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# A Probabilistic Framework To Diagnose Faults in Air Handling Units.

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## A Probabilistic Framework to Diagnose Faults of Air Handling Units

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### ABSTRACT

Air handling unit (AHU) is one of the most extensively used equipment in large commercial buildings. This device is typically customized and lacks quality system integration, which can result in, hardware failures and controller errors. Air handling unit Performance Assessment Rules (APAR) is a fault detection tool that uses a set of expert rules derived from mass and energy balances to detect faults in air handling units. Although APAR has many advantages over other methods, for example, no training data required and easy to implement commercially, most of the time it is unable to provide the diagnosis of the faults. There is no established way to have the correct diagnosis for rule based fault detection system. In this study, we developed a new way to detect and diagnose faults in AHU through combining APAR rules and Bayesian Belief Network. BBN is used as a decision support tool for rule-based expert system. BBN is highly capable to prioritize faults when multiple rules are satisfied simultaneously. The proposed model tested with real time measured data of a campus building at University of Texas at San Antonio (UTSA).

### 1. INTRODUCTION

Heating, ventilation and air conditioning (HVAC) equipment commonly fails to satisfy performance expectations from design due to problems caused by inadequate maintenance, improper installation, or equipment failure. These problems of faults include mechanical failures such as dampers or actuators, stuck broken or leaking valves; control problems related to frozen or biased sensors, poor feedback loop tuning of incorrect sequencing logic; fouled heat exchangers; design errors; or inappropriate operation intervention. By identifying and diagnosing faults to be repaired, FDD techniques can benefit building owners by reducing energy consumption improving operation and maintenance and increasing effective control over environmental conditions in occupied spaces. Approximately 50% of a commercial's building energy consumption is associated with HVAC systems [1] and more specifically Air handling unit's (AHU) energy consumption counts for around 40% of industrial sites total energy consumption [2] because of its inefficient operation. Overall it is estimated that HVAC energy consumption accounts for 10-20% of total energy consumption in developed countries with AHU associated energy use associated with the majority of this [3]. The energy potential saving of FDD is estimated at 10-40% of HVAC energy consumption depending on the age and condition of the equipment, maintenance practices, climate and building use [4]. In this study we tried to detect and diagnose faults of AHU through a probabilistic way by combining expert rules and Bayesian Belief Network (BBN). GENIE and SMILE decision support toolbox published by University of Pittsburg [5] are used to develop Bayesian Belief network.

### 2. LITERATURE REVIEW

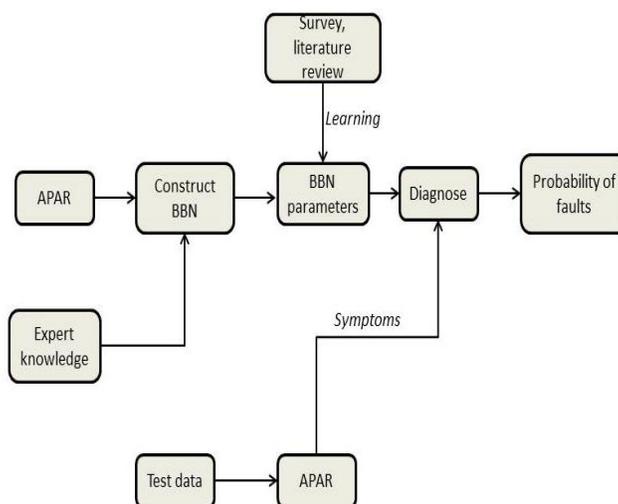
There were many researchers conducted on FDD of AHU and VAV in the last decades. Most of them are focused on AHUs. Among data driven based models, Principle Component Analysis (PCA) is most commonly used to detect and diagnose sensor faults like fixed bias, drifting bias or complete failure. Wang [6], Wu [7], Du [8] and many others developed PCA based FDD method for Air Handling Unit (AHU), Variable Air Volume (VAV) box and centrifugal chiller. Three kinds of diagnostic methods were used in those studies, which are Q-contribution plot,

Joint Angle Analysis (JAA) and Fisher Discriminant Analysis (FDA). However, it is found that JAA is more efficient than Q-contribution plots in diagnosing complex faults. The studies focused on both simulation and field data.

The use of Artificial Neural Network (ANN) as FDD strategy was developed [9-10]. Study used ANN to detect and diagnose faults in AHU can be proposed as two stages ANN, one is to detect the abnormality in the system and other is to isolate the subsystem. Residuals of different parameters are given as input and the trained network was used to diagnose root cause of the faults. The Neural Network trained with normal operating data to predict the parameters. The deviation of actual data from predicted value considered as a sign of fault. Similarly, Liang [11] used support vector regression to detect and diagnose sensor faults of AHU.

In summary, many of the methods usually provide good fault detection results. However, in certain cases fault may cause similar symptoms and propagate to other components. So, it becomes very hard to provide proper diagnosis. For example, a fault in mixed air temperature can influence parameters like cooling coil and damper signal etc. Therefore, it is more reasonable to give probabilities of faults at given symptoms in FDD analysis. Symptoms can be considered as abnormal parameter change or abnormal residuals, expert rules etc. Here, in this study we tried to use expert rules (APAR) as symptoms of faults. APAR is an established set of rules which are able to trigger an alarm if the system is running abnormally means if any fault happens. FDD of AHU can be very efficient and effective if the FDD strategy can work in a similar way as that used by FDD experts. In this study, a Bayesian Belief network (BBN) simulates diagnostic thinking of experts, where APAR rules are used as symptoms of fault.

### 3. METHODOLOGY



**Figure 1:** Flowchart of the proposed FDD model.

The flowchart of the proposed BBN based FDD strategy is illustrated in Figure 1. The steps of the proposed strategy are described below:

Step 1: First using the APAR rules (as symptoms) and expert knowledge (cause-effect) Bayesian Belief Network (BBN) is constructed.

Step 2: Then from literature reviews, survey results and maintenance records (AHU1 of AET campus building, University of Texas at San Antonio) parameters of BBN are identified. There are two types of parameters. Prior probability of faults and conditional probabilities.

Step 3: In the third step, we placed a reference outdoor air temperature sensor. We were very careful to place the two outdoor air temperatures close to each other. Also checked if the sensors are showing real outdoor air temperature that is entering into AHU as intake air. If there is a difference between the two outdoor air temperature sensors outdoor air temperature sensor fault is diagnosed. In addition, if supply air temperature set point is unreasonably low or high set point fault will be diagnosed.

Step 4: Testing data are passed through rule-based analysis. In this process, at first based on the control signals of dampers and cooling/heating coils, the mode of operation is selected. Then the appropriate rule sets are applied.

Step 5: The results of rule-based analysis are passed through BBN for diagnosis. The states of the rules (True/False) are the inputs of BBN. If any rule or multiple rules are satisfied Bayesian Network will provide a list of faults with probability of occurrence.

#### 4. SYSTEM DESCRIPTION

The expert rules were developed for application to single duct variable volume or constant volume air handlers with hydraulic heating and cooling coils and economizer capabilities and logic. The rules focus on temperature control in an AHU. Hence, the system description will be restricted to components and control strategies directly related to this purpose. The control loops of AHU include damper control, temperature control and pressure control. The fresh air through the fresh air damper is mixed with the return air with recirculation air damper. Typical but advanced control strategies are implemented to provide adequate outdoor air ventilation and suitable supply air temperature and indoor pressure, and to minimize energy use. PID controllers are employed to control the supply air temperature, supply static pressure, outdoor air flow rate and return fan speed. Optimal control strategies are used to reset the set points of the local PID control loops of supply air temperature and supply static pressure.

AHUs have four primary modes of operation during occupied periods for maintaining the supply air temperature at set point. Sequencing logic determines the mode of operation of an AHU at any particular time. The four modes of operation are: 1) Mode 1: Heating, 2) Mode 2: Cooling with outdoor air, 3) Mode 3: Mechanical cooling with 100% outdoor air, 4) Mode 4: Mechanical cooling with minimum outdoor air, and 5) Mode 5: Simultaneous heating and cooling.

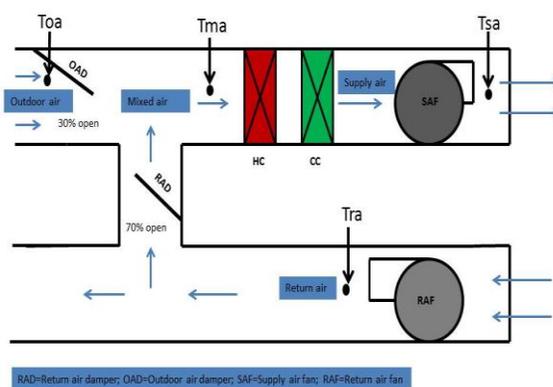


Figure 2: AHU Operation on Mode-4.

Our scope of the study only limited to mode-4, which is mechanical cooling with minimum outdoor air. In mode-4 cooling coil valve is modulated to satisfy the temperature set point. Heating coil valve remains closed. Mixing box dampers are open and set to meet the minimum outdoor air requirements which is 30% in our study. Figure 2 shows an AHU operating on Mode-4.

#### 5. AHU PERFORMANCE ASSESSMENT RULES (APAR)

APAR is a set of 28 rules that uses control signals and occupancy information to identify the mode of operation of the AHU, thereby identifying a subset of the rules that specify temperature relationships that are applicable for that mode. The two main mode classifications are occupied and unoccupied. The four modes of operation are applied for occupied periods. Because the direct digital control output to the actuators of the heating and cooling coil valves and the mixing box dampers are known, the mode of operation can be ascertained. Table 1 lists all the expert rules associated with Mode-4 which is cooling with minimum outdoor air. Also some rules are applied to all modes of operation. Rule based detection is computationally simple and can be easily implemented in commercial buildings. According to a study by NIST (2001), number of false positives and negatives are low in rule-based detection. In addition, different rules can be considered symptoms of different faults. For example, 'True' state of Rule-18 is a

symptom of mixing box related faults and sensor related faults. ‘True’ state of Rule-15 is a symptom of controller logic error.

**Table 1:** Rules associated with mode-4

<b>Cooling with minimum outdoor air temperature</b>	<b>15</b>	$T_{oa} < T_{co} - E_t$
	<b>16</b>	$T_{sa} > T_{ma} + \Delta T_{sf} - E_t$
	<b>17</b>	$T_{sa} > T_{ma} - \Delta T_{sf} + E_t$
	<b>18</b>	$\left  T_{ra} - T_{oa} \right  \geq \Delta T_{min}$ where $\left  Q_{oa/sa} - T_{(oa/sa)min} \right  \geq E_f$
	<b>19</b>	$\left  U_{cc} - 1 \right  \leq E_c$ and $T_{sa} - T_{sa,s} > E_t$
	<b>20</b>	$\left  U_{cc} - 1 \right  \leq E_c$
	<b>25</b>	$\left  T_{sa} - T_{sa,s} \right  > E_t$
	<b>26</b>	$T_{ma} < \min(T_{oa}, T_{ra}) - E_t$
	<b>27</b>	$T_{ma} > \max(T_{oa}, T_{ra}) + E_t$
	<b>28</b>	Max. num of transitions > MTmax

## 6. BAYESIAN BELIEF NETWORK

Bayesian Belief Network (BBN) is a probabilistic graphical model that represents a set of random variables and their conditional dependencies via a directed acyclic graph. It has been successfully applied in the domain of knowledge discovery and probabilistic inference since it was introduced by Pearl in early 80's [12-13]. It is very powerful to represent and to diagnose complex systems with uncertain incomplete and even conflicting information. There is very little application in HVAC systems. Najafi [14] and Wall [15] introduced BBN to detect and diagnose faults of AHU. Both works required a full set of faulty dataset to learn the fault patterns. However, faulty datasets are very hard to get in real building applications. Therefore In this study we used expert knowledge based Bayesian Belief Network (BBN), which does not require any training datasets.

There are two basic components of BBN Structure and parameters. The structure of the network should capture qualitative relationships between variables. In particular, two nodes should be connected directly if one affects or causes the other, with indicating the direction of the effect. Cause and effect can be termed as parent and child node respectively. An arc points from a parent to child node. In this study node presents faults and fault symptoms or expert rules. The arc indicates direct probabilistic dependencies among nodes. The node without any input arc is called root node. A node may have several states. For example, a fault node has two states Faulty & Not Faulty. Each state is an event. When an event occurs, it is evidence for diagnosing faults. Each root node has a prior probability corresponding to its each state. A conditional probability table is used to specify all parameters or probabilities of a child node, considering all possible combinations of its own states and its parent node states. The number of parameters needed in a conditional probability table exponentially grows with the number of its parent nodes. It is very difficult to obtain all the conditional probabilities in the FDD applications.

Once the structure of a BBN is defined, the posterior probability can be obtained by Bayesian inference. The Bayesian theory plays a very important role in Bayesian inference. The equation of the Bayesian theorem can be written as:

$$P(A|B) = \frac{P(AB)}{P(B)} = \frac{P(A)P(B|A)}{P(B)} \quad (1)$$

Where  $P(AB)$  is the joint probability of the event A and B. For any given event A the marginal probability can be calculated by:

$$P(A) = \sum_{i=1}^n P(B_i)P(A|B_i) \quad (2)$$

The Bayesian theorem can be obtained based on the conditional probability and marginal probability.

$$P(B_i|A) = \frac{P(AB_i)}{P(A)} = \frac{P(B_i)P(A|B_i)}{\sum_{i=1}^n P(B_i)P(A|B_i)} \quad (3)$$

Items on right hand side called prior probabilities and on left hand, side is called posterior probabilities. The Bayesian network provides the posterior probabilities from the prior probabilities.

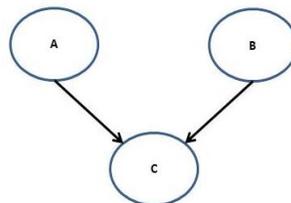
## 7. LEAKY NOISY-OR GATES

Considerable reduction in effort can be obtained by using noisy-OR gate [12-13]. The noisy-OR influence structure applies when there are several possible logical causes,  $x_i, i=1, 2, 3, 4, \dots, n$  of a binary effect variable  $y$ . Where (a) each of which has a probability  $P_i$ , is being sufficient to produce the effect in the absence of all other causes and (b) the probability of each cause sufficient is independent of the presence of other causes. Pearl showed that the probability of  $y$ , given a subset of  $x$  of the  $x_i$ , which is present:

$$p(y|X) = 1 - \prod_{i, x_i \in X} (1 - P_i) \quad (4)$$

The complete conditional distribution for  $n$  binary predecessors would require the specification of  $2^n$  parameters, but if the Noisy-OR assumption applies, we need to specify only  $n$  for each  $P_i$ . Like any model, Bayes network is never complete and so there will often be possible causes of an effect that are not explicitly modelled. To allow for this in a Noisy-OR it is useful to access a base rate probability,  $P_o$  for all other causes i.e. the event that the effect will occur apparently spontaneously in the absence of any of the cause is modelled explicitly. Base rate probability is often called leak probability. If the expert assesses the probability that each predecessor is sufficient to cause the effect variable in the absence of any other, explicit cause the number needs readjustment to obtain the formulae for the probability of  $y$ .

$$p(y|X) = 1 - (1 - P_o) \prod_{i, x_i \in X} \frac{1 - P_i}{1 - P_o} \quad (5)$$



**Figure 3:** Example of Leaky Noisy OR Gate.

Figure 3 shows a potential example of the leaky Noisy-OR gate. If each node has, two states named Yes/No, also, A & B both independently can cause C with a probability then we can assume this node as noisy-OR gate. C has two states True/False. If Leak probability is given then we can calculate the Conditional Probability Table (CPT) from equation (5). In our study, we assumed the Leak probability of the rules is .01, which can be increased based on different system design and efficiency.

## 8. TYPICAL FAULTS AND PRIOR PROBABILITIES

International Energy Agency (IEA) published some survey results listing most important faults of HVAC system based on frequency of occurring, environmental effect, and recovery cost and energy impact [16]. The survey included fabricators, designers, constructors and maintenance staffs. After that through Annex-34 and Annex-40 projects IEA provided a comprehensive list of frequently occurring natural faults [17-18]. In 2003, National Institute of Standards and Technology (NIST) also published a project result where they used a rule based detection tool to detect and diagnose faults of 13 AHUs monitored from eight different sites [19]. Most of the field studies are based on artificially created faults in AHU. Therefore, the studies are not in our scope of study.

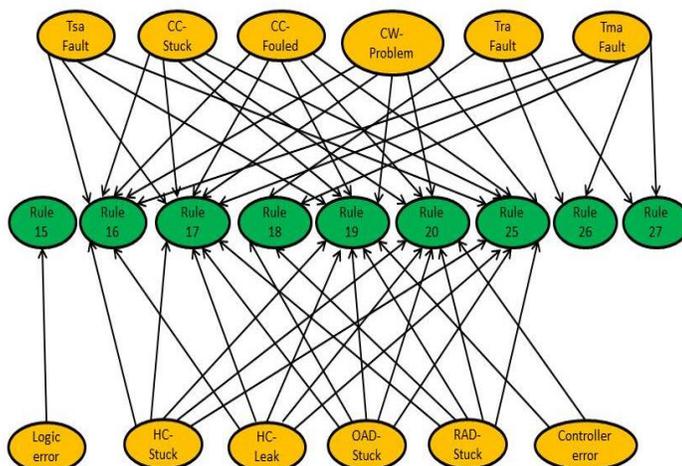
Based on all the literature reviews, a list of most frequently occurring natural faults can be found. We considered five major components/type of faults, which are heating coil, cooling coil, mixing box, controller logic error, and sensor related faults. Table 2 shows the frequency of occurrence of faults. In addition, we collected one-year maintenance records of “HVAC trouble calls” of Applied Engineering and Technology (AET) building at University of Texas at San Antonio (UTSA) to find the most frequent faults for whole AET. Table 2 also shows the calculated prior probabilities, which are simply the proportion of each fault.

**Table 2:** Probabilities of faults

Faults	Counts	Probability
HC-Leak	5	0.108695652
HC-Stuck	2	0.043478261
HW Temperature Low	4	0.086956522
CC-Leak	3	0.065217391
CC-Stuck	3	0.065217391
CC-Fouled	3	0.065217391
CW Temperature High	4	0.086956522
Logic Error	1	0.02173913
Controller Signal Error	1	0.02173913
T <sub>sa</sub> Biased	4	0.086956522
T <sub>ma</sub> Biased	4	0.086956522
T <sub>ra</sub> Biased	4	0.086956522
RAD Stuck	5	0.1
OAD Stuck	3	0.074
Total	46	1

## 9. STRUCTURE OF BBN

The structure of BBN is a graphical illustration of expert’s diagnostic thinking which can illustrate qualitatively the relationships among fault and fault symptoms. To train BBN we can either use probabilities developed by experts or machine learning methods using full datasets including both normal and faulty data. The second approach is impractical because full datasets for AHU is quite hard to achieve (both normal and faulty data). Therefore first approach is adopted in this study. In developing the BBN for FDD of AHU, the diagnostic thinking process of FDD experts are reflected and simulated. FDD experts usually diagnose faults based on the fault symptoms. Therefore, BBN should consist two types of node at least, one is fault node and another is fault symptom node. Here fault nodes represent different typical faults of AHU represented in table-2. Symptom nodes are the event (True/False) of the nine rules. Figure 4 shows the constructed BBN with nine rules and twelve fault nodes. Rules and fault nodes are connected with each other by cause and effect relationship.



**Figure 4:** Proposed BBN.

## 10. CONDITIONAL PROBABILITIES

Parameter of a BBN represents the quantitative dependencies among faults and symptoms using Probabilities. A conditional probability table is used to define the probabilities of all states of child node given the state of its parent nodes. In these study nodes with only one parent node is considered general nodes. Nodes with more than one parent nodes are considered to be Leaky Noisy-OR nodes. For the Leaky Noisy-OR nodes, the conditional probabilities and leak probabilities are needed. Therefore, the parameters of DBN are the prior probabilities for all the root nodes, conditional probability table for fault category nodes and conditional probability for general nodes as well as Leaky Noisy-OR nodes. Table 3 and 4 provide the conditional probability of different rules given the faults.

**Table 3:** Conditional Probability for Rule 15-17.

Faults/Rule	Rule 15	Rule 16	Rule 17
Tsa biased	N/A	0.167	0.142
Tma biased	N/A	0.167	N/A
Tra biased	N/A	N/A	0.142
HC-Stuck	N/A	0.167	0.142
HC-Leak	N/A	0.167	0.142
CC-Stuck	N/A	0.167	0.142
CC-Leak	N/A	N/A	0.285
CC-Fouled	N/A	0.167	N/A
Logic error	0.99	N/A	N/A

**Table 4:** Conditional Probability for Rule 18-20.

Faults/Rule	Rule 15	Rule 16	Rule 17
Tma biased	0.285	N/A	N/A
Tra Biased	0.285	N/A	N/A
Tsa biased	N/A	.153	N/A
HC-Stuck	N/A	0.076	0.11
HC-Leak	N/A	0.153	0.22
CC-Stuck	N/A	0.076	0.11
CC-Leak	N/A	0.076	0.11
CC-Fouled	N/A	0.076	0.11

CW temp. too high	N/A	0.076	0.11
OAD Stuck	0.142	0.076	0.11
RAD Stuck	0.285	0.153	0.11
Controller error	N/A	0.076	0.11

For example, the probability of Rule-15 is ‘True’ when sensor fault happened is expressed as  $P(\text{Rule-15}|\text{sensor fault})$ . The entire conditional probability is obtained from different FDD project reports based on APAR rule. At first, the different faults found against each rules are listed not found against a rule then a minimum amount of fault is considered to be happened against that rule. Later every column is normalized to one to get the conditional probabilities developed by experts and machine learning using full datasets including both normal and faulty data. The second approach is impractical because full datasets for AHU is quite hard to achieve (both normal and faulty data). Therefore first approach is adopted in this study. Again, Figure 4 shows the constructed BBN with nine rules and twelve fault nodes. Rules and fault nodes are connected with each other by cause and effect relationship.

## 11. DATA COLLECTION

Real time data are collected from one of the campus buildings of University of Texas at San Antonio (Main Campus) named Applied Engineering and Technology Building (AET). One month’s data are collected from June 2014 to July 2014 and further analyzed. The results will be discussed in the next section.

## 12. RESULTS

As the first step testing data from AET are conducted through rule based analysis. From the control signals of cooling coil, heating coil and dampers the mode of operation is ascertained which is mode-4. After that the appropriate rule set are applied. The results of rule based analysis can be seen through figure-5. Y-axis value 1 represents the true state of the rule. From Figure 5(a) we can see rule-16 was true four different times. That means supply air temperature was greater than mixed air temperature in the cooling period. The next figures (b) and (c) show that rules 25 and 26 were also true for multiple time periods. That means for some period of time supply air set point did not met set point and mixed air temperature was showing out of range temperature. Figure (d) shows that minimum outdoor air requirement was not met at the later period of the day.

According to Figure 5 (a), (b), (c), (d) rule-16, 18, 25 and 26 were true for some period. Sometimes rules were simultaneously true. This information was given to BBN as inputs and BBN prioritized the faults, which can be seen through Figure 6 (a) and (b). Every time step is of 5 minutes interval. Figure 6(a) shows the BBN diagnosis from 4:00-5:00pm period. During this one-hour period, Tma had the highest probability (.66) to be biased. The next highest probable faults are Tra biased (.30), cooling coil stuck (.19) and Tsa biased (.18) respectively. Between 18:00pm-4:00am. Rules 18, 25, 26 were true. However, most of the time rule-18 was true. The diagnosis results can be seen through Figure 6(b). Also, between 21:10pm-21:50pm rule-18, 25, 26 were true. During the period, Tma biased (.75) had the highest probability of occurrence. In other periods RAD-Stuck (.25), Tra biased (.25) and Tma biased (.25) had the highest probability. The proposed model is mainly effective when multiple rules are true simultaneously. When a single fault affects other parameters severely then multiple rules can be simultaneously true. In addition, when two or more faults simultaneously exist that can also cause multiple rules to be true. Further study include to analyze the multiple faults probability by expanding the Bayesian formulae.

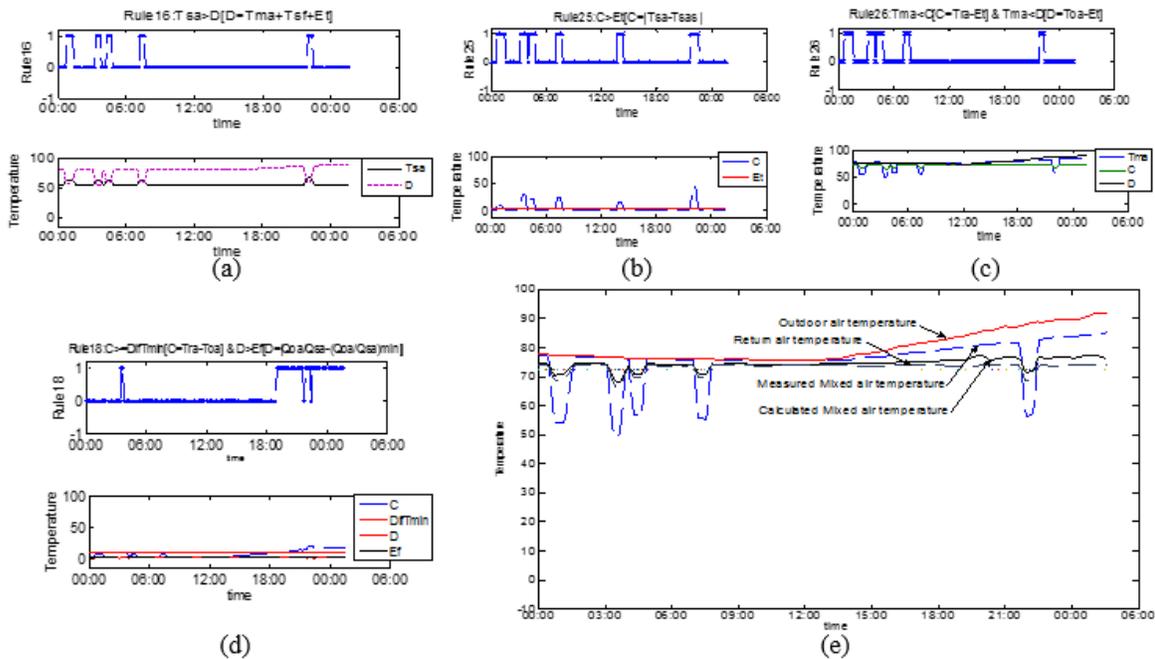


Figure 5 : Rule based Detection (15<sup>th</sup> June).

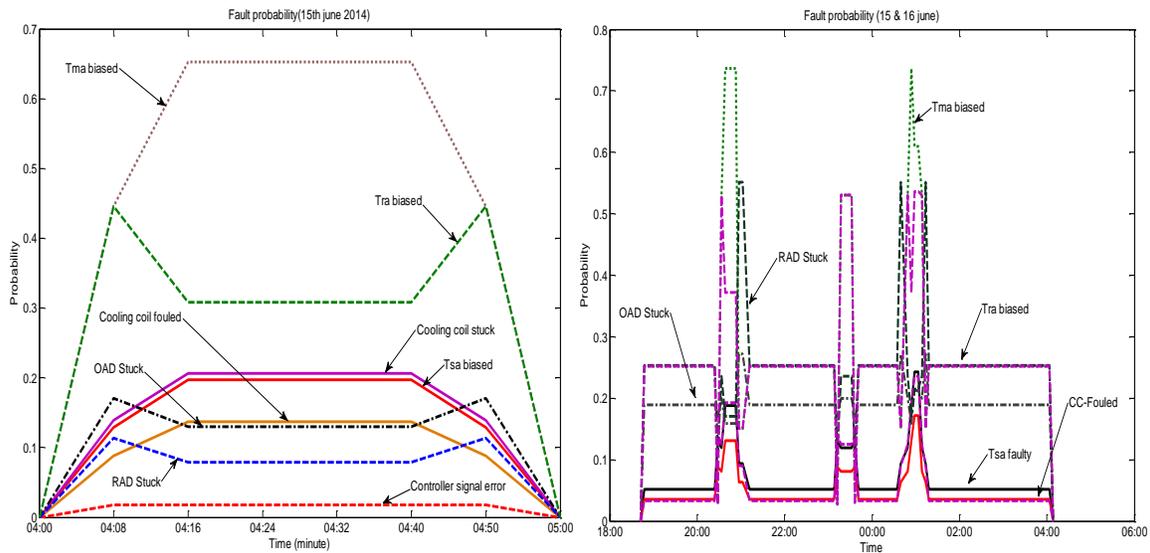
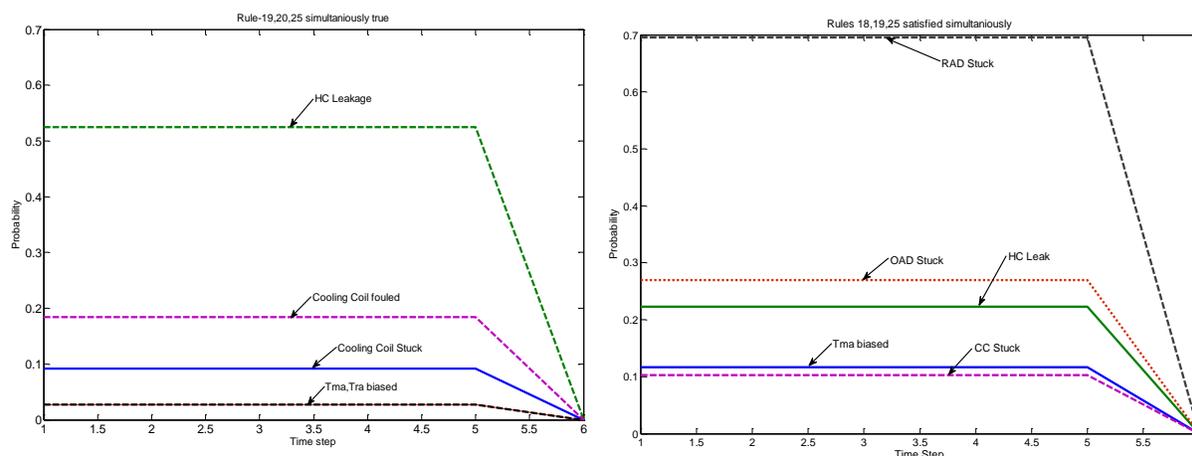


Figure 6 : BBN Results.

### 13. VALIDATION

Figure-5 (e) shows a plot of mixed, outdoor and return air temperature. As AHU is running on mode-4, the damper signal is set for minimum outdoor air. Based on the damper control signal mixed air temperature should be very close to return air temperature. However actual Tma is more towards Toa. For that reason most of the time rule-18 was true. Also sometimes, other rules were simultaneously true. So based on the priors and conditional probability BBN calculates that many of the times mixed air and return air temperature sensor biased were the highest probable faults. To validate our result we arranged onsite investigation. From the investigation, it is confirmed that sometimes-

mixed air temperature is biased toward outdoor air temperature. Figure-7 shows two case scenario when multiple rules satisfied. In a simulation study [28] it was seen that when rule 19, 20 and 25 are simultaneously true then HC-Leakage was the actual fault. In addition, when rule 18, 19 and 25 were simultaneously true RAD-Stuck was the actual fault. We tried to validate our model with these two Combinations .The result shows that HC-leakage was the diagnosed faults for the first combination with .55 probability. For the second combination, RAD-Stuck was the diagnosed fault with .7 probability.



**Figure 7 :** Validation of the Model.

## 14. CONCLUSION

Expert rule based fault detection is proved to be very robust and computationally simple for commercial implementation. Bayesian Belief Network can be a very effective tool to diagnose the best possible root cause behind the satisfaction of a rule or multiple rules. In addition, it is proved effective in the current study. In future, the study can be expanded to different modes of operation. Future scopes of study can be,

- The FDD tool can be implemented to all modes of operation.
- More survey and projects can be performed to improve the parameters of BBN.

## NOMENCLATURE

Tco	Changeover temperature
TRA	Return air temperature
TOA	Outdoor air temperature
TMA	Mixed air temperature
TSA	Supply air temperature
Et	Threshold parameter accounting for errors in temperature measurements
Ef	Threshold parameters accounting for errors related to airflows
Tsf	Temp. rise with supply fan
Trf	Temperature rise across return fan
TSA, S	Supply air set point
UCC	Cooling coil control signal
UHC	Heating coil control signal
Q	Outdoor air fraction

MTMAX	Maximum allowed mode transition per hour
OEC	Threshold parameter for cooling coil valve control signal

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