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A comparative investigation between rule- and inverse model-based fault detection and diagnostics for HVAC control systems

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Abstract. Fault detection and diagnostics (FDD) tools provide valuable information regarding system faults and deviation from expected operation. Most existing FDD tools apply rule-based fault detection algorithms that generate an alarm when a rule is met; however, these tools cannot evaluate the overall performance of a system. Inverse-model-based FDD algorithms can be deployed to complement the fault alarms triggered by rule-based building energy management systems (BEMS). This paper examines the faults detected by rule- and inverse model-based algorithms used to detect faults in multiple zone variable air volume air handling unit systems. The capability of the rule- and inverse model-based algorithms in detecting and diagnosing faults is demonstrated through illustrative examples using data from three commercial buildings in New Brunswick, Canada. The results show that inverse model-based algorithms could diagnose faults that were not detected by the rule-based FDD algorithms implemented in a commercially available BEMS tool.

1. Introduction

Efficient operation and maintenance (O&M) of heating, ventilation, and air conditioning (HVAC) systems serving commercial and institutional buildings improve the energy performance of a building, reduce greenhouse gas (GHG) emissions, and improve indoor environmental quality. Fault detection and diagnostics (FDD) tools allow users to capture deviations from normal operations and plan maintenance tasks to address the underlying issues. These tools can utilize rule or inverse model-based algorithms to capture system faults. Most existing building energy management systems (BEMS) employ rule-based FDD algorithms that generate alarms when the rule thresholds are exceeded. These rule-based FDD tools play an essential role in the operation and maintenance planning of a building; however, they are limited in: a) providing insights regarding the HVAC system's health, b) diagnosing the root causes of detected faults, and c) capturing faults masked by interactions between HVAC systems and thermal zones [1]. On the other hand, inverse model-based FDD algorithms rely upon knowledge of the underlying physical processes to detect and identify the root causes of detected faults and provide insights regarding the overall HVAC system's health. Therefore, the findings from inverse model-based algorithms are necessary for complementing findings from rule-based FDD tools.

Both rule and inverse model-based FDD algorithms are used to detect faults associated with variable air volume air handling unit (VAV AHU) systems. These faults are either hard faults, which refer to deficiencies related to sensors, dampers, actuators, and valves, or soft faults, which refer to controller tuning errors, sequencing logic errors, and programming mistakes. FDD algorithms reviewed in the literature concerning faults associated with VAV AHU systems can be broadly categorized as follows:

a) Rule-based: these algorithms use qualitative methods, such as expert rules, to derive a set of rules that generate an alarm when a rule is violated [2-4]. For example, Schein et al. [3] developed AHU performance assessment rules (APAR) that define the four modes of operation for AHUs to detect deviation from the expected mode of operation.

b) Inverse model-based: these algorithms employ data-driven models, such as black- and grey-box models, to approximate the system's operation. The estimated parameters of the model help identify the underlying physical quantities they represent and estimate unmeasured values [5-8]. For example, Gunay et al. [8] developed an inverse model-based FDD method to detect programming logic faults in VAV AHU systems. The method could detect programming logic faults by comparing expected sequences of operation, as per ASHRAE Guideline 36 [9], to the measured ones.

The FDD algorithms reviewed in the literature for VAV AHU systems employed either rule- or inverse model-based methods to detect and diagnose the system's faults. However, a study examining the findings of both rule- and inverse model-based algorithms for VAV AHU systems has not been conducted. This paper examines the findings of rule- and inverse model-based FDD algorithms employed to detect the VAV AHU system's faults. The operational benefits of the algorithms are demonstrated through illustrative examples using data collected from three VAV AHU systems serving large commercial buildings in New Brunswick, Canada. The rule-based fault alarms triggered by the BEMS, and operational data are collected from the buildings. The data are used to train inverse model-based FDD algorithms to detect and diagnose hard and soft faults in seven fault categories concerning VAV AHU systems. The faults detected by the rule- and inverse model-based FDD algorithms are presented with illustrative examples showing the operational benefits of combining the findings of the two approaches.

2. Methodology

2.1. Data collection and processing

Data from multiple zone VAV AHU systems serving three commercial buildings in New Brunswick, Canada, are collected from January to December 2022 at one-hour intervals. The AHUs of these systems comprise a mixing box regulating the fresh air intake and heating and cooling coils that condition the supply air. The supply air is ducted from the three AHUs to 21, 33, and 21 VAV terminals. A modulating damper controls the discharge airflow rate from the VAV boxes. The measurements collected from the building automation system (BAS) for the AHUs include outdoor ($\mathrm{T_{oa}}$(°C)), return ($\mathrm{T_{ra}}$(°C)), and supply ($\mathrm{T_{sa}}$(°C)) air temperatures, mixing box damper state ($\mathrm{S_{mb}}$(%)), heating ($\mathrm{S_{hc}}$(%)) and cooling ($\mathrm{S_{cc}}$(%)) valve states, supply fan state ($\mathrm{S_{fan}}$), and supply air pressure ($\mathrm{P_{sa}}$(Pa)). Additionally, trend data for the VAV zones are collected at the same resolution as the AHU data, including zone air temperatures ($\mathrm{T_{za,i}}$(°C)), VAV box discharge airflow rate ($\mathrm{q_{vav,i}}$(L/s)), VAV box discharge airflow rate setpoint ($\mathrm{q_{vav,sp,i}}$(L/s)), and VAV damper position ($\mathrm{S_{vav,i}}$(%)), for each VAV zone i.

2.2. Inverse model-based FDD algorithms

2.2.1. Mixing box hard faults: The mixing box in an AHU consists of outdoor, return, and exhaust air dampers. These dampers could encounter hard faults, causing them to become irresponsive to the control signal that adjust the damper opening, such as stuck at a certain position or leaking at 0% opening signal. To detect these faults, the relationship between the outdoor air fraction (OAF(%)) and the mixing box damper position (S_{mb}(%)) is modelled as follows [8]:

$$\mathrm{OAF} = \frac{\mathrm{x_{1,mb}}}{\exp\left(\mathrm{x_{2,mb}} \cdot \mathrm{S_{mb}} + \mathrm{x_{3,mb}}\right)} \tag{1}$$

$$\mathrm{OAF} = \frac{T_{ma} - T_{ra}}{T_{oa} - T_{ra}} \tag{2}$$

where T_{ma} (°C) is the mixed air temperature, and x represents the regression parameters of the model. In cases where T_{ma} is not measured, it could be approximated by considering the timesteps when heating and cooling valves are fully closed (i.e., economizer state), as follows:

$$T_{ma} = T_{sa} - \left(\frac{P_{sa}}{\rho \cdot c_p \cdot \eta}\right) \tag{3}$$

where ρ (kg/m[3]) is the density of air, c_p (J/kg°C) is the specific heat of air, and η is the fan efficiency (assumed as 0.7). A mixing box damper fault is detected if the relationship between OAF and S_{mb} is outside the acceptable range for parallel blade dampers defined by AMCA [10].

2.2.2. Heating and cooling coil hard faults: The heating and cooling coils of the AHU utilize modulating valves to control the amount of hot or chilled water circulating through the coils. These modulating valves could encounter hard faults, causing them to get stuck at a certain valve position or leak at 0% valve opening. To detect these possible faults, the relationship between the temperature difference across the heating or cooling coil ($\Delta T_{hc/cc}$ (°C)) and the valve position ($s_{hc/cc}$ (%)) is modelled as follows [8]:

$$\Delta T_{hc/cc} = \frac{x_{1,hc/cc}}{\exp\left(x_{2,hc/cc} \cdot s_{hc/cc} + x_{3,hc/cc}\right)} \tag{4}$$

where x represents the regression parameters of the model and $\Delta T_{hc/cc}$ is the temperature difference across the heating or cooling coil, defined as $\Delta T_{hc/cc} = T_{sa} - T_{ma}$. In cases where T_{ma} is not measured, it could be approximated using Eqn. (3). A heating or cooling coil fault is detected if the trained model detects a temperature rise higher than 5 °C across the heating coil when the heating valve is fully open or a temperature drop less than 5 °C across the cooling coil when the cooling valve is fully open.

2.2.3. VAV damper hard faults: The damper in the VAV box receives a control signal that adjusts the damper opening to control the airflow discharged into the VAV zone. The damper could encounter hard faults causing it to become irresponsive to the control signal, such as stuck at a certain position or leaking at 0% opening. To detect these faults, the relationship between the discharge airflow rate ($q_{vav,i}(L/s)$) and the damper position ($S_{vav,i}$(%)) is modelled as follows [8]:

$$q_{vav,i} = \left(S_{vav,i} \cdot x_{1,vav,i} + x_{2,vav,i}\right) \cdot \sqrt{P_{sa}} \tag{5}$$

where x represents the regression parameters of the model for each VAV zone i. A VAV damper fault is detected if the estimated parameter value for $x_{1,vav,i}$ returns a negative value.

2.2.4. State of operation soft faults: The state of operation of a VAV AHU system is divided into the following states [9]: heating, economizer, economizer with cooling, and cooling. The expected mixing box damper position ($\hat{S}_{mb}$) for these states is modelled as follows [8]:

Economizer with cooling state
$$\hat{S}_{mb} = 1 \tag{6}$$

Economizer state
$$\hat{S}_{mb} = \frac{\ln\left(\frac{x_{1,mb}}{\frac{T_{ma} - T_{ra}}{T_{oa} - T_{ra}}}\right) - x_{3,mb}}{x_{2,mb}} \tag{7}$$

Heating or cooling state
$$\hat{S}_{mb} = S_{mb,min} \tag{8}$$

The AHU is expected to operate in the economizer state when $T_{oa} \leq T_{sa} \leq T_{ra}$. In this state, the heating and cooling coils are expected to stay closed since the supply air temperature setpoint ($T_{sa,sp}$) could be met by modulating the mixing box dampers. The AHU is expected to turn into an economizer with cooling state when $T_{sa} \leq T_{oa} \leq T_{ra}$. In this state, the outdoor air is expected to be used instead of the return air to minimize the cooling requirement. Therefore, the outdoor air damper opens fully with the cooling coil running to meet the $T_{sa,sp}$. Finally, when the conditions for the economizer and the economizer with cooling states are not met, the AHU is expected to operate in the heating or cooling states at the minimum outdoor air damper position. A state of operation sequencing logic fault is detected if the measured mixing box damper position (S_{mb}) deviates from the expected ($\hat{S}_{mb}$) for more than 20% of operational time.

2.2.5. Mode of operation soft faults: VAV AHU systems work under the following operation modes: occupied, unoccupied, warm-up, cool-down, set-up, set-back, and freeze protection [9]. It is expected that the supply fan of the AHU starts in the morning to warm up or cool down the building in preparation for occupied mode and to turn off in the evening when the building is unoccupied. Therefore, the number of daily fan state changes is inspected to detect deviation from the expected mode of operation. A mode of operation sequencing logic fault is detected if the fan experiences more than or less than two daily operating mode changes for more than 30% of the weekdays [11].

2.2.6. Supply air temperature setpoint reset soft faults: In order to maximize the economizer operation and minimize unnecessary heating and cooling loads, the supply air temperature (SAT) setpoint ($T_{sa,sp}$) is expected to follow a reset logic based on the outdoor air temperature and the heating or cooling demand from the VAV zones. When the VAV zones demand more heating or less cooling, the $T_{sa,sp}$ should increase, whereas $T_{sa,sp}$ should decrease when the zones demand more cooling or less heating. $T_{sa,sp}$. A reset programming logic fault is detected if $T_{sa,sp}$ falls outside the recommended higher and lower limits introduced by Gunay et al. [8].

2.2.7. Supply air pressure setpoint reset soft faults: In order to optimize fan electricity use, the supply air pressure (SAP) setpoint ($P_{sa,sp}$) is expected to follow a reset logic that adjusts the fan speed based on the airflow demand from the VAV zones. When the demand for airflow increases, the $P_{sa,sp}$ is expected to increase, whereas when the demand for airflow decreases, the $P_{sa,sp}$ is expected to decrease. When less than two or more than five dampers are fully open simultaneously, it indicates that the SAP is higher or lower than expected, respectively. A reset programming logic fault is detected if more than five or less than two dampers are fully open for more than 20% of operating hours.

2.3. Rule-based FDD algorithms

The BEMS serving the three VAV AHU systems described in Sec 2.1 receives and stores time-series data from the BAS. The data are processed by an analytic engine that employs rule-based algorithms to generate alarm reports. The reports typically include the alarm, time of occurrence, frequency, and duration. The BEMS uses predefined rulesets to detect faults and generates alarms when the rules are met. The VAV AHU system faults triggered by the built-in rulesets between January and December 2022 are collected from the BEMS for the three systems serving the commercial buildings under study.

3. Results and discussion

The faults detected by the BEMS built-in rulesets and the inverse model-based algorithms are summarized in Table 1 for the three VAV AHU systems regarding the seven fault categories discussed in Sec 2.2. It is noticed that the inverse model-based algorithms could detect faults that were not detected by the commercial BEMS tool regarding faults related to 1) the mixing box, 2) the heating and cooling coil, 3) VAV dampers, 4) the mode of operation, and 5) SAT and SAP setpoint resets. The ability of the inverse model-based algorithms to detect these faults is attributed to their structure compared to the rule-based BEMS tool structure. For example, the mixing box inverse model-based algorithm detected a mixing box damper fault for the AHU serving System 3. This fault is illustrated in Fig. 1, where the red line represents the best-fit line for the relationship between the outdoor air fraction and the mixing box damper signal, given by Eqn. (1). A fault was detected since the best-fit line was partially outside the expected range represented by the green shaded area as per AMCA [9]. The mixing box model was able to detect this fault because inverse modelling provides a means to estimate the mixed air temperature and the outdoor air fraction. In contrast, a rule-based algorithm's structure is built upon available measurements, which leaves critical values unmeasured and results in undetected faults.

Table 1: A summary of faults reported by rule-based BEMS versus those detected by inverse model-based algorithms for VAV AHU Systems serving three commercial buildings

	VAV AHU System 1		*VAV AHU System 2*		*VAV AHU System 3*	
Fault category	*Faults reported by rule-based BEMS algorithms*	*Faults detected by inverse model-based algorithms*	*Faults reported by rule-based BEMS algorithms*	*Faults detected by inverse model-based algorithms*	*Faults reported by rule-based BEMS algorithms*	*Faults detected by inverse model-based algorithms*
Mixing box	0	0	0	1	0	1
Heating and cooling coil	0	0	0	1	0	0
VAV damper	0/21	0/21	0	3/33	0	0
State of operation	0	0	0	0	0	0
Mode of operation	1	1	1	0	0	1
SAT setpoint reset	0	1	0	1	0	1
SAP setpoint reset	0	1	0	1	0	1

While the rulesets employed by the BEMS are mostly system specific, the inverse-model-based algorithms investigate zone-to-system level interactions to detect faults masked by these interactions. For example, the inverse model-based algorithm for the VAV damper faults presented in Sec 2.2.3 was deployed to inspect the 33 VAV dampers serving VAV AHU System 2. Three VAV dampers were found faulty since the relationship between the discharge airflow rate and the damper position returned a negative or zero value for the parameter $x_{1,vav,i}$ presented in Eqn. (5). One of these faults is presented in Fig. 2 where the relationship between the VAV damper position and airflow rate indicates a faulty behaviour since the airflow rate did not increase as the open damper position increased. This fault was not detected by rule-based algorithms since zone-level heating devices could meet the heating load and mask this fault. Therefore, the inverse model for the VAV damper is capable of detecting faults masked by zone-to-system level interactions.

4. Conclusions

This paper examined the faults detected by rule-based and inverse model-based FDD algorithms employed to detect faults in seven categories related to VAV AHU systems. The rule-based fault triggered alarms and one-year operational data were collected from three VAV AHU systems serving commercial buildings in New Brunswick, Canada. Inverse model-based FDD algorithms for the seven fault categories were deployed to detect and diagnose the faults encountered by the VAV AHU systems. The operational benefits of combining the findings of the rule- and inverse model-based algorithms were demonstrated through illustrative examples.

The inverse model-based algorithms could detect and diagnose faults that were not detected by the BEMS in six of the seven fault categories, including the mixing box, the heating and cooling coil, VAV dampers, the mode of operation, and SAT and SAP setpoint resets.

This paper provided a preliminary comparison and analysis of rule- and inverse model-based FDD algorithms. However, opportunities for further research remain, such as a) collecting data from additional buildings to analyze a broader range of faults detected by the BEMS and the inverse model-based algorithms and b) developing a framework that incorporates the findings of rule- and inverse model-based algorithms into HVAC operation troubleshooting and maintenance planning.

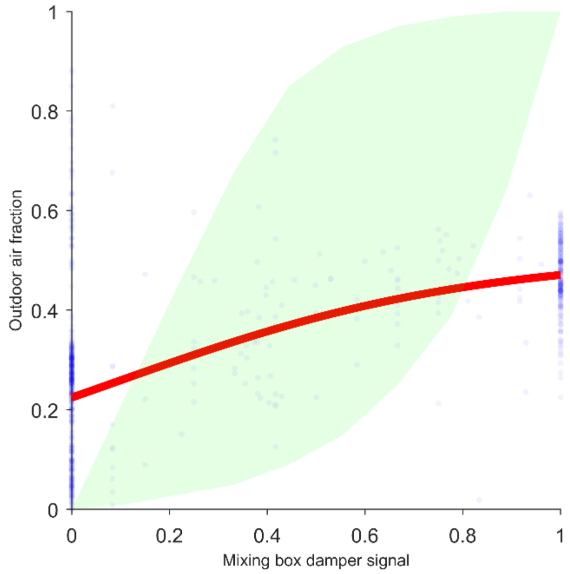

Figure 1: The relationship between the outdoor air fraction and the mixing box damper estimated by the mixing box inverse model.

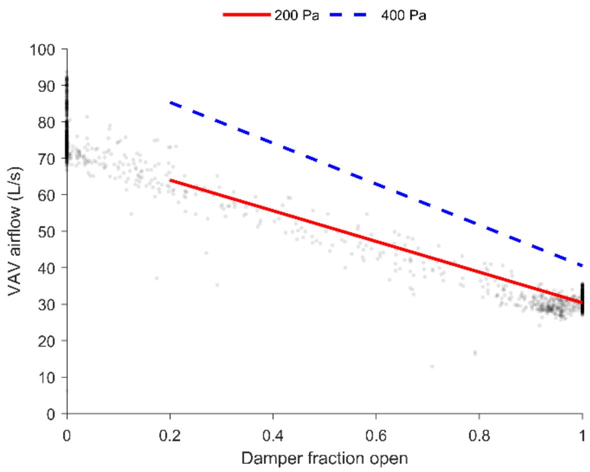

Figure 2: Faulty relationship between VAV terminal damper position and airflow rate detected by the inverse model-based algorithms

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