ADAPTABLE, SCALABLE, PROBABILISTIC FAULT DETECTION AND DIAGNOSTIC METHODS FOR THE HVAC SECONDARY SYSTEM

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ADAPTABLE, SCALABLE, PROBABILISTIC FAULT DETECTION AND DIAGNOSTIC METHODS FOR THE HVAC SECONDARY SYSTEM

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

1.1 Introduction

Because of global warming and depletion of resources, controlling the domestic energy demand has been made one of the primary policy targets by many countries. One of the most famous efforts undertaken so far is the Kyoto Protocol [69]. As of September 2011, 191 countries have signed and ratified the protocol. Although the United States has not signed the Kyoto protocol, it has recognized the importance of reducing green house gases, and taken measures to reduce them. On January 2010, President Obama announced the target to reduce greenhouse gas emissions from federal government buildings by 28 percent by 2020 [68].

Buildings consume a large portion of energy in many countries. In the United States, the building sector consumes 40.4% of the total primary energy, and this number is estimated to grow to 45% by 2030 [1]. In the European Union, the building sector alone occupies 40% of the total energy [3]. In China, buildings account for 28% of total energy consumption, and this share is likely to grow because of the current urbanization process [20].

Among all the contributors, system faults have been found to be one of the significant causes of energy waste. According to [62], "the faults studied increase commercial building primary energy consumption by approximately one quad, or about 11% of the energy consumed by HVAC, lighting, and larger refrigeration systems in commercial buildings". The rank of the faults based on their impacts is the following (from highest to lowest impact): duct leakage, HVAC left on when space unoccupied, lights left on when space unoccupied, air flow not balanced, improper refrigerant charge, etc.

Although Fault Detection and Diagnostics (FDD) in general has existed for more than thirty years, HVAC and other building systems were not part of the field until the late 1980s and early 1990s. Areas such as nuclear, aerospace, process control, and national defense were more important to the pioneer researchers [32].

The earliest effort in building system fault detection and diagnostics started at Purdue university, with the target on household refrigerators [43, 60]. In 1991, the International Energy Agency (IEA) formed Annex 25 (Real Time HVAC Simulation) to study the simulation of HVAC systems, with the purpose of building optimization, fault detection and diagnostics. Researchers from Canada, Germany, Finland, France, Japan, Netherlands, Switzerland, UK and USA participated in this effort [28]. Following Annex 25, IEA formed another Annex - Annex 34 (Computer-Aided Evaluation of HVAC System Performance) in 1997 to "assess the cost effectiveness and applicability of FDD methods, identifying potential constraints" [29].

In the United States, FDD research began in the mid 1990s, when the Department of Energy funded a research group including researchers from PNNL, Honeywell, and the University of Colorado to develop a whole-building diagnostic tool [31]. At almost the same period, DOE also funded a research group in LBNL to develop model based FDD methods [53, 59]. At this time, ASHRAE formed a technical committee TC 4.11 (Smart Building Systems, which has been merged with TC 7.4 and now renamed TC 7.5 on 2008), in which fault detection and diagnostics is one of the four subcommittees. TC 7.5 has funded a number of FDD research projects in chillers (RP1275 [51], RP1486 [39]), AHUs(RP1312 [40]), whole buildings(RP1020 [47]) and a general literature review(RP1043 [15]). The California Energy Commission (CEC), through its public interest energy research (PIER) program, has also funded a number of research projects, for example, development of APAR (rule based methods) for AHUs ([55]), and the development of FDD methods for fans ([66]). Recently, the Department of Defense(DOD) has formed an environmental research program - ESTCP, which funded a number of FDD research projects ([19]).

In sum, through twenty years of development, a set of FDD methods for major building systems have been developed, as listed in Table 1.

Table 1: FDD Method and Tool Overview

Target	Method	Tool	Reference
Whole Building	NILM	/	[47]
Whole Building	Rule based	ENFORMA	[31]
Whole Building	/	EEMSuite	[2]
Whole Building	Model Based	IMDS	[49]
Whole Building	/	Infometrics	[13]
Whole Building	/	F.P.I.	[34]
Whole Building	/	E. W.	[5]
Fan	Model based	AHU Toolkit	[66]
RAC	Model based, classifier	/	[11]
AHU	Model based	SAFTT	[73]
AHU	APAR, VPACC	/	[55]
Economizer	/	UT	[33]
HVAC	/	PACRAT	[6]

In 2007, the New Building Institute and the Western Cooling Efficiency Center organized a FDD round table, to discuss the challenges and problems this field is facing, and actions that could be taken to promote the use of FDD [50]. One of the key challenges found is the difficulty to deploy a FDD tool appropriately at the whole building, system/subsystem, and device level. A technical vision set by the experts is to integrate FDD function within control systems in the future.

Due to the inherent complexity and diversity of HVAC systems, this thesis focuses on FDD for Air Handling Units (AHU), because it is the most commonly used system in the United States, it is a relatively complex system, and it has many variants.

CHAPTER II

RELATED WORK, TARGET AND APPROACH

In this chapter, related work is introduced which is divided into three sections: (1) FDD for sensors in general (2) FDD methods for HVAC system (3) field testing. After introducing related work, the current problems and challenges are listed, which are followed by the targets of this thesis and the approach to achieve the targets.

2.1 Related Work

2.1.1 FDD Methods for Sensors

Correctly working sensors are the key in successfully detecting faults in HVAC systems. Jagpal [29] divided sensor faults into three categories: location faults (wrongly placed), electrical installation faults (bad joints, incorrect power supply, etc.), and sensor related faults (drift, no signal, etc.). Some of the faults (e.g., electrical installation fault) are easy to detect, while the others are more difficult to detect and can have adverse impact on system operational efficiency (e.g., location faults).

A literature review suggests that the work in this area can be categorized based on if the sensor faults are detected separately from component faults [74, 75, 18, 26, 64, 65] or together with component faults [55, 36]. These work can also be categorized based on the detailed FDD methods deployed, including model based method, rule based method, machine learning method and statistical analysis method.

The model based method is used by relatively few to detect sensor faults, and was only found in one of the early publications [64], partially attributed to the uncertainty in model prediction.

The rule based method is studied by more researchers due to its simplicity. Various rules have been developed in the past decades. Yang [74] used the physical constraints between neighboring sensors to determine the possibly faulty sensors. However, this method is not practical because it requires many more sensors than are existing in the current system. Schein [55] developed a rule based method (APAR) to detect common faults in air handling units, sensor faults included. These rules have a reasonable requirement on available sensor information, and have been tested in the field. Similar to the APAR rules, Yang [75] has also developed a set of rules to detect faults for only temperature sensors in air handling units.

The machine learning method is relatively new. The use of it in sensor FDD has just happened in the last ten years. A few examples are listed below. Lee [36] used Artificial Neural Network (ANN) to detect sensor faults in AHUs, Zhou [26] combined Rough Set (RN) with ANN to detect sensor faults. This method requires little domain knowledge about the system, but requires a long training and configuration period, furthermore, the performance is unpredictable in many cases.

Principal Component Analysis (PCA) as a statistical analysis method has existed for many years, but the use of it in HVAC system FDD started in 2004 [65], and since then developed by [63], [71], [18] and [17]. The PCA method has been suggested as a quick and effective method in detecting sensors in air handling units[65]. Similar to machine learning method, it also requires little domain knowledge about the system, but it is less computationally intensive. The use of this method is as simple as rule based method, but it is more sensitive than rule based method. However, the fault diagnostic capability is poor. For that purpose, an expert knowledge base has to be combined with it [65].

2.1.2 FDD methods For HVAC System

Various FDD methods have been developed for HVAC systems. In the final report of Annex 25 - 'Building optimization and fault diagnosis source book', FDD methods were categorized as: innovation based approach, parameter estimation based

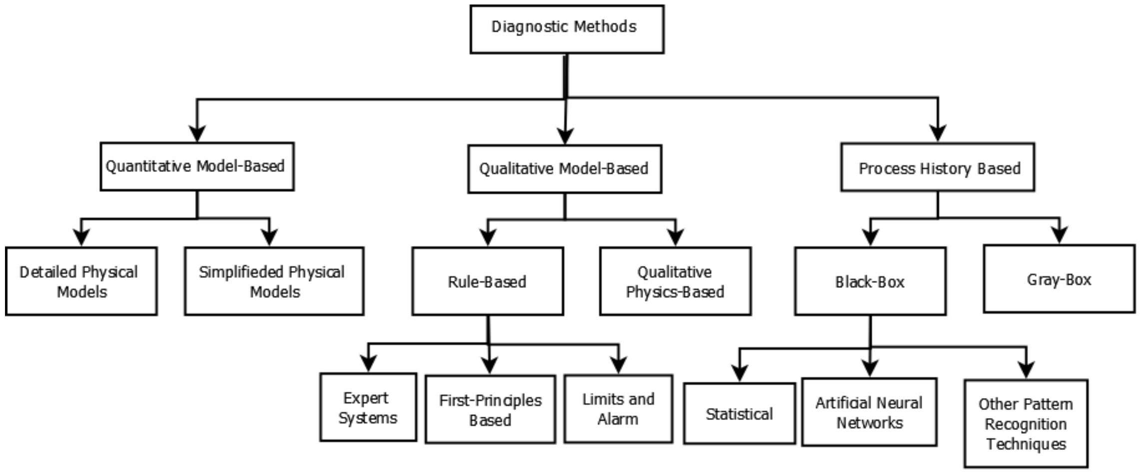

Figure 1: FDD methods overview by Katipamula[32]

approach, classification based approach and expert system approach, etc.[28].

Another way to categorize FDD methods is found in [32], in which FDD methods were classified into three categories: quantitative model-based, qualitative model-based and process history based, each of which was classified further into a set of subcategories. Figure 1 illustrates the classification scheme of FDD methods. The literature review here follows this structure.

2.1.2.1 Process History Based Methods

Two reasons contribute to the rise of process history based methods: lack of knowledge about the system and uncertainty associated with model based modeling. Take a mixing air box as an example. First there is leakage in both outside air and return air dampers, second, the authority of the outdoor/return air damper is difficult to estimate, third, as outside wind changes, the pressure boundary condition always changes, and thus the fan operating point changes accordingly [72]. On the other hand, process history based methods require little knowledge about the detailed component, and typically are more flexible in dealing with uncertainties.

Popular methods in this category include autoregressive moving average with exogenous input (ARMAX), autoregressive with exogenous input (ARX), artificial neural network (ANN), principal component analysis (PCA), support vector machine (SVM), etc.

Lee, House, et al. [37] used both the residual method (output innovation) and the parameter identification method to detect faults in air handling units. The models employed are ARMAX and ARX, with MISO and SISO structures. It is concluded by the authors that both models can be used to detect the presence of faults in air handling units. A similar approach is used in [77] to detect common faults in air-conditioning systems.

Lee, House, et al. [35] have also applied artificial neural network (ANN) to diagnose eight severe faults in air handling units, in the following procedure: (1)select system variables that could be used to quantify the dominant symptoms of faulty operation mode (2) train an ANN to learn the steady state relationship between dominant symptoms and variables selected above under normal operation condition, then (3) use the trained ANN to diagnose possible faults in real system. The procedure was used again in [36], which also considered the problem of sensor failure. In [36], a regression model based sensor correction technique is proposed, which extends one step beyond fault diagnostics.

Support vector machine (SVM), a method arising from statistics, quickly became popular in artificial intelligence because of its efficiency and performance. Its potential to be used in HVAC FDD was shown in [42], in which the author used the residual of four state variables (supply air temperature, mixing air temperature, outlet water temperature, and valve control signal) as inputs, designed two SVM classifiers, one for fault detection purpose and the other for fault diagnosis. It was concluded that four layer SVM classifier can recognize faults quickly and accurately with small amount of training samples.

Schein and House[56] developed a statistical analysis based tool - VPACC (VAV Box Performance Assessment Control Charts) to detect faults in VAV boxes. This tool compares a measured quantity with upper and lower limits that define fault free operation. If the measured quantity falls outside these limits, the exceeded amount is then cumulated and compared with a pre-determined threshold. An alarm is then issued if the cumulative sum (CUSUM) exceeds the threshold. Lab tests show that this method can successfully detect the faults being tested.

2.1.2.2 Qualitative Model Based Methods

Qualitative model based methods typically are based on expert domain knowledge about the system, which specifies the characteristics of the system in normal operation from several selected variables. This method can be used for fault diagnostics if the characteristics of the system behavior under specific faults are specified as well.

Dexter [16] developed a fuzzy model based method, comparing the output of fuzzy reference models with system operational data to detect and diagnose the faults. With this method, fuzzy models for fault-free and many kinds of faulty plant operations were generated from simulations. Then a fuzzy partial model reflecting the real system is identified based on online operation data, and compared with each model identified in the previous step. A range of 'degree of belief' for each comparison is then calculated, based on which fault detection and diagnosis task is performed.

Glass, Gruber, Roos, et al. [22] suggested a qualitative model that correlates control variables (heating coil valve, cooling coil valve and bypass damper) with system steady-state status (outdoor temperature, discharge air temperature, return air temperature and discharge air temperature set point), to detect and diagnose faults in air handling units. A rule table is then generated from simulations to correlate status variables to control variables qualitatively in fault free and various faulty conditions.

House, Nejad and Whitcomb [27] suggested a rule set drawn from expert knowledge about air-handling units, called Air-handling unit Performance Assessment Rules (APAR). In this rule set, operational modes of air-handling units are divided into five categories: heating, cooling with outdoor air, mechanical cooling with 100% outdoor air, mechanical cooling with minimum outdoor air, unknown occupied modes. For each mode, there are a number of rules, violations of which are indicators of certain faults. In total there are twenty four rules in the rule set. The function of APAR rules is limited at fault detection, since no fault diagnostic rule is provided. Another challenge in applying this method is the need to tune the error parameter to balance the sensitivity and false alarm rate.

Kaldorf and Gruber [30] described a rule based expert system, called Performance Audit Tool (PAT), which could detect and diagnose faults for HVAC component, controller, sensors, etc. This system is a strengthened version of a simple rule based system, with stronger data handling capability, stronger error handling capability and more friendly user interface. But this system is supposed to work off-line and in batch mode.

2.1.2.3 Quantitative Model Based Methods

Under this specific categorization, quantitative model based method means the first principle based method, which describes physical components based on the theoretical or empirical laws between physical inputs and outputs. These laws could either describe normal behavior (as typically used in simulation models [14]) or describe faulty behavior (for fault detection and diagnostics purpose [54]).

Clark [14] described the model for actuator. It is described in the following equation:

$$\delta_a = \delta_c - (\delta_c - \delta_a^-)exp(\frac{\Delta\tau}{\tau_a}) \tag{1}$$

where δ_a is the actuator position, δ_c is the control signal, δ_a^- is the actuator position at a previous time step, $\Delta\tau$ is the simulation time step, τ_a is the actuator time constant. Typically, pneumatic actuators have time constants of two seconds or less.

The hysteresis model developed in Clark [14] was further extended in Salsbury [54] to include the slack parameter υ, which describes the barrier in the linkage between valve stem and actuator. By definition the actuator can not move until υ is overcome.

Haves [23] described a model for control damper with the following equations:

$$\Delta p = K_\theta \frac{\rho v^2}{2} \tag{2}$$

$$\ln K_\theta = a + b\theta \tag{3}$$

$$K_0 = 2\rho A_f^2 R_0 \tag{4}$$

$$K_{90} = f_l^{-2} 2\rho A_f^2 R_0 \tag{5}$$

where Δp is the pressure drop, ρ is the density, v is mean velocity referred to the face area of the damper, K_θ is the loss coefficient, θ is the angle between blade and direction of flow, a and b are constant parameters depending on the blade geometry. It should be noted that in equation 2, K_θ does not hold when θ is close to full open or full close position. In this model the valid range is set to between $\frac{15}{90}$ and $\frac{55}{90}$. For regions at the two ends, K needs to be calculated using equation 4 and equation 5. To calculate K_0 and K_{90}, other parameters like open resistance R_0, the face area A_f , the leakage f_l are needed as well. Typical values of K_0 is 0.2-0.5. Quadratic interpolation function is used to fit the data between the valid range and two ends.

Salsbury [54] developed model for equal percentage valve, in which both inherent characteristic and installed characteristic are considered. For inherent characteristic, because the standard equal percentage characteristic is not complete close-off at zero stem position, the author modified the standard function so that zero stem position leads to zero flow rate, and added the leakage parameter to reflect the valve leakage behavior. In a real situation, since the pressure drop across the valve keeps changing depending on the operation condition, the installed characteristic is different from inherent characteristics. To reflect the difference, authority parameter is used. In total, there are three free parameters in the valve model: leakage, curvature (equal percentage constant), and authority.

Haves [23] described the model for flow resistance, which is a square law relationship at high flow rates and linear relationship at low flow rates:

$$\Delta p = R_T w \left|w\right| (\left|w\right| > w_c) \tag{6}$$

$$\Delta p = R_L w(\left|w\right| \leq w_c) \tag{7}$$

$$R_L = R_T w_c \tag{8}$$

where w is mass flow rate(kg/s), R_T is a user specified value depending on the material of the duct. R_T could be calculated as following:

$$R_T = \lambda \frac{L}{D} \frac{1}{2\rho f^2} \tag{9}$$

where L is the length of pipe, D is the diameter of pipe, ρ is the density of medium, f is the face area of pipe. λ is the pipe friction coefficient at the turbulent flow dependent upon the flow regime. In turbulent flow, λ is calculated as following:

$$\frac{1}{\sqrt{\lambda}} = -2\log(\frac{2.51}{R_{ec}\sqrt{\lambda}} + 0.269\frac{K}{D}) \tag{10}$$

The critical mass flow rate w_c is calculated as following:

$$w_c = \frac{R_{ec}\mu\pi D}{4} \tag{11}$$

where R_{ec} is the critical Reynolds number at which transition to turbulent starts, the empirical value for R_{ec} is 4000. μ is the dynamic viscosity of the medium, D is the duct diameter.

Brandemuehl [10] described models for fans and pumps, which share the common equations:

$$\Phi = \frac{\dot{m}}{\rho N d^3} \tag{12}$$

$$\Psi = \frac{\Delta P}{\rho N^2 d^2} \tag{13}$$

$$\eta_s = \frac{\dot{m}\Delta P}{\rho W_s} \tag{14}$$

$$\Psi = a_0 + a_1\Phi + a_2\Phi^2 + a_3\Phi^3 + a_4\Phi^4 \tag{15}$$

$$\eta_s = b_0 + b_1\Phi + b_2\Phi^2 + b_3\Phi^3 + b_4\Phi^4 \tag{16}$$

$$W_t = \frac{W_s}{\eta_{mot}} \tag{17}$$

where m is mass flow rate, Φ is the dimensionless flow coefficient, Ψ is the dimensionless pressure head coefficient, η_s is the fan or pump shaft efficiency, W_s is the shaft power consumption, η_{mot} is the motor efficiency, W_t is the total power consumption.

To calculate the leaving air condition of the fan, following equations are used:

$$q_{loss} = W_s + (W_t - W_s) f_{loss} \tag{18}$$

$$h_{lvg} = h_{ent} + \frac{q_{loss}}{m} \tag{19}$$

$$w_{lvg} = w_{ent} \tag{20}$$

where q_{loss} is the heat transferred to fluid, h_{lvg} is the leaving air enthalpy, w_{lvg} is the leaving air humidity ratio.

To calculate the leaving liquid temperature of the pump, following equations are used:

$$q_{loss} = W_s(1 - eff) + (W_t - W_s)f_{loss} \tag{21}$$

$$T_{lvg} = T_{ent} + \frac{q_{loss}}{C_p} \tag{22}$$

where eff is the pump efficiency, f_{loss} is the fraction of motor loss to fluid stream, C_p is the specific heat of liquid.

Salsbury [54] used the NTU method to calculate heat exchange rate of heating coil. In this method, the key variables are effectiveness efficient ϵ and NTU (number of transfer units). ϵ is a function of NTU, C_r (heat capacity ratio), and the geometrical flow arrangement of heat exchanger. NTU is a function of UA (overall conductance) and C_{min} (minimum heat capacity).

Salsbury [54] used the SHR (Sensible Heat Ratio) method to calculate heat exchange rate of cooling coils. In this method, the dry-bulb temperature difference is assumed to be the heat transfer driving potential, although it can be easily modified to use enthalpy difference as driving potential. There are two coefficients in the method that need to be solved iteratively: effectiveness coefficient ϵ and SHR. The iteration stops after the difference of two successive result of heat exchange rate is smaller than a threshold.

In sum, physical models for various air handling unit components in normal behavior have been developed. Further more, models for some HVAC components in faulty behavior have also been developed. In a faulty sensor model, an offset constant is used as the drift fault parameter. In actuator faulty model, a slack constant v is used to account for hysteresis faulty behavior. In valve and damper faulty model, a leakage parameter l is used to take into account leakage behavior. In heat exchanger faulty model, the conductive resistance R_w through the material separating fluids is chosen to reflect the fouling behavior. A list of advantages and disadvantages of different FDD methods is shown in table 2.

Table 2: FDD Methods for AHUs

Method	Advantages	Disadvantages
History based	No pre-knowledge needed	Requires long training period
Rule based	Simple, convenient	Poor adaptability and scalability
PCA method	Sensor drift detection ability	Requires many sensors
Physics based	No training needed	Pre-knowledge is necessary

2.1.3 Field Testing

Salsbury [54] tested the quantitative model based method on a full size facility at the UK Building Research Establishment. Using normal operation data, the 'nominal' parameters in various components were estimated, which were then used for fault detection. It was demonstrated that three types of faults - coil fouling, valve leakage and sensor fault - could be detected successfully using this method, but following problems were also noticed:

- This method can only deal with slowly changing faults, for abrupt faults the estimated parameter fluctuates.
- To compensate for factors that are not considered in the model, estimated parameters deviate from meaningful values, therefore the original physical meanings were lost.
- How well this method can work depends on the initial 'nominal' training data, if the training data is only a small portion of total operation range, the false

alarm rate may increase.

- The performance of the parameter estimator is dependent on the local non-linearity of the model being studied.

Norford, Wright, Buswell, et al. [46] applied both the quantitative model based method and electric meter data based gray-box method to three air handling units operating in a building in UK. Results showed the gray-box method to be more successful in diagnosing the detected faults than first principle based methods. For first principle based method, difficulties have been found in detecting and diagnosing leaking dampers in mixing air boxes, leaking coil valves, and fouling faults in low duty operation range. As in Salsbury [54], the quality of sensor data, the discrepancy between model and reality, the lack of training data across all operation ranges are attributed as reasons of the failure. It was found that if the threshold of a steady state detector is set too high, then a large portion of measured data were regarded by the method as transient and hence almost no data could be used to monitor the system. This was attributed as one of the main reasons why the cooling coil valve leakage fault was not detected.

Smith [58] has applied both Air-handling unit Performance Assessment Rules (APAR) and VAV Box Performance Assessment Control Charts (VPACC) to laboratory test sites. Test results showed that APAR could successfully detect and diagnose selected faults, in combination with operational personnel, problems can be quickly found and repaired. VPACC was also successful in detecting selected faults in these sites. Default values for threshold parameters were recommended for user to use, procedures to determine site-specific threshold parameters were also developed and documented.

Xu, Haves and Kim [73] described a function testing tool based on first principle based models, which could be used in HVAC commissioning. This function testing tool compares the model prediction with observed performance , significant difference suggesting the presence of faults. Test site results showed that this approach can successfully detect multiple faults in the mixing box, and one fault in an air-handling unit fan. In [24] this tool was extended to additional fault diagnosis function, which was performed by analyzing variations of the difference between operating points and model outputs, using expert rules and fuzzy inference.

Finally, typically available sensor information in an air handling unit is shown in Table 3 [40]. When a typical air handling unit is combined with a recovery unit, the sensors installed are shown in Table 4. Sensors listed in Table [40] and Table 3 could be found in typical configurations. In a highly equipped building, more sensors would be installed.

Table 3: Typical Sensors for AHUs

Typical Sensors	Highly potential Sensors	Potential Sensors
OAT	RAT	HCOAT
MAT	OAH	CCOAT
DAT	DAH	
SSP	RAH	
DAF	SFDP	
SAF_POW	RFDP	
RAF_POW	RAF	
SAF_PCT		
RAF_PCT		
MAD		
HCV		
CCV		

2.2 Motivation

Based on the literature review, following characteristics are identified in the air handling unit system FDD related work.

1. Due to the nonlinear, transient, low transparency, low monitoring level nature of HVAC system, fault detection and diagnostics is a difficult problem in most cases.

Table 4: Sensors for AHUs in a Typical AHU with Recovery Unit

Sensors	Setpoints	Control Signals
DAT	DAS	CCV
HRDAT	HR_ENS	HCV
HRRWT	MAS	HR_ENA
HRSWT	MIN	MAD
MAO		HRCV
MAT		OAD
OAC		
OAE		
OAH		
RAE		
RAF_ERR		
RAF_PCT		
RAF_POW		
RAH		
RAT		
RSP		
SAF_ERR		
SAF_PCT		
SAF_POW		

2. There are many variants of air handling units, which leads to the low adaptability of the rule based method.

3. The majority of the tools currently deployed are either based on rules (heuristic or expert rules), or based on various mathematical models. More complex machine learning methods have not been widely used.

4. In many situations, multiple FDD methods are available to choose from, each with its own pros and cons.

5. The key value of FDD to building operators has not been fully realized and delivered by the current FDD tools.

6. The information that FDD systems should deliver to the end user has not been standardized.

7. The uncertainty inherent in FDD methods has not been fully realized and addressed in current tools.

The first and second characteristic leads to the low adaptability of FDD method. In case a user renovates the system, updating the FDD system could be very challenging. The fourth characteristic requires user to have a FDD method selection strategy, therefore further increases the difficulty to use. The fourth and fifth characteristic indicates that the value of FDD tool still needs to be exploited and advertised by the community. The sixth characteristic shows another area where FDD tools can improve.

Many of the above characteristics are interrelated, for example, the difficulty in correct fault diagnostics leads to the limited use in practice. However, among all the problems identified, the low adaptability and strong system dependency is recognized as the biggest constraint in the current world, lack of information comes in the second.

2.3 Target

To remove the constraints, this thesis targets 1) decreasing FDD method dependency on the type of system, and 2) improving FDD method performance at low information availability levels. To achieve the first target, a highly scalable, purely relying on control required information FDD method will be developed. To achieve the second target, an integration approach is identified as the technical route, which will (a) choose the right FDD method/methods to use (b) combine the results from different FDD methods.

The benefits of this new method will be:

- Improved reliability, due to more than one FDD method being used.
- Improved adaptability, due to the pool of FDD methods and the automatic selection function.

- Improved scalability, since the time spent to accommodate new building systems is less.

From the methods investigated above, four methods are chosen as the elementary methods in this thesis: (1) CUSUM based method (2) Rule based method (3) Principal Component Analysis (PCA) method and (4) First principle based method. CUSUM based method and principal component analysis method require no knowledge about the system for fault detection, therefore the use of them meets the goal to improve adaptability and scalability. Rule based method is also widely applicable for fault detection. It is expected that the integration of these three methods is able to improve both adaptability and performance. First principle based method is a high information demand method, the reason to choose it is that in situation where it can be used, it can improve the performance through the integration.

2.4 Approach

To achieve the target, a three step approach is taken:

1) Define a standardized FDD delivery information specification, which also serves as the interface where different FDD methods are connected.

2) Exploit the current FDD methods in fault detection and diagnostics. If the fault diagnostic function does not exist yet, extend the method's function to fault diagnostic.

3) Deploy Bayesian integration approach to combine the deterministic results from different FDD methods, and transform them to probabilistic results.

In the following, chapter 3 defines the standard information delivery specification, chapter 4 introduces the development of stable state detector that is used in the thesis, chapter 5, 6, 7, 8 sequentially introduces the fault detection and diagnostic approach of rule based method, rule augmented CUSUM method, model based method, and principal component analysis method, respectively, each tested with a testing case. Then in Chapter 9, the probability extension approach using Bayesian method is applied to all four methods introduced above and tested. After all methods are introduced, the integration of them with both deterministic and probabilistic approaches are discussed and compared in Chapter 10, in which the method selection strategy under different information availability scenarios is also suggested. Finally, Chapter 11 gives on overview of this thesis.

CHAPTER III

FDD DELIVERY INFORMATION STANDARDIZATION

The content in this chapter is separated into two parts. The first part introduces the common faults of a typical air handling unit. The second part defines the standard format for FDD output information.

3.1 Air Handling Unit FDD Problem Description

The diagram of a typical Air Handling Unit (AHU) system is shown in Fig 2, which is composed of mixing air box, filter, heating/cooling coil, supply/return fan, controller (not shown), humidifier/dehumidifier (not shown), etc. It should be noted that there are some variants. For example, (1) depending on the humidify control precision requirement, humidifier/dehumidifier may nor may not be necessary in the system. (2) To recover energy, in many systems there is a heat recovery unit between outdoor air and mixing air box. (3) In dedicated outdoor air system (DOAS), the mixing air box is optionally replaced by an air-to-air heat exchanger. Other variants can follow.

Common components in air handling unit and their related faults are listed below:

- Mixing Air Box
  - Fresh (Outdoor) air damper
    - Damper leakage
    - Damper stuck
    - Damper sticking
  - Return air damper
    - Damper leakage

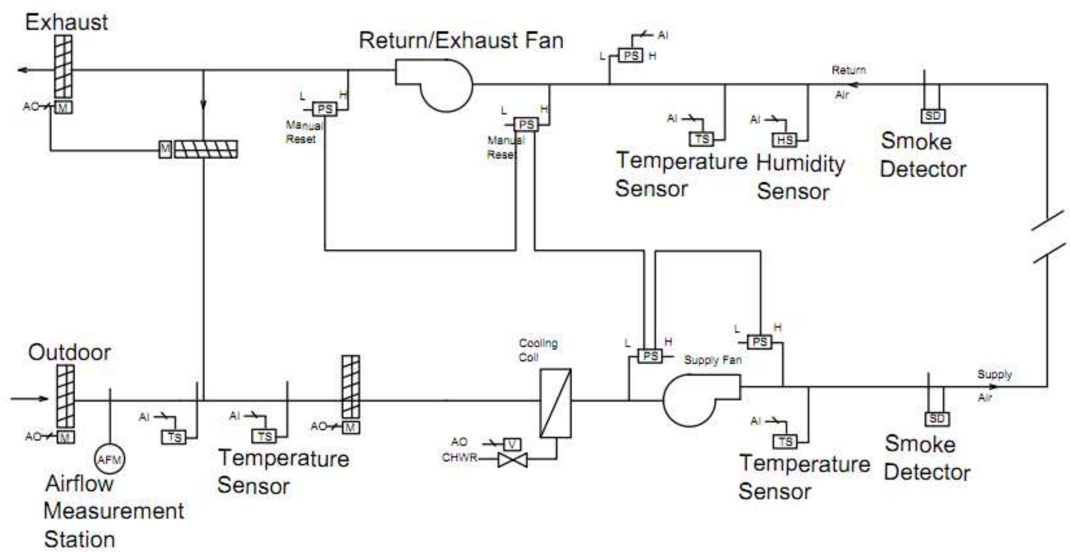

Figure 2: Diagram of a Typical AHU System

    * Damper stuck
    * Damper sticking
  - Exhaust air damper
    * Damper leakage
    * Damper stuck
    * Damper sticking
- Coil
  - Heating coil
    * Leaking heating coil valve
    * Stuck heating coil valve
    * Fouled heating coil
    * Undersized heating coil
    * Hot water supply temperature too low
    * Hot water circulating pump problem

- Cooling coil
  - Leaking cooling coil valve
  - Stuck cooling coil valve
  - Fouled cooling coil
  - Undersized cooling coil
  - Chilled water supply temperature too high
  - Chilled water circulating pump problem

- Fan
  - Supply Fan
    - Undersized fan
    - Oversized fan
    - Low efficiency
    - Undersized fan motor
  - Return Fan
    - Undersized fan
    - Oversized fan
    - Low efficiency
    - Undersized fan motor

- Distribution
  - Duct
    - Duct cloggy
    - Duct leakage

- Humidifier

  - Malfunction

- Dehumidifier
  - Malfunction

- Sensors
  - All sensors in the system
    - Sensor noise
    - Sensor drift
    - Sensor failure

- Air-to-air Heat Exchanger
  - Fouled heat exchanger

- Controller
  - All controllers in the system
    - Poor tuning
    - Controller failure

3.2 FDD Output Format Standardization

It is the intention of this thesis to deliver not just qualitative FDD results (faulty or normal), but also quantitative results. Ideally, these information should be included in the final delivery report:

1. System level efficiency (like COP), measuring how well the whole system is currently performing.

2. A list of faulty equipment candidates and possible faults.

3. A list of faulty equipment candidates associated with fault probabilities.

4. A measure of criticality for each possible fault, quantifying how critical a specific fault is to the overall system operation.

5. A measure of risk for not fixing the fault, indicating the consequence of not fixing the fault.

A standard FDD output format therefore is defined in the following table 5 with some pseudo data filled in.

Table 5: FDD Output Format for AHUs

Component	Subcomponent	Fault	Explanation	Probability	Criticality	Risk
AHU 1	all	low η_s	Low efficiency	/	/	/
MAB 1	oad	small l_{od}	Less than 5%	/	/	/
MAB 1	oad	large l_{od}	Larger than 5%	/	/	/
MAB 1	oad	fixed P_{od}	Stuck	/	/	/
MAB 1	oad	lagged P_{od}	Sticking	/	/	/
MAB 1	ead	small l_{ed}	Less than 5%	/	/	/
MAB 1	ead	large l_{ed}	Larger than 5%	/	/	/
MAB 1	ead	fixed P_{ed}	Stuck	/	/	/
MAB 1	ead	lagged P_{ed}	Sticking	/	/	/
MAB 1	mad	small l_{md}	Less than 5%	/	/	/
MAB 1	mad	large l_{md}	Larger than 5%	/	/	/
MAB 1	mad	fixed P_{md}	Stuck	/	/	/
MAB 1	mad	fixed P_{md}	Sticking	/	/	/
Cooling coil 1	coil	low η_{cc}	Coil fouling	/	/	/
Cooling coil 1	valve	small l_{ccv}	Less than 5 %	/	/	/
Cooling coil 1	valve	large l_{ccv}	Larger than 5%	/	/	/
Cooling coil 1	valve	fixed P_{ccv}	Stuck	/	/	/
Cooling coil 1	valve	lagged P_{ccv}	Sticking	/	/	/
Heating coil 1	coil	low η_{hc}	Coil fouling	/	/	/
Heating coil 1	valve	small l_{hcv}	Less than 5 %	/	/	/
Heating coil 1	valve	large l_{hcv}	Larger than 5%	/	/	/
Heating coil 1	valve	fixed P_{hcv}	Stuck	/	/	/
Heating coil 1	valve	lagged P_{hcv}	Sticking	/	/	/
Supply Fan 1	fan	Complete failure	Zero head	/	/	/
Supply Fan 1	fan	Out of control	Constant speed	/	/	/
Supply Fan 1	fan	Low efficiency	High temperature rise	/	/	/
Return Fan 1	fan	Complete failure	Zero head	/	/	/
Return Fan 1	fan	Out of control	Constant speed	/	/	/
Return Fan 1	fan	Low efficiency	High temperature rise	/	/	/
Duct Section 1	Cloggy	Resistance increases	/	/	/	
Sensor	Sensor	Drifty	Constant bias	/	/	/
Sensor	Sensor	Failure	No data, complete failure	/	/	/
Sensor	Sensor	discrete	Sensor data is discrete	/	/	/
MAB Controller	Controller	Sluggish	Slow to respond to environment	/	/	/
MAB Controller	Controller	Unstable	Deviate from set point	/	/	/
Coil Controller	Controller	Sluggish	Slow to respond	/	/	/
Coil Controller	Controller	Unstable	Deviate from set point	/	/	/
Fan Controller	Controller	Sluggish	Slow to respond	/	/	/
Fan Controller	Controller	Unstable	Deviate from set point	/	/	/

It is realized that to study all of the information above is beyond the scope of this thesis. Therefore, among the three quantitative measures only the fault probability is addressed in this thesis. The topics of criticality and risk will remain as part of the future work.

3.3 Input Information Assumption

In terms of the information source, input information could be categorized as sensor input, control signal input and control setpoint input. In the work conducted in this thesis, following assumptions are made regarding the input information:

- All the sensors installed are calibrated.
- None of the sensors has noise.
- Control signal fully reflects the system status.

CHAPTER IV

STABLE STATE DETECTOR DEVELOPMENT

The operation modes of HVAC system can be categorized based on if the current state is stable (the changes of variables are relatively small) or transient (the changes variables are relatively large). Transient state is the transition from one stable state to another due to the change of system loads. Due to the drastic change of the variables, the system could often be detected as faulty in transient states. Therefore, to reduce the false alarm rate, transient data is typically filtered out during the FDD process.

4.1 Method

Suppose y is the dynamic variable of interest, $y = f(t)$ is the function describing y, $\dot{y}(t)$ is the derivative of y at time t.

$$h(t) = \frac{df(y,t)}{dt} \tag{23}$$

Since the meaning of $\dot{y}(t)$ is the speed at which y changes at time t, the value of $\dot{y}(t)$ therefore indicates if the state is stable or transient. Suppose the threshold at which stable state transits to transient state is T, then based on the relationship between $\dot{y}(t)$ and T, the state at time t can be determined.

There are various ways to calculate $h(t)$, some examples are listed as following.

$$\dot{y}(t) = \frac{y(t+\Delta t) - y(t)}{\Delta t} + O(\Delta t^2) \tag{24}$$

$$\dot{y}(t) = \frac{y(t) - y(t-\Delta t)}{\Delta t} + O(\Delta t^2) \tag{25}$$

$$\dot{y}(t) = \frac{y(t+\Delta t) - y(t-\Delta t)}{2\Delta t} + O(\Delta t^3) \tag{26}$$

In off-line analysis, either one of these three equations can work, however, in real time operation only equation 25 can work for obvious reasons. Therefore, equation 25 is used in this thesis.

4.2 Threshold setting

The speed at which a variable changes depends on the current system status (transient or stable), the control setting of the variable (controlled/uncontrolled, controller accuracy), the nature of the variable (temperature, pressure, etc.), the accuracy of the sensor, etc. Therefore, to use the variable change speed to indicate the system status, the impacts of the other factors should be minimized as much as possible.

To illustrate the impacts of controller setting (controlled/uncontrolled), nature of the variable (temperature, pressure, etc.) on the variable change, selected variables from monitored data (one month) of a real building are shown in the following, which include outdoor air temperature (uncontrolled temperature), zone air temperature (controlled temperature), outdoor air humidity (uncontrolled humidity), return air humidity (controlled humidity), outdoor air enthalpy (uncontrolled enthalpy).

Fig3 shows the outdoor temperature change in 5 minute interval, Fig4 shows the outdoor air humidity in 5 minute interval, Fig5 shows the outdoor air enthalpy in 5 minute interval, Fig 6 shows the indoor air temperature in 5 minute interval, Fig 7 shows the return air humidity in 5 minute interval.

A comparison of the variance of the above variables is shown in table 6.

Table 6: Variable 5 Min Change Variance

	outdoor	indoor&controlled
Temperature ($°C$)	0.0343	0.0108
Humidity (%)	23.9	0.0248
Enthalpy (kJ/kg)	0.0091	/

The results suggest that three factors could affect a variable's variance: 1) If a variable is controlled or uncontrolled 2) The unit of the variable 3) The type of the

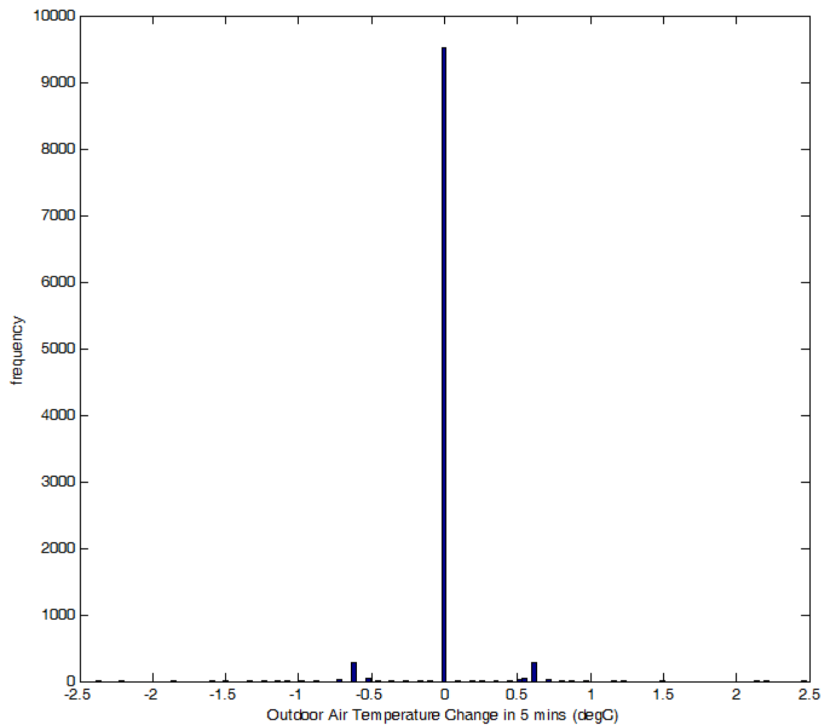

Figure 3: Outdoor Air Temperature Change in 5 mins Interval

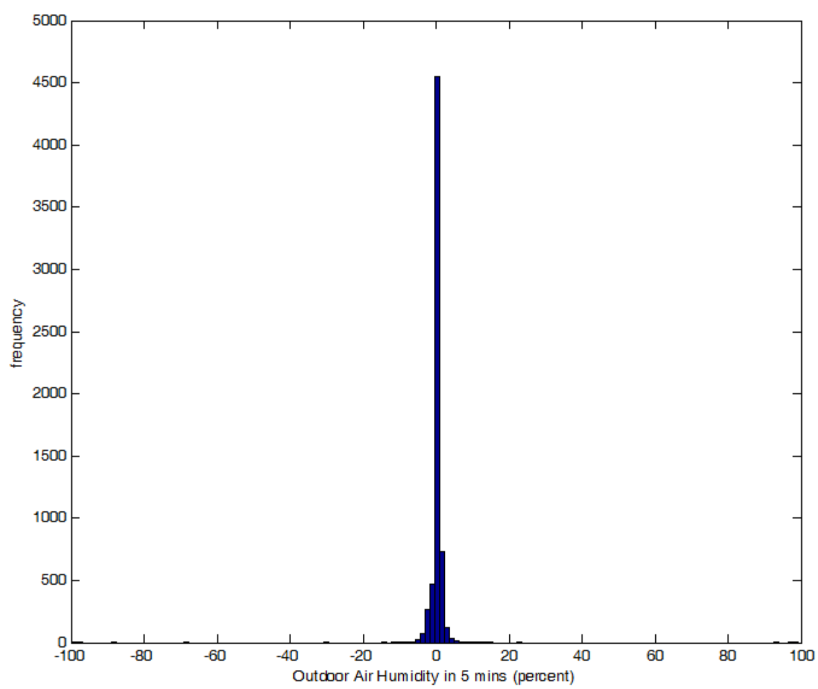

Figure 4: Outdoor Air Humidity Change in 5 mins Interval

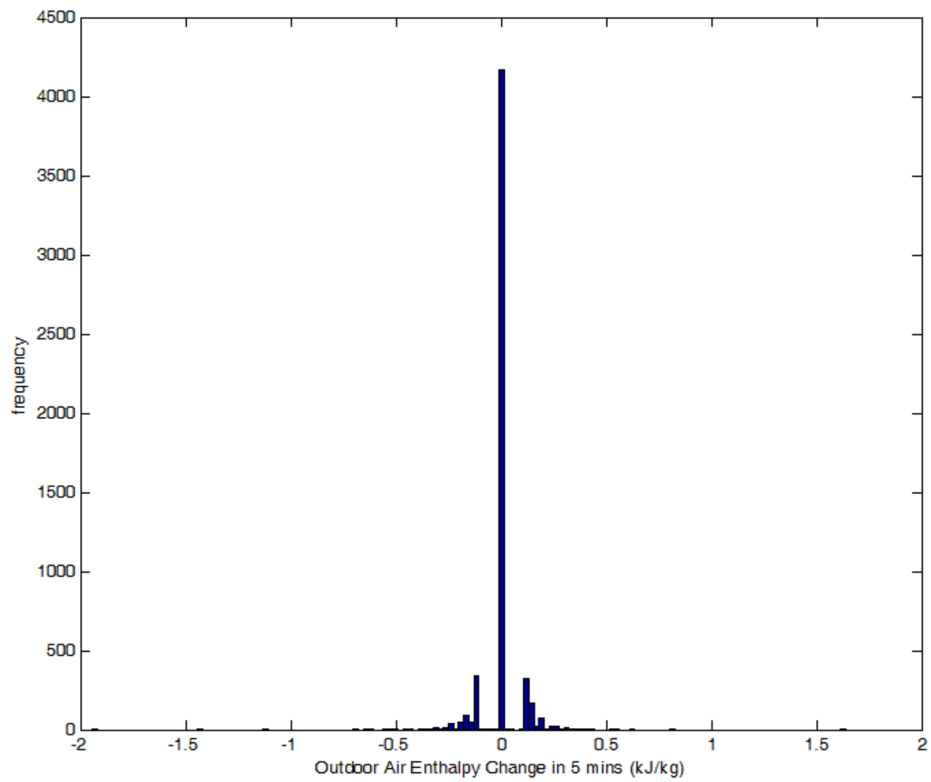

Figure 5: Outdoor Air Enthalpy Change in 5 mins Interval

variable (temperature, humidity, etc.). Furthermore, 4) the accuracy, bias of the sensor could also contribute to the variance.

This suggests that the variables used for a stable state detector should have small variances, and be controlled and measured with high accuracy, so that the system status (stable/transient) and not other factors (as listed above) is the dominant factor on the variable change.

4.3 Choose Representative Variable

Glass, Gruber, Russ, et al. [22] chose to use outdoor temperature, discharge air temperature, return air temperature and discharge air temperature set point. Lee, House and Kyong [38] used cooling coil valve control signal, mixing air temperature, supply air duct static pressure and return air flow rate as the representative of all the

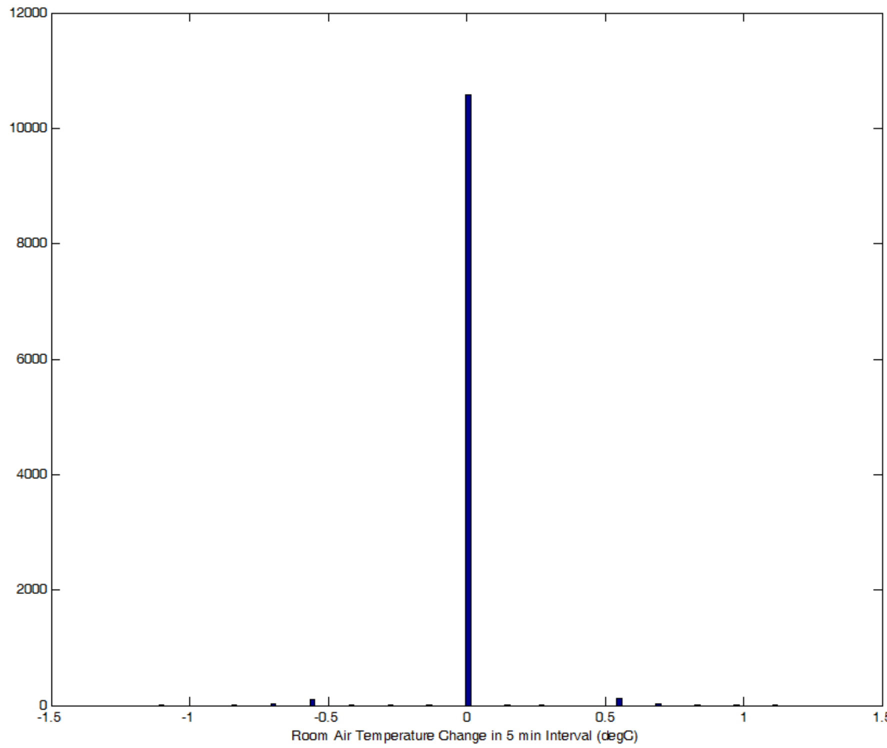

Figure 6: Room Air Temperature Change in 5 mins Interval

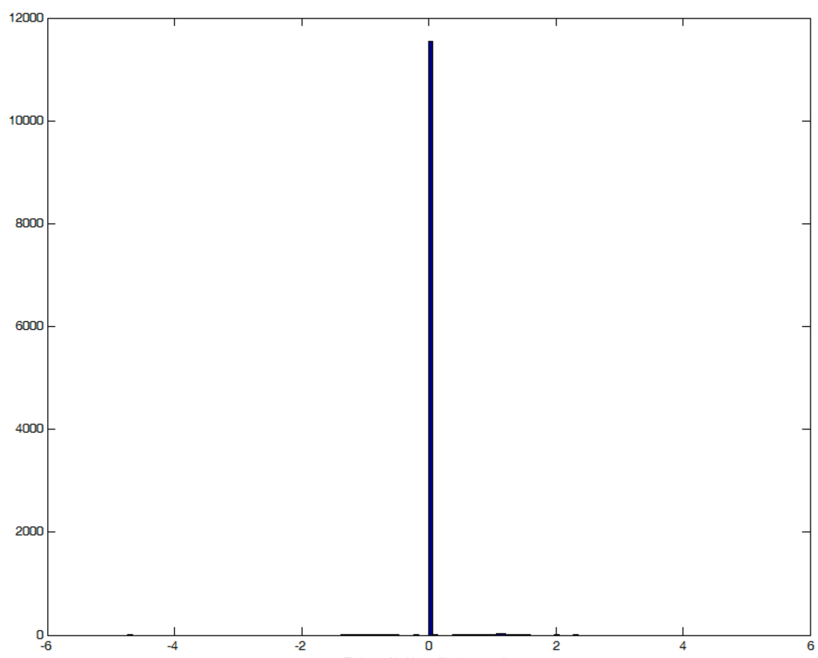

Figure 7: Return Air Humidity Change in 5 mins Interval

system variables. Li [40] chose cooling coil control signal, discharge air temperature, supply air duct static pressure and supply fan speed to represent the whole system.

In this thesis, the representative variables chosen are the same as the ones used in Li [40], i.e., heating/cooling coil valve control signals, discharge air temperature, supply air duct static pressure and supply fan speed are used to detect if the state is stable.

4.4 Derive Stable State Criteria

Both controlled experiments and simulation experiments can be conducted to observe the stable state behavior, the results of which can then be used to derive stable state criteria.

In this thesis, simulation experiments were performed to simulate an air handling unit in stable state operation. The derivative of the chosen variables are calculated using equation 25 at each time step, and summed together, to generate a vector of the derivative sums of four variables. The region $[Th_{av} - 3Th_{var}, Th_{av} + 3Th_{var}]$ is then used for the stable state region. Th_{av} and Th_{var} are respectively the average and variance of the derivative sum vector derived from normal operation results. If at a certain time step the derivative sum falls out of this region, the system state is regarded as transient.

CHAPTER V

ENHANCED RULE BASED METHOD

5.1 Introduction

Rule based methods have several advantages over more advanced FDD methods, such as model based method, machine learning based method, etc. It is simple to use, requires fewer sensors and works well in a targeted system. These advantages motivate researchers to develop rule based methods for various HVAC components.

For air handling units, among the existing rules, AHU Performance Assessment Rules (APAR) rules are arguably the most widely acknowledged. Developed by NIST, APAR rule set has a total of 28 rules divided into five operational modes: heating, cooling with outdoor air, mechanical cooling with 100% outdoor air, mechanical cooling with minimum outdoor air and unknown. The operational mode can be determined based on control signals, upon which the corresponding subset of rules are then used to judge if faults exist in the system.

However, when applying APAR rules to real air handling units, there are two major problems. First, APAR rules are used only for fault detection, they are not intended to provide information about what are the possible faults. Although there are some fault diagnostic tables provided [58], the use of these tables is limited because the system configuration could be different from the one tested in [58]. Second, this method typically suggests more than one fault candidate. If the number of faulty candidates is too large, the quality of diagnostic information is decreased.

This chapter reviews the current APAR rules, examines them in a typical air handling unit running in heating mode. To improve the sensitivity of the method, three additional rules are added to the current APAR rules, the effects are also studied.

5.2 *Enhanced APAR Rules*

In Schein [55], AHU operational modes are divided into five types: heating, cooling with outdoor air, mechanical cooling with 100% outdoor air, mechanical cooling with minimum outdoor air, and unknown. In this thesis, rules in Mode 1 - heating mode, and Mode -4 mechanical cooling with minimum outdoor air are implemented.

The following rules are implemented for mode 1.

- Rule 1: $T_{sa} < T_{ma} + \Delta T_{sf} - \epsilon$

  AHU discharge air temperature is less than mixing air temperature plus temperature rise across supply air fan minus a tolerance.

- Rule 2: For $|T_{ra} - T_{oa}| \geq \Delta T_{min}$, $|\frac{Q_{oa}}{Q_{sa}} - \frac{Q_{oa}}{Q_{sa}}_{min}| > \epsilon$

  If the difference between return air temperature and outdoor air temperature is big, mixing air damper should not be larger than a threshold.

- Rule 3: $|u_{hc} - 1 \leq \epsilon|$

  Heating coil valve should not be very close to fully open.

- Rule 4: $T_{sa} - T_{sa,s} \geq \epsilon$

  Discharge air temperature deviates from discharge air temperature set point.

- Rule 5: $T_{ma} < min(T_{ra}, T_{oa}) - \epsilon$

  Mixing air temperature is less than the minimum of outdoor air temperature and return air temperature

- Rule 6: $T_{ma} > max(T_{ra}, T_{oa}) + \epsilon$

  Mixing air temperature is larger than the maximum of outdoor air temperature and return air temperature

The following rules are implemented for mode 4.

- $T_{sa} > T_{ma} + \Delta T_{sf} + \epsilon$

  AHU discharge air temperature is larger than mixing air temperature plus temperature rise across supply air fan plus a tolerance.

- $T_{sa} > T_{ra} - \Delta T_{rf} + \epsilon$

  AHU discharge air temperature is larger than return air temperature minus temperature rise across return air fan plus a tolerance.

- For $|T_{ra} - T_{oa}| \geq \Delta T_{min}$, $|\frac{Q_{oa}}{Q_{sa}} - \frac{Q_{oa}}{Q_{sa}}_{min}| > \epsilon$.

  If there is a significant difference between return air temperature and outdoor air temperature, mixing air damper should not be larger than a threshold.

- $T_{sa} - T_{sa,s} \geq \epsilon$

  Discharge air temperature minus discharge air temperature setpoint is larger than a threshold.

- $|u_{cc} - 1| \leq \epsilon$

  Cooling coil valve is very close to fully open.

In this thesis, in addition to above rules, three rules are implemented and tested. The first rule is to detect duct pressure related faults, the second rule is related with fan energy consumption, and the third rule concerns the coil heat exchange rate.

- Rule 7: $P_{ss} > P_{sm} + \epsilon$

  Static pressure measurement should not deviate too much from static pressure setpoint.

- Rule 8: $W_f < W_{ref} + \epsilon$

  Actual fan power should not exceed the reference fan power too much.

- Rule 9: $Q_{hc} < Q_{hcr} + \epsilon$

  Actual heating coil heat exchange rate should not exceed the reference heat exchange rate too much.

The rules could be categorized based on if they are describing the system behavior (rule 1-7) or if they are describing the energy related inequality (rule 8-9). In general, system behavior rules are given higher attention than energy related rules because of the consequences. This concern contributes to the fault diagnostic approach described in the following section.

5.3 Experimental Setup

In this experiment, a typical AHU working in heating mode is simulated. Outdoor air mixes with return air in a mixing air box, and then is transported by the supply air fan to the heating coil. The air leaving from the heating coil is then supplied to the terminal zone. Since the study target is air handling unit, terminal unit is not modeled in the system. The system configuration is shown in Fig 8.

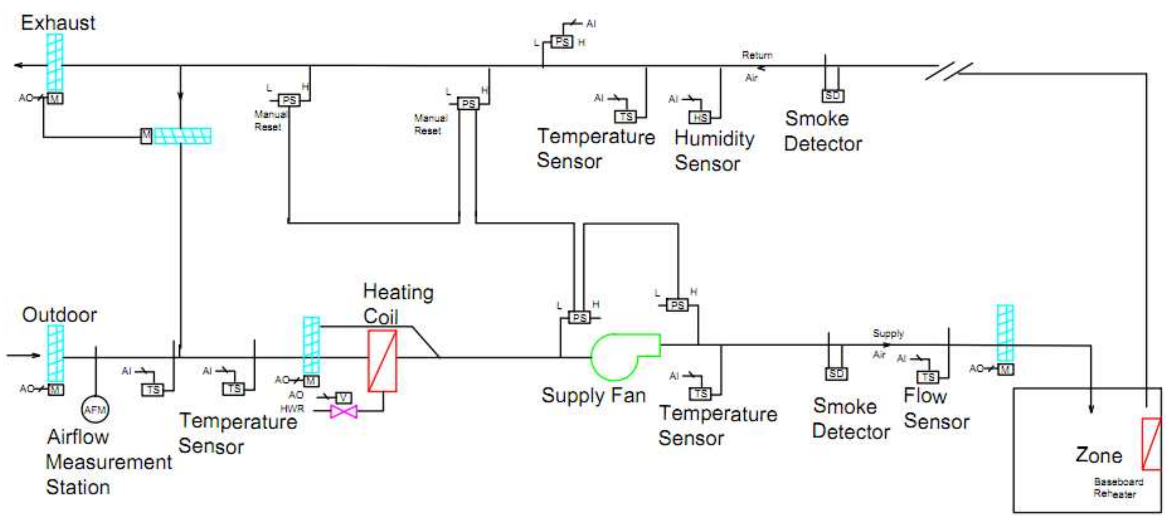

Figure 8: AHU System Configuration

The outdoor air temperature is based on TMY weather data of a real city, as shown in Fig10. The mixing air box is controlled by a PI controller, with a setpoint of 19 $°C$. Supply fan is controlled by a PI static pressure controller with setpoint of 40 Pa. The location of static pressure sensor is right after the supply fan. The

AHU discharge air temperature is controlled by a heating coil valve controller, which modulates the heating coil valve based on discharge air temperature sensor. The discharge air temperature set point is 25 $°C$. The serving zone has an external heating load simulated with a sawtooth model, repeatedly vibrating between 1E4 W and 1.5E4 W within each hour.

The model is defined using Modelica and simulated in Dymola. The Modelica model is shown in Fig 9. The simulation time is 5 days (432000 secs).

In normal operation, the time series plot of three controlled variables (mixing air temperature, static pressure and discharge air temperature) are shown in following figures. The mixing air temperature is shown in Fig 11. The static pressure is shown in Fig 12. The discharge air temperature is shown in Fig 13.

In normal operation, the values of APAR rule detectors are shown in Fig 14, which shows that except for the initialization stage, all six rules are obeyed during the simulation.

Following the stable state detector threshold calculation method in Chap 4, using the discharge air temperature (K), heating coil valve position (0-1), static pressure (Pa), and supply fan speed (/s), the calculated mean of stable state threshold Th_{av} is 0, the calculated variance of stable state threshold Th_{var} is 0.0011.

5.4 Testing Case

A total of 15 of faults are listed in table 7, along with the faulty component, fault type(abrupt/incipient) and numeric label. In testing the performance rule based method, two scenarios are studied separately: single fault case and multiple fault case.

5.4.1 Single Fault Case

In single fault case, in each test only one of the fifteen faults is seeded and simulated. A parametric study is performed for each fault, the range of which is shown in table

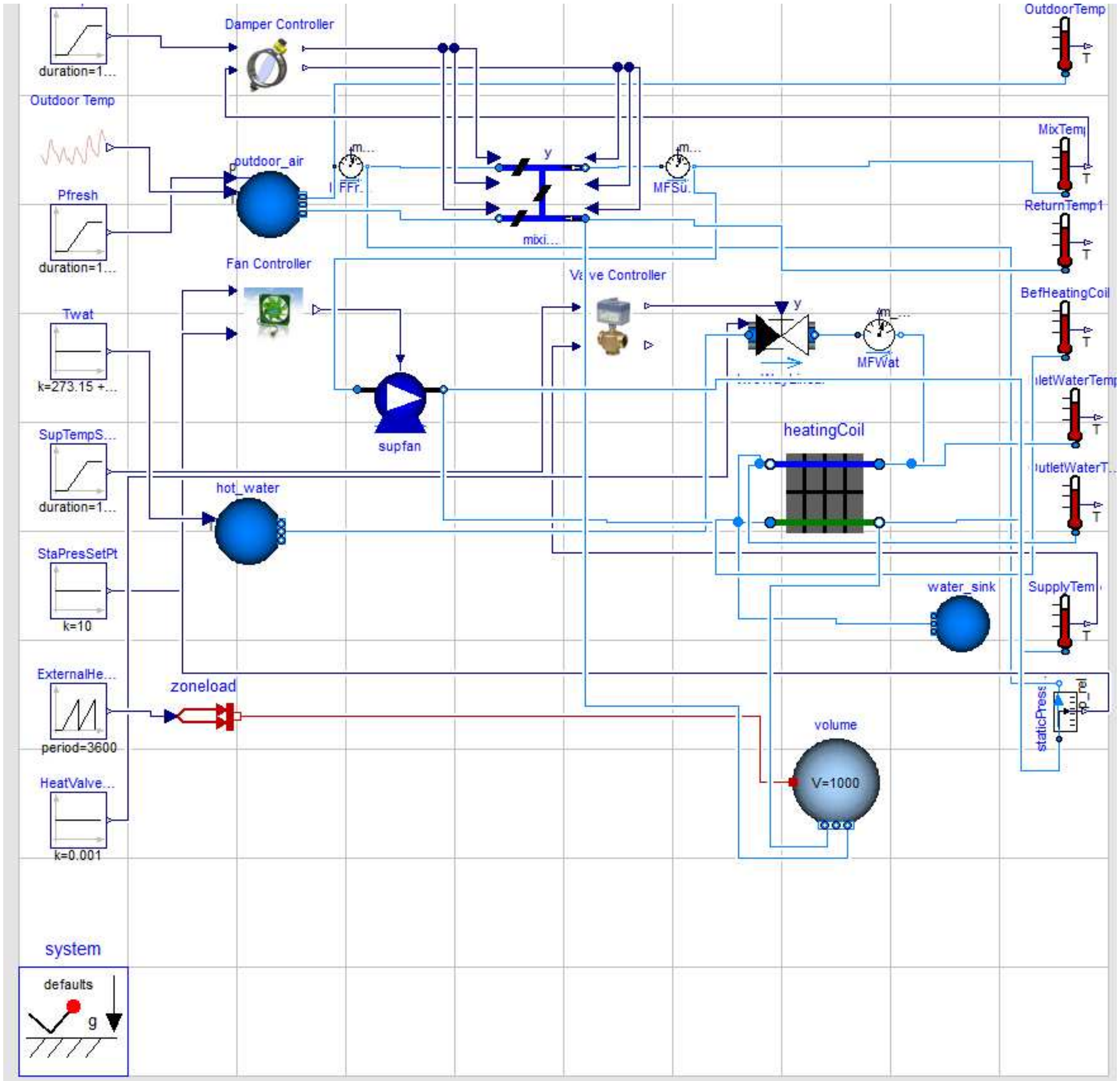

Figure 9: AHU Simulation Model in Dymola

7.

For all simulation cases, data in the first 10000 seconds are thrown away to eliminate the simulation initialization stage. During the simulated period, in the normal state the energy consumption of the fan is 4.4 kwh, the heat exchange rate of heating coil is 1462.1 kwh.

The simulation results are listed in table 8. It should be noted that the same fault

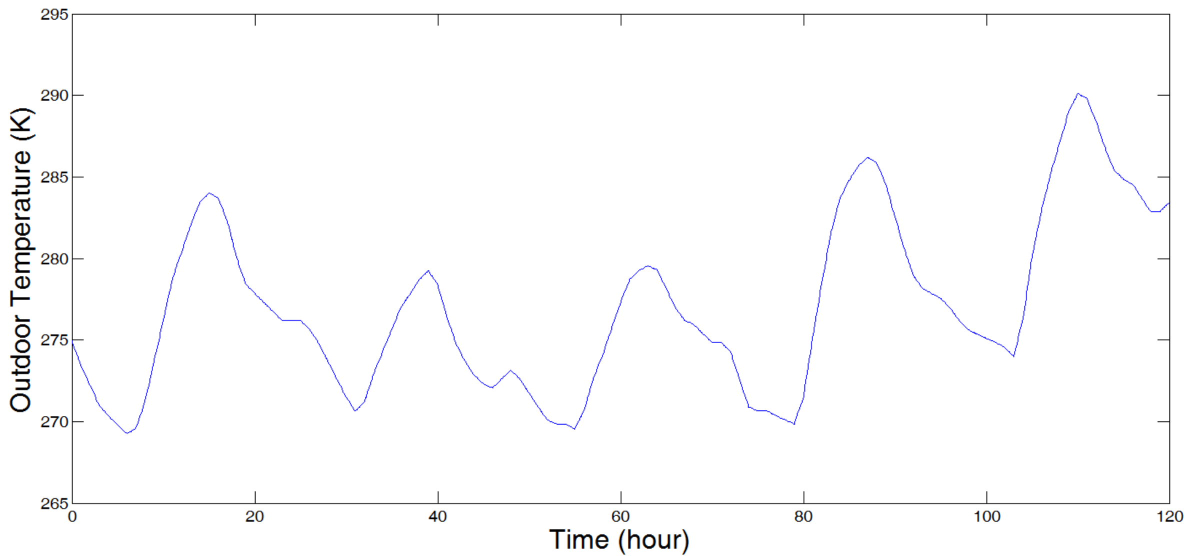

Figure 10: Outdoor Temperature

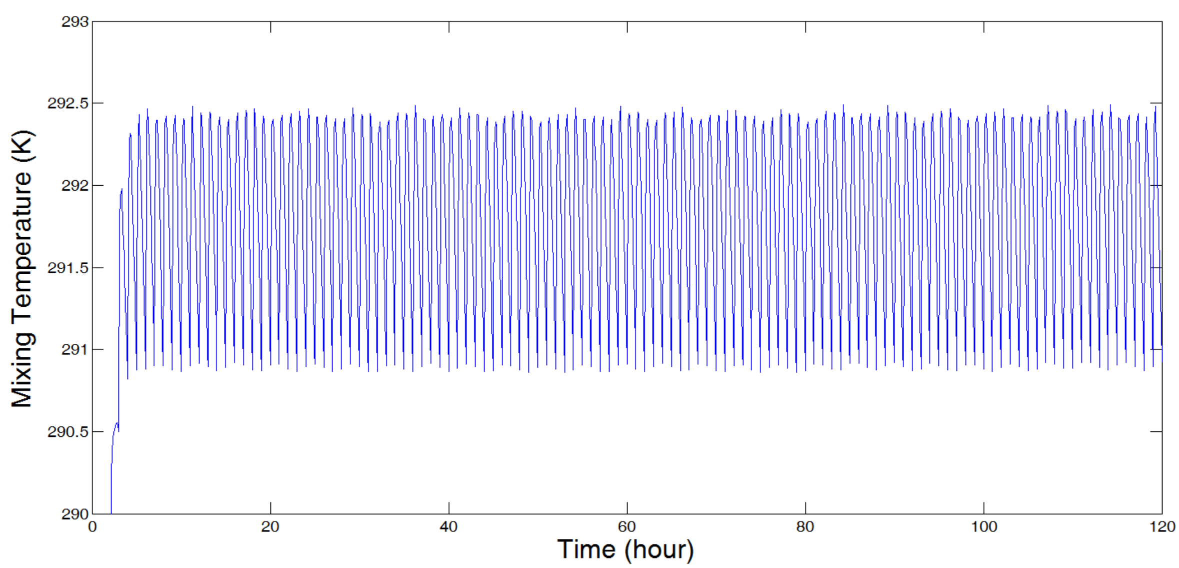

Figure 11: Mixing Air Temperature in Normal AHU operation

may or may not causes the violation of a rule, depending on the extent of the fault. Based on the experimental results, several observations were made and listed below.

- All abrupt faults (fault 2, 5, 9, 11) can easily be detected by the APAR rules.
- Depending on the extent, incipient faults may or may not be detected by the

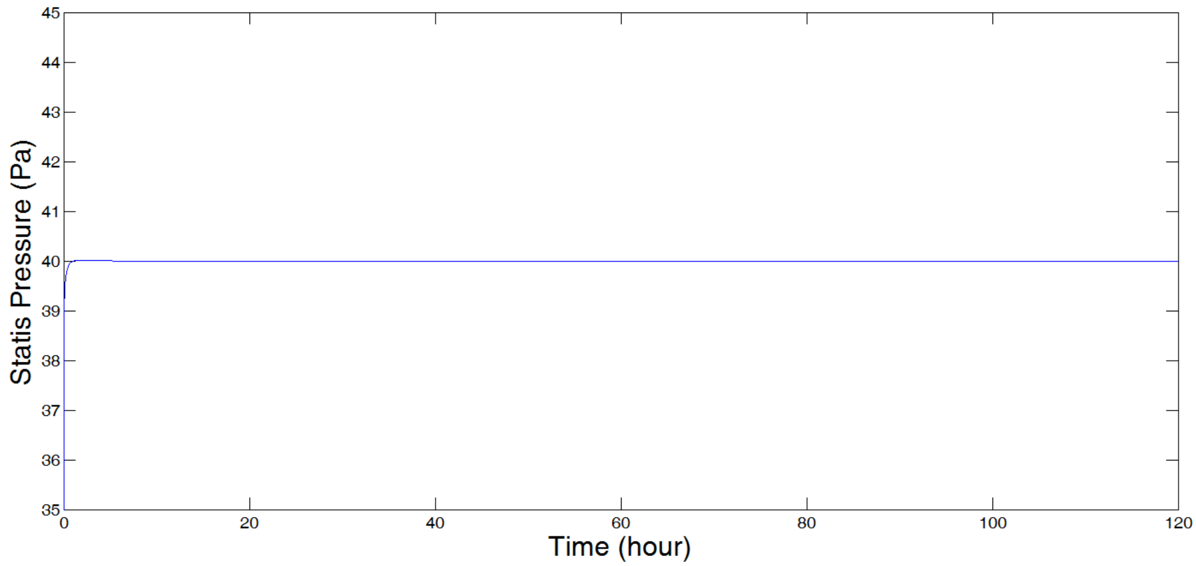

Figure 12: Static Pressure in Normal AHU operation

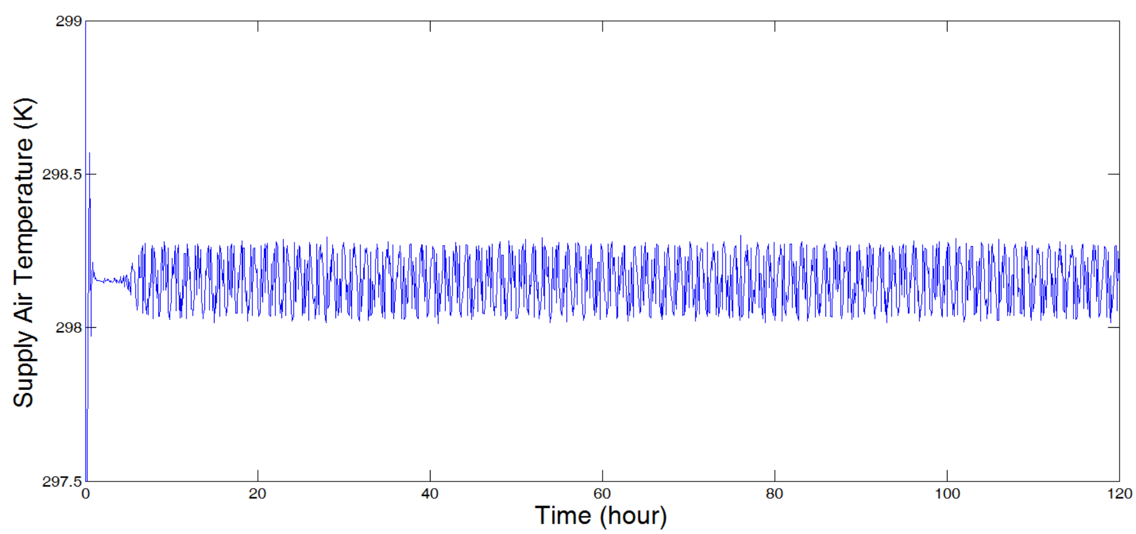

Figure 13: Discharge Air Temperature in Normal AHU operation

APAR rules. If the extent is small, incipient faults can not be detected by the APAR rules.

- The two additional energy consumption related rules (rule 8 and rule 9) can detect small incipient faults that can not be detected by APAR rules(fault 1, 4, 6, 12), therefore the number of detected faults is increased from 8 to 14.

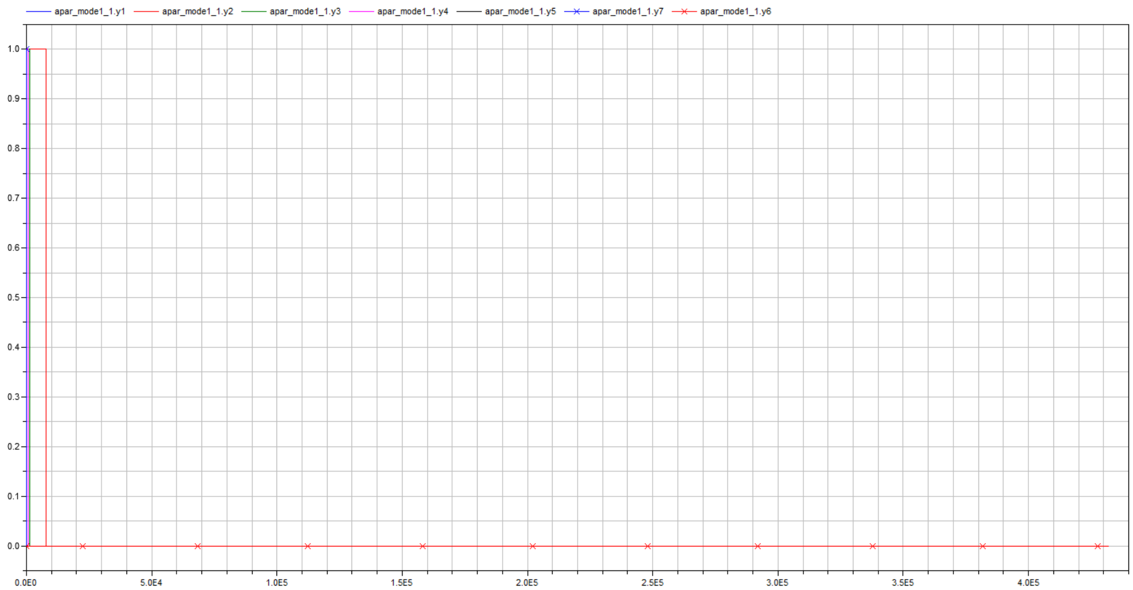

Figure 14: APAR Detector Values in Normal AHU operation

Table 7: Fault List

Component	Fault	Type	Label
	No fault		0
MAB	MAB oad leakage (1%-9%, step 1%)	incipient	1
MAB	MAB oad stuck (10%-90%, step 10%)	abrupt	2
MAB	MAB oad sticking (T_{cons}=5 min - 15 min, step 1 min)	incipient	3
MAB	MAB ead leakage (1%-9%, step 1%)	incipient	4
MAB	MAB ead stuck (10%-90%, step 10%)	abrupt	5
MAB	MAB ead sticking (T_{cons}=5 min - 15 min, step 1 min)	incipient	6
Coil	Heating Coil Fouling ($\frac{UA_{nv}}{UA_{ov}} = \frac{1}{6}$-$\frac{5}{6}$, step $\frac{1}{6}$)	incipient	7
Coil	Heating Coil Valve Leakage (1%-9%, step 1%)	incipient	8
Coil	Heating Coil Valve Stuck (10%-90%, step 10%)	abrupt	9
Coil	Heating Coil Valve sticking (T_{cons}=5 min - 15 min, step 1 min)	incipient	10
Fan	Supply fan Out of Control (N = 1-15 /s , step 1 /s)	abrupt	11
Fan	Supply fan low efficiency (eta = 0.1-1, step 0.1)	incipient	12
Duct	Duct cloggy ($\frac{\Delta P_n}{\Delta P_o}$ = 1-5, step 0.5)	incipient	13
Sensor	Supply Temperature Sensor Drift (ΔT_s = -2°-2°, step 1°)	incipient	14
Coil Controller	Sluggish heating coil controller (Gain k = 0.01-0.1, step 0.01)	incipient	15

- The additional static pressure rule - rule 7 helps distinguish fault 11 from other faults.

- If dividing the rules based on their detection sensitivity, rule 1-7 are less sensitive, they can only detect system behavior related faults, on the other hand, rule 8-9 are sensitive to both system behavior related faults and energy related faults.

- It was found that the violation of a specific rule could be caused by: (1) multiple faulty components (2) multiple faults in one component (3)multiple fault extents. Although it is possible to associate a violated rule with the possible components for a given AHU, this mapping changes if the system configuration changes. Therefore, a generalized fault diagnostic table that works for all AHUs does not exist. This will be further discussed in section 5.5.

Table 8: APAR Detector Values For Each Faulty Case

Rule 1	Rule 2	Rule 3	Rule 4	Rule 5	Rule 6	Rule 7	Rule 8	Rule 9	Faulty Case
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	1
0	/	0	0	0	0	0	/	1	2
0	0	0	0	0	0	0	/	1	3
0	0	0	0	0	0	0	1	1	4
0	/	0	0	0	0	0	1	1	5
0	0	0	0	0	0	0	0	1	6
0	0	/	/	0	0	0	0	1	7
0	/	0	/	0	0	0	0	1	8
0	/	1	1	0	0	0	0	/	9
0	/	0	/	0	0	0	0	/	10
0	/	/	/	0	0	1	/	/	11
0	0	0	/	0	0	0	1	/	12
0	0	0	0	0	0	0	/	/	13
0	/	/	0	0	0	0	0	/	14
0	0	0	0	0	0	0	0	/	15

5.4.2 Multifault case

Three cases are used to illustrate the aggregated behavior of two different faults. In case 1, both faults (fault 1 and 3) are incipient faults and only cause violation of energy related rules (rule 8, 9). In case 2, one fault (fault 1) is incipient fault and causes energy related rules violation, the other fault (fault 9) is abrupt fault, causing the violation of both system behavior rules (rule 1-7) and energy related rules (rule 8, 9). In case 3, both faults (fault 9 and 11) are abrupt faults, both cause the violation of system behavior rules (rule 1-7) and energy related rules (rule 8, 9). The results are shown in table 9.

Table 9: APAR Detector Values For Multi Faulty Case

Rule 1	Rule 2	Rule 3	Rule 4	Rule 5	Rule 6	Rule 7	Rule 8	Rule 9	Case
0	0	0	0	0	0	0	0	1	1 (Fault 1, 3)
0	/	/	1	0	0	0	0	/	2 (Fault 1, 9)
0	/	/	/	0	0	1	/	/	3 (Fault 9, 11)

Based on the results presented in table 9, following observations are made for the two simultaneous faults case:

- If each fault only causes a violation of energy related rules (rule 8, 9), the combination of the two faults also only causes a violation of energy related rules.
- If one fault only causes a violation of energy related rules, and the other fault causes a violation of both system behavior rules and energy related rules, the combination causes violation of both system behavior rules and energy related rules.
- If each fault causes a violation of both system behavior rules and energy related rules, the rules violated by the combination are the union of the rules violated by both faults.

5.4.3 Discussion of the Effects of Multiple Faults

In this section, the effects of multiple faults on rules will be studied. The purpose is to find out the effect of multiple faults on the rule check, and to identify the appropriate approach to diagnose the faults.

For an individual fault, there are three basic scenarios between fault and rules. In the first scenario, there is a one to one mapping between the fault and the violated rule. In the second scenario, one fault could cause the violation of multiple rules. In the third scenario, multiple faults cause the violation of the same rule.

In the multiple faults case, depending on the type of each individual fault, there could be many combination.

In the first combination scenario, each individual fault affects the system behavior or energy consumption independently, i.e., there is no interaction between the faults and there is only one candidate for each violated rule. In this scenario, to diagnose the fault, a three step approach could be used: 1) decompose the violated rules into multiple single violation cases 2)corresponding to each single case, find the fault candidates that contain only one fault 3)aggregate the fault candidates. This scenario does not show in the testing case.

In the second scenario, some of the faults have one-to-one mapping relationship with the rules, the others cause the violation of multiple rules. In this scenario, two situations could happen. First, there is no interaction between the faults, second, the rules violated by each individual fault overlap with each other. The difference between these two situations cause the discovery of the same fault multiple times in the second situation. Although the situation is different, the diagnostic approach for both situations could be unified by using the same approach in the first scenario, and doing an union aggregation for the fault candidates in step 3. Case 1 and 2 in the multiple testing case are in this scenario. In case 1, fault 1 causes the violation of rule 9, rule 3 causes the violation of rule 9, may cause the violation of rule 8. The testing result shows that the violated rule by the combination is rule 9. In case 2, fault 1 causes violation of rule 9, fault 9 causes violation of rule 2, 3, 4 and 9. The combination causes violation of rule 2, 3, 4, and 9, which is the union of the rules violated by each individual fault.

In the third scenario, each individual fault causes the violation of multiple faults. This scenario is very similar to the second situation in the second scenario, therefore, the same diagnostic approach could be applied to this scenario. Case 3 in the multiple testing case falls in this scenario. In Case 3, fault 9 causes the violation of rule 3, 4, may cause the violation of rule 2 and 9, fault 11 causes the violation of rule 7, may cause the violation of rule 2, 3, 4, 8 and 9. The combination of these two causes the violation of rule 7, and may cause the violation of rule 2, 3, 4, 8 and 9.

In the fourth scenario, multiple faults cause the violation of the same rule. In this scenario, the approach used in the third scenario could be still be used.

There could be more combination options, but however different individual faults are combined, as long as there is no interaction between the faults, the three step approach used above could be applied. Therefore, with the assumption that individual fault does not interact with each other, the multiple fault scenarios could all be solved with the three step approach.

If the interaction strengthens the effect and causes the rules violated, as long as these faults are in the diagnostic table, they will be suggested as fault candidates. On the other hand, the interaction could weaken the effects, e.x., simultaneous sensor fault may hide the existence of coil fouling, in that case, the faults are beyond the detection sensitivity of this method.

5.5 *Fault Diagnostics*

5.5.1 Fault Diagnostics Approach

To extend the capability of rule based methods from fault detection to fault diagnostics, there are two possible routes. One is to map the violated rule to a list of faults, the other is simply mapping the violated rule to the component.

The former route enables the discovery of detailed faults, therefore provides more specific information about the causes. On the other hand, the latter route enables information fusion at the component level, which will be discussed in later chapters. By differentiating the faults/components that cause the violation of system behavior rules and that cause the violation of energy related rules, a more informative diagnostic result could be achieved. The fault diagnostic table is shown in Table 8. The faulty component diagnostic table is shown in Table 10.

The detailed diagnostic approach is the following. First, rules are separated into system behavior rules and energy related rules, second, from the rules that are violated, a set of faults or faulty components are fetched from the knowledge base, two groups of fault candidates are then derived. By comparing the components in these two groups, the faults that cause the violation of system behavior rules and the faults that cause the violation of energy related rules could be derived. This diagnostics process is illustrated in Fig 15. The dependency of the rules on sensor information is shown in Table 11.

Table 10: Rules and Detectable Components

Rule Index	Mode Cont	h/c coil/cont	MAB/cont	Coil Valve	DAT Sensor	Fan/Cont	Duct
Rule 1	*	*					
Rule 2			*	*	*	*	
Rule 3		*		*	*	*	
Rule 4	*	*		*	*	*	
Rule 5		*	*				
Rule 6		*	*				
Rule 7						*	*
Rule 8			*			*	*
Rule 9	*	*	*	*	*	*	*

Table 11: Required Sensor Information

Rule	Required Sensor
Rule 1	DAT, MAT
Rule 2	OAT, RAT, MAD
Rule 3	DAT, DAS, HCV
Rule 4	DAT, DAS
Rule 5	OAT, RAT, MAT
Rule 6	OAT, RAT, MAT
Rule 7	SSP, SSPS
Rule 8	P_f, P_{fref}
Rule 9	H_c, H_{cref}

The following example further illustrates the diagnostics process. Suppose the rule check results of a new set of operational data is [0 1 0 1 0 0 0 1 1], which means fault 2, 4, 8 and 9 are violated. Since rule 2, 4 are system behavior rules, the fault component

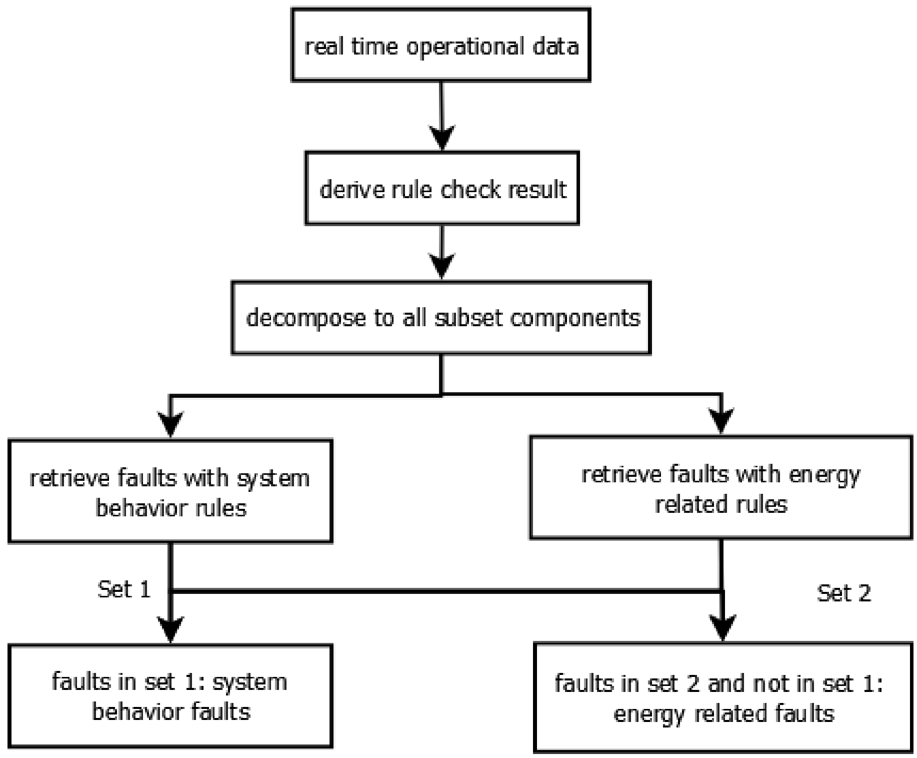

Figure 15: Rule Based Fault Diagnostics Process

candidates fetched are therefore in set 1, which include MAB, MAB controller, mode controller, coil controller, coil, coil valve, DAT sensor, fan and fan controller. Rule 8 and 9 are energy related rules. Since both are violated, the knowledge base suggests all components in the system are possible faulty. Therefore, the diagnostic result suggests that MAB, MAB controller, mode controller, coil controller, coil, coil valve, DAT sensor, fan and fan controller may have serious faults, duct may have incipient fault (leakage or cloggy).

5.5.2 Fault Diagnostics Testing

Applying the first diagnostic approach to the faulty simulation results, the diagnostic result is shown in table 12, in which the number is the index of the fault in the fault list shown in Table 7. Applying the second diagnostic approach to the faulty simulation results, the diagnostic result is shown in table 13. The results show that without energy related rules, 9 out of 15 faults can be detected, and the true fault is always included in the possible fault/faulty component candidate list.

Table 12: Fault Diagnostic Result

Seeding Fault Index	System Behavior Faults	Energy Faults
0	0	0
1	0	1-15
2	8-11,14	1-7,12,13,15
3	0	1-15
4	0	1-15
5	8-11,14	1-7,12,13,15
6	0	1-15
7	7-12,14	1-6,13,15
8	2,5,7-12,14	1,3,4,6,13,15
9	2,5,7-12,14	1,3,4,6,13,15
10	2,5,7-12,14	1,3,4,6,13,15
11	2,5,7-12,14	1,3,4,6,13,15
12	7-12	1-6, 13-15
13	0	2-5, 11-13
14	2-5,7-11,14	1,6,12,13,15
15	0	1-15

Table 13: Fault Diagnostic Result

Fault Index	Faulty Comp (Serious Fault)	Faulty Comp (Incipient Fault)
0	0	0
1	/	all comps
2	MAB/cont, valve, dat sensor, fan/cont	other comps
3	/	all comps
4	/	all comps
5	MAB/cont, valve, dat sensor, fan/cont	other comps
6	/	all comps
7	coil/cont, valve, dat sensor, fan/cont, mode cont	other comps
8	mab/cont, valve, dat sensor, fan/cont, mode cont, coil/cont	other comps
9	mab/cont, valve, dat sensor, fan/cont, mode cont, coil/cont	other comps
10	mab/cont, valve, dat sensor, fan/cont, mode cont, coil/cont	other comps
11	mab/cont, valve, dat sensor, fan/cont, mode cont, coil/cont, duct	other comps
12	mode cont, coil/cont, valve, dat sensor, fan/cont	other comps
13	/	fan/cont, duct
14	coil/cont, mab/cont, valve, dat sensor, fan/cont	other comps
15	/	all comps

5.6 Summary

In this chapter, the rule based FDD method for air handling units developed by NIST (APAR) is implemented and tested. Three additional rules are added to the existing APAR rules, which are related to the static pressure sensor, fan power consumption, and coil heat exchange rate.

Based on the rationale behind the rule, the rules could be separated into system behavior rules and energy related rules. It is found that faults that cause the violation of system behavior rules are either abrupt faults or serious incipient faults, and the faults that only cause violation of energy related rules are less severe incipient faults.

Fault diagnostic tables at both specific fault level and component level are derived. Given the rule check results, the possible faults or faulty components can be found by looking up in the diagnostic tables. Combining the fault candidates information with the type of rules that are violated (system behavior related or energy related), more detailed diagnostic information can be achieved.

In the testing case, two diagnostic tables for an air handling unit running in heating mode are derived through simulation experiments. while the first table relate nine rules with fifteen faults, the second table relates nine rules with the components. Testing shows that compared with the APAR method, the new rule based method is more sensitive to incipient faults. With the new method, the number of detectable faults increases from 9 to 15. All the newly detected faults are incipient faults.

The limitation of this method is that the energy consumption reference data is rarely known in practice. Without the energy consumption reference information, the fault detection ability is low (60% in the testing case), and the diagnostic information in many cases include too many candidates, therefore is not very helpful.

CHAPTER VI

RULE AUGMENTED CUSUM METHOD

6.1 Introduction

The CUSUM (Cumulative Sum) method is derived from the control chart based method, which is a popular tool in statistical process control to determine if the current process being monitored is still under control.

The earliest publication of statistical process control methods dated back to the 1930s [57], in which Shewhart chart (also called control based chart, or Xbar and R chart) was used. In this method the sample size is fixed (usually less than 10), the mean value and standard deviation value for all samples are plotted to show the current status . This type of chart is effective when the changes to a process are sharp and intermittent, because of the small sample size. To detect small shifts in the process, two other charts have been invented: the EMWA chart [45] and the CUSUM chart [9, 56].

The Exponentially Weighted Moving Average (EWMA) chart uses values from all previous samples, with a scaling factor that exponentially decreases the impact of old samples. It is suitable for situations with a fixed set point. The Cumulative Sum (CUSUM) chart accumulates the deviation of a monitored value from the set point of the control variable for all samples, and reports an alarm if the cumulated value exceeds a certain limit.

In HVAC system, the most common control variables are temperatures. Typically the HVAC system can maintain the controlled temperature (indoor air temperature, AHU discharge air temperature, etc.) well within a limited range. The extent to which the monitored control variable exceeds the control band depends on the controller and the sensor accuracy, the control error typically is small and continuous. The control set point varies depending on the operational schedule.

Comparing the three methods, the Shewhart chart is suitable for a sharp change case, the EWMA method is suited for the fixed set point case, and the CUSUM method is ideal for the small change and varying set point case. Considering the characteristics of the HVAC control variables, the CUSUM method is best suited, so it is chosen as the process monitoring method in this thesis.

The CUSUM (Cumulative Sum) chart is a general method in control engineering to monitor control variables. By accumulating the difference between a process variable and the expected value of this variable, it shows if the monitored process is still in or out of control. To calculate the accumulated error, first the process error has to be normalized.

$$z_i = \frac{x_i - \bar{x}}{\sigma} \tag{27}$$

where x_i is the process error at sampling time i, $\bar{x}$ is the estimate of the mean value of process error, σ is the estimate of the standard deviation of the process error.

Then the error is used to compute two cumulative sums

$$S_i = max(0, z_i - k + S_{i-1}) \tag{28}$$

$$N_i = max(0, z_i + k + T_{i-1}) \tag{29}$$

where S_i is the cumulative sum for positive errors at sampling time i, N_i is the cumulative sum for negative errors at sampling time i, k is the slack parameter. A process is then judged to be out of control if either $\mid S \mid$ or $\mid N \mid$ exceeds the threshold value.

6.2 Fault Diagnostic Extension

The traditional way to use CUSUM is limited to fault detection. If the cumulated error exceeds a certain limit, an alarm will be reported and sent to the technician.

Researchers in NIST have applied CUSUM in this fashion [56].

To extend the function of CUSUM method from fault detection to fault diagnostics, a network based approach is proposed in this thesis, which is explained below.

A causal network reflects (1) the causal relationship between all control variables in a system (2) the causal relationship between controlling components and control variables. The former is needed to update the fault counter, the latter is required to relate the control process to the controlling components.

To derive this network, the following steps could be followed: (1) identify the control variables in the system (2) identify the controlling components for each control variable (3) identify the dependency between control variables. An example network is shown in Fig 16.

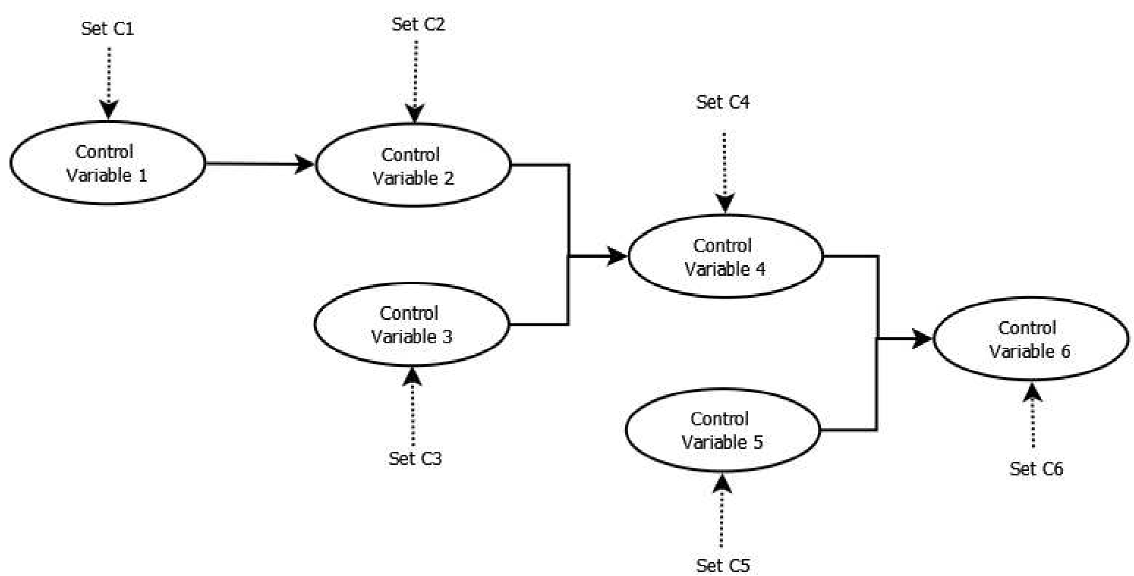

Figure 16: CUSUM Causal Network Example

To diagnose the problem in the system, a fault counter approach is proposed. In this approach, a fault counter is set for each component in the system, which is intended for indicating the extent of the 'faultiness' of the associated component. The value of the counter is updated by a updating algorithm. To explain the algorithm, a few terms are defined here: 'free control variable' refers to the control variable that is not affected by other control variables, 'non-free control variable' refers to the control variable that is affected by other control variables.

The following rules are used to update the fault counter:

- If a control variable is under control, the counters for its controlling components do no change.
- If a free control variable is out of control, the counters for its controlling components increase by one.
- If a non-free control variable is out of control, and its upstream control variable is under control, then the counters for the components that control it increase by one.
- If a non-free control variable is out of control, and its upstream control variable is also out of control, then both the components that control it and the components that control its upstream control variable increase by one.

6.3 Testing Case

In this section two cases were used to test the performance of the CUSUM method. The first case is an air handling unit working in heating mode, with the same configuration as described in section 5.3. The second case is a more complete secondary system, including an air handling unit and a VAV terminal unit.

6.3.1 Testing Case 1: AHU

6.3.1.1 Causal Network

In this testing case, there are three control variables: mixing air temperature, static pressure and discharge air temperature. Among them, mixing air temperature and static pressure are free variables, while discharge air temperature is a non-free variable. The causal network is illustrated in Fig 17.

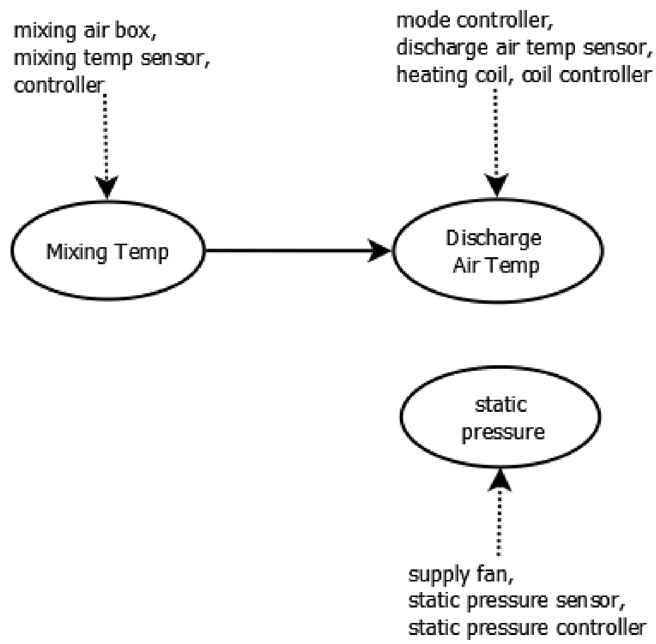

Figure 17: CUSUM Causal Network for Testing Case 1

Using the information from Fig 17, the mapping of counter to dependent component is shown in table 14.

Table 14: Relation of Counter to Faults

Counter	Component
MAT	MAB/controller, mode controller, MAT Sensor
DAT	Coil/controller, valve, mode controller, DAT Sensor
SSP	Supply Fan, Duct, SSP sensor

6.3.1.2 Normal State

The CUSUM method requires setting a threshold, which determines the method sensitivity. As a prerequisite, at normal state the CUSUM fault counter value should be close to 0. Balancing this prerequisite with the method sensitivity, the threshold values are determined, as shown in table 15.

Table 15: Testing Case 1 Threshold Values

Threshold Variable	Value
MAT Mean Error	1.5
MAT Standard Error	0.5
MAT Slack	1.0
DAT Mean Error	0.5
DAT Standard Error	0.1
DAT Slack	0.1
SSP Mean Error	0.1
SSP Standard Error	0.05
SSP Slack	0.1

6.3.1.3 Single Fault Case

In single fault case, each of the 15 faults listed in table 7 is seeded into the simulation and tested. For each case, the simulation results are listed in table 16.

Among all fifteen cases, seven cases (fault 1, 2, 7, 8, 9, 10, 11) are detected. In case 1 and 2, the faults exist in mixing air box, which controls the mixing air temperature, so MAT counter has the largest value. In fault 7, the fault exists in heating coil, which controls the discharge air temperature, so the DAT counter has a large value. In this case, the MAT counter is affected as well, due to the low return air temperature from the zone. In fault 8, 9 and 10, the fault exists in the heating coil valve, which controls the discharge air temperature, therefore, the DAT counter has the largest value. In fault 11, the fault exists in supply fan, which controls the duct static pressure, so the SSP counter has a large value. The MAT counter also has a large value due to the uncontrolled zone air temperature.

Using the diagnostic table shown in Table 14, the diagnostic results are derived and given in Table 17. The results show that out of the fifteen faults, seven are detected. In fault 1,2,8,9,10, the faulty component only causes the directly controlled variable to fall out of the control band, however, in fault 7 and 11, not only the directly controlled variable, but also indirectly controlled variables are affected by

Table 16: Testing Case 1 Results

MAT Counter	DAT Counter	SSP Counter	Case
3	0	0	0
119	0	0	1 ($l = 0.1$)
119	0	0	2($y = 0.5$)
5	0	0	3($\tau = 15min$)
1	2	0	4 ($l = 0.1$)
2	0	0	5 ($y = 0.2$)
5	2	0	6 ($\tau = 15min$)
237	119	0	7 ($UA = 2000W/K$)
3	118	0	8 ($l = 0.1$)
4	119	0	9 ($y = 0.1$)
3	119	0	10($\tau = 15min$)
120	1	120	11 ($N = 2/s$)
5	2	0	12 ($\eta = 0.1$)
6	2	0	13 ($\Delta P = 50Pa$)
3	3	0	14($\Delta T = -2°C$)
3	3	0	15($k = 0.01$)

the faulty component.

The result suggests that CUSUM method is able to detect both abrupt faults and incipient faults. Seven out of fifteen faults are detected in this case. The diagnostic accuracy is not high since in most cases the control variables are affected by more than one component.

6.3.2 Testing Case 2: AHU and VAV Unit

In this testing case, supply air from the AHU is distributed to a VAV unit, which is controlled by a VAV controller with zone temperature setpoint of $21°C$. The system configuration is shown in Fig 18. The simulation model in Dymola is shown in Fig 19. In this testing case, there are four control variables, mixing air temperature (MAT), discharge air temperature (DAT), zone air temperature (ZAT) and static pressure (SSP). The causal network is shown in Fig 20.

The following faults are simulated in the testing case: MAB damper stuck, heating coil fouling, supply fan out of control, DAT sensor drift and VAV damper stuck. The

Table 17: Low Information Availability, Deterministic

Fault	Detected	Diagnosed	Number of Candidates
MAB OAD Leakage	yes	yes	3
MAB OAD Stuck	yes	yes	3
MAB OAD sticking	no	no	0
MAB EAD Leakage	no	no	0
MAB EAD Stuck	no	no	0
MAB EAD Sticking	no	no	0
Coil Fouling	yes	yes	7
Coil Valve Leakage	yes	yes	4
Coil Valve Stuck	yes	yes	4
Coil Valve Sticking	yes	yes	4
Fan Out of Control	yes	yes	6
Fan Low Efficiency	no	no	0
Duct cloggy	no	no	0
DAT Sensor Drift	no	no	0
Sluggish coil controller	no	no	0

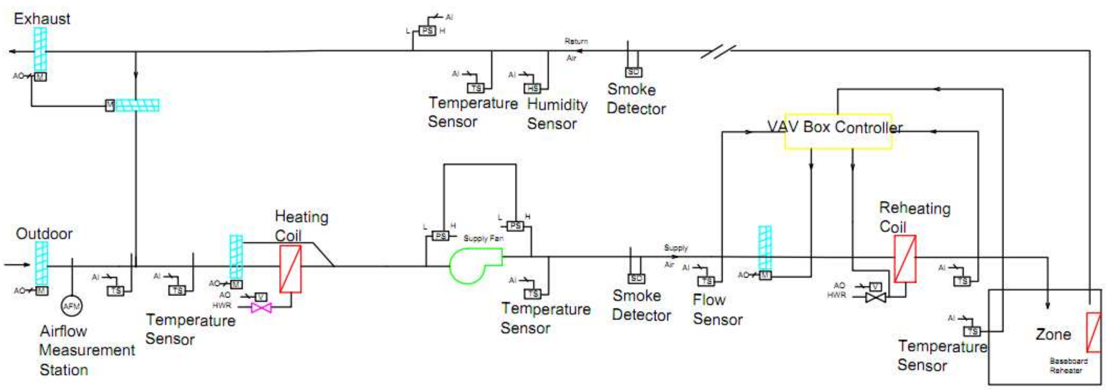

Figure 18: Testing Case 2 System Configuration

Table 18: Testing Case 2 Fault

Fault	Label
No fault	0
MAB damper stuck (90%)	1
Heating Coil Fouling ($\frac{UA_{nv}}{UA_{ov}} = \frac{1}{6}$)	2
Supply fan Out of Control ($N = 5$ /s)	3
Supply Temperature Sensor Drift ($\Delta T = 1^{\circ}$)	4
VAV damper stuck (10%)	5

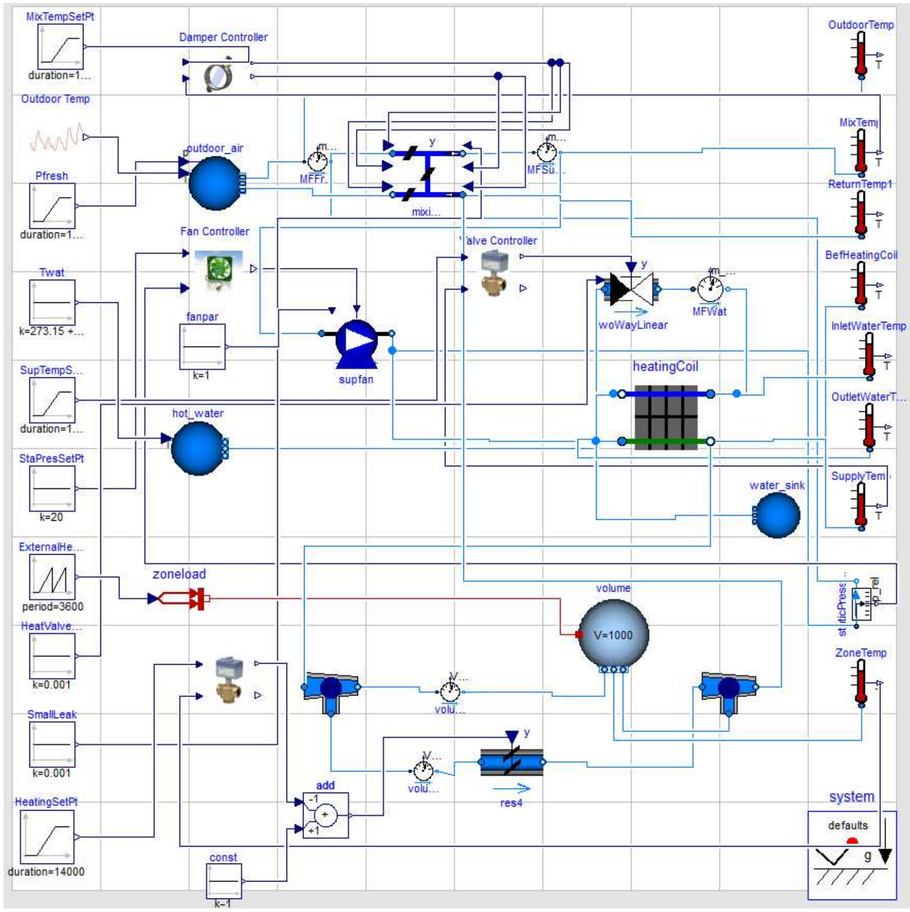

Figure 19: AHU plus VAV simulation model in Dymola

Table 19: Testing Case 2 Results

MAT Counter	ZAT Counter	DAT Counter	SSP Counter	Case
6	0	1	0	0
121	121	2	0	1
16	127	237	0	2
9	126	4	237	3
11	127	4	0	4
9	127	2	0	5

fault name, fault extent and numerical label are shown in Table 18. The simulation results in each case are shown in table 19. Based on the simulation results, the diagnostic result is shown in Table 20.

The result of this testing case shows that with an appropriate threshold setting,

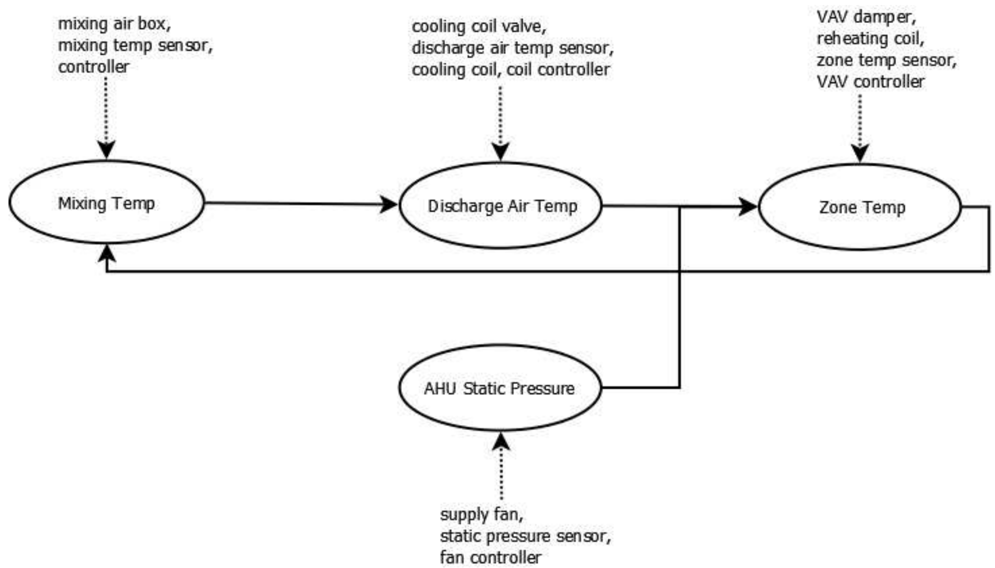

Figure 20: CUSUM Causal Network for Testing Case 2

Table 20: Testing Case 2 Diagnostic Output

True fault	Diagnosed Fault
0	0
1	MAB/cont, mix sensor, vav damper/cont, reheat coil, zat sensor
2	valve, dat sensor, coil/cont, vav damper/cont, zat sensor
3	ssp sensor, fan/cont, vav damper/cont, zat sensor, reheat coil
4	vav damper/cont, zat sensor, reheat coil
5	vav damper/cont, zat sensor, reheat coil

the CUSUM method is able to detect the abrupt faults and some of the incipient faults. In all cases but case 4, the true faulty component is included in the fault candidates. It is also found that the ratio of specific component counter value to the total sum could be a useful measure of the fault likelihood.

6.4 Summary

In this chapter, a rule augmented CUSUM method is developed for fault detection and diagnostic purposes, which combines the CUSUM method with a simple rule based method.

This approach has three elements: a fault counter, a causal network and a fault count mechanism. The causal network is derived from the causal relationship between the control variables and the causal relationship between components and control variables. The count mechanism is different for components that control free variable and that control non free variable. Based on the information in the network, when a counter for a control variable increases, the counters for relevant components also increase, whose values are then used for fault diagnostic purpose.

The testing of this method in two cases shows that: (1) The more variables that are controlled, the more accurate the CUSUM method is at diagnosing the faults. (2) In all testing cases, abrupt faults are easier to detect by this approach than incipient faults. (3)In all but one testing case, if a fault is detected, the true fault is successfully diagnosed and included in the fault candidates.

CHAPTER VII

MODEL BASED METHOD

7.1 Introduction

Model based fault detection for AHUs has been an active research area for almost thirty years. There have been enormous models created for various components in AHU [14, 54, 23, 10, 25, 24]. These models have been continuously refined, validated and improved. Some of these models are based on empirical evidence, as those used in DOE2 and EnergyPlus. Some of these models use a set of equations and employ a numeric solver to get the solution, such as the simulation model used in Simulation Problem Analysis and Research Kernel (SPARK) and Modelica.

In this chapter, the physical models for major components in AHUs used in this thesis are introduced sequentially. For the purpose of fault detection and diagnostics, a deterministic innovation based approach is introduced, which is tested in the same testing cases shown in previous chapters.

7.2 Model Description

7.2.1 Damper

The damper model used in this thesis follows the exponential damper model specified in [23].

$$\Delta p = K_\theta \frac{\rho v^2}{2} \tag{30}$$

$$\ln K_\theta = a + b\theta \tag{31}$$

$$K_0 = 2\rho A_f^2 R_0 \tag{32}$$

$$K_{90} = f_l^{-2} 2\rho A_f^2 R_0 \tag{33}$$

where Δp is the pressure drop, ρ is the density, v is mean velocity, A_f refers to the face area of the damper, K_θ is the loss coefficient, θ is the angle between blade and direction of flow, a and b are constant parameters depending on the blade geometry. The above equations only hold for θ in a limited range; for regions outside this range, a quadratic interpolation function is used to fit the data at two ends. To calculate K_0 and K_{90}, other parameters like the open resistance R_0, the face area A_f , and the leakage f_l are needed as well. Typical values of K_0 are 0.2-0.5.

To use the damper model, a user needs to know the damper face area A_f, nominal mass flow rate $\dot{m}_n$, nominal face velocity v_n, and nominal pressure drop Δp_n. For a damper with nominal face area 1 m^2, nominal mass flow rate 1 kg/s, nominal pressure drop 20 Pa, the mass flow rate - damper position curve is shown in Fig 21. A linear curve is also shown in Fig 21 for reference purpose.

7.2.2 Mixing Air Box

7.2.2.1 Single Control Signal

A mixing air box (also called an economizer) mixes fresh air with return air, to reuse the heat of return air before it is exhausted. A typical mixing air box has three dampers: a fresh air damper, a return air damper and an exhaust air damper. These dampers are controlled for two purposes: reuse the return air heat, and maintain the air pressure inside the building (as shown in Fig 22).

The model for a mixing air box can be differentiated by the level of detail. In the coarse level, the inputs are damper control position, fresh air enthalpy, return air enthalpy and mixing air enthalpy. Due to the reason mixing air enthalpy is

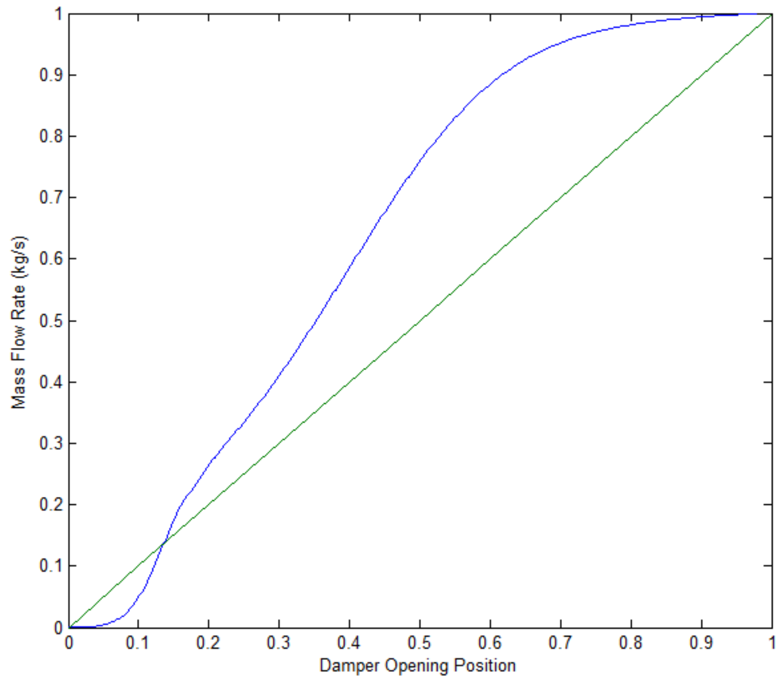

Figure 21: Damper Performance

typically not available, the enthalpy is often replaced by the temperature. Therefore, the required inputs are damper control position, fresh air temperature, return air temperature and mixing air temperature. In finer level, the required inputs include physical parameters for all three dampers, the damper control signal, the air flow rate through each damper, and static pressure before and after each damper.

The outdoor air fraction can be calculated by the outdoor air temperature, return air temperature and mixing air temperature.

$$OAF = \frac{T_{ret} - T_{mix}}{T_{ret} - T_{out}} \tag{34}$$

Ideally, there should be a linear relationship between mixing air box control signal and OAF, as shown in Fig 23 left. However, due to problems such as hysteresis, leakage, etc., the relation between these two variables in reality deviate from the linear relation, as shown in Fig 23 right.

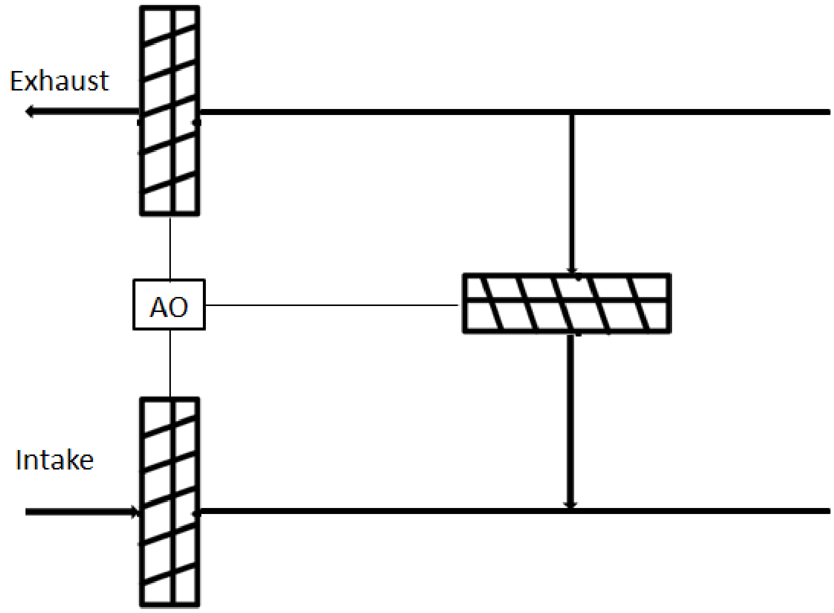

Figure 22: Mixing Air Box

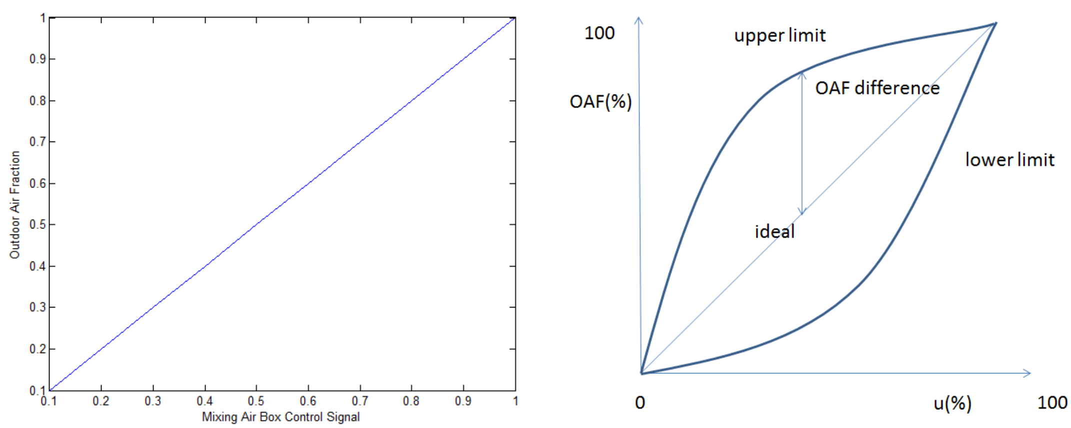

Figure 23: Mixing Air Box Control Signal and OAF (left: ideal right: reality[24])

To detect the faults, it is proposed to use the difference between actual OAF and reference OAF as the fault indicator. In practice, it is possible to set up a table that links the MAD signal with OAF value during the commissioning stage. Then during operation, by looking up in the reference table, comparing the actual OAF value with reference value, the difference - innovation of OAF - can be calculated.

As an example, the characteristic of the mixing air box model used in the simulation is shown in table 21.

Table 21: Mixing Air Box Characteristics

Attribute	Value
Outdoor Air Damper Face Area (m^2)	0.001
Outdoor Air Damper Nominal Mass Flow Rate (kg/s)	1
Outdoor Air Damper Nominal Pressure Drop (Pa)	20
Return Air Damper Face Area (m^2)	0.001
Return Air Damper Nominal Mass Flow Rate (kg/s)	1
Return Air Damper Nominal Pressure Drop (Pa)	20
Exhaust Air Damper Face Area (m^2)	0.001
Exhaust Air Damper Nominal Mass Flow Rate (kg/s)	1
Exhaust Air Damper Nominal Pressure Drop (Pa)	20

It is realized that pressure changes in the duct can also result in a change in OAF, even if the mixing air box is the same. To test how pressure change affects OAF, the following test is conducted. The outdoor air pressure is 1bar, in case 1, the supply air pressure is 1bar-15Pa, return air pressure is 1bar+15Pa, in case 2, the supply air pressure is 1bar-5Pa, return air pressure is 1bar+25Pa, in case 3, the supply air pressure is 1bar-25Pa, return air pressure is 1bar+5Pa. The MAD-OAF relation in these three cases are shown in Fig 24. It shows that although the supply air pressure and return air pressure may vary, the OAF value difference in all cases are within 25%. Therefore, if the OAF innovation is extraordinarily large (larger than 30%), faults might exist in the mixing air box.

For the mixing air box used in the simulation, the MAD - OAF relation performance data in the simulation is stored in Table 22.

7.2.2.2 Dual Control Signal

In this type of mixing air box, the outdoor air damper is controlled by an OAD control signal, the exhaust and return air dampers are controlled by a MAD control signal, as illustrated in Fig 25.

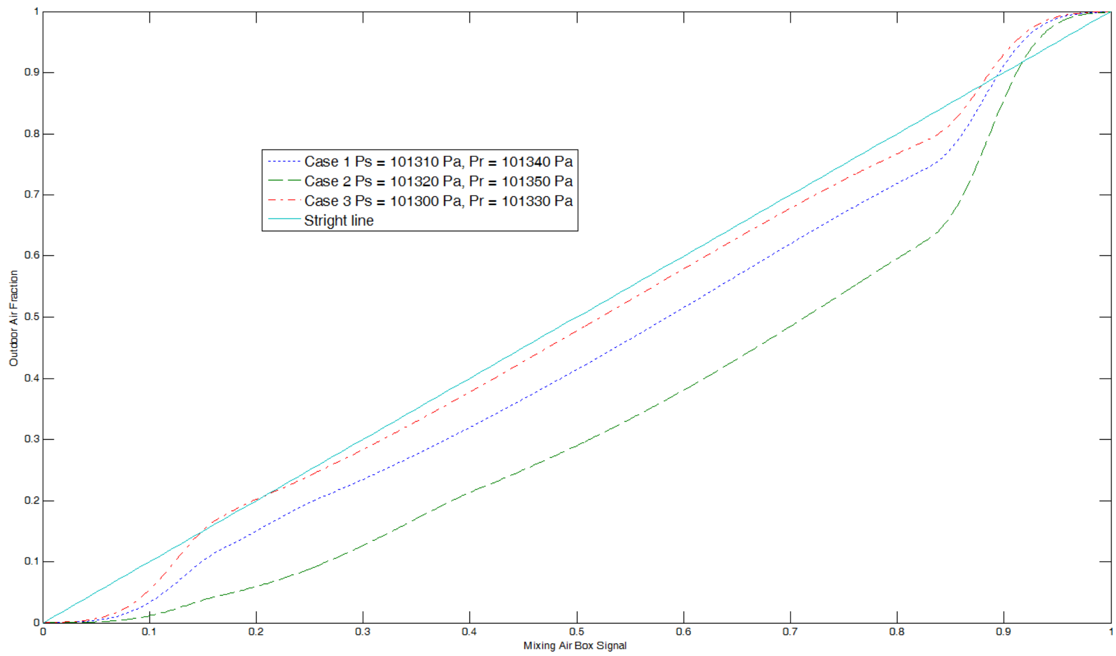

Figure 24: Effect of Pressure Change on OAF

Table 22: Single Damper Signal Mixing Air Box

Damper Signal	Outdoor Air Fraction
0.01	0.01
0.1	0.0290
0.2	0.1370
0.3	0.2329
0.4	0.3197
0.5	0.4133
0.6	0.5156
0.7	0.6190
0.8	0.7194
0.9	0.8920
1	0.9993

For a mixing air box with the same characteristics as shown above, the outdoor air damper position - outdoor air fraction relation when mixing air damper position is 10%, 30%, 50% and 70% is shown in Fig 26.

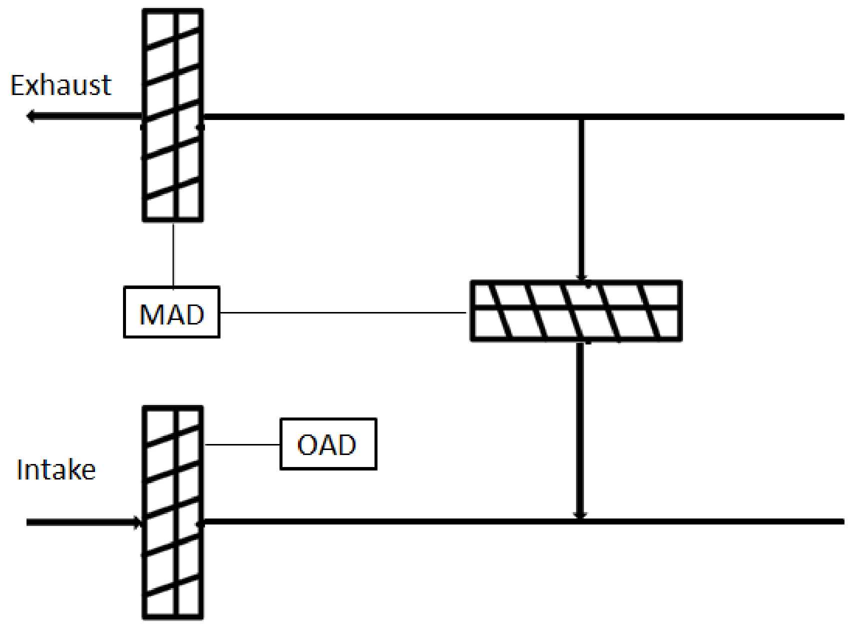

Figure 25: Dual Damper Signal Mixing Air Box in Simulation Model

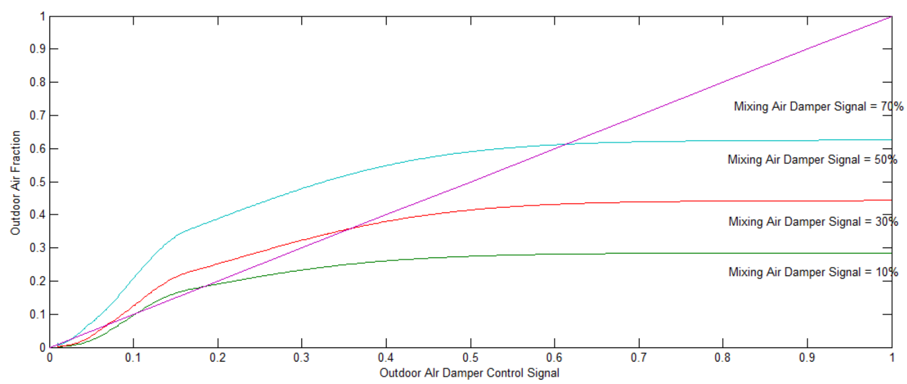

Figure 26: Dual Damper Signal Mixing Air Box Performance Curve

7.2.3 Duct

The author of [23] described the model for flow resistance, which is a square law relationship at high flow rates and linear relationship at low flow rates:

$$\Delta p = R_T w\,|w|\,(|w| > w_c) \tag{35}$$

$$\Delta p = R_L w(|w| \leq w_c) \tag{36}$$

$$R_L = R_T w_c \tag{37}$$

where w is mass flow rate(kg/s), R_T is a user specified value.

To use the duct model, the user needs to specify the nominal mass flow rate and nominal pressure drop. For a duct with nominal mass flow rate as 5 kg/s, nominal pressure drop 10 Pa, the actual pressure drop - square of the actual mass flow rate is shown in Fig 27. For this specific case, $R_T = 0.4(Pa * s/kg)$.

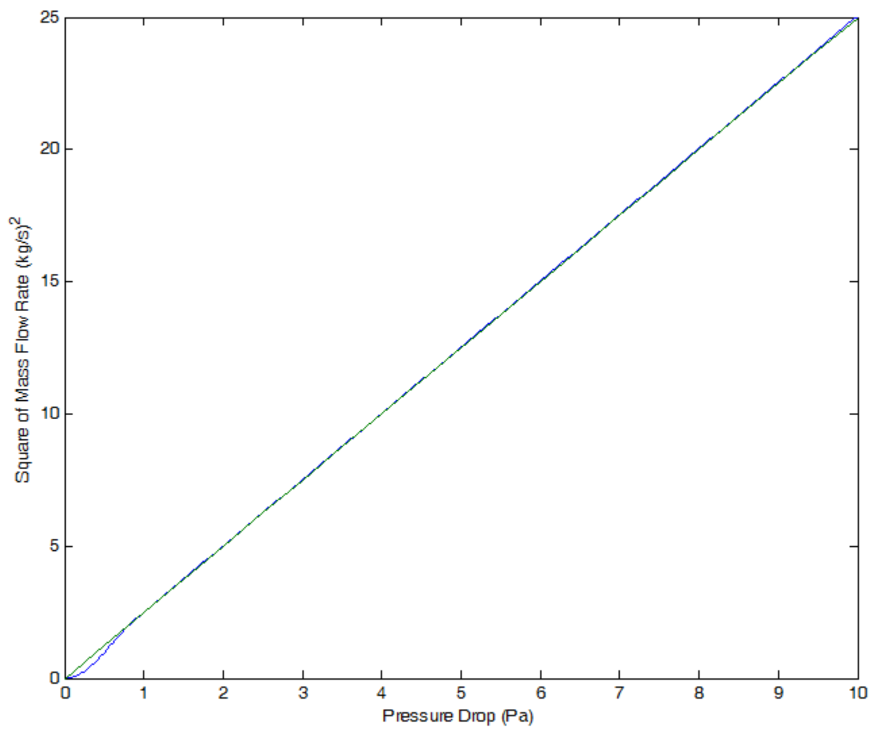

Figure 27: Duct Performance Curve

7.2.4 Valve

Dividing the valves based on the number of outlets, there are two types of valves: two way valve and three way valve. The three way valve can be seen as a combination of two two way valves. On the other hand, valves can be distinguished based on their characteristic performance curve, there are linear valves, equal percentage valves and quick opening valves. In the following, valve models are introduced.

7.2.4.1 Two Way Valve

In valve model, y is the valve opening, l is defined as the valve leakage, ϕ is defined as the ratio of actual flow rate to the nominal flow rate when the valve is fully open.

For linear valve, the following model is used

$$\phi = l + y * (1 - l) \tag{38}$$

To use this model, user needs to specify values for leakage parameter l, nominal mass flow rate $\dot{m}_n$ and nominal pressure drop ΔP. For a linear valve with $l = 0.001$, $\dot{m}_n = 8kg/s$, $\Delta P = 1000Pa$, the valve opening - mass flow rate relation is shown in Fig 28. In this case, since leakage is small, ϕ is almost equal to y.

For equal percentage valve, two additional parameters: rangeability parameter R and deviation parameter δ are needed. The model is shown below:

$$\phi = l + \frac{y(R^{\delta-1} - l)}{\delta} \; (y < 0.5\delta) \tag{39}$$

$$\phi = R^{y-1} \; (y > 1.5\delta) \tag{40}$$

For y between 0.5 δ and 1.5 δ, a cubic spline curve is used to fit the data. To use this model, the user needs to specify the rangeability R, leakage l, nominal mass flow rate $\dot{m}_n$ and nominal pressure drop ΔP. For an equal percentage valve with $l = 0.001$, $R = 10$, $\delta = 0.01$,$\dot{m}_n = 8kg/s$, $\Delta P = 1000Pa$, the valve opening - mass flow rate relation is shown in Fig 29.

For quick opening valve, an additional characteristic parameter α is needed. The model is shown below:

$$\phi = l + y^{\frac{1}{\alpha}}(1 - l) \tag{41}$$

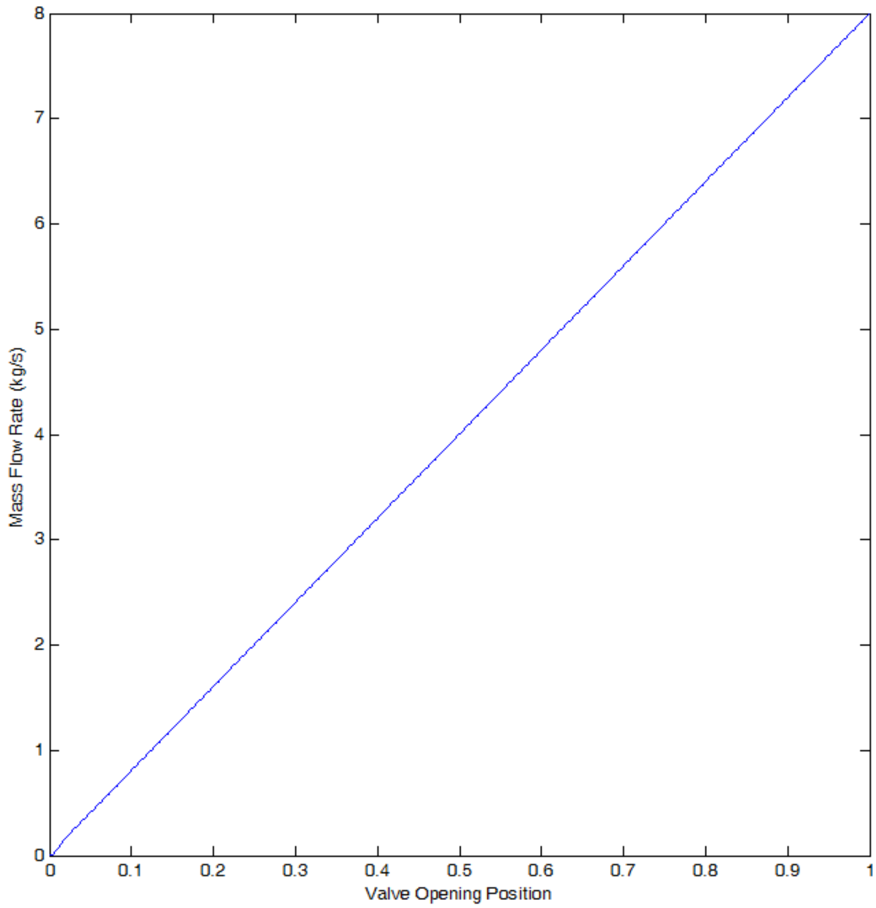

Figure 28: Two Way Linear Valve Performance Curve

To use this model, the user needs to specify the characteristic parameter α, leakage parameter l, nominal mass flow rate $\dot{m}_n$ and nominal pressure drop ΔP. For a quick opening valve with $l = 0.001$, $\alpha = 2$,$\dot{m}_n = 8kg/s$, $\Delta P = 1000Pa$, the valve opening - mass flow rate relation is shown in Fig 30.

7.2.4.2 Three Way Valve

A three way valve is composed of two two way valves. A typical configuration for a three way valve is shown in Fig 31. Since there are three types of characteristics for two way valves, there are nine types of characteristics for a three way valve.

Depending on the type of two way valves, the required information input for three

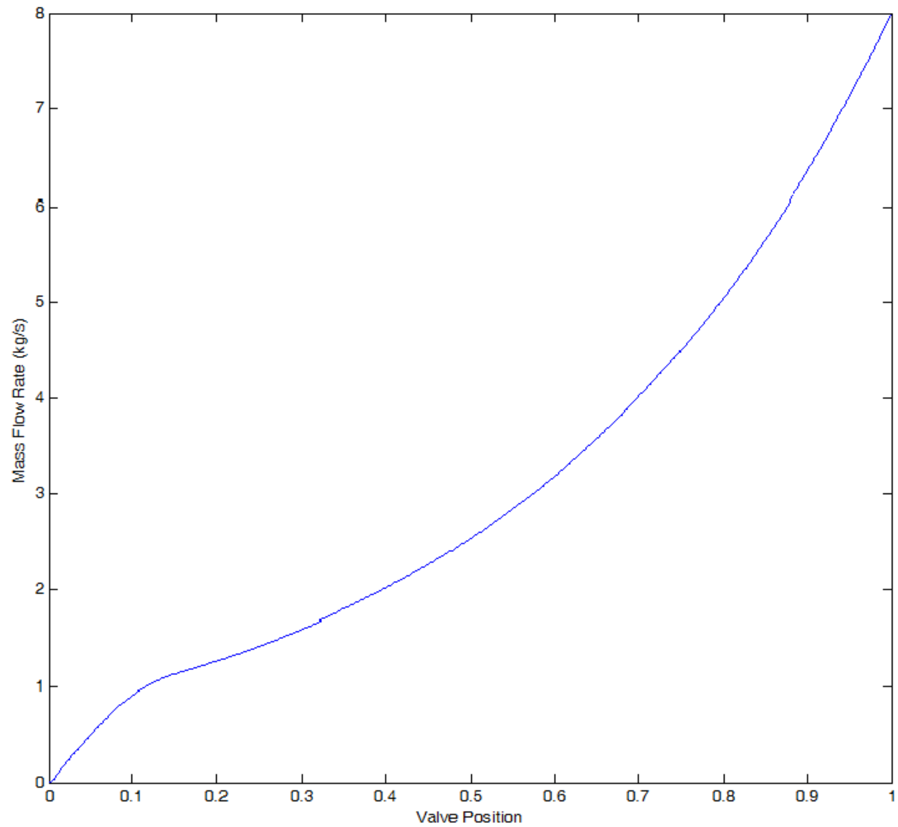

Figure 29: Two Way Equal Percentage Valve Performance Curve

way valve varies. For a three way linear valve, which includes two linear two way valves, user needs to specify two leakage parameter l, two nominal mass flow rate $\dot{m}$ and two nominal pressure drop ΔP. As an example, for a three way linear valve with $l_1 = l_2 = 0.001$, $\dot{m}_{n1} = \dot{m}_{n2} = 8kg/s$, $\Delta P_1 = \Delta P_2 = 1000Pa$, the mass flow rate through outlet 1 and outlet 2 could be seen in the following Fig 32.

7.2.5 Fan

The model for fan used in the simulation is described below:

$$\Phi = \frac{m}{\rho N d^3} \tag{42}$$

$$\Psi = \frac{\Delta P}{\rho N^2 d^2} \tag{43}$$

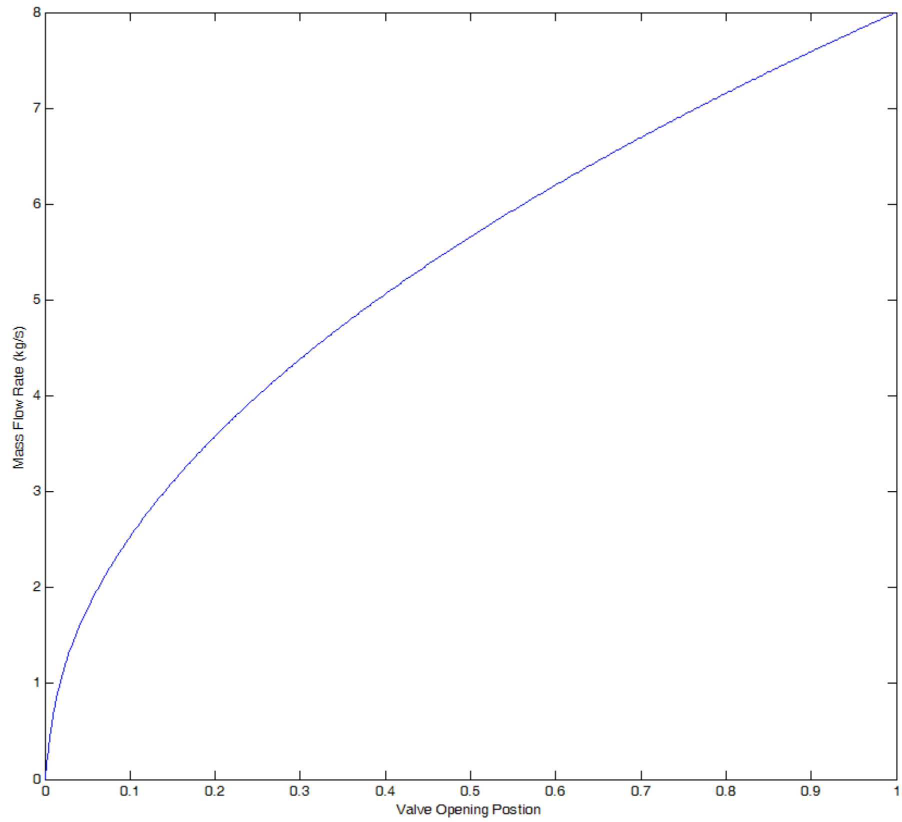

Figure 30: Two Way Quick Opening Valve Performance Curve

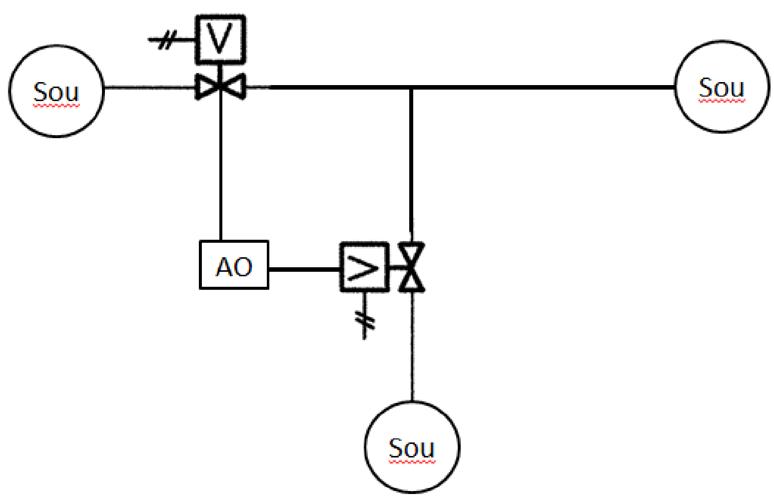

Figure 31: Three Way Valve Configuration

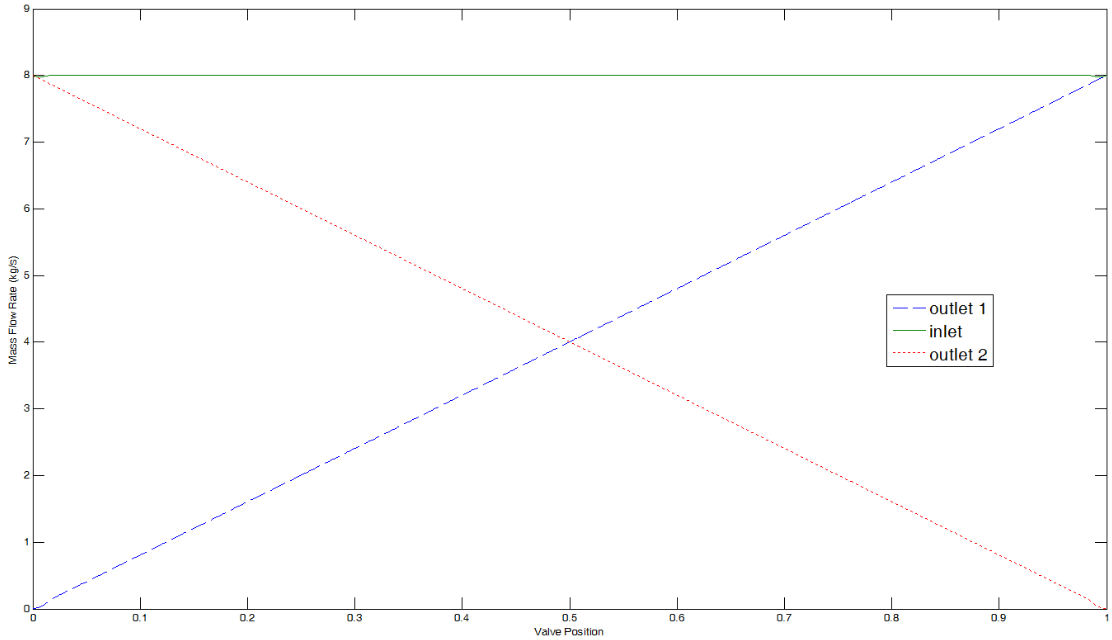

Figure 32: Three Way Valve Performance Curve

$$\eta_s = \frac{m\Delta P}{\rho W_s} \tag{44}$$

$$\Psi = a_0 + a_1\Phi + a_2\Phi^2 + a_3\Phi^3 + a_4\Phi^4 \tag{45}$$

$$\eta_s = b_0 + b_1\Phi + b_2\Phi^2 + b_3\Phi^3 + b_4\Phi^4 \tag{46}$$

$$W_t = \frac{W_s}{\eta_{mot}} \tag{47}$$

where m is mass flow rate, Φ is the dimensionless flow coefficient, Ψ is the dimensionless pressure head coefficient, η_s is the fan or pump shaft efficiency, W_s is the shaft power consumption, η_{mot} is the motor efficiency, W_t is the total power consumption, N is the fan rotation speed.

To use this model, the user needs to specify the fan diameter D and two sets of coefficients **a** and **b**, **a** for pressure head calculation and **b** for power consumption calculation.

The performance curves are derived for a fan with diameter $D = 0.6858m$, $\mathbf{a}$ = [22,-1.387,4.2293,-3.92920,0.8534], and $\mathbf{b}$=[0.1162,1.5404,-1.4825,0.7664,-0.1971]. When the fan head is fixed to 20 Pa, fan speed increase from $1/s$ to $20/s$, the mass flow rate and fan power consumption is shown in Fig 33. When the fan speed is fixed at $5/s$, pressure head changes from $320Pa$ to $120Pa$, the mass flow rate and power consumption is shown in Fig 34. Fig 35 shows the mass flow rate - pressure relation given different rotation speed. Fig 36 shows the mass flow rate - power consumption relation given different rotation speed.

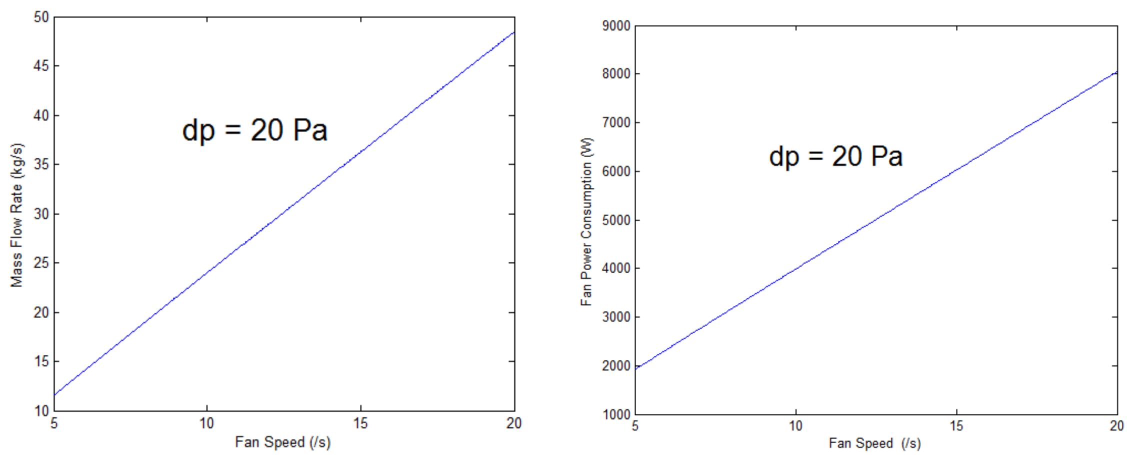

Figure 33: Fan Curve when Pressure Drop is Fixed (left: Mass Flow Rate versus Fan Speed right: Power Consumption versus Fan Speed)

7.2.6 Coil

The coil model used in the simulation is developed in the Building library [67]. It is a discretized coil consisting of multiple heat exchange elements. The configuration of the coil is assumed to be cross. These small heat exchange elements are the pipe segments along the pipes. At each heat exchange element, the driving force for the heat transfer is the temperature difference between fluid and solid. The equation for air side heat exchange rate is in equation 48, the equation for water side heat exchange

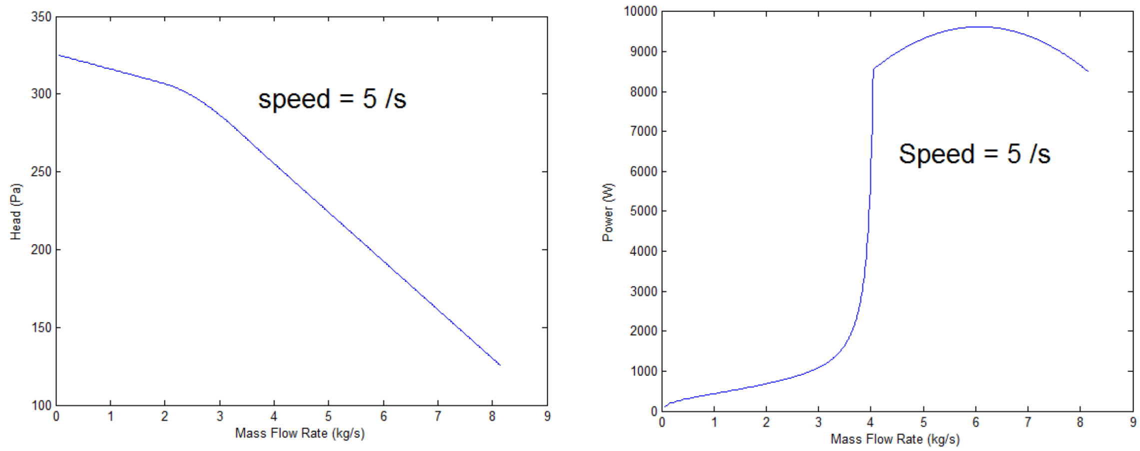

Figure 34: Fan Curve when Fan Speed is Fixed (left: Mass Flow Rate versus Head right: Power Consumption versus Head)

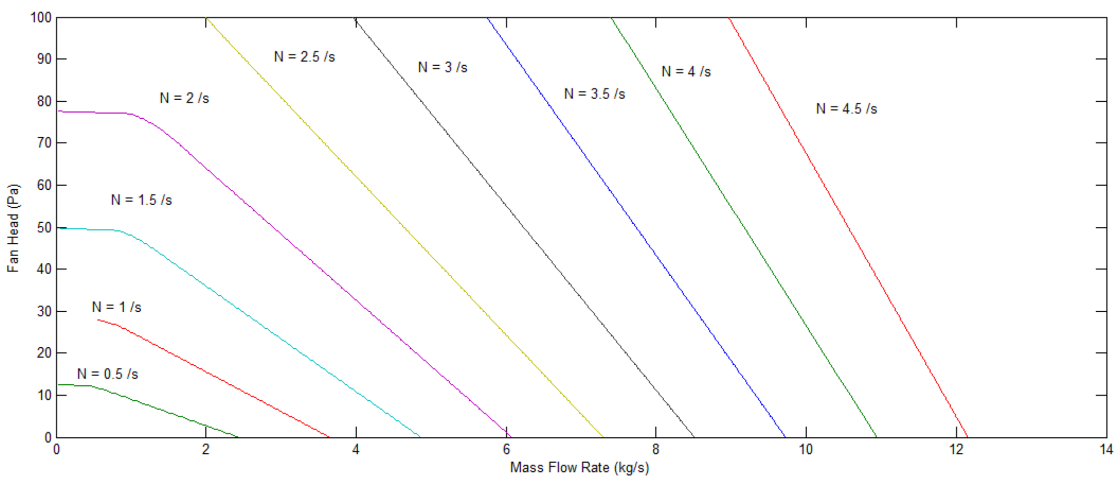

Figure 35: Fan Head - Mass Flow Rate Under Different Speed

rate is in equation 49, the equation for coil heat exchange rate is in equation 50.

$$\frac{dH_a}{dt} = hA_a(T_a - T_m) \tag{48}$$

$$C_w \frac{dT_w}{dt} = hA_w(T_w - T_m) \tag{49}$$

$$C_m \frac{dT_m}{dt} = hA_a(T_a - T_m) + hA_w(T_w - T_m) \tag{50}$$

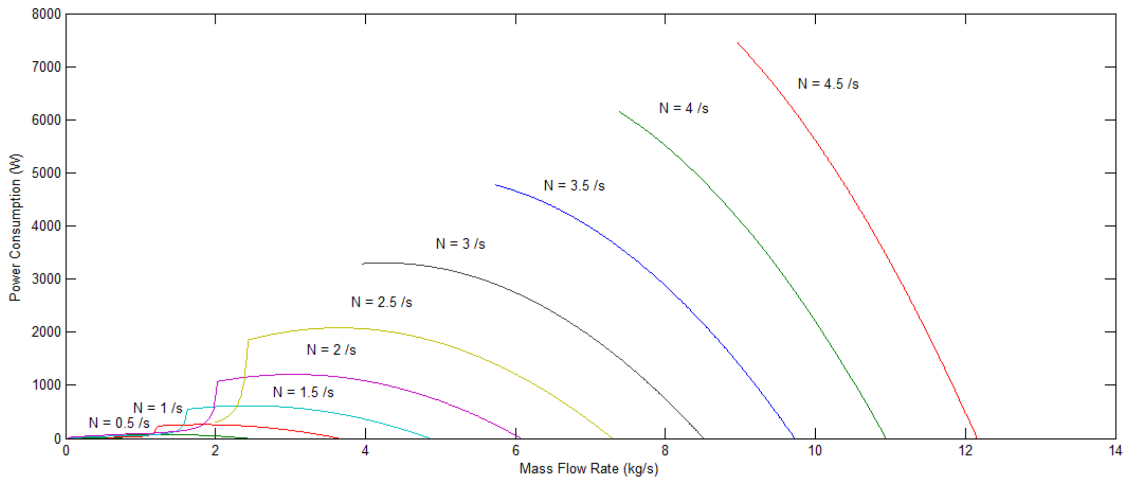

Figure 36: Power Consumption - Mass Flow Rate Under Different Speed

Here H_a is the air flow enthalpy, hA_a is the heat exchange rate coefficient on air side, T_a is the air flow temperature, T_m is the metal temperature, hA_w is the heat exchange rate coefficient on water side, T_w is the water flow temperature, C_w is the heat capacity of water, C_m is the heat capacity of metal.

To use the coil model, the user needs to provide the a set of configuration values, which are listed in table 23.

Table 23: Coil Input Information

Variable	physical meaning	Unit	Ex(heat)	Ex(cool)
m_{wn}	nominal mass flow rate of water	kg/s	5	5
dp_{an}	nominal pressure drop of air	Pa	200	200
dp_{wn}	nominal pressure drop of water	Pa	5000	5000
UA_n	nominal metal thermal conductance	W/K	32000	32000
T_{ai}	nominal inlet air temperature	$°C$	5	30
T_{ao}	nominal outlet air temperature	$°C$	20	10
T_{wi}	nominal inlet water temperature	$°C$	60	5
T_{wo}	nominal outlet water temperature	$°C$	40	10
dh_a	hydraulic diameter for duct	m	1	1
dh_w	hydraulic diameter for pipe	m	0.025	0.025
$nReg$	number of registers	/	2	2
$nPipPar$	number of parallel pipes in each register	/	1	1
$nPipSeg$	number of pipe segments per register	/	3	3

To characterize the coil performance, two variables are used: the overall conductance UA and the effectiveness ϵ. The calculation of UA is shown in equation 51, the calculation of ϵ is shown in equation 52

$$\frac{1}{UA} = \frac{1}{hA_a} + \frac{1}{hA_w} \tag{51}$$

$$\epsilon = \frac{T_{ao} - T_{ai}}{T_{wi} - T_{ai}} \tag{52}$$

Here, T_{wi} is the hot fluid (water) inlet temperature, T_{ai} is the cool fluid (air) inlet temperature.

For the heating coil and cooling coil example in table 23, the UA - ϵ curve is shown in Fig 37. Given $UA = 32000$, ϵ depends on $\dot{m}_a$, $\dot{m}_w$, which could be combined into one variable C_r, which is described in equation 53. To derive the $C_r - \epsilon$ relation for each C_{min}, a two order polynomial approximation is used.

$$C_r = \frac{C_{min}}{C_{max}} \tag{53}$$

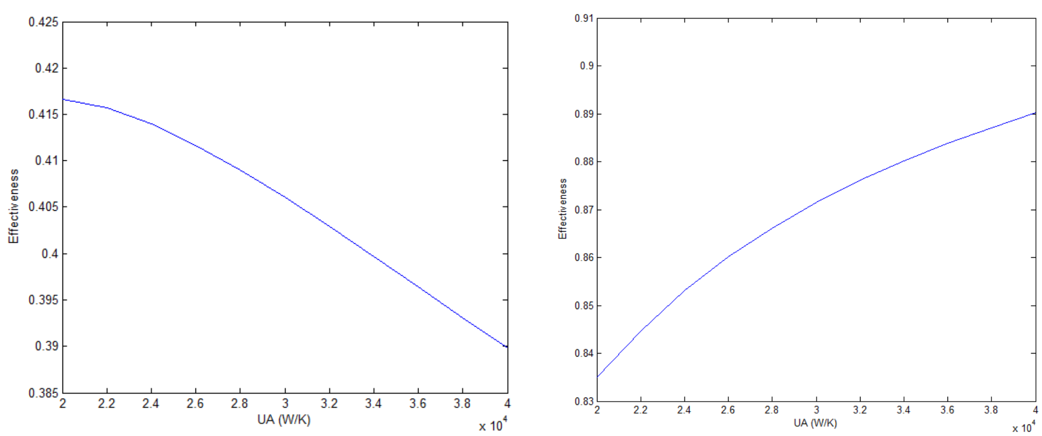

Figure 37: Coil Performance Curve (left: heating coil right: cooling coil)

For the heating coil example, the C_r - ϵ relation for different C_{min} is shown in Fig 38.

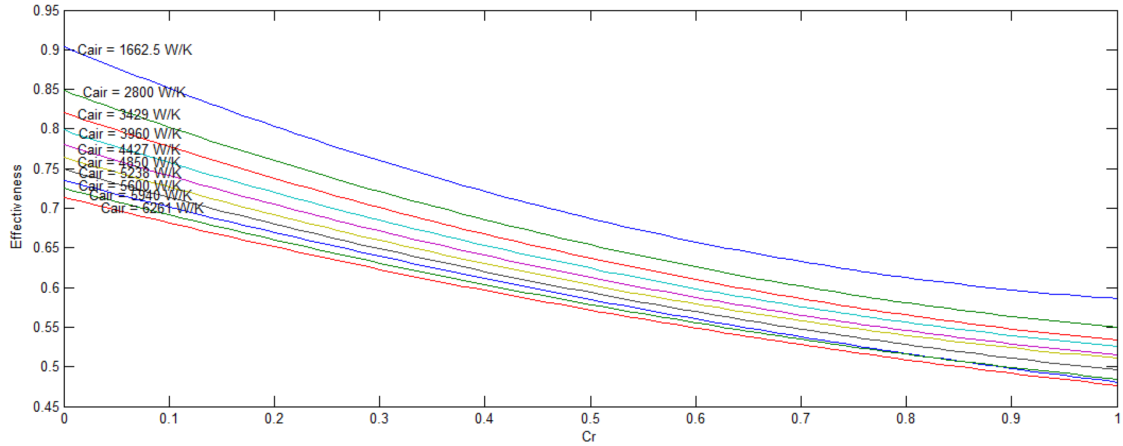

Figure 38: Heating Coil Cr - Effectiveness Relation

7.3 Fault Detection and Diagnostics Method

In this section, the deterministic fault detection and diagnostics approach for model based method is proposed.

7.3.1 Fault Detection

To detect if a fault exists in a component, a p-value approach is used. Given the hypothesis that the component is functioning correctly, monitored data that yields a p-value equal to 0.05 suggests a 95% chance it is malfunctioning. This is illustrated in Fig 39.

7.3.2 Overall Process

For each component, the overall FDD process is shown in Fig 40. In this approach, there are four steps to get the final result. In step 1, user sets up a reference model for the component based on the configuration document. In step 2, based on the real time monitored data, the reference model provides reference value for the performance variable. In step 3, the performance variable value from both reference model and monitored value are compared, and the deviation is calculated. In step 4, based on the deviation and standard error mean, a z-statistics is used to determine if a fault

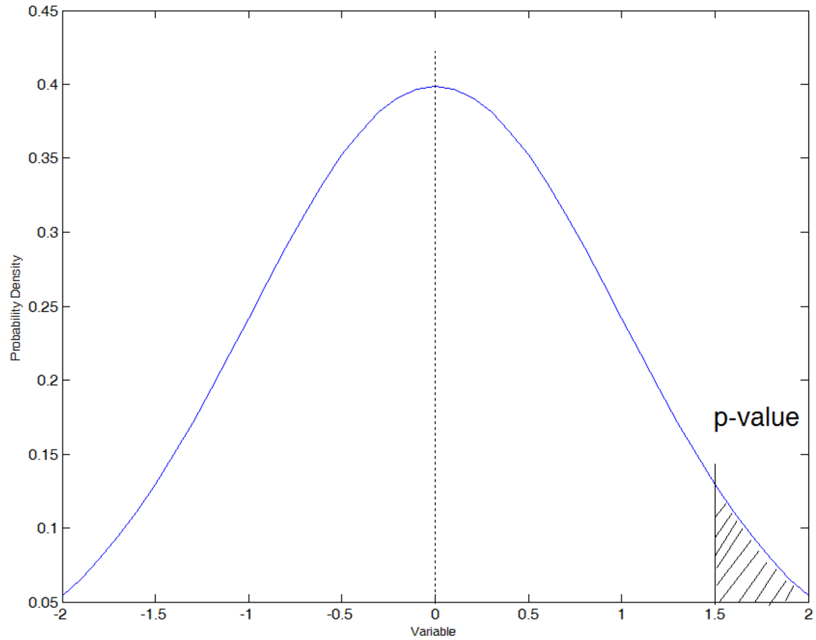

Figure 39: Fault Detection Approach of Model Based FDD Method

exists.

Note that in this approach, a probability of a fault corresponds to a performance variable. Therefore, to diagnose the faults for a component, a link between performance variable and faults needs to be created.

7.4 Information Requirement and Performance Variable

In the following, the information input requirement, the reference performance variable will be given for all typical components.

7.4.1 Damper

For a damper, the required inputs are: (1) pressure drop through the damper (2) damper opening position. The reference performance variable is the mass flow rate through the damper.

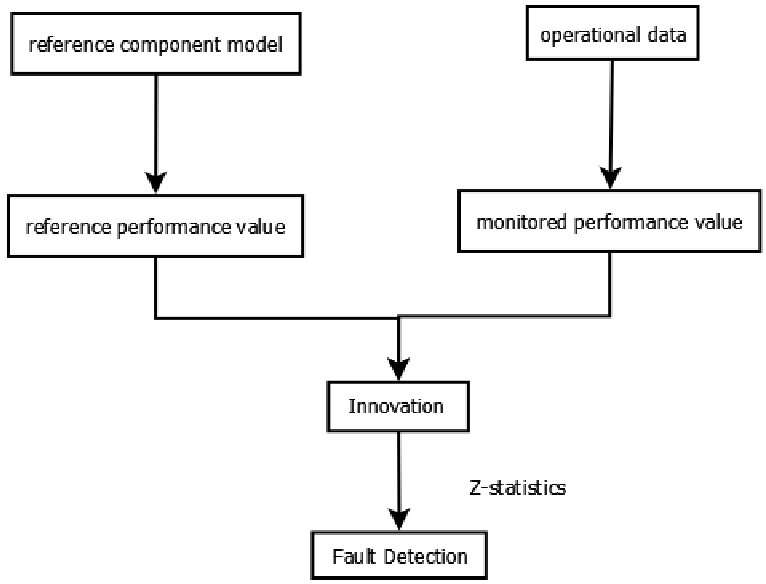

Figure 40: Model Based FDD Method

7.4.2 Mixing Air Box

For a single control signal mixing air box, the required input is the damper position signal. For a dual control signal mixing air box, the required inputs are mixing air damper position signal and outdoor air damper position signal. For both types of mixing air box, the outdoor air fraction (OAF) is used as the performance variable.

7.4.3 Duct

For a duct, the required information input is pressure drop ΔP, the performance variable is the mass flow rate.

7.4.4 Valve

For a two way valve, the required information input is the valve opening position y. The performance variable is the mass flow rate through the valve $\dot{m}$. For a three way valve, the required information input is also y, the performance variable is the ratio of mass flow rate through outlet 1 to the total mass flow rate.

7.4.5 Fan

For a fan, the required information input is mass flow rate. There are two performance variables: static pressure and power consumption of the fan.

7.4.6 Coil

For a coil, the required information input is the ratio of air flow mass flow rate to water flow mass flow rate. The performance variable is effectiveness.

Table 24 lists the information requirements, performance variables as well as associated faults for all the components.

Table 24: Component Information and Fault

Component	Input	PerfVariable	Faults
Damper	ΔP, y	$\dot{m}$	stuck, Leakage, Sticking
Single Signal Mixing Air Box	y	ϕ	stuck, leakage, sticking
Dual Signal Mixing Air Box	y_{oad}, y_{mad}	ϕ	stuck, leakage, sticking
Duct	ΔP	$\dot{m}$	cloggy, leakage
Two way valve	y,ΔP	$\dot{m}$	stuck, leakage, sticking
Three way valve	y, ΔP	$\frac{\dot{m}_1}{\dot{m}}$	stuck, leakage, sticking
Fan	$\dot{m}$,N	ΔP	fan out of control
Fan	$\dot{m}$,N	P_o	fan low efficiency
Coil	$\dot{m}_a$,$\dot{m}_w$	ϵ	coil fouling

7.5 Testing Case

The description of the testing case can be found in section 5.3. To introduce variability into the system, the mixing air temperature setpoint is changed to 17 $°C$. Due to this change, the mixing air temperature can be seen in Fig 41, the supply air rate can be seen in Fig 42, the discharge air temperature can be seen in 43.

In the following, the faults listed in table 7 will be simulated, the results will be diagnosed with model based method.

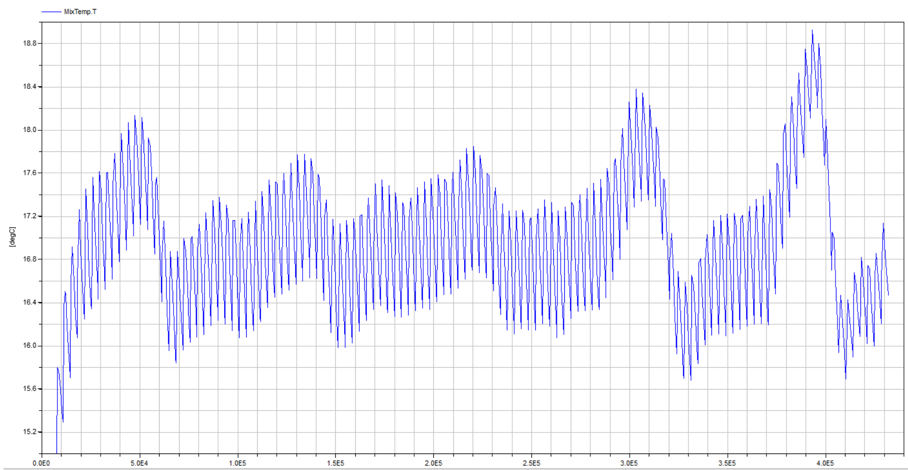

Figure 41: Mixing Air Temperature in Normal Operation

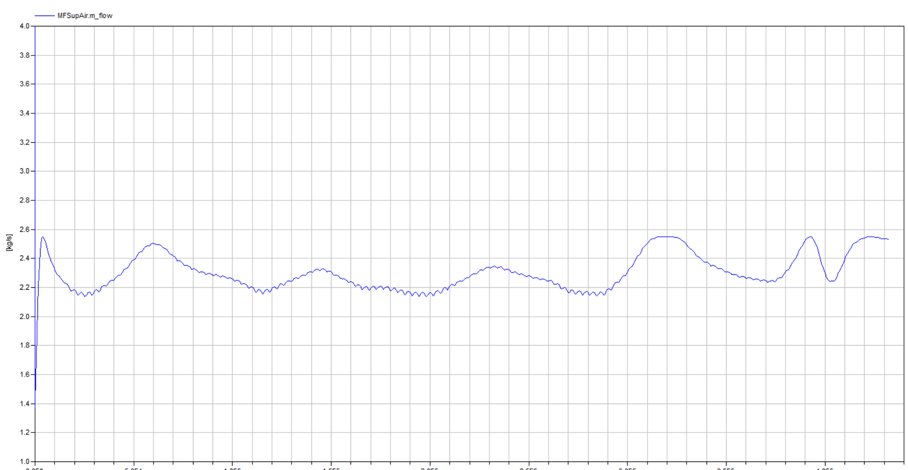

Figure 42: Supply Air Flow Rate in Normal Operation

7.5.1 Mixing Air Box

In this test, for fault detection purpose, the standard deviation of OAF is set to 0.2. When a working damper signal is given, the corresponding OAF value is calculated based on table 22 with interpolation. In normal operation, the minimum p-value is 0.1.

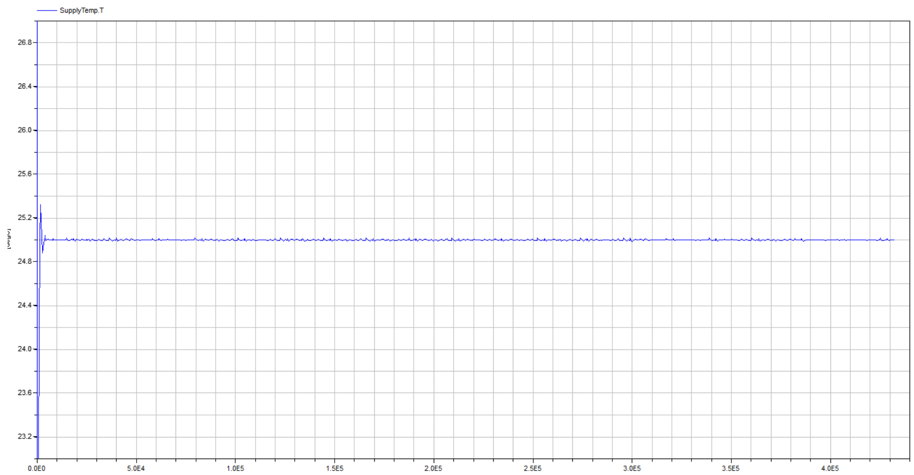

Figure 43: Discharge Air Temperature in Normal Operation

7.5.1.1 Fault 1 - MAB Outdoor Air Damper Leakage

For this fault, the leakage parameter l for the outdoor air damper is increased from 1% to 9%, with step 1%. For each value, the minimum p-value is shown in table 25.

Table 25: Outdoor Air Damper Leakage

Leakage (l)	Min p-Value
0.01	0.11
0.02	0.11
0.03	0.11
0.04	0.11
0.05	0.11
0.06	0.11
0.07	0.11
0.08	0.11
0.09	0.11

The result shows that with the current setting, the model based method is not able to detect the incipient leakage faults. This is because the effect of leakage fault is small, and the interpolation of lookup table is an approximation to the reference model.

7.5.1.2 Fault 2 - MAB Outdoor Air Damper Stuck

In this fault, the damper opening position y for the outdoor air damper increases from 10% to 90% (with step value 10%). The minimum p-value is shown in table 26. The result shows that when the damper is stuck at 10% and 20%, this fault can be detected.

Table 26: Outdoor Air Damper Stuck

Damper Pos (y)	Min p-Value
0.1	0
0.2	0.019
0.3	0.082
0.4	0.071
0.5	0.15
0.6	0.22
0.7	0.24
0.8	0.26
0.9	0.26

7.5.1.3 Fault 3 - MAB Outdoor Air Damper Sticking

In this fault, the damper opening position y has a first order delay with time constant τ changing from $5min$ to $15min$ (the step value is $1min$). The result in table 27 shows that this fault does not decrease the p-value to a significant level.

7.5.1.4 Fault 4 - MAB Exhaust Air Damper Leakage

In this fault, the leakage parameter l for the outdoor air damper is increased from 1% to 9% (with step 1%). The result in table 28 shows that in the current setting, the exhaust air damper leakage fault can not be detected.

7.5.1.5 Fault 5 - MAB Exhaust Air Damper Stuck

In this fault, the damper opening position y is fixed for the exhaust air damper. When y is increased from 10% to 90% (with step 10%), the minimum p-value is shown in

Table 27: Outdoor Air Damper Sticking

Delay Constant (min)	Min p-Value
5	0.10
6	0.10
7	0.11
8	0.11
9	0.11
10	0.10
11	0.10
12	0.10
13	0.10
14	0.10
15	0.10

Table 28: Exhaust Air Damper Leakage

Leakage (l)	Min p-Value
0.01	0.11
0.02	0.11
0.03	0.11
0.04	0.11
0.05	0.11
0.06	0.11
0.07	0.11
0.08	0.11
0.09	0.11

table 29. with the current setting, only when the damper stuck position is 20%, this fault can be detected.

Table 29: Exhaust Air Damper Stuck

Damper Pos (y)	Min p-Value
0.2	0.016
0.3	0.070
0.4	0.054
0.5	0.048
0.6	0.088
0.7	0.084
0.8	0.084
0.9	0.083

7.5.1.6 *Fault 6 - MAB Exhaust Air Damper Sticking*

In this fault, the damper opening position y has a first order delay, with time constant τ changing from $5min$ to $15min$ (the step value is $1min$). For each value, the minimum p-value is shown in table 30. The result shows that the sticking fault in all cases can not be detected.

Table 30: Exhaust Air Damper Sticking

Delay Constant (min)	Min p-Value
5	0.11
6	0.11
7	0.11
8	0.11
9	0.11
10	0.11
11	0.11
12	0.10
13	0.10
14	0.10
15	0.10

To sum, for both outdoor air damper and exhaust air damper, leakage and sticking fault are difficult to detect, stuck fault is much easier to detect.

7.5.2 Heating Coil

7.5.2.1 *Fouling*

In the heating coil test, the UA is changed from $10666W/K$ to $26665W/K$, with step $5333W/K$. For fault detection, the tolerance standard deviation is set to 7.5% of the monitored performance value. For each case, the minimum p-value is shown in the following table 31.

The result shows that with the setting in the detection, only UA value below $10666W/K$ can be detected.

Table 31: Heating Coil Fouling

UA (W/K)	Min p-Value
10666	0.02
15999	0.057
21332	0.12
26665	0.16
32000(normal)	0.17

7.5.3 Heating Coil Valve

In this testing case, the heating coil valve is a linear two way valve, with the nominal pressure drop as $1000Pa$, the nominal mass flow rate as $8kg/s$. Therefore, the actual mass flow rate given pressure drop ΔP and valve opening position y is calculated as in equation 54. In this testing case, 5% of the monitored flow is used as error standard deviation.

$$\dot{m} = 8y\sqrt{\frac{\Delta P}{1000}} \tag{54}$$

7.5.3.1 Valve Leakage

In the fault testing, the leakage parameter l is increased from 1% to 9%. For each value, the minimum p-value is shown in table 32. With the current setting, valve leakage at 3% or above can be detected.

Table 32: Heating Coil Valve Leakage

l (%)	Min p-Value
0.1(normal)	0.42
1	0.032
3	0
5	0
7	0
9	0

7.5.3.2 Valve Stuck

In this fault testing, the valve position y is increased from 10% to 90%, with step 10%. The results show that whatever the stuck position is, the fault is detectable.

Table 33: Heating Coil Valve Stuck

y (%)	Min p-Value
normal	0.42
10	0
30	0
50	0
70	0
90	0

Table 34: Heating Coil Valve Stick

τ (min)	Min p-Value
normal	0.42
5	0
7	0
9	0
11	0
13	0

7.5.3.3 Valve Sticking

In this fault testing, the valve position has a time lag, the time constant τ increases from $5min$ to $15min$, with step $2min$. The results show that all cases in this fault are detectable.

7.5.4 Fan

For fan, two faults are tested below. The 'fan out of control' fault is tested with the fan head - mass flow rate characteristic curve, the 'fan low efficiency' fault is tested with the fan power consumption - mass flow rate curve.

7.5.4.1 Fan Out of Control

In this fault, the pressure head is chosen as the performance variable. For detection, the error standard deviation is set to be 10% of the monitoring data.

Table 35: Fan Speed Out of Control

N (/s)	Min p-Value
normal	0.43
1	0
2	0
3	0
4	0
5	0

Table 36: Fan Low Efficiency

η (%)	Min p-Value
1(normal)	0.12
0.5	0.033
0.4	0.025
0.3	0.018
0.2	0.013
0.1	0.009

7.5.4.2 Fan Low Efficiency

The performance variable in this case is power consumption. For fault detection, the standard deviation is set to 40% of monitoring data. In the faulty case, the efficiency parameter η is changed from 0.1 to 0.5, with step 0.1. In this testing case, because linear interpolation is not a good approximation to the cubic curve, the error between prediction and monitored value in normal operation stage is relatively large. With the current setting, efficiency below 0.4 is able to be detected.

7.6 Conclusion

In this chapter, the models used in the simulation are reviewed, which are further used as a predictive model to calculate the performance variables.

A deterministic fault detection mechanism based on innovation is proposed. In this approach, a normal distribution for the innovation is assumed, and the user gives an estimate of the standard deviation for the innovation. Therefore, the z-statistic is used to detect the fault. A p-value less than 2.5% suggests that the malfunction is at significant level, and a positive alarm is issued.

The sensitivity of this method depends on the fidelity of the models employed. For example, the model for mixing air box has a relatively low fidelity than other components, consequently, the sensitivity for the mixing air box fault is lower than the other components.

The testing results suggest that model based approach does not necessarily outperform the other methods. It depends on the model fidelity, the sensor accuracy and the user's estimate of the standard deviation of performance variable in normal behavior.

CHAPTER VIII

PRINCIPAL COMPONENT ANALYSIS METHOD

8.1 Introduction

Correctly functioning sensors are the key in detecting faults in HVAC systems. Dexter and Pakanen [29] divided sensor faults into three categories: location faults (wrongly placed), electrical installation faults (bad joints, incorrect power supply, etc.), and sensor related faults (drift, no signal, etc.).

Principal Component Analysis (PCA) has been suggested as a quick and effective method in detecting sensor faults in air handling units[65], and since then developed in [63], [71], [18] and [17]. It has certain advantages compared to other methods: it is not as computationally intensive as ANN, it is effective towards most sensors in the system as opposed to rule based methods, it can separate component faults from sensor faults to some extent, and its results are reasonably accurate.

In this chapter, both traditional PCA method and an enhanced PCA method [65] are introduced and applied to the standard testing cases. While in the former approach, all information is put into one matrix, in the latter approach, information is separated into two groups: heat balance group and pressure balance group, to enhance the diagnostic capability. Following that, the testing results are discussed, and conclusion is made.

8.2 PCA Method

The Principal Component Analysis (PCA) method is a multivariate statistical analysis tool that can be used to reduce interdependent variables, so that the independent variables - principal components (PC) can be found. Since it appeared in Pearson [48], it has been used as a data analysis tool in bioinformatics [61], artificial intelligence [76], and HVAC systems [65].

Suppose we have an original matrix x ($x \in \Re^{m\times n}$)(m is the number of data points, n is the number of variables of each data). After normalizing x to x_n, the interdependence between all the variables can be found by calculating covariance matrix Σ ($\Sigma \in \Re^{n\times n}$).

$$\Sigma = \frac{{x_n}^T x_n}{n-1} \tag{55}$$

The loading matrix $U(U \in \Re^{n\times k}, k < n)$ is then composed by the eigenvectors corresponding to the k largest eigenvalues of Σ. Then the Principal Component y is calculated by

$$y = U^T X^T \tag{56}$$

When a new sample of data X_{new} comes, its principal component is calculated using the following equation

$$y_{new} = UU^T X_{new} \tag{57}$$

The error between new data and its principal component is calculated based on

$$e_{new} = \| y_{new} - X_{new} \|^2 \tag{58}$$

The sum of e_{new} for all features is the indicator as fault, each individual e_{new} is the indicator for that specific sensor, the larger e_{new} is, the more probable that sensor is faulty.

The traditional FDD scheme for PCA method in HVAC system is shown in Fig 44.

8.3 Traditional PCA Method

8.3.1 Training

The same AHU unit that has been tested in previous chapters is also tested here. In the testing, following monitoring sensors were chosen to compose the input matrix:

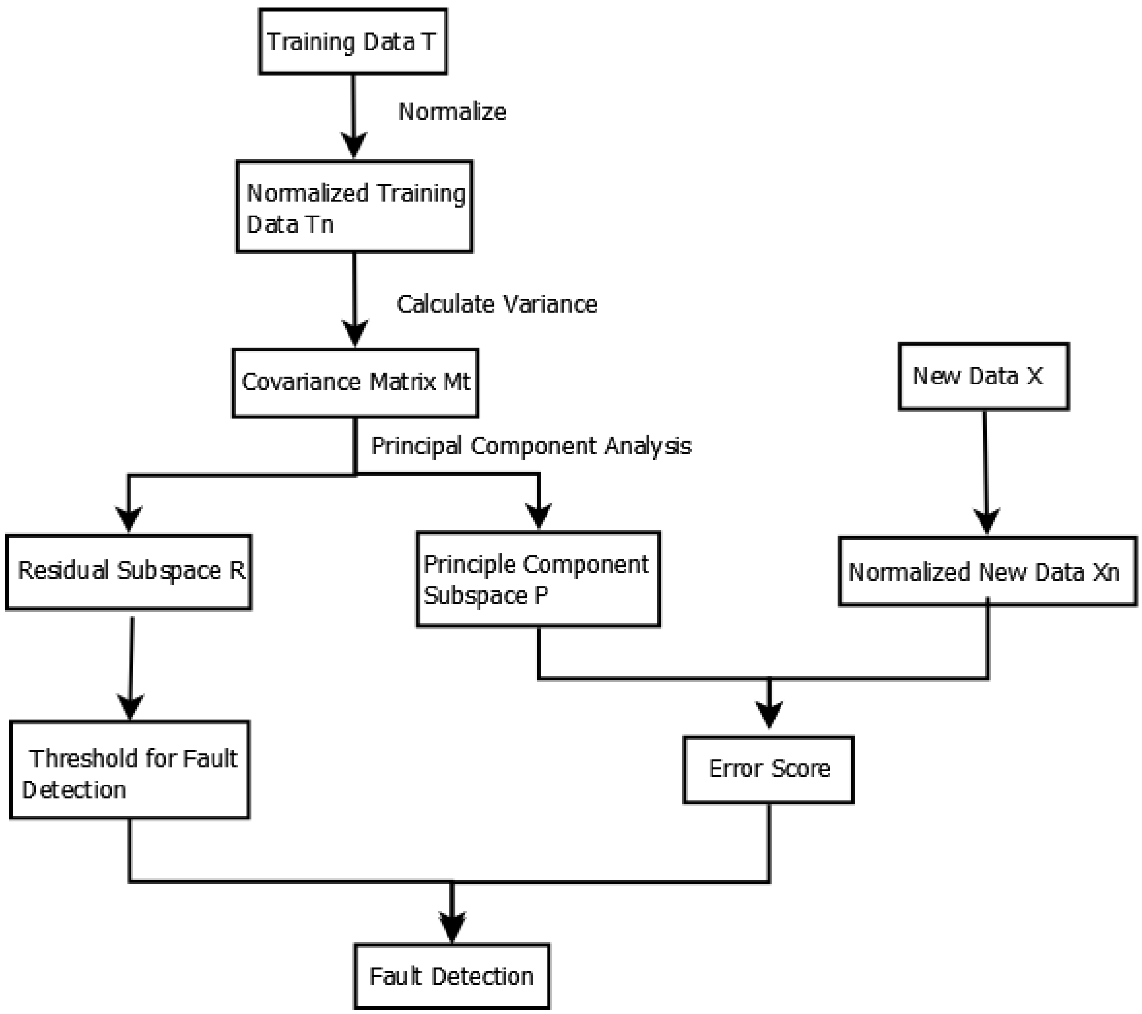

Figure 44: Traditional PCA Detection Scheme

fresh air temperature sensor (FAT), return air temperature sensor (RAT), mixing air temperature sensor (MAT), static pressure sensor (SSP), discharge air temperature (DAT), and supply air mass flow rate (DAF). In addition to the sensors, the following control signals are used: fan speed control signal (SFR), heating valve control signal (HCV) and mixing air box damper control signal (MAD). In total, there are nine variables in the matrix.

Using the normal operational data as training data, the generated eigenvalue from the covariance matrix is shown below:

$$\begin{matrix} 1.14e-6 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.02 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.03 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.25 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.52 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.60 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.99 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 2.53 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 4.06 \end{matrix} \tag{59}$$

Based on this result, eigenvalues from column 4 to column 9 account for 99% of the total variance. Therefore, columns from 4 to 9 in the eigenvector matrix are chosen as the principal component, and used as loading matrix in the fault testing case. Columns from 1 to 3 are the residual component, and used to calculate the threshold error score.

The error score in normal operational data is plotted as a histogram and shown in Fig 45. The mean value is 0.2, the maximum value is 0.6.The threshold setting is arbitrary in some sense. In this chapter, three times the maximum training error score is used as the threshold. Therefore, the threshold is set to 1.8. In the following

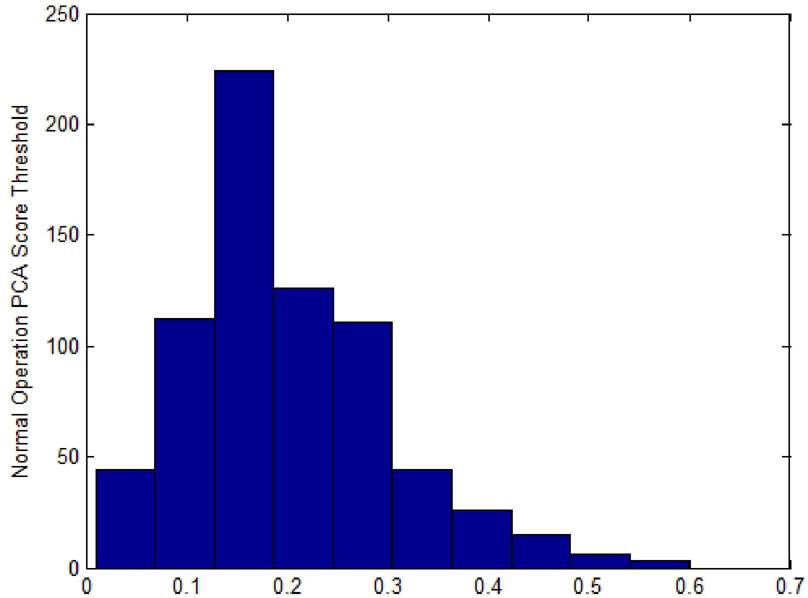

Figure 45: Normal Operation PCA Score

test cases, if the error score exceeds 1.8, then a fault is detected.

8.3.2 Mixing Air Box

8.3.2.1 Mixing Air Box OAD Leakage

In this case, the outdoor air damper leakage parameter l increased from 1% to 5% with step 1%. For each case, the error score is calculated and listed in table 37.

The results show that the outdoor air damper leakage fault will cause the PCA error score to increase significantly. All leakage cases are detected by PCA method.

Table 37: PCA Error Score For OAD Leakage

η (%)	Mean Error Score	Max Error Score
1(normal)	0.2	0.6
0.01	1.13	5.21
0.02	1.12	5.46
0.03	1.13	5.53
0.04	1.12	5.58
0.05	1.12	5.61

8.3.2.2 *Mixing Air Box OAD Stuck*

In this case, the outdoor air damper position is stuck at various locations, from 10% to 50%, with step 10%. The PCA error scores are shown in table 38.

The results show that a stuck outdoor air damper will also increase the PCA error score, the increment depends on the stuck position, at maximum (50%) it can achieve 19 times the original value. All stuck cases are detectable by PCA method.

Table 38: PCA Error Score For OAD Stuck

y (%)	Mean Error Score	Max Error Score
normal	0.2	0.6
10	1.4	4.38
20	1.15	2.58
30	1.11	7.14
40	1.09	10.55
50	1.12	12.36

8.3.2.3 *Mixing Air Box OAD Sticking*

In this case, the outdoor air damper is sticking, with time constant τ increased from $6min$ to $15min$, with step $2min$. The results are shown in table 39.

The results show that as the sticking time constant increases, the PCA error score also increases. However, compared to other faults, the increment is small. At the current setting, they are not detectable by PCA method.

Table 39: PCA Error Score For OAD Sticking

Time Constant (min)	Mean Error Score	Max Error Score
normal	0.2	0.6
5	0.37	1.31
7	0.41	1.30
9	0.43	1.41
11	0.45	1.44
13	0.46	1.46

8.3.2.4 *Mixing Air Box EAD Leakage*

In this case, the exhaust air damper leakage parameter l increased from 1% to 5% with step 1%. For each case, the error score is calculated and listed in table 40.

The results show that exhaust air damper leakage will also cause the PCA error score to increase to about four times the training error score. For all the leakage cases, they are detected by PCA method.

Table 40: PCA Error Score For EAD Leakage

η (%)	Mean Error Score	Max Error Score
0.001(normal)	0.2	0.6
0.01	0.82	2.86
0.02	0.82	2.68
0.03	0.82	2.56
0.04	0.81	2.50
0.05	0.81	2.45

8.3.2.5 *Mixing Air Box EAD Stuck*

In this case, the exhaust air damper position is stuck at various locations, from 10% to 50%, with step 10%. The PCA error score is shown below in table 41.

The results show that exhaust air damper stuck will cause PCA error score to increase. For different stuck position, the error score varies, however, they all exceed the threshold.

Table 41: PCA Error Score For EAD Stuck

y (%)	Mean Error Score	Max Error Score
normal	0.2	0.6
20	0.70	3.09
30	0.58	3.09
40	0.53	2.41
50	0.53	2.17

8.3.2.6 *Mixing Air Box EAD Sticking*

In this case, the exhaust air damper is sticking. The sticking time constant τ increased from $300s$ to $900s$, with step $120s$. The result is shown below in table 42. The results show that exhaust air damper sticking will cause the PCA error score to increase, however, the increment is small, all the sticking cases are not detected by PCA method.

Table 42: PCA Error Score For EAD Sticking

Time Constant (min)	Mean Error Score	Max Error Score
normal	0.2	0.6
5	0.39	1.15
7	0.42	1.18
9	0.45	1.22
11	0.47	1.29
13	0.50	1.41

8.3.3 Heating Coil

8.3.3.1 *Heating Coil Fouling*

In the heating coil test, the UA is changed from $10666W/K$ to $26665W/K$, with step $5333W/K$. The results are shown in table 43.

The results show that in this testing case, PCA method is not very sensitive to heating coil fouling. Only after the UA decreases to 10666 W/K, the fault is detected. This is related with the training variable selected in the training stage. It is expected that if water inlet temperature, outlet temperature, flow rate, air inlet temperature are included, this method will be more sensitive to the coil fouling fault.

8.3.3.2 *Heating Coil Valve Leakage*

The heating coil valve leakage parameter l is changed from 1% to 9%, with step 1%. The result is shown below in table 44.

Table 43: Heating Coil Fouling

UA (W/K)	Mean Error Score	Max Error Score
10666	0.41	2.56
15999	0.21	0.64
21332	0.19	0.59
26665	0.19	0.60
32000(normal)	0.2	0.6

The results show that in this case the error score is not very sensitive to valve leakage fault. All the leakage cases can not be detected. This is again attributed to not including the water flow, water temperature sensor data in the monitoring data.

Table 44: Heating Coil Valve Leakage

l (%)	Mean Error Score	Max Error Score
0.1(normal)	0.2	0.6
1	0.19	0.6
2	0.2	0.6
3	0.2	0.6
4	0.2	0.60
5	0.22	1.4

8.3.3.3 Heating Coil Valve Stuck

The heating coil valve position parameter y is changed from 10% to 50%, with step 10%. In this case, because the heating coil valve signal is always 1%, the error score is infinity. Therefore, all the stuck cases are regarded as detectable by PCA method.

8.3.3.4 Heating Coil Valve Sticking

The heating coil valve sticking time constant η is changed from $5min$ to $15min$, with step $2min$. The result is shown below in table 45.

The results show that heating coil valve sticking causes error score to increase significantly, therefore this fault is able to be detected by PCA method.

Table 45: Heating Coil Valve Sticking

τ (min)	Mean Error Score	Max Error Score
0(normal)	0.2	0.6
5	0.69	3.26
7	0.67	3.07
9	0.69	3.58
11	0.69	3.30
13	0.69	3.40

8.3.3.5 Sluggish Heating Coil Controller

In the normal operation, valve controller has a proportional gain k equals to 0.2. In the faulty case, k is adjusted from 0.01 to 0.05, with step 0.01. The result is shown below in table 46.

As shown, the sluggish coil controller causes the PCA error score to increase, the increment corresponds to the decrease of the proportional gain. All of the sluggish cases are detectable by PCA method.

Table 46: Sluggish Heating Coil Controller

k	Mean Error Score	Max Error Score
0.01	0.83	2.87
0.02	0.83	2.68
0.03	0.82	2.56
0.04	0.81	2.50
0.05	0.81	2.45
0.2 (normal)	0.2	0.6

8.3.4 Supply Fan

8.3.4.1 Supply Fan Out of Control

In this case, the error score will be infinity because the fan speed signal is fixed at maximum. Therefore, this fault is regarded as detectable by PCA method.

8.3.4.2 Supply Fan Low Efficiency

In this case, the fan efficiency parameter η is changed from 0.1 to 0.5 with step 0.1. The results are shown below in table 47.

As the fan efficiency decreases, the error score increases. However, only until τ decreases to 0.1 the fault is detectable by PCA method.

Table 47: Fan Low Efficiency

τ	Mean Error Score	Max Error Score
0.1	0.8	3.56
0.2	0.6	1.64
0.3	0.43	1.26
0.4	0.33	0.99
0.5	0.27	0.81
1 (normal)	0.2	0.6

8.3.5 Duct

8.3.5.1 Duct Cloggy

For this fault, the nominal pressure drop of duct is increased from $10Pa$ to $50Pa$. The result is shown below in table 48.

The result shows that as the pressure drop through the duct increases, the PCA error score also increases. However, the increment is small, and none of the cases are detected.

Table 48: Duct Cloggy

ΔP (Pa)	Mean Error Score	Max Error Score
10	0.22	0.61
20	0.24	0.72
30	0.27	0.79
40	0.30	0.94
50	0.34	1.35
(normal)	0.2	0.6

8.3.6 Sensor

8.3.6.1 Discharge Air Temperature Sensor Drift

For this fault, the sensor drift is changed from $-2°C$ to $2°C$, with step $1°C$. The result is shown below in table 49.

As shown, discharge air temperature sensor drift causes PCA score to increase. The increment depends on the drift extent. If the drift is small (1°), the error score is small and the fault is not detectable. However, when the drift is larger (2°), it is detectable by PCA method.

Table 49: Discharge Air Temperature Sensor Drift

$Drift(°C)$ (min)	Mean Error Score	Max Error Score
-2	0.46	2.42
-1	0.19	1.37
0 (normal)	0.2	0.6
1	0.39	0.94
2	1.08	10.2

8.3.7 Finding

Based on the testing cases, following findings were made:

- PCA method can detect most of the abrupt component faults and incipient faults.
- The sensitivity of PCA method depends on the number of variables included in the training matrix.
- For incipient faults, PCA error score in most cases is proportional to the extent of the fault. Therefore, whether PCA can detect a specific incipient faults depends on the fault extent and threshold setting of the method.

8.4 *Enhanced PCA Method*

8.4.1 Introduction

In contrast to the traditional PCA method that puts all input information in one group, in the enhanced PCA method proposed by [65], the input information are separated into two groups: heat balance group and pressure balance group. The PCA training matrix, loading matrix and error score are calculated in both groups, the results are then compared to get the final diagnostic output.

This method works in the following procedure. When a new set of operational data comes, they are organized into two groups: heat balance group and pressure balance group. Error scores for both groups are calculated, and compared with thresholds. In each group, if the threshold is exceeded, the possible faults are fetched through the diagnostic table. If faults are detected in both groups, the final diagnostic output is the intersection of the two fault lists. If only one group detects the fault, the components that could cause the fault in the other group are removed from the fault list, the rest are then suggested as the final output. This is illustrated in Fig 46.

8.4.2 Training

In this experiment, the input information is separated into two groups: one group encloses the heat exchange balance equation, including OAT, RAT, MAT, DAT, DAF, MAD and HCV, the other group encloses the pressure balance equation, including SSP, DAF, SFR and MAD.

The eigenvalue matrix derived from heat balance group is shown in 60. The last five eigenvectors are therefore selected as principal component. The threshold derived from the normal training data is 2.1.

The eigenvalue matrix derived from pressure balance group is shown in 61. The last three eigenvectors are selected as principal component. The threshold derived

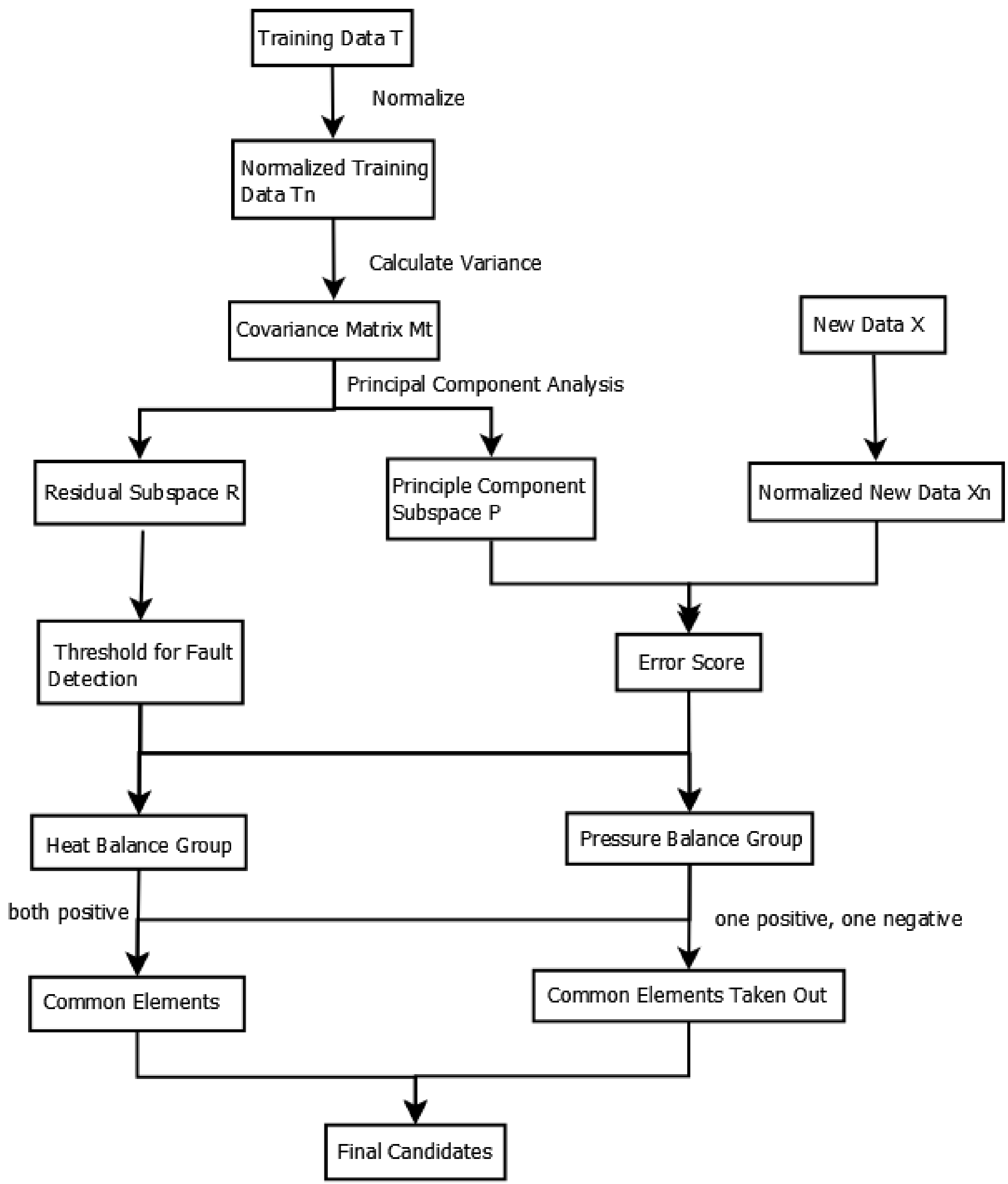

Figure 46: Enhanced PCA Detection and Diagnostic Scheme

from the normal training data is 0.011.

$$\begin{matrix} 0.018 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.034 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.197 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.538 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.953 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 2.216 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 3.045 \end{matrix} \tag{60}$$

$$\begin{matrix} 3.29e-6 & 0 & 0 & 0 \\ 0 & 0.28 & 0 & 0 \\ 0 & 0 & 0.92 & 0 \\ 0 & 0 & 0 & 2.80 \end{matrix} \tag{61}$$

In the following, the effects of the faults on the PCA error score of both heat balance group and pressure balance group are analyzed.

8.4.3 Mixing Air Box

8.4.3.1 Mixing Air Box OAD Leakage

In this case, the outdoor air damper leakage parameter l increased from 1% to 5% with step 1%. For each case, the error score is calculated and listed below in table 50.

The result shows that the outdoor air damper leakage fault causes PCA error score in both groups to increase. However, after the leakage parameter l exceeds 3%, its impact does not increase any more. All the cases are detectable by enhanced PCA method.

8.4.3.2 Mixing Air Box OAD Stuck

In this case, the outdoor air damper position is stuck at various locations, from 10% to 50%, with step 10%. The PCA error score is shown below in table 51.

Table 50: PCA Error Score For OAD Leakage

l (%)	Mean Error(Heat)	Max Error(Heat)	Mean Error(Pres)	Max Error(Pres)
normal	0.20	0.71	0.0016	0.0038
1	1.11	5.1	0.0061	0.22
2	1.09	5.33	0.0026	0.19
3	1.1	5.4	0.0026	0.18
4	1.1	5.4	0.003	0.17
5	1.1	5.5	0.003	0.17

The results show that outdoor air damper stuck will affect PCA error score in both heat balance group and pressure balance group. As the stuck position moves toward full open, the PCA score in heat balance group keeps increasing.

When the stuck position is at 10%, only error score in pressure balance group exceeds the threshold. However, at the other positions, both groups have high error scores. All cases are detectable by enhanced PCA method.

Table 51: PCA Error Score For OAD Stuck

y (%)	Mean Error(Heat)	Max Error(Heat)	Mean Error(Pres)	Max Error(Pres)
normal	0.20	0.71	0.0016	0.0038
10	0.59	1.9	1.14	3.75
20	1.2	2.6	0.09	0.55
30	1.1	7.4	0.01	0.58
40	1.1	11	0.0086	0.80
50	1.1	13	0.0039	0.54

8.4.3.3 Mixing Air Box OAD Sticking

In this case, the outdoor air damper is sticking. The sticking time constant τ increased from 300s to 900s, with step 120s. The result is shown below in table 52.

The results show that the sticking fault has no impact on PCA error score in heating balance group, but it affects the error score in pressure balance group. All the sticking faults are detectable.

Table 52: PCA Error Score For OAD Sticking

τ (min)	Mean Error(Heat)	Max Error(Heat)	Mean Error(Pres)	Max Error(Pres)
normal	0.20	0.71	0.0016	0.0038
5	0.20	0.67	0.25	0.87
7	0.20	0.65	0.29	1.02
9	0.20	0.64	0.31	1.1
11	0.21	0.63	0.32	1.12
13	0.21	0.63	0.33	1.1

8.4.3.4 Mixing Air Box EAD Leakage

In this case, the exhaust air damper leakage parameter l increased from 1% to 5% with step 1%. For each case, the error score is calculated and listed below in table 53.

The results show that exhaust air damper leakage has no impact on PCA error score of heat balance group, but it has impact on that of pressure balance group. All the leakage faults are detectable.

Table 53: PCA Error Score For EAD Leakage

l (%)	Mean Error(Heat)	Max Error(Heat)	Mean Error(Pres)	Max Error(Pres)
normal	0.20	0.71	0.0016	0.0038
1	0.28	0.8	0.66	2.2
2	0.30	0.91	0.64	1.9
3	0.31	1.0	0.62	1.8
4	0.32	1.0	0.61	1.7
5	0.32	1.1	0.6	1.6

8.4.3.5 Mixing Air Box EAD Stuck

In this case, the exhaust air damper position is stuck at various locations, from 10% to 50%, with step 10%. The PCA error score is shown below in table 54.

The results show that exhaust air damper stuck has impacts on PCA error score in both heat balance group and pressure balance group. All the stuck cases are detectable.

Table 54: PCA Error Score For EAD Stuck

y (%)	Mean Error(Heat)	Max Error(Heat)	Mean Error(Pres)	Max Error(Pres)
normal	0.20	0.71	0.0016	0.0038
20	0.66	2.95	0.039	0.24
30	0.55	3.0	0.051	0.30
40	0.50	2.2	0.052	0.36
50	0.50	2.1	0.055	0.37

8.4.3.6 Mixing Air Box EAD Sticking

In this case, the exhaust air damper is sticking. The sticking time constant τ increased from 300s to 900s, with step 120s. The result is shown below in table 55. The results show that exhaust air damper sticking has no impact on PCA error score of heat balance group, but it has impact on that of pressure balance groups. All the sticking cases are detectable.

Table 55: PCA Error Score For EAD Sticking

τ (min)	Mean Error(Heat)	Max Error(Heat)	Mean Error(Pres)	Max Error(Pres)
normal	0.20	0.71	0.0016	0.0038
5	0.21	0.63	0.24	0.78
7	0.22	0.64	0.25	0.78
9	0.22	0.64	0.27	0.81
11	0.22	0.69	0.29	0.92
13	0.23	0.76	0.30	1.01

8.4.4 Heating Coil

8.4.4.1 Heating Coil Fouling

In the heating coil test, the UA is changed from 10666W/K to 26665W/K, with step 5333W/K. The results are shown in table 56.

The results show that in this testing case, heating coil fouling has no impact on the PCA error of pressure balance group, and it affects the PCA error of heat balance group. Among all the cases, only after UA decreases below 10666 W/K, the fault is detectable.

Table 56: Heating Coil Fouling

UA (W/K)	Mean Error(Heat)	Max Error(Heat)	Mean Error(Pres)	Max Error(Pres)
normal	0.20	0.71	0.0016	0.0038
10666	0.40	2.43	0.0016	0.0038
15999	0.21	0.71	0.0016	0.0038
21332	0.19	0.71	0.0016	0.0037
26665	0.19	0.71	0.0016	0.0037

8.4.4.2 Heating Coil Valve Leakage

For this fault, the heating coil valve leakage parameter l is changed from 1% to 9%, with step 1%. The result is shown below in table 57.

The results show that PCA error score in both groups are not affected by heating coil valve leakage fault. This is again attributed to not including the water flow, water temperature sensor data. Therefore, this fault is not detectable by enhanced PCA method.

Table 57: Heating Coil Valve Leakage

l (%)	Mean Error(Heat)	Max Error(Heat)	Mean Error(Pres)	Max Error(Pres)
normal	0.20	0.71	0.0016	0.0038
1	0.20	0.71	0.0016	0.0038
2	0.20	0.71	0.0016	0.0038
3	0.20	0.71	0.0016	0.0038
4	0.20	0.71	0.0016	0.0038
5	0.20	0.71	0.0016	0.0038

8.4.4.3 Heating Coil Valve Stuck

In this case, the heating coil valve command value is constant. Therefore, the PCA score is infinity. This fault is regarded as detectable in this case.

8.4.4.4 Heating Coil Valve Sticking

For this fault, the heating coil valve sticking time constant η is changed from $300s$ to $900s$, with step $120s$. The result is shown below in table 58.

The results show that heating coil valve sticking has no impact on the PCA error score in pressure balance group, but it has impact on that in heat balance group. All the sticking cases are detectable by enhanced PCA method.

Table 58: Heating Coil Valve Sticking

τ (min)	Mean Error(Heat)	Max Error(Heat)	Mean Error(Pres)	Max Error(Pres)
normal	0.20	0.71	0.0016	0.0038
5	0.68	2.97	0.0013	0.0073
7	0.66	2.96	0.0013	0.0084
9	0.68	3.30	0.0013	0.0085
11	0.67	3.19	0.0013	0.0086
13	0.67	3.14	0.0013	0.0088

8.4.4.5 Sluggish Heating Coil Controller

In the normal operation, valve controller has a proportional gain k equals to 0.2. In the faulty case, k is adjusted from 0.01 to 0.05, with step 0.01. The result is shown below in table 59.

The result shows that sluggish coil controller has strong effect on PCA error score in heat balance group, has little effect on that in pressure balance group. There is no direct relation between error score and proportional gain. When k is at 0.05, the fault is detectable.

Table 59: Sluggish Heating Coil Controller

k	Mean Error(Heat)	Max Error(Heat)	Mean Error(Pres)	Max Error(Pres)
normal	0.20	0.71	0.0016	0.0038
0.01	0.32	1.04	0.0016	0.0039
0.02	0.26	0.72	0.0016	0.0037
0.03	0.30	0.95	0.0016	0.0037
0.04	0.24	0.71	0.0016	0.0037
0.05	0.34	10.4	0.26	5.36

8.4.5 Fan

8.4.5.1 Supply Fan Out of Control

In this case, the fan speed command value is constant. Therefore, the PCA score is infinity. This fault is regarded as detectable in this case.

8.4.5.2 Supply Fan Low Efficiency

In this case, the fan efficiency parameter η is changed from 0.1 to 0.5 with step 0.1. The result is shown below in table 60.

It is shown that fan efficiency can only affect PCA error score in heat balance group. After efficiency parameter η decreased below 0.1, this fault is detectable.

Table 60: Fan Low Efficiency

η	Mean Error(Heat)	Max Error(Heat)	Mean Error(Pres)	Max Error(Pres)
normal	0.20	0.71	0.0016	0.0038
0.1	0.79	3.4	0.0016	0.0046
0.2	0.59	1.61	0.0016	0.0038
0.3	0.42	1.24	0.0016	0.0036
0.4	0.33	0.97	0.0016	0.0038
0.5	0.27	0.81	0.0016	0.0038

8.4.6 Duct

8.4.6.1 Duct Cloggy

For this fault, the nominal pressure drop of duct is increased from $10Pa$ to $50Pa$. The result is shown below in table 61.

The result shows that as the pressure drop has a stronger effect on the PCA error score in pressure balance group than heat balance group. After the pressure drop increased above 30 Pa, this fault is detectable.

Table 61: Duct Cloggy

ΔP (Pa)	Mean Error(Heat)	Max Error(Heat)	Mean Error(Pres)	Max Error(Pres)
normal	0.20	0.71	0.0016	0.0038
10	0.22	0.78	0.0002	0.0012
20	0.24	0.83	0.0026	0.0089
30	0.26	0.85	0.0069	0.018
40	0.30	0.94	0.013	0.030
50	0.34	1.32	0.02	0.05

8.4.7 Sensor

8.4.7.1 Discharge Air Temperature Sensor Drift

For this fault, the sensor drift is changed from $-2°C$ to $2°C$, with step $1°C$. The result is shown below in table 62.

As the result shows, discharge air temperature sensor drift has strong effect on PCA error score in heat balance group, has little effect on that in pressure balance group. After sensor drift increased above 2 $°C$, the fault is detectable.

Table 62: Discharge Air Temperature Sensor Drift

$\Delta T(°C)$	Mean Error(Heat)	Max Error(Heat)	Mean Error(Pres)	Max Error(Pres)
normal	0.20	0.71	0.0016	0.0038
-2	0.45	2.08	0.0012	0.0091
-1	0.18	1.39	0.0012	0.0095
1	0.38	0.95	0.0012	0.0035
2	1.05	10.6	0.001	0.044

8.4.8 Findings

In this section, the fault detection sensitivity for incipient faults are compared between traditional PCA method and enhanced PCA method (since abrupt faults are always detectable). The results are shown in table 63.

Based on the comparison above, it is found that in this testing case, enhanced PCA method has better sensitivity than traditional PCA method, particularly for the

Table 63: PCA and Enhanced PCA Detection Maximum Detectable Fault

Fault	PCA Method	Enhanced PCA Method
MAB OAD Leakage (l)	0.01	0.01
MAB OAD Stick (τ)	Not detectable	5min
MAB EAD Leakage (l)	0.01	0.01
MAB EAD Stick (τ)	Not detectable	5min
Coil Fouling (UA)	$10666 W/K$	$10666 W/K$
Coil Valve Leakage (l)	Not detectable	Not detectable
Coil Valve Sticking (τ)	5min	5min
Fan Low Efficiency (η)	0.1	0.1
Duct cloggy (ΔP)	Not detectable	30
DAT Sensor Drift ($^{\circ}C$)	2	2
Sluggish Controller (k)	0.01	0.05

Table 64: Effect of Fault on PCA Group

	Heat Balance	Pressure Balance	Index
MAB Leakage	$*$	$*$	1
MAB Stuck	$*$	$*$	2
MAB Stick		$*$	3
Coil Fouling	$*$		4
Coil Valve Leakage			5
Coil Valve Stuck	$*$		6
Coil Valve Sticking	$*$		7
Sluggish Coil Controller	$*$		8
Fan Out of Control	$*$	$*$	9
Fan Low Efficiency	$*$		10
Duct Cloggy		$*$	11
DAT Sensor Drift	$*$		12
Mode Controller Fault	$*$	$*$	13
MAB Controller Fault	$*$	$*$	14
Fan Controller Fault	$*$	$*$	15
OAT Sensor Fault	$*$		16
RAT Sensor Fault	$*$		17
MAT Sensor Fault	$*$		18
DAF Sensor Fault	$*$	$*$	19
SSP Sensor Fault		$*$	20

incipient faults that are part of the pressure balance system. Overall, PCA method is a more sensitive method than other methods, considering that many of the sensor faults can be detected directly based on the error score.

Table 65: Effect of Component on PCA Group

	Heat Balance	Pressure Balance
MAB	*	*
Coil	*	
Coil Valve	*	
Coil Controller	*	
Fan	*	*
Duct		*
DAT Sensor	*	
Mode Controller	*	*
MAB Controller	*	*
Fan Controller	*	*
OAT Sensor	*	
RAT Sensor	*	
MAT Sensor	*	
DAF Sensor	*	*
SSP Sensor		*

Table 66: Fault Diagnostic Result

Seeding Fault	Diagnose(Fault)	Diagnose(Component)
1	1,2,9,13-15,19	MAB/controller, fan/controller, mode controller, DAF sensor
2	1,2,9,13-15,19	MAB/controller, fan/controller, mode controller, DAF sensor
3	3,11,20	duct, SSP Sensor
4	4,6-8,10,12,16-18	Coil/controller, coil valve, DAT sensor, OAT sensor, RAT sensor, MAT sensor
5	0	/
6	4,6-8,10,12,16-18	Coil/controller, coil valve, DAT sensor, OAT sensor, RAT sensor, MAT sensor
7	4,6-8,10,12,16-18	Coil/controller, coil valve, DAT sensor, OAT sensor, RAT sensor, MAT sensor
8	4,6-8,10,12,16-18	Coil/controller, coil valve, DAT sensor, OAT sensor, RAT sensor, MAT sensor
9	1,2,9,13-15,19	MAB/controller, fan/controller, mode controller, DAF sensor
10	4,6-8,10,12,16-18	Coil/controller, coil valve, DAT sensor, OAT sensor, RAT sensor, MAT sensor
11	3,11,20	duct, SSP sensor
12	4,6-8,10,12,16-18	Coil/controller, coil valve, DAT sensor, OAT sensor, RAT sensor, MAT sensor
13	1,2,9,13-15,19	MAB/controller, fan/controller, mode controller, DAF sensor
14	1,2,9,13-15,19	MAB/controller, fan/controller, mode controller, DAF sensor
15	1,2,9,13-15,19	MAB/controller, fan/controller, mode controller, DAF sensor
16	4,6-8,10,12,16-18	Coil/controller, coil valve, DAT sensor, OAT sensor, RAT sensor, MAT sensor
17	4,6-8,10,12,16-18	Coil/controller, coil valve, DAT sensor, OAT sensor, RAT sensor, MAT sensor
18	4,6-8,10,12,16-18	Coil/controller, coil valve, DAT sensor, OAT sensor, RAT sensor, MAT sensor
19	1,2,9,11,13-15,19	MAB/controller, fan/controller, mode controller, DAF sensor
20	3,11,20	duct, SSP Sensor

Based on the above result, the effects of component/faults on the PCA error score is listed in the following table 64. To help diagnose fault at component level, table 65 is created based on table 64. Applying the diagnostic approach to the faults listed, the diagnostic result is shown in the table 66.

8.5 Conclusion

In this chapter, we compared the capability of traditional Principal Component Analysis (PCA) method and enhanced PCA method in detecting and diagnosing the faults in air handling units.

It is found that for incipient faults, the detection capability depends on the variables selected to compose the training matrix, the threshold setting in PCA method and the fault extent. In general, the more the selected variables, the stronger detection capability it has.

It is found that both the traditional and enhanced PCA method are able to detect abrupt faults and many incipient faults, and enhanced PCA method has better fault detection capability than traditional PCA method. This is due to the separation of heat balance group and pressure balance group. In the testing case, those faults that cause abnormal behavior in pressure balance group are only able to be detected by enhanced PCA method.

The traditional PCA method has no diagnostic ability. The enhanced PCA method is able to diagnose the fault based on the diagnostic table in both heat balance group and pressure balance group. The testing result shows that in most cases the true fault is correctly included in the candidate list, although the number of candidates is large.

CHAPTER IX

PROBABILITY EXTENSION

The Bayesian approach is a widely accepted statistical inference method to estimate the true probability based on observation evidence. It has been successfully applied to many areas, such as mechanical engineering, computer engineering, medicine, etc.

In this chapter, the Bayesian approach is applied to the four methods discussed in previous chapters, with the purpose to give the results probabilistic meaning. In the content below, firstly the Bayesian probability approach is introduced, following that, the Bayesian approach is combined with all four methods discussed before, and tested against a testing case. Finally, the advantage and disadvantage of the probabilistic approach are discussed.

9.1 Bayesian Probability Approach

In a binary testing, sensitivity measures the proportion of actual positive which are correctly identified as such, specificity measures the proportion of negatives which are correctly identified as such [70].

Suppose $P(f)$ is the prior probability that a fault exists, the value of specificity is equal to $1-\alpha$, the value of sensitivity is equal to $1-\beta$, then the probability $P(o)$ that a positive observation is made can be calculated by equation 62, and the probability $P(n)$ that a negative observation is made can be calculated by equation 63.

$$P(o) = \alpha(1 - P(f)) + (1 - \beta)P(f) \tag{62}$$

$$P(n) = (1 - \alpha)(1 - P(f)) + \beta P(f) \tag{63}$$

Therefore, given a positive observation, the posterior probability that a fault exists is calculated as below in equation 64, given a negative observation, the probability that a fault exists is calculated as equation 65.

$$P(f|o) = \frac{(1-\beta)P(f)}{P(o)} \tag{64}$$

$$P(f|n) = \frac{\beta P(f)}{P(n)} \tag{65}$$

9.2 Probabilistic Approach Application

With the Bayesian approach, the deterministic result can be transformed to probabilistic result. This process is shown in Fig 47.

In this section, firstly the values of sensitivity and specificity of each method are calculated, then the Bayesian approach is sequentially combined with the four methods discussed before, and tested against a standard testing case.

9.2.1 Sensitivity and Specificity Calculation

In the last four chapters, although the system is the same, the operational conditions are different. In Chap 5 and Chap 6, the mixing air temperature set point is 19°, while in Chap 7 and Chap 8, the mixing air temperature set point is 17°. The parameter values for the faults in the testing case are also different. In this section, both the system operation condition and the fault seeds are standardized, as shown in table 67. Within the standardized fault space, the sensitivity and specificity of each method are derived and shown in table 68 and table 69.

In the following, a standard case is used to test the Bayesian approach, which is shown in table 70.

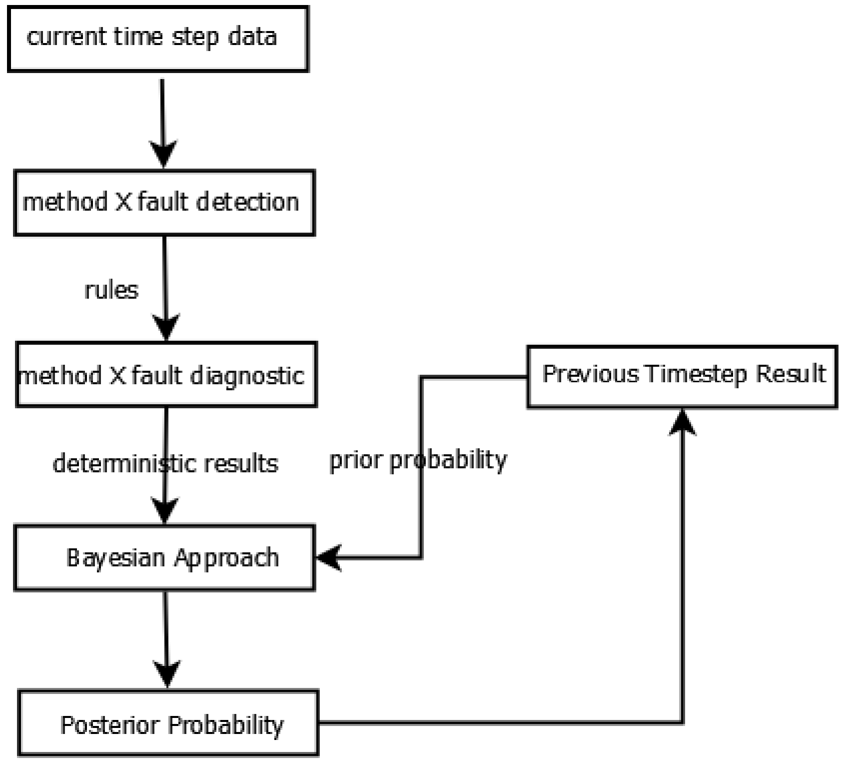

Figure 47: Combination of Bayesian Approach with Deterministic Result

Table 67: Fault List

Component	Fault	Type	Label
	No fault		0
MAB	MAB oad leakage (1%-9%, step 1%)	incipient	1
MAB	MAB oad stuck (10%-90%, step 10%)	abrupt	2
MAB	MAB oad sticking (T_{cons}=5 min - 15 min, step 1 min)	incipient	3
MAB	MAB ead leakage (1%-9%, step 1%)	incipient	4
MAB	MAB ead stuck (10%-90%, step 10%)	abrupt	5
MAB	MAB ead sticking (T_{cons}=5 min - 15 min, step 1 min)	incipient	6
Coil	Heating Coil Fouling ($\frac{UA_{nv}}{UA_{ov}}$ = $\frac{1}{6}$-$\frac{5}{6}$, step $\frac{1}{6}$)	incipient	7
Coil	Heating Coil Valve Leakage (1%-9%, step 1%)	incipient	8
Coil	Heating Coil Valve Stuck (10%-90%, step 10%)	abrupt	9
Coil	Heating Coil Valve sticking (T_{cons}=5 min - 15 min, step 1 min)	incipient	10
Fan	Supply fan Out of Control (N = 1-15 /s , step 1 /s)	abrupt	11
Fan	Supply fan low efficiency (eta = 0.1-1, step 0.1)	incipient	12
Duct	Duct cloggy ($\frac{\Delta P_n}{\Delta P_o}$ = 1-5, step 0.5)	incipient	13
Sensor	Supply Temperature Sensor Drift (ΔT_s = -2°-2°, step 1°)	incipient	14
Coil Controller	Sluggish heating coil controller (Gain k = 0.01-0.1, step 0.01)	incipient	15

9.2.2 Allowable Probability Range

During the testing, it is found that the allowable minimum and maximum probability value has an effect on the result. If the prior probability is 0, regardless of the observed evidence, the posterior probability is always 0. Similarly, if the prior probability is 1,

Table 68: Method Sensitivity Comparison

Method	Mode Cont	MAB/Cont	Coil/Cont	Valve	Fan/Cont	DAT Sensor	Duct
Rule	/	0.001	0.11	0.68	0.6	0.5	0.001
CUSUM	/	0.001	0.11	0.74	0.5	0.001	0.001
PCA	/	0.46	0.11	0.53	0.5	0.5	0.6
Model	/	0.07	0.11	0.95	0.9	0.001	0.001

Table 69: Method Specificity Comparison

Method	Mode Cont	MAB/Cont	Coil/Cont	Valve	Fan/Cont	DAT Sensor	Duct
Rule	0.99	0.999	0.84	0.95	0.83	0.85	0.95
CUSUM	0.999	0.999	0.85	0.98	0.999	0.84	0.95
PCA	0.74	0.98	0.87	0.96	0.72	0.58	0.999
Model	0.999	0.999	0.999	0.999	0.999	0.999	0.999

Table 70: Fault List

Component	Fault	Type	Label
	No fault		0
MAB	MAB oad leakage (1=10%)	incipient	1
MAB	MAB oad stuck (y=50%)	abrupt	2
MAB	MAB oad sticking (T_{cons} 15 min)	incipient	3
MAB	MAB ead leakage (l=10%)	incipient	4
MAB	MAB ead stuck (y=20%)	abrupt	5
MAB	MAB ead sticking (T_{cons}=15 min)	incipient	6
Coil	Heating Coil Fouling (UA=10666 W/K)	incipient	7
Coil	Heating Coil Valve Leakage (l=10%)	incipient	8
Coil	Heating Coil Valve Stuck (y=10%)	abrupt	9
Coil	Heating Coil Valve sticking (T_{cons}=15 min)	incipient	10
Fan	Supply fan Out of Control (N =2 /s)	abrupt	11
Fan	Supply fan low efficiency (eta = 0.1)	incipient	12
Duct	Duct cloggy (ΔP=50 Pa)	incipient	13
Sensor	Supply Temperature Sensor Drift (ΔT_s = -2°)	incipient	14
Coil Controller	Sluggish heating coil controller (Gain k = 0.01)	incipient	15

the posterior probability is always 1. Therefore, in this testing, the allowable minimal probability is set to 1e-5, the allowable maximal probability is set to 0.999.

9.2.3 Probabilistic Rule Based Method

Applying the probabilistic rule based method to testing case, the results are shown in Fig 48. It is found that seven faults are detected (valve fault, fan fault, coil fault and

DAT sensor fault). Among them, the fan low efficiency fault and DAT sensor drift fault can barely be detected, in which the fault probability bumps at certain time and then quickly disappear. The other detected faults have large probability values during the whole testing period.

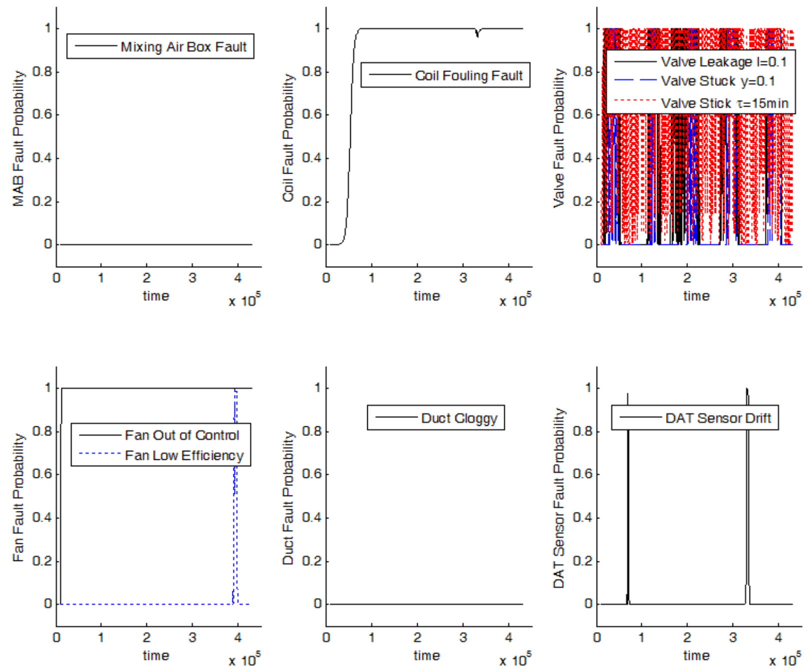

Figure 48: Application of probabilistic rule based method

9.2.4 Probabilistic CUSUM Method

Applying the probabilistic CUSUM method to the testing case, the result is shown in Fig 49. During the testing, five faults are detected (valve fault and fan fault). Because the CUSUM method detects and diagnoses fault based on the fault counter, whose values always increase, once a fault was detected, the fault probability stays at high level until the counter is reset.

9.2.5 Probabilistic Model Based Method

Applying the probabilistic model based method to the testing case, the result is shown in Fig 50. Among the faults, mixing air box outdoor air damper leakage, sensor drift

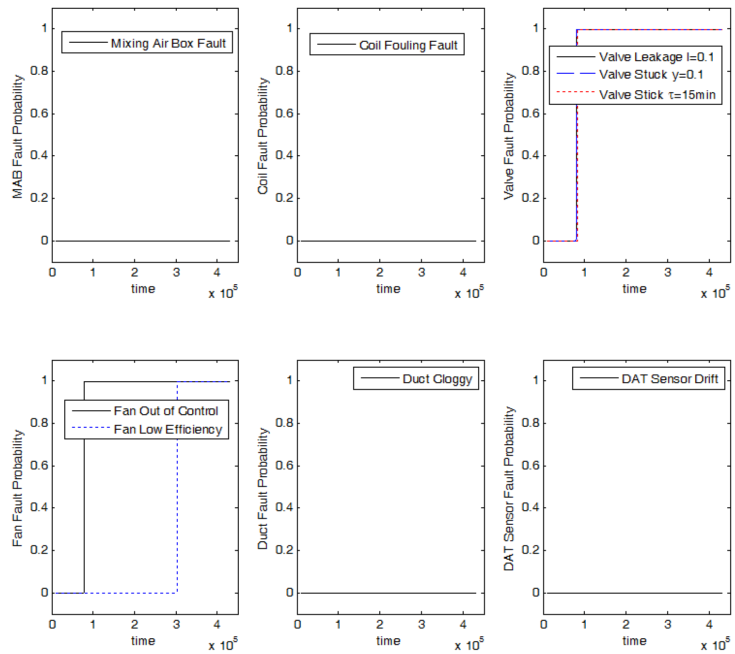

Figure 49: Application of probabilistic CUSUM method

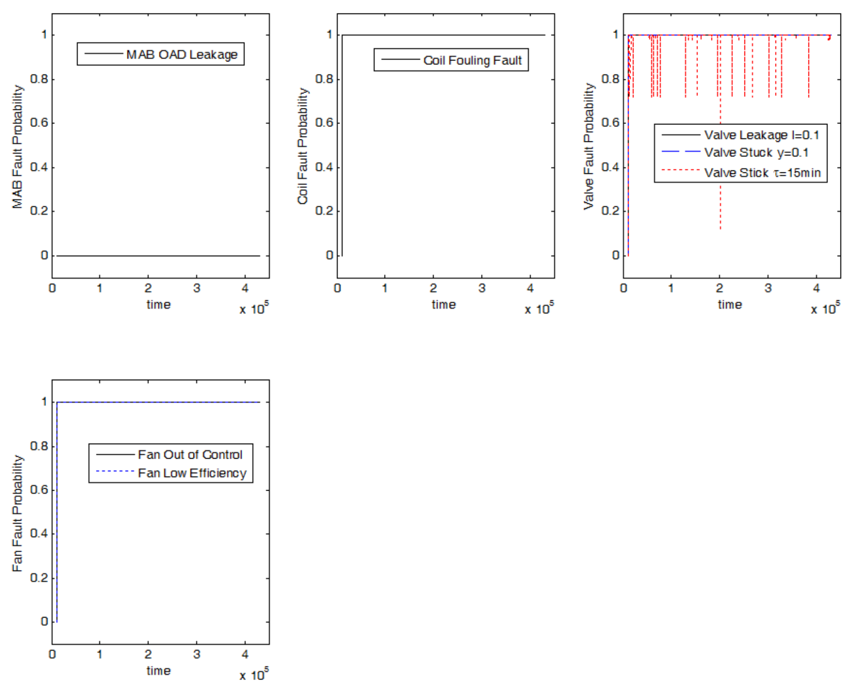

Figure 50: Application of probabilistic model based method

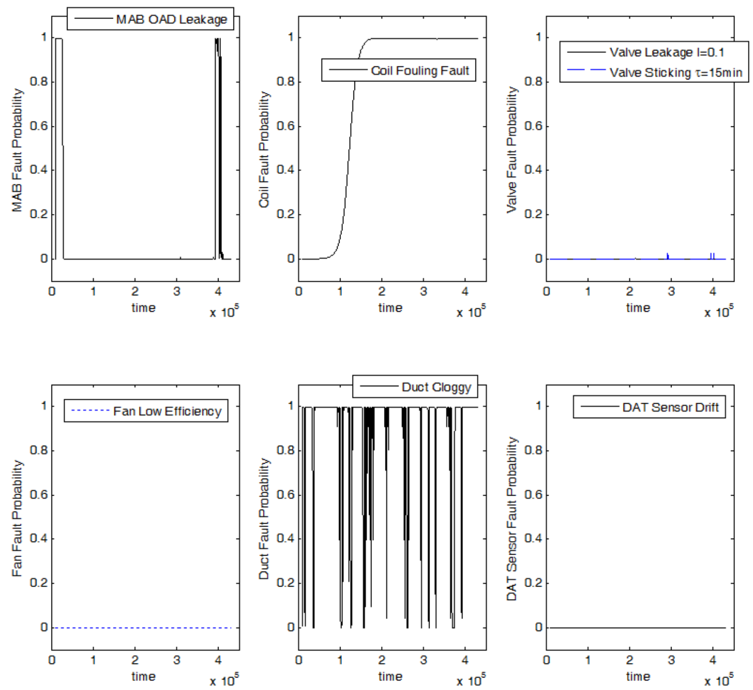

Figure 51: Application of probabilistic PCA method

and duct cloggy are not detectable. It should be noted that model based method works at the individual component level, therefore once the fault is detected, the diagnostics is accurate.

9.2.6 Probabilistic PCA Method

Applying the probabilistic PCA method to the testing case, the result is shown in Fig 51. Because the PCA error score for fan out of control fault and valve stuck fault does not exist, these two faults are not plotted. Among the other faults, fan low efficiency and dat sensor drift are not detectable, valve leakage and sticking are barely detectable.

9.3 Discussion

The results suggest that the parameter α and β play a big role in calculating the posterior probability. In the extreme case, if β is 0, with negative observation the

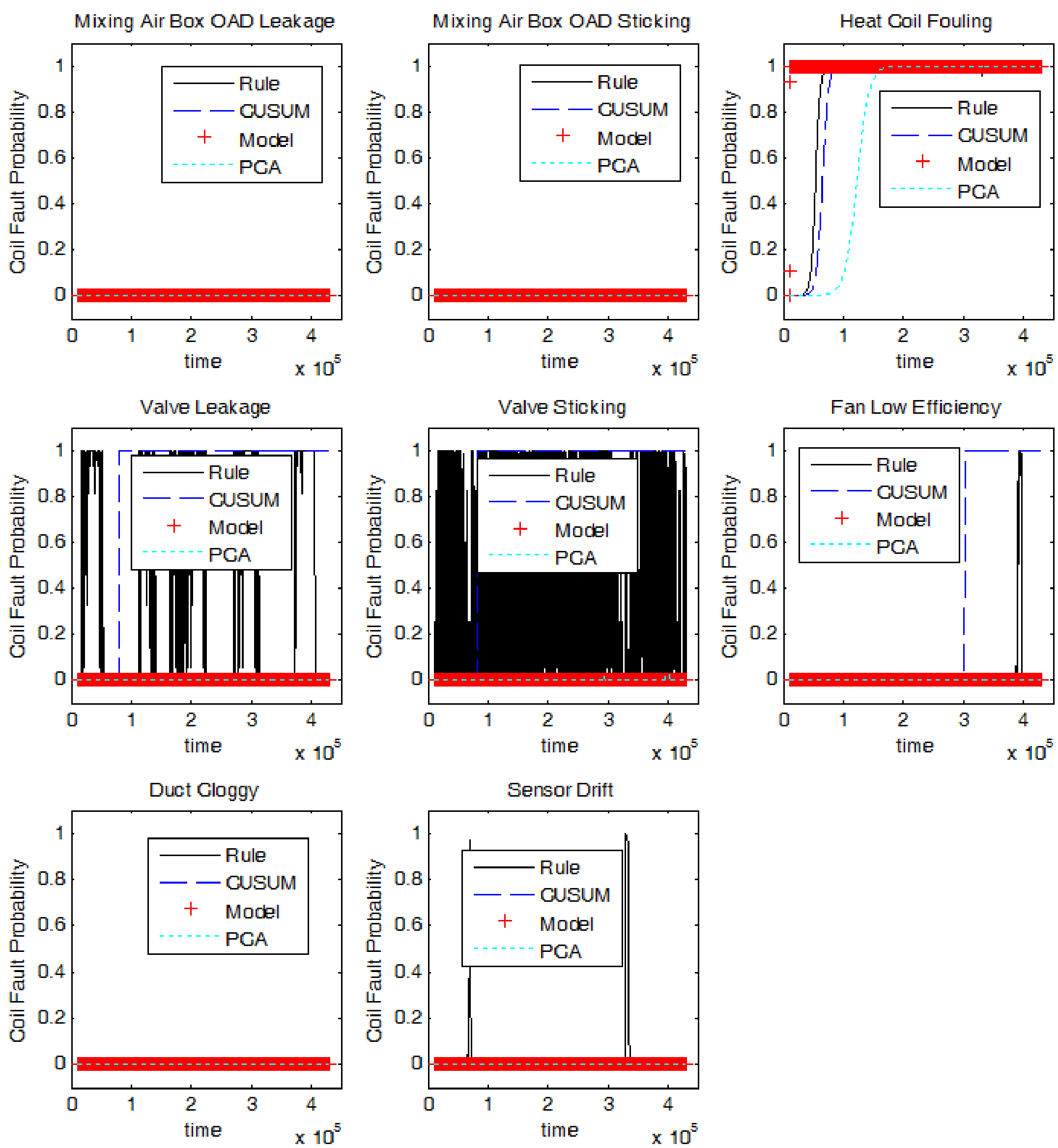

Figure 52: Cross Comparison on Heating Coil

posterior probability is always 0, if β is 1, with positive observation the posterior probability is always 0. Therefore, in practice, both α and β are suggested to use value other than 0 or 1.

Comparing the performance of four probabilistic methods, it is found that one fault that is detected by one method may not be detected by other methods. For example, mixing air box leakage is detected by PCA method but not other methods, DAT sensor drift is detected by rule based method, but not other methods. This suggests that combining multiple methods can detect more faults than using either method alone.

It is realized that rule based method, CUSUM method and PCA method have lower specificity than model based method, therefore the result could be over estimated in many cases. To illustrate this, a cross comparison is done for the fault probability of heating coil, as shown in Fig52.

Fig 52 shows that in calculating the fault probability for heating coil fouling, rule based method and CUSUM method tend to overestimate the fault probability, PCA method tends to underestimate the fault probability, model based method is the most accurate in determining the coil status. This suggests that combining multiple methods could achieve more accurate result.

9.4 Conclusion

In this chapter, the Bayesian probability approach is used to transform the deterministic results from different methods (rule based method, CUSUM method, model based method and PCA method) to probabilistic results.

A testing case is used to test and compare the four different probabilistic methods. The result shows each method has different sensitivity in detecting different faults, one fault that is able to be detected by one method may not be detected by other methods. In terms of sensitivity, there is no single method that out performs all the other methods. Each method detects only part of the complete fault list. This suggests that a combination of different methods can strengthen the sensitivity.

A cross comparison between all four methods on detecting the fault probability of heating coil is conducted, which shows that CUSUM method and rule based method tend to over estimate the fault probability, PCA method tends to under estimate the fault probability, model based method is the most accurate one in determining the coil status. This suggests that if model based method is not available, combining the other three methods can achieve a reasonable result, otherwise using model based method is a good choice.

CHAPTER X

INFORMATION FUSION

In this chapter, firstly the four FDD methods studied in previous chapters are compared in terms of information demand, detection ability and diagnostic ability. Secondly the method selection strategies under different information availability conditions are discussed. Following that, both deterministic and probabilistic integration approaches are proposed, several integration cases are tested. Finally, conclusion of this chapter is made.

10.1 Method Comparison

During the previous study, it was found that the amount of available input information is one of the determining factors of the detection and diagnostic capability of the method. Generally, the more information available, the better a method performs. However, this relation depends on the specific method. It was also found that the sensitivity and specificity of a particular method is fault type and fault component specific, there is no single method that outperforms the other method in both sensitivity and specificity on all fault cases.

In this section, the four methods are reviewed. First, the relation between information input and method capability for each method is illustrated. Second, the sensitivity and specificity of each method is listed and compared with each other. Finally, the four methods are compared in terms of scalability and adaptability.

10.1.1 Information Demand

10.1.1.1 Rule Based Method

The rule based method is developed on the basis of APAR rules. APAR rules essentially specify the inequality between different input variables when the system is under normal behavior. APAR rules by themselves do not have fault diagnostic function. For that purpose, the expert knowledge based diagnostic table has to be used. In addition to the APAR rules, three rules were proposed and tested. One is static pressure sensor should not deviate too much from set point. The second is that fan energy consumption should not exceed reference fan power too much. The third is that heating coil heat exchange rate should not exceed the reference case too much. The second and third requires the use of reference data.

Rule based method can deliver fault diagnostic output at specific fault level. However, to integrate with other methods, its resolution is enlarged to component level. As a result, the relation between input information and the detectable components for rule based method is shown in table 71.

Table 71: Rule Based Method Information vs. Capability

Information	Detectable Faulty Component
DAT, MAT	mode controller, coil/controller
OAT, RAT, MAD	MAB/controller, valve, DAT sensor, fan/controller
OAT, RAT, MAT	coil/controller, MAB/controller
DAT, DAS, HCV, CCV	coil/controller, valve, DAT sensor, fan/controller
DAT, DAS	mode controller, coil/controller, valve, DAT Sensor, fan/controller
SSP, SSPS	supply/return fan/controller, duct
P_f, P_{fref}	MAB/controller, fan/controller, duct
H_c, H_{cref}	all component

10.1.1.2 Rule Augmented CUSUM Method

CUSUM method is a statistical method to monitor any controlled process. The rule augmented CUSUM method requires an additional causal network as input, which describes the causal relationship between different control variables, and between control variable and controlling component. Combining the CUSUM method with the causal network, it is able to both detect and diagnose faults at component level.

Table 72 shows the input information - detectable faulty component relation for rule augmented CUSUM method.

Table 72: CUSUM Method Information vs. Capability

Information	Detectable Faulty Component
MAT, MAS (MAS exist)	MAB/controller, mode controller
DAT, DAS (MAS exist)	coil, coil valve, coil/mode controller, DAT Sensor
DAT, DAS (MAS not exist)	coil, coil valve, MAB, MAB/coil/mode controller, DAT Sensor
SSP, SSPS	supply/return fan, fan controller, duct

10.1.1.3 Model Based Method

The model based method specifies the performance variables for different component, uses the innovation between monitored value and reference value to indicate the existence of fault. Table 73 shows the input information - detectable component relation for model based method.

Table 73: Model Based Method Information vs. Capability

Information	Detectable Component
ΔP, y, $\dot{m}$	Damper
MAD, MAT, OAT, RAT	Single Signal MAB
OAD, MAD, MAT, OAT, RAT	Dual Signal MAB
ΔP, $\dot{m}$	Duct
ΔP, y, $\dot{m}$	Two way valve
ΔP, y, $\frac{\dot{m}_1}{\dot{m}}$	Three way valve
$\dot{m}$, N, ΔP	Fan
$\dot{m}$, N, SAF_POW	Fan
$\dot{m}_a$, $\dot{m}_w$, DAT, T_{ai}, T_{wi}, T_{wo}	Coil

10.1.1.4 Enhanced Principal Component Analysis Method

Principal component analysis method uses multivariate statistical analysis approach to analyze the monitored data. By comparing the monitored data and expected data, a PCA error score is calculated to indicate the existence of fault in the system.

Traditional PCA method only has fault detection function. In the enhanced PCA method, it is possible to diagnose the fault at specific fault level. However, to integrate with the other methods, the resolution is artificially enlarged to component level.

Table 74: PCA Method Information vs. Capability

Information	Component
SSP, DAF, SFR, MAD	Mode Controller
SSP, DAF, SFR, MAD	MAB/controller
SSP, DAF, SFR, MAD	fan/controller
SSP, DAF, SFR, MAD	duct
SSP, DAF, SFR, MAD	DAF Sensor
SSP, DAF, SFR, MAD	SSP Sensor
OAT, RAT, MAT, DAT, DAF, MAD, HCV	MAB
OAT, RAT, MAT, DAT, DAF, MAD, HCV	Coil/controller
OAT, RAT, MAT, DAT, DAF, MAD, HCV	Coil valve
OAT, RAT, MAT, DAT, DAF, MAD, HCV	fan
OAT, RAT, MAT, DAT, DAF, MAD, HCV	duct
OAT, RAT, MAT, DAT, DAF, MAD, HCV	DAT Sensor
OAT, RAT, MAT, DAT, DAF, MAD, HCV	OAT Sensor
OAT, RAT, MAT, DAT, DAF, MAD, HCV	RAT Sensor
OAT, RAT, MAT, DAT, DAF, MAD, HCV	MAT Sensor
OAT, RAT, MAT, DAT, DAF, MAD, HCV	DAF Sensor

10.1.2 Sensitivity and Specificity

Table 68 shows that rule based method can detect the fault of four components (coil, valve, fan, dat sensor), CUSUM method can detect three faulty components (coil, valve, fan), PCA is able to detect all six faulty components (MAB, coil, valve, fan, dat sensor, duct), model based method can detect four faulty components (MAB, coil, valve, fan). In terms of the number of detectable components, PCA > Rule > Model> CUSUM.

It also shows that model based method and PCA method are on the two extremes of accuracy and sensitivity. PCA method can detect the most number of faulty components, but the sensitivity is low. Model based method can detect the least number of faulty components, but the sensitivity is the highest in its detectable components (valve and fan). This suggests the combination of PCA and model based method is an ideal fit.

Table 69 shows that model based method is the most specific method among the four methods. For all components, the specificity is 1. This is due to its individual component level fault detection, which requires more sensor information.

Among the other three methods, since they work at system level, the specificity is relatively lower than model based method.

10.1.3 Scalability and Adaptability

Scalability measures the capability for a method to be applied to large number of similar systems, which may have different component parameters. Among the four methods, since model based method requires detailed component documents to make physical model, it is the least scalable method. The remaining three methods all require little system knowledge for fault detection, but require a certain knowledge base for fault diagnostics; if the knowledge base of each method could be reused, the scalability of these three methods are similar. Therefore, the rank of scalability is: PCA method = CUSUM method = rule based method > model based method.

Adaptability measure the easiness for one method to be applied to air handling units with different configurations. Model based method again has the least adaptability each time a different physical model needs to be made. Among the remaining three methods, for fault detection, they can all be applied to systems with different configurations. For fault diagnostics, PCA method and CUSUM method require less work to set up new knowledge base. Therefore, the rank of adaptability is PCA method = CUSUM method > rule based method > model based method.

10.1.4 Findings

In the above, the four methods: rule based method, rule augmented CUSUM method, model based method and principal component analysis method have been compared in three aspects: information demand, sensitivity/specificity and scalability/adaptability.

It is found that among these four methods, the information demand ranking is model based method > PCA method = rule based method > CUSUM method, the sensitivity comparison is complicated, because in terms of the number of detectable components, PCA method > rule based method = model based method > CUSUM method, in terms of the diagnostic accuracy, model based method is the highest, the other three methods are fairly close. The specificity comparison shows that model based method is the most specific method, PCA method is the least specific method, the other two methods are close in this metric. In terms of scalability, model based method is the lease scalable method, the other three are close. In terms of adaptability, PCA method is the most adaptable, followed by rule based method and CUSUM method, model based method is the least adaptable method.

Based on above findings, the performance of different methods are listed in table 75.

Table 75: Four Method Comparison

	CUSUM	APAR	Model	PCA	Enhanced Rule
Information Demand	low	medium	high	medium	high
Adaptability	high	medium	low	high	low
Scalability	high	high	low	high	low
Sensitivity	medium	medium	medium	high	high
Specificity	medium	medium	high	low	low

10.2 Method of Integration

There are two technical routes for the method integration: deterministic and probabilistic. The former only relies on the current observation, the latter also takes into account the information in previous time step. The former delivers a binary diagnostic result for each component, the latter provides a time series probabilistic result.

In this section, both the deterministic and probabilistic integration approaches are proposed and tested with the standard testing case. The performance of these two approaches are then compared based on the testing results.

10.2.1 Deterministic Integration

It is recognized that the four methods can be separated into two groups: system level method (rule based method, CUSUM method and PCA method) and individual component level method (model based method). The integration approach is also separated based on if individual component level method is used.

The first integration approach (without model based method) is shown in Fig 53. In this approach, given the input data, the methods that can not detect faults automatically quit, each of the rest methods provides a list of fault candidates, the common elements of them are taken as the final candidates.

The second integration approach (with both system level method and model based method) is shown in Fig 54. In this approach, component level method is given higher priority than system level method. If the component level method detects a fault, its diagnostic result is used as the final result, otherwise the common elements of the results from system level methods are used as the final results.

Applied to the standard testing case as listed in table 67, the deterministic result of rule based method is shown in table 76. The deterministic result of rule augmented CUSUM method is shown in table 77. The deterministic result of probabilistic model based method is shown in table 78. The deterministic result of enhanced PCA method is shown in table 79.

10.2.1.1 Integration of CUSUM Method and Rule Based Method

Using the system level method integration approach, the diagnostic result is shown in Table 80. It is found that after integrating these two methods, the accuracy (the ratio of the number of correctly diagnosed faults to the number of total fault candidates) is improved from 0.24 to 0.32.

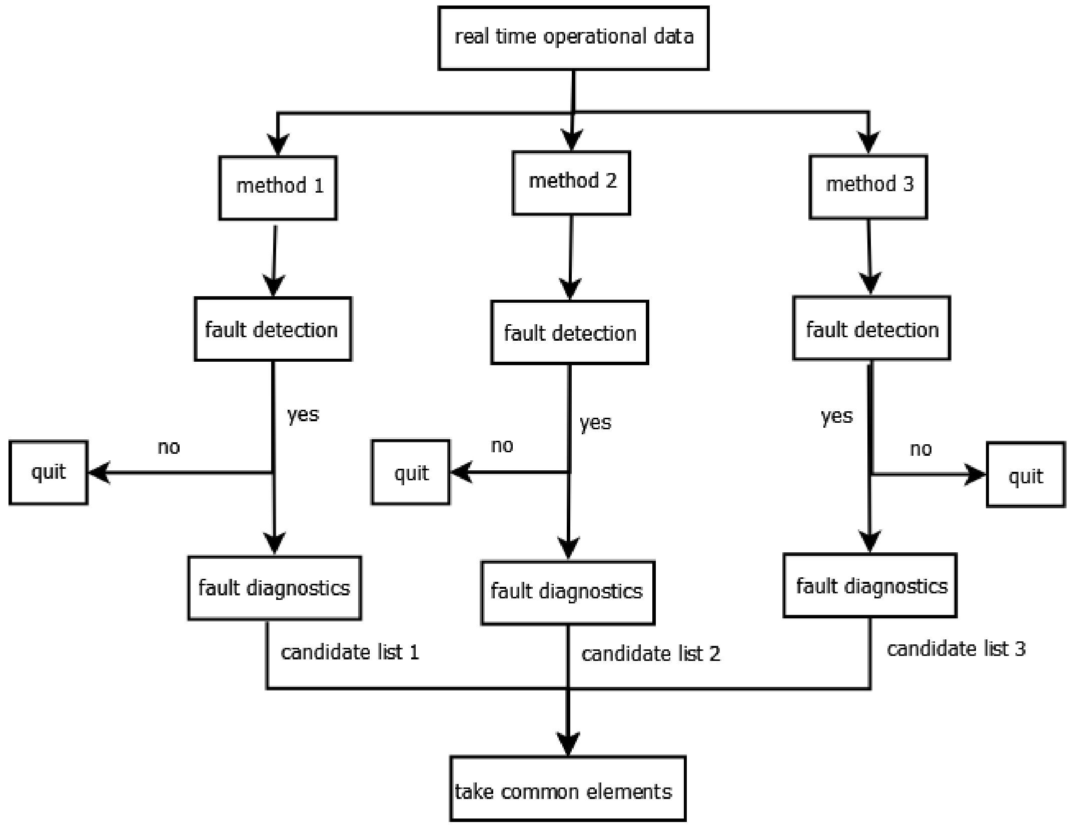

Figure 53: Deterministic Integration Approach for the System Level Method

Table 76: Testing Case - Rule Based Method

Rule 1	Rule 2	Rule 3	Rule 4	Rule 5	Rule 6	Rule 7	Rule 8	Rule 9	Faulty Case
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	$1(l = 0.1)$
0	0	0	0	0	0	0	0	1	$2(y = 0.5)$
0	0	0	0	0	0	0	0	1	$3(\tau = 15min)$
0	0	0	0	0	0	0	1	1	$4(l = 0.1)$
0	0	0	0	0	0	0	1	1	$5(y = 0.2)$
0	0	0	0	0	0	0	0	1	$6(\tau = 15min)$
0	0	1	0	0	0	0	0	1	$7(UA = 10666W/K)$
0	0	1	0	0	0	0	0	1	$8(l = 0.1)$
0	0	0	1	0	0	0	0	1	$9(y = 0.1)$
0	0	0	1	0	0	0	0	1	$10(\tau = 15min)$
0	0	0	0	0	0	1	0	1	$11(N = 2/s)$
0	0	0	1	0	0	0	1	0	$12(\eta = 0.1)$
0	0	0	0	0	0	0	0	0	$13(\Delta P = 50Pa)$
0	0	1	0	0	0	0	0	1	$14(\Delta T = -2°C)$
0	0	0	0	0	0	0	0	1	$15(k = 0.01)$

10.2.2 Integration of CUSUM and PCA Method

Applying the system level method integration approach to the testing case, the result is shown in table 81.

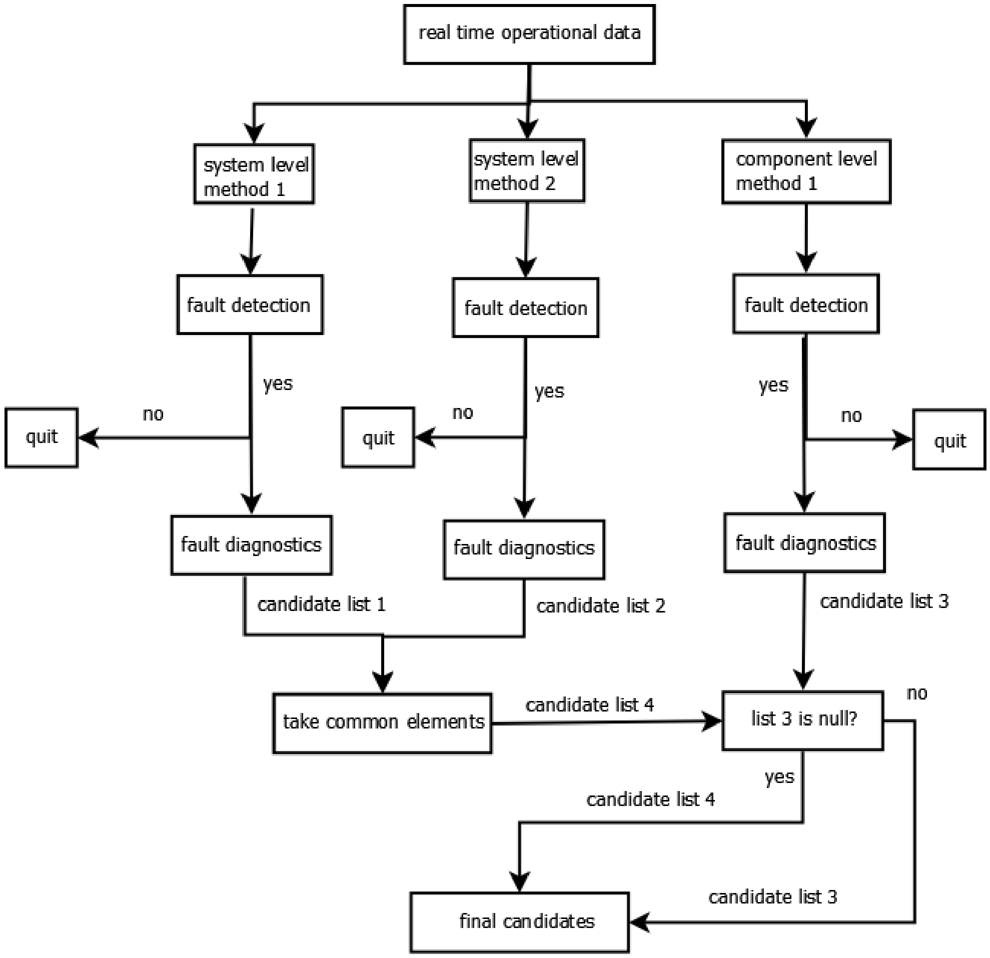

Figure 54: Deterministic Integration Approach for the Combined Level Method

The result shows that the integration improves the detection sensitivity of both methods. The integrated approach detects all 15 faults in the list, and increases the number of correctly diagnosed faults from 11 to 12.

10.2.3 Integration of CUSUM, Rule based and PCA Method

Applying the system level integration approach to the testing case, the result is shown in table 82. The result suggests that integration of PCA and CUSUM method improves both the detection and diagnostic capability. However, adding rule based method does not further improve the performance.

Table 77: Testing Case - CUSUM Method

MAT Counter	DAT Counter	SSP Counter	Case
2	2	0	0
0	2	0	1 ($l = 0.1$)
0	2	0	2($y = 0.5$)
0	2	0	3($\tau = 15min$)
0	2	0	4 ($l = 0.1$)
1	0	0	5 ($y = 0.2$)
0	2	0	6 ($\tau = 15min$)
0	10	0	7 ($UA = 10666W/K$)
0	120	0	8 ($l = 0.1$)
0	120	0	9 ($y = 0.1$)
0	119	0	10($\tau = 15min$)
5	2	119	11 ($N = 2/s$)
2	57	0	12 ($\eta = 0.1$)
3	0	2	13 ($\Delta P = 50Pa$)
0	6	0	14($\Delta T = -2°C$)
1	0	0	15($k = 0.01$)

Table 78: Testing Case - Model Based Method

Detectable	Case
No	1 ($l = 0.1$)
No	2($y = 0.5$)
No	3($\tau = 15min$)
No	4 ($l = 0.1$)
Yes	5 ($y = 0.2$)
No	6 ($\tau = 15min$)
Yes	7 ($UA = 10666W/K$)
Yes	8 ($l = 0.1$)
Yes	9 ($y = 0.1$)
Yes	10($\tau = 15min$)
Yes	11 ($N = 2/s$)
Yes	12 ($\eta = 0.1$)
No	13 ($\Delta P = 50Pa$)
No	14($\Delta T = -2°C$)
No	15($k = 0.01$)

10.2.4 Integration of CUSUM, PCA and Model based Method

Applying the combined level integration approach to the testing case, the result is shown in table 83.

The comparison shows that in this case, by integrating PCA and model based

Table 79: Testing Case - PCA Method

Heat Balance	Pressure Balance	Case
*	*	1 ($l = 0.1$)
*	*	2($y = 0.5$)
	*	3($\tau = 15min$)
	*	4 ($l = 0.1$)
*	*	5 ($y = 0.2$)
	*	6 ($\tau = 15min$)
*		7 ($UA = 10666W/K$)
		8 ($l = 0.1$)
*	*	9 ($y = 0.1$)
*		10($\tau = 15min$)
*	*	11 ($N = 2/s$)
*		12 ($\eta = 0.1$)
	*	13 ($\Delta P = 50Pa$)
*		14($\Delta T = -2°C$)
		15($k = 0.01$)

Table 80: Deterministic Integration of CUSUM and Rule based Method

Metric	CUSUM	Rule	CUSUM/Rule
Total fault detected	5	7	7
Total fault diagnosed	4	7	7
Accuracy	0.29	0.24	0.32

Table 81: Deterministic Integration of CUSUM and PCA Method

Metric	CUSUM	PCA	CUSUM/PCA
Total fault detected	5	14	15
Total fault diagnosed	4	11	12
Accuracy	0.29	0.19	0.21

Table 82: Deterministic Integration of CUSUM, Rule and PCA

Metric	CUSUM	Rule	PCA	CUSUM/PCA	CUSUM/Rule/PCA
Total fault detected	5	7	14	15	15
Total fault diagnosed	4	7	11	12	12
Accuracy	0.29	0.24	0.17	0.21	0.23

method, both detection and diagnostic capability improve. However, adding CUSUM method does not further improve the performance.

10.2.5 Integration of CUSUM, Rule based, PCA and Model based Method

Finally, CUSUM, rule based, PCA and model based method are integrated together, the result is shown in table 84.

Table 83: Deterministic Integration of CUSUM, PCA and Model

Metric	CUSUM	PCA	Model	Model/PCA	CUSUM/PCA/Model
Total fault detected	5	14	7	15	15
Total fault diagnosed	4	11	7	13	13
Accuracy	0.29	0.19	1	0.35	0.35

The result shows that in this testing case, integrating PCA and model method achieves the peak performance for both detection and diagnostics, adding CUSUM and rule based method does not further improve the performance.

Table 84: Deterministic Integration of CUSUM, Rule, PCA and Model

Metric	CUSUM/PCA	Model/PCA	CUSUM/PCA/Model	CUSUM/Rule/PCA/Model
Total fault detected	15	15	15	15
Total fault diagnosed	12	13	13	13
Accuracy	0.21	0.35	0.35	0.35

10.2.6 Findings

The testing of various deterministic integration options in this particular testing case shows that

- Although PCA method is the most sensitive method, integrating it with other methods can still improve its sensitivity.
- Model method is the most accurate method but with medium sensitivity, integrating it with other methods will improve its sensitivity, but decrease its accuracy.
- In general, the more methods used, the better detection sensitivity will be achieved, the diagnostic accuracy will take a value between the two extremes.

10.3 Probabilistic Integration

In the following, firstly the Bayesian integration approach is introduced, following that, several method combinations are tested using the testing case. Finally some observations are drawn based on the results.

10.3.1 Bayesian Integration Approach

Suppose $P(f)$ is the prior probability that a fault exists, method 1 and 2 are the deterministic methods to be integrated, whose specificity are $1-\alpha_1$ and $1-\alpha_2$, and the sensitivity are $1-\beta_1$ and $1-\beta_2$.

With above assumptions, the total probability that both methods give positive result can be calculated by equation 66, similarly, the total probability that method 1 gives positive result and method 2 gives negative result can be calculated by equation 67, the total probability that method 1 gives negative result and method 2 gives positive result can be calculated by equation 68, the total probability that both methods give negative result can be calculated by equation 69.

$$P(o1, o2) = (1-\beta_1)(1-\beta_2)P(f) + \alpha_1\alpha_2(1-P(f)) \tag{66}$$

$$P(o1, n2) = (1-\beta_1)\beta_2 P(f) + \alpha_1(1-\alpha_2)(1-P(f)) \tag{67}$$

$$P(n1, o2) = \beta_1(1-\beta_2)P(f) + (1-\alpha_1)\alpha_2(1-P(f)) \tag{68}$$

$$P(n1, n2) = \beta_1\beta_2 P(f) + (1-\alpha_1)(1-\alpha_2)(1-P(f)) \tag{69}$$

Consequently, the posterior probability $P(f|o1, o2)$ is calculated through equation 70, the posterior probability $P(f|o1, n2)$ is calculated through equation 71, the posterior probability $P(f|n1, o2)$ is calculated through equation 72, the posterior probability $P(f|n1, n2)$ is calculated through equation 73.

$$P(f|o1, o2) = \frac{(1-\beta_1)(1-\beta_2)P(f)}{P(o1, o2)} \tag{70}$$

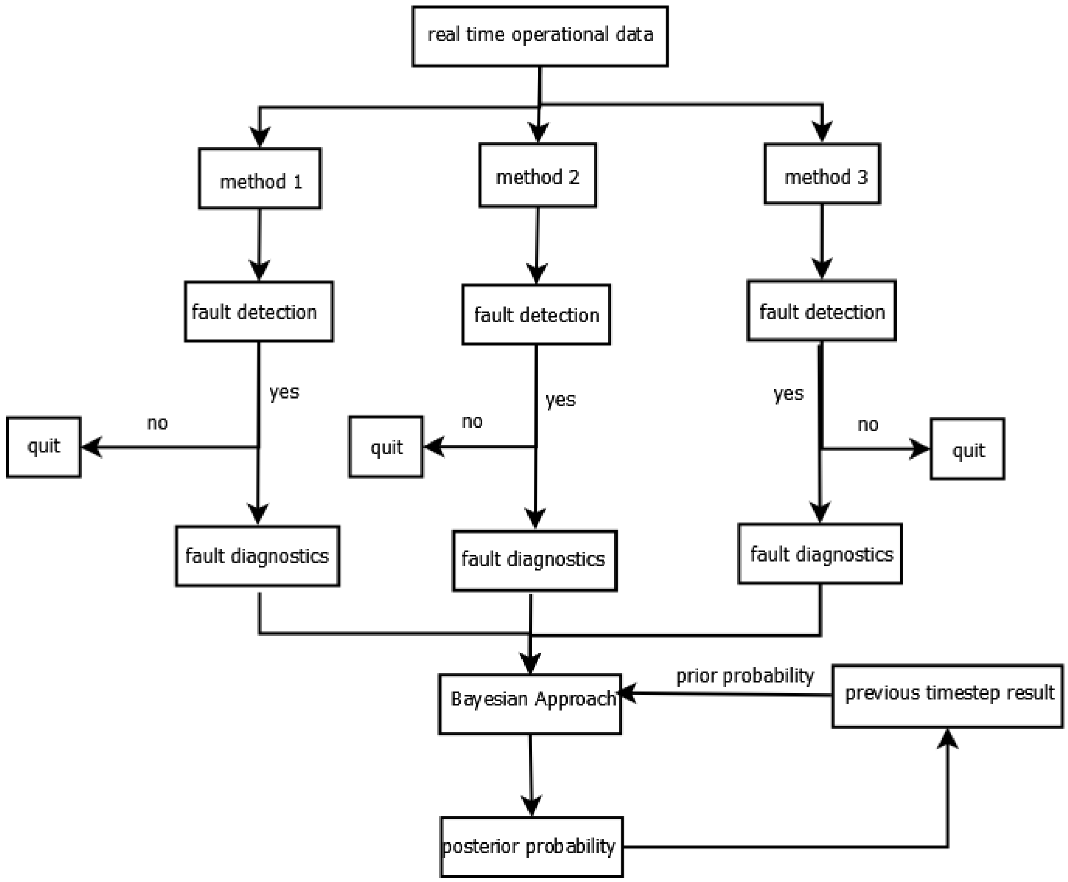

Figure 55: System Level Method Probabilistic Integration Approach

$$P(f|o1, n2) = \frac{(1-\beta_1)\beta_2 P(f)}{P(o1, n2)} \tag{71}$$

$$P(f|n1, o2) = \frac{\beta_1(1-\beta_2) P(f)}{P(n1, o2)} \tag{72}$$

$$P(f|n1, n2) = \frac{\beta_1\beta_2) P(f)}{P(n1, n2)} \tag{73}$$

The integration process is shown in Fig 55.

10.3.2 Integration of CUSUM and Rule based Method

The fault probability of coil is used to illustrate the performance of the integrated method, which is shown in Fig 56.

The results show that: (1)the performance of the integrated approach depends on the parameter setting, namely α_1, α_2, β_1, and β_2. In the fan low efficiency case, since CUSUM method has higher specificity than rule based method, the integrated result inclines to CUSUM method, and in the sensor drift case, since rule based method has higher sensitivity, the integrated result inclines to the rule based method. (2) The integrated method has a low diagnostic accuracy, attributed to the low specificity of both CUSUM method and rule based method.

Overall, since the integrated approach inclines to the method with higher sensitivity and specificity, which varies depending on the fault type, the integrated result is better than each method alone.

10.3.3 Integration of CUSUM and PCA Method

With the integration of CUSUM and PCA method, the fault detection result in various faults is shown in Fig 57, the fault probability of coil is shown in Fig 58.

Fig 57 shows that the integration of CUSUM and PCA method is able to detect all faults listed, which verifies the hypothesis that integration could increase the sensitivity.

For mixing air box fault, although PCA method detects the fault, it does not assign the fault to heating coil, so in both leakage and sticking case the fault probability is 0. For valve fault and fan fault, since PCA method is not able to detect the faults, the integrated result is determined by CUSUM method. This testing shows that the integrated CUSUM and PCA method has higher fault detection sensitivity than each method alone.

10.3.4 Integration of Model and PCA Method

With the integration of CUSUM and PCA method, the fault probability of coil is shown in Fig 59. Since model based method has low α and β value, the integrated results inclines to model based method. In this case, the integrated method works

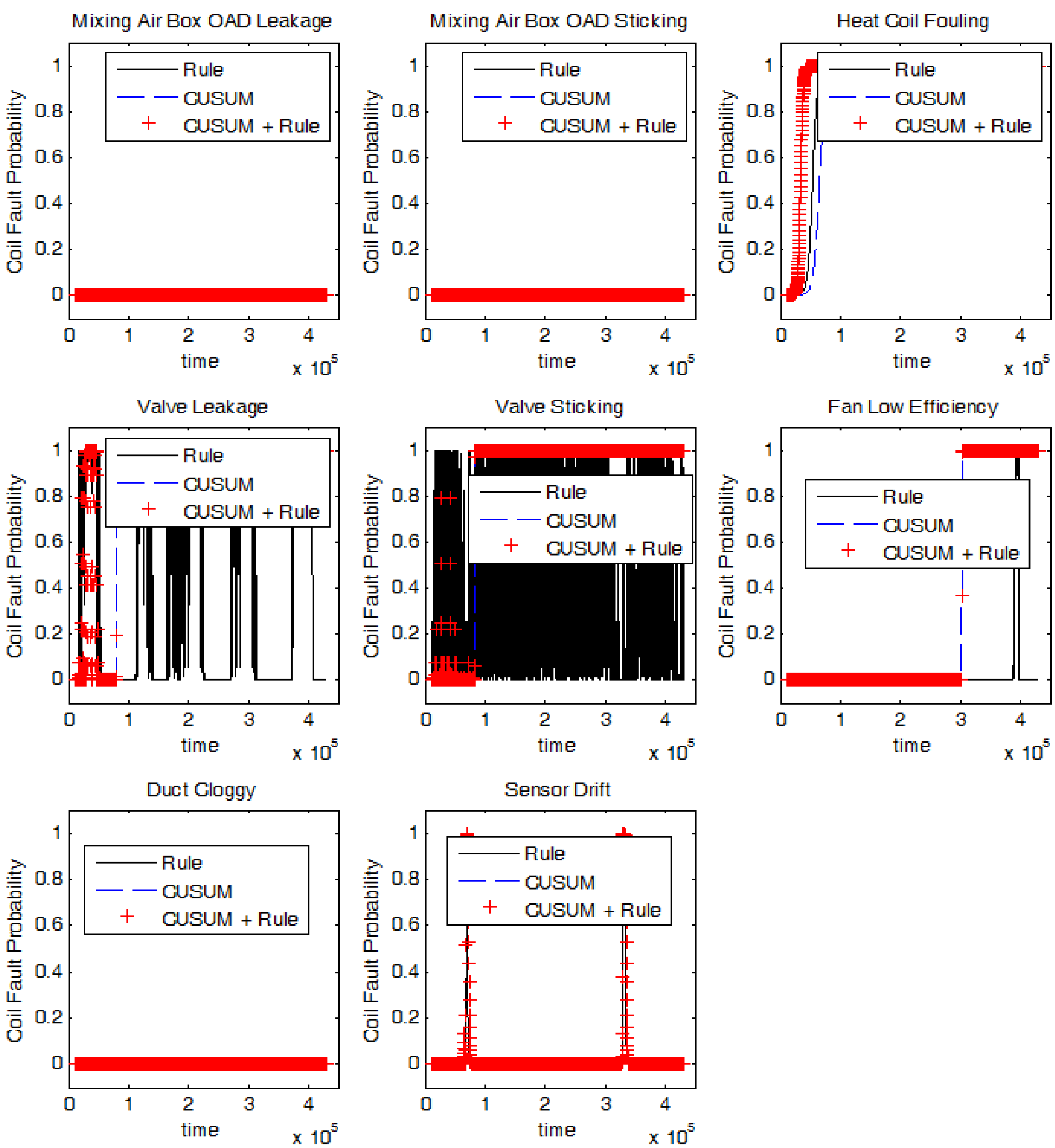

Figure 56: Integration of CUSUM and Rule Based Method

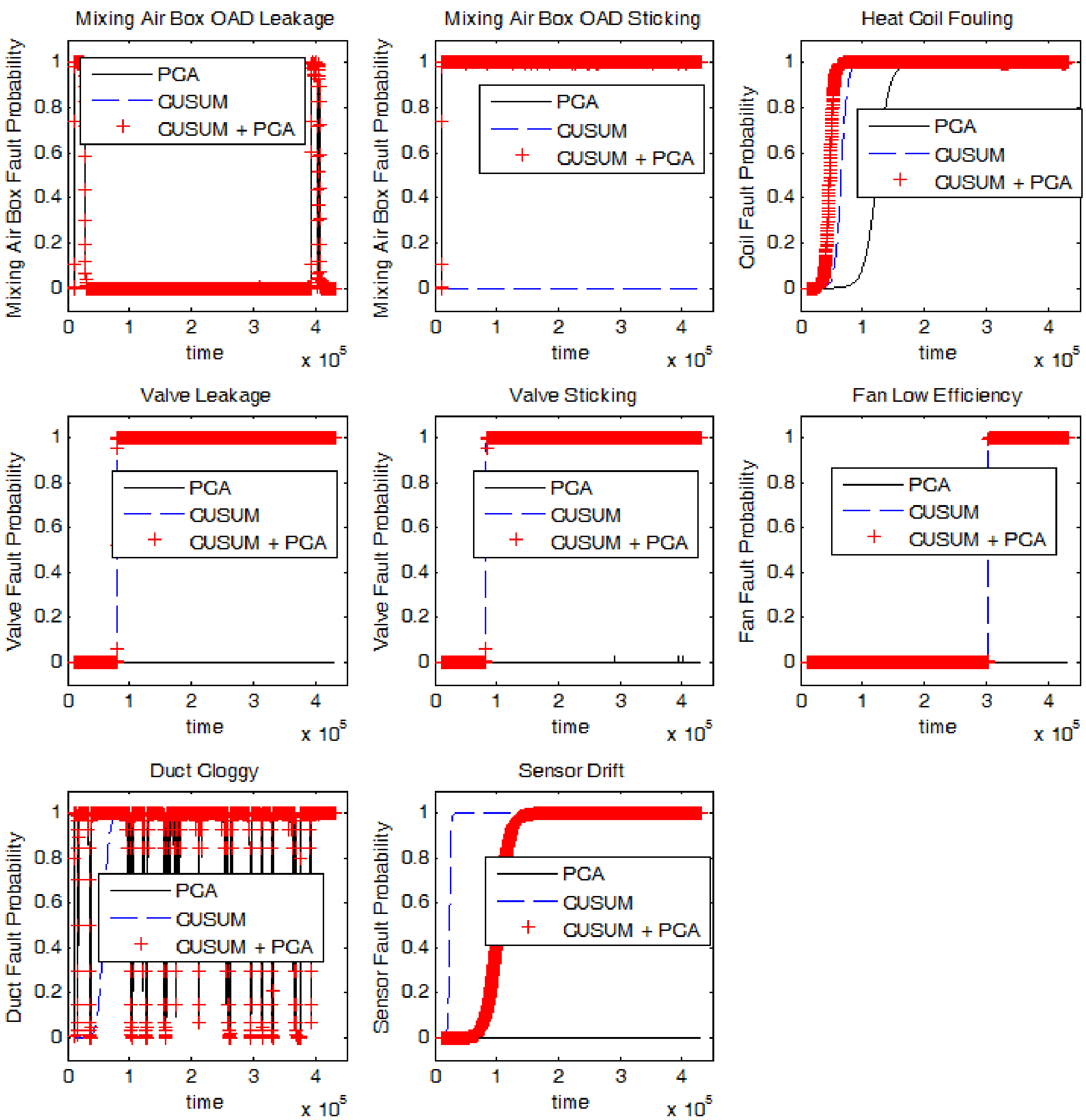

Figure 57: Integration of CUSUM and PCA Method - Detection

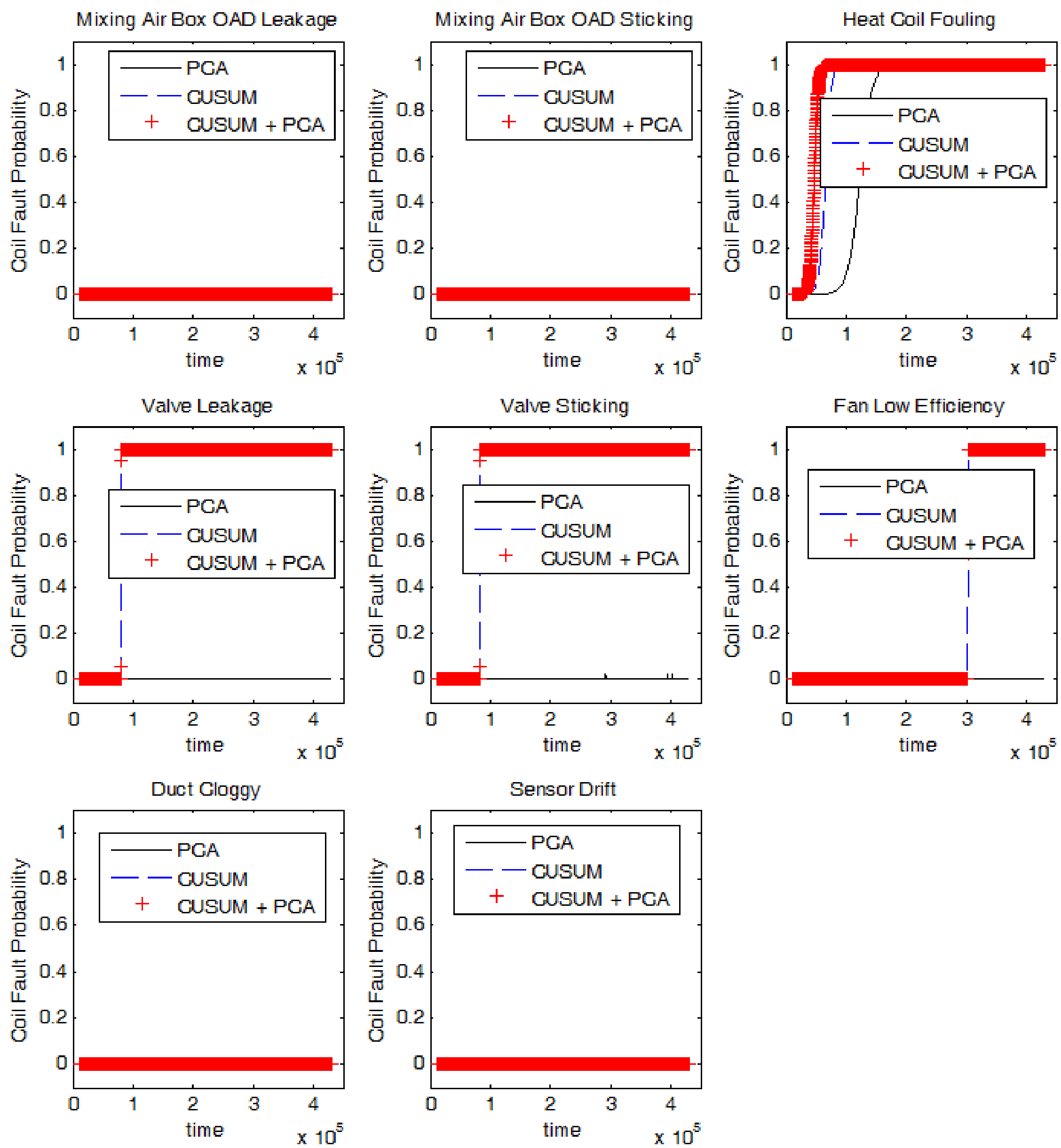

Figure 58: Integration of CUSUM and PCA Method - Diagnostics

exactly as model based method alone, and the diagnostic accuracy is the highest.

10.3.5 Findings

In this section, the Bayesian integration approach is applied to the testing case with three integration options: (1) CUSUM method and rule based method (2) CUSUM method and PCA method (3) PCA method and model based method.

The results show that (1) The performance of integrated method depends on the α and β value of each elementary method. The method with low α and β value gets higher priority in determining the final result (2) The integration improves the fault detection sensitivity, because each elementary method detects only partial faults (3) The integration improves the fault diagnostic capability, in that more accurate method (such as model based method) has higher priority in determining the final results.

10.4 Method Selection Options

The study above of both deterministic integration approach and probabilistic integration approach shows that the more methods included in the integration, the better the performance will be. However, the method available to use depends on the level of detail of information input.

This section discusses the methods available for use in different input information availability scenarios, namely low, medium, high, and unknown.

10.4.1 Low Information Availability

In low information availability scenario, only the control required sensors are installed. In a typical air handling unit, DAT and SSP are the two control required sensors. With the control setpoint DAS and SSPS, and control signals HCV, MAD, CCV and SFR, these are the only available information.

In this scenario, CUSUM method can work without any constraint. Rule based

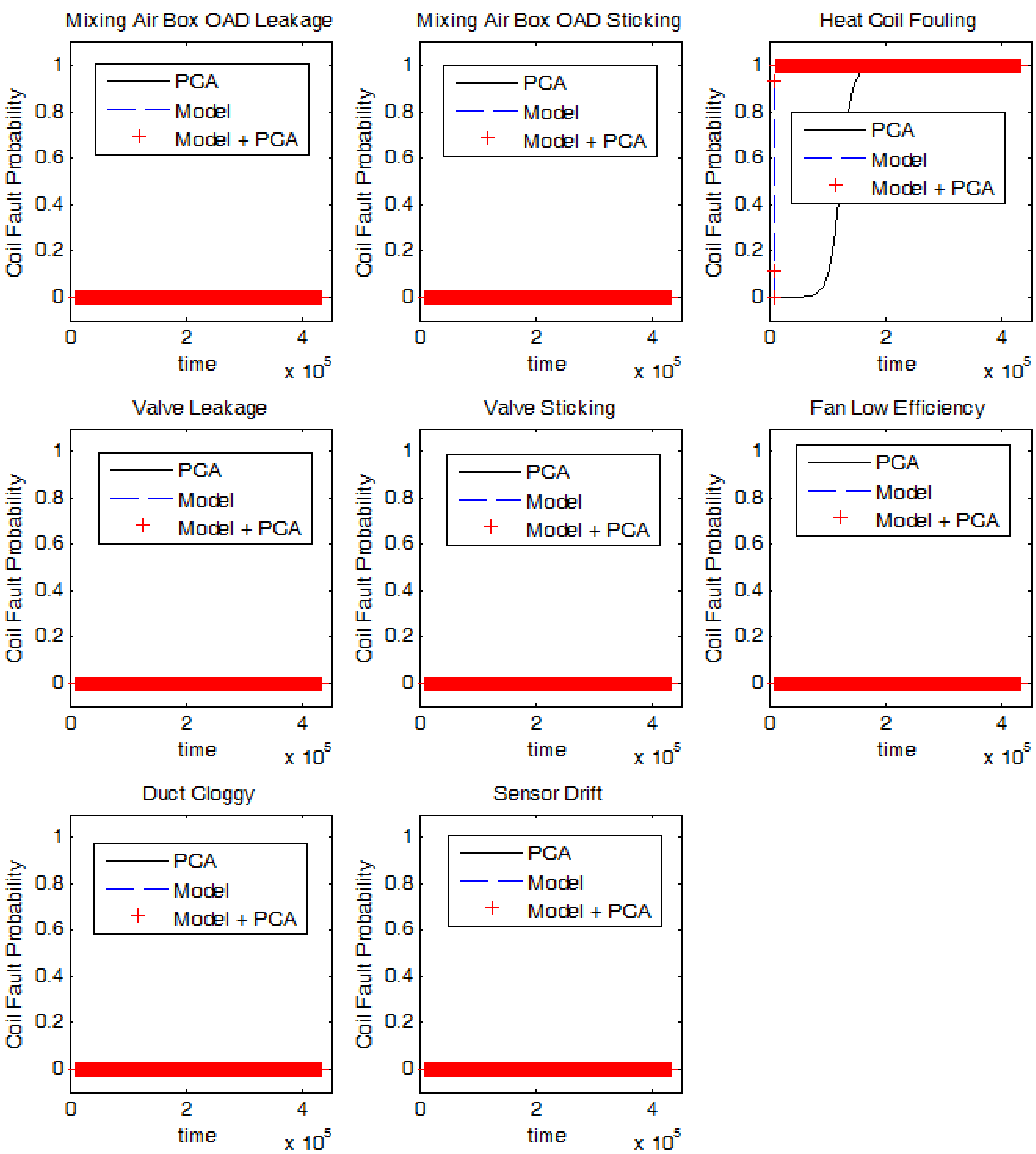

Figure 59: Integration of Model Based and PCA Method

method has enough information to detect the following components: mode controller, heating/cooling coil, coil controller, coil valve, fan, fan controller and duct. None of the models in model based method can work due to the limited input information. Similarly, PCA method can not work due to the limited information.

Therefore, in this scenario, the enhanced CUSUM method should be combined with rule based method.

10.4.2 Medium Information Availability

In medium information availability scenario, only the typically installed sensors are available. These include DAT, OAT, RAT, MAT, SSP, DAF. With the control set points DAS and SSPS, and control signals HCV, CCV, MAD and SFR, there may be other inputs as well, depending on the system configuration.

In this scenario, CUSUM method, rule based method and PCA method have sufficient information input. Although the information is enough for mixing air box model to analyze, due to the low fidelity of the model, the detection sensitivity is low. Therefore, rule based method, CUSUM method, and PCA method should be integrated.

10.4.3 High Information Availability

In high information availability scenario, besides the typically installed sensors (DAT, OAT, RAT, MAT, SSP), there are also air flow rate sensor (DAF), water flow rate sensor (SWF), power consumption sensor (SAF_POW), coil heat exchange rate sensor (H_c), and static pressure sensors for all the components.

In this scenario, all four methods have sufficient information to use. Therefore, all four methods should be combined to use.

10.4.4 Unknown Information Availability

In unknown information availability scenario, the available sensor information varies. To facilitate the choice of methods, an information - available method mapping is made for all four methods (shown in Table 85). In this mapping, the information is divided into different layers, the information in each layer plus all the upper layers (in the left column) enables the usage of methods on the right column. This mapping also serves as a guide for installing the sensors if a system needs to be monitored. Note that the control signals and control set points are not listed.

Table 85: Information - Available Method Mapping

Information Available	Method
DAT, SSP	CUSUM, Rule based (rule 3, rule 4, rule 7)
MAT	Rule based (rule 1)
OAT, RAT	Rule based (rule 2, rule 5, rule 6)
DAF	PCA
other	Model based

Table 86: Method Selection

Information Availability	Method
Low	CUSUM, Rule based
Medium	CUSUM, Rule based, PCA
High	CUSUM, Rule based, Model based, PCA
Unknown	flexible

10.5 Summary

In this chapter, the performance of the four method (rule based method, CUSUM method, PCA method and model based method) are compared in terms of information demand, sensitivity/specificity and scalability/adaptability. It is found that among the four methods, model based method requires much more information than the other three methods. If the faults are detected, model based method is the most specific and accurate in fault diagnostic, PCA method is the least accurate in fault diagnostic.

In terms of scalability and adaptability, CUSUM method and PCA method are the highest, model based method is the worst. In this testing case, the sensitivity ranking is PCA method > rule based method = model based method > CUSUM method.

Among the four methods, CUSUM and model based method can only deliver fault diagnostic output at component resolution, however, rule based method and PCA method can deliver diagnostic output at specific fault resolution. To integrate these four methods, component level diagnostic resolution is enforced to all methods.

Based on the diagnostic approach, these four methods are separated into two groups: system level diagnostics (rule based method, CUSUM method and PCA method) and component level diagnostics (model based method). Two deterministic approaches are proposed, which one to choose depends on if there is component level diagnostic method among the elementary methods. In case there is no component level diagnostic method, the equal priority approach should be used, in which the common elements of the candidates suggested by different methods are chosen as the final candidates. If component level diagnostic method is used, that method is given highest priority, whose outputs are taken as final candidates once fault is detected.

Applying the proposed deterministic approaches on the testing case shows that in general, the more diagnostic methods used, the better performance the integration can achieve. The most effective combination to achieve high performance is to integrate PCA method with model based method, given the enough level of detailed information.

The Bayesian probabilistic approach is proposed to integrate different probabilistic methods. To use this approach, the fault wise sensitivity and specificity of each method has to be known. In this approach, there is no differentiation on the priority of the method, how much the integrated result gets affected by each method is automatically determined by the sensitivity and specificity of that method.

The Bayesian integration approach is tested in three combinations: (1) CUSUM and rule based method (2) CUSUM and PCA method (3) PCA and model based method. The results show that the integration in all three cases improves the detection sensitivity and diagnostic capability of the elementary methods. This is attributed to the Bayesian integration algorithm, which by nature inclines to the method with highest sensitivity and specificity.

Finally, the method selection strategy is discussed, which can be stated as: all the available methods with sufficient input information should be selected and integrated. The available methods under different information availability (low, medium, high and unknown) are then discussed. The finding is shown in Table 86. It should be noted that (1) the high information availability scenario rarely exist in practice (2) rule based method and PCA method are flexible in terms of input information requirement. If the information availability is not part of the three scenarios above, Table 85 could be used to find the available methods.

CHAPTER XI

CONCLUSION

This chapter summarizes the findings from previous chapters. The findings are organized in three sections: (1) Method comparison. In this section, the four methods (rule based method, CUSUM method, model based method and PCA method) are reviewed in terms of information demand, detection sensitivity, diagnostic accuracy, scalability and adaptability. (2) Integration approach comparison. In this section, the deterministic approach and probabilistic approach are compared, based on their required input, delivered output, etc. (3)Information availability comparison. In this section, the best achievable fault detection and diagnostic results in low, medium and high information availability are compared, to illustrate the importance of information in FDD. Following that, a final remark is made to close this thesis.

11.1 Information demand, Accuracy and Sensitivity

Any FDD method can be measured in five metrics: information demand, detection sensitivity, diagnostic accuracy, scalability and adaptability. In this thesis, rule based method, CUSUM method, model based method and PCA method are compared in these five metrics. The results is shown in Fig 60.

Among these four methods, model based method is the best performing method, but this is at the price of more input information, lower scalability and lower adaptability. The other three methods have similar information demand, but vary in detection sensitivity and diagnostic accuracy. Note that these two metrics are fault type dependent, thus this chart only reflects a fault type averaged performance.

In general, higher information demand comes with higher accuracy and higher sensitivity, lower information demand comes with lower accuracy and lower sensitivity,

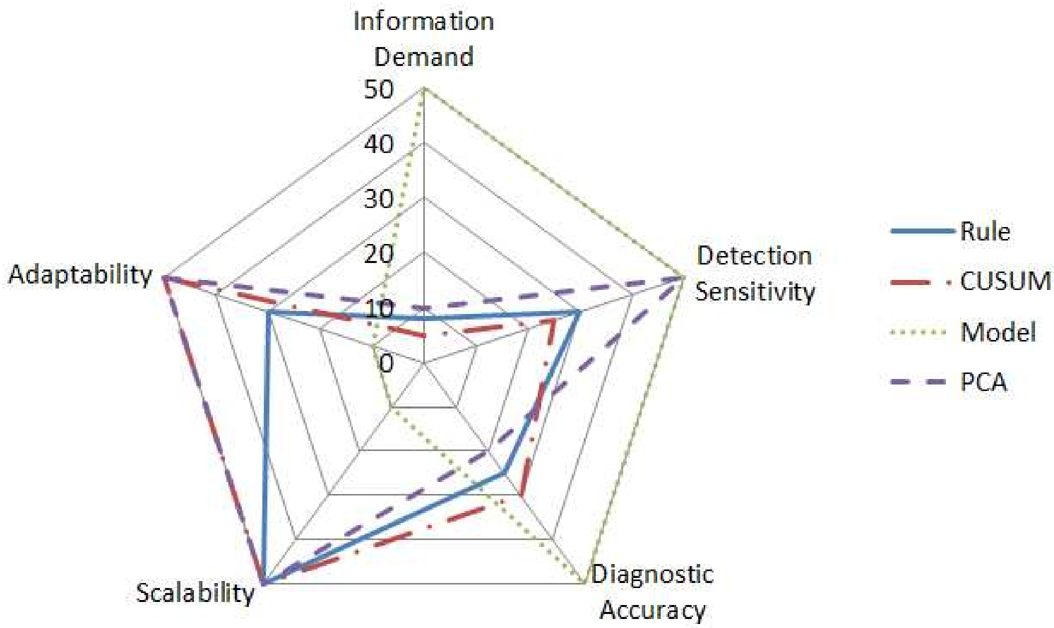

Figure 60: FDD method Comparison

but in some cases, this could change. For example, PCA method has much lower information demand than model based method, but it is more sensitive to certain types of faults, the overall detection sensitivity of both methods are similar.

It is also found that in general high sensitive method comes with high diagnostic accuracy. However, this does not apply to PCA method as well, which has a relatively high sensitivity but low diagnostic accuracy.

11.2 Deterministic Integration vs. Probabilistic Integration

The integration approaches (deterministic vs. probabilistic) are compared in terms of three metrics: (1)result correctness (2)result usefulness (3)ease of use.

11.2.1 Result Correctness

The result correctness is not guaranteed by deterministic integration approach. In this approach, the component level diagnostic method is assigned higher priority than system level diagnostic method. Among the system level methods, equal priority is assumed, therefore, the common elements are taken as final candidates. Two problems therefore arise: (1) If multiple methods detect the fault, but the diagnostic results do not overlap with each other, since the final results is suggested by taking the common elements from different candidate list, the final fault candidate is none, which conflicts with the detection result. (2) System level methods still have different detection sensitivity and diagnostic accuracy, by giving them equal priority, the method with low sensitivity and low accuracy has the same weight with the high sensitivity and accuracy method, therefore the integration may produce incorrect results.

Theoretically, the result from probabilistic integration is the best achievable result. This is due to an important feature that Bayesian integration provides, which gives more weight to the method with high sensitivity and accuracy during the integration.

Therefore, probabilistic approach is more reliable than deterministic approach in terms of result correctness.

11.2.2 Result Usefulness

With deterministic approach each component is labeled with a binary diagnostic result. Although binary result is easy to interpret, the uncertainty and probability that is associated with this diagnostic result is lost. With this approach, a fault positive with 99% probability and with 1% probability will be categorized as 'fault positive' without any differentiation.

On the other hand, probability information combined with the cost of that specific fault/component can lead to risk, which could be directly linked to the urgency of repairing a specific fault, which is very helpful to the system manager.

Therefore, probabilistic integration approach has a much bigger potential in providing useful information to the end user, and is favored over deterministic approach.

11.2.3 Ease of Use

The deterministic approach requires no additional information but the fault candidates from each method. If there are candidates from multiple methods at the same diagnostic level, the operation needed is simply comparing different groups and finding the common elements. Therefore, both the information input requirement and the process complexity are low.

On the other hand, the probabilistic approach requires the sensitivity and specificity information for all methods, which is also fault type dependent, which can not be known unless a parametric study on a system simulation model is conducted. This study should take into account all the variants in the system: operation condition, fault type, fault extent, etc. Depending on the complexity of the system, the effort this parametric study requires varies. In any case, it requires more input information and much more complex processing than deterministic approach.

Overall, the comparison between deterministic and probabilistic approach is shown in Fig 61.

11.3 Value of information

It has been found that the more information input, the more likely the fault in the system could be detected and the more accurate the diagnostic result could be. In this section, the best achievable detection and diagnostic results from low, medium and high information availability scenarios are shown and compared.

The mixing air box outdoor air damper leakage and sticking fault are only detected by PCA method, which can be used in medium and high information availability scenario. Therefore, in these two scenarios, for these two specific faults the best performance are achieved with PCA method alone. The coil fouling fault is detected by all four methods, therefore, in each information availability scenario, the best results are achieved by integrating all the available methods. As shown, the difference

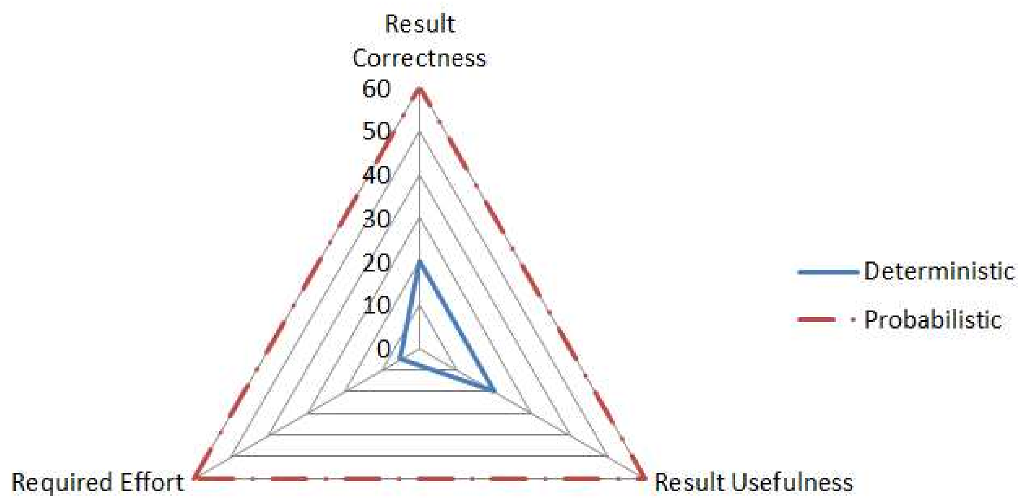

Figure 61: Probabilistic vs. Deterministic

between these three scenarios is small. In the valve leakage case, all methods but PCA method can detect the fault. In the valve sticking case, all four methods detect the fault, and participate in the integration. In the fan low efficiency case, all four methods detect the fault, but due to the small fault extent, the fault is not obvious in the PCA result. In the duct cloggy case and sensor drift case, since model based method is not applicable, the other three methods are used in both the medium and high information availability scenarios.

The fault detection results are shown in Fig 62. It shows that among all the faults tested, only mixing air box fault are not detected in low information availability scenario, i.e., all the other faults are detected and correctly diagnosed in low information availability scenario, although the fault probability varies in different scenarios.

Fig 63 is used to illustrate the diagnostic accuracy for coil in different information availability scenarios. It is found that in this testing case, high information availability does improve the diagnostic accuracy for valve leakage and sticking fault. For the

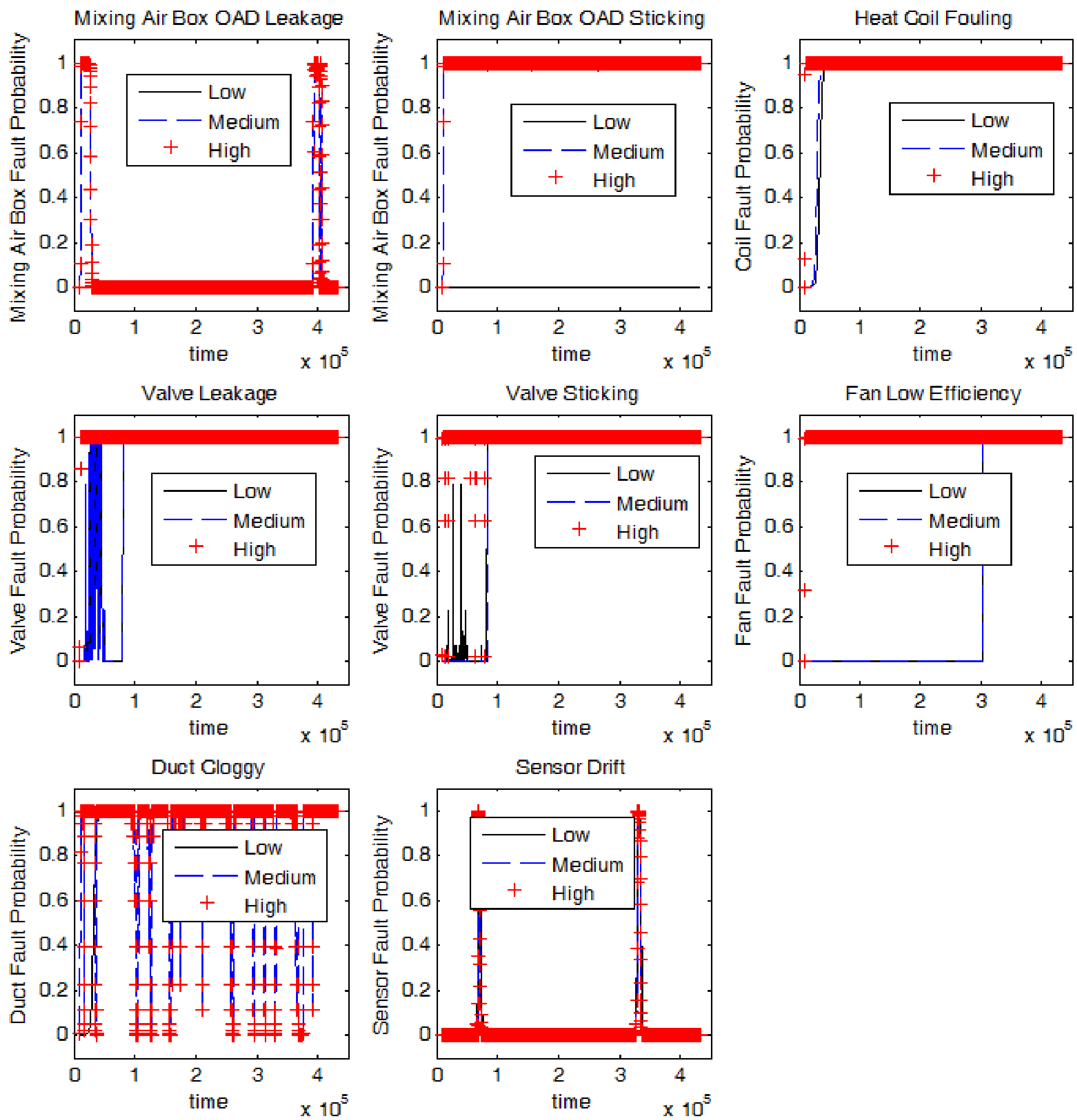

Figure 62: Information Availability Comparison: Fault Detection

other fault cases, there is no big difference between low and high information available scenario. Between low and medium information availability scenario, there is little difference in the diagnostic results.

Overall, in this testing case, information availability increase from low to medium helps detect the mixing air box fault (leakage, sticking), and further increase from medium to high helps improve the diagnostic accuracy for the valve faults (leakage, sticking). The discussion of related economic benefits is beyond the scope of this thesis.

11.4 Final Remarks

11.4.1 Hypothesis Verification

The hypothesis of this thesis is that by combining different FDD methods, the overall performance (detection sensitivity, diagnostic accuracy, etc.) could be improved. This hypothesis has been verified by the study in this thesis, and the reasons are listed below:

- The performance of Bayesian probabilistic integration inclines to the best performance method. One important feature of Bayesian probabilistic integration is that the integrated result tends to incline to the result produced by the elementary method with the highest sensitivity and specificity. Therefore, adding low performance method will not decrease the performance. Note that deterministic integration approach does not have this feature.

- Integration increases the detection sensitivity. The results in table 68 show that FDD method's detection sensitivity is fault dependent, among the four tested methods, no single method shows the highest sensitivity for all faults. Therefore, only through integration, the highest sensitivity for all types of fault could be achieved.

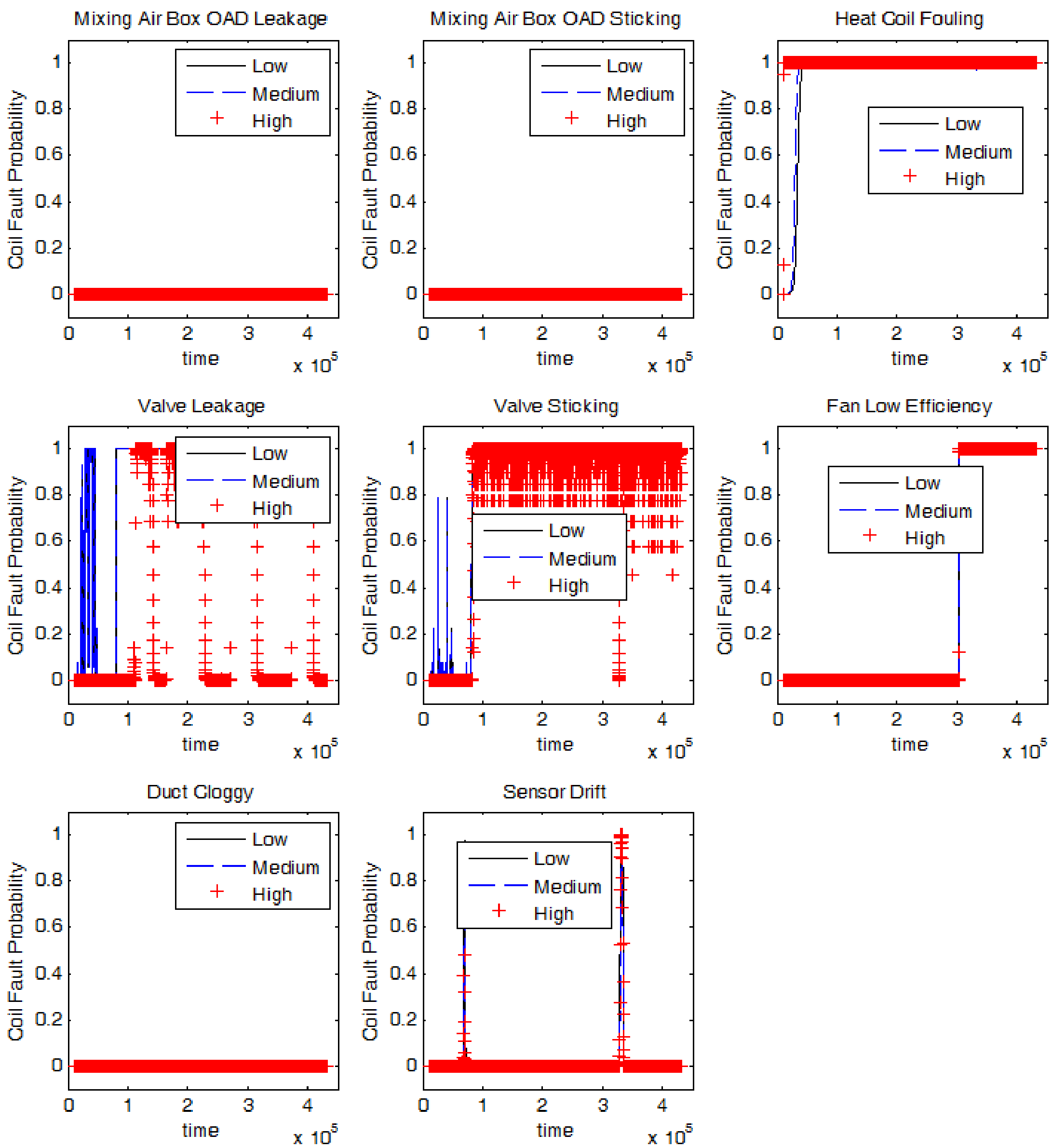

Figure 63: Information Availability Comparison: Fault Diagnostics

- Integration improves the diagnostic accuracy. While a FDD method's detection sensitivity depends on its sensitivity, its diagnostic accuracy depends on its specificity. It is rarely the case one method has both high sensitivity and specificity for all types of fault. Only by integrating different methods, the highest sensitivity and specificity for all faults could be achieved.

11.4.2 Application in Practice

Real world project typically has more than one AHUs, some of which may have unusual configurations due to customized renovations. Using either model based methods, rule based methods or machine learning methods requires a relatively long period of preparation before producing any results. The rule augmented CUSUM method is the right choice in this situation. All it needs is a site visit to understand (1) what are the control variables in the AHU (2) how are the control variables related (3) what are the components that control each control variables. For the purpose of comparing different AHUs and quickly identifying the problematic AHU, the threshold settings do not have to be so accurate since they are used consistently for all the AHUs. In this sense, rule augmented CUSUM method could serve as a preliminary quick diagnostic tool before deploying other more heavy methods.

In real project, the sensor could be out of calibration. Serious out of calibration may lead to comfort problems and therefore be detected. Less serious out of calibration cases may not be detected by any methods used in this thesis. In cases where sensor goes from unbiased at the beginning to biased state during the operation, PCA method could be used to detect the fault.

Due to the strong system dependency nature of rule based method and model based method, these two methods need certain level of modification whenever a new AHU system is under detection.

Although rule augmented CUSUM method and PCA method have the highest scalability, therefore the application of these two methods in practice has the largest potential, their diagnostic accuracy is not high. In cases where multiple FDD methods have sufficient information input, the integration approach is a possible route to improve both detection sensitivity and diagnostic accuracy. Between the two proposed integration approaches, deterministic approach is easier to use since it does not require any quantification of the uncertainty inherent in each method. On one hand, this is a great benefit because the uncertainty quantification process is against the scalability requirement, and in many cases is not even possible. On the other hand, the skip of this process leads to the enlarged uncertainty of the diagnostic results.

However, there are alternatives that can improve the accuracy without sacrificing the salability. One alternative could be using default sensitivity and specificity value. Since the accuracy of model based method is supported by its component level approach, its specificity for each component could set to highest value automatically. The sensitivity of model based method for different components depends on the model fidelity and the thresholds. With the results from testing case in this thesis, it seems that 0.05-0.2 could be assigned to low fidelity model, and 0.7-0.95 could be assigned to high fidelity model. PCA method is sensitive to most components, but the diagnostic is not very accurate. Although the sensitivity depends on the threshold and how it is used, it seems 0.4-0.6 could be set as the default sensitivity, and 0.6-0.9 could be set as the default specificity. Rule based method and rule augmented CUSUM method are both medium sensitive methods and less accurate methods. Their sensitivity depend on the thresholds again. Based on the results, it seems for all the sensors, 0.1-0.5 could be set as default value. For all the components, 0.4-0.7 could be set as default value. Regarding specificity, 0.8-0.9 seems good range.

11.4.3 Limitation and Future Work

It is realized that the works in this thesis is based on a theoretical hypothesis, which is only verified with simulation testing cases. The work is therefore limited in certain aspects and requires future improvement.

The first limitation lies in the input information assumption. It is assumed at the beginning that sensors are well calibrated and have no noise. This is not true in practice. In many real projects it is found that sensors are out of calibration and very noisy. These two problems could cause low quality of data and lead to poor FDD results. In the future, the impact of sensor out of calibration and sensor noise on the performance of FDD method should be investigated. Sensor noise fault could be detected by PCA method [41]. Although out of calibration sensor is able to be detected by model based method, more adaptable methods to detect this fault need to be developed and this should be a focus in the future.

The second limitation is in the limited testing cases. In the thesis, a set of 15 faults are used as the testing cases to compare different methods. This list only corresponds to the configuration of the testing AHU. If the configuration changes, some of the current faults may not exist any more, some others may need to be added to the list. Although the major conclusion about the method performance will still hold, the order in the ranking in some aspect could change.

The third limitation lies in the inconsistent threshold setting for fault detection among different FDD methods. The problem arises due to the different meaning of threshold in different methods. In rule based method, the meaning is the deviation of sensor from setpoint. In rule augmented CUSUM method, there are three threshold parameters $\bar{x}$, σ and k, which respectively define estimate of the error mean, estimate of the error standard deviation, slack parameter. In PCA method, the threshold defines the error score. In model based method, the threshold is the estimated standard deviation of performance variable in normal cases. To solve the problem, the definition of 'consistency' has to be redefined, also the metrics for 'consistency' need to be developed to facilitate the threshold derivation. This problem should be investigated in the future.

The fourth limitation lies in the way of retrieving the operational data. In practice, the operational data is typically retrieved at a fixed time interval. In this thesis, the operational data directly comes from simulation results without any sampling. This difference could be another contributor to a decreased data quality in practice, therefore the performance of FDD methods would be further decreased. The impact of the sampling interval on FDD performance should also be studied in the future.

APPENDIX A

NOMENCLATURE

η	efficiency
l	Leakage Parameter
P	pressure
ρ	density
v	velocity
θ	angle
K	loss coefficient
R	resistance
λ	friction coefficient
D	diameter
μ	dynamic viscosity
H	enthalpy
T	temperature
TH	threshold
Q	heat transfer
W	power consumption
U	valve/damper position
S	cumulative sum for positive score
N	cumulative sum for negative score

Subscript

d	damper
f	fan
s	AHU system
v	valve
av	average
cc	Cooling coil
ed	exhaust air damper
hc	heating coil
ma	mixing air
md	mixing air damper
nv	new value
oa	outdoor air
ov	original value
od	outdoor air damper

ra	return air
ref	reference
sa	supply air
sf	supply air fan
sm	static pressure measurement
ss	static pressure setpoint
var	variance

Acronym

AHU	Air Handling Unit
APAR	AHU Performance Assessment Rules
CCOAT	Cooling Coil Outlet Air Temperature
CCV	Cooling Coil Valve
CFC	Call for Cooling
CO_2	CO_2 Sensor
DAF	Discharge Air Flow rate
DAS	Discharge Air Setpoint
DAT	Discharge Air Temperature
EAD	Exhaust Air Damper
FDD	Fault Detection and Diagnostics
HVAC	Heating, Ventilation and Air Conditioning
HCV	Heating Coil Valve
HCOAT	Heating Coil Outlet Air Temperature
HCR	Heating Coil Heat Exchange Rate
HR_ENA	Heat Recovery Enable
HR_ENS	Heat Recovery Enable Setpoint
HRCV	Heat Recovery Valve
HRDAT	Heat Recovery Temperature
HRRWT	Heat Recovery Return Water Temperature
HRSWT	Heat Recovery Supply Water Temperature
MAB	Mixing Air Box
MAD	Mixing Air Damper
MAO	Mixing Air Content
MAS	Mixing Air Setpoint
MAT	Mixing Air Temperature
MIN	Minimum Outdoor Air Setting
NIST	National Institute of Standards and Technology
NILM	Non-intrusive Load Monitors
OAC	Cabinet Outdoor Air Temperature
OAD	Outdoor Air Damper
OAE	Outdoor Air Enthalpy
OAF	Outdoor Air Fraction
OAH	Outdoor Air Humidity
OAT	Outdoor Air Temperature

RAC	Rooftop Air Conditioners
RAE	Return Air Enthalpy
RAF	Return Air Flow Rate
RAFS	Return Air Flow Rate Setpoint
RAE	Return Air Enthalpy
RAF_ERR	Return Air Fan Variable Frequency Drive Error Status
RAF_PCT	Return Air Fan Variable Frequency Drive Percentage Output
RAF_POW	Return Air Fan Variable Frequency Drive Power Output
RAH	Return Air Humidity
RAT	Return Air Temperature
RFDP	Return Fan Differential Pressure
RSP	Return Static Pressure
SAFTT	Semi-Automated Functioning Testing Tool
SAF_ERR	Supply Air Fan Variable Frequency Drive Error Status
SAF_PCT	Supply Air Fan Variable Frequency Drive Percentage Output
SAF_POW	Supply Air Fan Variable Frequency Drive Power Output
SFDP	Supply Fan Differential Pressure
SFR	Supply Fan Rotation Speed
SSP	Supply Air Static Pressure
SSPS	Supply Air Static Pressure Setpoint
UT	Universal Translator

REFERENCES

[1] "2010 buildings energy data book," tech. rep., D&R International Ltd, March 2010.

[2] "About eem suite." `http://www.mckinstryeem.com/eemsuite/overview.html`, Dec 2011.

[3] "Energy: Energy efficiency in buildings." `http://ec.europa.eu/energy/efficiency/buildings/buildings_en.htm`, Dec 2011.

[4] "Energyplus energy simulation software." `http://www.apps1.eere.energy.gov/buildings/energyplus`, Dec 2011.

[5] "Energywitness enterprise management system and facilities data warehouse." `http://www.intdatsys.com/EnergyWitness.htm`, Dec 2011.

[6] "Facility dynamics: Pacrat." `http://www.facilitydynamics.com/pacrat.html`, Dec 2011.

[7] "Multi-engineering modeling and simulation." `http://www.3ds.com/products/catia/portfolio/dymola`, Dec 2011.

[8] "Transient system simulation tool." `http://www.trnsys.com`, Dec 2011.

[9] Barnard, G. A., "Control charts and stochastic process," *Journal of the Royal Statistical Society B (Methodological)*, vol. 21, no. 2, p. 32, 1959.

[10] Brandemuehl, M. J., "Hvac 2 toolkit: A toolkit for secondary hvac system energy calculations," tech. rep., 1993.

[11] Braun, J. and Li, H., "Automated fault detection and diagnostics of rooftop air conditioners for california," tech. rep., California Energy Commission, August 2003.

[12] Bruck, D., Elmqvist, H., Mattson, S. E., and Olsson, H., "Dymola for multi-engineering modeling and simulation," in *Proceedings of the 2nd International Modelica Conference*, (Oberpfaffenhofen, Germany), March 18-19 2002.

[13] Cimetrics, "Building commissioning." `http://www.cimetrics.com/index.php/infometrics-process.html`, Dec 2011.

[14] Clark, D. R., *HVACSIM Building Systems and Equuipment Simulation Program Reference Manual.* Gaithersburg, MD: U.S.Department of Commerce, National Bureau of Standards, National Engineering Laboratory, Center for Building Technology, Building Equipment Division, 1985.

[15] Comstock, M. C. and Braun, J. E., "Literature review for application of fault detection and diagnostic methods to vapor compression cooling equipment," tech. rep., ASHRAE, December 1999.

[16] Dexter, A. L., "Fuzzy model based fault diagnosis," *IEE proceedings. Control theory and application*, vol. 142, no. 6, p. 6, 1995.

[17] Du, Z. and Jin, X., "Detection and diagnosis for multiple faults in vav systems," *Energy and Buildings*, vol. 39, no. 8, p. 12, 2007.

[18] Du, Z. and Jin, X., "Detection and diagnosis for sensor fault in hvac systems," *Energy Conversion and Management*, vol. 48, no. 3, p. 10, 2007.

[19] ESTCP, "Automated continuous commissioning of commercial buildings." `http://archive.serdp-estcp.org/Technology/SI-0929-FS.cfm`, Dec 2010.

[20] Evans, M., Shui, B., Halverson, M., and Delgado, A., "Enforcing building energy codes in china: Progress and comparative lessons," tech. rep., Pacific Northwest National Laboratory, August 2010.

[21] Fritzson, P. and Engelson, V., "Modelica - a unified object-oriented language for system modeling and simulation," July 20-24 1998.

[22] Glass, A. S., Gruber, P., Roos, M., and Todtli, J., "Qualitative model-based fault detection in air-handling units," *IEEE, Control Systems Magazine*, vol. 15, no. 4, p. 12, 1995.

[23] Haves, P., "A standard simulation testbed for the evaluation of control algorithms and strategies (rp-825)," tech. rep., ASHRAE, 1997.

[24] Haves, P., Kim, M., Najafi, M., and Xu, P., "A semi-automated commissioning tool for vac air-handling units: Functional test analyzer," *ASHRAE Tranactions*, vol. 113, no. 1, p. 11, 2007.

[25] Haves, P., Salsbury, T., and Wright, J. A., "Condition monitoring in hvac subsystems using first principle models," *ASHRAE Transactions*, vol. 102, no. 1, p. 9, 1996.

[26] Hou, Z., Lian, Z., Yao, Y., and Yuan, X., "Data mining based sensor fault diagnosis and validation for building air conditioning system," *Energy Conversion and Management*, vol. 47, no. 15-16, p. 12, 2006.

[27] House, J. M., Nejad, H. V., and Whitcomb, J. M., "An expert rule set for fault detection in air-handling units," *ASHRAE Tranactions*, vol. 107, no. 1, p. 14, 2001.

[28] Hyvfirinen, J. and Karki, S., *Building Optimization and Fault Diagnosis Source Book*. 1996.

[29] Jagpal, R., "Computer aided evaluation of hvac system performance," tech. rep., IEA, 2006.

[30] Kaldorf, S. and Gruber, P., "Practical experiences from developing and implementing an expert system diagnostic tool," *ASHRAE Tranactions*, vol. 108, no. 1, p. 15, 2002.

[31] Katipamula, S., Pratt, R. G., Chassin, D. P., Taylor, Z. T., Gowri, K., and Brambley, M. R., "Automated fault detection and diagnostics for outdoor-air ventilation systems and economizers: Methodology and results from field testing," *ASHRAE Transactions*, vol. 105, no. 1, 1999.

[32] Katipamula, S. and Brambley, M. R., "Methods for fault detection, diagnostics, and prognostics for building systems - a review, part i," *HVAC&R Research*, vol. 11, no. 1, 2005.

[33] LBNL, "Performance monitoring in large commercial buildings," tech. rep., CEC, October 2008.

[34] Lee, J. M., Butler, J., Cantabene, M. E., and Fairman, H., "Standards for fault detection, diagnostics, and optimization in building systems," tech. rep., Cimetrics Inc., March 2007.

[35] Lee, W. y., House, J. M., Park, C., and Kelly, G. E., "Fault diagnosis of an air-handling unit using artificial neural networks," *ASHRAE Tranactions*, vol. 102, no. 1, p. 10, 1996.

[36] Lee, W. y., House, J. M., and Shin, D. R., "Fault diagnosis and temperature sensor recovery for an air-handling unit," *ASHRAE Transactions*, vol. 103, no. 621, p. 13, 1997.

[37] Lee, W. y., Park, C., and Kelly, G. E., "Fault detection in an air-handling unit using residual and recursive parameter identification methods," *ASHRAE Tranactions*, vol. 102, no. 1, p. 12, 1996.

[38] Lee, W., House, J. M., and Kyong, N., "Subsystem level fault diagnosis of a building's air-handling unit using general regression neural networks," *Applied Energy*, vol. 77, no. 2, p. 18, 2004.

[39] Li, H., "Fault detection and diagnostics for centrifugal chillers," tech. rep., ASHRAE, April 2011.

[40] Li, S., *A Model-Based Fault Detection and Diagnostic Methodology for Secondary HVAC Systems.* PhD thesis, 2009.

[41] Li, Z., Paredis, C. J., and Augenbroe, G., "A probability extension of pca to detect and diagnose sensor faults in air handling units," in *Eleventh International Conference of Enhanced Building Operations*, (New York), 2011.

[42] Liang, J. and Du, R., "Model based fault detection and diagnosis of hvac systems using support vector machine method," *International Journal of Refrigeration*, vol. 30, no. 6, p. 11, 2007.

[43] Mckellar, M., *Failure diagnosis for a household refrigerator.* Master, 1987.

[44] Mitchell, T., *Machine Learning.* McGraw Hill Inc., 1997.

[45] Montgomery, D. C., *Introduction to Statistical Quality Control.* Hoboken, New Jersey: John Wiley & Sons, Inc., 2005.

[46] Norford, L. K., Wright, J. A., Buswell, R. A., Luo, D., Klaassen, C. J., and Suby, A., "Demonstration of fault detection and diagnosis methods for air-handling units," *HVAC&R Research*, vol. 8, no. 1, p. 31, 2002.

[47] Norford, L., Wright, J., Buswell, R., and Luo, D., "Demonstration of fault detection and diagnosis methods in a real building," tech. rep., ASHRAE, 2000.

[48] Pearson, K., "On lines and planes of closest fit to systems of points in space," *Philosophical Magazine*, vol. 2, no. 6, p. 14, 1901.

[49] Piette, M. A., Kinney, S. K., and Haves, P., "Analysis of an information monitoring and diagnostic system to improve building operations," tech. rep., LBNL, February 2001.

[50] Program, P., "Fault detection and diagnostics roundtable summary," tech. rep., California Energy Commission, August 2007.

[51] Reddy, T. A., "Evaluation and assessment of fault detection and diagnostic methods for centrifugal chillers," tech. rep., ASHRAE, June 2006.

[52] S.A.Klein, W.A.Bechman, J.M.Mitchell, J.A.Duffie, and etc, "Trnsys17, a transient system simulation program," tech. rep., Solar Energy Laboratory, University of Wisconsion Madison, 2009.

[53] Salsbury, T. and Diamond, R., "Fault detection in hvac systems using model-based feedforward control," *Energy and Buildings*, vol. 33, no. 4, 2001.

[54] Salsbury, T. I., *Fault detection and diagnosis in HVAC systems usinh analytical models.* PhD thesis, Loughborough University, 1996.

[55] Schein, J., Bushby, S. T., Castro, N. S., and House, J. M., "A rule-based fault detection method for air handling units," *Energy and Buildings*, vol. 38, no. 12, p. 8, 2006.

[56] Schein, J. and House, J. M., "Application of control charts for detecting faults in variable-air-volume boxes," *ASHRAE Tranactions*, vol. 109, no. 2, p. 12, 2003.

[57] SHEWHART, W. A., *Economic Control of Quality of Manufactured Product*. 1931.

[58] SMITH, V., "Advanced automated hvac fault detection and diagnostics commercialization program - final report: Project 3," tech. rep., Architectural Energy Corporation, 2006.

[59] SREEDHARAN, P. and HAVES, P., "Comparison of chiller models for use in model-based fault detection," in *ICEBO*, 2001.

[60] STALLARD, L., *Model based expert system for failure detection and identification of household refrigerators*. Master, 1989.

[61] STURN, A., QUACKENBUSH, J., and TRAJANOSKI, Z., "Genesis: cluster analysis of microarray data," *Bioinformatics*, vol. 18, no. 1, p. 2, 2002.

[62] TIAX, L., "Energy impact of commercial building controls and performance diagnostics: Market characterization, energy impact of building faults and energy savings potential," tech. rep., November 2005.

[63] WANG, S. and QIN, J., "Sensor fault detection and validationof vav terminals in air conditioning systems," *Energy Conversion and Management*, vol. 46, no. 15-16, p. 19, 2005.

[64] WANG, S. and WANG, J. B., "Robust sensor fault diagnosis and validation in hvac systems," *Transactions of the Institute of Measurement and Control*, vol. 24, no. 3, p. 33, 2002.

[65] WANG, S. and XIAO, F., "Ahu sensor fault diagnosis using principal component analysis method," *Energy and Buildings*, vol. 36, no. 2, p. 14, 2004.

[66] WEBSTER, T. and BARTH, A., "Development of fan diagnostic methods and protocols for short term monitoring," tech. rep., California Energy Commission, February 2003.

[67] WETTER, M., "A modelica-based model library for building energy and control systems," 2009.

[68] WHITEHOUSE, "President obama sets greenhouse gas emissions reduction target for federal operations." `http://www.whitehouse.gov/the-press-office/`, 2010.

[69] WIKIPEDIA, "Kyoto protocol." `http://en.wikipedia.org/wiki/Kyoto_Protocol`, 2011.

[70] WIKIPEDIA, "Sensitivity and specificity," 2011.

[71] XIAO, F., WANG, S., and ZHANG, J., "A diagnostic tool for online sensor health monitoring in air-conditioning systems," *Automation in Construction*, vol. 15, no. 4, p. 15, 2006.

[72] Xu, P., Haves, P., and Curtil, D., "A library of hvac component models for use in automated diagnostics," in *SimBuild*, 2006.

[73] Xu, P., Haves, P., and Kim, M., "Model-based automated functional testing - methodology and application to air handling units," *ASHRAE Transactions*, vol. 111, no. 1, p. 11, 2005.

[74] Yang, C. h. and Jiang, Y., "Sensor fault detection of hvac system - system constraints and voting," *Pan Pacific Symposium on Building and Urban Environmental Conditioning in Asia*, 1995.

[75] Yang, H., Cho, S., Tae, C.-S., and Zaheeruddin, M., "Sequential rule based algorithms for temperature sensor fault detection in air handling units," *Energy Conversion and Management*, vol. 49, no. 8, p. 16, 2008.

[76] Yang, J., Zhang, D., Frangi, A. F., and Yang, J., "Two-dimensional pca: A new approach to appearance-based face representation and recognition," *IEEE Transactions On Pattern Analysis and Machine Intelligence*, vol. 26, no. 1, p. 7, 2004.

[77] Yoshida, H., Iwami, T., Yuzawa, H., and Suzuki, M., "Typical faults of air-conditioning systems and fault detection by arx model and extended kalman filter," *ASHRAE Tranactions*, vol. 102, no. 1, p. 8, 1996.

[78] Yuan, C. and Druzdzel, M. J., "Importance sampling algorithms for bayesian networks: Principles and performance," *Mathematical and Computer Modelling*, vol. 43, no. 9-10, p. 18, 2006.