Design of Fault Detection and Diagnostics Lab for HVAC System

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ABSTRACT

Fault detection and diagnostics (FDD) is a method to monitor a system, identify when a fault has occurred, and point out the type of fault and its location. This method improves comfort, and reduces the operation, maintenance, and utility costs, thus reducing the environmental impact.

In this paper, the design of FDD lab is presented where a user can create different types of faults in Heating, Ventilation and Air-conditioning (HVAC) systems, and develop and test algorithms for the detection and diagnostics of faults. This facility will help identify and analyse the faults pertaining to HVAC systems that are prevalent in India nowadays.

KEYWORDS

Fault detection and diagnostics, HVAC, EnergyPlus, and Machine Learning

INTRODUCTION

Building Heating Ventilation and Air-conditioning (HVAC) systems faults, including design problems, equipment and control system malfunction, result in energy wastage and occupant discomfort. Fault detection and diagnostics (FDD) is a method to automate the processes of detecting faults with physical systems and diagnosing their causes. This method improves comfort, and reduces the operation, maintenance and utility costs, thus reducing the environmental impact.

The objective of this research is to identify and analyse faults related to HVAC systems and develop effective FDD techniques for the common faults that are prevalent in India.

The basic building blocks of FDD systems are "the methods" for detecting faults and subsequently diagnosing their causes. Several different methods are used to detect and diagnose faults (Katipamula et al., 2005). The major difference in method approaches is the knowledge used for formulating the diagnostics.

Diagnostics can be based on two approaches first is based on priori knowledge (models based entirely on first principles) and other is driven completely empirically (black-box models). Both approaches use models and data, but the approach of

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formulating the diagnostics differs fundamentally. First-principle model-based approach use a priori knowledge to specify a model that serves as the basis for identifying and evaluating differences (residuals) between the actual operating states determined from measurements and the expected operating state and values of characteristics obtained from the model. Purely process data-driven approach (methods based on black-box models) use no priori knowledge of the process but instead derive behavioral models only from measurement data from the process itself.

A model-based system-level FDD method was proposed by Zhou et al. (2009). It was enhanced by considering sensor FDD (Wang et al. 2010). In this method, multiple linear regression (MLR) was used to develop reference performance index (PI) models to generate benchmarks. PIs can be direct measurements, such as power and temperature, or the direct products of measurements. They usually have physical meanings. A typical example of a PI for chiller is the coefficient of performance (COP). An online adaptive scheme was developed to estimate and update the thresholds for detecting abnormal PIs. The uncertainties coming from both model-fitting errors and measurement errors were analysed.

West S. R. et al. (2011) used statistical machine learning for automated fault detection and diagnostics for HVAC subsystems. They employed Hidden Markov Models to learn probabilistic relationships between groups of points during both normal and faulty operations. This can passively infer the likelihood of similar patterns in the data during future operation with a high degree of accuracy. Multiple parallel models and clustering were used to overcome issues with training state being stuck in local optima, and Data Fusion was employed to resolve conflicting diagnoses from multiple related models.

Zhengwei L. et al. (2012) has combined Cumulative Sum (CUSUM) chart method with a fault counter approach, which extends the functionality of CUSUM method from fault detection to fault diagnostics. To use this method, user needs to specify a causal relationship between all the control variables and their controlling components. Based on the real time monitored data, a CUSUM score is calculated for each control variable and a fault counter is then updated based on an automatic count mechanism.

Srivastav A. et al. (2013) has presented a novel approach based on Gaussian Mixture Regression (GMR) for modeling building energy use with parameterized and locally adaptive uncertainty quantification.

Magoulès F. et al. (2013) has proposed architecture for FDD using recursive deterministic perceptron (RDP) neural network. Four equipments under normal and abnormal conditions were simulated to evaluate the model. They experimentally demonstrated that the model is highly accurate in detecting all possible faults. On training set, accuracy remains 100% and on testing set it was achieved higher than 97%.

Bruton K. et al. (2014) has developed and tested a cloud based automated fault detection and diagnosis (AFDD) tool for air handling units using expert rules. A generic data extraction process is incorporated within the AFDD tool to facilitate the transmission of BMS data from the client's server to a cloud-based web server, irrespective of the type of data collection, storage and archiving methods employed by the BMS software on each site. The data extraction component of the AFDD tool addresses these constraints by employing software design patterns and object oriented principles, which provide a robust platform for developing extensible software components.

Du Z. et al. (2014) have developed FDD method for buildings and HVAC systems using combined neural networks and subtractive clustering analysis. They used a data mining technology and clustering analysis to classify the various faulty conditions adaptively in the buildings. By use of subtractive clustering analysis, the different faults are separated into different space zones in the data space. Du Z. et al. (2014) also published use of the combined neural networks for sensor fault detection in air handling units.

Zaho X. et al. (2014) have demonstrated that the decoupling-based FDD method has potential to be incorporated within commercial FDD products or embedded into the control system onboard the chiller to monitor the health of the chiller’s operation.

Li Shun. and Wen J. (2014) have developed a model based fault detection and diagnostic methodology based on Principle Component Analysis (PCA) method and wavelet transform for fault detection in air handling units. The wavelet is used as data pre-treatment to help PCA method improve its accuracy with detecting faults. In comparison to conventional PCA method, the Wavelet-PCA method is more robust to the internal load change and weather impact and generates no false alarms.

RESEARCH METHODS

For the FDD study, we have proposed an experimental set up and presented a basic schema where different faults can be studied and detection methods developed. The developed FDD techniques can then be applied to various HVAC systems.

Figure 1 shows the current plan of the Building Science Lab for the FDD study. The space to be used for the FDD experiment has been highlighted in the redirect angle. This space will be separated by partitions to create two identical rooms. Though the available room is small in size, we have planned to increase the internal loads of the room to replicate a small office space.

All sides of the test chamber, except for the south-east windows and walls will be insulated with 100 mm glass wool having thermal conductivity value of 0.041 W/m-K, which can restrict maximum heat gain to 2.5 W/m^2. The internal loads will be emulated using a resistance heater.

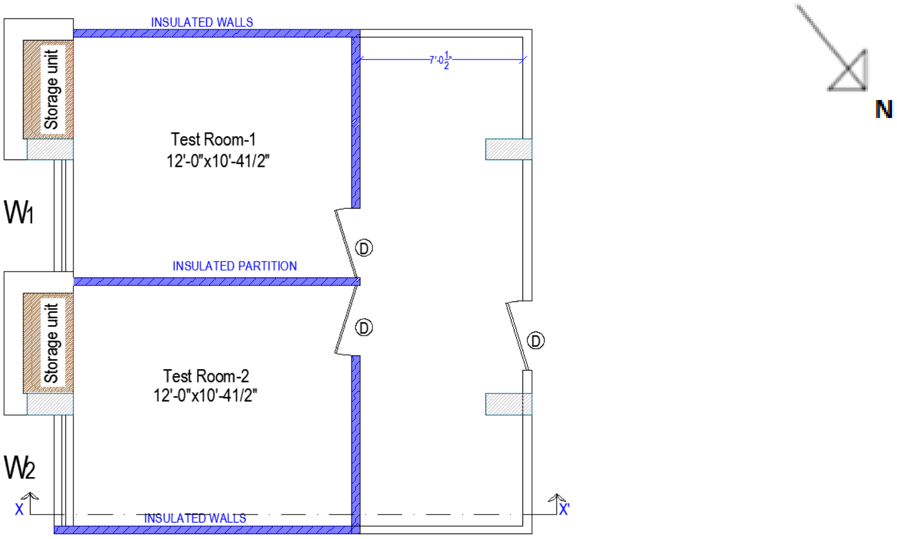

Figure 1. *Test rooms for FDD Setup (Plan)*

Table 1 provides the calculation done for the internal loads that would be in the 92.9 Square meter (1000 square feet) space.

Table 1. *Emulated load required for the setup*

Load component	**Considered value**	**Load**
Lighting	10.76 W/m^2	1 kW
Equipment	16.14 W/m^2	1.5 kW
Occupancy	60 Sqft/person	17 people
Occupancy load	100 W/person	1.7 kW
Fresh air	15 CFM/person	255 CFM

The indoor and outdoor design conditions for load calculation are shown in Table 2.

Table 2. *Indoor and outdoor design condition*

	Summer	**Monsoon**	**Winter**
Indoor condition	DB : 24˚C (75.2 ˚F) 40%<RH<60%	DB : 24 ˚C (75.2 ˚F) 40%<RH<60%	DB : 22 ˚C (71.6 ˚F) 40%<RH<60%
Outdoor condition	DB : 42 ˚C WB : 27.8 ˚C RH : 33.5%	DB : 30 ˚C WB : 27 ˚C RH : 79.1%	DB : 15.3 ˚C WB : 09 ˚C RH : 41.5

Cooling and Heating load calculation has been done using EnergyPlus simulation for all three outdoor conditions: summer, monsoon, and winter. For peak summer, air conditioning requirement for each test chamber is 3.5 TR and air supply flow required is 1145 CFM.

To study different faults in HVAC systems, we propose to incorporate ducted

Variable Air Volume (VAV) system and air-cooled chiller to supply chilled water to Air Handling Units (AHU). We also propose to have airside economiser and heat recovery wheel to study faults related to these systems.

We are proposing identical air side HVAC systems and pumps for the two identical rooms selected. The user can study the signatures of faults and train algorithm for efficient detection of faults. Figure 2 and 3 shows the schematics of the air side (low side) and water side (high side) systems. As the required tonnage is quite small, we are planning to use only one common air cooled chiller for both the experimental setups.

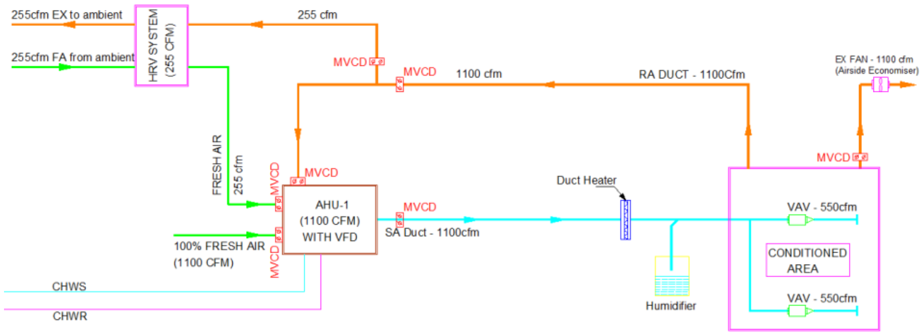

Figure 2 *Schematic of air side system*

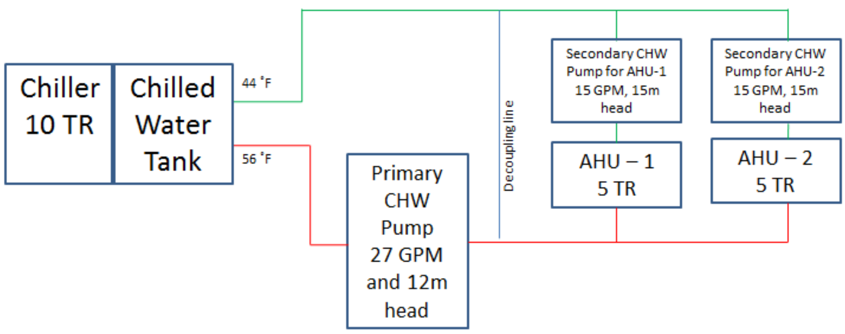

Figure 3 *Schematic of water side system*

The implementation methodology of the faults identified is provided in Table 3. Faults related to Chiller is not considered for the analysis as sizing of the chiller is quite small and FDD techniques for the chiller are already well established.

Table 3 *Faults, type and proposed implementation method*

Fault	**Type**	**Proposed implementation**
VAV Faults		
VAV damper stuck	Abrupt	Physical intervention: disconnect actuator input, position manually
VAV actuator fail	Abrupt	Physical intervention.
VAV leakage	Installation	Physical intervention: remove

		damper-blade seals
Controller hardware failure	Degradation	Install faulty controller
Air Handling Unit		
Fan Faults		
Unstable supply fan controller	Abrupt	Software override: change controller gain until oscillation observed at low airflow rate
Slipping supply-fan belt	Degradation	Physical intervention: move fan motor to reduce tension in fan belt
Fan belts too tight	Degradation	Physical intervention: move fan motor to increase tension in fan belt
Dry bearings	Degradation	Physical intervention: Removal of lubrication
Case Faults		
Improper AHU Drain connections	Installation	Physical intervention
Improper installation of fan motor	Installation	Physical intervention
Cooling Coil Faults		
Leaking cooling coil valve	Degradation	Physical intervention: connect by-pass around control value
Reduced cooling-coil capacity (water side flow restriction)	Degradation	Physical intervention: restrict water flow to coil
Filter Faults		
Blocked filter	Degradation	Physical intervention: Use of blocked filter
Pump Faults		
Foreign material deposits	Degradation	Physical intervention: Use of old pumps
Corrosion	Degradation	Physical intervention: Use of old pumps
Oscillations	Abrupt	Physical intervention: Provide unstable foundation
Leakage	Abrupt	Physical intervention: Use of old pumps
Sensor Faults		
Sensor offsets	Degradation	Use of faulty sensor
Positioning of Thermostats	Installation	By changing position of sensor
Duct Faults		

Rusting in Duct	Degradation	Use of ducts with rust
Poor sensor placement in ducts	Installation	By altering position of sensor
Pipe Faults		
Cleaning of chilled water strainers	Degradation	By installing used and un-cleaned strainer
Poor pipe insulation/ Condensation on pipe	Installation	By removing insulation
Air Side Economiser		
Economiser Damper Failure	Abrupt	Physical intervention
Non-optimal economiser set-point	Degradation	By change of set point
Air temperature sensor failure	Abrupt	Use of faulty sensor

CONCLUSION

This paper presents the design of the fault detection and diagnostic experimental set up at an educational institute. With the help of an EnergyPlus model, the heat load calculation is done and supply air from AHU has been identified. The proposed faults and implementation method have been have been discussed in this paper.

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