detailed performance data of an AC system across a wide range of operating conditions.

Table 5.1 shows the EPT data for the OU lab-house. The EPT data contains 24 datapoints, with outdoor air temperature ranging from 65 – 115 °F. This range sufficiently covers the typical range of outdoor air temperature in a cooling season. For the entering (return air) wet bulb temperature, the range of 59 – 71 °F also sufficiently covers typical values of return air wet bulb temperature during AC operation (cooling). Thus, the EPT data is well suited for training of the model.

Table 5.2 shows the EPT data for the Miami lab-house with similar observations made in the data for the OU lab-house.

Table 5.1: EPT data for OU lab-house

Model NO		14HPX-042-230-17 – CBX26UH-042					
Entering wet bulb temperature	Total air volume	Outdoor air temperature entering outdoor coil					
		65 °F	75 °F	85 °F	95 °F	105 °F	115 °F
	cfm	Total cooling capacity kBtuh					
59 °F	1450	47	45	43	41	39	36.6
63 °F	1450	47	45	43	41	39	36.6
67 °F	1450	50	48	46	43.5	41	38.5
71 °F	1450	52.5	50.5	48.5	46	43.5	41

Table 5.2: EPT data for Miami test house

Model N0		4TWA3036A3/4 + 4TEC3F36A1					
Entering wet bulb temperature	Total air volume	65 °F	75 °F	85 °F	95 °F	105 °F	115 °F
	cfm	Total cooling capacity kBtuh					
59 °F	1200	37.5	35	32.5	30.8	29.9	27.3
63 °F	1200	38.9	36.4	33.9	32.1	31.2	28.5
67 °F	1200	41.6	39.1	36.6	34.6	33.6	30.7
71 °F	1200	44.5	42	39.5	37.4	36.3	33.1

5.3 FDD Method Development

Figure 5.2 shows a schematic of the Smart thermostat-based FDD architecture. Real time evaporator performance monitoring was done by monitoring Δi across the evaporator, where Δi is the difference between the return air enthalpy, i_{ra} , and the supply air enthalpy, i_{sa} , as depicted in Equation (2.1).

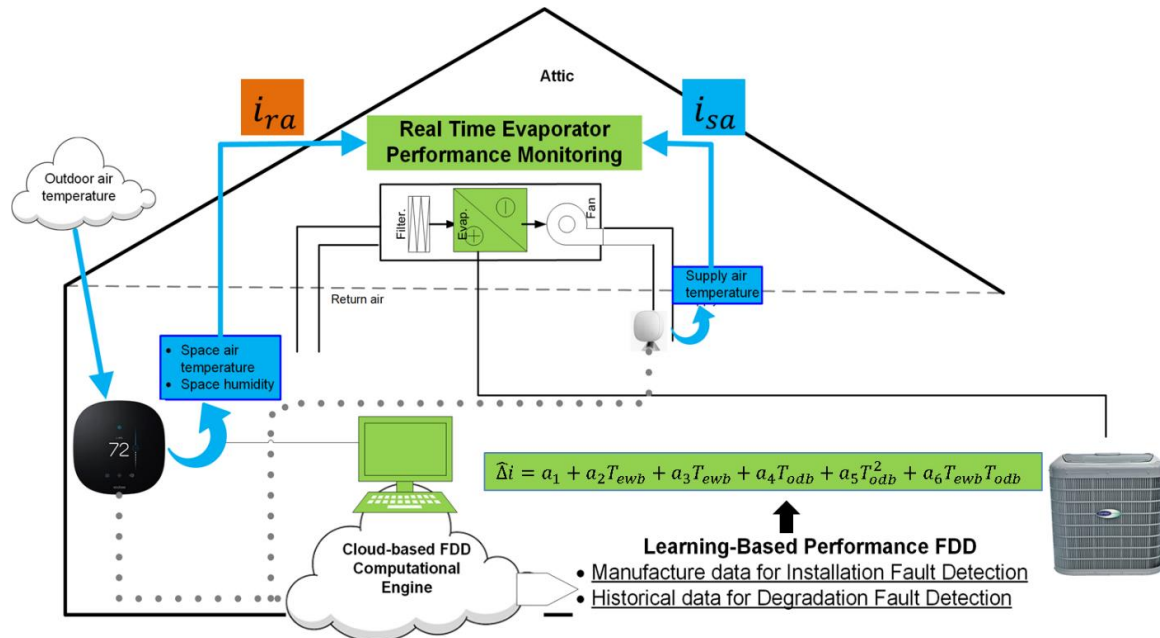


Figure 5.2: Architecture of the Smart thermostat-based FDD Method Using Δi

From psychrometry, any thermodynamic property of moist air can be obtained with three other known thermodynamic properties. Figure 5.3 shows a schematic of a psychrometric chart for moist air at a given pressure. With pressure given, two additional properties are needed to obtain any other property. For instance, with dry-bulb temperature and relative humidity given as 75 F and 50%, respectively, the wet-bulb temperature of moist air can be determined to be approximately 63 F as indicated by the red dot in the chart.

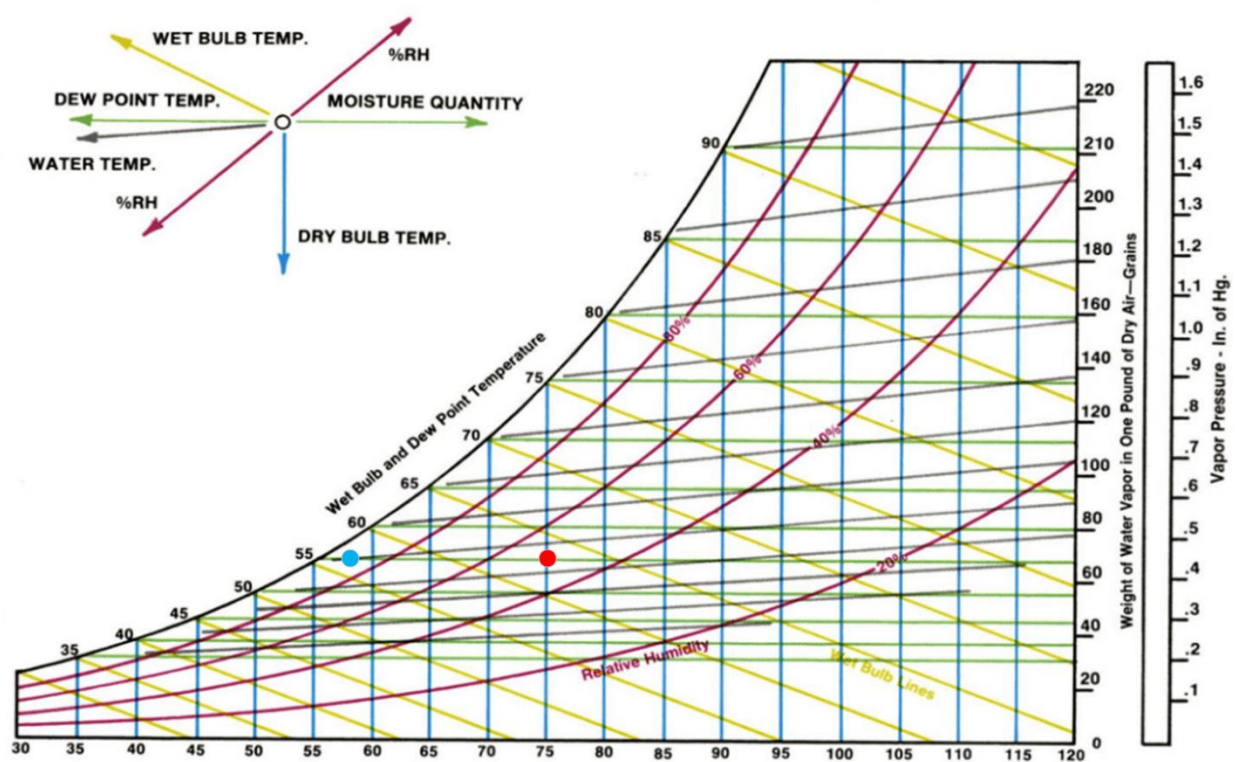


Figure 5.3: Schematic of A Psychrometric Chart [177]

With the above concept of psychrometry, i_{ra} is computed from the space air temperature and space humidity gotten from the smart thermostat, and processed with CoolProp [178]. CoolProp is an open-source thermophysical property library used for calculating fluid properties such as enthalpy, entropy, density, wet-bulb temperature, etc., for fluids like moist air. To compute i_{sa} , a node

sensor which typically comes with a smart thermostat is used. The node sensor is a temperature sensor provided by smart thermostat manufacturers to enable homeowners to monitor the temperature at another location in a building. The node sensor was strategically mounted on a diffuser to aid easy access for T_{sa} measurements. Figure 2.2n shows a diffuser with a node sensor mounted on it.

The T_{sa} is measured at the diffuser rather than at the exit of the evaporator due to the technical difficulty of installing a sensor right after the evaporator. To ensure that there is only a slight difference between the T_{sa} at the diffuser and the T_{sa} after the evaporator, the closest diffuser in the building was identified and used. However, the node sensor used to measure the T_{sa} can only measure temperature. To obtain i_{sa} , a second property is needed. This second property can be estimated from the consideration that for wet cooling (i.e., cooling with condensation on the evaporator coils), the T_{sa} after the evaporator is almost saturated thus suggesting a relative humidity, ϕ_{sa} , of about 90–95%. Then, for dry cooling (i.e., cooling without condensation on the evaporator coils), the supply air dew point temperature (T_{sadb}) would be the same as the return air dew point temperature (T_{radb}), and T_{radb} can be computed from T_{ra} and ϕ_{ra} . But as the T_{sa} is measured at the diffuser, ϕ_{sa} can significantly vary between the evaporator exit and the diffuser, thus making it more challenging to estimate ϕ_{sa} at the diffuser. So, instead of ϕ_{sa} , an estimated T_{sadb} after the evaporator is used because the T_{sadb} at the diffuser is the same as that at the evaporator exit. But to estimate T_{sadb} after the evaporator, some assumptions are required. These assumptions are described in Section 5.3.1.

5.3.1 Relevant Assumptions Made

The following assumptions are made in the development of the proposed Smart thermostat-based FDD method:

- (1) For residential units, the T_{sadb} is around 55 ± 2 F. This assumption is based on the consideration that the T_{sa} for a properly designed AC system typically ranges from 55 – 60 F (12.8 – 15.6 C), with a relative humidity ranging from 90 – 95%. With these typical values, the supply air condition (marked by the blue circle in Figure 5.3) indicates an T_{sadb} of approximately 55 F.
- (2) For $T_{sa} < 55$ F, $\phi_{sa} \approx 100\%$. Thus, $T_{sadb} \approx SAT$.
- (3) The thermostat data accurately represents the return air condition. This relies on the assumption that the thermostat is well located in the space, close enough to the return air ducts.
- (4) The EPT data used for training the model in Phase 1, is accurate and well representative of the expected behavior of the AC based on specifications.
- (5) Infiltration is the main source of outdoor air intake in residential buildings, and this contributes significantly to return air humidity. This assumption is based on the need to classify the evaporator coil condition as either wet or dry. The outdoor air dew point is thus used to make this classification, where at outdoor air dew point above 55 F, the cooling process is wet, and dry if not.
- (6) Though T_{odb} in Equation (2.26), which is same as T_{oa} in Table 2.2 is gotten from the Mesonet database, which has been reported to be reliable as discussed in Section 2.2.4, there might still be some uncertainties embedded in the data. These uncertainties are assumed to be minimal and captured already by the uncertainty in the quadratic regression

model where T_{oa} is used. Meanwhile, as long as such uncertainty would stay consistent over a reasonable period, the uncertainty in the weather data will have a minimum impact on the prediction of the enthalpy change.

Based on assumptions 1 and 2 above, the SADP was estimated from

$$T_{sadb} = \begin{cases} 55 \text{ F}, & \text{if } T_{sa} \geq 55 \text{ F} \\ T_{sa}, & \text{if } T_{sa} < 55 \text{ F} \end{cases} \quad (5.1)$$

5.3.2 Uncertainty Propagation Analysis

The FDD feature, Δi , cannot be measured directly but must be obtained from independent variables e.g., temperature and humidity or dew point, etc. But since these independent variables are obtained from sensors with built in uncertainties, an uncertainty propagation analysis must be conducted to ascertain the uncertainty in the Δi . This will help ensure that deviations caused by such uncertainty in the derived Δi is not misclassified as a fault. Thus, for the uncertainty propagation, the root sum square (RSS) method is used. The RSS method of uncertainty calculation has been used for traditional FDD methods [179] and is based on the formula:

$$\delta Y = \sqrt{\left(\frac{\partial Y}{\partial X_1} \delta X_1\right)^2 + \left(\frac{\partial Y}{\partial X_2} \delta X_2\right)^2 + \dots + \left(\frac{\partial Y}{\partial X_n} \delta X_n\right)^2} \quad (5.2)$$

where δY is the uncertainty of the dependent variable Y , δX_n is the uncertainty of the independent variable X_n .

So, for wet cooling, where $\Delta i = i_{ra} - i_{sa}$, and i_{ra} is a function of T_{ra} and ϕ_{ra} , and i_{sa} is a function of T_{sa} and T_{sadb} . Thus, Δi is a function of $T_{ra}, \phi_{ra}, T_{sa}, T_{sadb}$ and can be computed from a physics-based model shown in shown in Appendix D. The uncertainty for Δi in wet cooling, based on Equation (5.2) then becomes:

$$\delta(\Delta i) = \sqrt{\left(\frac{\partial(\Delta i)}{\partial T_{ra}} \delta T_{ra}\right)^2 + \left(\frac{\partial(\Delta i)}{\partial \phi_{ra}} \delta \phi_{ra}\right)^2 + \left(\frac{\partial(\Delta i)}{\partial T_{sa}} \delta T_{sa}\right)^2 + \left(\frac{\partial(\Delta i)}{\partial T_{sadb}} \delta T_{sadb}\right)^2} \quad (5.3)$$

The uncertainties for T_{ra} , ϕ_{ra} , T_{sa} and T_{sadb} were gotten for the smart thermostat, smart node sensor, and hobo data logger used to measure the relevant data as shown in Table 5.3. The uncertainty propagated into Δi due to the sensor uncertainties is also shown in Table 5.3. The Δi uncertainty was computed for two categories of data: category 1 are those collected with smart thermostat (ST) and smart node sensor (SNS); while category 2 are those collected with hobo data logger. Also, the respective data range for each variable used in the uncertainty propagation analysis is shown in the table.

Table 5.3: Uncertainties of Variables Based on Root Sum Square (RSS) Method

Type	Variable	Unit	Uncertainty (ST, SNS)	Range	Uncertainty (Hobo logger)	Range
Inputs	T_{ra}	$^{\circ}F(^{\circ}C)$	$\pm 1.0(0.6)$	70.7 – 82.9	$\pm 0.4(0.21)$	65.3 – 82.0
	T_{sa}	$^{\circ}F(^{\circ}C)$	$\pm 1.0(0.6)$	50.0 – 80.0	$\pm 0.4(0.21)$	47.8 – 81.0
	T_{sadb}	$^{\circ}F(^{\circ}C)$	$\pm 2.0(1.2)$	55.0	$\pm 0.4(0.21)$	45.7 – 68.2
	ϕ_{ra}	%	± 3	40.0 – 80.0	± 2	50.0 – 80.0
Output	Δi	Btu/lbm	± 1.2	0.7 – 11.0	± 0.6	3.6 – 8.0

For category 1, fault-free data from the respective homes described in Section 2.2.2.1 were used to provide the required data. The uncertainty in each input data were gotten from the specifications for the Ecobee smart thermostat used [180]. From the analysis, a ± 1.2 Btu/lbm was found to be

within a 95% confidence level for the Δi uncertainty.[180]. From the analysis, a ± 1.2 Btu/lbm was found to be within a 95% confidence level for the Δi uncertainty.

For category 2, fault-free data from the two lab-houses discussed in Section 2.2.1 were used to provide the required data. Hobo data loggers were used to collect the data and so the uncertainty in each input data was gotten from the specifications of the hobo logger used as discussed in Section 5.4.1. From the analysis, a ± 0.6 Btu/lbm was found to be within a 95% confidence level for the Δi uncertainty. The Δi uncertainty for category 2 was smaller than the one for category 1 because of the higher accuracy of the hobo data loggers and also because actual T_{sadb} measurement was used in this case. While for category 1 it was estimated because the smart node sensor can only measure temperature. However, the hobo logger data was only used for validation, so the ± 1.2 Btu/lbm was used for the testing of the proposed FDD method.

To see how this 1.2 Btu/lbm uncertainty in Δi corresponds to the IR thresholds proposed from the co-simulation study done in chapter 4, from Equation (1.3), $\Delta i = IR \times \Delta \hat{i}$. But $\Delta i = \Delta \hat{i} \pm \delta$ where δ is the uncertainty in Δi . Therefore,

$$\pm \delta = \Delta \hat{i}(IR - 1) \quad (5.4)$$

$IR - 1$ corresponds to the IR thresholds used in Section 4.3. Hence, for a given range of $\Delta \hat{i}$, say from 6 – 8 Btu/lbm, which covers the values of $\Delta \hat{i}$ obtained from experimental data (Section 5.4) and field data (Section 5.5) for AC operating under normal condition, Figure 5.4 is generated.

The dash red line in Figure 5.4 is the ± 1.2 Btu/lbm uncertainty. The computed $\Delta \hat{i}$ ranges from 6 - 8 Btu/lbm, covering the range of $\Delta \hat{i}$ gotten from the field data as will be seen later. This suggests that the corresponding IR threshold for the ± 1.2 Btu/lbm uncertainty gotten from the RSS

uncertainty propagation analysis must be at least 22% to compensate for uncertainties embedded in the sensors used to compute Δi .

At the 22% IR threshold in Figure 4.21, only the AF70 and AF40 faults showed the prospect of being detectable. Therefore, the field tests done in this chapter only considered two of the extreme faults: AF70 and RC70. The RC70 fault was considered because it is the most severe of the RC faults. On the other hand, AF40 was not considered because it is too extreme and AF70 is already sufficient.

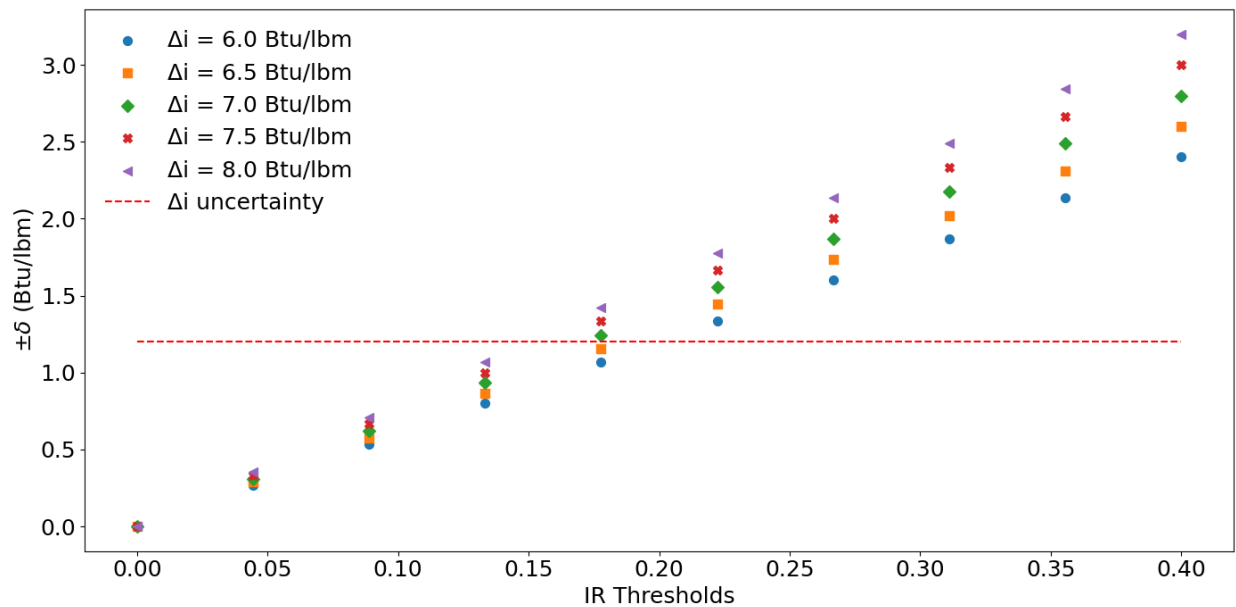


Figure 5.4: Correlation of the Uncertainty in Δi to IR Thresholds from Co-simulation

The observation from Figure 5.4 on the ± 1.2 Btu/lbm from the uncertainty propagation analysis, which suggests that only AF70 and AF40 faults can be reliably detected (Figure 4.21), further suggests that the ± 1.2 Btu/lbm is rather high. The high uncertainty is because of the approximation made for T_{sadb} . But with the hobo dataloggers, the uncertainty in Δi is significantly reduced to ± 0.6 Btu/lbm which corresponds to a threshold of about 10% in Figure 5.4. At the 10% IR

threshold in Figure 4.20, the FNR for RC70, RcLeak, AF85, AF70, AF40 and AF85RC85 are equal to or less than 30% with high SNRs (Figure 4.21). This means that these six fault categories can be reliably detected using Δi as reported in Table 4.2. Though this is based on hobo datalogger sensors which is not available for real-life implementation, it would be shown later that even for applications based on smart thermostat and smart node sensor data, the ± 0.6 threshold can still be tolerated without resulting in high FPR. Though the ± 1.2 threshold is safer for lower FPRs.

5.3.3 CUSUM Threshold

In the analysis done so far in chapters 3 and 4, where the CUSUM control strategy was implemented, historical data was used. For instance, the entire 70 days of data was first collected, processed and then analyzed. But for the implementation done in this chapter, real-time monitoring was done. This means that rather than waiting until the data for the entire summer has been collected before the analyses are done, the analyses are constantly done in real-time and thereby monitoring the health of the AC system. Therefore, for this real-time monitoring, a CUSUM threshold is needed.

A CUSUM threshold, S_{bar} , of 24 hours, was used for the implementation of the proposed method here. The choice of 24 hours as the duration threshold was based on the consideration that presumably, if due to severe fault conditions, the AC runs for the entire day on a hot summer day, such fault can be detected by the end of the day. While if based on homeowners' preference and weather conditions, AC does not run for long each day, an early fault detection can still be possible. For instance, if AC runs for only four hours per day on average, a fault can be detected in six – seven days' time. A 24-hour duration threshold would therefore prevent false fault alarms, while mitigating delayed fault detection.

5.4 Validation of Proposed FDD Method Using Enthalpy Change

5.4.1 Validation of the Proposed FDD Algorithm in the OU Lab-House

The validation was done mainly with just the T_{ra} , ϕ_{ra} , T_{sa} and T_{sadb} data collected with the hobo data loggers shown in Figure 2.2g. The MX1101 Hobo data loggers are high-precision measuring devices that have the capability of measuring and storing temperature and relative humidity data. For temperature measurement, the logger has an accuracy of ± 0.21 C, a resolution of 0.024 C at 25 C and a drift of < 0.1 C per year. For relative humidity, it has an accuracy of $\pm 2\%$, a resolution of 0.01% and a drift of $< 1\%$ per year. Also, it can store data at intervals as low as 1 second. These devices were used instead of the smart thermostat and smart node sensor, but only for model validation to ensure that the impact of sensor uncertainties is minimized.

5.4.1.1 Validation of Trained Model Using Normal Operation

The EPT data for the OU lab-house (Table 5.1) was used to train the model described in Equation (2.26). The model parameters were obtained using the least squares parameter estimation. Normal operation data were collected from October 7-12, 2021, to validate the model. For the training, validation, and testing of the AFDD algorithm, only the times when the AC was on are considered. Also, because steady-state operation is important in a general FDD process [3], the first 4 to 5 minutes and the last 2 minutes of each on cycle were filtered out. Only about 7 minutes of AC data from the beginning and end of each cycle were removed to ensure that sufficient data were collected for proof-of-concept purpose. But for the deployment in actual residential homes, it is recommended to remove data from the first 10 minutes, which is the typical time it takes most residential units to get to steady-state.

The validation was first conducted for the assumptions made for estimating T_{sadb} from Equation (5.1). The actual T_{sadb} was measured using the data logger instead of the smart node sensor. The estimated T_{sadb} was calculated using Equation (5.1). A comparison of the actual T_{sadb} with the estimated T_{sadb} is shown in Figure 5.5. The data covers the period of normal operation as well as the period when a fault is introduced. The results show that the estimated T_{sadb} matched the actual T_{sadb} within a ± 2 F error. This result thus validates the proposed method for obtaining T_{sadb} , and by extension i_{sa} from just temperature measurement which can be gotten from the smart node sensor.

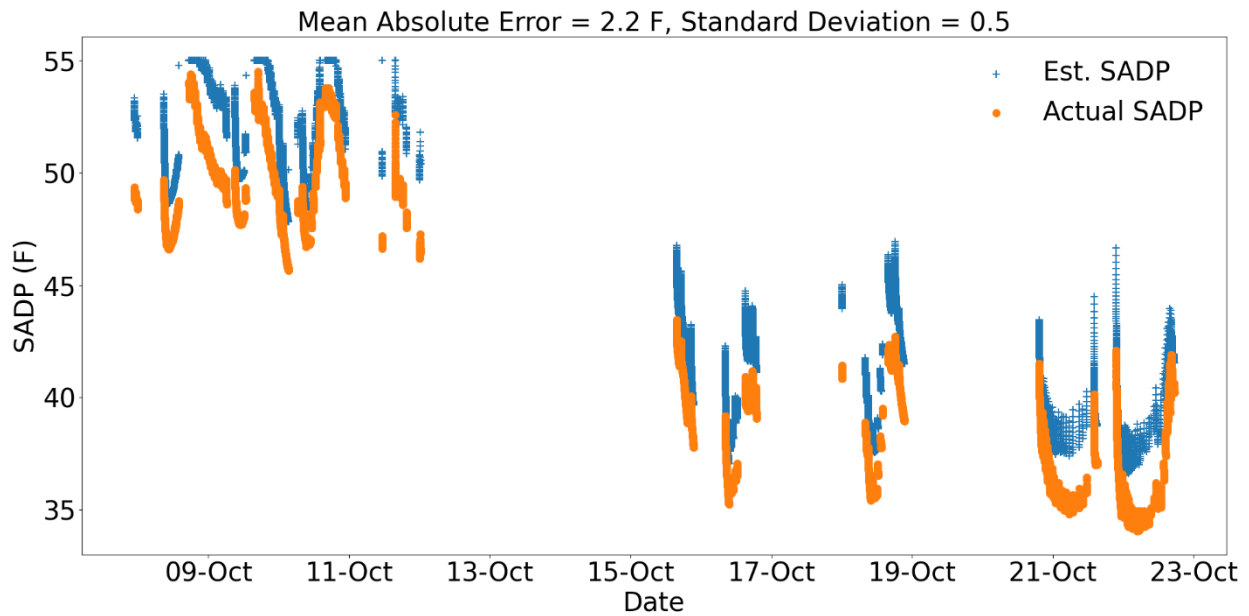


Figure 5.5: Comparison of actual and estimated supply air dew point temperature

Figure 5.6 shows the validation results for the quadratic regression model used to predict Δi . Equation (5.1) is used to calculate the T_{sadb} which is then combined with the T_{sa} to obtain i_{sa} for the calculation of Δi_{mea} in the figure. The enthalpy change predicted by the model trained with EPT data is also shown in both subplots of the figure as $\Delta i_{predicted}$. The deviation in the figure

is computed as the difference between $\Delta i_{predicted}$ and Δi_{mea} (i.e., $\Delta i_{predicted} - \Delta i_{mea}$), and is represented by the ‘x’ marker with a green color highlighting deviations within the threshold bound (suggesting no fault and thus labeled devNF in the figure), magenta/pink color for those above the upper bound (suggesting low charge and thus labeled devRC in the figure) and red for those below the lower bound suggesting low indoor airflow and thus labeled devAF in the figure). The only difference between the first and second subplot is how Δi_{mea} was obtained. For the first subplot, estimated T_{sadb} is used to compute Δi_{mea} , while in the second the actual T_{sadb} obtained through the hobo logger was used to compute Δi_{mea} . The upper and lower bounds are +1.2 Btu/lbm and -1.2 Btu/lbm, respectively, based on the uncertainty propagation analysis.

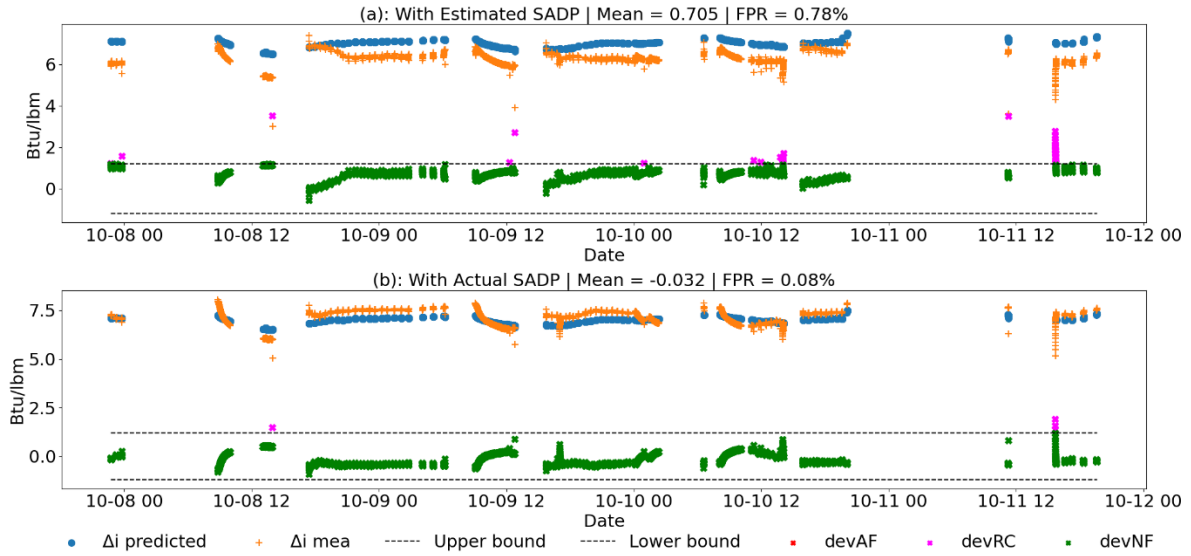


Figure 5.6: Comparison of the EPT-trained-model predicted Δi with (a) measured Δi involving estimated T_{sadb} , and (b) measured Δi involving actual T_{sadb} for OU house

The first subplot shows a good match between the predicted enthalpy change and the enthalpy change calculated using the estimated T_{sadb} . The deviations were within the threshold bounds for the most part with just a few outliers, with a mean deviation of 0.705 Btu/lbm. The subplot further shows an FPR of less than 1%.

The second subplot showed better match between the predicted and measured enthalpy. This is expected because the uncertainties associated with the T_{sadp} estimation are eliminated in this case. The deviations for this case had lesser outliers and had smaller values than those in the first subplot. A mean deviation of -0.032 Btu/lbm was obtained and shows that the deviations were very close to zero, further showing the accuracy of the model. The subplot further shows an FPR that is 10x smaller than the FPR in the first subplot.

Though the second subplot shows a better match between the predicted and measure Δi , the deviations in the first subplot still fall within the threshold of ± 1.2 Btu/lbm (from Section 5.3.2). The few observed outliers can easily be handled with the CUSUM control, to prevent false positives, as discussed in previous chapters.

5.4.1.2 Validation of the FDD Method Using Operational Data with An Introduced Fault

To test the effectiveness of the FDD method in fault detection, low indoor airflow is considered as an initial case study. Low indoor airflow is considered because it is one of the prevalent faults in residential AC systems and it is relatively easy to create both technically and cost-wise. Also, the investigation in Section 4.3 showed that Δi is more sensitive to low indoor airflow than it is to low charge fault.

The low indoor airflow is manually created by partially blocking the return air duct in the indoor unit of the AC system at the OU lab-house. As mentioned in Section 5.3.2, the AF70 fault (i.e., a 30% drop in the airflow) is chosen for the validation of the FDD method. The test was conducted from October 20 – 22, 2021.

Figure 5.7 shows the results of the test done with the AF70 fault. Both subplots show the predicted and measured enthalpy changes, as well as the deviation with the red ‘X’ markers highlighting

deviations that fall below the threshold lower bound while green shows those within the bounds. There were no pink markers (devRC) which suggests a zero or low misdiagnosis rate. For this case, the quadratic model was retrained using the operation data from Section 5.4.1.1, in line with the sequence reported in Figure 5.1 where Phase 1 uses EPT data for training while Phase 2 retrains the model with the operation data from Phase 1. So, the EPT data was only used for validating the model accuracy. But for validation of the FDD method's ability to detect faults, operation data is used for the training. The operation data used for training and testing, each consist of T_{wb} , T_{oa} and Δi gotten from measured T_{ra} , ϕ_{ra} , T_{sa} and T_{sadb} (estimated in the first subplot and measured in the second).

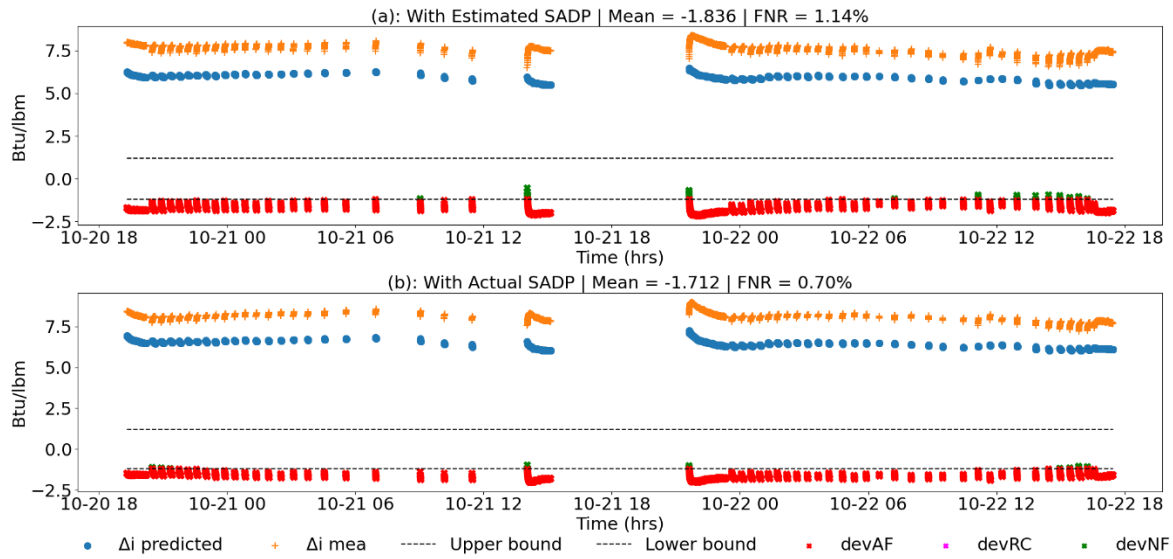


Figure 5.7: Detection of 30% low indoor airflow fault in OU lab-house

As seen from both subplots, there is a clear disparity between the measured and the predicted enthalpy changes. Thus, the deviations ($\Delta i_{predicted} - \Delta i_{mea}$) were outside the bounds for the most part, leading to an FNR of approximately 1%. Furthermore, the deviations were negative at all intervals with a mean of -1.836 Btu/lbm, which is consistent with the trend for low indoor

airflow. This shows that the FDD method was able to detect the significant increase in Δi due to low indoor airflow, which caused deviation below the -1.2 Btu/lbm threshold.

Again, the second subplot suggests better detectability than the first as more deviations were outside the bounds in the second subplot than in the first subplot, and thus a 0.7% FNR was recorded for this case. However, the first subplot still shows that even with the estimated T_{sadb} , the 30% low indoor airflow fault can be reliably detected.

As this is primarily proof-of-concept, the AC only ran for about 8 hours during the two days. So, the CUSUM algorithm could not be implemented for this test considering that the CUSUM threshold is 24 hours. But the large deviations demonstrate the potential of the algorithm to detect faults. In the field tests, the CUSUM algorithm was implemented.

5.4.2 Validation of the Proposed FDD Algorithm in the Miami Lab-House

This section is focused on the tests conducted in the Miami lab-house (described in Section 2.2.1.2) where the climate is very humid. Again, for proof-of-concept purposes, a set of portable data loggers were installed to collect return and supply air temperatures and humidity inside the test AC unit. The weather data are obtained from a local weather station.

5.4.2.1 Validation of Trained Model Using Normal Operation Data from Miami Lab-House

Using the EPT data for the AC unit in the Miami lab-house (Table 5.2), the quadratic regression model (Equation (2.26)) was trained. The trained model was then used to predict the enthalpy change. Figure 5.8 shows results of the comparison between the predicted and measured enthalpy change. For this house, the AC only runs for a short period of time per day. Hence, to aid visualization of the results, the plots are given in hours rather than days.

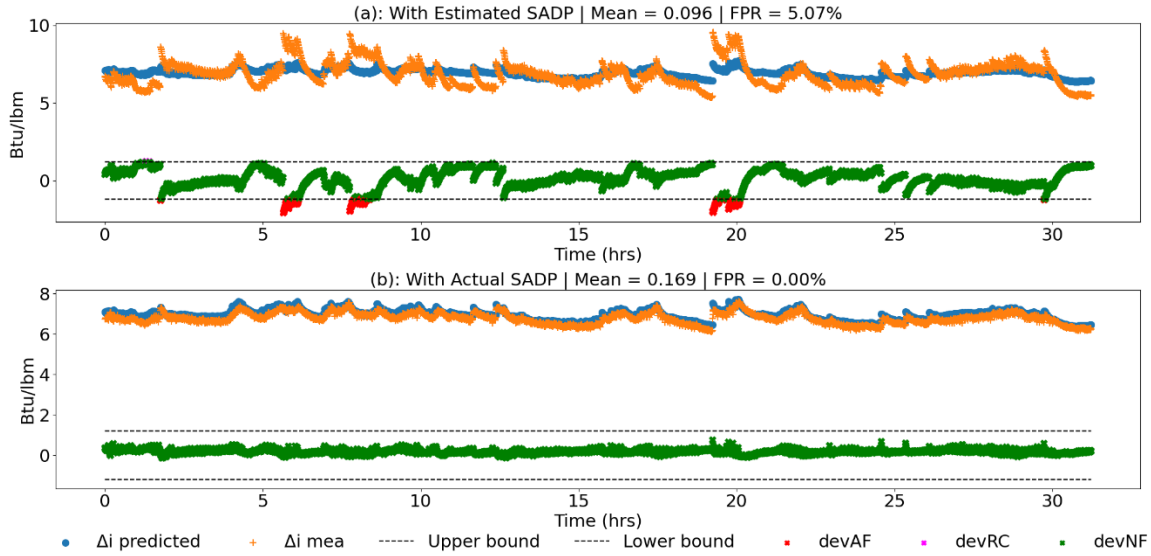


Figure 5.8: Comparison of the EPT-trained-model predicted Δi with (a) measured Δi involving estimated T_{sadp} , and (b) measured Δi involving actual T_{sadp} , for Miami house

Again, the difference between the first and second subplot is that for the first, estimated T_{sadp} is used while for the second, actual T_{sadp} is used. Both subplots show very good match between the predicted and measured enthalpy change with just few outliers observed in the first subplot while for the second, all the deviations were within the threshold bounds of ± 1.2 Btu/lbm. For the first subplot, a mean deviation of 0.096 Btu/lbm was observed and an FPR of about 5%. For the second subplot, a mean of 0.169 Btu/lbm was gotten with a 0% FPR. These results further validate the model used in the proposed FDD method.

5.4.2.2 Validation of the FDD Method Using Operational Data with An Introduced Fault

For this lab-house, low indoor airflow faults were also manually created. However, for this case, to alleviate the impact of the faults on the test unit, the faults were created by adjusting the fan speed setting instead of blocking filter area since a multi-speed fan is installed in the test unit. Due to the limitation of the system, the fault severity could not exceed 21%. The 21% low indoor airflow (AF79) test was from September 1 – 5, 2021.

Figure 5.9 shows results for the test conducted for the AF79 fault. The figure shows the predicted and measured enthalpy changes, and the resulting deviations ($\Delta i_{predicted} - \Delta i_{mea}$). Similar to the previous plots, the red 'X' markers show deviations outside the threshold bounds while the green shows those within.

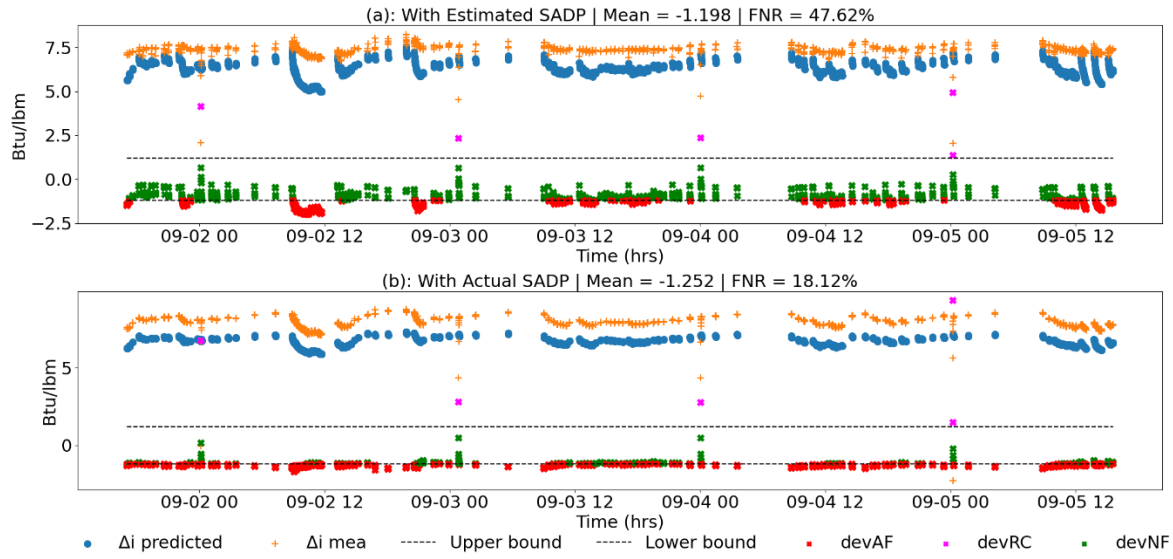


Figure 5.9. Validation of the FDD Method with Data from the Miami Lab-house

For the first subplot where estimated T_{sadb} was used, the deviations stayed within the threshold bounds for the most part and led to a significantly high FNR. The results suggest that the FDD method might not be able to detect the 21% low indoor airflow fault or at best may take a significantly long time to detect it. This is however due to the uncertainty in the T_{sadb} estimation. With the actual T_{sadb} , the chances of detecting this severity of fault can be increased as shown in the second subplot where more of the deviations turned red and a much lesser FNR of about 18% was recorded. Though the proposed FDD method in this chapter uses the estimated T_{sadb} , this finding indicates that with measured T_{sadb} , the performance of the proposed FDD method can be improved. This can be achieved if smart node sensors that can detect temperature and any other

thermodynamic property (e.g., relative humidity) can be manufactured by smart thermostat manufacturers.

5.5 Field Test and Real-time System Monitoring

For the field test, the four residential homes (including the OU lab-house) were used. Apart from the OU lab-house, the other homes are fully occupied residential homes, making them very suitable for implementation of the FDD method. Details of the test homes are provided in Section 2.2.2.1.

A smart thermostat and a smart node sensor were installed in each of the four test homes. The closest diffuser to the indoor unit in each home was identified and the smart node sensor was mounted on such diffuser. The smart node sensor was then installed and linked to the respective smart thermostat in each of such homes.

A FDD agent was built with the python programming language and a two-way communication platform was developed to query data from the smart thermostat database. Before using the data for training and/or by the FDD, the on/off signal from the thermostat was used to filter out the transient data, defined as data from the first 10 minutes of each AC on cycle. Also, the heating signal from the thermostat was used to filter out noise in the data due to switching from cooling to heating mode by homeowners, either mistakenly or deliberately. Further disturbances such as internet disruptions and power outages leading to the thermostat going offline and not storing data were also eliminated when collecting data. The outdoor air dew point was then computed using CoolProp and used to divide the data into wet cooling data and dry cooling data, as mentioned in Section 5.3.1. The appropriate dataset was subsequently used to carry out the FDD test based on Figure 5.1.

The implementation was done between May and September 2022, and was divided into two phases, with Phase 1 focusing on checking for installation faults while Phase 2 on checking for degradation faults. As earlier noted, for Phase 1 the EPT data for each AC unit in the respective test homes was used to train the quadratic model while for Phase 2, the operation data monitored during Phase 1 becomes the training data. Hence, Phase 2 does not begin until Phase 1 is completed.

5.5.1 Phase 1: Real-time System Monitoring for Installation Faults

5.5.1.1 OU Lab-House

Figure 5.10 shows results for the Phase 1 testing with smart thermostat and smart node sensor data from OU lab-house. The test was from July 14 – 24, 2022. The first subplot shows the measured and predicted enthalpy change, as well as the associated deviation. The second subplot shows the evolution of S (the CUSUM algorithm) for low indoor airflow and low charge due to their respective deviations. To reduce the load and storage cost on the InfluxDB database mentioned in Section 2.2.1.1, as well as optimize performance of the database, only the S values at the end of each day are uploaded to the database. This also aids visualization as depicted in Figure 5.10.

The first subplot shows a very large difference between the predicted and measured enthalpy change, causing very large deviations which far exceed the threshold. Hence the deviation markers were all red. Consequently, as shown in the second subplot, the low RC CUSUM increased rapidly and reached the CUSUM threshold eight days after the start of the FDD algorithm. At the point where the low RC CUSUM marker hits the CUSUM threshold, the marker turned red to indicate that an installation fault has been detected and the homeowner will be notified.

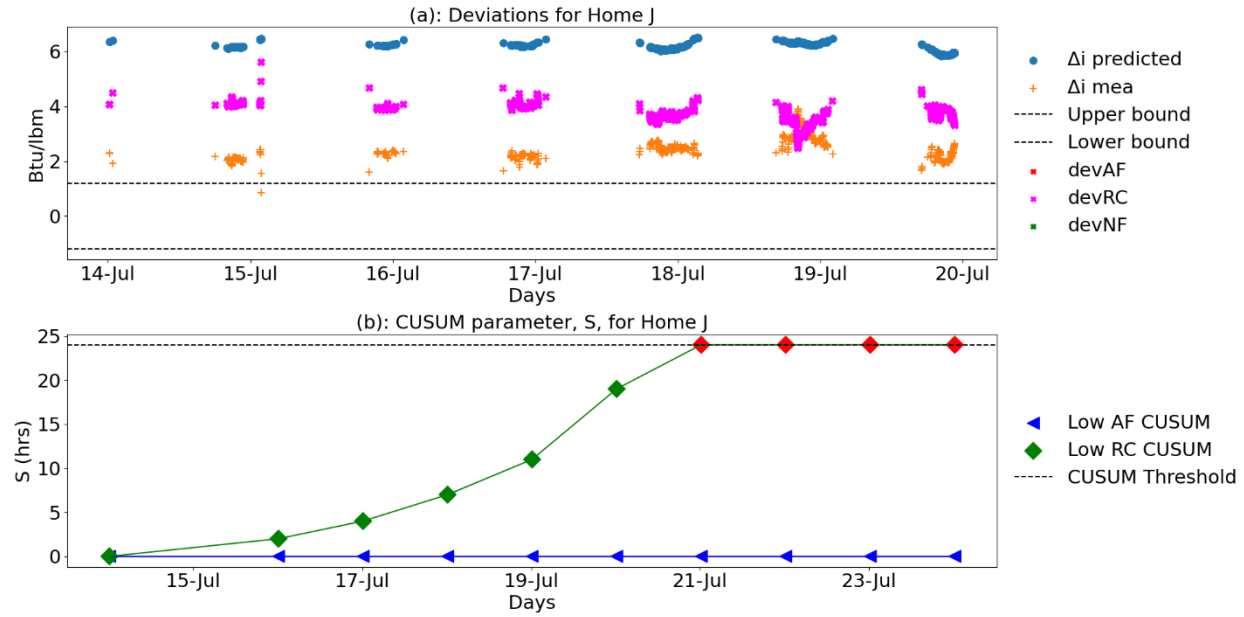


Figure 5.10: Real-time monitoring of Δi for OU Lab-House in Phase 1

The above result suggests that there is a low-charge installation fault in the lab-house. However, the AC during this period was operated under normal conditions. On closer examination, it was discovered that the large deviation was not caused by a low charge fault as wrongly diagnosed by the FDD algorithm. Rather, it was caused by a mismatch between the indoor and outdoor units of the AC system in the lab-house. As indicated in Section 2.2.1.1, the AC system has a 3.5-ton outdoor unit and a 4-ton indoor unit. Meaning the indoor unit is bigger than the outdoor unit. As the sizing of the indoor airflow rate is mainly based on the indoor unit capacity with a typically used rule-of-thumb being 400 cfm/ton of indoor unit, the indoor airflow rate in the AC system was larger than the airflow rate selected from the EPT data. The EPT data assumes that the indoor and outdoor units are matched properly e.g., a 3.5-ton outdoor unit installed with a 3.5-ton indoor unit. But in reality, this is not strictly followed for several considerations. While this is not exactly a fault, detection of such is still helpful as it can inform homeowners about potential installation issues.

Other potential installation issues that can lead to an oversupply of indoor airflow include:

1. An incorrect fan speed or settings. However, as this research considered just constant speed (fan and compressor) AC systems, this case is unapplicable to the proposed FDD method.
2. Poor ductwork design such as oversized ducts, duct leaks due to poor installation, etc.

Though the misdiagnosis in this case is undesirable, it is tolerable. This is because high indoor airflow faults are not as common as low indoor airflow which has been identified as a prevalent fault in residential AC systems. Also, except for installation issues like the one identified above, high indoor airflow has less tendency to occur because of degradation. For instance, degradation like an air filter becoming dirty over time (which is common) can only lead to a reduction in indoor airflow but not an increase. Therefore, the proposed FDD method is still very useful.

5.5.1.2 Home A

Figure 5.11 shows results for the Phase 1 test with smart thermostat and smart node sensor data from Home A. The test was from May 13 – June 13, 2022. The first subplot shows the measured and predicted enthalpy change, as well as the associated deviation. The second subplot shows the evolution of S (the CUSUM algorithm) for low indoor airflow and low charge due to their respective deviations.

The first subplot shows that the deviations mostly stayed within the threshold bounds for this case. Deviations outside the threshold bounds were well managed by the CUSUM control as shown in the second subplot. From the second subplot, the daily low RC CUSUM remained at zero for the entire Phase 1 period. Low AF CUSUM showed slight increase towards the end of the Phase 1 period. But as the rise was far less than the CUSUM threshold, no alarm was triggered for this home. The result obtained for this home is consistent with the facts about the AC unit installed in

this home as reported in Table 2.3, which showed that there was no indoor/outdoor unit mismatch for this home.

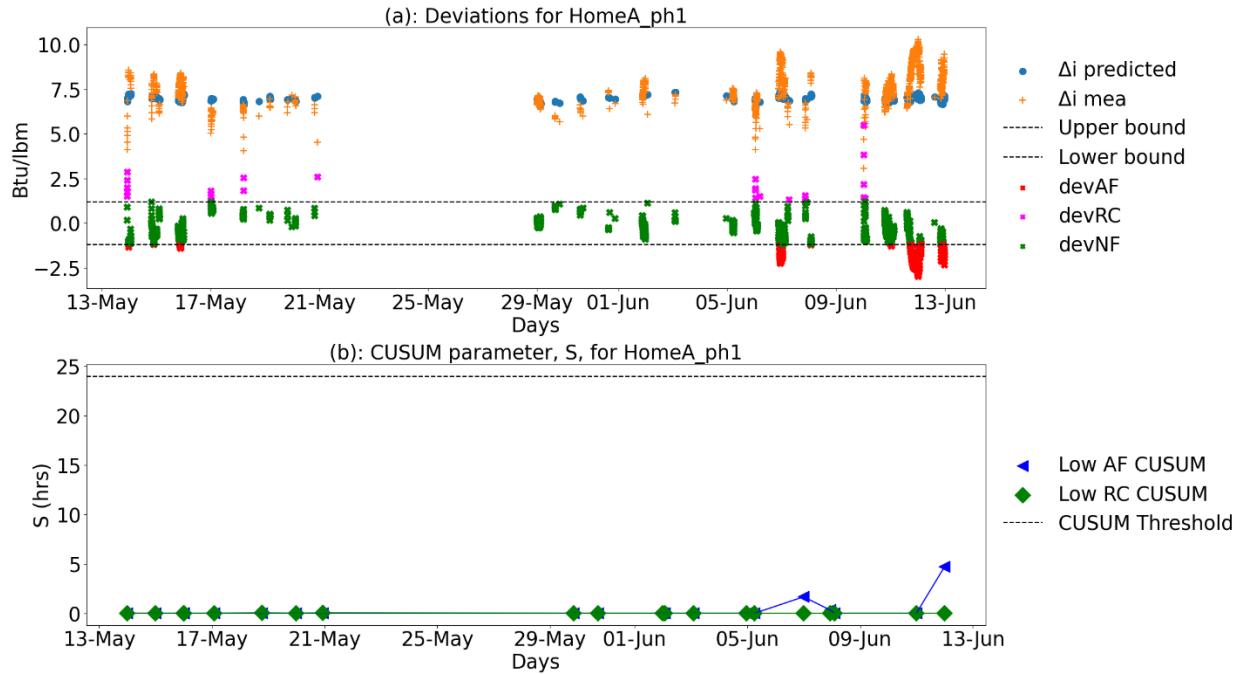


Figure 5.11: Real-time monitoring of Δi for Home A

5.5.1.3 Home I

Figure 5.12 shows results for the Phase 1 test with smart thermostat and smart node sensor data from Home I. The test was from May 15 – June 27, 2022. The first subplot shows the measured and predicted enthalpy change, as well as the associated deviation. The second subplot shows the evolution of S (the CUSUM algorithm) for low indoor airflow and low charge due to their respective deviations.

The test result for this home looks similar to those obtained for Home A. Though the results here look better. The first subplot shows that the deviations stayed within the threshold bounds for this case for the most part. The deviations outside the threshold bounds were well managed by the

CUSUM control as shown in the second subplot. From the second subplot, the daily low RC CUSUM and the daily low AF CUSUM remained at zero for the entire Phase 1 period with only slight non-monotonic increase at a few points. Hence no alarm was also triggered for this home. The result obtained for this home is also consistent with the facts about the AC unit installed in this home as reported in Table 2.3, which showed that there was no indoor/outdoor unit mismatch for this home.

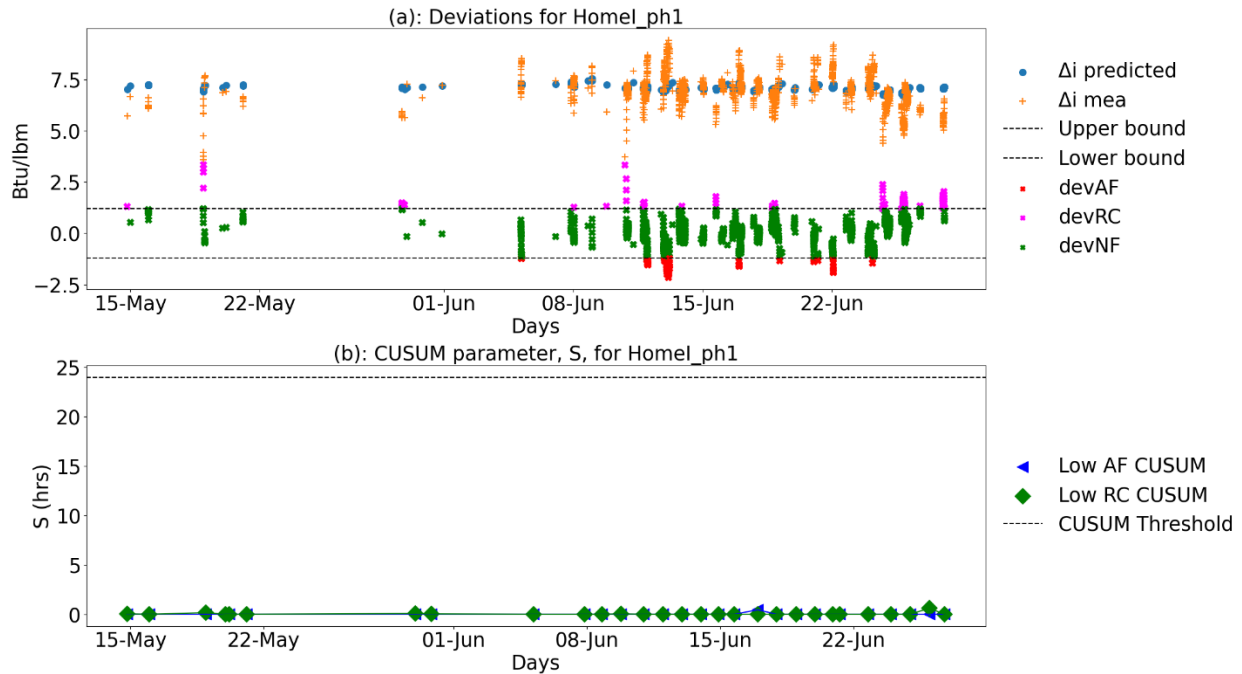


Figure 5.12: Real-time monitoring of Δi for Home I

5.5.1.4 Home J

Figure 5.13 shows results for the Phase 1 test with smart thermostat and smart node sensor data from Home J. The test was from July 16 – 27, 2022. The first subplot shows the measured and predicted enthalpy change, as well as the associated deviation. The second subplot shows the evolution of S (the CUSUM algorithm) for low indoor airflow and low charge due to their respective deviations.

The test result for this home looks similar to those obtained for OU lab-house. The first subplot shows a very large difference between the predicted and measured enthalpy change, causing very large deviations which far exceed the threshold. Hence the deviation markers were all red. Consequently, as shown in the second subplot, the low RC CUSUM increased rapidly and reached the CUSUM threshold a week after the start of the FDD algorithm. At the point where the low RC CUSUM marker hits the CUSUM threshold, the marker turned red to indicate that an installation fault has been detected, and the homeowner would be notified.

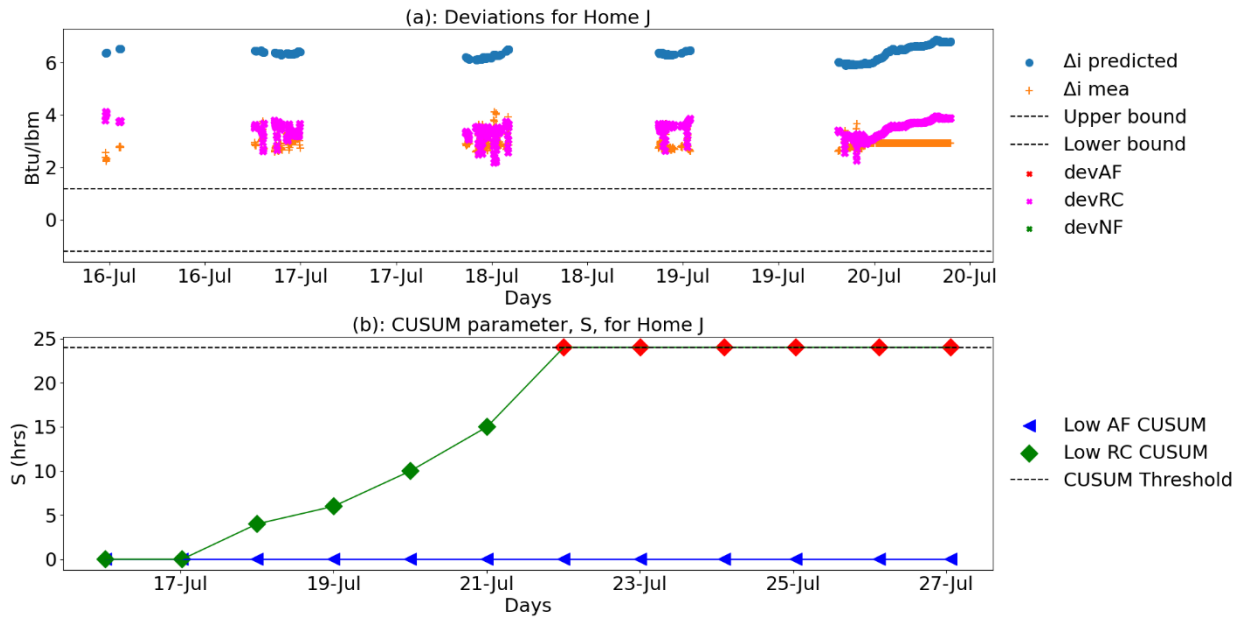


Figure 5.13: Real-time monitoring of Δi for Home J

Like with the OU lab-house, the reason for this large mismatch is believed to be due to the indoor/outdoor unit mismatch also identified for this home as shown in Table 2.3.

5.5.2 Phase 2: Real-time System Monitoring for Degradation Faults

As mentioned earlier, upon the completion of Phase 1 for each home, Phase 2 commences with the operation data from Phase 1 used to retrain the quadratic model which is then used to predict

enthalpy change to serve as benchmark for real-time monitoring of the AC system for low RC fault or low indoor airflow fault caused by degradation.

To confirm the ability of the proposed FDD method to detect degradation faults using the smart thermostat and smart node sensor data, a 30% low charge fault was manually created in OU lab-house by extracting 30% of the total refrigerant mass in the AC. For the other homes, the AC systems were simply monitored without attempting to intentionally introduce faults in them to avoid causing inconvenience to the occupants. Results on the tests for each of the homes are discussed in the subsequent sections.

5.5.2.1 OU Lab-House

Figure 5.14 shows the test results for real-time monitoring of the OU lab-house's AC system in Phase 2, using smart thermostat data and smart node sensor data. As mentioned earlier, a 30% low charge fault was manually created in the lab-house by extracting 30% of the total refrigerant mass in the AC on the evening of July 29, 2022. The AC system was thus operated with 70% refrigerant charge until the fault was detected on August 28, 2022. The first subplot shows the measured and predicted enthalpy change, as well as the associated deviation. The second subplot shows the evolution of S (the CUSUM algorithm) for low indoor airflow and low charge due to their respective deviations.

The first subplot shows a deviation of almost zero from July 26 – 28. This is because during this time the AC was still operated under normal conditions. However, this was added to the subplot to show the transition when the fault occurred. Then from July 30, after the AC had been discharged by 30%, the subplot shows a significant drop in Δi which caused significant deviations between the predicted and measured Δi . Hence the deviation exceeded the threshold bound for a significant portion. However, the performance of the method was not very impressive as observed

from the duration it takes for the fault to eventually be detected as indicated in the second subplot and discussed in the next paragraph.

Due to the deviations in the first subplot, there was a non-monotonic increase in the low RC CUSUM. However, the increase was slow between July 31 and August 18 and was rapid from August 18 – 23. From August 23 – 27, there was a slight decrease which switched to a rapid increase from August 27 – 28, bringing the low RC CUSUM to hit the CUSUM threshold on August 28. Therefore, it took approximately thirty days for the low charge fault to be eventually detected by the method.

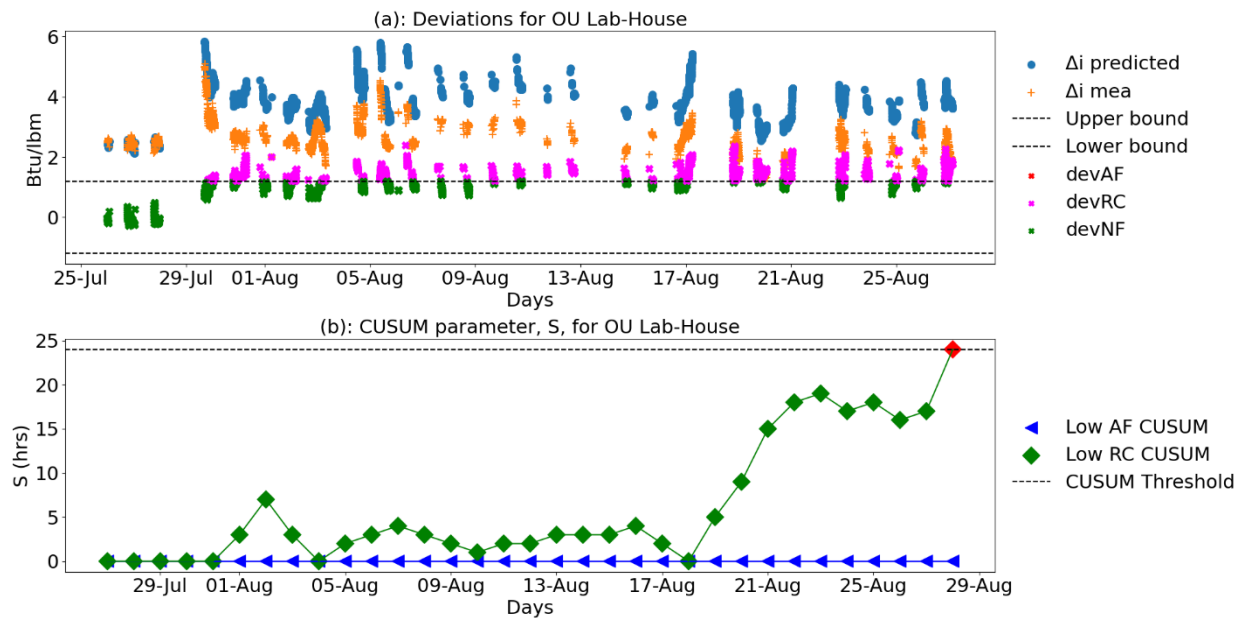


Figure 5.14: Real-time monitoring of Δi for OU Lab-House in Phase 2

The cause of the different increase rates in the subplot is likely due to the outdoor load on the AC system. Figure 5.15 shows the deviations in Δi alongside the corresponding outdoor air temperature (T_{oa}) plotted on the right y-axis. The plot suggests that for the most part, when T_{oa} is lower, the deviations ($devRC$) become bigger but smaller when T_{oa} drops.

Comparing this pattern with the pattern seen with the evolution of the low RC CUSUM in the second subplot of Figure 5.14, it can be seen that from July 31 – August 2, the monotonic increase in the low RC CUSUM is likely because there were more low Toa periods. But as Toa increases on August 2 and even further on August 3 to more than 100 F, the CUSUM reduced monotonically to zero on August 4. From August 4 – 18, there were more high Toa periods than low Toa periods which likely caused a non-monotonic evolution of CUSUM and brought it to zero on August 18. From August 18 – 23, there seem to be more low Toa periods which resulted in the rapid monotonic increase in the RC CUSUM.

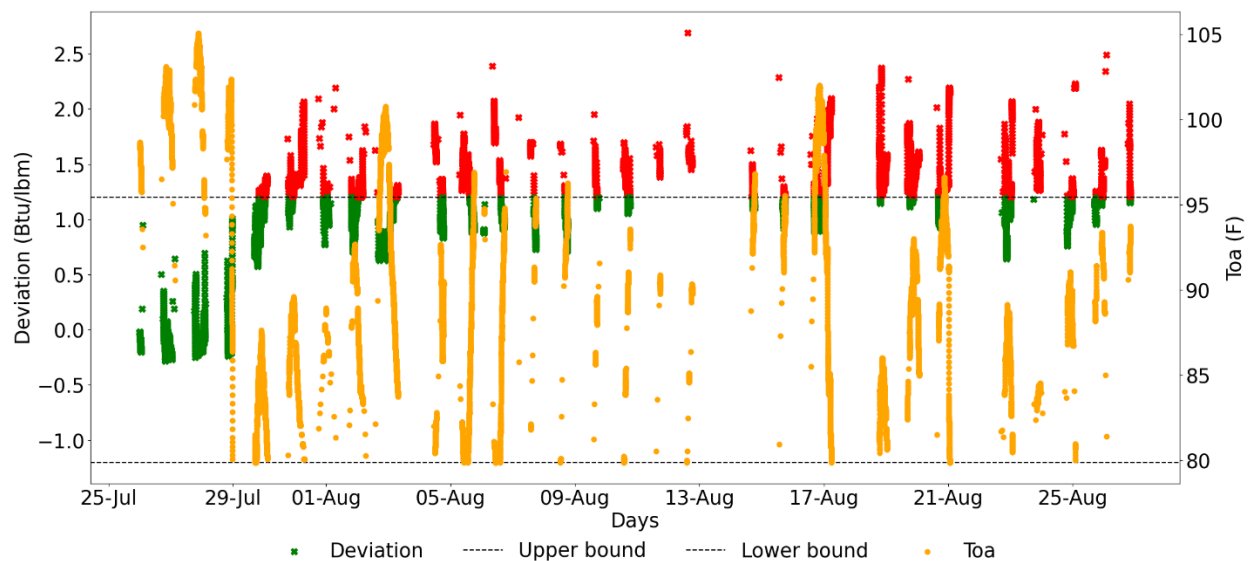


Figure 5.15: Comparison of the Deviations in Δi with the Outdoor Air Temperatures

While the observation and analysis made on Figure 5.15 may not be the only factor responsible for the different increase rates observed in the second subplot of Figure 5.14, it is more likely the reason. This can be explained further from the fact that an increase in Toa leads to an increase in the supply air temperature even in a fault-free system. So, for periods when Toa is high and the AC is operating under low charge, the increase in supply air temperature which mainly causes the

drop in Δi is driven by both the low charge and the high Toa. But when Toa is low, the increase in supply air temperature is mainly driven by the low charge, thus making the impact more visible under low outdoor load. This suggests that the performance of the FDD method improves as the outdoor load reduces.

5.5.2.2 Home A

Figure 5.16 shows the test results for real-time monitoring of Home A's AC system in Phase 2, using smart thermostat data and smart node sensor data. The system was monitored for over two months, from July 1 – September 11, covering the remaining Summer months for the year. This is because the FDD algorithm was designed for AC systems in cooling mode (which typically occurs during summer).

The first subplot of the figure shows the measured and predicted enthalpy change, as well as the associated deviation. The subplot shows that the deviations stayed within the threshold bounds for the most part during this period, with a few outliers indicated by the red markers. These outliers, however, did not affect the outcome of the FDD process as seen in the second subplot.

The second subplot shows the evolution of the S (the CUSUM algorithm) for low indoor airflow and low charge due to their respective deviations from the first subplot. Since most of the deviations were within the threshold bounds, there was no sustained increase in either of the CUSUMs that could lead to a suspected fault. The low RC CUSUM was zero for the entire period. The low AF CUSUM increased at some point but was reduced eventually to zero. These results indicate that there was no significant degradation (in terms of refrigerant leaks or dirty air filter) in the AC system for Home A.

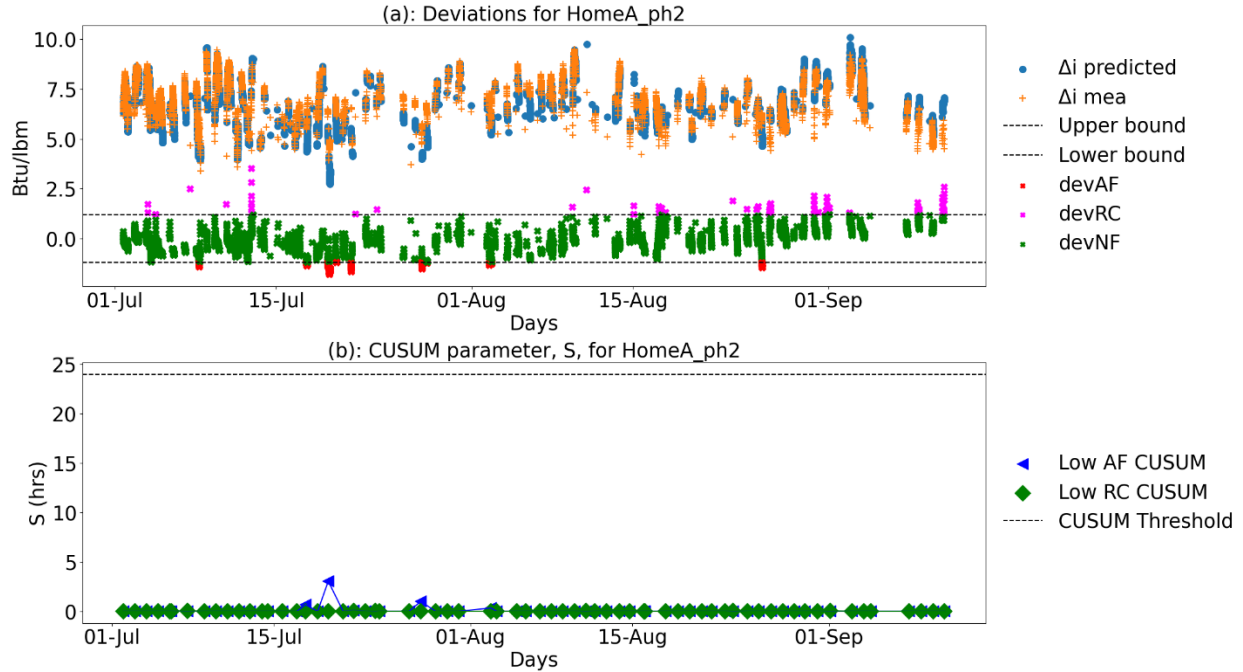


Figure 5.16: Real-time monitoring of Δi for Home A in Phase 2

5.5.2.3 Home I

Figure 5.17 shows the test results for real-time monitoring of Home I's AC system in Phase 2, using smart thermostat data and smart node sensor data. The system was also monitored for over two months, from July 1 – September 11.

The first subplot of the figure shows the measured and predicted enthalpy change, as well as the associated deviation. The subplot shows that the deviations stayed within the threshold bounds for the most part during this period, with a few outliers indicated by the red markers. These outliers, however, did not affect the outcome of the FDD process as seen in the second subplot.

The second subplot shows the evolution of the S (the CUSUM algorithm) for low indoor airflow and low charge due to their respective deviations from the first subplot. Since most of the deviations were within the threshold bounds, there were no sustained increase in either of the CUSUMs that could lead to a suspected fault. The low RC CUSUM was zero for the entire period.

The low AF CUSUM increased at some point but was reduced eventually to zero. These results indicate that there was no significant degradation (in terms of refrigerant leaks or dirty air filter) in the AC system for Home I.

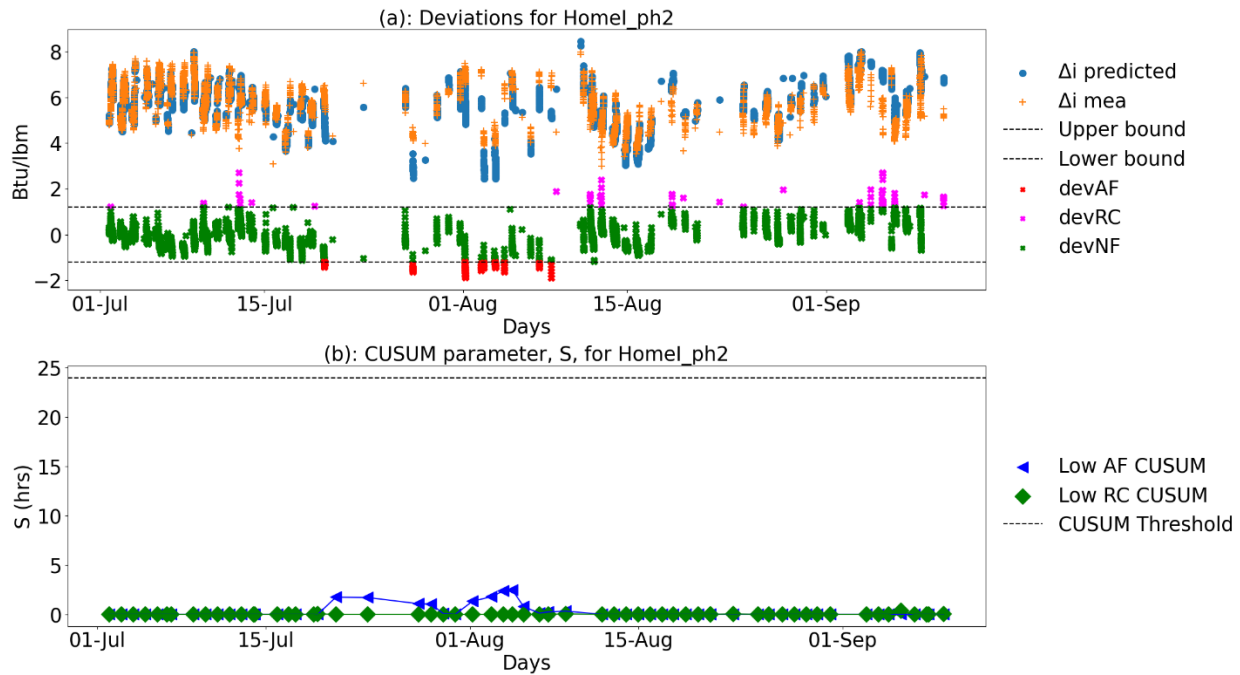


Figure 5.17: Real-time monitoring of Δi for Home I in Phase 2

5.5.2.4 Home J

Figure 5.17 shows the test results for real-time monitoring of Home J's AC system in Phase 2, using smart thermostat data and smart node sensor data. The system was monitored for slightly over a month, from August 5 – September 7.

The first subplot of the figure shows the measured and predicted enthalpy change, as well as the associated deviation. The subplot shows that the deviations stayed within the threshold bounds for the most part during this period, with a few outliers indicated by the red markers. These outliers, however, did not affect the outcome of the FDD process as seen in the second subplot.

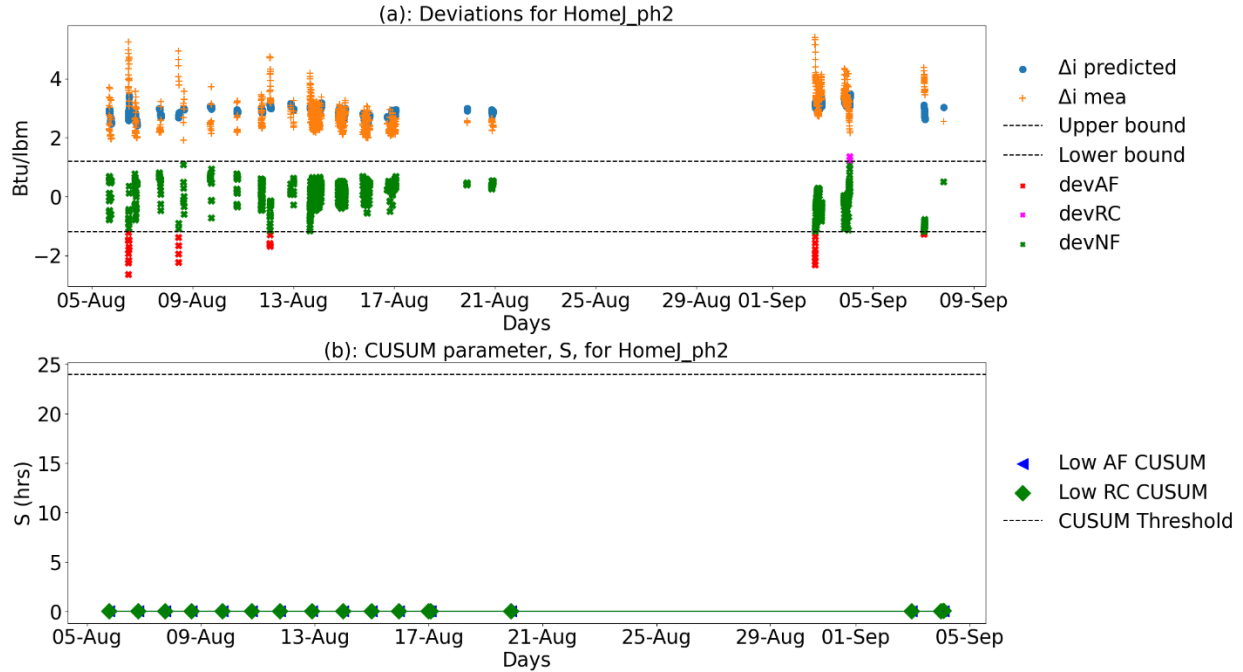


Figure 5.18: Real-time monitoring of Δi for Home J in Phase 2

The second subplot shows the evolution of S (the CUSUM algorithm) for low indoor airflow and low charge due to their respective deviations from the first subplot. Since most of the deviations were within the threshold bounds, there was no sustained increase in either of the CUSUMs that could lead to a suspected fault. The low RC CUSUM was zero for the entire period. The low AF CUSUM increased at some point but was reduced eventually to zero. These results indicate that there was no significant degradation (in terms of refrigerant leaks or dirty air filter) in the AC system for Home J.

5.6 Summary, Limitations and Recommendations

This chapter discussed a smart thermostat based FDD method that uses enthalpy change across the evaporator of an AC unit as a feature for detecting and diagnosing low charge and low indoor airflow faults in residential AC systems. Though the method requires the use of an additional sensor, leading brands like Ecobee offer smart thermostat options (like the Smart Thermostat

Premium) that come with a smart sensor which can be leveraged for the proposed FDD application. This smart sensor is usually connected to the smart thermostat, and so the proposed method is still regarded as a smart thermostat based FDD method.

The FDD method involves two phases. Phase 1 inspects the AC system for installation issues. Phase 2 inspects the AC system for degradation faults.

The method was first validated with experimental data from two different lab houses. The FDD method was then implemented in four different residential homes in Norman, Oklahoma (including a lab-house). The field test results demonstrate the prospects of the proposed FDD method to detect and diagnosis the faults considered. Even with the ± 1.2 Btu/lbm (or 22% IR) threshold which is relatively high, and suggested that only the AF70 and AF40 faults could be detected (Section 5.3.2), the results in Section 5.5.2.1 revealed that the RC70 could also be detected. Though, it took about a month for the RC70 fault to be detected. At lower thresholds or preferably more accurate measurements (especially for the supply air dew point temperature which was estimated), the RC70 fault can be detected faster. For instance, with the ± 0.6 Btu/lbm (or 10% IR), the RC70 fault can be detected in about five days as shown in Figure E- 6 in Appendix E. Meanwhile, other figures in Appendix E show that the ± 0.6 Btu/lbm (or 10% IR) threshold does not cause a false alarm with the help of the CUSUM algorithm.

Despite the prospects shown by the proposed FDD method, the following are some challenges/limitations with the method, as well as the associated recommendations:

1. Getting fault-free training data for Phase 1. This is a common challenge in most FDD methods in literature (both traditional and smart thermostat-based methods). Though this challenge was handled in this research by leveraging on the EPT data provided by AC

manufacturers, it was discovered that getting the relevant EPT data for some AC brands might be cumbersome. Therefore, to promote the advancement of the proposed FDD method into an adoptable technology in the residential market, studies on developing a cloud-based library of design data for different AC brands and specifications should be considered in future work. The AHRI (The Air Conditioning, Heating, and Refrigeration Institute) currently has a directory that almost meets this need. However, the directory is currently limited in terms of the level of data available. Future researchers can also explore enhancing the capacity of the existing AHRI directory.

2. The proposed method cannot diagnose high indoor airflow faults from low charge faults because both faults have similar impact on the enthalpy change feature used in the method. This also applies to low indoor airflow faults and refrigerant overcharge faults. This limitation can be handled by the addition of a power measuring device, based on the consideration that fan power is proportional to airflow rate. So, changes in the indoor airflow rate can be identified by changes in the fan power and this can be combined with the change in Δi to ascertain whether the fault is an airflow fault or a charge fault. Notwithstanding, the proposed FDD method is still very promising as low indoor airflow and low refrigerant charge are more prevalent than high indoor airflow and refrigerant overcharge.
3. The ± 1.2 Btu/lbm uncertainty threshold used for the proposed FDD method corresponds to a 22% IR threshold. This suggests that the uncertainty threshold used might be too high. The high value obtained from the uncertainty propagation analysis is due to the high uncertainties associated with the input data as shown in Table 5.3, as well as the approximations made in estimating the supply air dew point temperature.

4. The limitation of the smart node sensor to measuring only temperature was a challenge to the proposed FDD method. This challenge was addressed by estimating another thermodynamic property, namely: supply air dew point, which was then used to estimate the supply air enthalpy for the computation of the enthalpy change. Consequently, the detectability of the proposed method was affected by how accurate the supply air dew point estimate was. With measured data for the computation of the supply air enthalpy, improved performance of the FDD method can be achieved as suggested in Section 5.4. Therefore, it is recommended that smart thermostat manufacturers develop node sensors or similar measuring devices that not only measures temperature, but any additional thermodynamic property e.g., relative humidity. With such additional thermodynamic property, the actual supply air enthalpy can be computed.
5. The faults considered in this chapter are more like abrupt faults as they involve different fixed severities. In most cases in reality, fault severity is time-varying as depicted in Figure 4.1, rather than fixed. For the co-simulation study, a time-varying refrigerant leak fault was investigated. But such time-varying fault severity was not considered in this chapter, because it is challenging to design such experimentally for a constant speed AC system. Though slow refrigerant leak fault might be experimentally setup by slightly loosening the refrigerant cap, releasing refrigerant into the atmosphere may be a bridge against state regulations due to the environmental impact of refrigerants. For gradually reduced indoor airflow, this is even more challenging to design experimentally. A possible approach might be to use variable speed AC systems. For instance, variable speed indoor blower/fan can be used to vary the airflow rate. But the dynamics of such systems can affect the performance of the proposed FDD method.

Chapter 6: Summary, Conclusion and Recommendations

6.1 Summary

The objective of this work was to propose possible strategies for improving the performance of Smart thermostat-based FDD methods applied to residential air-conditioning (AC) systems.

Within the past decade, there have been increased research interest in the use of smart thermostat data to develop ‘sensorless’ FDD methods which are more cost effective than traditional FDD methods because of the additional costs incurred by the traditional methods for procuring relevant sensors. A review of the different methods that have been proposed for leveraging smart thermostat data for FDD is given in Chapter 1 of this dissertation. Based on the review, three major gaps were identified in the existing literature, namely:

1. Lack of studies evaluating the impact of uncontrollable building load disturbances (UBLDs) on Smart thermostat-based FDD methods.
2. Lack of standardized evaluation methods/metrics for Smart thermostat-based FDD methods.
3. Lack of Smart thermostat-based studies on fault diagnosis.

To address these gaps, the following hypotheses were proposed in Chapter 1 of this dissertation and investigated in the course of this work:

1. The use of an integrated model which couples the building dynamics and the AC dynamics together, and contains representative models for infiltration mechanism, occupancy behavior, thermostat features, etc., can be used to evaluate the impact of UBLDs on AC operation and by extension Smart thermostat-based FDD methods.

2. The combination of existing performance evaluation metrics like thresholds, false positive rate (FPR) and false negative rate (FNR) with metrics like signal-to-noise ratio (SNR) can serve as standardized evaluation metrics for smart thermostat-based FDD methods.
3. Enthalpy change (Δi) across the evaporator of an AC system can be processed from smart thermostat-data and its node sensor and used to perform diagnosis of two prevalent faults (low charge and low indoor airflow) in residential AC systems.

Some aspects of the review done in Chapter 1 of this dissertation have been published in: Ejenakevwe, K. A., & Song, L., 2022. "Review of Fault Detection and Diagnosis Studies on Residential HVAC Systems." *Proceedings of the ASME International Mechanical Engineering Congress and Exposition. Volume 8B: Energy*. <https://doi.org/10.1115/IMECE2021-72745>.

Chapter 2 describes the methodology used for the research which includes a description of the FDD features used, the data types, the faults and fault severities, and a brief introduction of two strategies proposed in this research for improving the performance of smart thermostat-based FDD methods. Two features were considered, namely: duty factor which is commonly used in smart thermostat-based FDD methods; and enthalpy change which is a new feature proposed and used for the first time in this research. A description of the model used for predicting this new feature was also presented in this chapter and a sensitivity analysis was conducted to compare the performance of this new feature with previously used features like the duty factor and cooling capacity.

Chapter 3 discussed the investigation of UBLD impact on AC operation. It begins with the design of the respective UBLDs from people gain, infiltration gain, and thermostat setpoint. The UBLDs were then used to develop eight case studies (including a baseline case). These UBLDs were used to typify the dynamics of occupants, weather and thermostat settings which can potentially affect

the dynamics of AC systems during operation in buildings. The chapter also discussed the development and validation of a novel co-simulation testbed which combines modelica and EnergyPlus to couple the different dynamics (like building dynamics, AC dynamics, infiltration dynamics, etc) into an integrated system. This testbed presents a more representative model for a building/AC system, than those in the existing literature for both traditional and smart thermostat-based FDD. Traditional FDD methods typically focus on just the AC dynamics because the FDD features used in these methods are system based e.g., the degree of AC subcool, the pressures of the refrigerant in the AC, the refrigerant mass flow rate, etc. But, for smart thermostat-based methods, the available FDD features are building related. Therefore, a proper coupling of the dynamics of the building and AC together is important. This has, however, not been done in previous studies. Furthermore, the chapter discussed the development and validation of a novel automated calibration framework which uses genetic algorithm for AC calibration, and 2R2C model for building envelope calibration. With the validated co-simulation testbed, the eight cases were simulated under an ideal scenario and a real scenario, providing relevant data for investigating the impact of the designed UBLDs on AC operation. The main findings from this investigation are that UBLDs have significant impact on AC operation in terms of cost as well as causing changes to the commonly used duty factor FDD feature, which can compromise the reliability of FDD methods. It also proposed reasonable thresholds and techniques like the CUSUM technique, which can be used to mitigate UBLD impact. The automated calibration framework presented in this chapter has the following draft manuscript *K. A. Ejenakevwe, L. Xie, J. Wang, R. Hurt, and L. Song, "An Automated Framework Based on RC Model and GA Optimization for Calibrating Coupled Residential Buildings and HVAC Systems," Journal of*

Building & Environment. Manuscript number: BAE-D-25-00749. <http://ssrn.com/abstract=5122637>, currently under review.

Chapter 4 extended the work in Chapter 3 to compare the impact of the most severe UBLD from Chapter 3 to the impact of different faults in residential AC systems. The two prevalent faults at different severities were used to develop nine cases (including the baseline case and the worst UBLD case) for the comparative study. The validated co-simulation testbed from Chapter 3 was used to simulate these cases under the ideal and real scenario, thereby generating data for evaluating the respective performance of an FDD method that uses duty factor and enthalpy change as FDD feature. The evaluation was done using impact ratio (IR), FNR and SNR. The main conclusion of the comparative analysis and evaluation is that the FDD method using enthalpy change performed significantly better than the method using duty factor, in terms of effectiveness, capability and reliability. Some aspects of this chapter and Chapter 4 have been published in: K. A. Ejenakevwe and L. Song, 2024. “Investigation of smart thermostat fault detection and diagnosis potential for air-conditioning systems using a Modelica/EnergyPlus co-simulation approach,” *Energy & Buildings*, vol. 309, doi: 10.1016/j.enbuild.2024.114053. Three journal manuscripts are also currently being drafted from the results in this chapter.

In Chapter 5, the enthalpy-change FDD feature which was proven to be more effective than the duty factor FDD feature was used to develop a novel smart thermostat-based FDD method that can both detect and diagnose low indoor airflow fault and low charge fault. Previous smart thermostat-based FDD methods could only detect faults but were unable to identify the cause of the fault. But with this method, the cause of the fault can be identified in addition to detecting the fault. The method however involves the use of an additional sensor which is provided by some manufacturers. The method was validated and tested in four residential homes and demonstrated

the potential to detect and diagnose these two prevalent faults. An aspect of this chapter is published in K. Ejenakevwe, J. Wang, and L. Song, 2022. “*Investigation of an IoT-Based Approach for Automated Fault Detection in Residential HVAC Systems,*” *ASHRAE Transactions*, vol. 128, no. 2. Another aspect is published in K. A. Ejenakevwe, J. Wang, Y. Jiang, L. Song, and R. L. Kini, 2023. “*Automated fault detection and diagnosis of airflow and refrigerant charge faults in residential HVAC systems using IoT-enabled measurements.,*” *Science and Technology for the Built Environment*, vol. 0, no. 0, doi: 10.1080/23744731.2023.2234231.

6.2 Conclusion

The following conclusions are drawn from the research discussed in this dissertation:

1. Uncertainties in occupancy, infiltration and thermostat setpoint schedules significantly affect AC operation in a manner that can compromise the reliability of smart thermostat-based FDD methods, if they are unaccounted for in such methods.
2. Setting appropriate thresholds is an effective way to handle the uncertainties in #1. But a more effective way is by using FDD feature processing techniques like the CUSUM technique described and used in this work.
3. The combination of evaluation metrics like the false negative rate (FNR) and the signal-to-noise ratio (SNR) is very helpful in proper evaluation of the performance of an FDD method.
4. An optimal FDD feature that can significantly improve the performance of smart thermostat-based FDD methods is the enthalpy change across the evaporator. Though this feature requires an additional sensor which may already be available with the smart thermostat purchased by a homeowner. Otherwise, it can be procured for less than \$50 and easily installed by a homeowner for the FDD application.

5. In addition to improving the performance of smart thermostat-based FDD methods, the proposed feature in #4 also extends the capability of the current state-of-the-art of smart thermostat-based FDD beyond just detection to diagnosis.
6. This research also demonstrates the need for FDD developers to come up with and incorporate algorithms into their tools that can detect not just faults, but also irregularities in the dynamics of buildings (called UBLDs in this dissertation) thereby potentially saving homeowners significant operation cost, especially if rates increase in the future.

6.3 Recommendations

Based on the research conducted, presented and discussed in this dissertation, the following questions and recommendations are posed for future work:

1. How effective is the proposed enthalpy-based smart thermostat-driven FDD method in detecting and diagnosing gradual refrigerant leaks and gradual indoor airflow faults in reality? As these faults are more typical, there is need to explore ways to design experiments to test the performance of the proposed method in detecting and diagnosing these faults. This will help promote the concept of smart thermostat-based FDD in the residential market.
2. Studies on developing a cloud-based library of design data for different AC brands and specifications should be considered in future work. The AHRI (The Air Conditioning, Heating, and Refrigeration Institute) currently has a directory that almost meets this need. However, the directory is currently limited in terms of the level of data available. Collaborations with industry and societies like ASHRAE, AHRI, etc., can make this achievable.

3. The proposed enthalpy-based smart thermostat-driven FDD method relies on the assumption that the smart thermostat is properly located within the building. However, this might not be the case in some homes. Therefore, studies on the effect of thermostat location on the performance of the proposed method are recommended for future work. One way such study can be done is by using a computational fluid dynamic (CFD) based thermal zone model in the co-simulation testbed developed in this research (Section 3.2) instead of the EnergyPlus based thermal zone model which assumes a fully mixed air.
4. Smart node sensors that can measure temperature and any other thermodynamic property (e.g., relative humidity) should be manufactured by smart thermostat manufacturers. Currently, there are no such sensors which are compatible with existing smart thermostats. The availability of such will significantly improve the performance of the proposed enthalpy-based smart thermostat-driven FDD method and promote the concept of smart thermostat-based FDD in the residential market
5. Research on ways of integrating UBLD detection into smart thermostat based FDD framework can also help promote the concept of smart thermostat-based FDD in the residential market. This can be pursued by collaborative efforts with on-going research on occupancy prediction and so on.
6. Research on how to use the FDD results to quantify the fault impact is also vital because it will help homeowners and technicians to make better decisions on how to respond to a fault alarm. For instance, if the IR or deviation can be used to ascertain the fault severity, that can help to estimate the potential impact and serve as a basis to decide whether to tolerate or address a fault.

7. Research on the development of standard FDD evaluation tools that incorporate the metrics proposed in this work, which can be used to evaluate the performance of different FDD protocols. Just like the FDD evaluator web app [181] developed by Yuill et al. [50] for traditional FDD in unitary AC systems.

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Appendices

Appendix A UBLD Impact Ratio (IR) Plots Against Threshold

The plots in this appendix show the impact of the different cases discussed in Section 3.6.2 with respect to different thresholds.

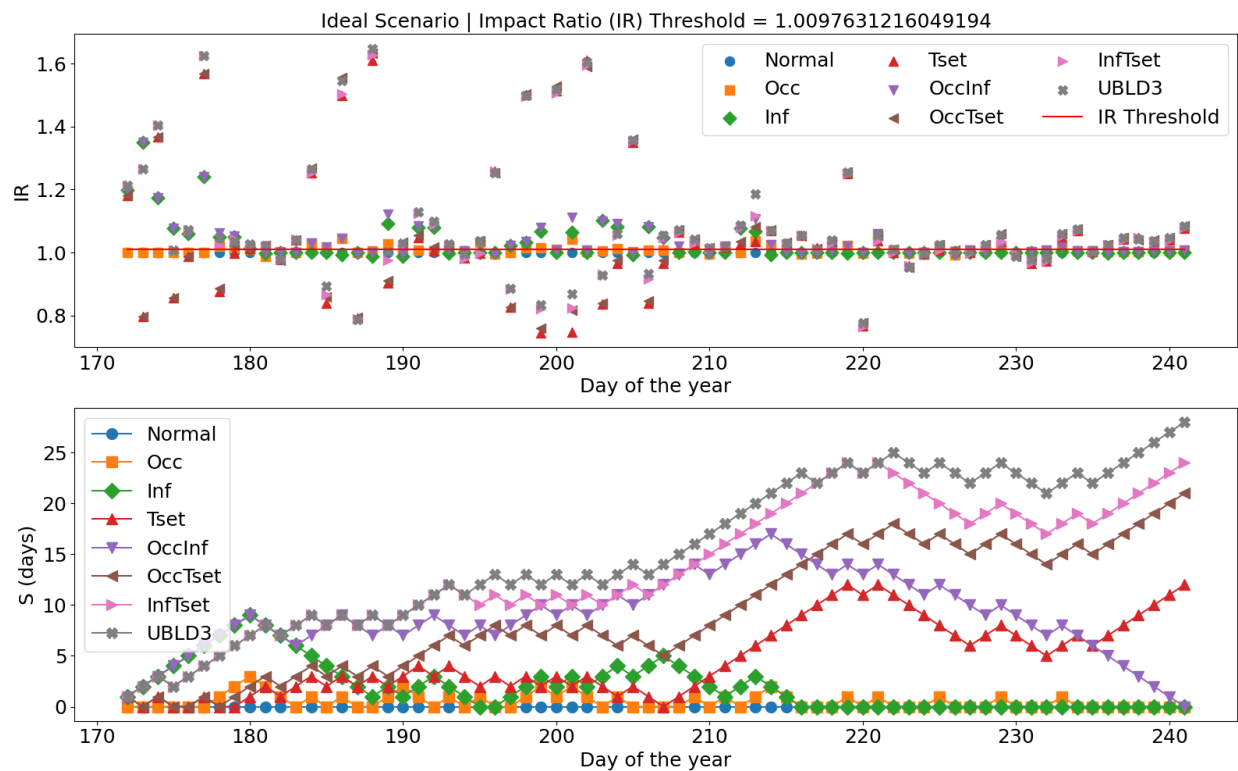


Figure A- 1: UBLD IR for Ideal Scenario with a threshold of 1.01 using Duty Factor

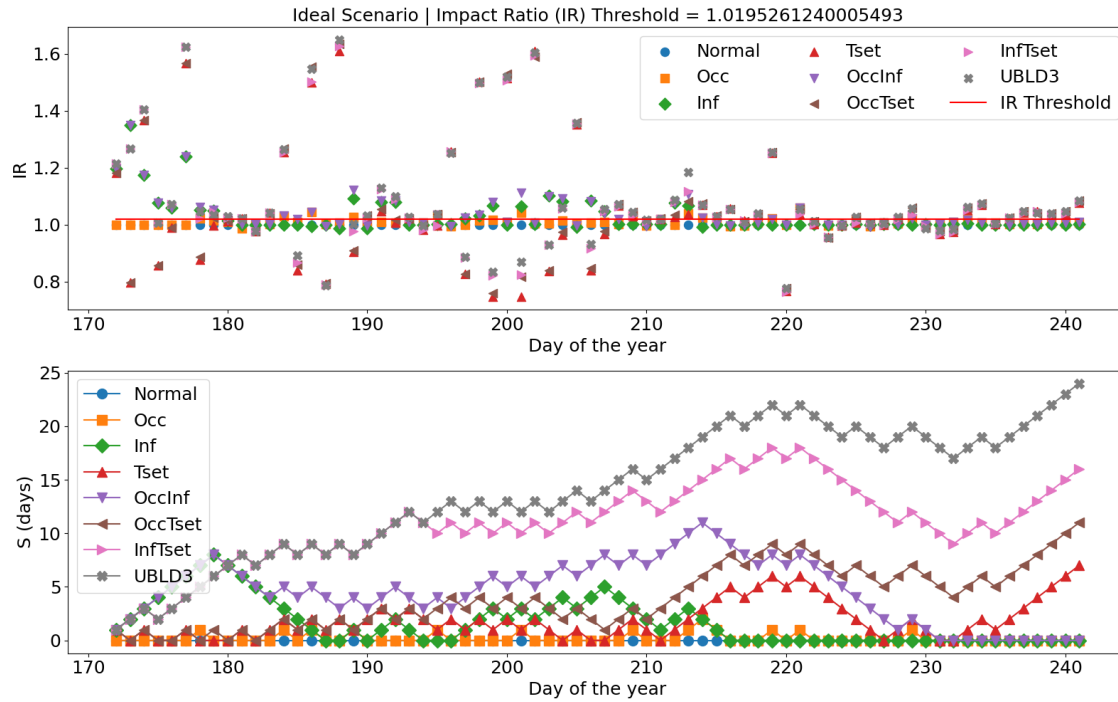


Figure A- 2: UBLD IR for Ideal Scenario with a threshold of 1.02 using Duty Factor

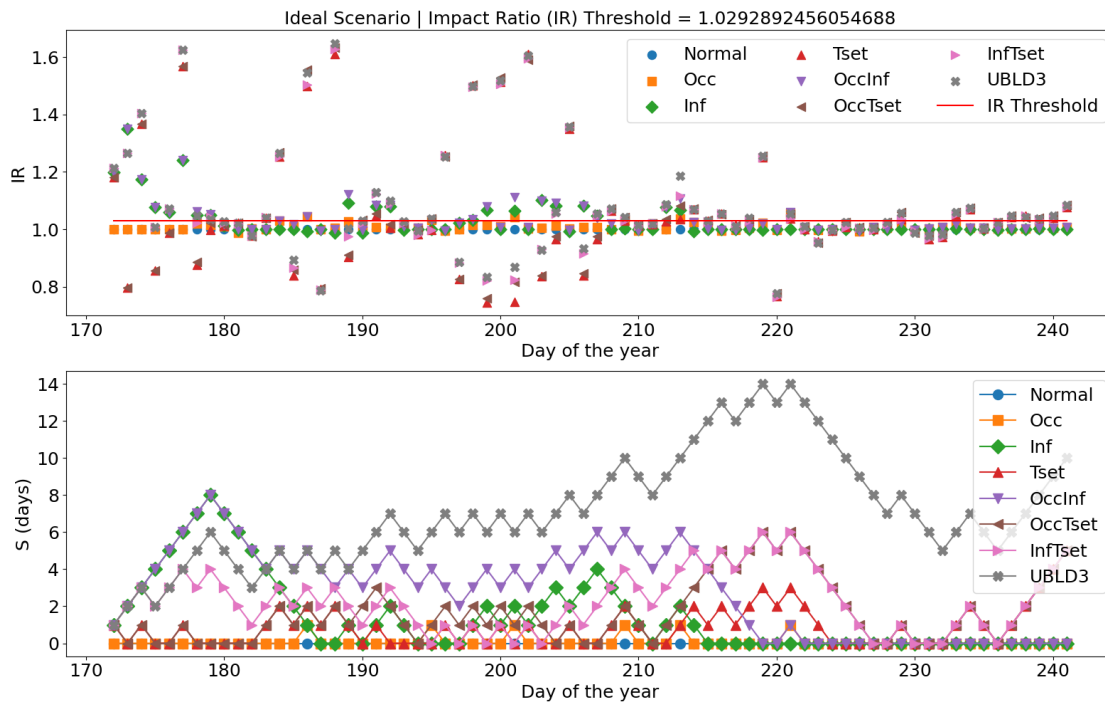


Figure A- 3: UBLD IR for Ideal Scenario with a threshold of 1.03 using Duty Factor

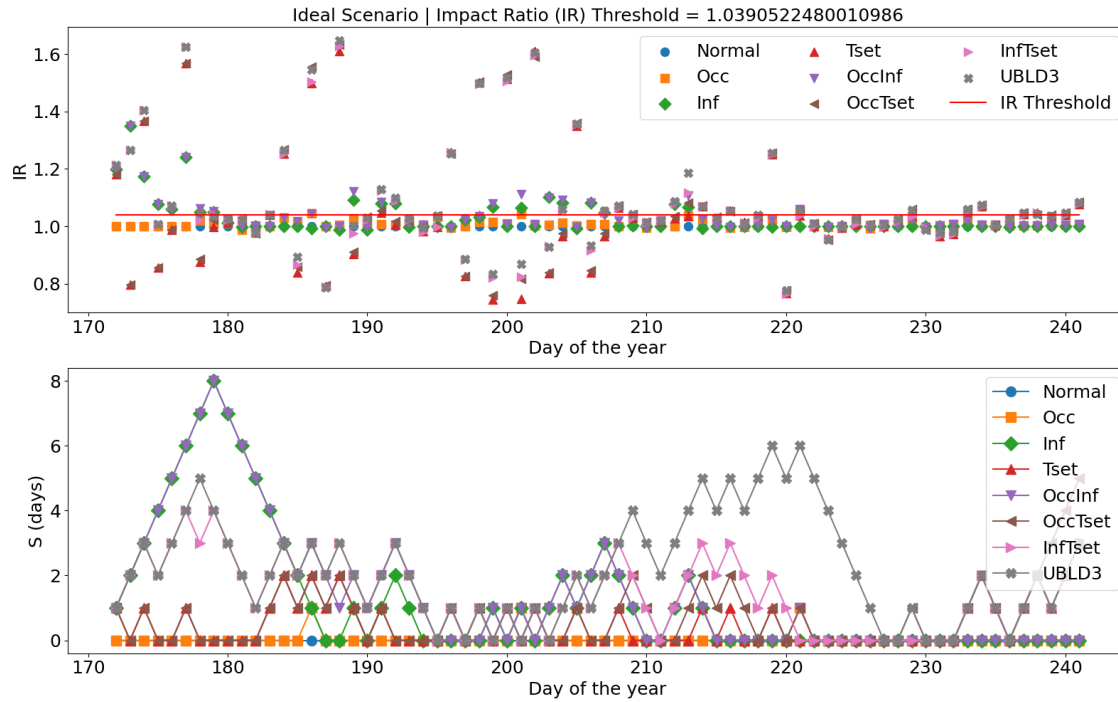


Figure A- 4: UBLD IR for Ideal Scenario with a threshold of 1.04 using Duty Factor

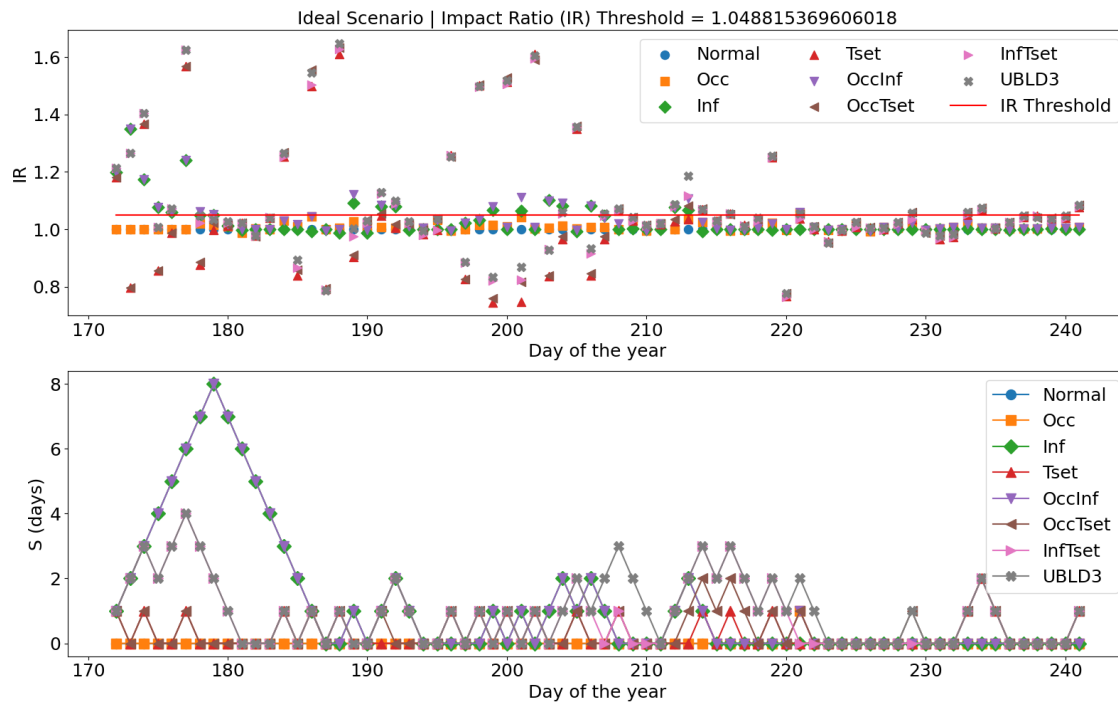


Figure A- 5: UBLD IR for Ideal Scenario with a threshold of 1.05 using Duty Factor

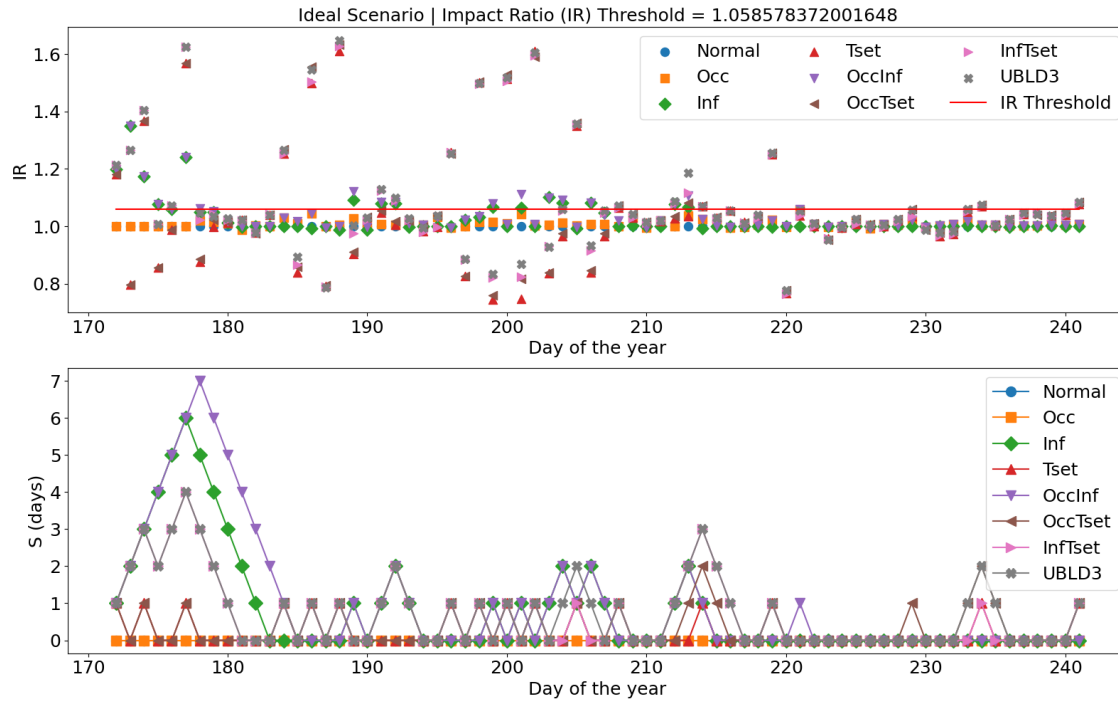


Figure A- 6: UBLD IR for Ideal Scenario with a threshold of 1.06 using Duty Factor

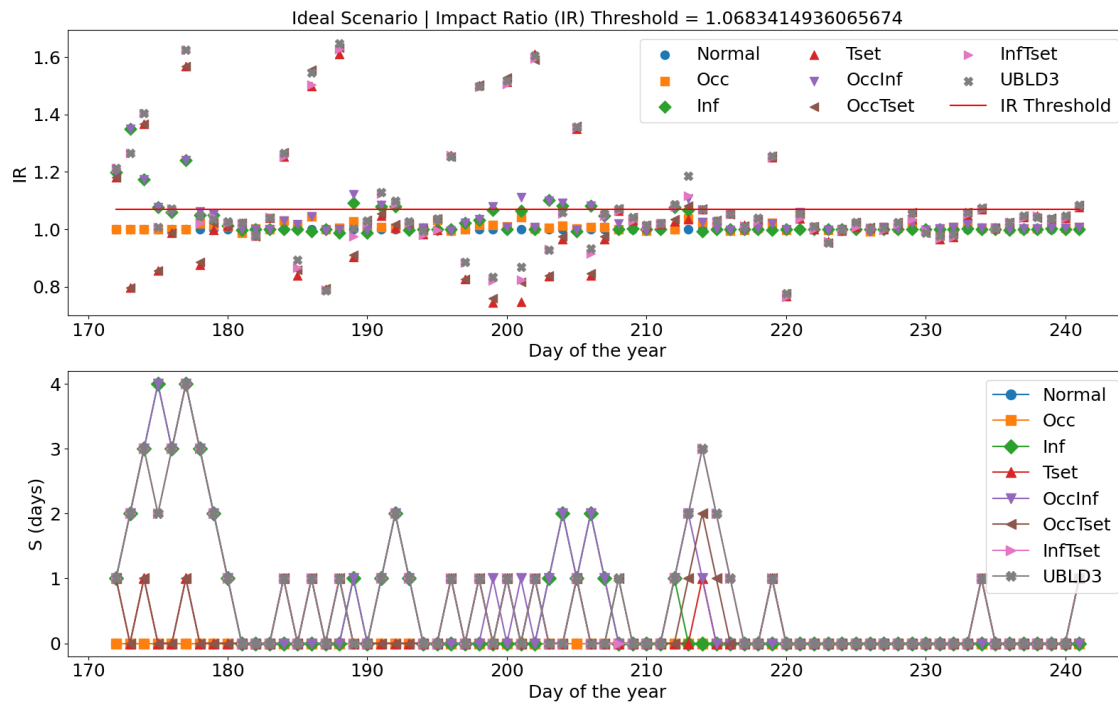


Figure A- 7: UBLD IR for Ideal Scenario with a threshold of 1.07 using Duty Factor

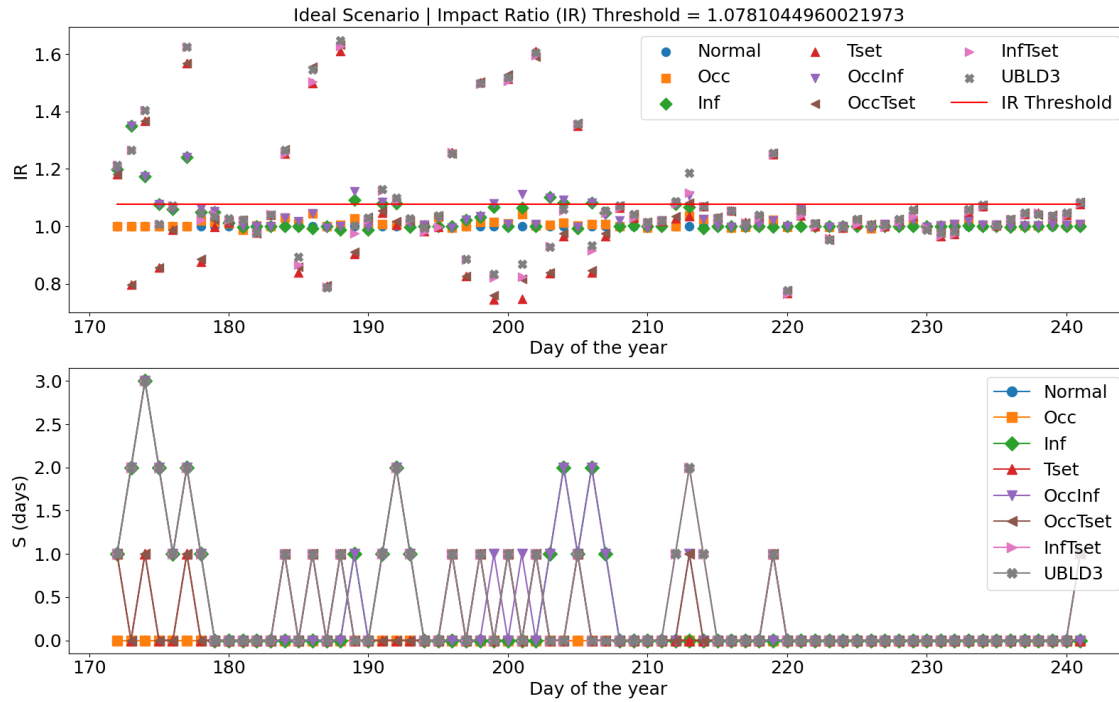


Figure A- 8: UBLD IR for Ideal Scenario with a threshold of 1.08 using Duty Factor

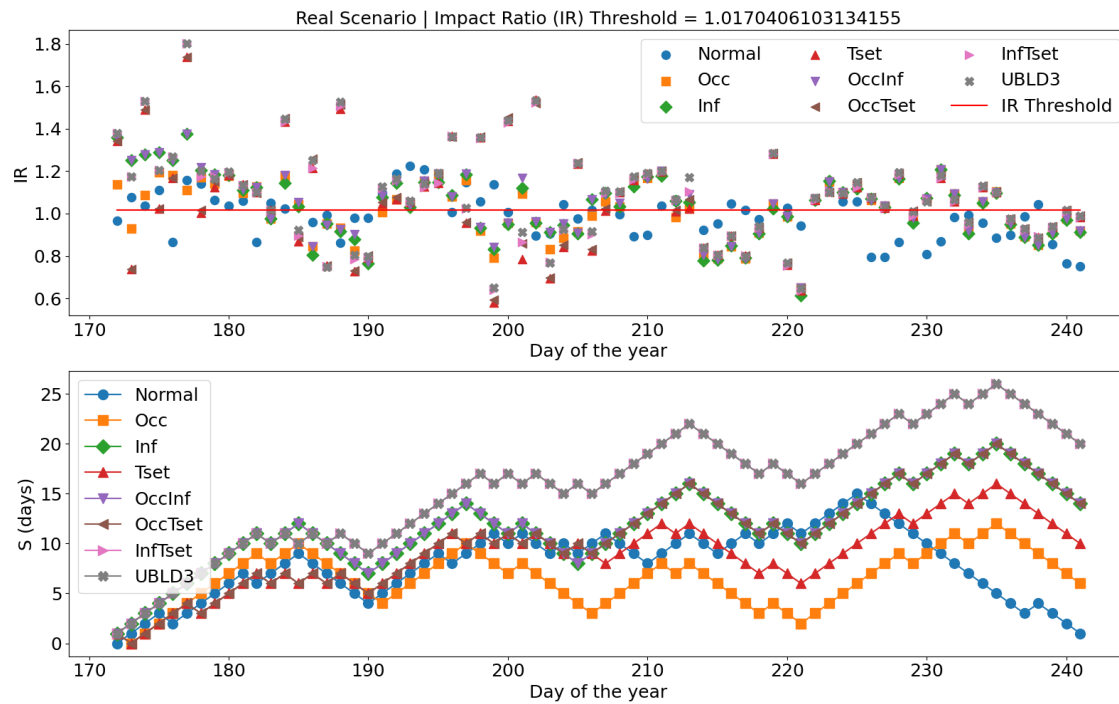


Figure A- 9: UBLD IR for Real Scenario with a threshold of 1.02 using Duty Factor

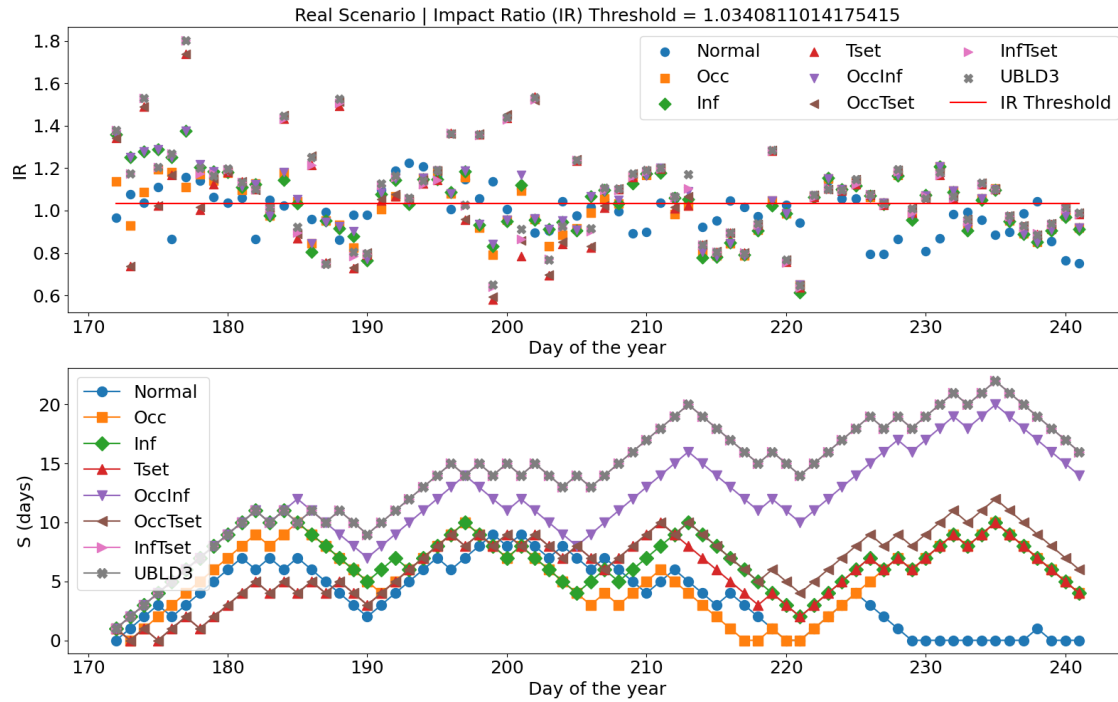


Figure A- 10: UBLD IR for Real Scenario with a threshold of 1.03 using Duty Factor

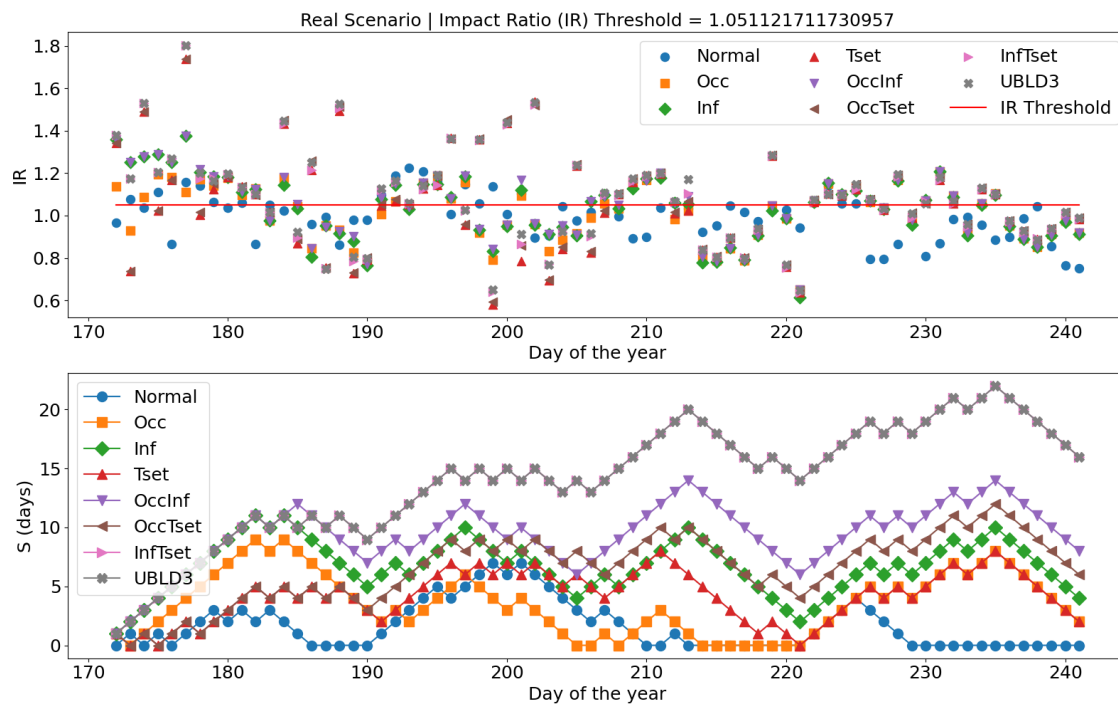


Figure A- 11: UBLD IR for Real Scenario with a threshold of 1.05 using Duty Factor

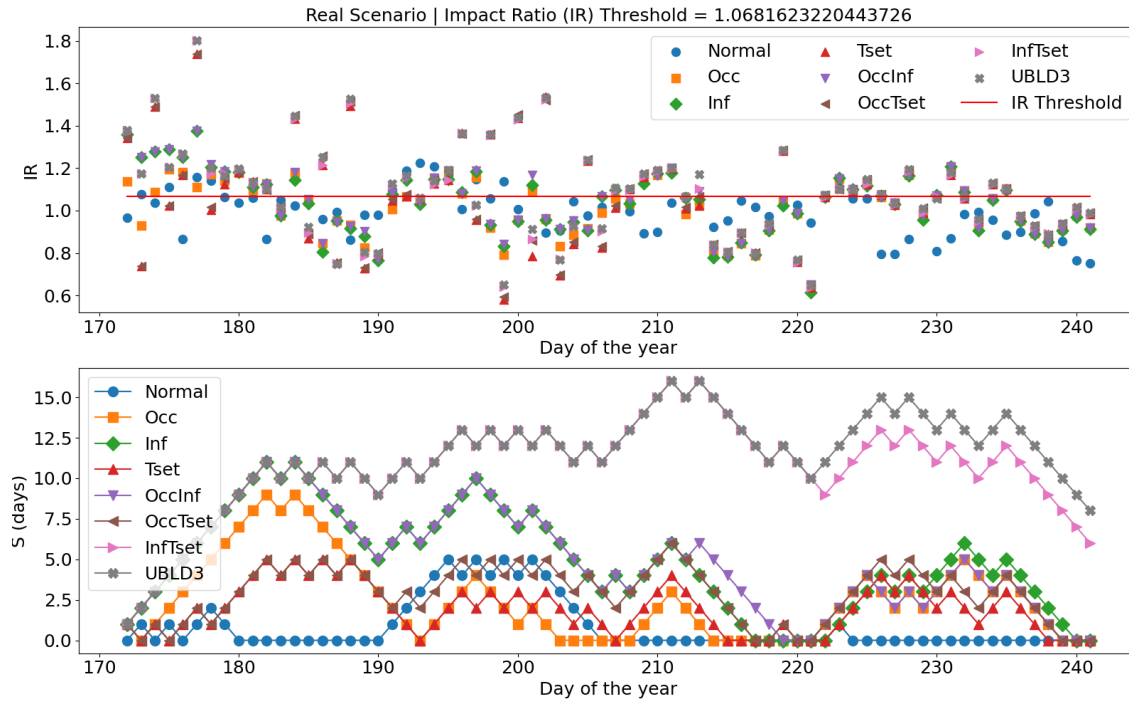


Figure A- 12: UBLD IR for Real Scenario with a threshold of 1.07 using Duty Factor

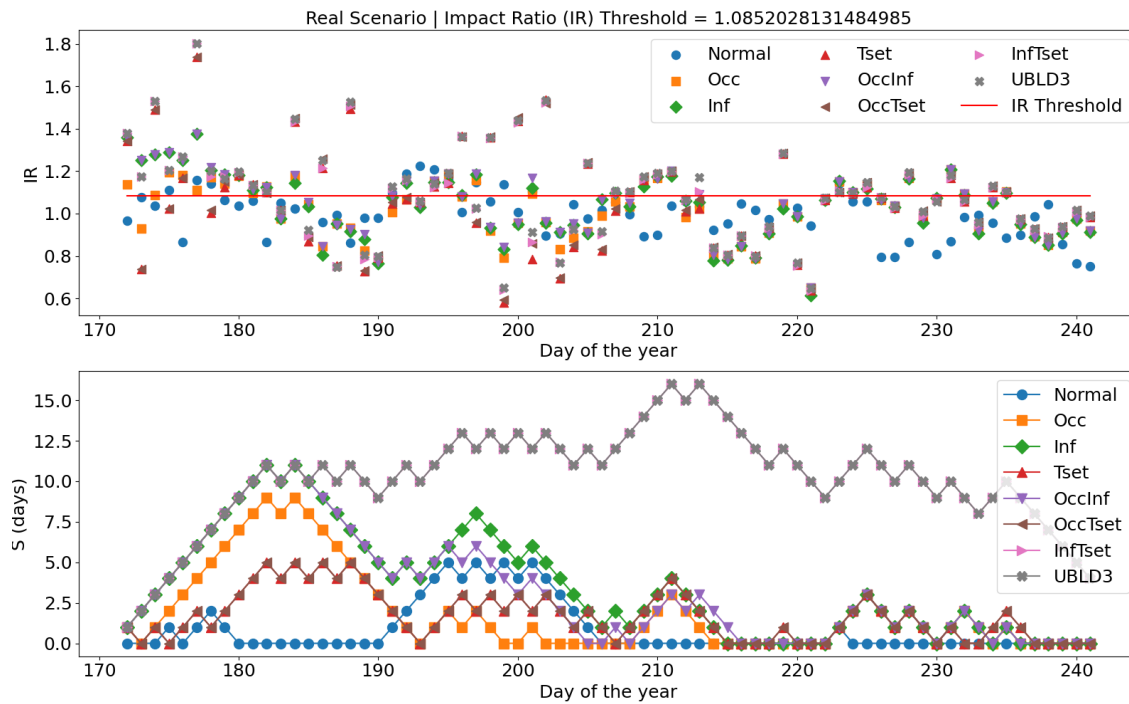


Figure A- 13: UBLD IR for Real Scenario with a threshold of 1.09 using Duty Factor

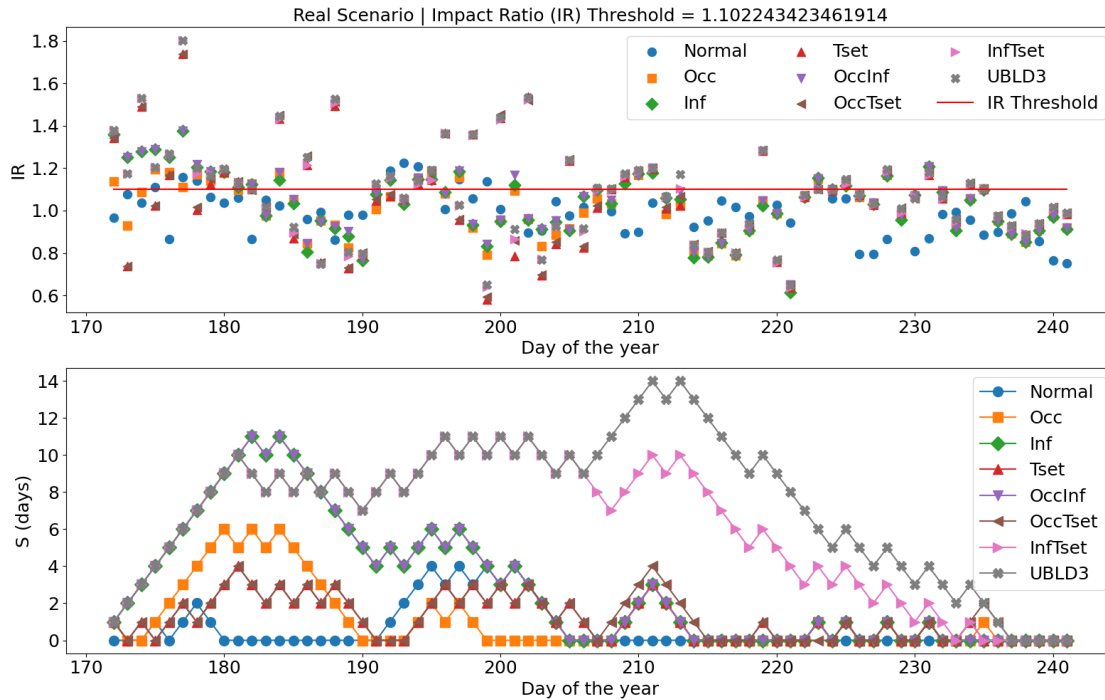


Figure A- 14: UBLD IR for Real Scenario with a threshold of 1.10 using Duty Factor

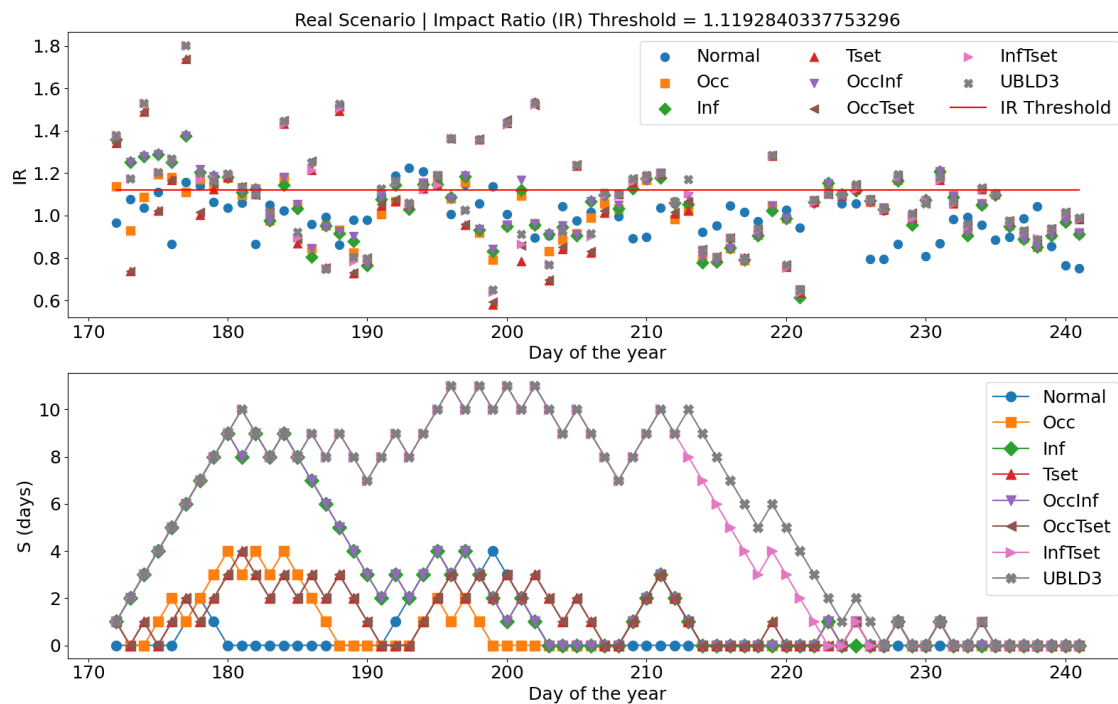


Figure A- 15: UBLD IR for Real Scenario with a threshold of 1.12 using Duty Factor

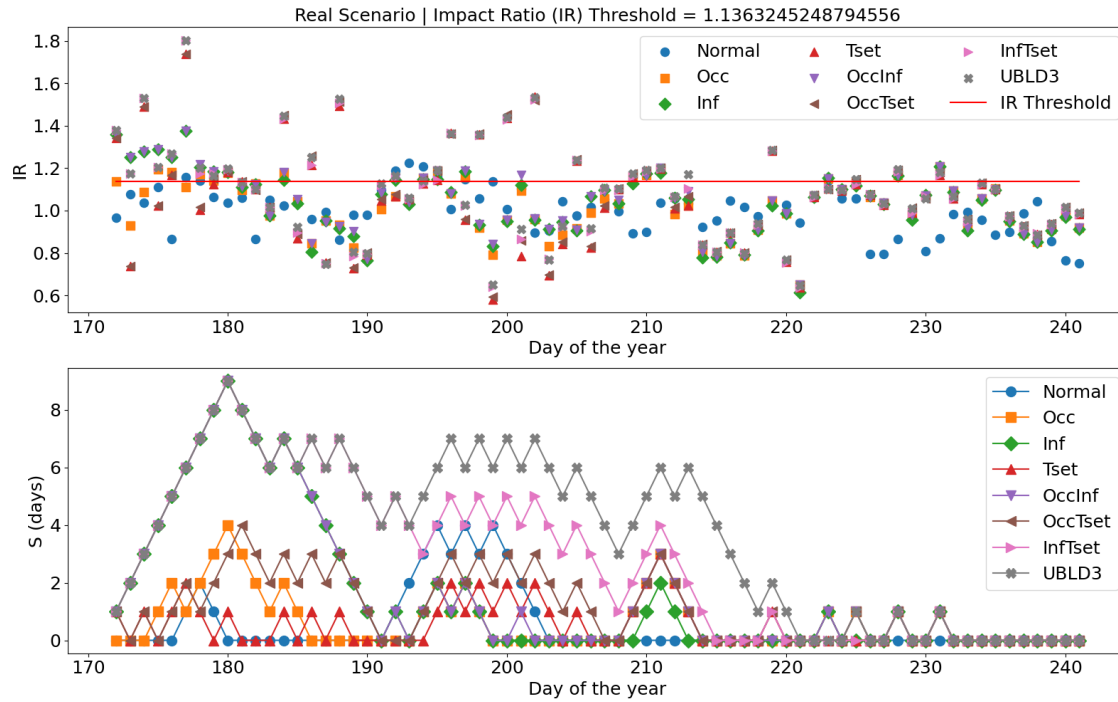


Figure A- 16: UBLD IR for Real Scenario with a threshold of 1.14 using Duty Factor

Appendix B Duty Factor Fault Impact Ratio Plots Against Threshold

The plots in this appendix show the impact of the different cases discussed in Section 4.2.1 with respect to different thresholds.

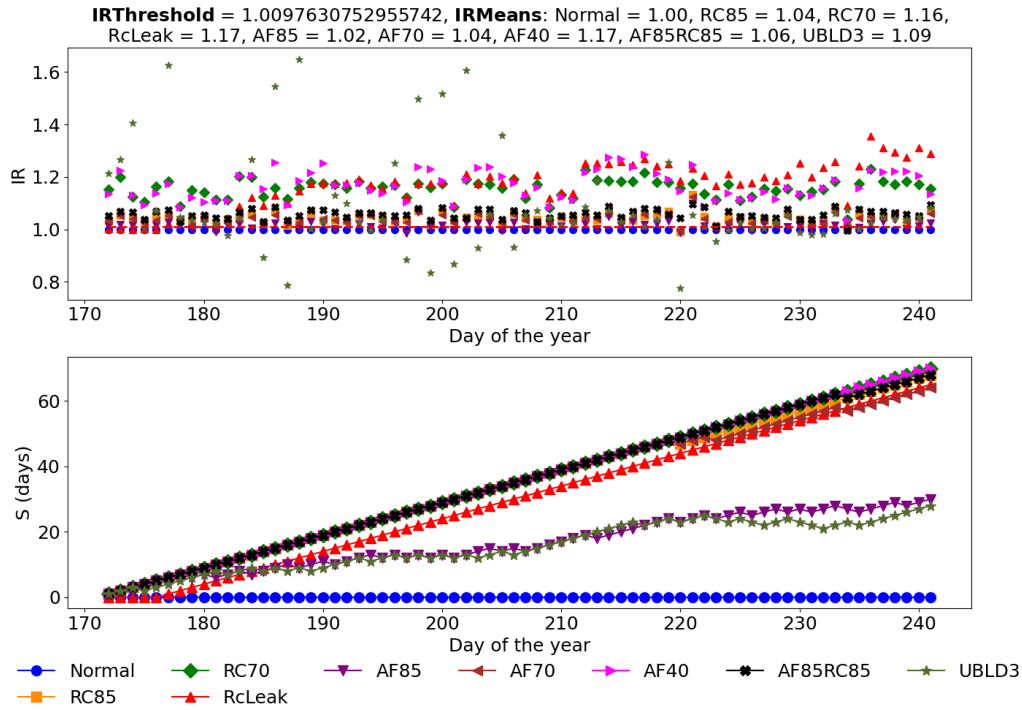


Figure B- 1: Fault IR for Ideal Scenario with a threshold of 1.01 using Duty Factor

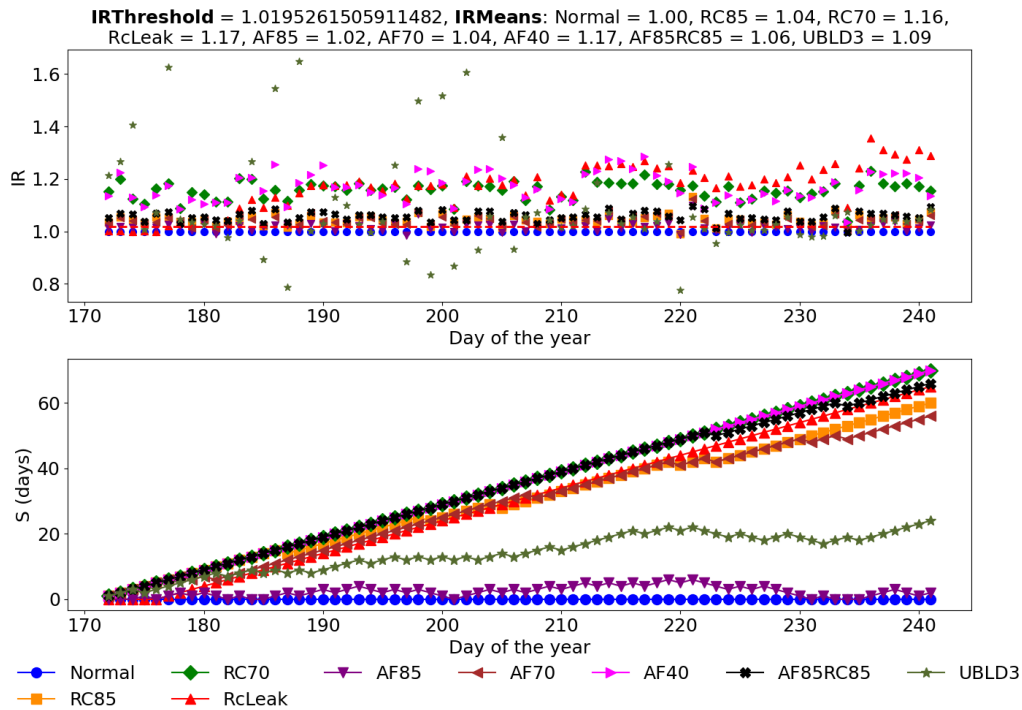


Figure B- 2: Fault IR for Ideal Scenario with a threshold of 1.02 using Duty Factor

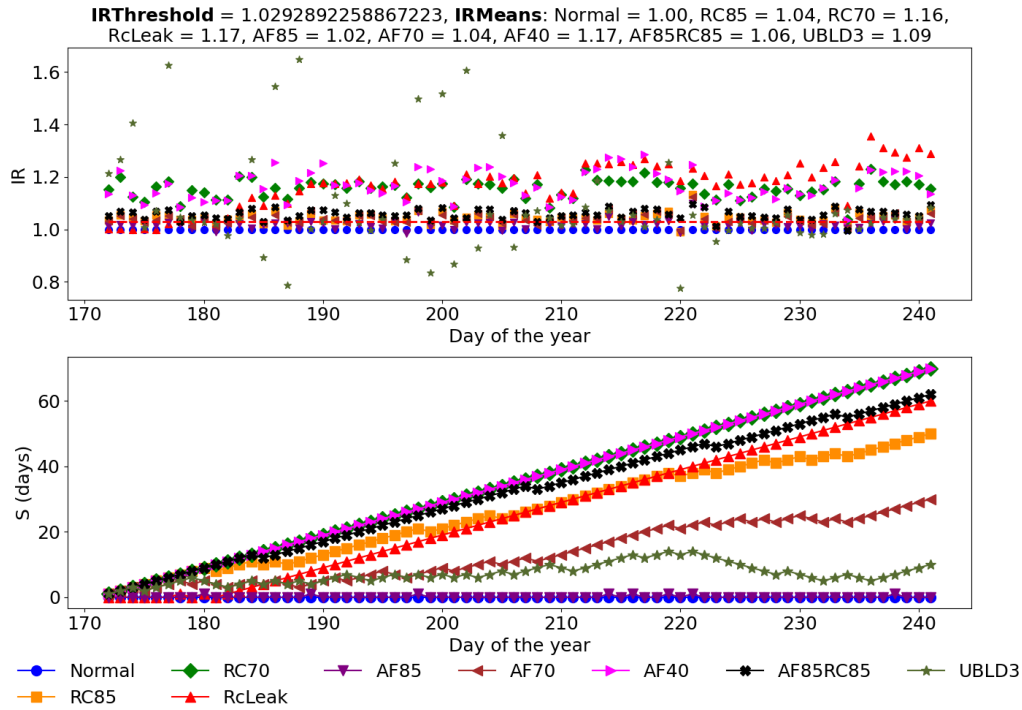


Figure B- 3: Fault IR for Ideal Scenario with a threshold of 1.03 using Duty Factor

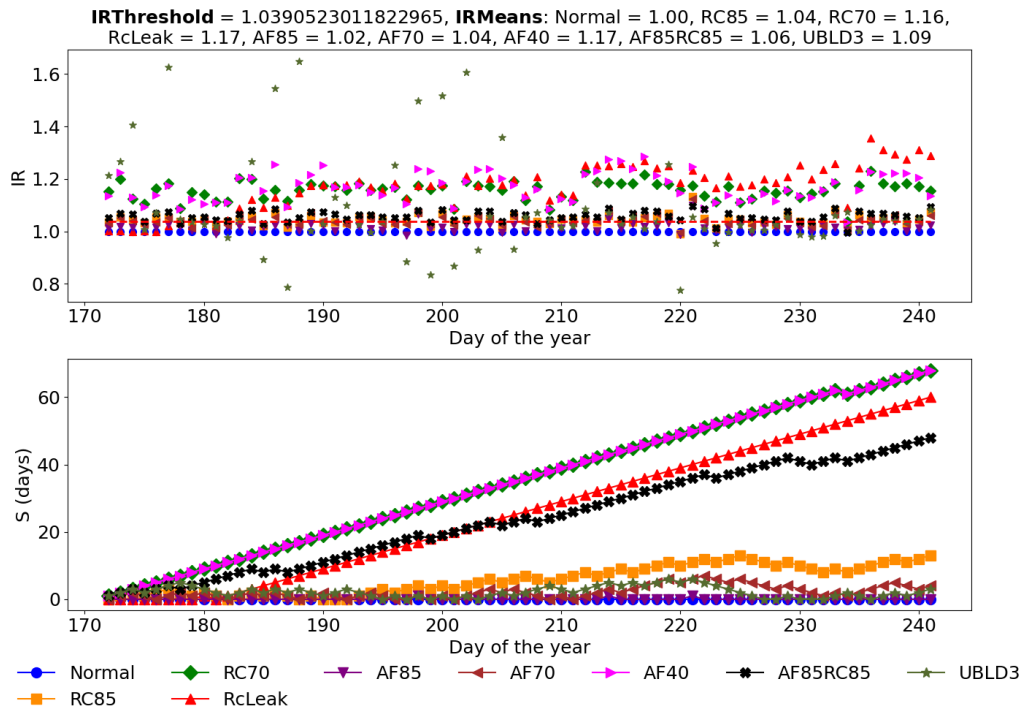


Figure B- 4: Fault IR for Ideal Scenario with a threshold of 1.04 using Duty Factor

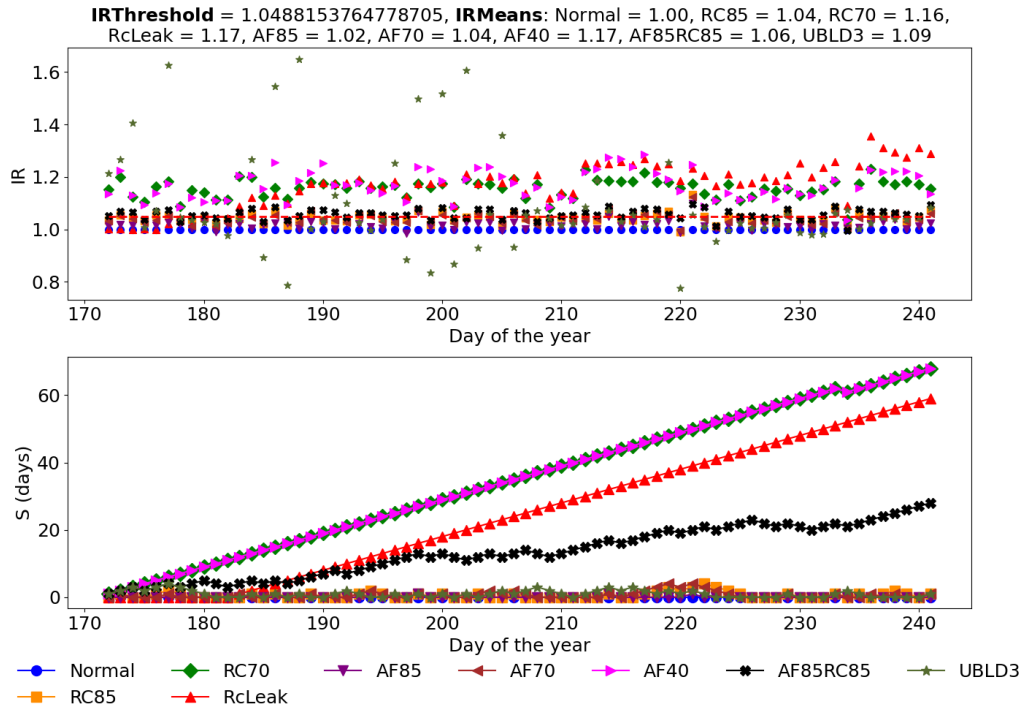


Figure B- 5: Fault IR for Ideal Scenario with a threshold of 1.05 using Duty Factor

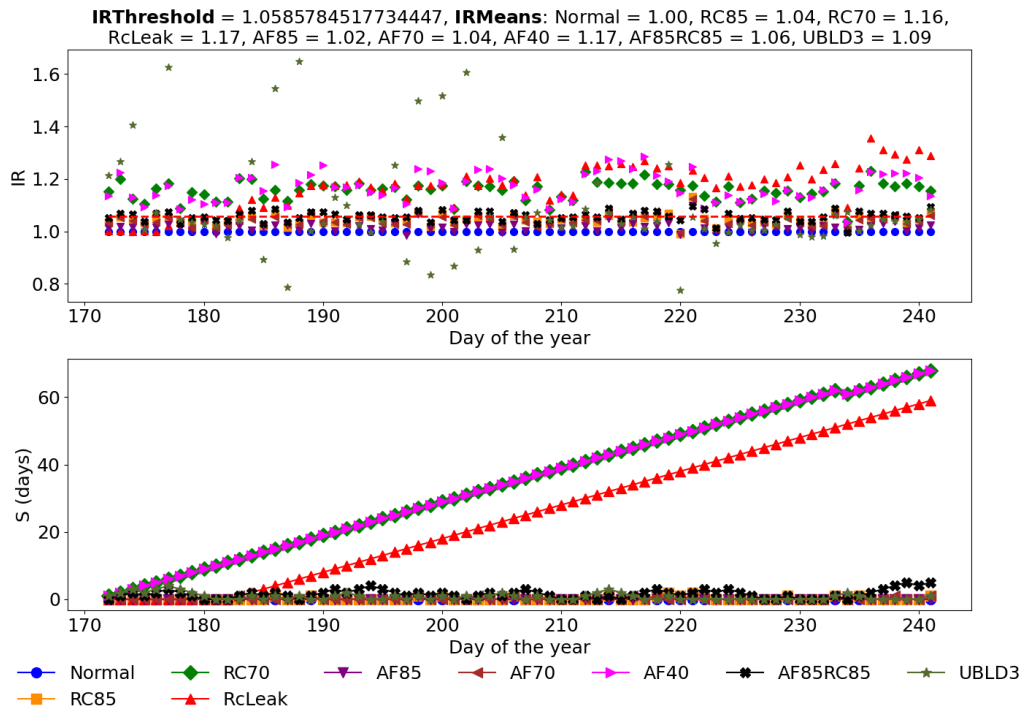


Figure B- 6: Fault IR for Ideal Scenario with a threshold of 1.06 using Duty Factor

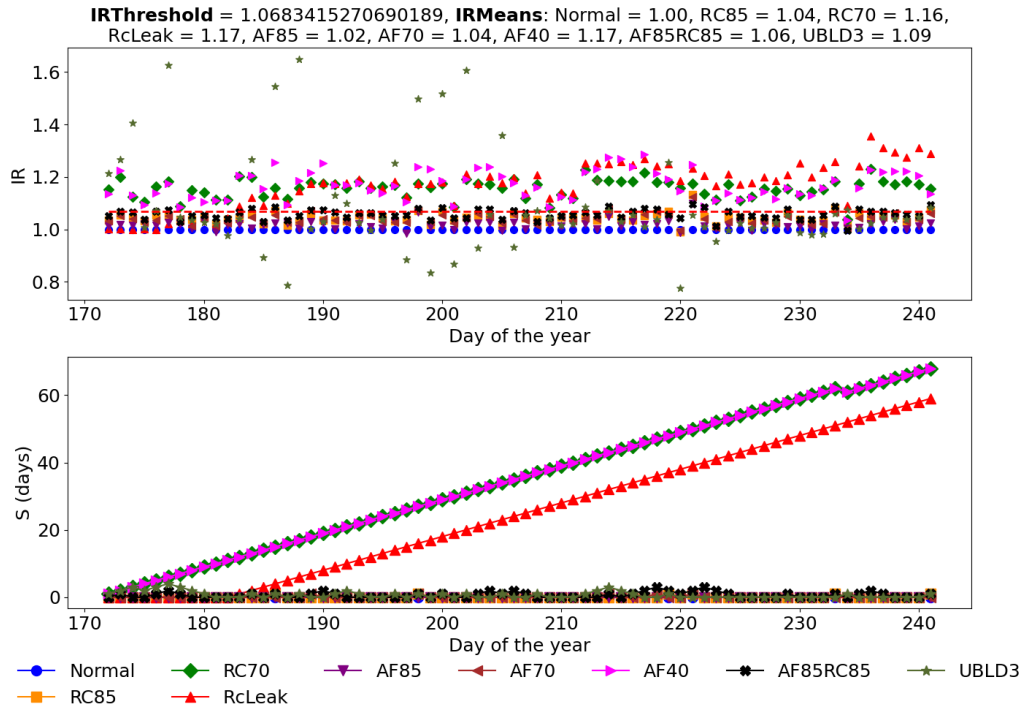


Figure B- 7: Fault IR for Ideal Scenario with a threshold of 1.07 using Duty Factor

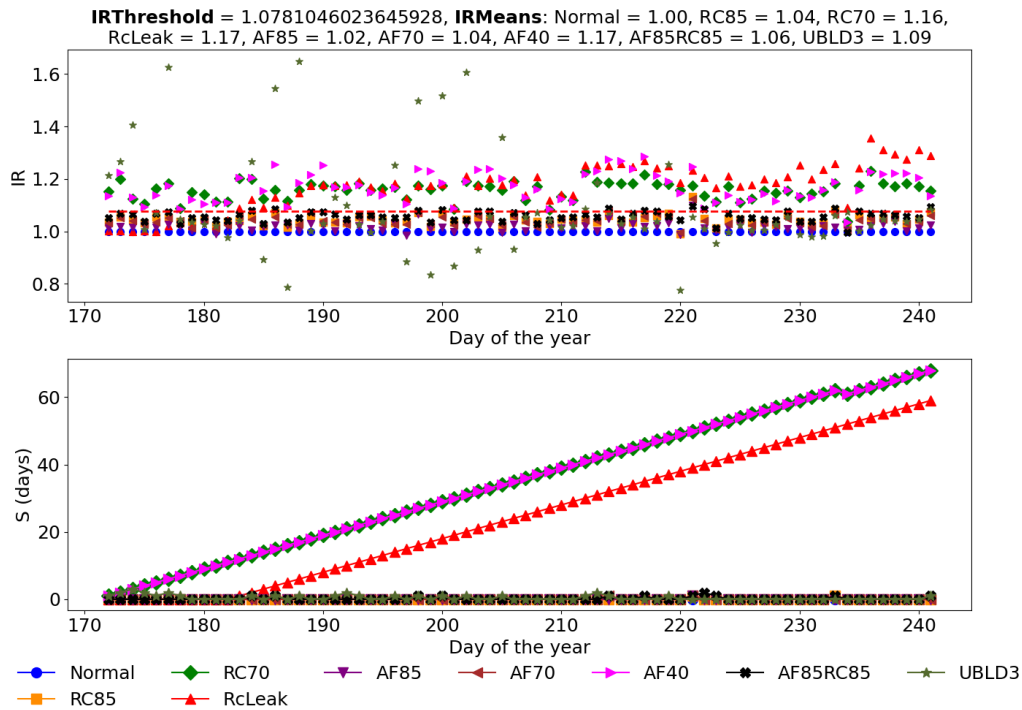


Figure B- 8: Fault IR for Ideal Scenario with a threshold of 1.08 using Duty Factor

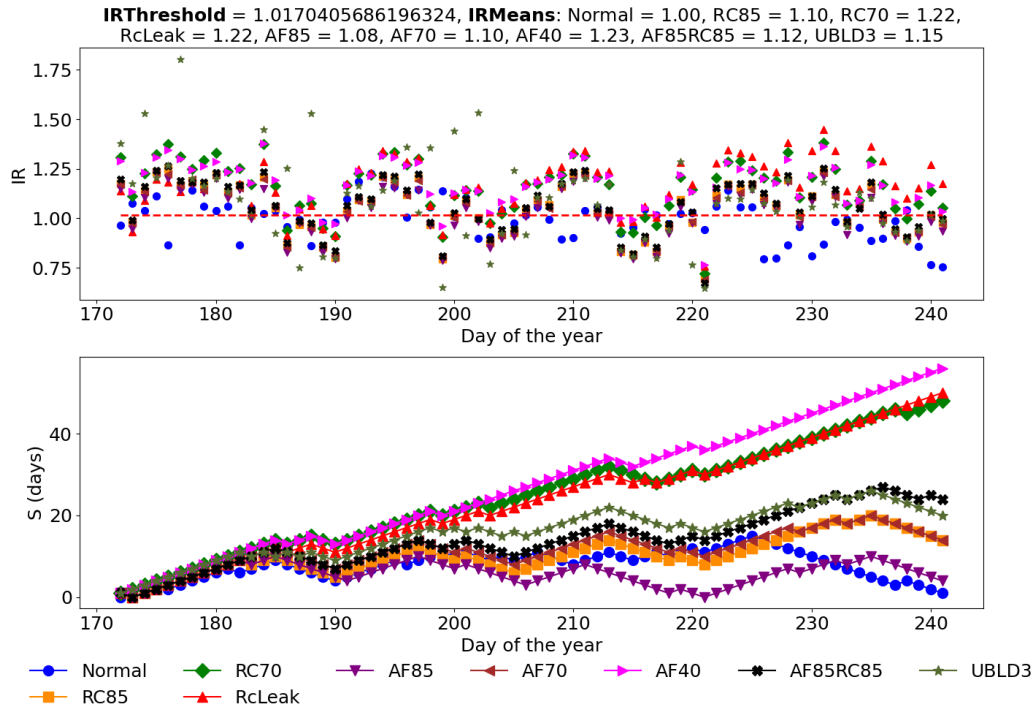


Figure B- 9: Fault IR for Real Scenario with a threshold of 1.02 using Duty Factor

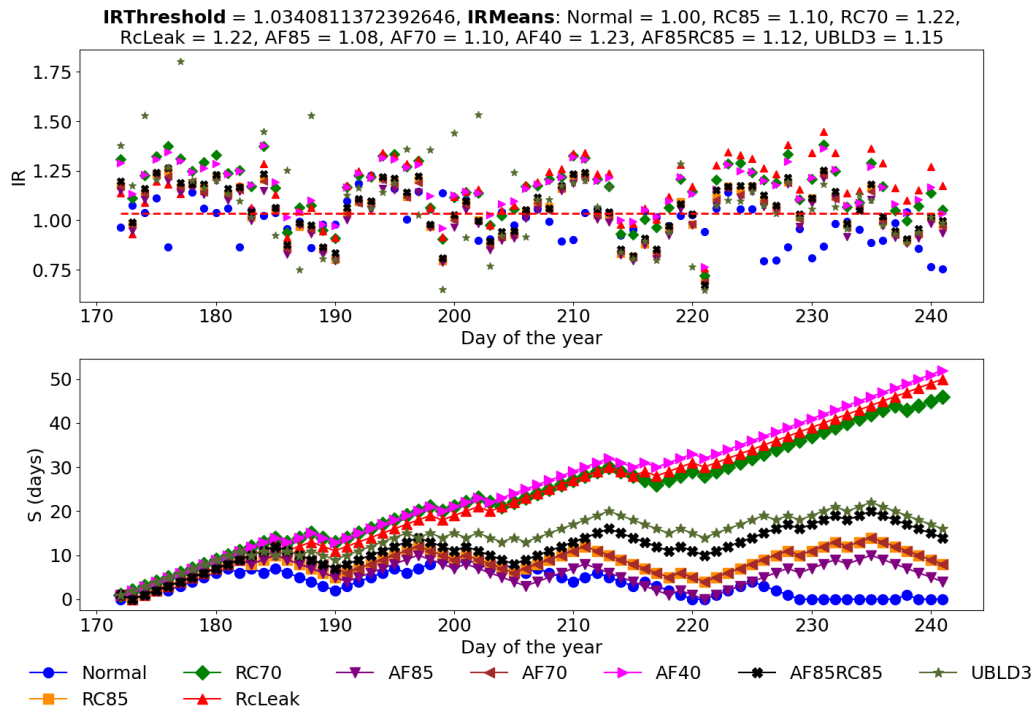


Figure B- 10: Fault IR for Real Scenario with a threshold of 1.03 using Duty Factor

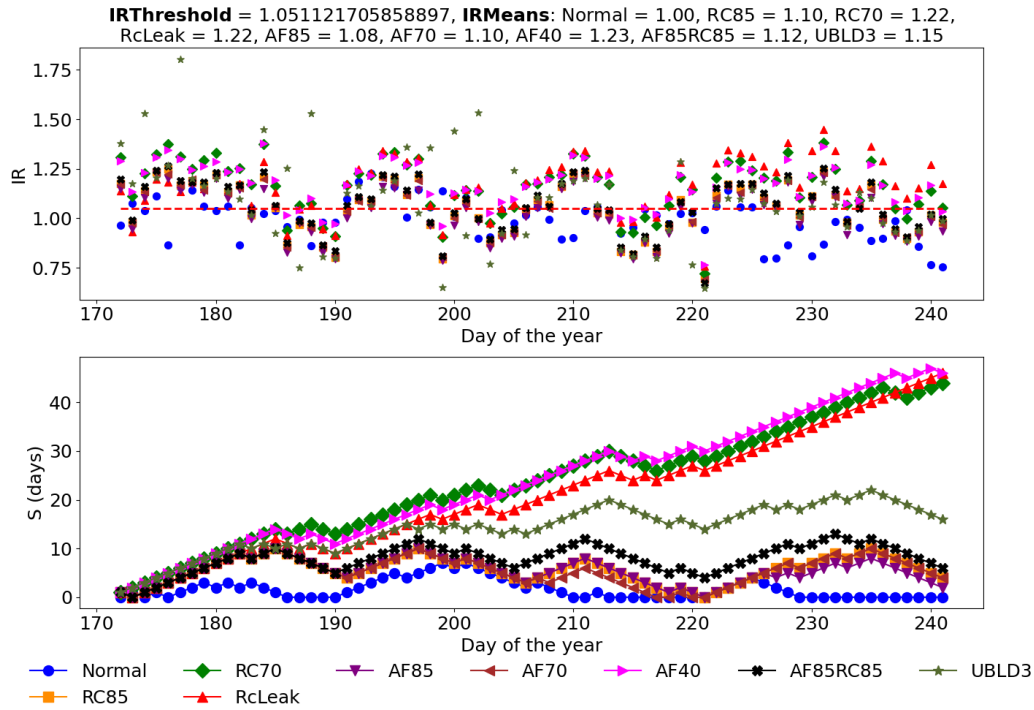


Figure B- 11: Fault IR for Real Scenario with a threshold of 1.05 using Duty Factor

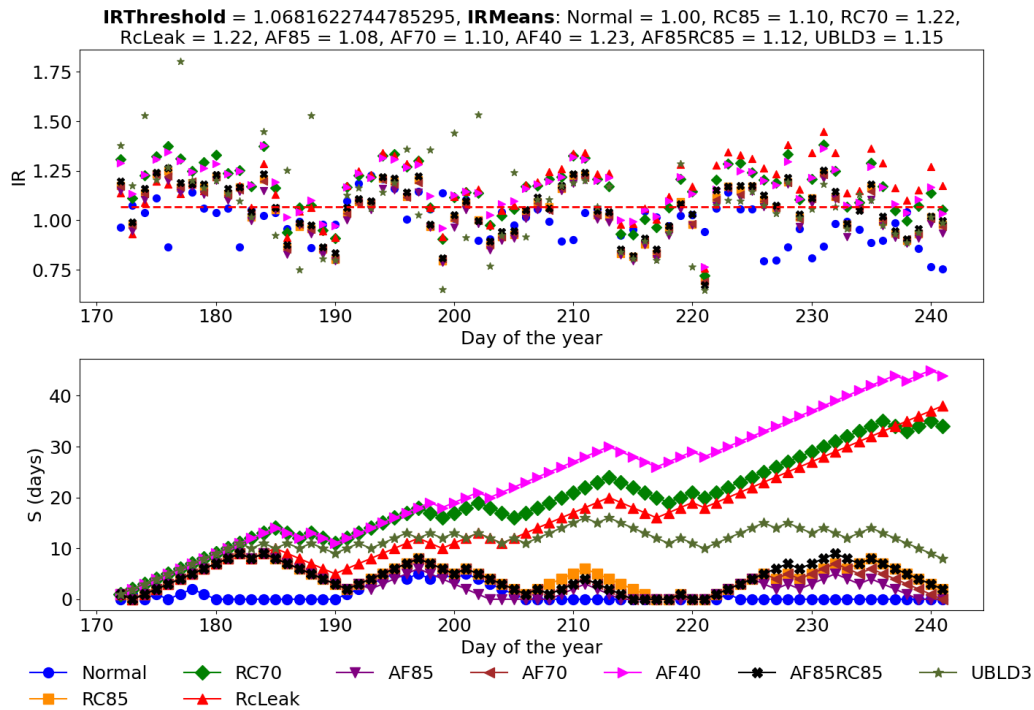


Figure B- 12: Fault IR for Real Scenario with a threshold of 1.07 using Duty Factor

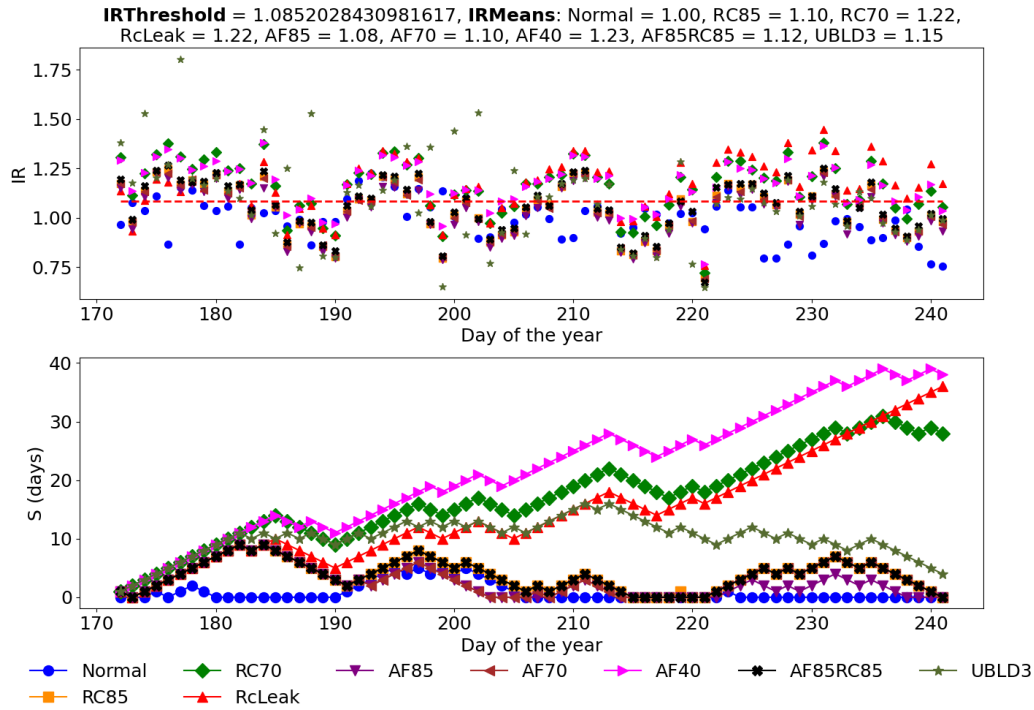


Figure B- 13: Fault IR for Real Scenario with a threshold of 1.09 using Duty Factor

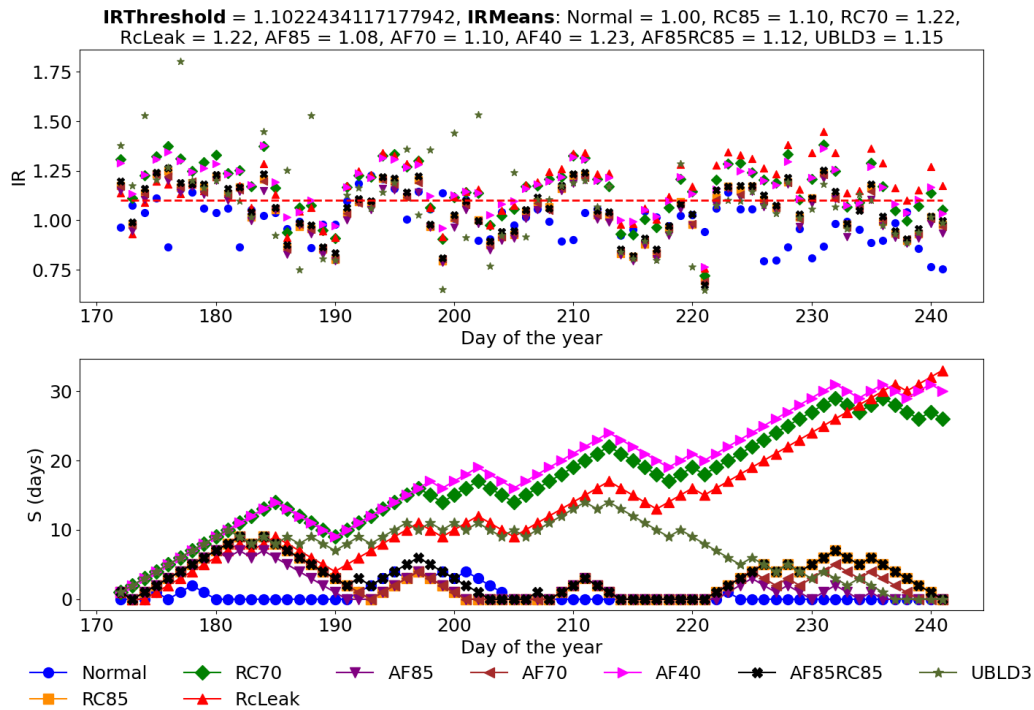


Figure B- 14: Fault IR for Real Scenario with a threshold of 1.10 using Duty Factor

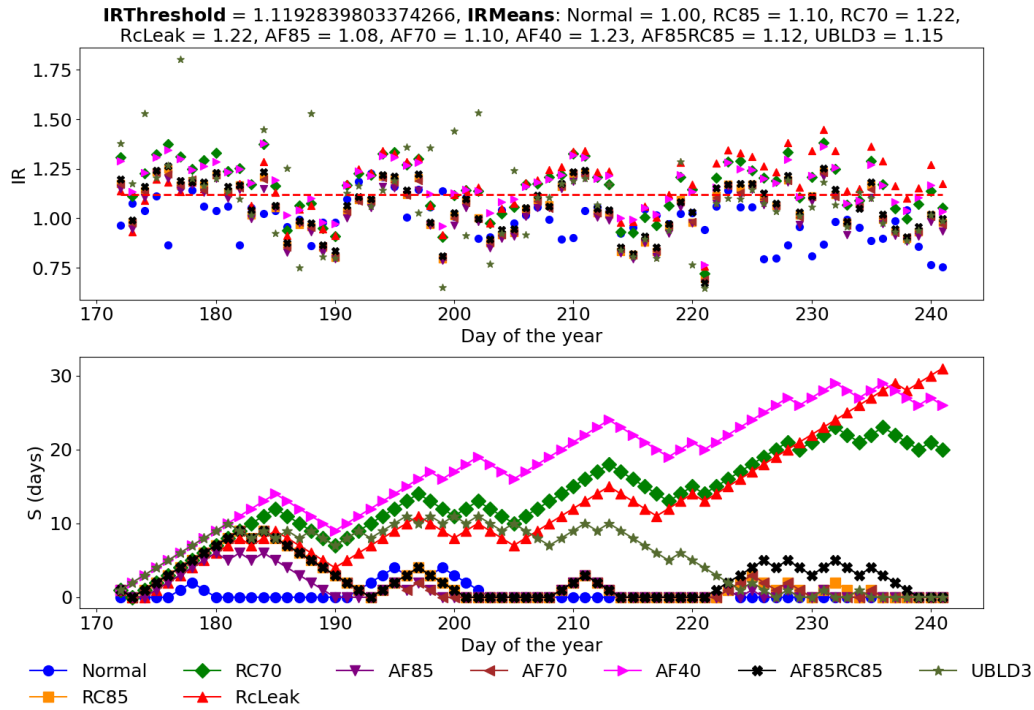


Figure B- 15: Fault IR for Real Scenario with a threshold of 1.12 using Duty Factor

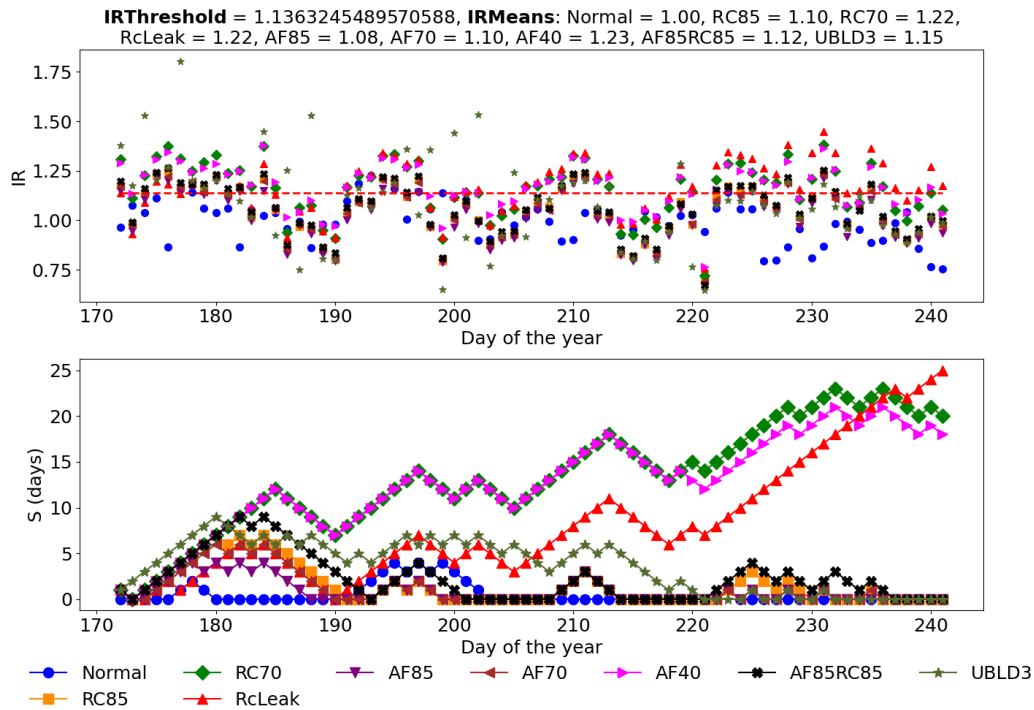


Figure B- 16: Fault IR for Real Scenario with a threshold of 1.14 using Duty Factor

Appendix C Enthalpy Change Fault Impact Ratio (FIR) Plots Against Threshold

The plots in this appendix show the impact of the different cases discussed in Section 4.3.1 with respect to different thresholds.

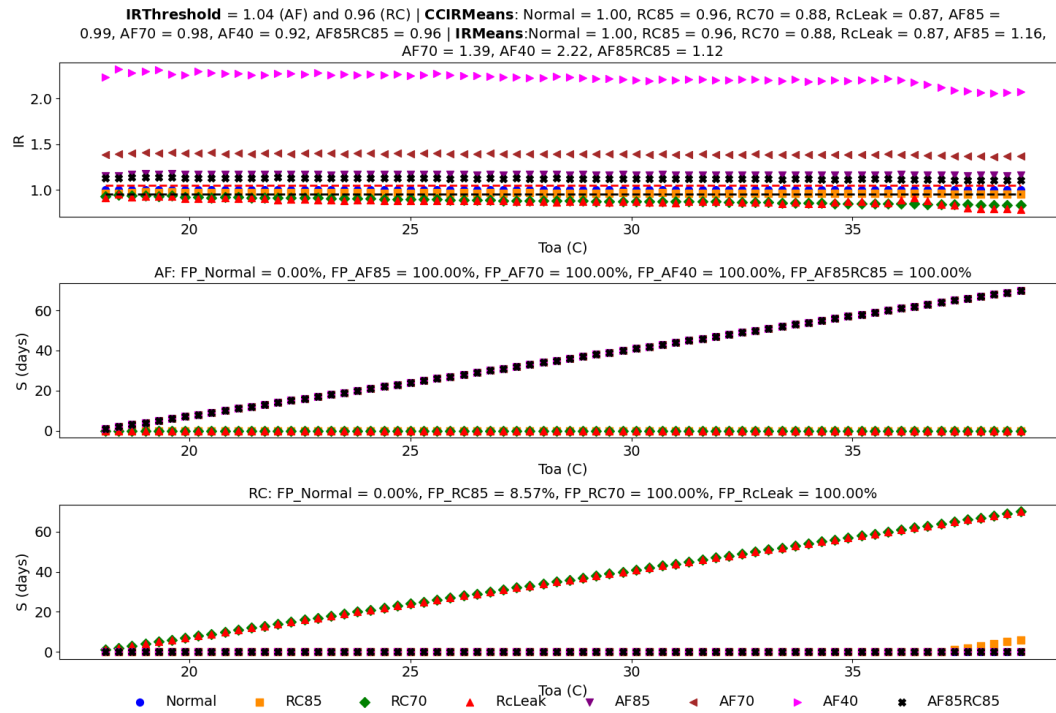


Figure C- 1: Fault IR for Ideal Scenario with a threshold of 4% using Enthalpy Change

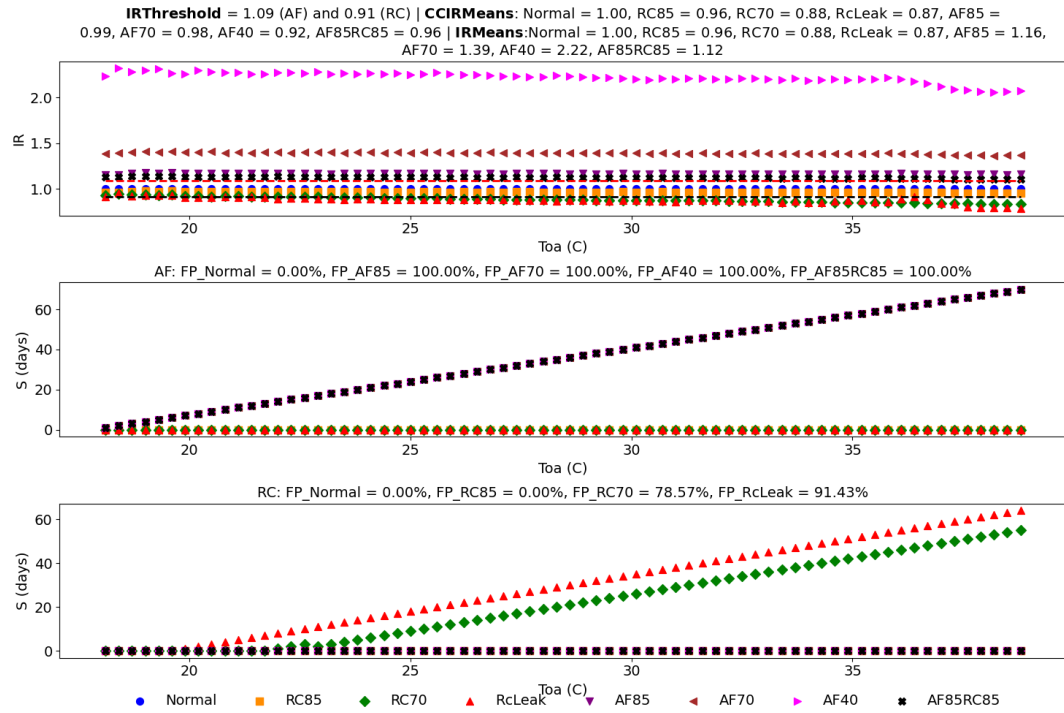


Figure C- 2: Fault IR for Ideal Scenario with a threshold of 9% using Enthalpy Change

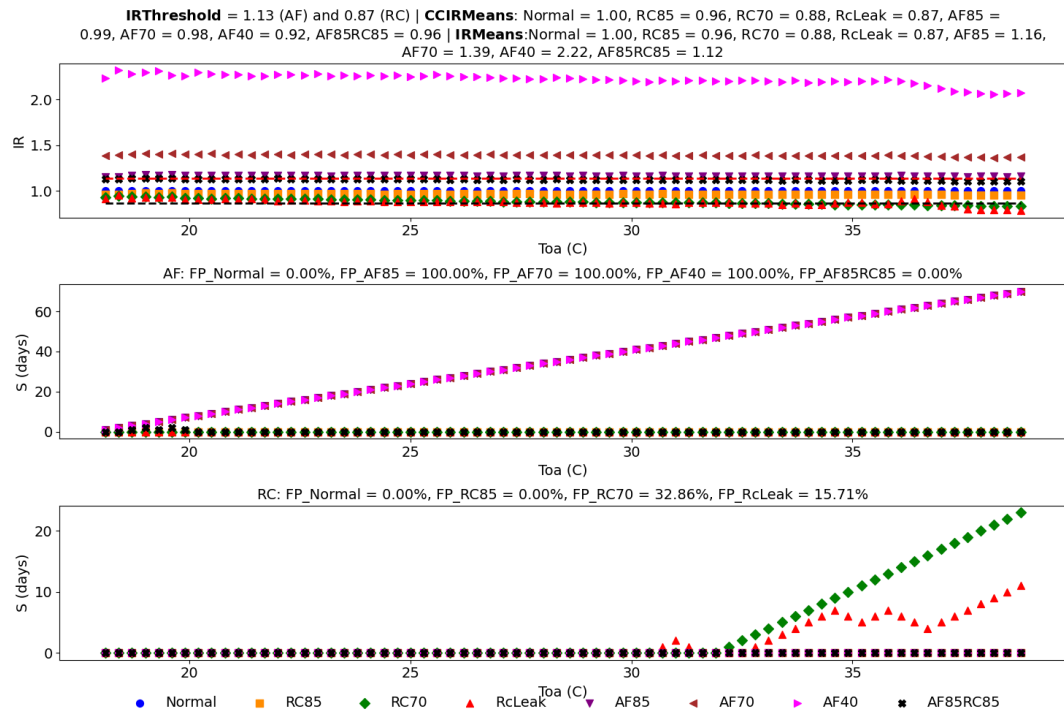


Figure C- 3: Fault IR for Ideal Scenario with a threshold of 13% using Enthalpy Change

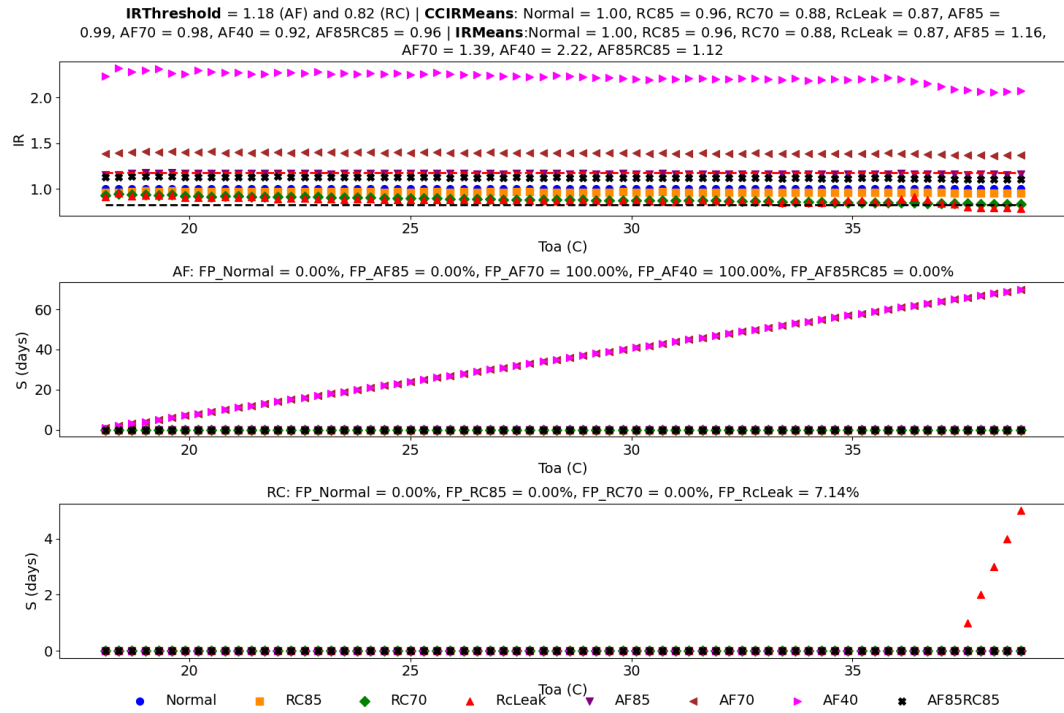


Figure C- 4: Fault IR for Ideal Scenario with a threshold of 18% using Enthalpy Change

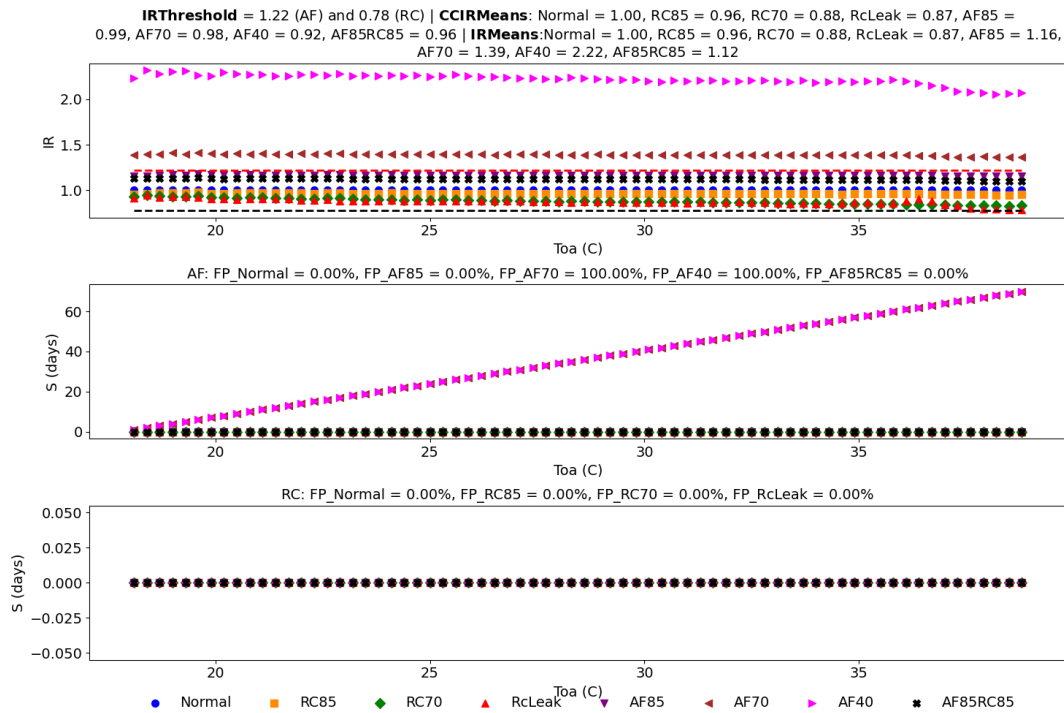


Figure C- 5: Fault IR for Ideal Scenario with a threshold of 22% using Enthalpy Change

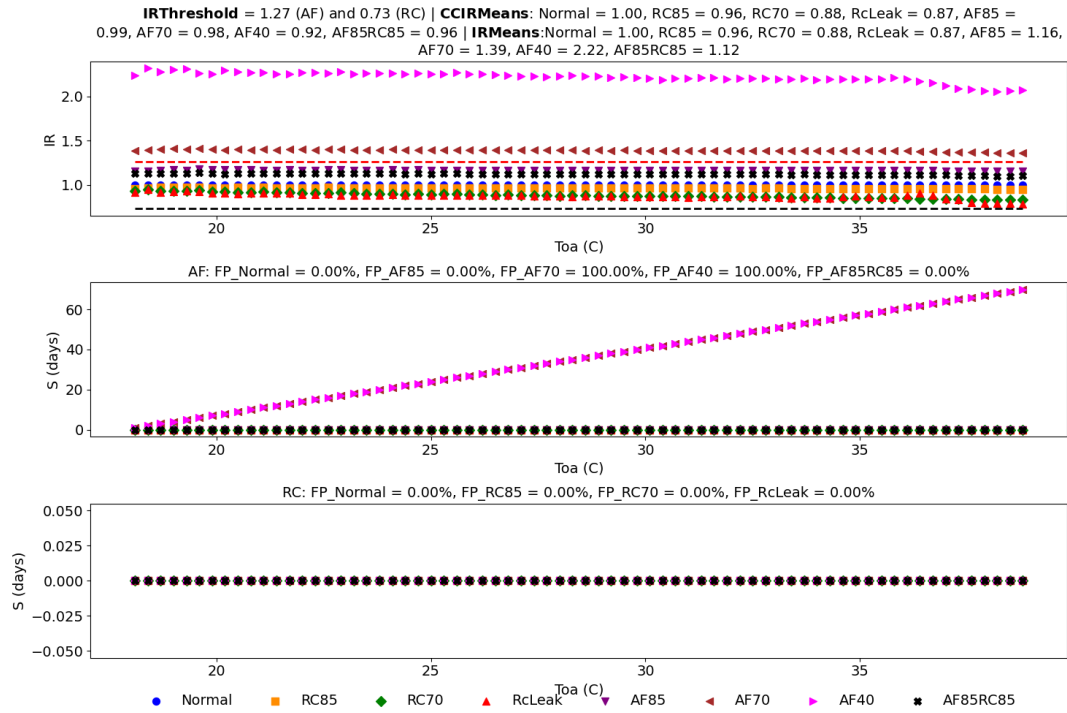


Figure C- 6: Fault IR for Ideal Scenario with a threshold of 27% using Enthalpy Change

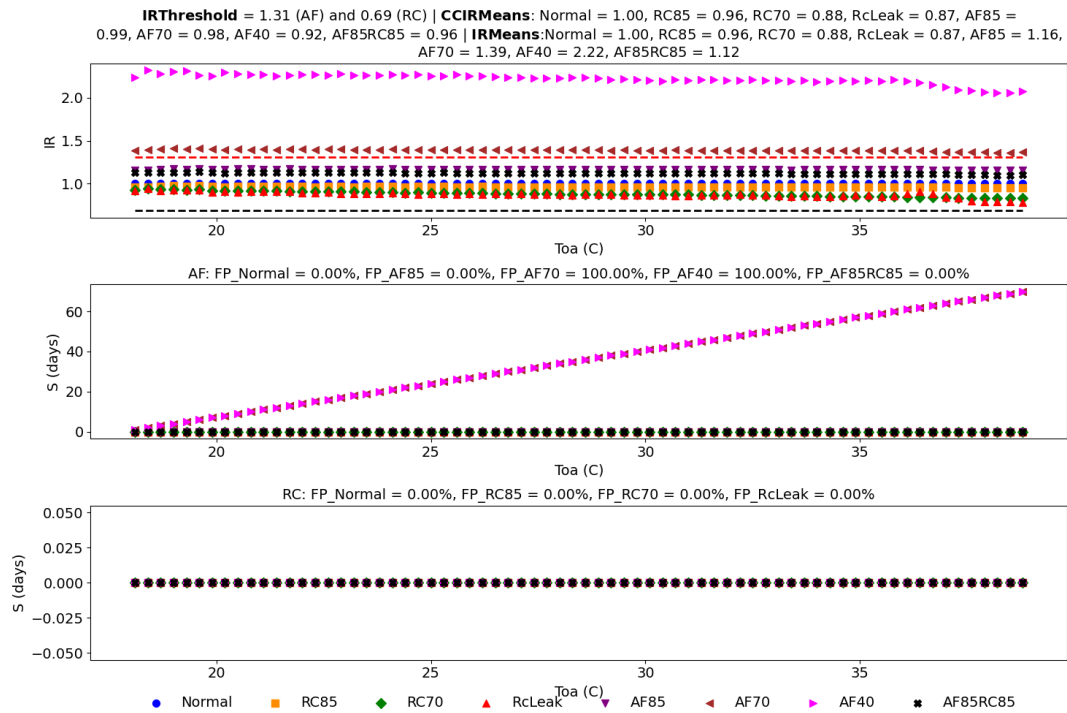


Figure C- 7: Fault IR for Ideal Scenario with a threshold of 31% using Enthalpy Change

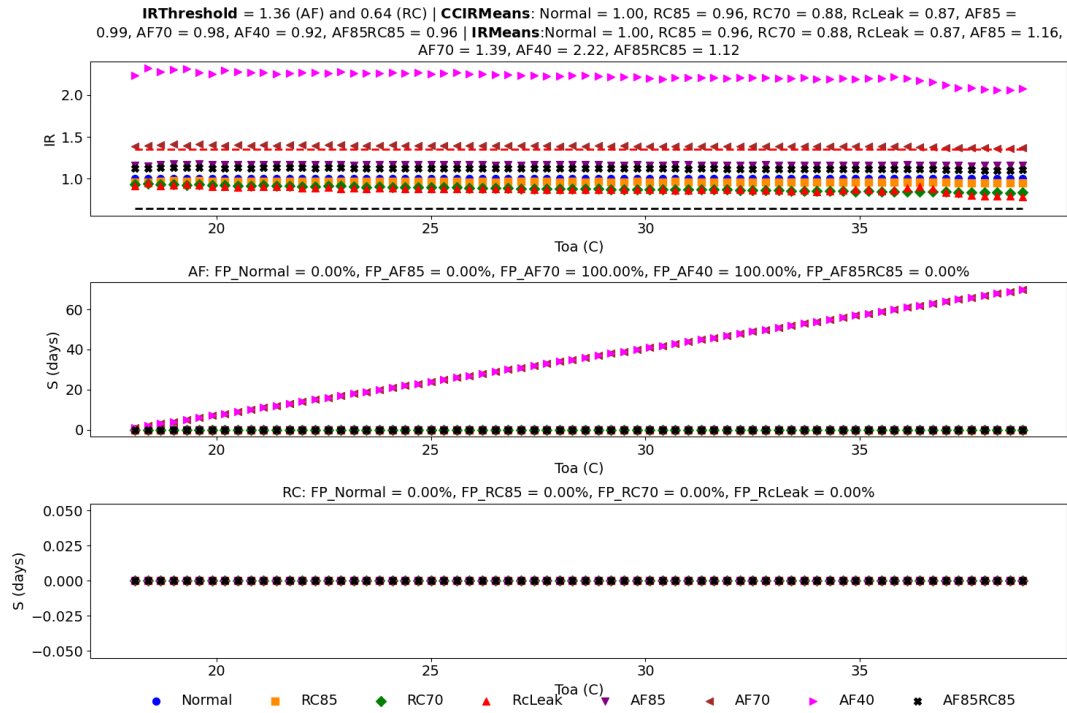


Figure C- 8: Fault IR for Ideal Scenario with a threshold of 36% using Enthalpy Change

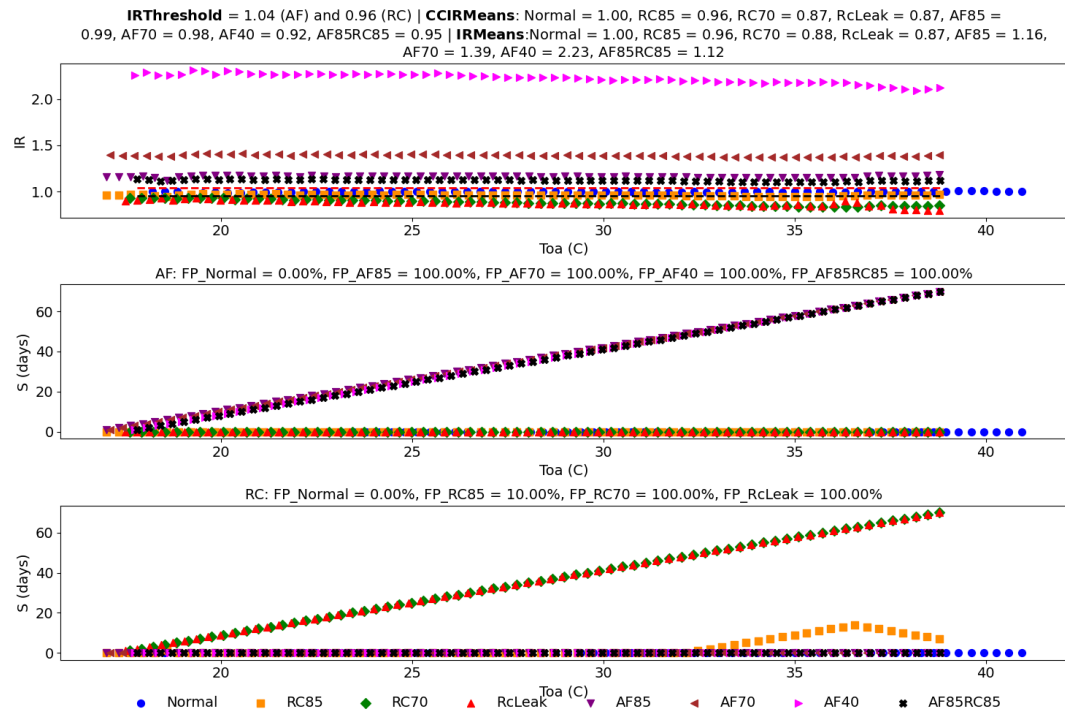


Figure C- 9: Fault IR for Real Scenario with a threshold of 4% using Enthalpy Change

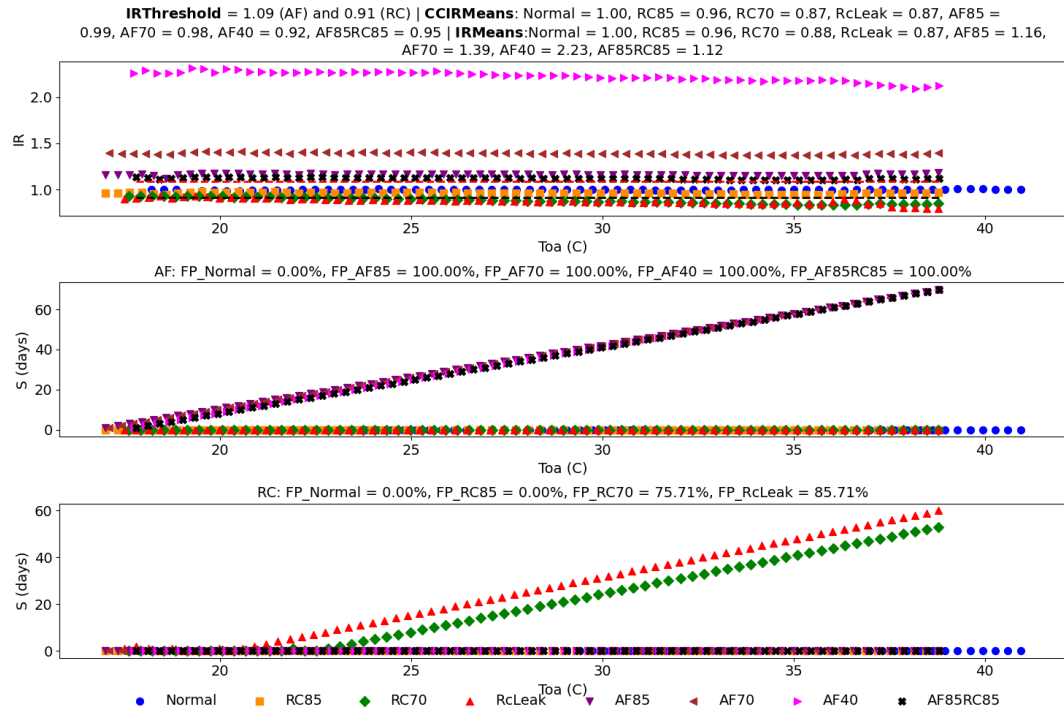


Figure C- 10: Fault IR for Real Scenario with a threshold of 9% using Enthalpy Change

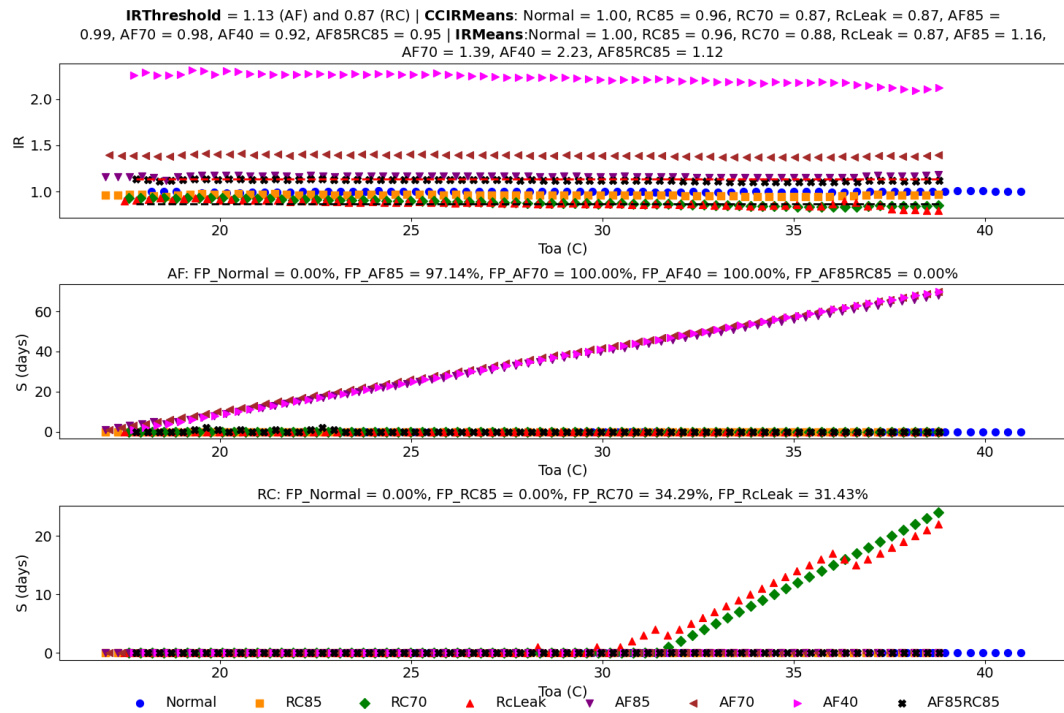


Figure C- 11: Fault IR for Real Scenario with a threshold of 13% using Enthalpy Change

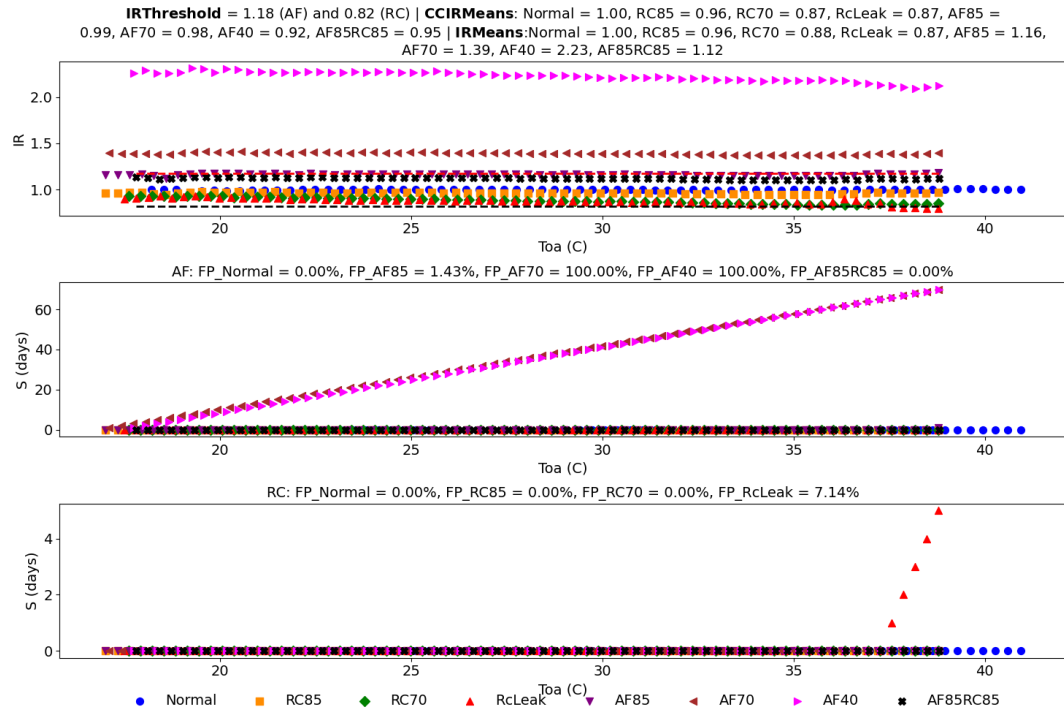


Figure C- 12: Fault IR for Real Scenario with a threshold of 18% using Enthalpy Change

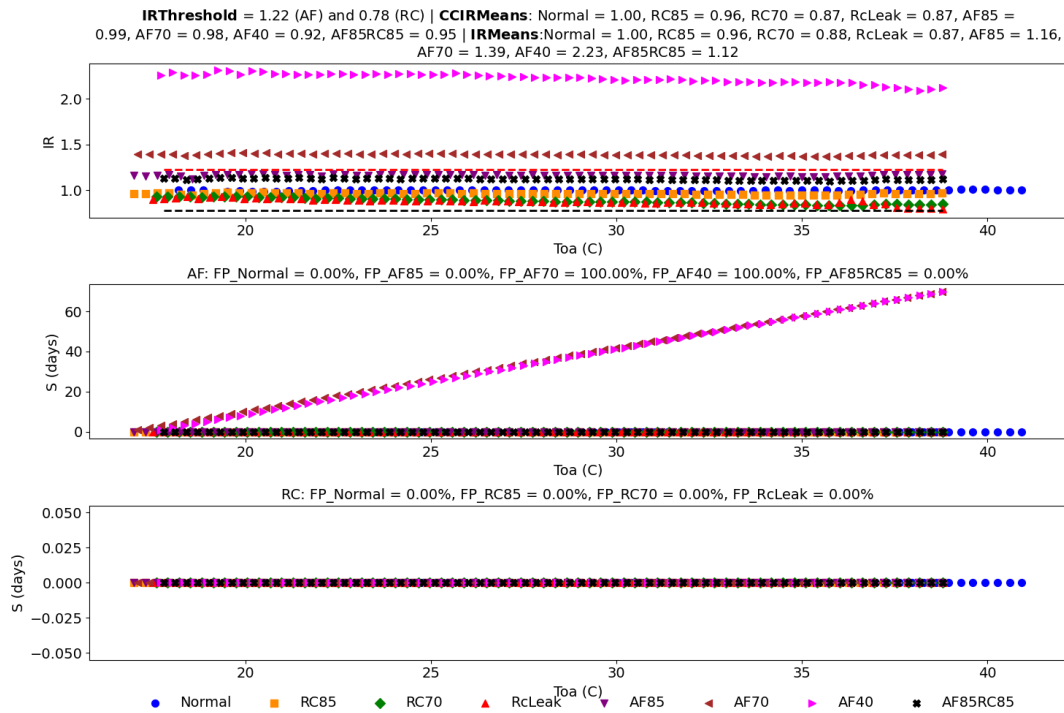


Figure C- 13: Fault IR for Real Scenario with a threshold of 22% using Enthalpy Change

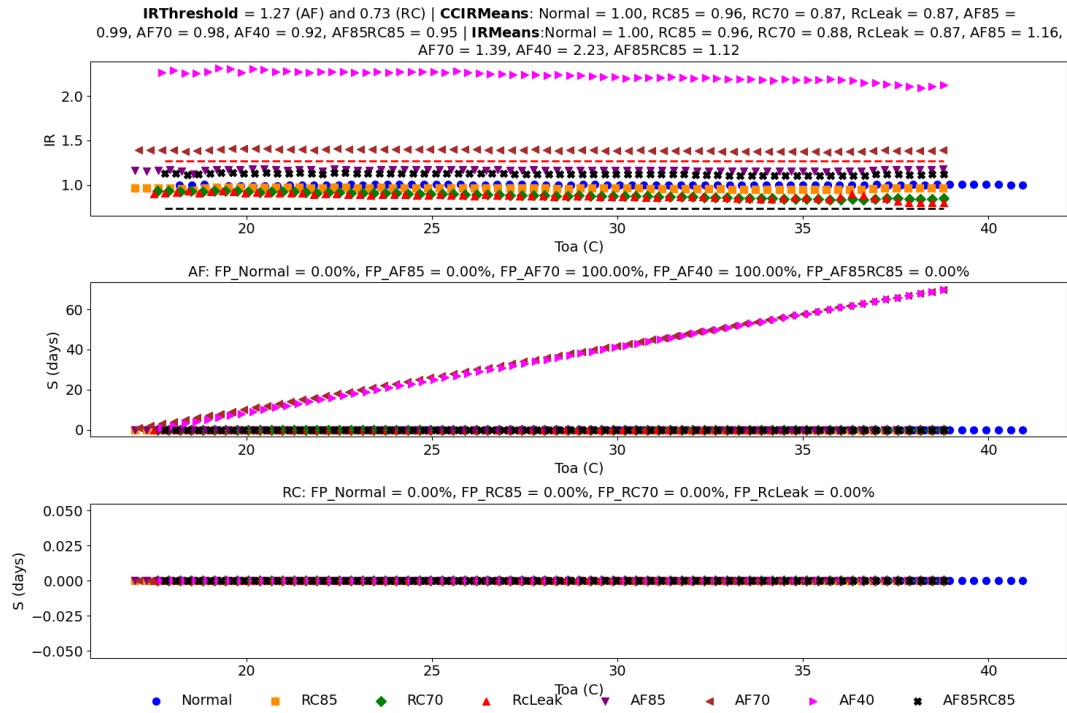


Figure C- 14: Fault IR for Real Scenario with a threshold of 27% using Enthalpy Change

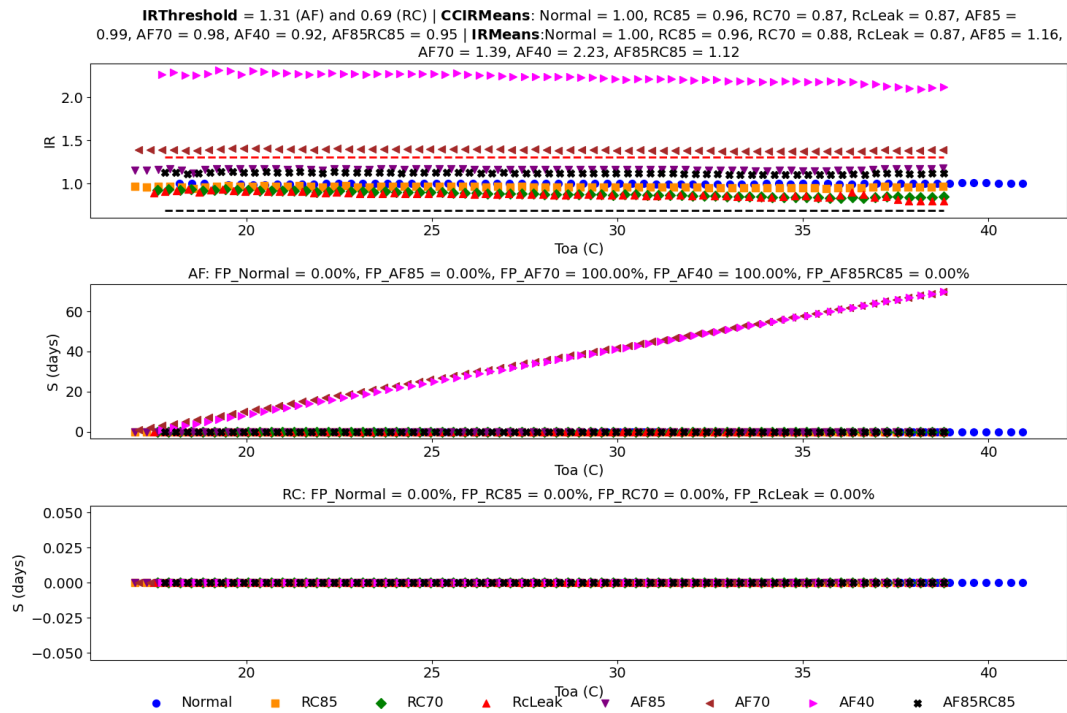


Figure C- 15: Fault IR for Real Scenario with a threshold of 31% using Enthalpy Change

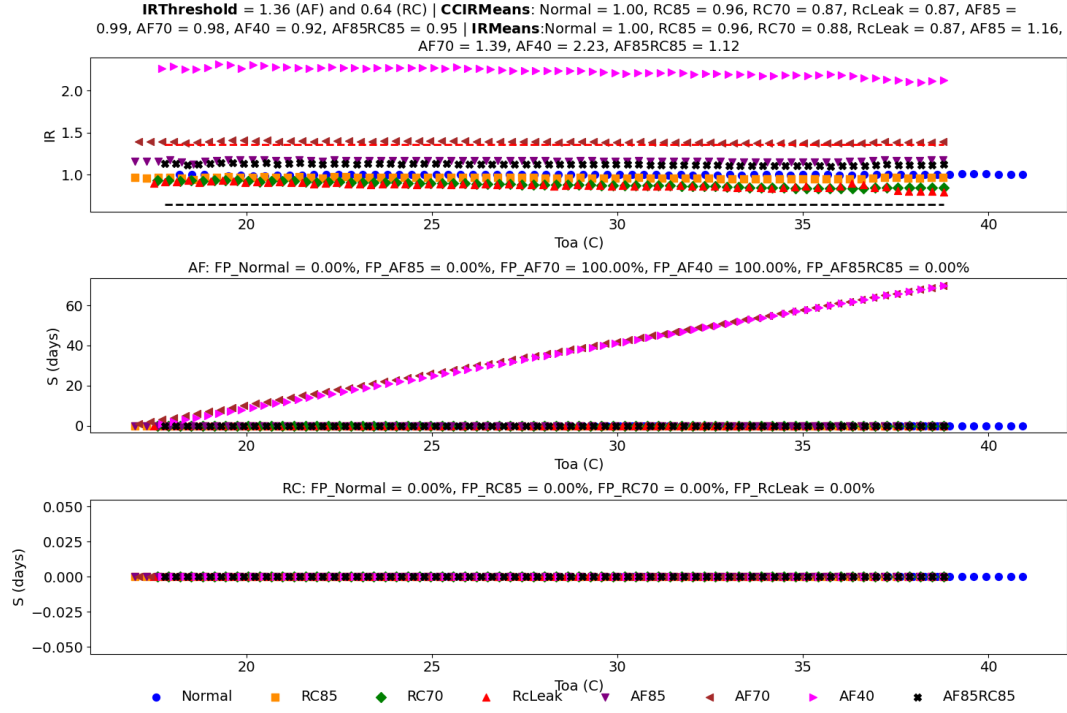


Figure C- 16: Fault IR for Real Scenario with a threshold of 36% using Enthalpy Change

Appendix D Derivation of Equation used in Uncertainty Propagation Analysis

For the uncertainty propagation analysis discussed in Section 5.3.2 of the dissertation, an expression for Δi was first developed from standard equations and correlations. First, Δi can be expressed as

$$\Delta i = i_{ra} - i_{sa} \quad (D.1)$$

Where the standard formula for enthalpy of moist air can be expressed as

$$i = k_1 \cdot T + W \cdot (k_2 + k_3 \cdot T) \quad (D.2)$$

The humidity ratio in Equation (D.2) can be expressed as either Equations (D.3) or (D.4)

$$W = \frac{k_4 \cdot p_v(T, \phi)}{k_5 - p_v(T, \phi)} = \frac{k_4 \cdot \phi \cdot p_{sat}(T)}{k_5 - \phi \cdot p_{sat}(T)} \quad (D.3)$$

$$W = \frac{k_4 \cdot p_v(T_{dp})}{k_5 - p_v(T_{dp})} \quad (D.4)$$

where p_v is the pressure of the water vapor in the air, p_{sat} is the saturation vapor pressure at temperature, T , ϕ is the relative humidity (in %) of the moist air, and T_{dp} is the dewpoint temperature. Equation (D.3) is used if T and ϕ are given as is the case for the return air in the proposed FDD method in Chapter 5 of the dissertation. But if T and T_{dp} are given as is the case with for the supply air in Chapter 5 of the dissertation, then Equation (D.4) is used. Furthermore, based on Tetens equation,

$$p_{sat}(T) = k_6 \cdot \exp\left(\frac{k_7 \cdot T}{T + k_8}\right) \cdot k_9 \quad (D.5)$$

$$p_v(T_{dp}) = k_6 \cdot \exp\left(\frac{k_7 \cdot T_{dp}}{T_{dp} + k_8}\right) \cdot k_9 \quad (D.6)$$

Since T and ϕ are given for the return air, i_{ra} is thus modeled with Equations (D.2), (D.3) and (D.5). While i_{sa} is modeled with Equations (D.2), (D.4) and (D.6) since it involves T and T_{dp} .

Table E-1 shows the respective values for $k_1 - k_9$ used in the above equations.

Table E- 1: Values of Constants used in the Enthalpy Equations

Parameters	Value	Unit	Description
k_0 or c_p	0.24	Btu/(lb·°F)	specific heat of dry air
k_1	0.61078	kPa	An empirical constant representing the saturation vapor pressure at 0°C
k_2	17.27	-	An empirical coefficient
k_3	237.3	-	An empirical coefficient
k_4	0.145038	-	Conversion factor from kPa to psi
k_5	0.62198	-	ratio of the molecular weight of water vapor to dry air
k_6	14.696	psi	atmospheric pressure at sea level
k_7	1061.2	Btu/lb	latent heat of vaporization
k_8	0.444	Btu/(lb·°F)	specific heat of water vapor at constant pressure

Appendix E Plots for Enthalpy-Driven Smart Thermostat-based FDD Method at A Threshold of ± 0.6 Btu/lbm

This appendix shows plots of analysis done for the tests performed in Chapter 5 using a low threshold of ± 0.6 Btu/lbm which was obtained with the hobo logger data.

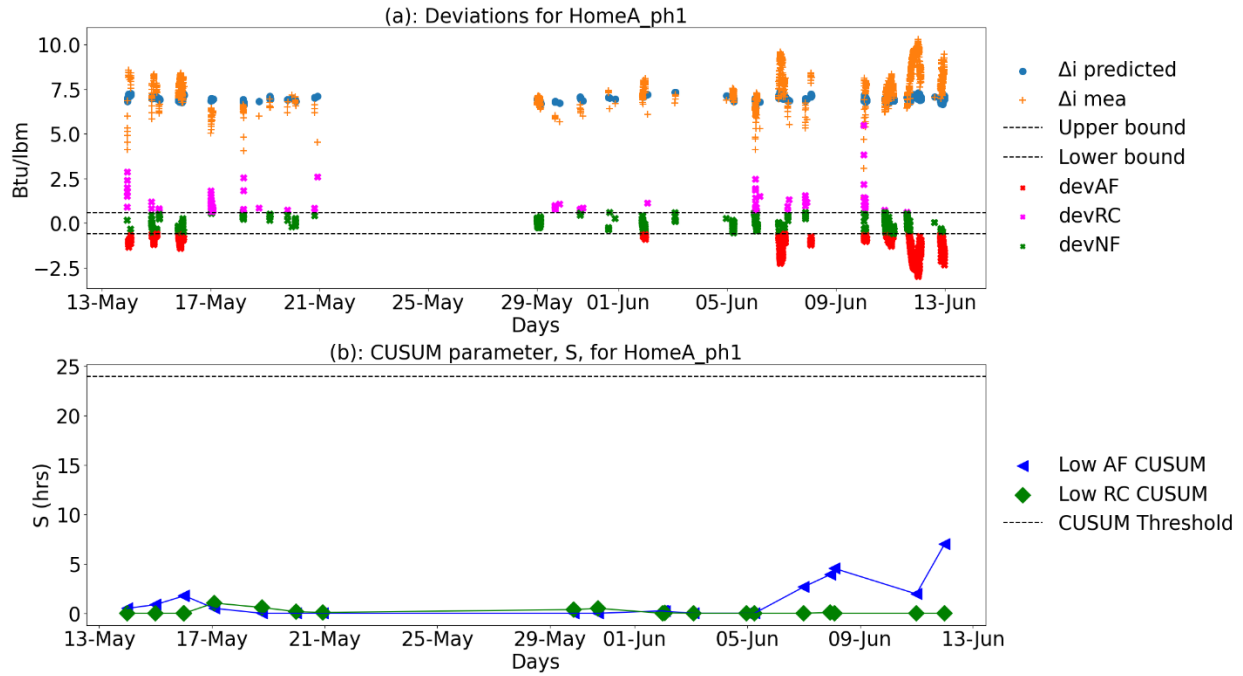


Figure E- 1: Real-time monitoring of Δi for Home A in Phase 1 with ± 0.6 Btu/lbm threshold

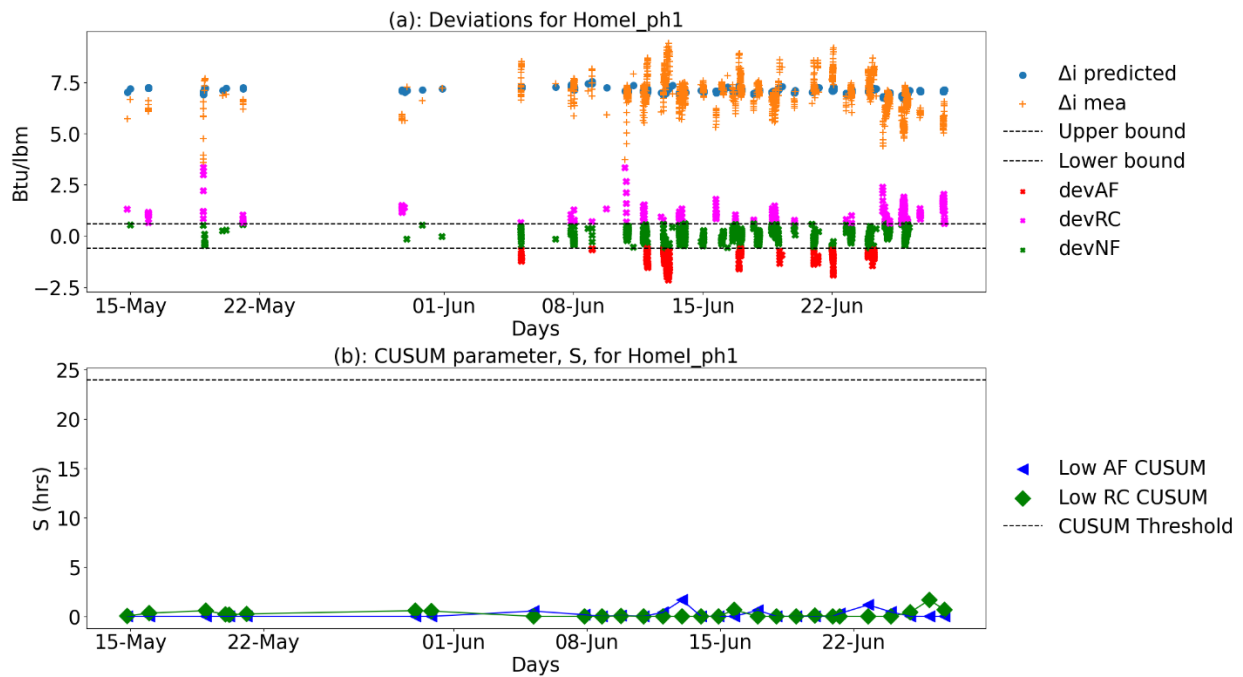


Figure E- 2: Real-time monitoring of Δi for Home I in Phase 1 with ± 0.6 Btu/lbm threshold

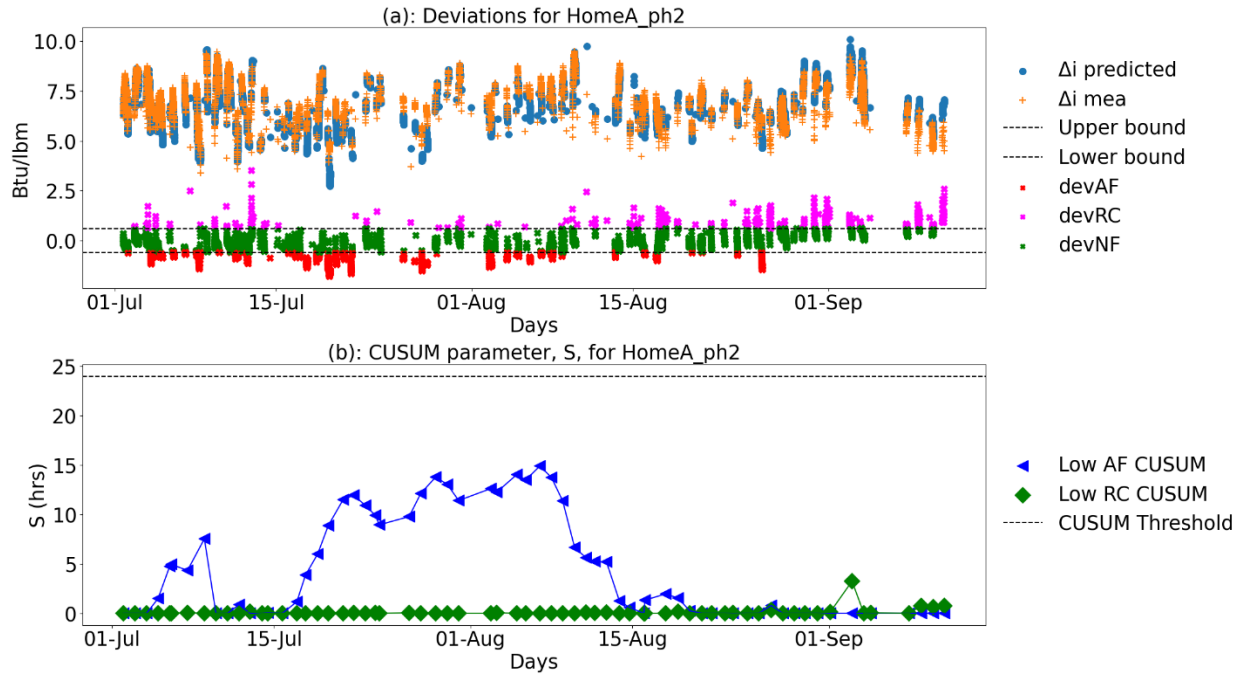


Figure E- 3: Real-time monitoring of Δi for Home A in Phase 2 with ± 0.6 Btu/lbm threshold

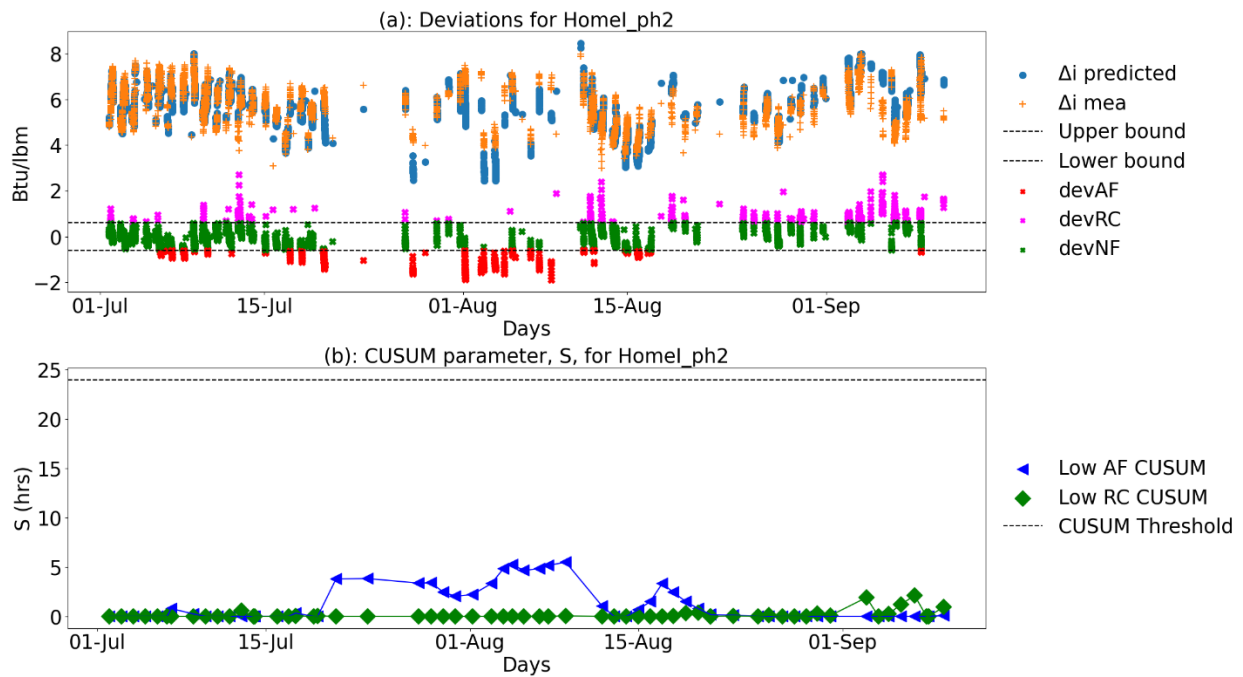


Figure E- 4: Real-time monitoring of Δi for Home I in Phase 2 with ± 0.6 Btu/lbm threshold

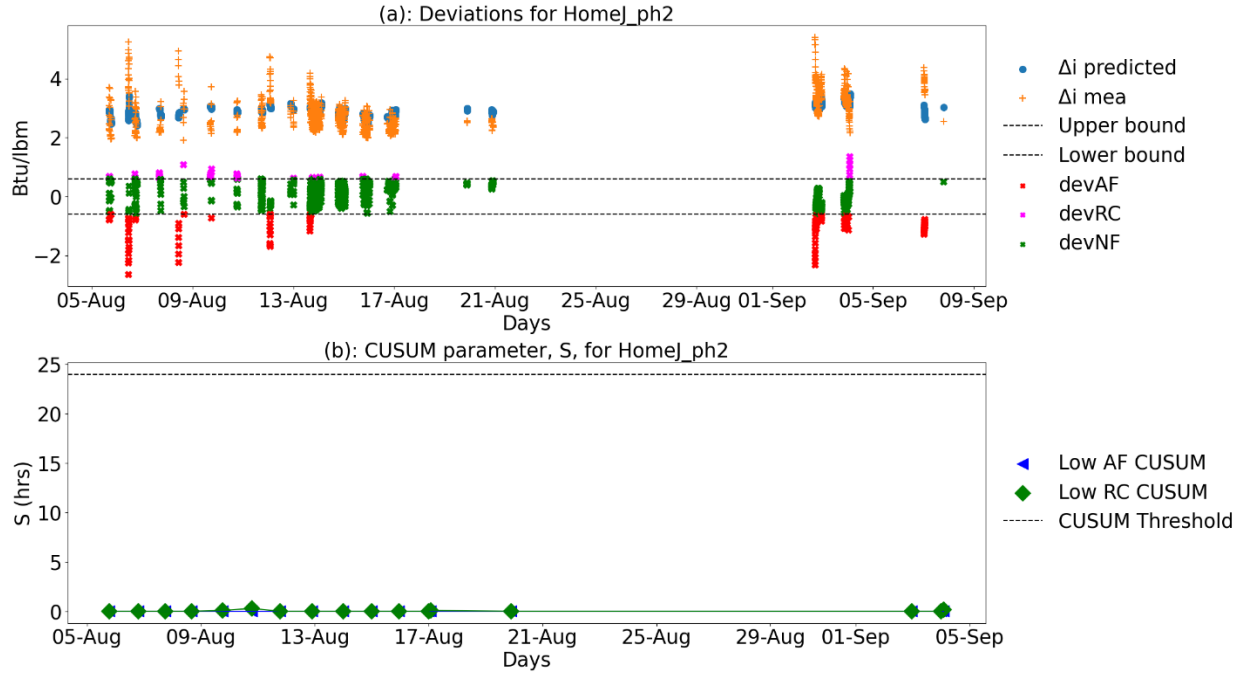


Figure E- 5: Real-time monitoring of Δi for Home J in Phase 2 with ± 0.6 Btu/lbm threshold

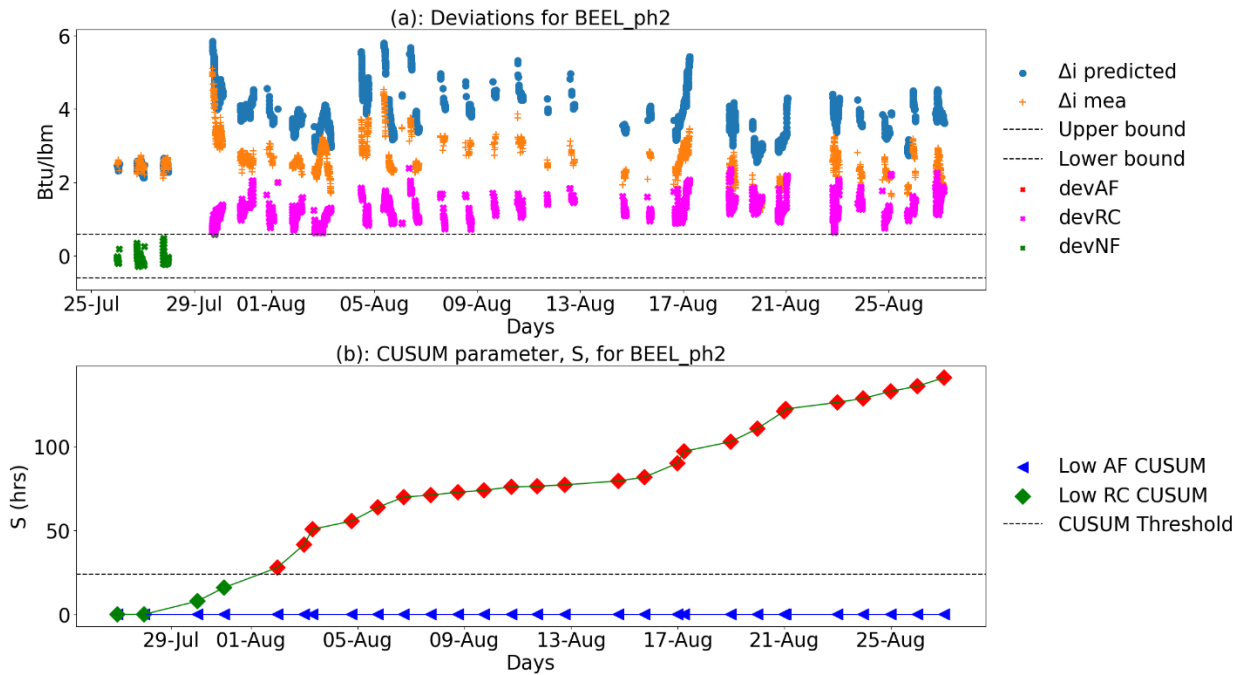


Figure E- 6: Real-time monitoring of Δi for OU Lab-House in Phase 2 with ± 0.6 Btu/lbm threshold