Automatic Model-Based Fault Detection and Diagnosis Using Diagnostic Directed Acyclic Graph for a Demand-Controlled Ventilation and Heating System in Simulink

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***Abstract*— In green and smart buildings, the main purpose of a demand-controlled ventilation system is to prevent over ventilation which leads to energy saving through automatic adjustment of ventilation damper while it maintains thermal comfort for occupants and indoor air quality in an acceptable range. These complex systems include sensors and actuators. Several problems such as system failure or performance degradation can arise due to faults in each component. A major contribution of this paper is to test and implement diagnostic directed acyclic graph as the fault detection and diagnosis method in demand-controlled ventilation systems. The introduced simulation framework is a helpful operation platform for this means. In this study, different types of faults such as sensor faults including wrong sensor readings or noisy sensors, and actuator faults such as a stuck damper actuator or stuck heater actuator are modeled, simulated, and injected into the system. Based on the framework, fault detection and diagnosis using diagnostic directed acyclic graphs are proposed. The results show that better energy efficiency can be achieved with automatic fault detection and diagnosis.**

Keywords*— *Demand-controlled ventilation simulation; energy efficiency; fault detection and diagnosis; acyclic graph

I. Introduction

The building sector in the European Union (EU) consumes 40% of the total energy in the union [1, 2]. The energy consumption in the office building sector is almost 18% of the global energy consumption [3]. These statements demonstrate the importance of energy saving in office buildings. Heating, ventilation and air conditioning (HVAC) systems are one of the largest consumers of energy, especially in office buildings [4]. HVAC systems keep the thermal conditions in a comfort zone and indoor air quality in an acceptable range. Recent research trends emerged based on advanced control strategies in building energy management systems (BEMS) which indicate that there could be a potential energy saving up to 30% of total energy consumed in a building [5]. To optimize a complex building automation model, it is important to get the knowledge about the system behavior by analyzing the system model, because the model specifies what a system does.

Lapusan et al. developed a multi-room building thermodynamic model based on 3R-2C network (3 resistors and 2 capacitors) using Simscape library from MATLAB/Simulink [6]. Thavlov et al. presented a model for prediction of indoor air temperature and power consumption from electrical space heating in an office building, using stochastic differential equations [7]. This model was developed with SYSLAB. Thavlov showed that due to the high amount of natural ventilation in FlexHouse and especially the nonlinear properties of wind, conditions should be integrated into the model, due to their influence on the indoor temperature. Natural ventilation is an effective method to improve indoor air quality (IAQ) and to dilute indoor CO_2 concentration in offices. Therefore, Behravan et al. considered another concept for the simulation, which also included carbon dioxide (CO_2) proliferation in office spaces due to human respiration that could cause some negative characteristics for occupant comfort, e.g. feeling unwell, lack of concentration, and deterioration in efficiency [8].

Demand-controlled ventilation (DCV) is a control strategy that modifies the amount of fresh air coming from the outside environment delivered to a room by automatic adjustment of damper actuators based on the CO_2 sensor measurements. Most codes and standards specify some constant for required air change volume per person or per area for different places which can lead to over ventilation and increased energy consumption [9], while DCV increases the potential energy saving in heating systems by preventing excess outside low-temperature air from coming into the building spaces. Studies demonstrate that 15% to 25% of the HVAC system's energy can be saved by setting the ventilation rates based on the occupancy's fresh air requirement [10].

Several problems such as system failure or performance degradation can arise due to faults in components, e.g. sensors and actuators. A survey of faults in HVAC systems has been performed as part of the international energy agency's annex 25

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[11]. The faults can be categorized as design faults, installation faults, abrupt faults, and degradation faults. Examples are sensor faults such as wrong sensor readings or noisy sensors, and actuator faults such as a stuck-at fault. These faults waste more than 20% of the energy consumed by HVAC systems [12]. Basarkar et al. reported that the presence of HVAC faults can influence the total HVAC energy use by as much as 22%, depending on the type of faulty behavior and the severity of the faults [13]. Based on the National Institute of Standards and Technology (NIST), fault detection and diagnosis (FDD) methods have a potential of 10% to 40% energy savings in HVAC systems [14]. Studies have indicated that 20-30% energy savings are achievable by re-commissioning HVAC systems to rectify faulty operation [15]. For example, a stuck damper can cause significant heating, cooling, comfort, and energy consumption issues depending on which position the damper is stuck at. Lee et al. documented the energy penalty associated with various air-side system faults. There is a report of 36% excess cooling energy consumption due to a single VAV box damper being stuck open [16]. Katimapula et al. found that poorly maintained, degraded and improperly controlled equipment wastes an estimated 15% to 30% of energy in commercial buildings [17]. Around 15% to 30% of the energy loss in buildings is due to the performance degradation, improper control strategy, and malfunctions of HVAC systems [18].

Therefore, there is a great potential to develop a reliable fault detection and diagnosis tool to guarantee the normal operation of HVAC and DCV systems which causes better energy efficiency. Zhou et al. described that it is necessary to implement the fault detection and diagnosis methods for HVAC systems to keep them working properly for energy saving, life-prolonging and indoor air quality enhancement [18]. Different methods were deployed for fault detection and diagnosis in last years. Yu et al. considered energy consumption as a useful parameter to detect faults using the Fuzzy Neural Networks (FNN) model [19]. Sterling et al. compared two model-based diagnostic solutions of qualitative and quantitative models and encoded failure modes in their Modelica model [20]. The simulation is a helpful operation platform to develop and test fault detection and diagnosis strategies for component-level or system-level faults. Basarkar et al. identified, characterized and prioritized common faults of HVAC equipment and control systems in the EnergyPlus building performance simulation tool, but the EnergyPlus tool has limited capability of modeling HVAC faults [13]. In this study, different types of faults are modeled, simulated, and injected into a complex demand-controlled ventilation and heating system using MATLAB/Simulink, and model-based fault detection and signal rule-based diagnostics using acyclic directed graphs are successfully implemented.

II. Model Description

A. Modeling and Simulation of the System

This paper presents a model which is simulated by Matlab/Simulink version R2017a, using the Simscape toolbox. The model contains six office rooms and one corridor based on the real dimensions and thermal specifications of a building at the University of Siegen, Germany, during a typical winter day in February. Figure 1 shows the office building sketch, based on which the complex model was established with thermal dependencies among different rooms, spaces, and the outside environment. The model dynamics consist of various equations and coefficients that can show the heat transfer effects of different zones of the building depending on each other, as well

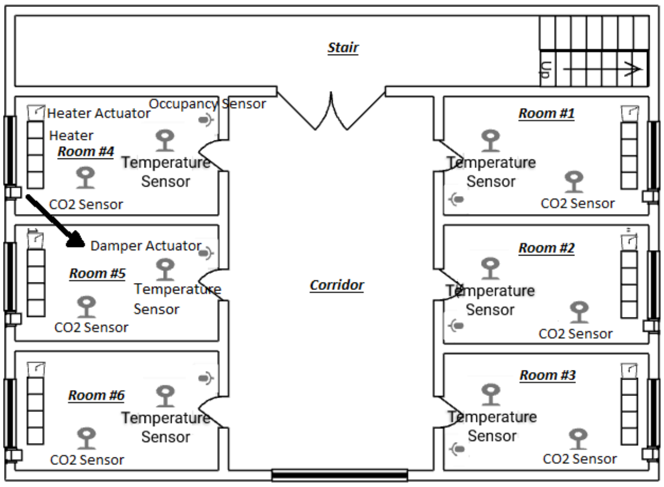

Fig. 1. Office building sketch.

as the ventilation which is affected by outdoor wind, Buoyancy phenomena, and indoor/outdoor temperature [8]. Figure 2 demonstrates the Simulink model for one room which is equipped with four fault injection blocks (subsystems) that are highlighted in red color. The occupancy in each room was simulated as an occupancy pattern which determines the number of persons. This occupancy pattern can be taken from an occupancy sensor that is modeled and simulated [22]. This pattern was modeled in a matrix by MATLAB code (occupants.mat) and can be seen in the middle subplot of figure 15. Each room has one temperature sensor, one CO_2 concentration sensor, one occupancy sensor, one damper actuator which was coupled to a damper, one heater actuator (thermostat), and one fault injection dashboard to manually inject the fault into the system. The demand-controlled ventilation system can control the position of the damper (open/close) and the heater actuator can control the status of the heater (on/off).

III. Fault Injection

A fault is an unpermitted deviation of at least one characteristic property of the system from its normal, acceptable, usual and expected behavior [23]. This fault may initiate a failure or a malfunction or it may not affect the correct functioning of a system. A failure is a permanent interruption of a system's ability to perform a required function under specified operating conditions which results from one or more faults. After the model implementation for a normal case, it is important to inject some artificial faults into the system to check how the system behaves under faulty condition. The behavior that is recorded during fault conditions is used for fault detection.

Figure 3 shows the fault injection dashboard in the Simulink model. The behavior of the system in the presence of faults can be studied by activating faults (fault injection) and the effects can be monitored. The dashboard consists of four fault cases for CO_2 sensor, damper actuator, temperature sensor, and heater actuator (thermostat), which can be activated through sliders, and an indicator in front of each slider shows the status of the fault case, e.g. the green color means that a component behaves in normal condition and the red color is the sign of a faulty behavior of the component. Figure 4 belongs to the CO_2 sensor fault case that describes a continuous wrong sensor reading with a constant value of 700 ppm for indoor CO_2 concentration or noisy fault values within the range of 550 ppm to 750 ppm. Figure 5 shows this switch model. The fault case of a damper actuator describes a stuck damper in a closed position and as a result, the indoor air temperature is increased and the CO_2 concentration goes above the maximum permitted threshold. The fault case of a temperature sensor describes wrong sensor

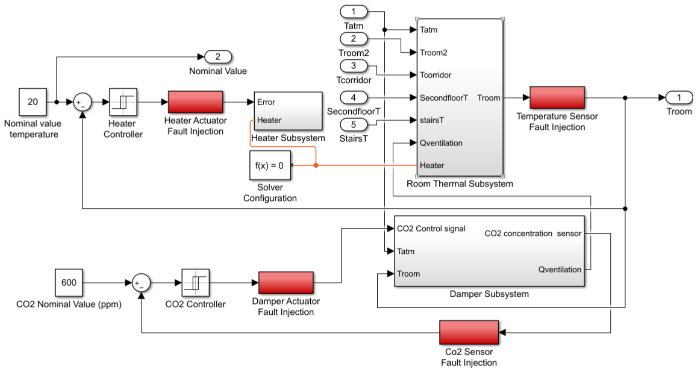

Fig. 2. Simulink model of an office room with fault injection blocks.

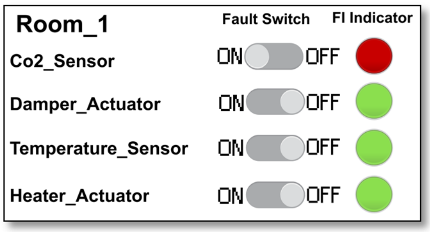

Fig. 3. Fault injection dashboard.

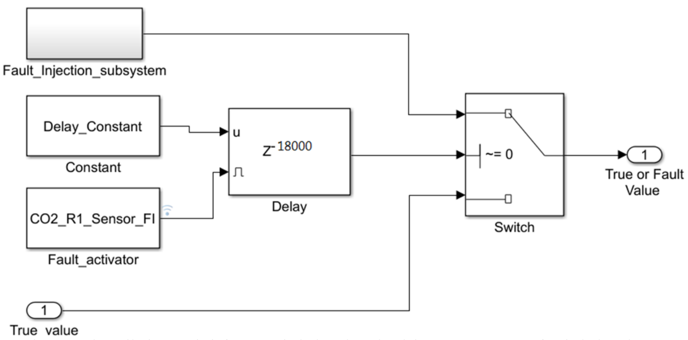

Fig. 4. Simulink model for Fault injection inside CO2 sensor fault injection subsystem.

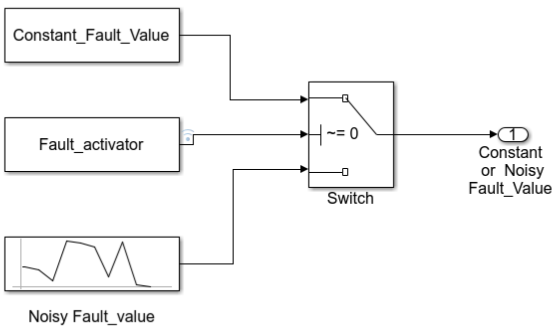

Fig. 5. Switch for noisy or constant value fault injection.

readings with a constant value of 15°C, and the fault case of the heater actuator describes a stuck-at fault in the heating mode. The corridor subsystem consists of two fault cases because there is no CO_2 sensor and no damper. In the case of fault injection, the switch block receives the values from the fault injection subsystem. The model has the ability for fault injection at any time by using a delay block and in this study, the fault was injected after 18,000 seconds of simulation time. This value can be changed in the Simulink model workspace.

IV. Fault Detection and Diagnosis

Fault detection and diagnosis (FDD) is an area of investigation concerned with automating the process of detecting faults in a physical system and diagnosis their causes. The primary objective of an FDD system is the early detection of faults and diagnosis of their causes, enabling correction of

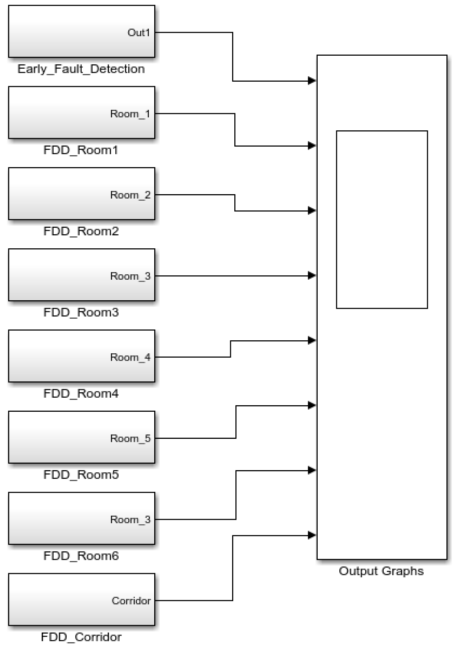

Fig. 6. Fault detection and diagnosis system.

the faults before additional damage to the system or loss of service occurs. This is accomplished by continuously monitoring the operations of a system, using FDD to detect and diagnose abnormal conditions and the faults associated with them [17].

In HVAC systems, fault detection is the determination that the operation of the building is incorrect or unacceptable in some respect. Unacceptable behavior may occur over the whole operating range or be confined to a limited region and hence only occur at certain times. The most simple and frequently used method for fault detection is the limit checking of a directly measured variable [23]. To detect and diagnose these faults, getting the knowledge about the system by monitoring abnormalities in the behavior through modeling is substantial. FDD determines the size, time of occurrence, location and cause of the faults (fault diagnosis) and even in some cases making the system fault tolerant. Herewith, faults are compensated in such a way that they do not lead to system failures. The measured variables of a process are monitored and checked if their absolute values or trends exceed certain thresholds.

A further possibility is the plausibility check. Model-based methods of fault detection use the relations between several measured variables to extract information on possible changes caused by faults. By comparing the observed features with their nominal values and applying methods of change detection, the analytical symptoms are generated. [23]. These symptoms are the basis for fault diagnosis. This paper mainly concentrates on faults occurring in sensors and actuators. The faults are usually classified as short faults, noise faults, and constant faults. Constant faults have a large number of successive samples with a constant value. The reported constant values are usually either very high or very low compared to the "normal" sensor readings or uncorrelated to the underlying physical phenomena. A short fault causes a sharp change in the measured value between successive data points. In case of noise faults, the variance of the sensor readings increases. Unlike short faults that affect a single sample at a time, noise faults affect a number of successive samples [24]. Since the temperature parameter is less sensitive to the short faults, it's better to analyze the system with constant and noise faults. Figure 8 represents the

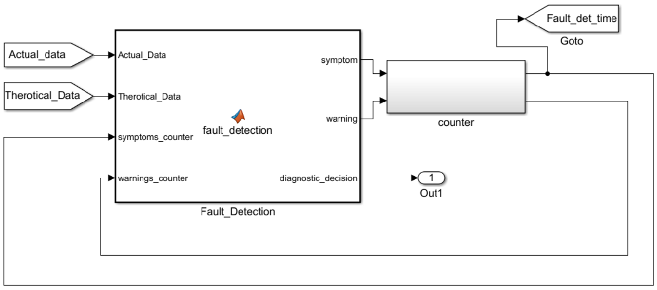

Fig. 7. Model-based fault detection subsystem.

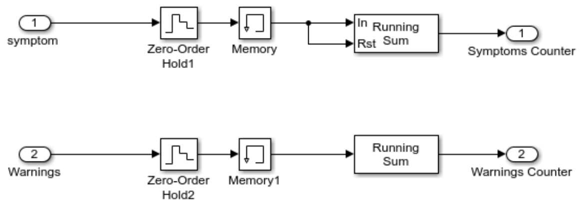

Fig. 8. Symptoms and warnings counter.

symptoms and warnings counter. This block holds and delays its inputs by one iteration using a memory block.

A. *Diagnostic directed acyclic graph*

Faults in the system are reflected in the measured signals or residuals. Diagnostic features are extracted from these signals. They hold characteristic information about the current status of the system and will, accordingly, indicate a fault. The fault detection and identification process in such a fault diagnosis system is conducted by evaluating confirmative and unsupportive diagnostic information by means of diagnostic tasks. Such a task may be limit checking in a simple case or may comprise of different processing steps to evaluate more complex plausibility relations, amongst others. These tasks are embedded in the MATLAB function blocks. Through the extraction of the diagnostic information, their processing and combination, particular faults get included or excluded during the process, eventually specifying the actually occurred fault. The dependencies between different diagnostic tasks are modeled in a diagnostic directed acyclic graph (DDAG) [25]. For each node of the graph, we specify the diagnostic operations to be performed as well as the necessary input signals. In case of a fault, the attained diagnostic results at a certain node initially provide indications for a certain fault, however, may yet hold inconclusive information. As the process advances, the degree of confidence of a correct fault identification increases. The DAG in figure 9 models the dependencies of diagnostic operations for the detection and identification of the faults specified in Table 1, namely complete failure of heater actuator, complete failure of damper actuator, permanent failure of temperature or CO_2 sensor. In the simplified scenario, we assume that only one fault occurs at a time. Table 2 summarizes the required signals for the different evaluation steps of the graph. With the signals S_{A1}, S_{A2} and S_{A3} for instance, the heater actuator status is determined at node A by means of a plausibility check. The outcome is further analyzed at node B which observes the actuator status over a longer period of time. At this node, a decision on the health status is made which on the one hand is forwarded to the final decision node J and on the other hand, serves as an intermediate result for the temperature sensor evaluation at node C.

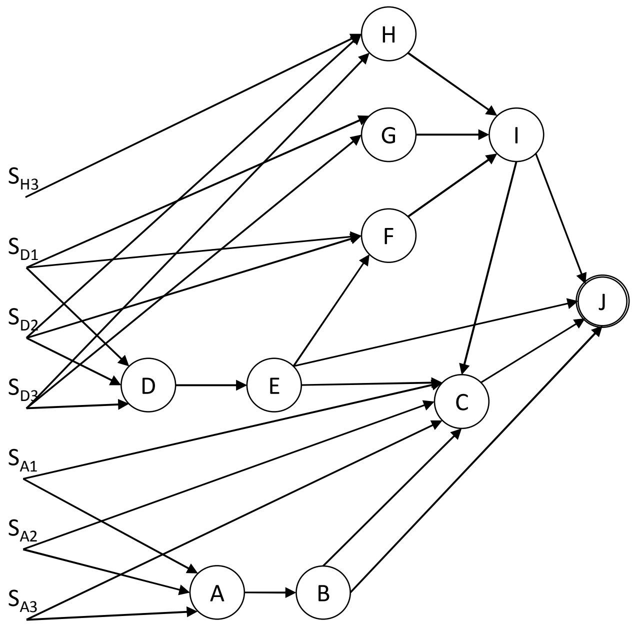

Fig. 9. Diagnostic directed acyclic graph.

Table. 1. Diagnostic tasks and signals

Node	Task	Failed component
A	Plausibility check of heater actuator status	Heater actuator
B	Evaluation of heater actuator health status	
C	Plausibility check of temperature sensor health status	Temperature sensor
D	Plausibility check of CO_2 concentration	Damper actuator
E	Evaluation of damper health status	
F, G, H	Plausibility checks of CO_2 sensor status	CO_2 sensor
I	Intermediate decision on CO_2 sensor health status	
J	Final fault decision	Summary of faults

Table. 2. Diagnostic tasks and signals

Signal	Measurements
S_{A1}	Heater on/off status
S_{A2}	Temperature reference value
S_{A3}	Temperature measured value
S_{D1}	CO_2 nominal value
S_{D2}	CO_2 measured value
S_{D3}	Damper open/close status
S_{H3}	Number of occupants

B. *Fault diagnosis subsystems*

Figure 10, 11, 12, 13 and 14 show the Simulink model and its subsystems that are designed to diagnose faults in the CO_2 sensor, damper actuator, temperature sensor, and heater actuator. Based on the plausibility checks the Simulink model produces the fault symptoms. These fault symptoms are used to detect the type, the size, and the location of the faults. The model supports the detection of the real faults from generated symptoms. The positive effect of using a demand-controlled ventilation system can be inferred from this figure, which has been reported in previous work for the healthy mode [8].

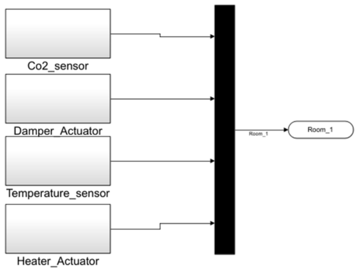

Fig. 10. Fault diagnosis model.

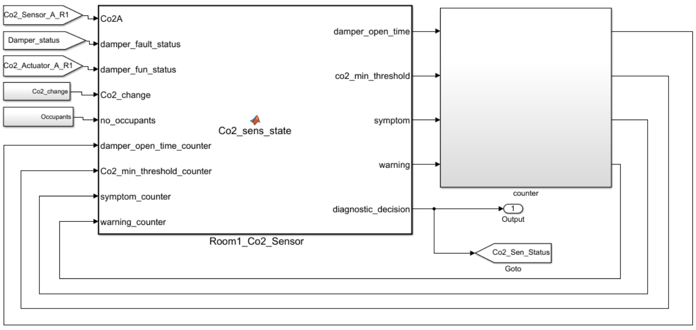

Fig. 11. CO_2 sensor fault diagnosis subsystem.

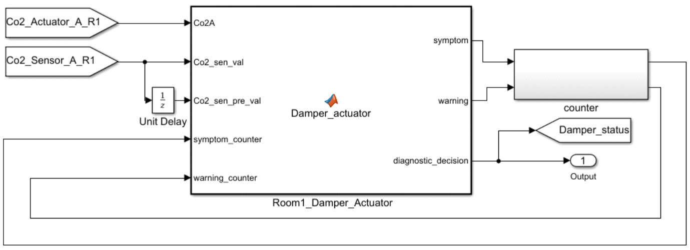

Fig. 12. Damper actuator fault diagnosis subsystem.

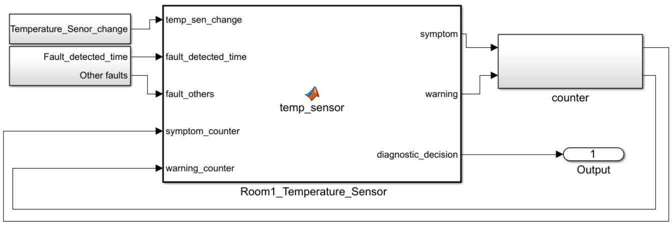

Fig. 13. Temperature sensor fault diagnosis subsystem.

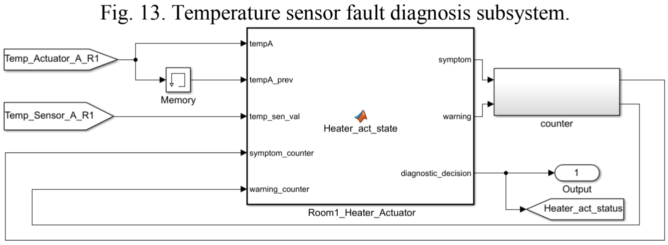

Fig. 14. Heater actuator fault diagnosis subsystem.

V. Results

The investigated model of this study shows that Simulink-based environment has the ability to implement fault detection and diagnosis methods using MATLAB functions. Another ability of the system is its scalability with respect to input parameters. It means that the operator can easily change the value of parameters in the system. The diagnostic directed acyclic graph approach is implemented for the aim of diagnosis in Simulink and the results show that the model can automatically detect and diagnose the faults injected into the demand-controlled ventilation and heating system. This model is able to produce the output signals which are indoor temperature and CO_2 concentration variation, the duty cycle of the heater, and the frequency of on/off switching for heater and damper of each room. Also, the value and the cost of the heating system for each zone can be calculated by putting a gain after the heater gain block in the heater subsystem [8].

Some assumptions are considered for simulation. The outdoor air temperature was modeled as a sinusoidal wave during a day or 86400 seconds (simulation stop time) where the initial temperature is 7°C (considered 6:00 a.m.) and it fluctuates between 2°C and 12°C. The value of temperature for the second floor and the adjacent stair space were considered 20°C and 13.5°C, respectively. Generally, outdoor environment CO_2 concentrations range between 300 ppm and 500 ppm, and indoor CO_2 concentrations in office buildings range often between 400 ppm and 900 ppm [26]. In this study, the outdoor CO_2 concentration was considered to be at a constant value of 400 ppm. The desired indoor CO_2 concentration was considered as the value of 600 ppm with upper and lower fluctuation thresholds that were controlled by the demand-controlled ventilation system. Figure 15 shows the indoor CO_2 concentration based on the occupancy and damper status in healthy mode and faulty mode of a CO_2 sensor fault. In healthy system mode (green color signal), the open position of the damper is more frequent in more populated times. As a result, the damper status could remain closed in the rest and it prevents the coming of low-temperature excess air from the outside into the building (potential energy saving). The frequency of damper switching also depends on the size. It can be seen that in the faulty mode (red color signal), the heater will remain in the on position, and more energy will be consumed by the system.

The system has the ability to detect the fault from normal operation of the system and diagnose this fault by specifying the special cause (faulty component) using the mentioned diagnostic approach. Therefore, the system will trigger an alarm and the correction work can be done, which comes with better energy efficiency. The double y-axes figure 16 shows the room number one temperature variation based on the outside temperature variation, heating system and damper status in healthy mode (green color) and faulty mode (black color) of the system for different fault cases. Heater and damper are considered to have just two possible statuses, 1 for on and 0 for off in heater, or 1 for open and 0 for close in damper. The upmost figure is the response of the system when a CO_2 sensor fault is manually activated by the user. Corresponding to this manner, the second upmost figure indicates the damper actuator fault mode, the third upmost figure shows the temperature sensor fault mode, and the fourth figure describes the heater actuator fault mode.

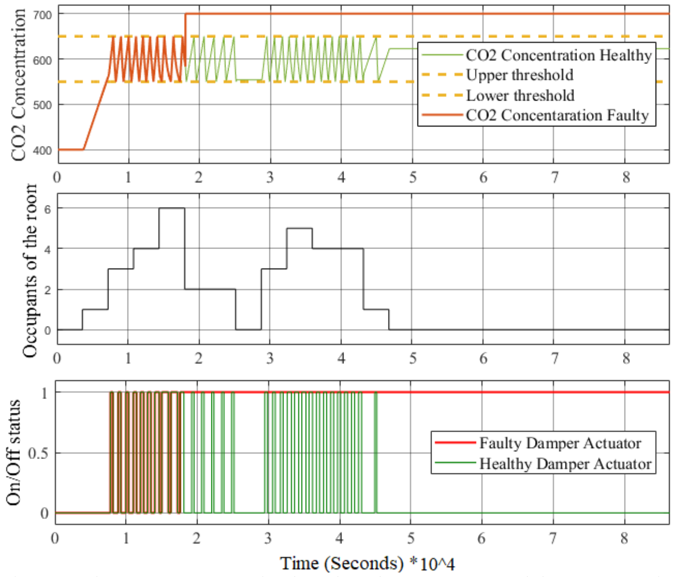

Fig. 15. Indoor CO_2 concentration based on the occupancy and damper status in healthy and faulty modes.

CONCLUSION

This paper has presented automatic model-based fault detection and diagnosis using diagnostic directed acyclic graphs for a demand-controlled ventilation and heating system. The main purpose of a demand-controlled ventilation system is to prevent over ventilation which leads to energy saving through automatic adjustment of the ventilation dampers while it maintains thermal comfort for occupants and indoor air quality in an acceptable range. Several problems such as system failure or performance degradation can arise due to faults in each component such as a sensor fault including wrong sensor readings or noisy sensors, and actuator faults such as a stuck fault detection and diagnosis method and was implemented using the MATLAB/Simulink simulation tool for the detection and diagnosis of manually injected faults. The model has the damper actuator or a stuck heater actuator. In this paper, a diagnostic directed acyclic graph served as a signal model-based ability to represent the effect of fault injection on different parameters in one room and also in the adjacent rooms. The result shows that better energy efficiency can be achieved with automatic fault detection and diagnosis in demand-controlled ventilation systems. The modeling and simulation of other types of faults can be done in future works.

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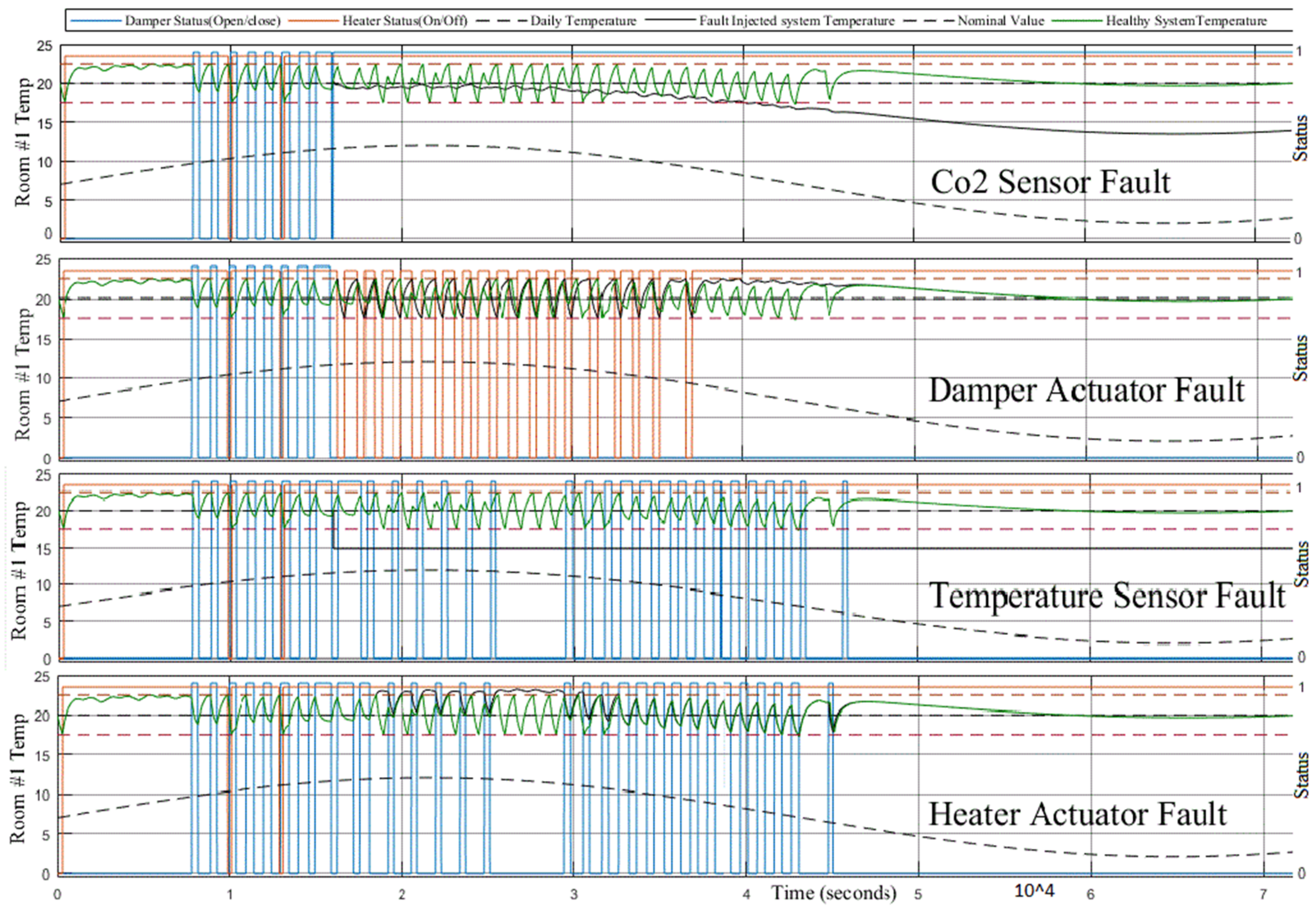

Fig. 16. The room number one temperature variation in healthy mode (green color) and faulty mode (black color) of the system for different fault cases.

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