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Modeling Air Handling Units to Create a Diverse Fault Dataset for FDD Innovation: Lessons Learned and Recommendations

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ABSTRACT

As energy management and information systems (e.g., automated fault detection and diagnostics [AFDD] tools) become more prevalent in the commercial building stock, it is important to determine the effectiveness of these technologies by benchmarking their performance. The authors have been working to develop the largest publicly available dataset of HVAC fault datasets for performance benchmarking applications, covering the most common HVAC systems and designs including chiller plants, rooftop packaged units, dual duct air handling unit and single duct air handling units. This study covers the development, modeling, and validation of a synthetic fault dataset for the air handling unit (AHU), one of the most common HVAC configurations found in the commercial building stock. Despite this being a common system, real-world time series data are scarce and usually do not span a wide range of weather conditions. Due to this limitation, two detailed AHU models, which included the single duct AHU and dual duct AHU developed in the Modelica language and HVACSIM+ were employed to carry out annual simulations of numerous common sensor faults, mechanical faults, and control sequence faults. The fault inclusive data were then validated by comparing fault effects on system performance to expected symptoms. We summarize the nature of each fault and their impacts under different weather and operation conditions. We report some lessons learnt during the efforts of validating the high volumes of the FDD data sets. Finally, we highlight considerations for FDD developers that may want to use this dataset to assess their algorithms' performance and their improvement over time.

1. INTRODUCTION

As building data becomes more readily available, and as the budding field of data science and analytics comes to buildings, fault detection and diagnostics (FDD) is of increasing relevance to the research and product development communities. A primary method of improving building controls and operational efficiency is through algorithms developed to perform automated fault detection and diagnostics (AFDD), which use building data to identify the presence of faults and potentially isolate root causes. Estimated energy use reduction from these improvements have been estimated at an average of 29%, which accounts for approximately 5% of overall national energy consumption (Fernandez 2017). Practically, building owners and operators have already leveraged the benefits of AFDD technology, using it to enable median whole-building portfolio savings of 9% (Kramer *et al*. 2020).
Development of FDD for air distribution subsystems, including hydronic air handling units (AHU) system, for example, are presented in a number of studies dating back decades (House, Vaezi-Nejad, and Whitcomb 2001) (Bushby *et al*. 2001) (Bushby and Schein 2006). Since then, a diversity of techniques have been developed for FDD in AHU systems, spanning analytical-based physical or gray box models, data-driven approaches, and knowledge-

based heuristic approaches (Yu, Woradechjumroen, and Yu 2014), and developers continuously strive to develop improved algorithms. A persistent challenge, however, has been the lack of common datasets and test methods to benchmark the performance accuracy of FDD methods, and gauge improvement of these tools over time. Granderson (2018) most recently developed a test and benchmarking framework for FDD algorithm performance, demonstrating a growing need for HVAC fault datasets that can be used to further determine the accuracy and effectiveness of FDD algorithms. HVAC performance datasets have been developed before in the form of ASHRAE's RP1312 fault dataset. ASHRAE Project 1312-RP data (Li *et al*. 2010a, Li *et al*. 2010b) is the resulting dataset from a series of experiments that were performed on two multi-zone VAV AHUs (AHU-A and AHU-B) with the same configuration running simultaneously. Further work was initiated to fill this gap with the introduction of an open sourced dataset for FDD evaluation purposes (Granderson *et al.* 2020), which introduced a first of its kind public dataset with ground-truth data on the presence and absence of faults for multiple HVAC systems, including a simulated SDAHU system. This paper will dive into more specifically the expansion of the AHU fault dataset, which is considered one of the most typical HVAC system designs in commercial buildings. Specifically we will be covering two configurations of this system in single duct and dual duct AHU. The data set consists of high resolution, simulated time series HVAC operational data (e.g. temperatures, pressures, control signals, component status, etc.) under a diversity of operating and weather conditions, combined with information on the presence and absence of faults and their associated intensity. Furthermore, the paper applies our previously established data validation and ground truth assessment protocol for the successful development of the AHU FDD test dataset (Casillas *et al.* 2020).

2. METHODS

Two types of AHUs, i.e., the single duct AHU (SDAHU) and the dual duct AHU (DDAHU) were simulated based on the various simulation software tools such as Modelica, EnergyPlus and HVACSIM+. For each type of the fault, the fault was injected to the system and the simulation was performed to output one-year (i.e., 365 days) fault inclusive data. Consequently, the fault inclusive data cover all operating conditions of the AHUs under one year time scope. In this section, we illustrate the simulation method for each type of equipment.

2.1 Single-duct AHU (SD-AHU)

The SDAHU model was developed in the Modelica language by developers at PNNL, based on model components available in open-source Modelica libraries such as the Modelica Buildings, IBPSA libraries. Modelica is an equation-based, objective-oriented modeling language for complex dynamic systems. In order to capture the building's thermal response a reference commercial building model from EnergyPlus (Deru et al. 2011) was integrated. The data exchange between the EnergyPlus IDF model and the Modelica system model was handled by a co-simulation framework, exporting the IDF file as a functional mockup unit, analogous to the methods in Huang et. al (2021). In addition to calculating the thermal loads of the space, the IDF file also stores pertinent weather information that is fed into the modelica model, which allows for annual modeling of a building based on a historical weather data set. For this study's purposes, the climate data modeled was that of Chicago, Il. The major components of the modeled for the SDAHU, as shown in Figure 1, are supply air fan with a variable frequency drive (VFD), return fan with a VFD, cooling coil, cooling control valves, outdoor air (OA) and return air (RA) dampers. The measurement points made available for end users are related to the aforementioned components, including temperature, airflow and static pressure readings, temperature and pressure setpoints, control signal and positions for actuated components, speed and power output for motorized components. The AHU's baseline control sequence is applied from engineering standard best practices (e.g. ASHRAE 90.1). These control parameters and sequences are programmed in the modelica language with control and logic components.

The control loops are mostly concerned with three different components:

- Fan speed control determined by occupancy state and static pressure setpoints
- Cooling coil valve determined by occupancy state and supply air temperature setpoint
- Damper positions determined by occupancy state, outdoor air temperature and mixed air temperature setpoint

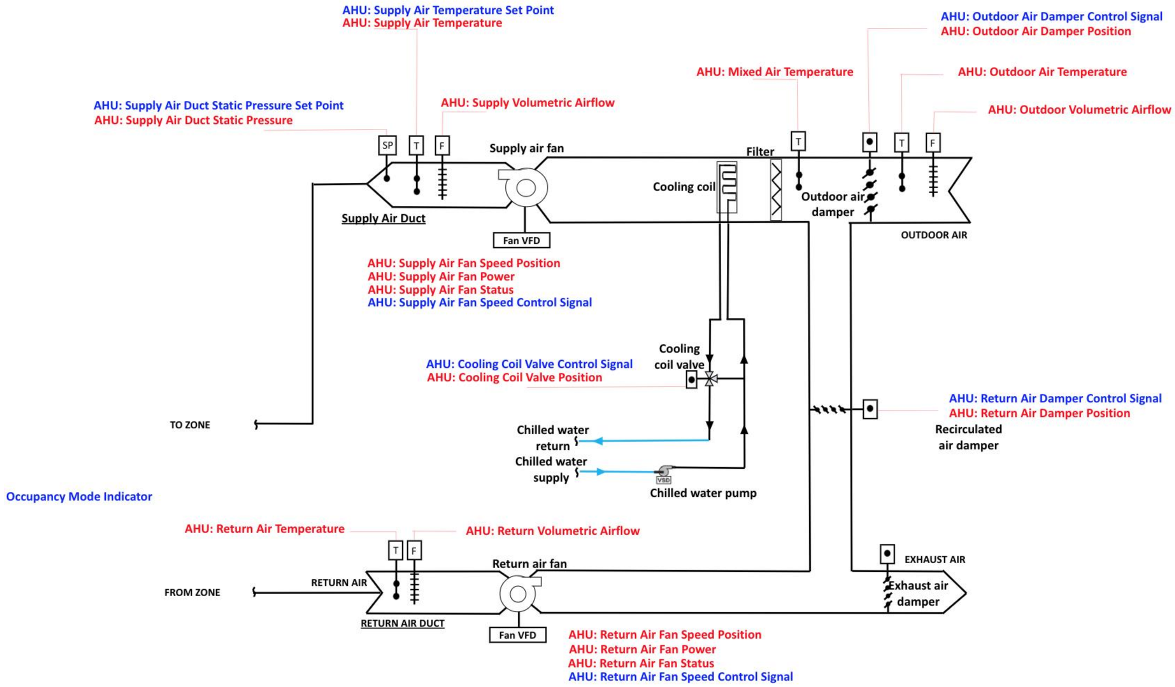

Figure 1: SDAHU diagram with all measurement points denoted

2.2 Dual-duct AHU (DDAHU) system

The DDAHU system equips two separate supply air ducts as hot duct and cold duct, and two supply air fans in each duct to provide desired air circulation and thermal comfort to different zones. In this system, both the heating and cooling coils can operate at the same time. The hot air and the cold air will be mixed with dampers in VAV terminal units at each zone. In this study, the DD-AHU system was developed by HVACSIM+ software tool which was developed by the National Institute of Standards and Technology (Clark & May, 1985). The system contains a dual-duct AHU and four associated VAV terminal units which serve four zones as shown in Figure 2. In the HVACSIM+ simulation platform, various elements such as parts, components and control sequences in a HVAC system can be modeled to create various instance blocks referred to as different “TYPE” components. Various components can be grouped into “superblocks” for simultaneous solution. Consequently, each superblock is a numerically independent subsystem of the overall simulation. Each superblock can independently handle its time evolution and internal solution during the simulation process. In addition, the time step in a superblock is a variable that is automatically and continuously adjusted by a solver subroutine to maintain numerical stability.

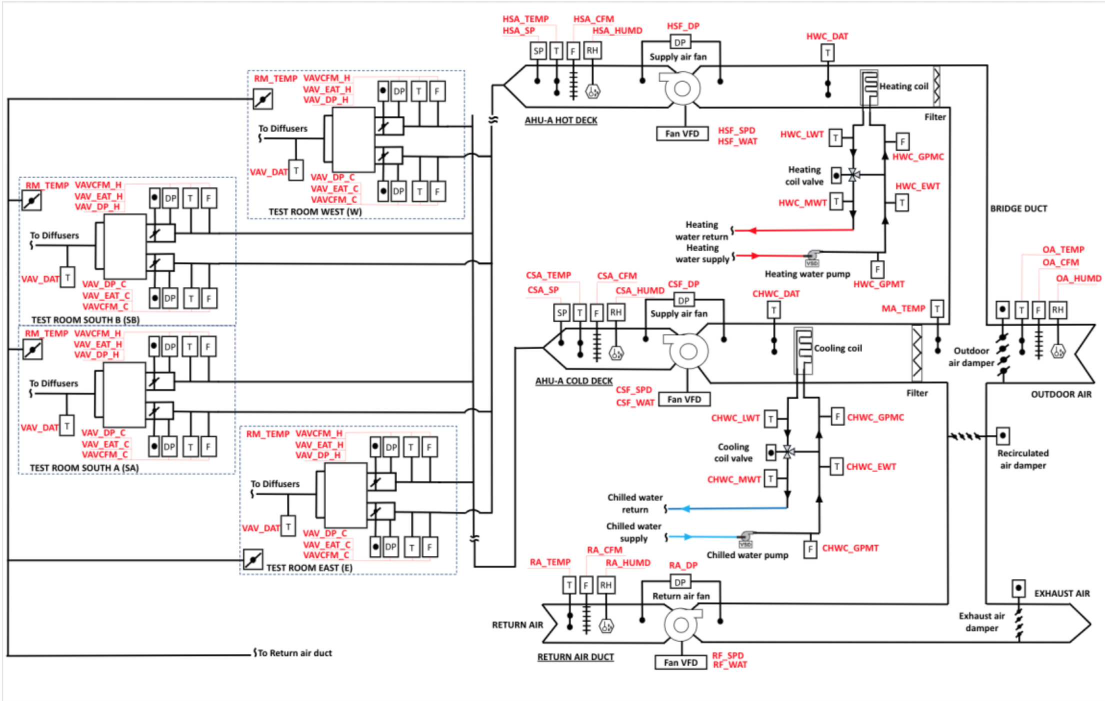

Figure 2: DDAHU diagram with all measurement points denoted

Before imposing faults on the simulation platform, various simulation settings were determined to ensure the simulation accuracy. The simulation setting includes three parts as 1) control sequence and parameter settings, 2) zone load settings, and 3) environment parameter settings. The control sequence includes the operation mode sequence, and individual component control sequences for fan, dampers, cooling coil valve and heating coil valve. The hourly zone internal load value was set according to (Park *et al.*, 1986). The TMY3 weather data for Des Moines, IA was used as the weather inputs as the system model was developed in Iowa Energy Center.

2.3 Fault Modeling

Three different components were targeted for fault modeling in the SDAHU model: the outdoor air damper, the cooling coil and the temperature sensors. The faults are all implemented by modifying or overriding the baseline control logic of the model. For example, the outdoor air damper stuck fault is implemented by overriding the position of the damper component. The fault imposition methods are summarized in the table below. As an example, for each intensity of the OA damper stuck fault, the fault is imposed by overriding the position of the modeled damper to the predetermined value. The scaled dataset creation is carried out with a parametric simulation Modelica script. This allows for the intensity of each fault to be modeled based on a single value that is passed as a parameter into the fault model component such as "TwoWayValveStuck" for both the cooling coil valve and OA damper.

In the DDAHU study, a total of 15 types of faults which are commonly studied by academic publications and reported by field engineers in the AHU side were imposed to obtain fault inclusive operation data (Chen *et al.* 2021; Roth *et al*. 2004; Schein *et al.* 2006; Wang and Xiao 2004; Zhao, Wen, and Wang 2015; Zhao *et al.* 2017). For hardware faults, the simulations with multiple severity levels were performed for each type of the fault. For the software faults, the simulations with single severity level were performed for each type of the fault. Consequently, a total of 55 fault simulation cases were carried out in this study. Each fault case was simulated to generate one year of operation data so that all system's operational conditions can be covered to fully evaluate the measurement sensitivity under various operational conditions.

Table 1: Overview of HVAC fault modeled and imposition method

Fault	**Method of fault imposition**
Supply, Outdoor Air Temperature Sensor Bias	Add or subtract constant value from initial sensor reading
OA Damper,Cooling Coil Valve Stuck	Automated override of OA damper position to indicate that OA damper is stuck. Automated override of coil valve position to indicate that cooling coil valve is stuck.
Cooling Coil Valve Leak	Adjusted the minimum coil valve position value when control signal is zero
Cooling/Heating coil fouling fault (air side)	Modified fin and tube heat transfer coefficients in the coil component
Cooling/Heating coil fouling fault (water side)	Modified fin heat transfer coefficient, tube heat transfer coefficient, and the coil fluid flow resistance in the coil components
Cooling/Heating control sequence unstable	Changed the absolute value of the proportional band of the cooling and heating control sequences from a properly tuned value 45.7 to an improper value 4

The symptoms of each fault are detailed below:

The **outdoor air damper stuck fault** is a mechanical fault by nature and will directly affect the AHU's ability to take advantage of outdoor air to maintain supply temperatures while minimizing cooling energy as well its ability to maintain effective supply temperature control. During instances in which the OA damper is stuck above minimum position and supply air is cooler than desired setpoint, excess outdoor air may cause the cooling energy to be minimized while dramatically reducing the supply air temperature of the AHU. The case in which warmer temperatures are seen outdoors, the excess outdoor air will cause more cooling energy to be used, driving the control signal of the OA damper to minimum while maximizing the cooling coil control signal. Higher than normal supply air temperatures may occur.

A **stuck cooling coil valve** directly affects the AHU's ability to maintain effective supply temperature control. During instances in which the supply air is warmer than desired, the control signal will be driven to 100% due to the inability of the system to maintain cool enough air to the zone level. This will cause higher than normal supply temperatures, higher than normal return air temperatures, and higher overall cooling energy consumed. During instances in which the cooling coil is providing too much cooling, or a supply temperature colder than the setpoint, the control signal will eventually be driven to zero due to the inability of the system to maintain supply air temperature set point. This will ultimately lead to lower than desired supply and return air temperatures and higher overall cooling energy consumed.

A **leaking cooling coil valve** affects the AHU's ability to fully close the cooling coil valve. During instances in which the control signal is driven to a level below the leakage level or to 0, the ground truth position of the valve will bottom out at the leakage level. This will cause lower than normal supply temperatures during these instances, and higher overall cooling energy consumed. During instances in which the leakage level is higher than the control signal, the fault will behave more like a stuck valve fault.

A **temperature sensor bias fault in the outdoor temperature sensor** would cause an adverse effect on supply temperature control, mainly the modulation of the outdoor air damper according to the economizer control sequence.

As the bias becomes more positive (4C), the seemingly higher outdoor air temperature would result in less activity in the economizer control signal, resulting in higher overall cooling energy consumption.

A **temperature sensor bias fault in the supply temperature sensor** would cause an adverse effect on supply temperature control, mainly the modulation of the cooling coil valve to meet setpoint. As the bias becomes more positive (4C), the seemingly higher supply temperature would result in higher control signal for added cooling, resulting in higher overall cooling energy consumption, cooler rooms (lower return air temperatures)

Both **the coil fouling air side fault and water-side fault** would cause several typical symptoms such as decreased water flow rate, increased coil valve position to provide desired cooling/heating capacity, and increased or decreased supply air temperature. For example, if the heating coil is severely fouling, the heating water flow will be significantly decreased. In the winter season, this may lead the heating coil valve position to be higher than normal to provide the desired heating. Under some extremely cold weather conditions, the supply air temperature may be lower than normal due to the severe impacts on the heating supply capacity. For the fouling fault types, three fault severity levels (minor, moderate and severe) were imposed by decreasing the fluid flow rate and the decreasing heat transfer rate.

Both **cooling and heating control sequence faults occuring in the valve controllers.** The control sequence fault causes valve position to be unstable and consequently causes supply air temperature to be fluctuating. The fault was imposed by changing the absolute value of the proportional band setting from 45.7 to -4 in the PID controller until the valve operation was unstable.

3. RESULTS

The annual fault cases are modeled in their respective tools, then validated to ensure the fault behaviors are as expected based on our knowledge based approach. An example of the SDAHU fault model for an outdoor air damper stuck at minimum (10%) is presented below in Figure 3. The fault is most easily discernible by the constant position reading of 10% throughout the day. More telling however, is the increase in cooling coil valve signal, which indicates the faulted case consumes more cooling energy due to the lack of ability to take advantage of mild conditions and economize.

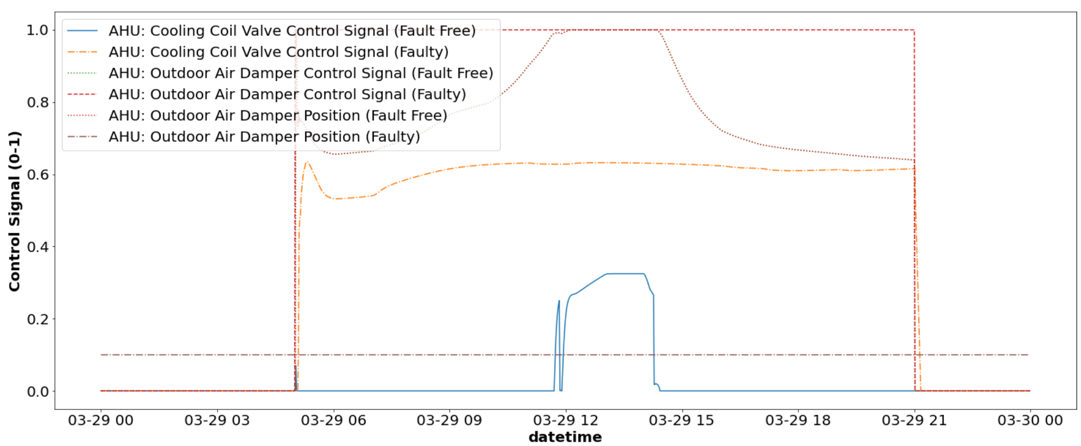

Figure 3: SDAHU fault symptom validation (outdoor damper stuck at minimum [10%])

Figure 5 shows another case example to demonstrate the fault symptoms under the cooling coil valve stuck fault in the DDAHU. When the cooling coil valve is stuck at 80% opening position which is higher than the normal position, the coil valve position signal is frozen at 80% and the valve control signal reaches to 0 to try to offset the effects of the higher coil valve position as shown in the left of the Figure 4. However, because the cooling coil valve is out of control, this fault causes the supply air temperature in the cold deck to be lower than the normal value (i.e., around 10 °C instead of 13 °C under the fault-free operation as given in the right of the Figure 5). In addition, this fault causes the cascading abnormal operation in the downstream VAV terminal units.

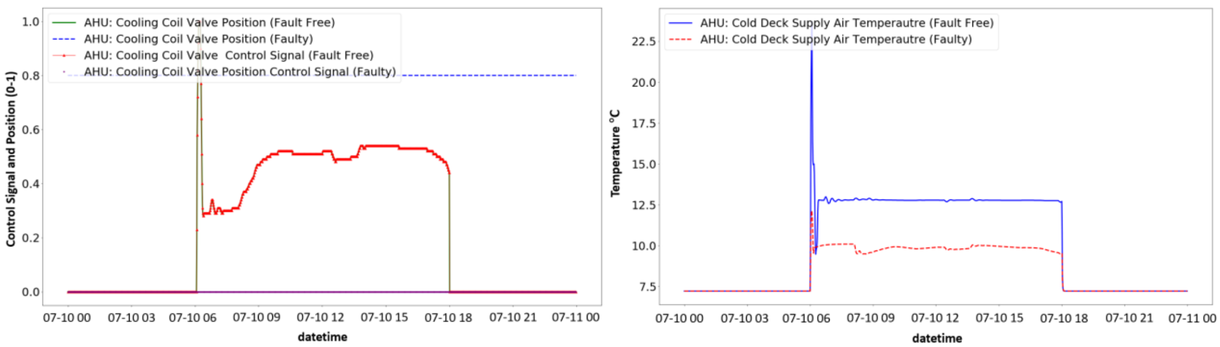

Figure 4: DDAHU fault symptom validation (cooling coil valve stuck at a 80% position fault)
Left: coil control signal and position; Right: cold deck supply air temperature

4. DISCUSSION

A large scale simulation task like this is a multi-year, multi-partner effort that presents challenges along the way. We have compiled these lessons in the following section by system type. These considerations are meant for other model developers so they are able to avoid inefficiencies and pitfalls in their own approaches. The lessons learned are categorized and summarized in Table 2 below.

Table 2: Overview of lessons learned from AHU fault modeling efforts

Lesson	**Details**	**Solutions**	**System affected**
Control sequence refinement	Freeze protection, competing PID loops for economizer	Add preheating, disable cooling coil until OA damper has reached 100% during economizing.	Coil, OA damper
Fault imposition methods	Actuator-related faults (e.g., a damper stuck fault), the changed value should be injected to freeze the actuator	Add position variable to give the control signal the ability to behave according to its PID control loop output	Actuated components (damper, coil valve)
Inappropriate sizing of components	Error of the component model needed better control to enable the acceptable output error of the system model.	Resize components based on observed load given climatic conditions and internal loads of the space conditioned by the system	Supply air temperature, zone level
Modeling low flow conditions	Limitations during low flow conditions. Causes abnormal conditions which manifest in different ways during modeling.	Create virtual bypass values that pass the incoming coil temperatures through the coil without heat transfer calculations applied.	Coil, OA damper, temperature sensor measurements

4.1 DDAHU (HVACSIM+)

Compared with the previous fault model validation process in which a few days were selected and only employed, it is necessary to add control sequences which enable a complete simulation under all operational conditions. For example, in the DDAHU control, a freezing protection functionality was added after encountering an issue during winter operation. In the original DDAHU model, there was no freezing protection control sequence during the unoccupied hours when the system was completely shut off. This caused the SAT to be extremely low (e.g., as low as 10 F) when the OAT was low in the winter season. In the real system, the freezing protection control sequence may be adopted even when the system was switched to the unoccupied mode (i.e., the system does not provide the desired cooling or heating during unoccupied hours). The freezing protection sequence often enables the preheating, or triggers the freezing alarm so that the operators can fix the fault quickly. This issue may only occur when whole year simulation is performed to enable the system control simulation to mimic this operating condition.

The model validation under all operational conditions was also applied to the equipment physical model validation to ensure the equipment model accurately outputs values. For example, in the simulated cooling valve model, the operating position limit should be set to be 100 (i.e., fully opened) as the maximum value even though the cooling supply may not be enough in extremely hot weather. After encountering this issue, all the actuator models were re-examined to add the actuator operating position limit.

Another challenge addressed is the system level fault simulation. In the DDAHU simulation, the system model, which was developed in HVACSIM+ software, consists of various component models (i.e., coils, valves, dampers) in the DDAHU equipment and terminal unit model. Various models were connected with each other to complete the system level simulation. When performing simulation, the output error of the component model needed to be well controlled to enable the acceptable output error of the system model. For example, the heating coil was downsized in the model, this component output error caused the whole system output error, and consequently supply air temperature to be abnormal. This error was eliminated by increasing the heating coil size.

When imposing actuator-related faults (e.g., a damper stuck fault), the changed value should be injected to freeze the actuator action, but not fix the control signal. This is because in the real practice, the actuator stuck was believed to be some mechanical/communication issues (e.g., the linkage between the driver and actuator is broken, or the communication between the DDC and the drive is lost). The DDC should output the proper control signal to compensate/tolerate the fault. Therefore, the control signal should not be frozen. To address this issue, some extra points (i.e., valve position feedback) should be added in the original equipment model to mimic the control behavior and simulate the fault effects.

4.2 SDAHU (Modelica)

A common occurrence for the Modelica based model are indeterminate conditions when fluid flows are near zero. This happens often during overnight scenarios, in which the flow provided to a water coil or the airflow approaches zero due to the lack of demand in the system in unoccupied hours. This low flow causes abnormal conditions which manifest in different ways during modeling. One example is **its effects on supply air temperature during severe damper fault cases.** In reality, when the temperature of the air is too low (less than the temperature of the inlet water), it is possible that it “absorbs” heat from the cooling coil. In simulation, the process for calculating the water temperature in a heat exchanger becomes unreliable when the water flow is approaching 0. Low flow conditions can also cause abnormal temperature deviations and flat profiles given limitations of the sensor modules we use during simulations. These flat temperatures may have effects on their associated control loops, for instance the supply air temperature control loop sends a **cooling coil valve control signal of** 100% due to the flat measurement of the supply air temperature sensor when the supply air flow is zero.

In addition to limitations with modeling low flows, there were some inconsistencies between the control sequence programmed in the model and best practices that we caught during our validation process. The model has two PID control loops, one for the economizer control and one for the cooling coil valve control. The economizer control uses the mixed air temperature as the control variable while the supply air temperature controls the second loop. The problem occurs when economizing is enabled during mild conditions. Both controls loops compete against each other to satisfy their setpoints, which leads to cooling while the outdoor air damper is modulating. Best practice prescribes the cooling coil valve stay disabled until the economizer output is 100%. Modulating the cooling coil valve before this condition results in unnecessary energy consumption and does not allow the economizer to take full advantage of ideal outdoor air conditions. These types of interconnected control loops need to be programmed in sequence so that the cooling coil valve control is disabled in economizing mode until the outdoor air damper reaches 100% open position.

Another consideration is related to co-simulation frameworks such as the one presented here for the SDAHU models. The change of data between the EnergyPlus idf file FMU and the AHU system model is not only limited to building thermal loads but also used to determine when the building is in Occupied or unoccupied mode. The documented occupied times of 6pm to 10pm are scheduled in the FMU and the occupied output is fed to the model as a boolean value. The problem observed during validation is related to the daylight savings time option in the idf file was set to true, which meant that the start of daylight savings time resulted in a 1-hr shift in time reporting from the FMU. This manifests in the model as an occupied time of 5am to 9pm, which is inconsistent with the provided documentation.

5. CONCLUSION

In this study we have established our methods and results of our large-scale fault modeling work. Once validated and fully documented, we plan to publish this dataset in the largest ever publicly available fault database. The study presented here is a short summary of the work we have done for AHU systems. The lessons learned presented in the discussion are common issues found in all modeling approaches and are intended to help developers avoid inefficiencies in their own approach.

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