Virtual testbed on evaluating automated fault detection and diagnostic (AFDD) algorithms for common faults of a single duct VAV system

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Abstract

Fault detection and diagnostics (FDD) are important for detecting and diagnosing faulty operations in HVAC systems. It is common that system performance fail to satisfy design expectations due to improper equipment installation, equipment degradation, sensor failure, or incorrectly configured control systems. However, few FDD technologies have been successfully implemented in actual buildings. One of main reasons is that false alarms and missed detection have been identified as common problems when AFDDs have been applied in non-experimental facilities. This study proposed and created a virtual testbed to evaluate the developed automated fault detection and diagnostic (AFDD) with simulation data or measurement data before implementing AFDD to the HVAC system in field.

The virtual AFDD testbed was developed under Matlab environment. Data from building simulation models and HVAC systems in existing buildings or lab experiments can be used to test AFDD algorithms through the virtual AFDD testbed. Via the virtual testbed, AFDD algorithms can communicate with building simulation models or existing HVAC systems for collecting data or adjusting system operation modes. Based on reports on fault diagnosis generated by AFDD algorithms, the tested results can be evaluated on the accuracy of diagnosis when tested faults are known. We used fault diagnosis indices including false alarms, missed detection and misdiagnoses for evaluating the AFDD algorithms.

In this study, we demonstrated a case having a Dymola model for a single duct VAV system and AFDD algorithms running on the virtual tested. We have developed two AFDD algorithms for demonstration and testing: a fuzzy logic algorithm and a Naïve Bayesian Classifier algorithm. This study proposed a convenient and inexpensive method to test and evaluate AFDD algorithms on a virtual testbed for validation before deployment in field.

Introduction

In commercial buildings in U.S., HVAC accounts for nearly 40% of the energy in buildings. Faulty operation of HVAC systems and equipment can lead to significant energy wastage, equipment degradation and discomfort. In order to avoid deteriorating consequences of faulty operation of HVAC system, algorithms that detect and diagnoses faults in early stage are of great importance.

Faulty operation exists in most of building HVAC systems. Common faults in HVAC systems can be categorized into mechanical faults and control faults. Mechanical faults refer to the faults associated with mechanical components such as dampers, valves, sensors, and coils; while control faults refer to the inefficient issues associate with control sequences such as oscillation, controlled variables out of boundary, and incorrect/inefficiency control logics.

Automated fault detection and diagnostic (AFDD) algorithms for HVAC systems have been studied for a couple of decades. Glass (Glass, Gruber et al. 1995) developed a qualitative rule-based fault detection model for air-handling units and tested the model to detect faults on a laboratory AHU. House et al. (House, Lee et al. 1999) compared several classification techniques including artificial neural network, nearest neighbor classifier, nearest prototype classifier, a rule-based classifier and a Bayes classifier in detecting and diagnosing faults for a variable-air-volume air-handling unit using HVACSIM+ simulation data, and described the strengths and weakness of each techniques. Peitsman and Soethout (1997) applied auto regressive exogenous (ARX) models for real-time fault detection and diagnosis of an air-handling unit. A system-level ARX model was used to detect faults and component-level ARX models were used to diagnose the problem. Ngo and Dexter (1999) used generic fuzzy reference models incorporating sensor bias for fault diagnosis and showed that the proposed approach can reduce false alarms in FDD. Dexter and Ngo (2001) presented a multi-step approach built upon the previous generic fuzzy model-based approach to significantly reduce processing overhead associated with combining evidence. The multi-step fuzzy model-based FDD has been demonstrated for commissioning an air-handling unit in a commercial office building. Bynum et al.(2012) developed and tested a prototype AFDD tool –Automated Building Commissioning Analysis Tool (ABCAT)– intended to reduce excess energy consumption. ABCAT utilizes a calibrated mathematical model to predict energy consumption for given weather conditions. Masuda and Claridge(2015) proposed a data-driven analysis method to detect abnormal energy data using the recursive least squares (RLS) filter and the cumulative sum (CUSUM) test. Pang et al.(2012) developed a whole building AFDD framework that allows a comparison of building actual performance and expected performance in real time. Wang and Haves (2014) developed and implemented an uncertainty analysis method for model-based fault detection and diagnosis and examining its performance in the diagnosis of common faults for airside economizers. However, few AFDD technologies have been successfully implemented in actual buildings. One of main reasons is that false alarms and missed detection

https://doi.org/10.26868/25222708.2017.658

have been identified as common problems when AFDDs have been applied in non-experimental facilities. Testing on AFDD algorithms are important before deploying them to existing buildings. Conducting experiments on evaluating AFDDs is expensive and often interrupts HVAC system operation.

This study proposed and created a virtual testbed to evaluate the developed automated fault detection and diagnostic (AFDD) with simulation or measurement data before implementing AFDDs to the HVAC system in field. The virtual AFDD testbed on evaluating AFDD algorithms gives opportunities to efficiently test and validate existing AFDD algorithms for HVAC systems. Instead of implementing and testing AFDD algorithms in field, the virtual AFDD testbed connects AFDD algorithms in development with real-time monitoring data or database for faulty operation from experiments or simulation results. If AFDD algorithm testing results are satisified, the virtual AFDD testbed can serve as midware for real-time fault detection and diagnosis in buildings.

Methodology

The schematic diagram of the AFDD testbed is shown in Figure 1. The virtual building testbed include major components such as: HVAC data sources (first-principle based HVAC models with fault simulation, HVAC systems in existing buildings or lab experiments), historical or real-time data from simulation or measurement, AFDD algorithms, and AFDD evaluation.

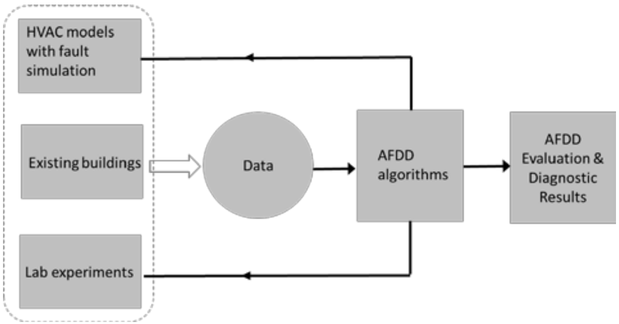

Figure 1: Schematic Diagram of Virtual AFDD Testbed

Data from building simulation models and HVAC systems in existing buildings or lab experiments can be used to test and validate AFDD algorithms through the virtual AFDD testbed. The data can be historical measurement data or real-time simulation/measurement data. For example, experimental testing data from ASHRAE research projects (Norford, Wright et al. 2002; Jin and Li 2012) can be connected to virtual AFDD testbed for validating existing AFDD algorithms of HVAC systems. Software such as sMAP (Dawson-Haggerty, Jiang et al. 2010) and Volttron (Akyol, Haack et al. 2012) provide us the capability of communicating with actuators and sensors in building HVAC systems in real-time via BACnet/Modbus drivers or agents. AFDD algorithms at whole building, air system and AHU subsystem/component levels can be implemented into the virtual AFDD testbed. The virtual AFDD testbed make management decisions to control detection and diagnostic process, start and stop AFDDs at a specific level and receive diagnostics results. Via the virtual testbed, AFDD algorithms can communicate with building simulation models or existing HVAC systems to adjust system operation modes. Based on collected data, AFDD algorithms generate reports on fault diagnosis. Finally, the tested results are evaluated on the accuracy of diagnosis if tested faults are known. We used diagnosis indices including false alarms, missed detection and misdiagnoses for evaluating the AFDD algorithms.

Creating the virtual AFDD testbed

In this study, the virtual AFDD testbed was developed under Matlab environment. We used simulation data from a Modelica model for a single duct VAV system (Wang and Haves 2014). Common faults have been implemented into the Modelica model in air systems, AHUs, and VAV terminal units. The specific faults to be tested include stuck damper, sensor offset, reverse actuator and hysteresis. The simulated data can be used to test and validate two existing AFDD algorithms for VAV systems.

There are different methods of creating this virtual AFDD testbed. Building Controls Virtual Test Bed (BCVTB), built upon Ptolemy II software, is a common method to interface two different software (Wetter 2011). Using functional mock-up interface (FMI) is alternative to create co-simulaiton(Nouidui, Wetter et al. 2013). In addition, Simulink environment in Matlab can generate an S-function from Dymola model. Therefore, the Dymola model can be imported to Simulink as a block. This method needs creating Dymola connectors for each parameters that we want to change its value or monitor it. Besides, syncoronizing Matlab and Dymola to create S-function is limited to specific version of softwares.

We propose a virtual testbed to directly exchange data between Matlab and Dymola. The specific data exchange scheme of the virtual tested for this study is shown in Figure 2.

The Modelica model for the VAV system runs in time sequence. Each run of the Modelica model simulate the VAV system for a full day. Simulated data from the Modelica model were exchanged with the AFDD algorithms on a daily basis for fault detection and diagnosis. At the end of each run, simulation results for key parameters from Dymola were obtained by the two Dymola functions for Matlab: “dymload” and “dymget”. Then these parameters will be fed to the two AFDD algorithms. Both AFDD algorithms look for signatures or innovations to identify faulty operation or normal operation of the system or components based on the features of performance.

For the preparation of next run, “script.mos” will be created to setup system operation modes and fault operations for the Modelica model via scripting commands. “dsfinal.txt” contains final states from previous run and will be passed for initialization of next run of Modelica model.

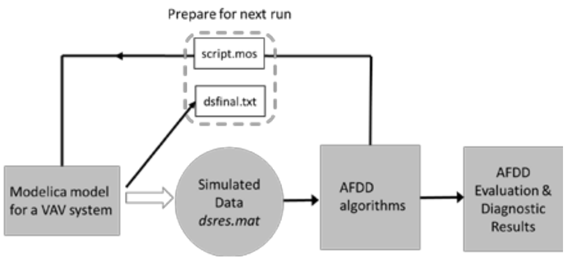

Figure 2: Data exchange scheme for virtual AFDD testbed between Modelica models and AFDD

The two sets of existing AFDD algorithms are 1) a fuzzy logic algorithm and 2) a Naïve Bayesian algorithm. A fuzzy logic algorithm employs a set of expert-based rules with fuzzy inferencing to perform fault diagnosis for each component or subsystem. Fuzzy inferencing system used membership functions for both inputs and outputs. The membership functions maps numerical values of key features linguistic values. The degree of fulfillment (DOF) for the set of expert rules for diagnosing the presence of a particular fault is determined using fuzzy inferencing. Naïve Bayesian algorithm is a type of supervised learning algorithms based on Baye's theorem. It assumes that every pair of features are independent.

Both sets of AFDD algorithms employ first principle-based models to predict key performance identifier (e.g. outdoor air fraction for a mixing box) for individual components of VAV systems and then apply specific diagnosis methods (fuzzy logic or Naïve Bayesian) to diagnose faulty or normal operation based on the patterns or feature of key performance identifiers. Both algorithms were developed in Matlab and based on data of faulty operation summarized from simulation on common faults in VAV systems (Wang and Haves 2014).

VAV system model

In this research a single duct VAV system composed of an air-side economizer, heating coil, cooling coil, terminal unit and a supply fan has been used as HVAC system (Figure 3). System model has been developed in Dymola environment taking advantage of Modelica building library (Wetter et al. 2014).

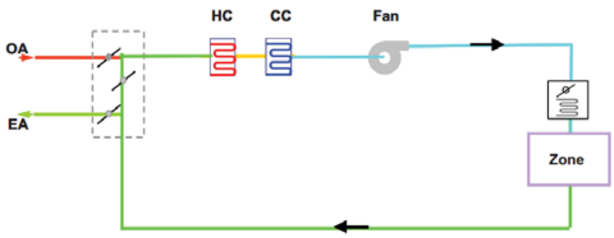

Figure 3: Single duct VAV system (Wang and Haves 2014)

Air-side economizer is composed of three air dampers. Damper characteristics is defined as an exponential function of damper opening angle.

$$K_d(y) = e^{(a+b(1-y))} \qquad y_l < y < y_u \qquad (1)$$

Where $K_d(y)$ is damper characteristic, y is damper position, y_l is lower position for damper curve, y_u is upper position for damper curve and a, b are coefficients for damper characteristics. Damper flow coefficient can be computed as function of damper characteristics.

$$K(y) = A\sqrt{\frac{2\rho}{K_d(y)}} \qquad (2)$$

Where ρ is air density and A is face area. Air mass flow rate in damper is a function of damper characteristics and pressure drop.

$$\dot{m} = K(y)\sqrt{\Delta p} \qquad (3)$$

Fan temperature rise can be computed as pressure rise across the fan (Haves et al. 2005).

$$\Delta T_{fan} = \frac{\Delta P_{fan}}{\eta \rho c_p} \qquad (4)$$

$$\Delta P_{fan} = P_{set}\left(1 - \frac{V^2}{V_D^2}\right) + \Delta P_D\left(\frac{V^2}{V_D^2}\right) \qquad (5)$$

P_{set} is static pressure in supply duct, V is flow rate, V_D is design flow rate, ΔP_D is design pressure rise, η is supply fan efficiency and c_p is Specific heat capacity of air at constant pressure.

Outside air fraction can be calculated as a function return air temperature, outdoor air temperature and mixed air temperature. Outside air fraction will be used as main feature in fault detection and diagnosis algorithm.

$$OAF = \frac{T_{ma} - T_{ra}}{T_{oa} - T_{ra}} \qquad (6)$$

Where T_{ra} is return air temperature, T_{oa} is outdoor air temperature and T_{ma} is mixed air temperature.

$$T_{ma} = T_{sa} - \Delta T_{fan} \qquad (7)$$

Fuzzy inferencing

The first set of AFDD algorithm we discussed in the paper is based on a fuzzy inferencing system for common faults in air-handling units. Table 1 summarized rules for detecting and diagnosing common faults in air-side economizer (Wang and Haves 2014). Six different states of operation, based on outdoor air damper position, have been considered for air-side economizer.

These fault detection and diagnosis rules were transformed to a fuzzy inferencing system by creating membership functions in presence of different faults. The fuzzy inferencing system can provide the most probable fault and associated confidence level for any identified faults or normal operation. Figure 4 shows fault detection and diagnosis scheme based on the AFDD algorithm based on the fuzzy inferencing system .

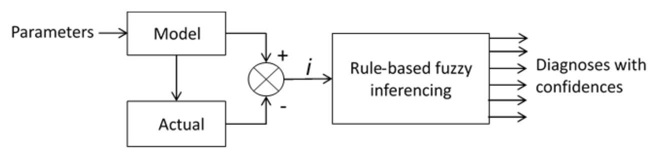

Figure 4: Fault detection and diagnosis framework with fuzzy inferencing(Wang and Haves 2014)

Table 1: Fault detection and diagnosis rules (Wang and Haves 2014)

	Operating points					
	1	2	3	4	5	6
u (OA damper position)	0	10%	50%	90%	100%	50%
Normal	0	0	0	0	0	0
Stuck OA damper(fully closed position)	0	+	+	+	+	+
Stuck OA damper (u<50%)	-	-/0		+	0	
Stuck OA damper (u>50%)	-	-		+/0	0	
Stuck RA damper(fully closed position)	-	-	-	-	0	-
Stuck RA damper (u<50%)	0	-		+/0	+	
Stuck RA damper (u>50%)	0	-/0		+	+	
OA damper leakage	-	0	0	0	0	0
RA damper leakage	0	0	0	0	+	0
Hysteresis	0	0	+	0	0	-
Nonlinearity	0	+/0(-/0)	+(-)	+/0(-/0)	0	+(-)
Actuator reversing acting	-	-	0	+	+	0
SAT sensor offset	+(-)	+(-)	+(-)	+(-)	+(-)	+(-)
OAT sensor offset	0	0		+(-)	+(-)	
RAT sensor offset	+(-)	+(-)		0	0	

+ (positive innovation) , - (negative innovation), +(-) (each positive or negative),
0 (negligibly small innovation)

Naïve Bayesian

Naïve Bayesian is a learning based algorithm which can be used as classifier in fault detection and diagnosis framework. Naïve Bayesian falls into supervised classification methods, which is constructed based on training data. Training data contains a set of features value and associated labelled classes (Manning & Raghavan 2008). Features are outdoor air fraction innovations and outdoor air damper positions. Naïve Bayesian classification obeys Bayes theorem adding the assumption that features presumed to be independent. Figure 5 shows graphical representation of Naïve Bayesian classifier. Given the new set of data for features, Naïve Bayesian classifier determines the probability of dependency of data to each class. Classification ends up with the class adopting the maximum probability. In this paper, we used the Matlab statistic and machine learning toolbox to develop the Naïve Bayesian classifier.

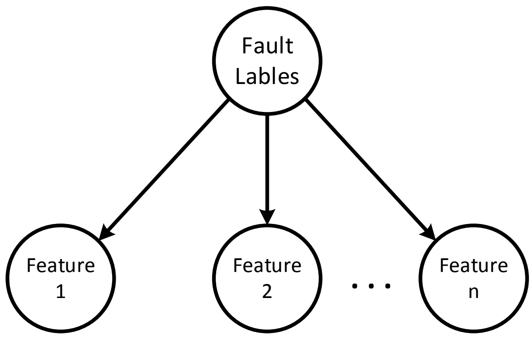

Figure 5: Naïve Bayesian graphical model

Results

In this section, we demonstrated the testing procedure and results on the two AFDD algorithms using the developed virtual tested. We conducted testing on the virtual AFDD testbed for a period of sixty days in total with Dymola simulation. At the end of each day, the two AFDD algorithms received the data from virtual tested to detect and diagnose faults.

In total, we tested nine different faults and normal operation of VAV systems. The nine faults are stuck outdoor air damper, outdoor air damper leakage, return air damper leakage, reverse acting actuator, actuator mismatch, hysteresis, and sensor offsets for supply air, return air and outdoor air. Every day, one scenario, either normal operation or faulty operation, is given by the virtual testbed to be simulated in Dymola. With the sixty-day simulation period, each faulty or normal operation scenario was tested for six different days.

In this demonstration, we use the mixed boxes as an example for fault detection and diagnosis. The key performance identifier for a mixing box is outdoor air fraction. In order to diagnose the root causes of each individual fault, the AFDD algorithms need to recognize patterns or features of the key performance identifier–outdoor air fraction. We used the measured outdoor fractions when outdoor air damper was commanded to operate at the six different positions as the features for diagnosing common faults in the mixed box. The six different positions are 0%, 10%, 50% (control signal increasing), 90% and 100% and 50% (control signal decreasing).

If there are duplicated control positions within the simulation results for the day, the last performance at this particular positon was taken for fault detection and diagnosis. If there are missing key control positions, the testbed can send commands to control the simulation to exercise the actuator of the mixing box and obtain the performance of the key positions for AFDD testing.

Once the performance of the six key control positions was ready, both AFDD algorithms conduct fault detection and fault diagnosis.

Table 2 listed testing results from both algorithms. There are sixty testing cases in total. Neither of the two AFDD algorithms correctly detect and diagnose the entire testing cases. The AFDD algorithm with fuzzy logic is capable of detecting and diagnosing most of the faulty operations and normal operation. However, half of the stuck damper cases were misdiagnosed as sensor offset faults and the cases for mismatch cannot be detected. The AFDD algorithm with Naïve Bayesian classifier only correctly detected faulty operations for stuck damper and sensor offset and failed in other cases.

Table 2: Comparison on percentage of correct detection and diagnosis for each fault from two AFDD algorithms

	Fuzzy logic	*Naïve Bayesian*
Normal Operation	100%	0%
Reverse Actuator	100%	0%
OAD_Leak	100%	0%
RAD_Leak	100%	0%
Sensor_offset	100%	100%
Stuck damper	50%	100%
Mismatch	0%	0%
Hysteresis	100%	0%

Discussion

Based on the results as shown in Table 2, the AFDD algorithm with a fuzzy inferencing system has better detection and diagnostic capability than the algorithm with Naïve Bayesian classifier. However, the accuracy of fuzzy logic algorithms depends a lot on experiences to set up rules and threshold values. The Naïve Bayesian classifier in this case study has limited training data from simulation results on faulty operation.

The assumption in Naïve Bayesian that each pair of features are independent cannot be met because the six measured outdoor air fractions at the six key positions are correlated. House, Lee et al. (1999) suggested Bayesian classifier is a better choice for fault detection and diagnostics when comparing with other AFDD algorithms. We should conduct further development and testing in order to thoroughly compare the capability of fuzzy logic algorithm and Bayesian classifiers for AFDD. In this study, these two AFDD algorithms were developed for demonstrating the concept of the virtual testbed on AFDD algorithms.

Both algorithms should be further developed and tested with simulation and measurement data. There are a few methods to improve the AFDD algorithms: 1) implement uncertainty analysis on sensors and input variables into AFDD algorithms to reduce the false alarms and misdiagnoses; 2) increase the dataset for training and validation of AFDD algorithms; 3) AFDD algorithms may need to be adjusted before being used for diagnosis of another system.

We also developed an evaluation system for AFDD results. Given true operation scenario of the system, the AFDD algorithms can be evaluated based on the comparison between diagnose results and true operation scenario. In the virtual testbed, the evaluation was based on three diagnosis indices: false alarms, missed detection and misdiagnoses. The evaluation results on both AFDD algorithms are summarized in Table 3. The numbers in Table 3 indicate the total number of cases for each defined category.

There are sixty cases in total. AFDD with fuzzy inferencing can correctly detect and diagnose 85% of the entire cases, while Naïve Bayesian is only able to detect and diagnose 40% of the entire cases.

False alarms in AFDD indicate that the AFDD algorithm found a false faulty operation while system/component was actually in normal operation. False alarms occurred six times within entire testing cases from Naïve Bayesian classifier. Misdiagnosis in AFDD refers to the cases that AFDD detected and diagnosed a specific fault in a system or component while another fault exists in the operation. The AFDD algorithm with fuzzy logic has three misdiagnosed cases and the AFDD with Naïve Bayesian has thirty misdiagnosed cases. Missed detection referred to the cases that AFDD algorithms cannot detect a particular fault(s) while this fault(s) actually exists in the operation. The AFDD algorithm with Naïve Bayesian did not have missed detection. However, fuzzy logic has six undetected faults for mismatch cases.

Table 3: Evaluation results on two AFDD algorithms

	Fuzzy logic	*Naïve Bayesian*
Correct detection and diagnosis	51	24
False alarms	0	6
Misdiagnosis	3	30
Missed detection	6	0

Conclusion

In this study, we presented a virtual AFDD testbed for building HVAC systems. Through two AFDD algorithms, we demonstrated the process of using this virtual testbed for testing and evaluating AFDD algorithms. We summarized the evaluation results on the two AFDD algorithms and discussed opportunities to further improve the robustness of AFDD algorithms based on our virtual testing on AFDD algorithms.

Before implementing any AFDD algorithms into physical systems in field, virtual AFDD testbed can be used to test and validating the algorithms. The virtual AFDD testbed can be connected to building simulation models, to real-time or historical data collected from physical building systems. In future study, we will setup connection between the AFDD virtual testbed and physical HVAC systems for real-time data collection, and fault diagnosis. Different sets of AFDD algorithms will be further developed and tested for HVAC systems.

Acknowledgement

This work was supported by School of Energy Resource at the University of Wyoming.

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