# A SIMULATION BASED APPROACH FOR IMPACT ASSESSMENT OF PHYSICAL FAULTS: LARGE COMMERCIAL BUILDING HVAC CASE STUDY

Yan Chen, Sen Huang, and Draguna Vrabie
Pacific Northwest National Laboratory, Richland, WA

## ABSTRACT

We developed a simulation-based approach for fault impact analysis for a single duct variable air volume (VAV) system, and analyzed the dynamic and steady-state impact of equipment physical faults on building operation. The simulation model, a virtual testbed, can capture physical faults in the HVAC system of a large commercial building. The model can be used to generate data that can then be analyzed to quantify the impact of single or multiple faults. This paper illustrates the implementation of three physical faults: supply air temperature sensor bias, outdoor air temperature sensor bias, and cooling coil valve stuck. Each fault was simulated with several fault intensity levels and under different seasonal operating conditions. Then, we analyzed the impact of the above-mentioned faults using the energy and comfort metrics. The results show that the impact of a given physical fault depends on implemented control logic sequence and the seasonal operating conditions.

## INTRODUCTION

Equipment physical faults occur during the building operation life cycle due to mechanical fatigue and wear and tear. Physical faults in the heating, ventilation, and air conditioning (HVAC) equipment affect the nominal performance of system, causing energy waste, thermal discomfort, deterioration of indoor air quality, occurrence of maintenance costs, and operation downtime. Because more than one fault can be present in the system at a given time, there is a need to prioritize what faults to address based on their impact on system performance. Studies related to system faults can be categorized into two types: a) fault detection and diagnostics (FDD) and its automated implementations (Beghi et al. 2016; Seem, House, and Monroe 1999; Schein and Bushby 2006), and b) fault impact analysis to guide the prioritization and maintenance decisions (Fernandez et al. 2017; Wang and Xiao 2004; Lee and Yik 2010).

Implemented in a context of real-time system performance monitoring, FDD methods can alert the building operators and guide effective maintenance actions. When introduced in building operation work-flow, automated FDD methods can reduce the negative effects associated with fault occurrence. Notable studies addressing diverse types of building systems include Beghi et al. (2016),Schein and Bushby (2006), and Seem, House, and Monroe (1999). For the fault impact analysis, Roth et al. (2005) reviewed the literatures and identified thirteen faults related to building operation. Based on estimation, these faults can account for up to 11% of the total energy used by commercial buildings in the U.S. Among these faults, the top three hardware faults that have the highest energy impacts are duct leakage, improper refrigerant charge, and damper fault.

At the individual building level, several studies used existing simulation tools or experiments set up to analyze the impact of different faults. Breuker and Braun (1998) conducted lab test for evaluating the impact of a number of air handling unit (AHU) faults, including refrigerant leakage, liquid line restriction, compressor valve leakage, condenser fouling, and evaporator fouling. This study identified up to 23.8% of reduction in coefficient of performance as the largest fault impact. Wang and Xiao (2004) used TRNSYS based model for a single-duct variable air volume (VAV) multi-zone system, and evaluated the impact of nine sensor faults (i.e., outdoor, supply, return airflow sensors; supply, outdoor, return air temperature sensors; outdoor and return humidity sensors; and supply air pressure sensor). They found that sensor bias of supply air temperature sensor had the largest negative impact (-5%) on total energy, while return airflow rate bias (-20%) had the highest positive impact (14%) on total energy. Lee and Yik (2010) used an EnergyPlus model for a large office building in Hong Kong, and simulated several hardware faults, which included temperature sensor bias, stock damper, and cooling coil valve leakage. This study varied the fault intensity level, and quantified the impact of each individual fault on energy usage, thermal comfort, and indoor air quality. Depending on the fault intensity level, these faults can have an impact of -19% to 36% on energy consumption.

Although some efforts have been made in fault impact analysis, a recent survey indicated that there is still a need to test and quantify the fault impact and evaluate the cost and benefit of applying the FDD method in different building systems (Granderson et al. 2017). We also identify some limitations associated with past efforts that utilized a simulation-based approach for fault impact analysis. First, there is limited fault modeling capability in existing simulation tools. For example, the EnergyPlus *FaultModel* object, recently developed by Zhang and Hong (2017), expanded the fault simulation capability of EnergyPlus. It can simulate typical air temperature sensor offset, humidity sensor offset, heating and cooling coil fouling, and dirty air filters. Additional effort is still needed to expand the fault simulation such as water temperature sensor fault.

Second, multiple fault intensity levels are rarely analyzed. Most of the existing studies focused on one or two fault intensity levels. More quantitative analysis of different fault intensity levels is needed.

Third, the impact of equipment fault depends on the building energy system and its control system, but existing simulation models typically do not capture all control sequence elements. Some modeling tools can only provide approximate estimates of the potential impact of faults. For example, the performance of static pressure reset sequences may be affected by the health state of VAV dampers, air resistance at duct network, and supply/return fan performance curves. Therefore, such effects cannot be captured by simulation tools where duct pressure modeling is abstracted out.

In this manuscript, we present a model-based approach to fault impact analysis that addresses the limitations highlighted above. Herein we use co-simulation between EnergyPlus and Modelica to develop a virtual testbed based on modeling a large commercial building served by a VAV-based system.

This virtual testbed can be used to evaluate and analyze the impact of single or multiple faults at various fault intensity levels. Furthermore, the testbed can be used to generate representative simulated data for testing performance of fault detection and diagnosis methods.

This paper is organized as follows: Section 2 describes the fault modeling, the virtual testbed and its fault insertion capability, and evaluation metrics for fault impact analysis. Section 3 explains the simulation method and scenarios design for fault impact analysis. Section 4 includes several examples of using the virtual testbed to conduct a fault impact assessment study on the HVAC system in a large commercial building model. The conclusion section includes discussion of future research.

## VIRTUAL TESTBED, FAULT MODELING AND PERFORMANCE METRICS

Our approach is to use a dynamic simulation platform (a virtual testbed) to assess the fault impacts of two main scenarios: 1) fault onset from normal condition, and 2) continuous faulty scenario. This section introduces the testbed, fault modeling, and performance evaluation metrics, and fault onset data generation. First, we approximate the occurrence of fault by mathematic representation for simulation purpose fault formulation. Second, we implement such fault model in the simulation platform (virtual building). Third, we design specific simulation scenarios. Considering the dynamic performance and long-term performance of a control system, simulation scenarios are typically selected from two aspects of evaluations, quantitative long-term (week / month /year) impacts, and chronological short-time (within hours) dynamic impacts, which can be also used to generate a fault onset data set for FDD method testing. The following further explains the details of each step.

### Virtual testbed and fault insertion capability

To simulate the fault, we use a dynamic co-simulation framework, consisting of the EnergyPlus model for the building envelope and thermal load and the Modelica model for the HVAC system. Specifically, we select a large office building as the primary focus because this building type represents the largest floorspace among all commercial building types in U.S. based on 2012 Commercial Buildings Energy Consumption Survey Data (U.S. EIA 2016). For modeling, we primarily use the U.S. Department of Energy large office reference model developed by Deru et al. (2011) to capture the envelope characteristics and the associated building load. The large office building model has twelve floors and each floor has five thermal zones, i.e., east, south, west, north, and core zones. The building has a single duct multi-zone HVAC system (shown in Figure 1), served by chilled water loop and hot water loop. Each zone is served by the VAV box with water-based reheat coil. Such an HVAC system configuration is representative of, and is commonly found in large office buildings across the States. To model dynamics of the HVAC system and control sequences, we use Modelica Buildings library developed by Wetter et al. (2014) and also develop new component models.

This co-simulation framework can simulate the performance of building thermal dynamics as well as the immediate control response for a given control baseline. The control baseline used in this study is assumed to represent a typical existing building, and is composed of specific control sequences for each HVAC actuator and systems. The control baseline is defined based on representing the majority of existing building stocks, following the control specification from ASHRAE 90.1-1989, 90.1-1999. It has a fixed control setpoint for supply and return fan, outdoor air damper, and supply air temperature setpoint (shown in Table 1). We assume this represents the typical control sequences in existing commercial buildings. More details of the HVAC configurations and co-simulation setup can be found in Huang et al. (2018). Hardware faults are simulated in addition to the normal operational model as an overwrite process. Figure 1 illustrates the fault insertion capability for this simulation model. This includes all the temperature sensors, airflow sensors, humidity sensors, occupancy sensors, cooling coil valves, heating coil valves, and dampers. This capability can be easily ex-

Table 1: Brief description of control baseline.

| Control category (component) | Typical building control specification |
|---|---|
| System operation occupied mode | Start the HVAC system 2 hours (called warm-up period) ahead of occupancy schedule. System running continuously to maintain the occupied heating and cooling setpoint. |
| System operation unoccupied mode | System cycling ON and OFF to maintain the unoccupied heating and cooling setpoint |
| Supply fan control | Fixed static pressure |
| Return fan control | Fixed differential speed ratio between supply and return fan. |
| Supply air temperature control | Fixed supply air temperature |
| Minimum outdoor air (OA) control | Fixed minimum OA damper position |
| Economizer control | Fixed dry bulb |
| Terminal box airflow control | Single maximum control logic (fixed heating airflow, and modulating cooling airflow) |
| Relevant ASHRAE standard | Modified based on ASHRAE 90.1-1989 and 1999 |

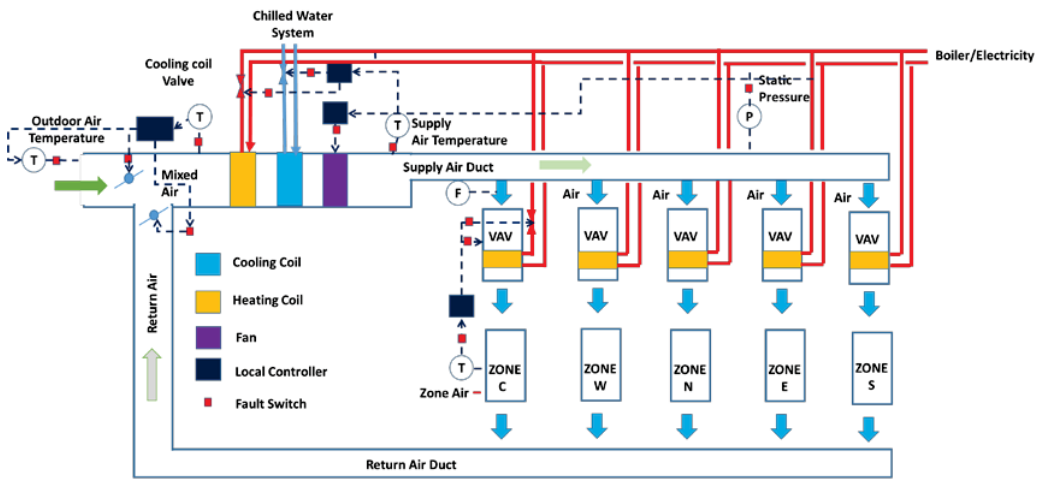


Figure 1: Fault simulation capabilities are shown as red boxes in the figure, i.e., all the sensors and actuators.

tended to incorporate more hardware fault simulation into the virtual testbed.

**Fault modeling**

This model-based fault impact evaluation approach requires definition of physical faults of the HVAC equipment. Typical hardware faults include (but are not limited to) sensor bias, drift, valve/damper stuck, leakage, fan belt loose, and coil fouling. Mathematical representations of these physical faults have been developed in previous studies (Lee and Yik 2010; Zhang and Hong 2017), illustrated in Eq. (1)-(5). In these equations, we use $^t$ to represent the value under faulty conditions.

Sensor bias/offset means the sensor reading ($V_s^t$) deviates from the actual sensor output at no-fault condition ($V_s$) with a constant error ($e_b$):

$$V_s^t = V_s + e_b \tag{1}$$

Sensor drift means the sensor reading ($V_s^t$) deviates from the actual sensor output at no-fault ($V_s$) with a time depended draft error ($e(t)$):

$$V_s^t = V_s + e(t) \tag{2}$$

Actuator stuck means actuator like valve or damper ($V_d^t$) gets stuck at a certain position ($p_s$) regardless of the change in control signal ($c$). The stuck position ($p_s$) for damper/valve typically ranges from 0% to 100%:

$$V_d^t = p_s \forall c \in C \tag{3}$$

Fan belt slippery means the fan belt is loose, and causes a slippery error ($e_s$). Thus, the actual fan rotational speed ($V_f^t$) is slower than the fan rotational speed under the no-fault condition ($V_f$):

$$V_f^t = V_f - e_s \tag{4}$$

Coil fouling means deposit built up inside the coil. As a result, the overall heat transfer coefficient of fouled coil ($V_{ua}^t$) is reduced by a fouling factor ($R_f$), comparing to the overall heat transfer coefficient of coil under no fouling condition ($V_{ua}$):

$$(V^{t}_{ua})^{-1} = (V_{ua})^{-1} + R_f \quad (5)$$

Here we used sensor bias and valve stuck faults as examples to explain that the fault can be modeled using Eq. (1) and (3), and inserted in the simulation model to overwrite the original true value.

### Performance evaluation metrics

Comparing with the fault onset analysis, long-term impact analysis aims to estimate seasonal or annual impact of fault occurrence on energy, comfort, air quality, and other aspects of building performance. For example, for the same fault example mentioned above, the week-long assessment will evaluate how much energy is wasted due to such a fault, what is the percentage of economizer status disabled compared with the baseline (non-fault condition), how many zone temperature setpoints are not satisfied during occupied period, etc. Here we propose a number of metrics to quantify such impact for the simulated HVAC system in this study. Electric energy impact is estimated by summing up all the electric equipment power demands, including chiller, cooling tower, pumps (chilled water primary/secondary pumps, hot water pump), supply fan, and return fan.

$$P_{e,total} = \sum_{t=t_0}^{t_n} (P_{chiller} + P_{coolingtower} + P_{pumps} + P_{fans})\Delta t \quad (6)$$

Gas heating energy impact is estimated from the gas heating

$$P_{heat} = \sum_{t=t_0}^{t_n} P_{boiler}\Delta t \quad (7)$$

Economizer enable status (only the mid-floor AHUs)

$$S_{total} = \sum_{t=t_0}^{t_n} S_{economizer}\Delta t \quad (8)$$

where $S_{economizer} = 1$, if economizer is enabled; $S_{economizer} = 0$, if economizer is disabled.

Zone temperature setpoint unmet hours (only the mid-floor zones) are used as a rough assessment of thermal comfort.

$$S_{T,ctrl} = \sum_{t=t_0}^{t_n} \sum_{i=1}^{5} S_{t,Z_i}\Delta t \quad (9)$$

where $S_{t,Z_i} = 1$, if room temperature is unsatisfied; $S_{t,Z_i} = 0$, if room temperature is satisfied.

Then, we compare the fault result to the baseline (no fault), and calculate the impact in percentage, for example:

$$\frac{P_{e,total}(fault) - P_{e,total}(baseline)}{P_{e,total}(baseline)} 100\% \quad (10)$$

### Fault onset simulation

The fault onset simulation serves two purposes: 1) it assesses the chronological responses (i.e., operational change) of different HVAC elements to the occurrence of fault(s); and 2) it can generate the data for testing and evaluating FDD methods/tools. When a fault happens, there is typically a series of reactions resulting from HVAC elements executing the control sequence (logic) under faulty conditions. For example, if an outdoor temperature sensor has a fault described as a negative bias, this fault enables economizer operation at higher-than-desired outdoor temperatures. This will lead to increased outdoor flow rate and mixed air temperature, resulting in larger cooling demand. In the end, it will cause the building to over-ventilated, using extra energy for cooling and ventilation. Because thermodynamic processes take time, each response will proceed chronologically.

The ability to simulate such a transient response for fault onset can provide the simulated data set for FDD method development and testing. We can also use data visualization to analyze the consequential influence of such fault, by plotting multiple variables against the same time axis.

## SIMULATION

Using our co-simulation platform, we conducted a series of fault intensity analyses. Fault intensity level is one of the parameters that affect a fault's impact. The parametric evaluation of fault impact can be expressed as Eq.(11):

$$y = f(u_1, u_2, u_3, , u_i) \quad (11)$$

where $u_1$ represents different weather, $u_2$ represents different fault intensity, $u_3$ represents different fault type, and $u_i$ represents other factors for parametric analysis.

As an initial effort, we selected three faults to evaluate (as shown in Table 2), including outdoor air temperature sensor fault, supply air temperature sensor fault, and cooling coil valve fault. These faults were reported by professionals as some of the common AHU faults (Hyvarinen and Karki 1996), and were previously analyzed using EnergyPlus (Lee and Yik 2010). Particularly, temperature sensor error was identified as the most common fault in a field survey (Qin and Wang 2005).

Our study primarily focuses on two types of analysis: fault onset, and week-long fault impact. For the fault onset impact assessment, the fault occurrence is simulated with one or two fault intensity levels. The simulation time lasts one day and the fault happens in the middle of the day. For the long-term impact assessment, the fault occurrence is simulated with five to six fault intensity levels. The simulation time lasts one week. We used Chicago as our building location (ASHRAE climate zone 5A), and used TMY3 data in Chicago as the simulation weather input.

For each simulation scenario, we first generated the data set using the simulation model, then analyzed the data for fault onset impact and long-term impact assessment as discussed in the following section.

## DISCUSSION AND RESULT ANALYSIS

### Week-long impact analysis

The results for long-term impact analysis include three scenarios: the supply air temperature sensor bias, outdoor air temperature sensor bias, and the cooling coil valve stuck. As the fault intensity varies, their impacts on energy and comfort also vary.

For the outdoor air temperature sensor bias (shown in Figure 2), negative bias increases its economizer-enabling status, and increases thermal discomfort, while decreasing electrical energy consumption. Positive bias decreases economizer enabling status, decreases gas energy consumption, and decreases thermal discomfort, while increasing electrical energy consumption.

For the fault of supply air temperature sensor bias (shown in Figure 3), negative bias decreases both gas and electrical energy consumption, while decreasing thermal comfort. The positive bias increases both the gas and electrical energy consumption, while slightly increasing thermal comfort.

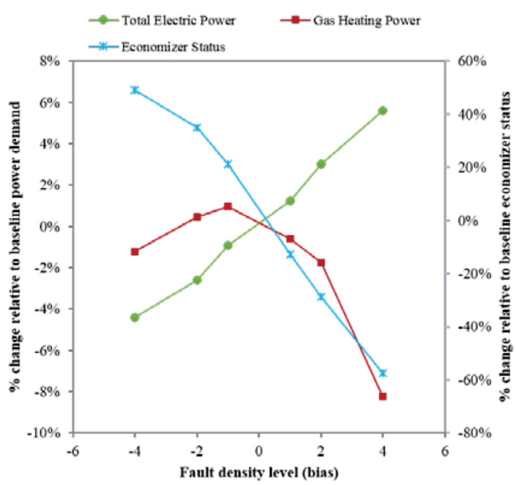


Figure 2: Week-long (May 7-14) total energy and operation impact of outdoor air temperature sensor bias at different fault intensity levels

For the cooling coil valve stuck (shown in Figure 4), because the valve typically opens around 10% under no-fault scenario in the selected simulation case, as the valve fault intensity varies: 1) Valve stuck (larger than 10%) will result in an energy usage increase; the larger the valve stuck position is, the more energy will be wasted; 2) valve stuck on smaller opening (e.g., 0%) will result in energy reduction. However, the zone temperature setpoint cannot be met (significant thermal discomfort), because of insufficient cooling capacity.

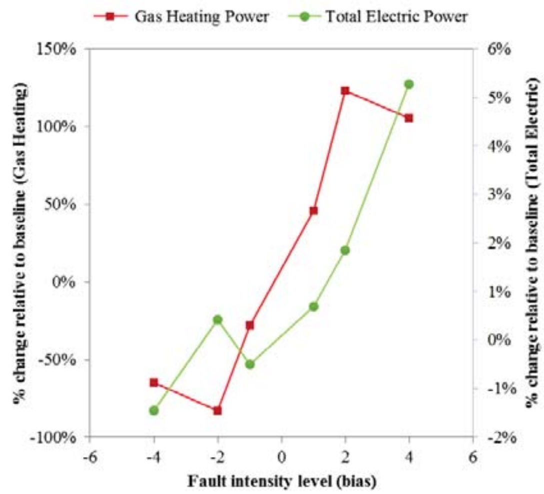


Figure 3: Week-long (August 6-13) impact of supply air temperature sensor bias at different fault intensity levels

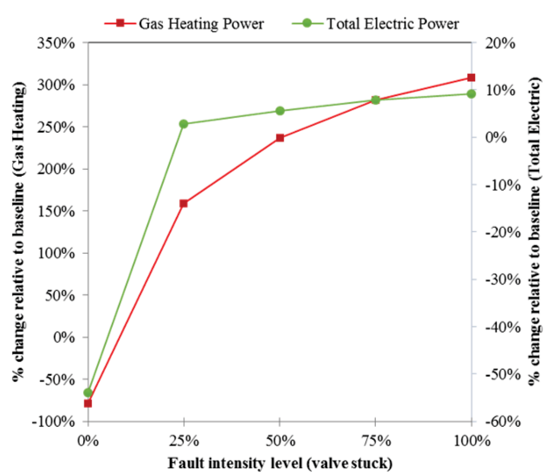


Figure 4: Week-long (August 6-13) impact of cooling coil valve stuck at different fault intensity levels

### Fault onset impact analysis

Results from three fault scenarios are shown below. We use the same baseline scenario with no fault injection (shown in solid green line in Figures 5-7). The other plotted data (shown in red round dots and brown square dots in Figures 5-7) are simulated with one or two faults in-

Table 2: Design of the fault simulation scenarios.

| Impact analysis | Hardware Type | Different weather $u_1$ | Fault intensity $u_2$ | Fault type $u_3$ | Simulation time $u_4$ |
|---|---|---|---|---|---|
| Fault onset | Outdoor air temperature sensor | May 10th | a = ±4 (˚C) | Bias | Daily** |
| | Cooling coil valve | | 50% | Stuck | Daily** |
| | OA sensor fault and cooling coil valve fault | | 50% & a = -4 (˚C) | Stuck and Bias | Daily** |
| Long-term | Outdoor air temperature sensor | Feb, May, Aug, Nov * | a = ±1, ±2, ±4 (˚C) | Bias | Weekly |
| | Supply air temperature sensor | Aug* | a = ±1, ±2, ±4 (˚C) | Bias | Weekly |
| | Cooling coil valve | May, Aug * | 0%, 25%, 50%, 75%,100% | Stuck | Weekly |

*Selected weeks (winter: Feb 5-12, mild season: May 7-14, and Nov 5-12, summer: Aug 6-13)
** Selected day, fault occurs during the day at noon

jected at the noon of the day.

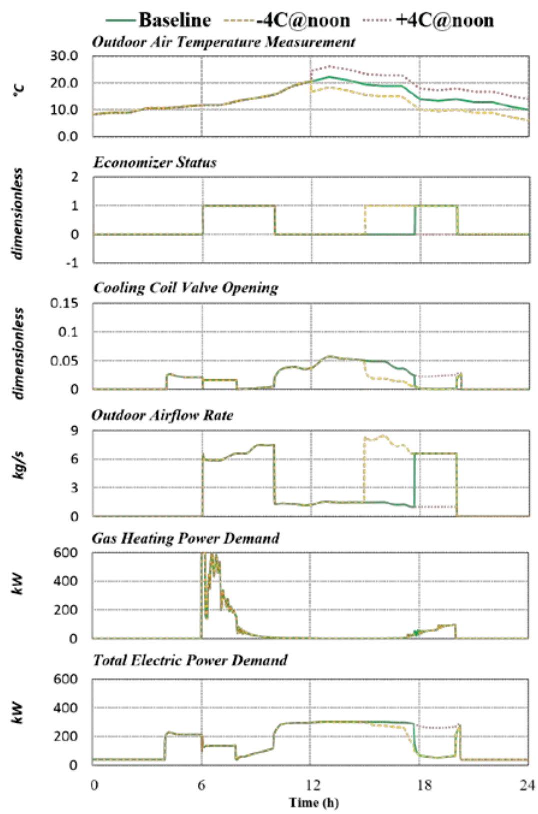


Figure 5: Impact of fault onset: outdoor air temperature sensor bias

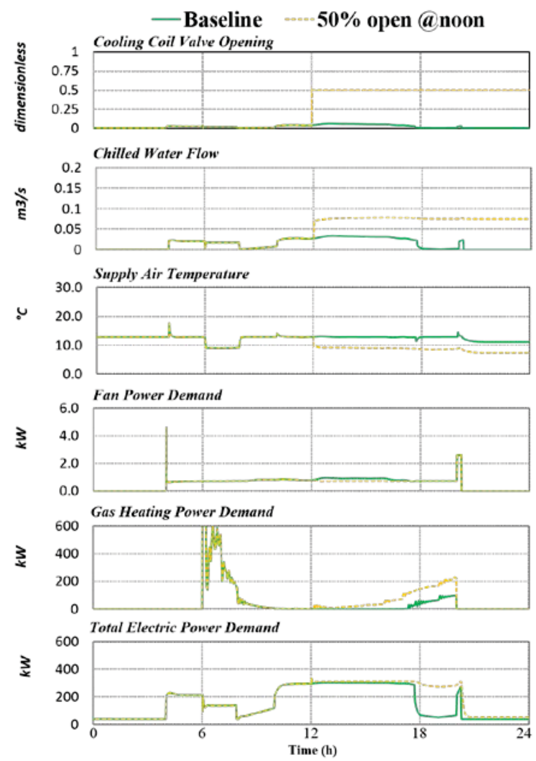


Figure 6: Impact of fault onset: cooling coil valve stuck

Simulated scenario (a): Outdoor temperature sensor bias +4˚C and -4˚C happened on May 10, at 12:00 pm. Dynamic impact is shown in Figure 5: The sensor bias of +4˚C disables the economizer, reduces the outdoor air flow, reduces the fan speed, and increases heating power demand for reheat, increases total electric power demand. The sensor bias of -4˚C enables the economizer at a higher outside air temperature (compared to the normal condition). Then, it increases the outdoor air flow and decreases total electric power demand.

Simulated scenario (b): Cooling coil valve gets stuck (50% open) on May 10, at 12:00 pm. Dynamic impact (shown in Figure 6): Cooling coil valve stuck at 50% open (higher than no-fault scenario) increases chilled

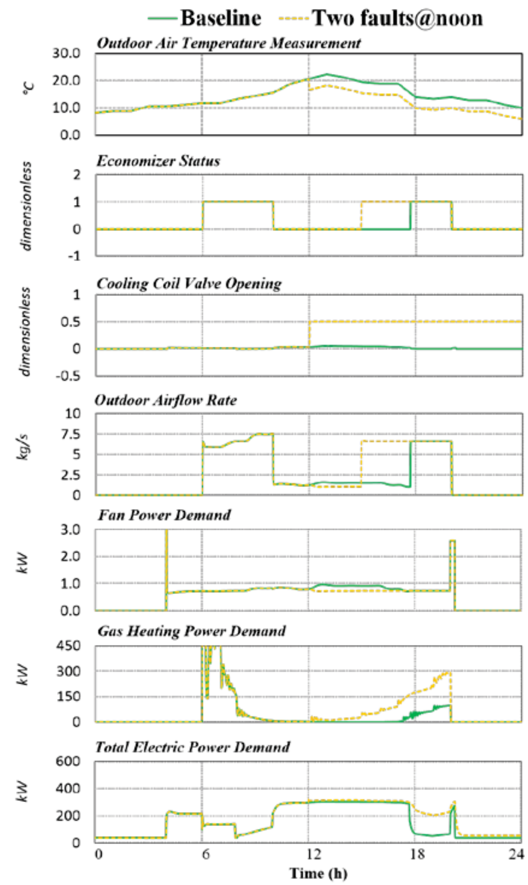


Figure 7: Impact of outdoor air temperature sensor bias and cooling coil valve stuck inserted at 12pm on system operation and power consumption

water flow, and reduces the supply air temperature. Then, it reduces the fan speed and reduces the zone temperature. As a result, it increases heating power demand for reheat and increases total electric power demand.
Simulated scenario (c): Cooling coil valve gets stuck (50% open) and outdoor temperature sensor bias (-4°C) on May 10, at 12:00 pm. Dynamic impact (shown in Figure 7): Comparing to the individual fault onset analysis, combination of the two faults has some similarity from each of the separate fault onset scenarios. However, the separate impacts don't simply sum up because the system is non-linear.

From the result and analysis above, we found the following characteristics for the transient impact of faults:

- Each fault disrupts the normal operation of HVAC components at different time periods depending on the control event. The impact of sensor or actuator faults might be either immediate or manifest in the future depending on the implemented control sequence and system operating conditions.
- In general, a larger fault intensity leads to a larger impact on system performance; and the impact magnitude is nonlinearly correlated with the fault intensity.

These characteristics are related to the thermal inertia for building envelope and environment, a relatively slow actuation process in HVAC system and components, and complex interactions between different control loops.
Table 3 summarizes the findings for both fault onset and fault long-term impact analysis. We believe the analysis presented in this paper not only provides a starting point for further evaluation and fault impact analysis, but also provides insights on how the fault occurrence affects the operation of the HVAC system and that of HVAC equipment.

## CONCLUSION

Physical faults can affect building operation at various levels depending on several factors, including fault type, fault intensity level, operational status, and weather. This paper described a simulation-based approach to fault impact analysis on a single duct VAV system. The use of a virtual testbed enabled us to quantitatively evaluate the impact of simulated physical faults on the energy, comfort, and operational performance for different fault intensity levels and under different weather conditions.
The use of this virtual testbed allows for quantifying the potential long-term impact of different faults this way, enabling maintenance schedule definition to minimize the cost of building operation. Furthermore the virtual testbed can be used in the process of developing and testing fault detection and diagnosis algorithms to test the efficacy of these tools in different operating conditions and in conjunction with specific control sequences.
Predictive analytics focused on estimating remaining useful life of equipment have been developed and are a common practice in other industries with reliability driven business models. Such algorithms have not been used for HVAC and the building systems industry. Future research will investigate topics such as prediction of fault occurrence time, based on analysis of equipment health state indicators. In this way, the fault impact can be eliminated by taking remedial actions prior to fault occurrence.

## ACKNOWLEDGMENTS

This work has been supported by the Building Technologies Office of the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy.

Table 3: Summary of fault impact result analysis.

| Impact Analysis | Hardware Type | Fault Type | Generic Findings | Specific Findings |
|---|---|---|---|---|
| Fault onset | Outdoor air temperature sensor | Bias | The onset of fault affects relevant HVAC components sequentially based on the control logic flow. Impact of multiple faults are not linearly added up. | Fault −→ economizer enabling −→ mixing box control, fan control, and cooling demand. |
| | Cooling coil valve | Stuck | | Fault −→ chilled water flow −→supply air temperature control, fan control, and VAV box reheat control. |
| | OA sensor fault and cooling coil valve fault | Bias | | Fault −→ chilled water flow−→ economizer enabling −→mixing box control, supply air temperature control, fan control, and VAV box reheat control. |
| Long-term fault | Outdoor air temperature sensor | Bias | The impact of hardware fault varies with fault intensity, fault types, and hardware types. These faults typically affect energy or thermal comfort, or both. They tend to reduce energy with increased thermal discomfort, or purely increase energy usage. | temperature sensor \, economizer usage /total energy usage \, thermal discomfort /; Vice versa. |
| | Supply air temperature sensor | Bias | | temperature sensor \, total energy usage \, thermal discomfort /; Vice versa. |
| | Cooling coil valve | Stuck | | Valve stuck at smaller position \, total energy usage \, thermal discomfort /; Vice versa. |

Meaning of symbols: −→affect, / increase, \, decrease

## REFERENCES


Beghi, A., R. Brignoli, L. Cecchinato, G. Menegazzo, M. Rampazzo, and F. Simmini. 2016. "Data-driven Fault Detection and Diagnosis for HVAC water chillers." *Control Engineering Practice* 53:79–91.

Breuker, M., and J. Braun. 1998. "Common Faults and Their Impacts for Rooftop Air Conditioners." *HVAC&R Research* 4 (3): 303–318.

Deru, M., K. Field, D. Studer, K. Benne, B. Griffith, P. Torcellini, B. Liu, M. Halverson, D. Winiarski, and M. Rosenberg. 2011. "U.S. Department of Energy commercial reference building models of the national building stock." NREL Report No. TP-5500-46861.

Fernandez, N., S. Katipamula, W. Wang, Y. Xie, and M. Zhao. 2017. "Energy savings potential from improved building controls for the US commercial building sector." *Energy Efficiency*, pp. 1–21.

Granderson, J., R. Singla, E. Mayhorn, P. Ehrlich, D. Vrabie, and S. Frank. 2017. "Characterization and survey of automated fault detection and diagnostics tools." 11/2017.

Huang, S, Y. Chen, D. Vrabie, and P. Ehrlich. 2018. "A control-oriented building envelope and HVAC system simulation model for a typical large office building." *2018 Building Performance Analysis Conference and SimBuild co-organized by ASHRAE and IBPSA-USA*, September 26-28, Chicago, IL.

Hyvarinen, J, and S. Karki. 1996. "Building optimization and fault diagnosis source book." *IEA Annex 25*, no. 1996.8.

Lee, S.H., and F.W.H. Yik. 2010. "A study on the energy penalty of various air-side system faults in buildings." *Energy and Buildings* 42 (1): 2–10.

Qin, J., and S. Wang. 2005. "A fault detection and diagnosis strategy of VAV air-conditioning systems for improved energy and control performances." *Energy and buildings* 37 (10): 1035–1048.

Roth, K.W., D. Westphalen, M.Y. Feng, P. Llana, and L. Quartararo. 2005. "Energy Impact of Commercial Building Controls and Performance Diagnostics: Market Characterization, Energy Impact of Building Faults and Energy Savings Potential." Report, TIAX LLC.

Schein, J., and S. Bushby. 2006. "A Hierarchical Rule-Based Fault Detection and Diagnostic Method for HVAC Systems." *HVAC&R Research,* 12 (1): 111–125.

Seem, J.E., J.M. House, and R.H. Monroe. 1999. "On-line monitoring and fault detection." *ASHRAE journal* 41 (7): 21–26.

U.S. EIA. 2016. 2012 Commercial Buildings Energy Consumption Survey (CBECS) Survey Data. Accessed on August 8, 2017.

Wang, S. W., and F. Xiao. 2004. "AHU sensor fault diagnosis using principal component analysis method." *Energy and Buildings* 36 (2): 147–160.

Wetter, M., W. Zuo, T. Nouidui, and X. Pang. 2014. "Modelica Buildings library." *Journal of Building Performance Simulation* 7 (4): 253–270.

Zhang, R. P., and T. Z. Hong. 2017. "Modeling of HVAC operational faults in building performance simulation." *Applied Energy* 202:178–188.