S. Huang, W. Zuo, D. Vrabie, R. Xu 2021. "Modelica-based System Modeling for Control-related Faults in Chiller Plants and Boiler Plants Serving Large Office Buildings." *Journal of Building Engineering*, 44, pp 102654, https://doi.org/10.1016/j.jobe.2021.102654.

Modelica-based system modeling for control-related faults in chiller plants and boiler plants serving large office buildings ¹

Sen Huang a, Wangda Zuo b,c, , Draguna Vrabie a, Rong Xu a

5

10

15

20

2.5

^a Pacific Northwest National Laboratory, Richland, WA 99352, U.S.
 ^b University of Colorado Boulder, Boulder, Colorado, CO 80309 U.S.
 ^c National Renewable Energy National Laboratory, Golden, CO 80401. U.S.

Abstract

Dynamic modelling the faulty operation of chiller plants and boiler plants can help identify their impacts and support the development of fault detection methods. However, adequate models are seldom reported in the literature. In this study, we aim to develop high-fidelity models for approximating the dynamic behaviors of chiller plants and boiler plants under control-related faults. Specifically, we first designed a typical configuration of the chiller plants and the boiler plants; we then modeled both the physical systems and controllers of this typical plants with Modelica. When developing the Modelica models, we created a hierarchical model structure while modules in each layer can be redeclared and parameterized at upper layers. This model structure facilitates the implementation of fault scenarios through intuitive model modifiers. At last, we applied the proposed models in a comprehensive fault impact evaluation of the thirteen control-related faults of chiller and boiler plants. In this evaluation, the proposed models are coupled with the EnergyPlus™ thermal load model to study the impact of various faulty scenarios. Based on the fault impact evaluation results, we identified the faults that have the most significant impacts on the operation of the chiller and boiler plants, respectively. We also found that the relationship between the impacts of the studied faults and the severity level of the faults may be highly non-linear. This study contributes to the literature by providing the first dynamic models of chiller plants and boiler plants which can be used to study control-related faults on a large-scale.

Keywords: Fault Modeling, Chiller Plant, Boiler Plant, Modelica, Impact Analysis

¹ This material is partially based upon work supported by the U.S. Department of Energy (DOE), Building Technologies Office through its Emerging Technologies program. Pacific Northwest National Laboratory is operated for the U.S. Department of Energy by Battelle Memorial Institute under Contract DE-AC05-76RL01830.

1. Introduction

30

35

40

45

50

55

60

Chiller plants and boiler plants represent about 35% of the primary energy used by commercial building cooling and 21% of the primary energy used by commercial building heating, respectively, in the U.S. [1]. The energy efficiency of chiller plants and boiler plants can be significantly affected by operation faults [2] [3]. Cheung and Braun [4] found the electricity consumption of chiller plants under faulty conditions can be increased by up to 14.8%. García, Álvarez, etc. pointed out that [5] poor air inlet settings can lead to 20% higher fuel consumption by boiler plants. Owing to their significant impacts on the energy efficiency of chiller plants and boiler plants, substantial efforts have been devoted to better understand those faults and thereby eliminate them when operating chiller plants and boiler plants. Those efforts can be divided into two groups: fault impact analysis and automated fault detection & diagnostics (AFDD). Fault impact analysis aims to quantify the impacts of various faults during the building operation. It helps building operators to identify the critical faults and researchers to identify the critical research directions [4] [6]. AFDD attempts to develop methods to detect operational faults and then isolate the cause of the detected faults. AFDD has been an active area of research in HVAC systems. There have been a considerable number of AFDD methods for chiller plants and boiler plants proposed over the past two decades [7] [8] [9].

For both the fault impact analysis and AFDD, modeling faulty chiller plants and faulty boiler plants is indispensable. It is so far the most common way to quantify the impacts of faults [6]. In general, fault models of chiller plants and boiler plants can be categorized into three groups. In the first group, those fault models can be obtained by modifying the parameter values of fault-free models. For example, Basarkar, Pang, etc. [10] modified the rated capacity of a fault-free chiller model and the rated efficiency of a fault-free boiler model to model a refrigerant leak fault and a fouled water tube fault, respectively. Those fault-free models were developed in EnergyPlusTM [11]. In the second group, the models of faulty building systems are obtained by introducing new parameters to fault-free models while those parameters define the degree or extent of the studied faults. For example, Cheung and Braun [4] added six parameters to the chiller model in EnergyPlusTM to calculate how the chiller power is influenced by faults

such as overcharging, excess oil, non-condensable in the refrigerant, and condenser fouling. In the third group, the models of faulty building systems are developed by treating the fault(s) explicitly based on underlying physics. In this case, major increases in the modeling detail are usually required if fault-free models are leveraged. For example, Shohet, Kandil, etc. [12] developed a physics-based model of a non-condensing boiler to investigate faults that occur within boilers. When developing this model, they added a significant number of new equations to the existing fault-free boiler models. For instance, a governing equation for the combustion process was added for abnormal combustion conditions caused by faults such as excess air. Cheung and Braun [13] developed gray box models for components in chillers, such as compressors, condensers, and expansion valves. They calibrated the coefficients of those models with data sampled from real chillers under normal and faulty conditions.

Despite the encouraging results from fault modeling for chiller plants and boiler plants, existing fault models have two major drawbacks, limiting their potentials for supporting general fault-related studies. First, they tend to ignore fast building dynamics and adopt ideal control. Most of the existing fault models are implemented by modifying or adding parameters to fault-free models. In the literature, EnergyPlusTM is used frequently as the fault-free model for implementing fault models. However, the extent to which faults can be approximated is subject to the basic assumptions of EnergyPlusTM. Specifically, EnergyPlusTM assumes that fast dynamics are negligible [14]. Therefore, the fault models implemented in EnergyPlusTM may not capture the fast building dynamics over short-term periods. However, those fast building dynamics can play an important role in determining the impacts of operation faults, especially the control-related ones.

Second, the usage of existing fault models can be labor-intensive, especially when it comes to large-scale fault-related studies. In those studies, it is common to consider multiple faults occurring at different operating conditions. The combination of faults and operation conditions can easily generate a large number of simulation cases. This number can be further increased substantially if fault occurrence probability is considered [15]. On the other hand, a simulation-based validation of AFDD methods may require a co-simulation set up to communicate the simulation models with the

testing methods in real-time. However, configuring the existing fault models for this purpose can be troublesome [16].

95

100

105

110

115

120

Some studies aim to mitigate those issues in large-scale studies. For example, Li and O'Neil developed a software framework for facilitating fault impact analysis [6]. This framework can automatically generate EnergyPlusTM input files based on predefined fault conditions. Wang and Karami [17] proposed a virtual testbed to evaluate the developed AFDD methods with simulation data. However, most of those studies rely on ad hoc software implementation and very few of those studies consider those issues when developing fault models, limiting their abilities for supporting large-scale studies.

In this paper, we present high-fidelity models for approximating the behaviors of chiller plants and boiler plants under faulty conditions. Compared to existing ones, the proposed models have two advantages: first, they better characterize the dynamic patterns in the system operation. In those models, control architecture and control logic are faithfully implemented. Thus, they can be used to study control-related faults, such as incorrect staging control due to sensor bias and high steady-state errors owing to mistuned feedback control. In this study, we used Modelica [18], which is an equationbased object-oriented modeling language, to establish the system model. Modelica is very suitable for modeling multidomain systems [19] [20] that contain not only the physical system but also the control system. Second, they are readily extensible, supporting large-scale investigations to explore different faulty conditions/scenarios. Those models are established in a hierarchical structure while modules in each layer can be redeclared and parameterized at upper layers. fault scenario can be described through intuitive model modifiers. In sum, the proposed models, for the first time, provide a solution to study control-related faults in chiller plants and boiler plants on a large-scale. We applied the proposed models in a comprehensive fault impact evaluation on thirteen control-related faults. In this evaluation, the proposed models are coupled with the EnergyPlusTM thermal load model to represent various faulty scenarios.

The rest of this paper is organized as follows. In Section 2, a detailed description of the studied chiller plant and the studied boiler plant is provided. After that, the studied control-related faults are discussed in Section 3. Then, system models of the studied

plants are elaborated in Section 4. We elaborate on how we implement models in Modelica, validate the models, and extend the models for large-scale fault-related studies. After that, a comprehensive fault impact analysis is conducted in Section 5. Conclusions can be found in Section 6.

2. Studied System

125

130

135

140

The studied system provides chilled water and hot water to a prototypical large office building in the U.S. This office building consists of twelve floors while each floor is served by one air handling unit (AHU). Each AHU has one cooling coil where chilled water cools the air leaving the AHU. There are five thermal zones on each floor, and each zone is served by one variable air volume (VAV) terminal. In each VAV terminal, hot water heats the air entering the thermal zone. More detailed information about this prototypical office building can be found in [21].

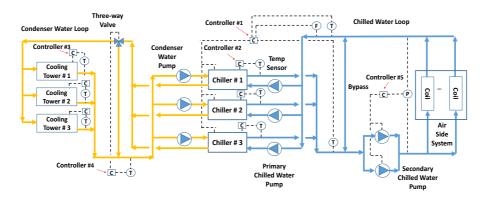


Figure 1 Schematic of the studied chiller plant

The studied system consists of a chiller plant and a boiler plant. Figure 1 illustrates the configuration of the chiller plant. This plant has three identical chillers. For each chiller, there is one dedicated condenser water pump and one dedicated primary chilled water pump. Chillers connect with one condenser water loop and one chilled water loop. In the condenser water loop, there are three identical cooling towers and one three-way valve. The chilled water loop consists of two identical secondary chiller water pumps, one bypass pipe, and provides chilled water to cooling coils in the air-side system. The

chiller plant is controlled by five controllers, as summarized in Table 1. As shown in Figure 2, the number of operating chillers is determined based on the thermal load via a state machine while the thermal load is calculated based on [22] and by

$$\dot{Q} = \dot{v}_{chw} \rho C_p (T_{chw}^{ent} - T_{chw}^{lea}), \tag{1}$$

where \dot{Q} is the thermal load, \dot{v}_{chw} is the volumetric flow rate of the chilled water, ρ and C_p are the density and specific heat of water, respectively, and T_{chw}^{ent} and T_{chw}^{lea} are the temperatures of the chilled water entering and leaving the chiller plant, respectively.

145

Table 1 Controllers in the chiller plant

Index	Controlled Variables	Description	
maex	Controlled variables	Description	
1	Number of the operating chillers	Chillers are staged based on the measured cooling load, as elaborated in Figure 2.	
2	The cooling power of the operating chillers	The cooling power of each operating chiller is controlled by a feedback loop to maintain the temperature of the chilled water leaving each chiller to be a setpoint that is reset every hour based on Equation(2).	
3	Speeds of the operating cooling towers	All the operating cooling towers share the same fan speed that is controlled by a feedback loop to maintain the temperature of the condenser water leaving cooling towers to be a setpoint that is reset every hour based on Equation (3).	
4	Position of the three-way valve	The position of the three-way valve is controlled by a feedback loop to maintain the temperature of the condenser water leaving the condenser water loop to be larger than 15.56°C.	
5	Speeds of the operating secondary chilled water pumps	Pumps are staged based on the pump speed, as elaborated in Figure 3. The operating secondary chilled water pumps share the same speed that is controlled by a feedback loop to maintain the pressure difference in the chilled water loop.	

 \dot{Q}_c : Cooling load cc^k : Rated cooling capacity of chiller k ξ^k : Threshold to starting chiller k+1 All OFF plant is on plant is off $\dot{Q}_c > \xi^1 cc^1$ $\dot{Q}_c > \xi^1 cc^1$ $\dot{Q}_c > \xi^{N-1} \sum_{k=1}^{N-1} (cc^k)$ $\dot{Q}_c \leq 0.9 \xi^{N-1} \sum_{k=1}^{N-1} (cc^k)$

Figure 2 Staging control of chillers ($\xi = 0.9$, waiting time: 30 min, N = 3)

N On

The setpoint for the temperature of the chilled water leaving chillers is reset based on [23] and by

150

155

160

$$T_{chw}^{set} = max \left(min \left(T_{chw}^{set,min} + \frac{T_{chw}^{set,max} - T_{chw}^{set,min}}{(T_o^{min} - T_o^{max})} \right) \right)$$

$$T_o^{max}, T_{chw}^{set,max}, T_{chw}^{set,min},$$

$$T_{chw}^{set,min},$$

where T_{chw}^{set} is the temperature of the chilled water leaving each chiller, $T_{chw}^{set,min}$ and $T_{chw}^{set,max}$ are the minimum and maximum values (5.56°C and 11.11°C) of T_{chw}^{set} , T_o is the outdoor dry bulb temperature, and T_o^{min} and T_o^{max} (15.56°C and 26.67°C) are the minimum and maximum values of T_o for this reset. Similarly, the supervisor controller determines the temperature of the condenser water leaving cooling towers based on the equation [24] below

$$T_{cw}^{set} = min(T_{wb} + T_{app}, T_{cw}^{set,min}), \tag{3}$$

where T_{cw}^{set} is the temperature of the condenser water leaving each cooling tower, $T_{cw}^{set,min}$ is the minimum value (15.56°C) of T_{cw}^{set} , T_{wb} is the outdoor wet bulb temperature, and T_{app} is a fixed approach temperature (4.44°C). The state machine to determine the number of secondary chilled water pumps is illustrated in Figure 3.

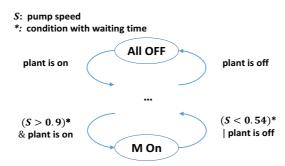


Figure 3 Staging control of secondary chilled water pumps (waiting time: 30 min, M = 2)

Figure 4 shows the configuration of the boiler plant. This subsystem has two identical boilers. Boilers connect with one hot water loop. The hot water loop consists of two identical hot water pumps. The boiler plant subsystem is controlled by three controllers, as summarized in Table 2.

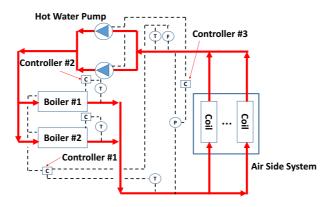


Figure 4 Schematic of the studied boiler plant

Table 2 Controllers in the boiler plant

165

Index	Controlled Variables	Description
1	Number of operating boilers	Boilers are staged based on the measured heating load, as elaborated in Figure 5.
2	The heating power of operating boilers	The heating power of each operating boiler is controlled by a feedback loop to maintain the temperature of the hot water leaving each boiler to be 80 °C.
3	Speeds of the operating hot water pumps	Pumps are staged based on the pump speed, similar to that is elaborated in Figure 3. The operating hot water pumps share the same

speed that is controlled by a feedback loop to
maintain the pressure difference in the hot
water loop.

As shown in Figure 5, the number of operating boilers is determined based on the thermal load via a state machine while the thermal load is calculated based on [22] and by

$$\dot{Q} = \dot{v}_{hw} \rho C_p (T_{hw}^{ent} - T_{hw}^{lea}), \tag{4}$$

where \dot{v}_{hw} is the volumetric flow rate of the hot water, and T_{hw}^{ent} and T_{hw}^{lea} are the temperatures of the hot water entering and leaving the boiler plant, respectively.

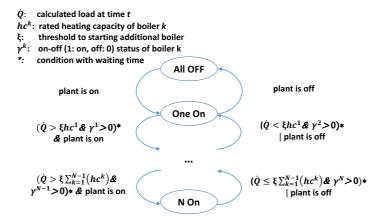


Figure 5 Staging control of boilers ($\xi = 0.9$, waiting time:30 min, N = 2)

3. Operational Faults

We consider three types of operational faults that are commonly observed in chiller and boiler plants. Those faults are sensor bias, leaking valve, and untuned Proportional-Integral (PI) control. The following elaborate on how we describe those faults quantitatively.

1) Sensor bias

175

170

Sensor bias refers to differences between measured and actual values of observed variables. A sensor bias can be described by

$$u = \hat{u} + e, \tag{5}$$

where u and \hat{u} are the measured value of an observed variable from sensors and the actual value of the observed variable, respectively, and e is a constant or varying deviation that can be a function of \hat{u} and/or time.

2) Leaking valve

180

185

190

195

200

A leaking valve means the actual position of the valve/damper is always larger than a constant value, c, regardless of the input signal. In such a case, the openness of the valve, y, is determined by

$$y = \max(\hat{y}, c), \tag{6}$$

where \hat{y} is the position of the valve/damper based on the input signal when there is no fault.

3) Mistuned proportional-integral (PI) control

A mistuned PI control refers to PI controllers that generate large steady-state errors due to inappropriate selections of the values for the proportional gain and the integral time of the PI controller, i.e., a relatively large proportional gain and a relatively lower integral time.

Note that all three types of operational faults can affect controllers in both the chiller plant and the boiler plant. For example, the sensor bias may affect the input of Controller #1 (chiller staging controller) in the chiller plant. The leaking valve may affect the actuation of Controller #2 (boiler heating power controller) in the boiler plant. The inappropriate settings of PI controllers may affect the generation of the control signal of Controller #3 (hot water pump controller) in the boiler plant.

4. System Models

In this section, we elaborate on how we develop high-fidelity models of the chiller plant and the boiler plant with Modelica. We also discuss how those high-fidelity models can support large-scale fault-related studies.

4.1 Model Development

We develop the system model of the chiller plant and the boiler plant with a hierarchical structure. As an example, Figure 6 illustrates the structure of the chiller

plant model. This chiller plant model contains five layers: the first layer (named as *top* level) has the system model for the entire chiller plant; the second layer (named as *subsystem* level) contains the subsystem of this plant; the third layer (named as *component* level) contains the major physical components of each subsystem and supervisor-level controllers; the fourth layer (named as *device* level) consists of devices and the associated local controllers for each device; and the last layer (named as *element* level), contains the elements of each controller: *Sensor*, *Control Sequence*, and *Actuator*.

210

215

220

225

There are three major benefits of having a hierarchical structure. First, it simplifies the process of developing models. This structure splits the complicated model into isolated simpler models. Each simpler model can be separately tested before integrating into complicated ones. Second, it eliminates model duplication. With this structure, as illustrated by Figure 6, the *Local Control* model and the *Staging Control* model can share the same *Sensor* model of the temperature sensor. Third, it boosts the extensibility potential of the system models. This structure reduces the impacts from modifying models at one layer on models at other layers. In such cases, new models can be generated with less effort.

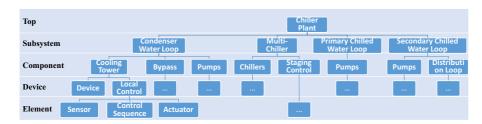


Figure 6 The structure of the model for the chiller plant

We implement system models with Modelica. Modelica is an equation-based, objective-oriented modeling language for complex dynamic systems. The model at the *Top* level has three inputs: the cooling load, the heating load, and the wet bulb temperature of the outdoor air, denoted by *CooLoad*, *HeaLoa*, and *WetBul*, respectively. The *TWetBul* is from weather data while *CooLoad* and *HeaLoa* are from pre-generated datasets or a co-simulation with the system model of the air-side systems (e.g. air handling unit and thermal zones). When implementing models at lower level,

we leverage components from existing Modelica libraries. For example, the *Device* model of the *Pumps* under the *Condenser Water Loop* is modeled with the *Buildings.Fluid.Movers.SpeedControlled_y*, which is from the Modelica Buildings Library [24]. A few *Device* models are built based on the modified components from the Modelica Buildings Library. For example, we remove the idealized control loop in the component *Buildings.Fluid.Chillers.ElectricEIR* when building the *Device* model of the *Chillers* to better capture the local control dynamics. Note that we implemented the models at the *element* level for modeling both the normal operation and the faulty operation. As shown in Table 3, we develop three *sensor* models, two *control sequence* models, and three *actuator* models for the normal operation. Those models are built with components from existing Modelica libraries. For example, the Control Sequence model of the Stage Control model is implemented with components from Modelica.StateGraph, a part of the Modelica Standard Library [25], as shown in Figure 7.

Table 3 Models in the *element* level

Type/Case	Normal Operation	Faulty Operation	
Sensor	temperature sensor, pressure sensor, flow sensor	temperature sensor with a bias, pressure sensor with a bias	
Control Sequence	state machine, PI control	untuned PI control	
Actuator	speed of devices, openness of valves, on-off status of devices	openness of leaking valves	

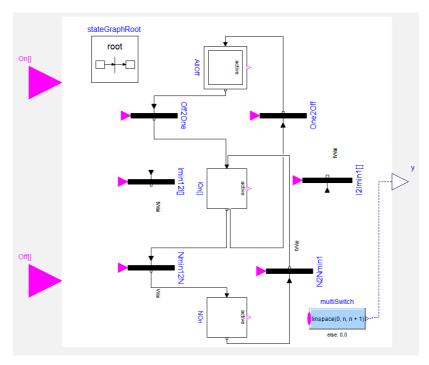


Figure 7 Implementation of the Stage Control model

For the faulty operation, we develop four fault models by modifying the components from existing Modelica libraries. Precisely, we model the temperature sensor with a bias by

$$\hat{T}^t = T_0^t + dT,\tag{7}$$

where \hat{T}^t and T_0^t are the temperatures measured with and without a bias fault, respectively, T_0^t is the output of the *Building.Fluid.Sensors.TemperatureTwoPort* from the Modelica Building Library, dT is a constant deviation.

Likewise, we model the pressure sensor with a bias by

$$\hat{p}^t = (1+\alpha)p_0^t,\tag{8}$$

where p^t and \hat{p}^t are the pressures measured with and without a sensor bias, respectively, p_0^t is the output of the *Building.Fluid.Sensors.Pressure*, and α is a deviation fraction.

We model a leaking valve by

245

250

$$\hat{\mathbf{y}}^t = \max(\mathbf{y}_0^t, c). \tag{9}$$

Note that y_0^t , the position of valves without faults, is calculated by *Building.Fluid.Actuators.BaseClasses.PartialTwoWayValveKv* from the Modelica Buildings Library. When modeling the untuned PI control, we introduce a coefficient β ($\beta > 0$) to define how fast the PI controller responds to the control signals. Hence the mistuned values of the proportional gain and the integral time deviate are given by

$$\hat{k} = \beta k,\tag{10}$$

$$\widehat{T}_{l} = \frac{T_{l}}{\beta},\tag{11}$$

where k and T_i are the tuned values of the proportional gain and the integral time, respectively, and \hat{k} and \hat{T}_i are the mistuned values of the proportional gain and the integral time, respectively.

4.2 Model Validation

255

260

265

270

275

As mentioned in Section 4.1, most of the models at the *device* level are from existing Modelica libraries directly. As validations have already been performed for those libraries [24], we don't perform a further valuation on those models in this study. On the other hand, for the models at other levels, especially the *element* level, we have performed validations to make sure they can generate expected outputs when inputs are given. As shown in Figure 8, we used the validation results of the *Stage Control* model as examples to elaborate the validation process. As described in Section 2, the *Stage Control* model is supposed to kick on/off an additional chiller when the measured cooling load exceeds/is below the threshold with a waiting time of 30 minutes. As shown in Figure 8, the cooling load exceeds the threshold at 05:03 and the number of operation chillers increases from 1 to 2 at 05:33. In addition, the cooling load is below the threshold at 21:02 and the number of operation chillers decreases from 2 to 1 at 21:32. The behavior of the *Stage Control* model is consistent with the expected one.

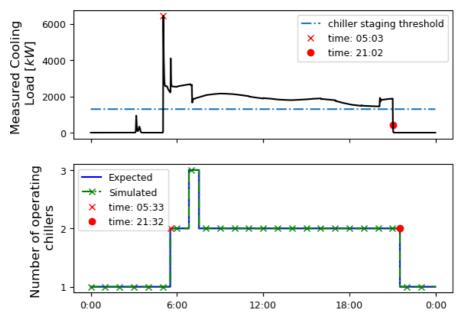


Figure 8 Validation of the Stage Control model

4.3 Model Extension for Supporting Fault-related Studies

To support the requirements when performing simulation-based fault-related studies, we include the features for co-simulation and fault insertion in the system model.

4.3.1 Co-simulation Interface

280

285

290

To facilitate the communication between the simulation models and the testing AFDD methods in real-time, we include two Modelica modules for signal exchange in the models at the *element* level. Both modules are from the Modelica IBPSA library [26]. The first module is *IBPSA.Utilities.IO.SignalExchange.Overwrite* (*Overwrite*), which can switch the output of the module between input and external signals. It allows the Modelica model to take external signals for resetting setpoints or directly modifying the device status, such as the openness of valves. Therefore, it increases the flexibility of the chiller plant model for including different control strategies when being used for evaluating the performance of AFDD methods. The second module is *IBPSA.Utilities.IO.SignalExchange.Read* (*Read*), which passes an input signal through to the output. It facilitates the process of passing the simulation data to external AFDD

methods. It is worth mentioning there is already a software framework, Building Operations Testing Framework [27], developed to facilitate the usage of those two modules for simulation-based testing of advanced building control. This framework can be used to perform large-scale AFDD methods with the resulting chiller plant model.

4.3.2 Fault Insertion Implementation

In this study, we first develop the fault-free model of the studied chiller plant with models at the *element* level for normal operation. We then extend the fault-free model to be fault models by adding model modifiers. Figure 9 shows an example of a fault model of the chiller plant. This example is designed for modeling the sensor bias fault occurring at the temperature sensor of the local controller for Chiller #1. When modeling this fault, the logic for resetting the setpoint of the chilled water temperature is considered as an external signal. Those model modifiers we added to the fault-free model redeclare the temperature sensor model and map the external signal with the setpoint for the chilled water temperature. There are two unique features of the model modifiers: 1) they are defined at the *top* level and thus no changes at lower levels are needed, and 2) they are intuitive and can be generated with predefined rules. Because of the above features of the model modifiers, the base models are readily extensible. Note that one can redeclare multiple models with modules for fault scenarios or the control-overwriting scenario simultaneously to model more sophisticated faulty scenarios.

```
model example
// Inputs for external control signals
Modelica.Blocks.Interfaces.RealInput TCHWSet_u "External set point";
Modelica.Blocks.Interfaces.BooleanInput TCHWSet_activate "Activation flag for set point";
// top level
ChillerPlant_base fault(
     // subsystem level
     Mutil chiller(
                 // component level
                        ch1(
                         // device level
                         local_control(
                                     // element level
                                     // redeclare the temperature sensor at the element level
                                     redeclare Fault.TemSensorDev senTCHWLea(dT=2),
                                     // mapping the external signal to the setpoint
                                      TCHWSet(
                                          uExt(y=TCHWSet_u),activate(y=TCHWSet_activate)
                                     )
                 )
);
end example
```

Figure 9 An example of the model modifier

5. Fault Impact Analysis

5.1 Simulation Settings

315

320

We conduct a fault impact analysis on thirteen faults, as shown in Table 4. The sensor bias faults affect the input of Controller #1, #2, #3, #5 in the chiller plant and that of all the controllers in the boiler plant, the leaking value fault impacts the actuation of the output signals of Controller #4 in the chiller plant, and the untuned PI control faults influence output signals of Controller #2 and #3 in the chiller plant and Controller #2 in the boiler plant. Note the simulation is performed for a whole year.

Table 4 Control-related faults

Index	Fault	Location	Abbreviation
Туре			
1	sensor bias	The temperature sensor of the chilled water entering the chiller plant	SCHW_T

2		The temperature sensor of the chilled water leaving Chiller #1	CH_T
3		The temperature sensor of the condenser water leaving Cooling Tower #1	CT_T
4		The pressure sensor of the pressure difference in the secondary chilled water loop	SCHW_PRE
5		The temperature sensor of the hot water entering the boiler plant	HW_T
6		The temperature sensor of the hot water entering leaving Boiler #1	BO_T
7		The pressure sensor of the pressure difference in the hot water loop	HW_PRE
8	leaking valve	The bypass valve of the condenser water loop in the chiller plant	VAL_LEA
9		Chiller #1	CH_PI
10	untuned	Cooling Tower #1	CT_PI
11	PI	The secondary chilled water loop	SCHW_PI
12	Controller	Boiler #1	BO_PI
13		The hot water loop	HW_PI

When simulating the above faults, we design a co-simulation between EnergyPlusTM and Modelica to capture interactions between the supply-side and the demand-side of the cooling and heating power. Specifically, the building envelope and the air-side system of the studied office building are modeled in EnergyPlusTM. The time synchronization between EnergyPlusTM models and Modelica models is realized as shown in Figure 9.

1) The EnergyPlusTM model sends the temperature and the flow rate of chilled/hot water entering plants at time t to the Modelica model.

325

330

335

- 2) Based on the temperature and the flow rate of chilled/hot water leaving and entering chillers/boilers, the Modelica model calculates the cooling or heating load at time t and calculate the temperature of the chilled/hot water leaving and entering chillers/boilers at time t + dt, which is sent to the EnergyPlusTM model.
- 3) The EnergyPlusTM model used the received temperature of the chilled/hot water leaving and entering chillers/boilers as the setpoints for the chilled/hot water and calculates the temperature and the flow rate of chilled/hot water entering plants at time t + dt.

The above process repeats until the simulation reaches the end. Note that this cosimulation design is built based on one major assumption: the cooling/heating load doesn't change significantly within the period of dt. Building systems usually have a relatively large time constant due to mechanical and thermal inertias. Therefore, we assume that the cooling/heating load for large commercial buildings changes insignificantly within a short period, e.g., 1 min.

340

345

350

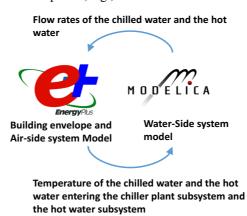


Figure 10 Co-simulation between EnergyPlus and Modelica

Both the EnergyPlusTM model and the Modelica model are converted into Functional Mockup Units (FMUs) [28] and those FMUs are simulated in the JModelica [29] environment. When developing the building energy model, we leveraged the U.S. Department of Energy's Commercial Prototype Building Models (hereinafter referred to as *Prototype Building Model*) [30]. We made the setpoint of the chilled water leaving chillers and that of the hot water leaving boilers overwritable via *ExternalInterface:FunctionalMockupUnitExport:To:Schedule* (details to do so can be found in [31]). The Modelica model is developed with components from the Modelica Standard Library [25] and the Modelica IBPSA Library [26]. In addition, the major parameters of the system model are set based on Table 5.

Table 5 Major parameters of the system model

Subsystem	Component	Parameter	Value/Data Set
	chiller	performance curve	Performance curve for the chiller mode Trane_CVHE_1442kW_6_61COP_ VSD
	primary	flow rate [kg/s]	61.75
	chilled water	head [Pa]	210,729
	pump	efficiency	0.87
		rated flow rate [kg/s]	92.63
		rated head [Pa]	478,250
	secondary chilled water pump	flow rate ratio v.s. relative head curve	[(0.4, 2.2), (0.6,1.2), (0.8, 1.1), (1,1), (1.2,0.75)]
chiller plant		flow rate ratio v.s. efficiency curve	[(0.4, 0.6), (0.6, 0.76), (0.8, 0.87), (1, 0.86), (1.2, 0.74)]
	cooling tower	rated fan power [kW]	37.5
		air flow rate ratio v.s. fan power curve	[(0.3,1), (0.6,8.1), (1,37.5)]
		rated wet bulb temperature [°C]	19.45
		rated approach temperature [°C]	4.44
	condenser water pump	flow rate [kg/s]	71.09
		head [Pa]	283,961
		efficiency	0.87
boiler plant	boiler	rated heating capacity [kW]	1381.87
1		rated efficiency	0.8

	rated Flow rate [kg/s]	16.4
	rated Head [Pa]	239,124
hot water pump	flow rate ratio v.s. relative head curve	[(0.4, 2.2), (0.6,1.2), (0.8, 1.1), (1,1), (1.2,0.75)]
	flow rate ratio v.s. efficiency curve	[(0.4, 0.6), (0.6, 0.76), (0.8, 0.87), (1, 0.86), (1.2, 0.74)]

5.2 Sensitivity Analysis

5.2.1 Sensor Bias

355

360

Figure 11 quantifies the impacts of the sensor bias faults on the energy performance and the unmet hours of the chiller plant. The unmet hours are defined as the hours when the temperature of the supply chilled/hot water is 0.5° C higher/lower than the chilled/hot water setpoint. One can see that the impacts of the CH_T are the most significant and those of the CT_T are the least significant. The CH_T affects not only the operation of Chiller #1 and Cooling Tower #1 but also the operation of the secondary chilled water pumps. We also found that the CH_T and $SCHW_T$ influence the unmet hours significantly when dT is negative.

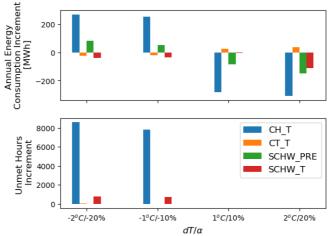


Figure 11 The impacts of the sensor bias faults on the energy consumption and the unmet hours of the chiller plant

As shown in Figure 12, when dT increases, the annual energy consumption of the chillers increases while that of the secondary chilled water pumps decreases significantly. With a higher dT, the temperature of the supply chilled water temperature is lower under the effect of the CH_T fault. As a result, the efficiency of the chillers decreases while the required chilled water flow is reduced. On the contrary, the CT_T fault only affects the operation of Chiller #1 and Cooling Tower #1 and thus its impacts are not so obvious.

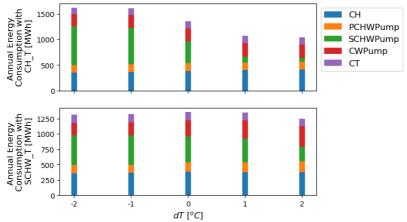


Figure 12 The impacts of *CH_T* (top) and *SCHW_T* (bottom) on the energy consumption of components in the chiller plant

We also observe that the impacts of the sensor bias faults are proportional to the bias for all the studied faults, except the $SCHW_T$ fault. Under the effect of the $SCHW_T$ fault, as shown in Figure 12, the energy consumption of the primary chilled water pumps and the condenser water pumps increase while that of the secondary chilled water pumps decreases, when the dT increases, respectively. This is mainly because that the $SCHW_T$ fault affects the staging control of chillers. The ratio of the measured cooling load to the actual load increases when the dT increases. In other words, the number of operating chillers may be higher when dT is higher. As a result, the number of operating primary chilled water pumps and operating condenser water pumps increases. On the other hand, with fewer operating chillers, the temperature of the supply chilled water temperature may be higher, which affects the operation of the secondary chilled water pumps.

Figure 13 illustrates the operation of the chiller plant under the effect of the $SCHW_T$ fault during a typical summer day. One can see that when there is no fault (denoted by baseline), two chillers are operating, and the secondary chiller is operating during the early morning and the late afternoon. When there is an $SCHW_T$ fault and the dT is larger, there are three chillers operating as the cooling load is over-estimated. When the $SCHW_T$ occurs and the dT is lower, there is only one chiller operating as the cooling load is under-estimated. As a result, the temperature of the supply chilled water cannot always be maintained based on the setpoint and is thereby larger than that during the fault-free scenario and the faulty scenario where dT is larger. Consequently, the chilled water flow rate, when there is a $SCHW_T$ fault and the dT is lower, is larger than that in the other two scenarios.

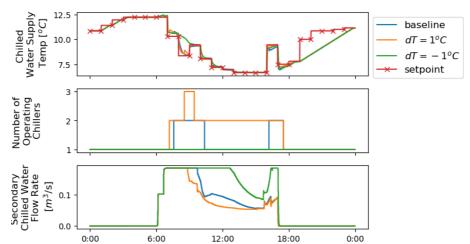


Figure 13 Operation of the chiller plant under the effect of *SCHW_T* fault during a typical summer day

Figure 14 shows the results of the impacts of the sensor bias faults on the energy performance of the boiler plant. Note that the gas consumption by the boilers is found to be insensitive to the presence of the sensor bias, thus only the energy consumption by the hot water pumps is considered in the evaluation results. Like the chiller plant, the responses of the boiler plant to the sensor bias tend to be proportional to dT/α . In addition, Only the BO_T significantly increases the unmet hours when dT is negative.

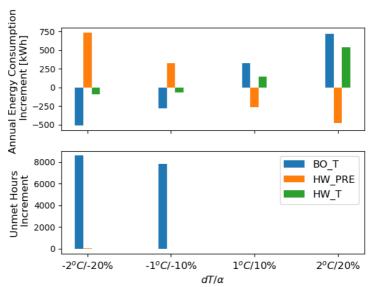


Figure 14 The impacts of the sensor bias faults on the energy consumption and the unmet hours of hot water pumps in the boiler plant

5.2.2 Leaking Valve

405

Figure 15 shows the results of the impacts of *VAL_LEA* on the energy performance and the unmet hours of the chiller plant. One can see that the total annual energy consumption of the chiller plant slightly increases when the leaking valve fault occurs. Specifically, the energy consumption of the chillers and the secondary chilled water pumps increases. This is mainly because the temperature of the supply condenser water increases when the leaking valve fault occurs, resulting in decreased cooling capacities and the decrease energy efficiencies of the operating chillers, as illustrated in Figure 16.

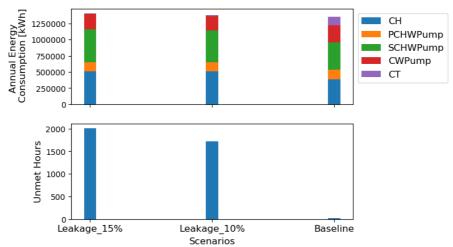


Figure 15 The impacts of *VAL_LEA* on the energy consumption and the unmet hours of the boiler plant

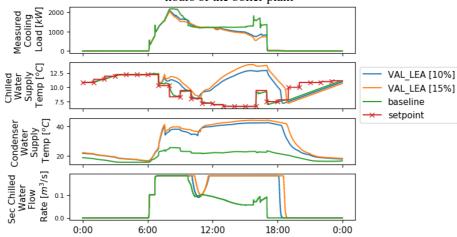


Figure 16 Operation of the chiller plant under the effect of *VAL_LEA* fault during a typical summer day

410

415

On the other hand, as the amount of the condenser water processed by the cooling towers reduces, the energy consumption of the cooling tower decreases significantly. Note that the cooling load decreases when the temperature of the chilled water temperature increase, as a result of the decreased cooling capacities of the chillers. This explains why the energy consumption of the chillers doesn't change much when the leakage becomes worse. On the other hand, VAL_LEA significantly increases the unmet hours.

5.2.3 Untuned PI Control

420

425

430

The impacts of the untuned PI control faults on the chiller plant and the boiler plant are similar. As an example, Figure 17 shows the impacts of the CH_PI on the operation of the chiller plant. One can see that when $\beta=0.1$, meaning the PI control has slow responses, the total energy consumption of the chiller plant increases while the secondary chilled water pumps contribute mostly to the increase. In addition, the unmet hours also increase significantly. When $\beta=10$, meaning the PI control is overreact to the control signal, the changes in the total energy consumption and the unmet hours are not significant.

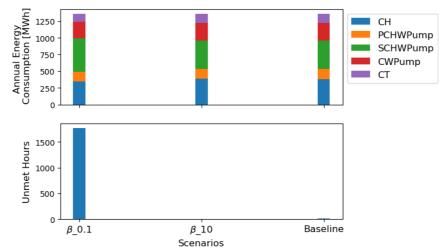


Figure 17 The impacts of the untuned PI control faults on the energy consumption and the unmet hours of the chiller plant

To better understand the impacts from the CH_PI , we investigate the behaviors of the chiller plant during a typical summer day. As shown in Figure 18, when $\beta = 0.1$, due to the slow responses, the temperature of the supply chilled water is far from the setpoint. In this case, the flow rate of the supply chilled water increases when the temperature of the supply chilled water is larger than the setpoint. When $\beta = 10$, the temperature of the supply chilled water follows the change of the setpoint in a closer fashion than that in the baseline. However, differences are not significant and thereby the impacts on the operation of the chiller plant are not obvious.

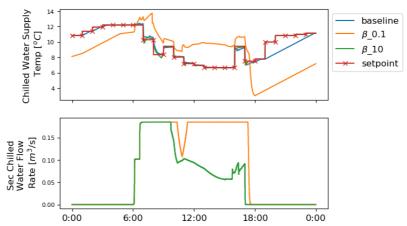


Figure 18 The impacts of *CH_PI* on the operation of the chiller plant during a typical summer day

5.3 Impact Analysis

435

440

Based on the above analysis, we present the impact analysis results of all the studied faults in Table 6. One can see for the chiller plant, the most critical fault is the *CH_T*. The *CH_T* causes electricity consumption changes by 19.8% and the unmet hour increases by 8,576. For the boiler plant, the most critical fault is *BO_T*. The *BO_T* causes electricity consumption to change by 16.2% and the unmet hour increases by 8,649.

Table 6 Impacts of control-related faults

Faults	Fault Intensive	Electricity Consumption Absolute Increment [%]	Unmet Hour Increment
SCHW_T	$dT = 2^{\circ}C$	8.0	-15
CH_T	dT = -2 °C	19.8	8,576
CT_T	dT = 2 °C	2.7	-1
SCHW_PRE	$\alpha = -20\%$	6.0	0
HW_T	dT = 2 °C	16.2	47
BO_T	dT = 2 °C	12.2	8,649
HW_PRE	$\alpha = 20\%$	16.7	2
VAL_LEA	<i>c</i> = 15 °C	8.3	1,705

CH_PI	$\beta = 0.1$	18.5	1,746
CT_PI	$\beta = 0.1$	1.0	162
SCHW_PI	$\beta = 0.1$	5.6	19
BO_PI	$\beta = 0.1$	5.3	2,795
HW_PI	$\beta = 0.1$	1	1

6. Conclusions

In this study, we present a set of high-fidelity models for a typical chiller plant and a typical boiler plant. Those models faithfully represent the control architecture of the studied plant and thereby can be used for studying the control-related faults on a large scale. The usage of proposed models is demonstrated via a comprehensive evaluation of the impacts of common control related faults on the energy performance of the plants. In this evaluation, sensitivity analysis is performed to quantify how the impacts from faults change by the severity level of those faults. Detailed analysis is also provided to better explain how the faults affect the operation of different components via the control process.

The evaluation results suggest that the sensor bias faults of chillers impact the operation of the chiller plant more significantly. This is not only because chillers contribute substantial energy consumption, but also due to the strong coupling relationship between the operation of chillers and the secondary chilled water pumps. Also, the interaction between the supply-side and demand-side of the chiller plant influences the behaviors of the chiller staging under the effect of those faults. Likewise, the sensor bias faults of the boiler have higher impacts on the operation of the boiler plant. Besides, the impacts of the studied faults on the energy performance of the studied plants are not always proportional to the severity level of the faults. This is mainly caused by the interactions between components in the plants through control loops or physical processes. How to handle those nonlinearities can be an interesting research topic when developing AFDD methods to diagnosis those faults. In the future, we will further explore the potential of the proposed models to support various fault-related studies. For example, we will study how multiple faults affect the operation of

the chiller plant and the boiler plant simultaneously. We will also evaluate the performance of the AFDD methods under complicated faulty conditions.

Acknowledgement

470

475

480

This research is partially supported by the of the U.S. Department of Energy, Energy Efficiency and Renewable Energy, Office of Building Technologies, Emerging Technologies Program, under Contract no. DE-AC05-76RL01830. This research is also partially supported by the National Science Foundation under Awards No. IIS-1802017. This work also emerged from the IBPSA Project 1, an internationally collaborative project conducted under the umbrella of the International Building Performance Simulation Association (IBPSA). Project 1 aims to develop and demonstrate a BIM/GIS and Modelica Framework for building and community energy system design and operation. The authors acknowledge the valuable comments from Dr. Hayden Reeve, Senior Technical Advisor at the Pacific Northwest National Laboratory.

References

- [1] D. Westphalen and S. Koszalinski, "Energy Consumption Characteristics of Commercial Building HVAC Systems Volume I: Chillers, Refrigerant Compressors, and Heating Systems," Arthur D. Little, Inc., 2001.
- [2] B. Widarsson and E. Dotzauer, "Bayesian network-based early-warning for leakage in recovery boilers," *Applied Thermal Engineering*, vol. 28, no. 2008, pp. 754-760, 2008.
- [3] X. Xu, F. Xiao and S. Wang, "Enhanced chiller sensor fault detection, diagnosis and estimationusing wavelet analysis and principal component analysis methods," *Applied Thermal Engineering*, vol. 28, no. 2008, pp. 226-237, 2008.
- [4] H. Cheung and J. E. Braun, "Empirical modeling of the impacts of faults on water- cooled chiller power consumption for use in building simulation programs," *Applied Thermal Engineering*, vol. 99, no. 2016, p. 756–764, 2016.
- [5] R. García, A. Alvarez, C. Pizarro, A. G. Lavin and J. L. Bueno, "Size-up, monitorization, performanceoptimization and waste study of a 120 kWin-use wood pellet boiler: A case study," *Renewable Energy Focus*, vol. 27, pp. 33-43, 2018.
- [6] Y. Li and Z. O'Neill, "An innovative fault impact analysis framework for enhancing building operations," *Energy and Buildings*, vol. 199, no. 2019, pp. 311-331, 2019.
- [7] S. Katipamula and M. R. Brambley, "Review Article: Methods for Fault Detection, Diagnostics, and Prognostics for Building Systems—A Review, Part I," *HVAC&R Research*, vol. 11, no. 1, pp. 3-25, 2005.
- [8] M. S. Mirnaghi and F. Haghighat, "Fault detection and diagnosis of large-scale HVAC systems in buildings," *Energy & Buildings*, vol. 229, no. 2020, 2020.
- [9] H. Han, B. Gu, Y. Hong and J. Kang, "Automated FDD of multiple-simultaneous faults (MSF) and the application to building chillers," *Energy and Buildings*, vol. 43, no. 2011, p. 2524–2532, 2011.
- [10] M. Basarkar, X. Pang, L. Wang, P. Haves and T. Hong, "Modeling and simulation of hvac faults in EnergyPlus," in *12th Conference of International Building Performance Simulation Association*, Sydney, 2011.
- [11] D. B. Crawley, L. K. Lawrie, F. C. Winkelmann, W. F. Buhl, Y. J. Huang, C. O. Pedersen, R. K. Strandd, R. . J. Liesen, D. E. Fisher, M. J. Witte and J. Glazer, "EnergyPlus: creating a new-generation building energy simulation program," *Energy and Buildings*, vol. 32, no. 2001, pp. 319-331, 2001.
- [12] R. Shohet, M. S. Kandil, Y. Wang and J. J. McArthur, "Fault detection for non-condensing boilers using simulated building," *Advanced Engineering Informatics*, vol. 46, no. 2020, p. 101176, 2020.

- [13] H. Cheung and J. E. Braun, "Simulation of fault impacts for vapor compression systems by inverse modeling. Part I: Component modeling and validation," *HVAC&R Research*, vol. 19, no. 7, pp. 892-906, 2013.
- [14] M. Wetter, T. S. Nouidui, D. Lorenzetti, E. A. Lee and A. Roth, "Prototyping the next generation energyplus simulation engine," in *14th Conference of International Building Performance Simulation Association*, Hyderabad, India, 2015.
- [15] Y. Li and Z. O'Neill, "A critical review of fault modeling of HVAC systems in buildings," *Building Simulation*, vol. 2018, no. 11, pp. 953-975, 2018.
- [16] S. Huang, W. Wang, M. R. Brambley, S. Goyal and W. Zuo, "An agent-based hardware-in-the-loop simulation framework for building controls," *Energy and Buildings*, vol. 181, no. 2018, pp. 26-37, 2018.
- [17] L. Wang and M. Karami, "Virtual testbed on evaluating automated fault detection and diagnostic (AFDD) algorithms," in *Building Simulation 2017*, San Francisco, California, U.S., 2017.
- [18] S. E. Mattsson, H. Elmqvist and M. Otter, "Physical system modeling with Modelica," *Control Engineering Practice*, vol. 6, no. 4, pp. 501-510, 1998.
- [19] S. Huang, W. Zuo and M. D. Sohn, "Amelioration of the cooling load based chiller sequencing control," *Applied Energy*, vol. 168, no. 2016, pp. 204-215, 2016.
- [20] S. Huang, W. Zuo and M. D. Sohn, "Improved cooling tower control of legacy chiller plants by optimizing the condenser water set point," *Building and Environment*, vol. 111, no. 2017, pp. 33-46, 2017.
- [21] M. Deru, K. Field, D. Studer, K. Benne, B. Griffith, P. Torcellini, B. Liu, M. Halverson, D. Winiarsk, M. Rosenberg, M. Yazdanian, J. Huang and D. Crawley, "U.S. Department of Energy commercial reference building models of the national building stock," National Renewable Energy Laboratory, 2011.
- [22] Honeywell Inc., Engineering Manual of Automatic Control for Commercial Buildings, 1997.
- [23] ASHRAE, "ANSI/ASHRAE/IES Standard 90.1-2019 -- Energy Standard for Buildings Except Low-Rise Residential Buildings," ASHRAE, 2019.
- [24] M. Wetter, W. Zuo, T. S. Nouidui and X. Pang, "Modelica Buildings library," *Journal of Building Performance Simulation*, vol. 7, no. 4, pp. 253-270, 2014.
- [25] Modelica Association, "Modelica Standard Library," [Online]. Available: https://doc.modelica.org/om/Modelica.html. [Accessed 16 Nov. 2020].
- [26] LBNL, "Modelica IBPSA libraray," [Online]. Available: https://github.com/ibpsa/modelica-ibpsa. [Accessed 16 Nov. 2020].
- [27] D. Blum, F. Jorissen, S. Huang, Y. Chen, J. Arroyo, K. Benne, Y. Li, V. Gavan, L. Rivalin, L. Helsen, D. Vrabie, M. Wetter and M. Sofos, "Prototyping the BOPTEST Framework for Simulation-Based Testing of

- Advanced Control Strategies in Buildings," in *IBPSA Building Simulation* 2019, Roma, 2019.
- [28] T. Blochwitz, M. Otter, J. Akesson, M. Arnold, C. Clauß, H. Elmqvist, M. Friedrich, A. Junghanns, J. Mauss, D. Neumerkel, H. Olsson and A. Viel, "Functional Mockup Interface 2.0: The Standard for Tool independent Exchange of Simulation Models," in 9th International Modelica Conference, Munich, Germany, 2012.
- [29] J. Åkesson, K. E. Årzén, M. Gäfvert, T. Bergdahl and H. Tummescheit, "Modeling and optimization with Optimica and JModelica.org—Languages andtools for solving large-scale dynamic optimization problems," *Computers and Chemical Engineering*, vol. 34, no. 2010, p. 1737–1749, 2010.
- [30] U.S. Department of Energy, "Commercial Prototype Building Models," [Online]. Available: https://www.energycodes.gov/development/commercial/prototype_models. [Accessed 16 Nov 2020].
- [31] T. Nouidui, M. Wetter and W. Zuo, "Functional mock-up unit for cosimulation import in EnergyPlus," *Journal of Building Performance Simulation*, vol. 7, no. 3, pp. 192-202, 2014.
- [33] K. W. Roth, D. Westphalen, P. Llana and M. Feng, "The energy impact of faults in US commercial buildings," in *International Refrigeration and Air Conditioning Conference*, West Lafayette, Indiana, 2004.
- [34] B. Gunay, W. Shen, B. Huchuk, C. Yang, S. Bucking and W. O'Brien, "Energy and comfort performance benefits of early detection of building sensor and actuator faults," *Building Services Engineering Research and Technology*, vol. 39, no. 6, p. 652–666, 2018.
- [35] Y. Chen, S. Huang and D. Vrabie, "A simulation based approach to impact assessment of physical faults: large commercial building hvac case study," in *Building Performance Modeling Conference and SimBuild co-organized by ASHRAE and IBPSA-USA*, Chicago, Illinois, 2018.
- [36] F. Xiao, C. Zheng and S. Wang, "A fault detection and diagnosis strategy with enhanced sensitivity," *Applied Thermal Engineering*, vol. 31, no. 2011, pp. 3963-3970, 2011.
- [37] L. Zhang, S. Frank, J. Kim, X. Jin and M. Leach, "A systematic feature extraction and selection framework for data-driven whole-building automated fault detection and diagnostics in commercial buildings," *Building and Environment*, vol. 186, no. 2020, 2020.
- [38] P. Haves, "Fault Modelling in Component-based HVAC Simulation," in *Building Simulation* '97, Prague, Czech, 1997.
- [39] Z. Rongpeng and T. Hong, "Modeling of HVAC operational faults in building performance simulation," *Applied Energy*, vol. 202, no. 217, pp. 178-188, 2017.

- [40] J. Kim, S. Frank, J. E. Braun and D. Goldwasser, "Representing Small Commercial Building Faults in EnergyPlus, Part I: Model Development," *Buildings*, vol. 9, no. 11, p. 233, 2019.
- [41] S. E. Mattsson, H. Elmqvist and M. Otter, "Physical system modeling with Modelica," *Control Engineering Practice*, vol. 6, no. 1998, pp. 501-510, 1998.
- [42] F. Pezoa, L. J. Reutter, F. Suarez, M. Ugarte and D. Vrgoč, "Foundations of JSON Schema," in *25th International Conference on World Wide Web*, Montréal, Canada, 2016.
- [43] D. Blum, F. Jorissen, S. Huang, Y. Chen, J. Arroyo, K. Benne, Y. Li, V. Gavan, L. Rivalin, L. Helsen, D. Vrabie, M. Wetter and M. Sofos, "Prototyping the BOPTEST Framework for Simulation-Based Testing of Advanced Control Strategies in Buildings," in *Building Simulation* 2019, Rome, Italy, 2019.
- [44] S. Wilcox and W. Marion, "Users Manual for TMY3 Data Sets," National Renewable Energy Laboratory, 2008.