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Diagnostic Bayesian Networks for Diagnosing Air Handling Units Faults - Part I: faults in dampers, fans, filters and sensors

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Abstract

Faults in air handling units (AHUs) affect the building energy efficiency and indoor environmental quality significantly. There is still a lack of effective methods for diagnosing AHU faults automatically. In this study, a diagnostic Bayesian networks (DBNs)-based method is proposed to diagnose 28 faults, which covers most of common faults in AHUs. The basic idea is to fully utilize all diagnostic information in an information fusion way. The DBNs are developed based on a comprehensive survey of AHU fault detection and diagnosis (FDD) methods and fault patterns reported in three AHU FDD projects including NIST 6964, ASHRAE projects RP-1020 and RP-1312. The study is published in two parts. In the Part I, the methodology is described firstly. Four DBNs are developed to diagnose faults in fans, dampers, ducts, filters and sensors. There are 10 typical faults concerned and 14 fault detectors introduced. Evaluations are made using the experimental data from the ASHRAE Project RP-1312. Results show that the DBN-based method is effective in diagnosing faults even when the diagnostic information is uncertain and incomplete.

Keywords: Air handling unit, fault diagnosis, fault detection, Bayesian network.

1. Introduction

Air handling units (AHUs) connect primary heating/cooling plants with building zones. They contribute a significant portion to the energy consumption in heating, ventilation, and air conditioning (HVAC) systems. Large varieties of faults in AHUs could lead to uncomfortable indoor environment, poor indoor air quality, occupant complains and energy wastes. The automated fault detection and diagnosis (FDD) tools are useful to alarm and identify faults timely.

Over the last decades, a considerable amount of researches had been carried out in the developments of FDD methods for AHU [1][2][3][4], chiller [5] and HVAC systems [6][7], etc. The existing AHU FDD methods can be broadly categorized as [8][9]: model-based methods [10][11][12][13][14], rule-based methods [15][16][17][18] and data-driven methods [19][20][21][22][23]. Generally, fault detection and fault diagnosis are processed separately. Fault detection process determines whether the AHUs concerned are fault-free or not. Fault diagnosis process identifies the root cause of the fault symptoms after a fault is detected. Most of the previous publications mainly concerned fault detection. However, the problem of AHU fault diagnosis has not handled properly. AHU fault diagnosis is much more difficult than fault detection. There is still a lack of effective methods for diagnosing AHU faults.

The major challenge in AHU fault diagnosis is the incompleteness and inaccuracy of the AHU measurements. Firstly, AHU measurements are rich in data but often poor in information. There is limited amount of sensors equipped in AHUs. Only the most essential sensors needed for control are installed due to cost considerations. Measurements are generally not enough for fault detection, and rather insufficient diagnosis. Secondly, various levels of uncertainties exist in the AHU measurements and fault symptoms. The relationships faults and fault systems exist in the term of probabilities. They make the fault diagnosis more complex. Thirdly, there are too many possible faults in AHUs. There are 31 devices in AHUs according to survey in ASHRAE project 1312 [38], including 12 sensors, 6 controlled devices (3 dampers and 3 valves of coils), 5 pieces of equipment (fan, duct and coil) and 8 controllers. Every device might be faulty with various faults. A fault might lead to several fault symptoms, and a same fault symptom might be caused by various faults. It is rather difficult to isolate the root fault with others using a few sensors. With the amount of faults considered, the difficulty would increase sharply. Most of previous publication only concerned a few amount of faults. The challenge has not been overcome in the conventional AHU fault diagnosis methods.

However, there are interesting facts that AHU experts can always diagnose faults efficiently. They might have a look of configuration of AHU, check historical data and operation records, or conduct a few on-site tests. Sometimes, if information is too poor, they can also provide a list of suspected faults with probabilities. AHU experts use prior knowledge to design the FDD process, and introduce prior knowledge, experiments, various of information besides sensor measurements, to handle the information poor problems. A variety of information resources besides sensor measurements is also helpful for fault diagnosis, e.g. maintenance records and health status of related equipment. For instance, the fault of filter fouling is likely existing if the filter has not been properly treated for a long time. A sensor is at higher risk of frozen fault if its value has not changed at all for an extensive period (i.e., several hours), especially at the system starting up and shutting down periods. Such kind of diagnostic information is very useful to the information poor fault diagnosis. The inference of AHU experts is based on probabilities, which is also efficient to handle problems of the incompleteness and inaccuracy of the AHU measurements. This is rather different from the rule-based AHU FDD methods. It comes with the question that whether it is possible to simulate the diagnostic thinking of AHU experts to overcome the AHU diagnosis problems?

In the field of artificial intelligence, Bayesian network is a powerful tool to develop expert systems. It is good at representing and to diagnosing complex systems with uncertain, incomplete and even conflicting information. A Bayesian network is a probabilistic graphical model that represents relationships of probabilistic dependence within variables via directed acyclic graphs. Since introduced by Pearl in early 1980s [24][25], it has been successfully applied in the domain of knowledge discovery and probabilistic inference [26]. Applications can be found in FDD methods for nuclear power systems [27], aircraft engines [28], semiconductor manufacturing systems [26] and medical diagnostic decision support systems [29][30][31], etc. In the HVAC field, M. Najafi et al. [32] and J. Wall et al. [33] introduced Bayesian network to detect and diagnose AHU faults. Both works trained Bayesian network in machine learning ways using both fault and fault-free data. However, fault data are generally not available in practice. Different from their works, the authors had proposed a diagnostic Bayesian network (DBN)-based method which does not require fault data. The DBNs were developed using physical laws, experts' knowledge/experiences, operation and maintenance records, historical and real-time measurements, etc. Applications had made for chiller FDD [34] and VAV terminal FDD [35]. Evaluations demonstrated that the DBN-based method is powerful to overcome the challenges in AHU fault diagnosis. It is effective to fuse different kinds of information, and the fault diagnosis is robust when diagnostic information is uncertain and incomplete.

Inspired by the diagnostic thinking of experts, this paper aims to solve the problem of AHU fault diagnosis by simulating the FDD process of experts using Bayesian networks. The methodology of the DBNs-based method is introduced firstly. Then, DBNs are developed for the diagnosis of faults in AHU airside subsystems, including fans (supply air fan and return air fan), dampers (outdoor air damper, return air damper and exhaust air damper), ducts, filter, air flow sensor and pressure sensor. Ten typical faults are considered. This paper is organized as follows. Section 2 introduces the Bayesian network theory. Sections 3 and 4 describe the methodology. Section 5 makes evaluations of the DBNs. Conclusions and recommendations of this study are given in Section 6.

2. Bayesian Network Theory

A Bayesian network is defined by two components, i.e., structure and parameters. The structure of a Bayesian network is a graphical and qualitative illustration of the relations among the modeled variables. A Bayesian network for AHU fault diagnosis is actually a directed acyclic graph in which nodes represent AHU faults and evidences from measurements or observations (fault symptoms) and arcs represent direct probabilistic dependences among them (an example for AHU FDD can be found in Figure 4). Therefore, the structure of a Bayesian network for AHU fault diagnosis is a straightforward illustration of casual relationships of AHU faults and AHU fault symptoms. A node has several possible states. Each state is an event. When an event occurs, it is an observed state. The node without any input arc is a root node. AHU fault nodes are always root nodes since they are root causes of fault symptoms. For AHU fault diagnosis in this study, all root nodes are fault nodes.

Parameters represent the quantitative probabilistic relationships among the nodes. Every state in root nodes has a prior probability. In this study, prior probabilities represent prior knowledge about the probabilities of AHU faults. A child node has a conditional probability table which represents all possible combinations of its states and its parent nodes' states. The number of parameters in the conditional probability table exponentially grows with the number of its parents. In case of a child node with two Boolean states has *n* parents which are also Boolean, 2^{n+1} parameters are to be specified. It may be impossible to obtain or estimate so many parameters in the AHU fault diagnosis. In this study, Noisy-Max is introduced to reduce the number of parameters needed to specify conditional probability distributions. It is based on the assumption that parent nodes act independently in producing the effect on a child node. If a node is considered as a Noisy-MAX node, the number of parameters is reduced from exponential to linear to the number of parents. Assume that all nodes in a Bayesian network are Boolean, only 2*(n+1) parameters are needed, rather than 2^{n+1}. More details about Noisy-MAX can be found in [36]. For AHU fault diagnosis, if an evidence node has more than one parent fault node, it is generally considered to be a Noisy-MAX node in this study.

The inference using a Bayesian network is to calculate the posterior probability $P(X_q|X_e)$, where X_q is the node of interest (e.g. the fault concerned) and X_e is the node or a set of nodes in which a state has been observed (e.g. fault symptoms). More details can refer to papers of the authors about chiller FDD [34] and VAV terminal FDD [35], and reference [24][25].

3. Outline of the AHU fault diagnosis method

3.1. Overview of the DBN-based AHU fault diagnosis

The flow chart of the proposed DBN-based AHU fault diagnosis is illustrated in Figure 1. It consists of three processes, i.e., data pre-processing, fault detection and fault diagnosis. Detailed descriptions are provided in the following sections respectively.

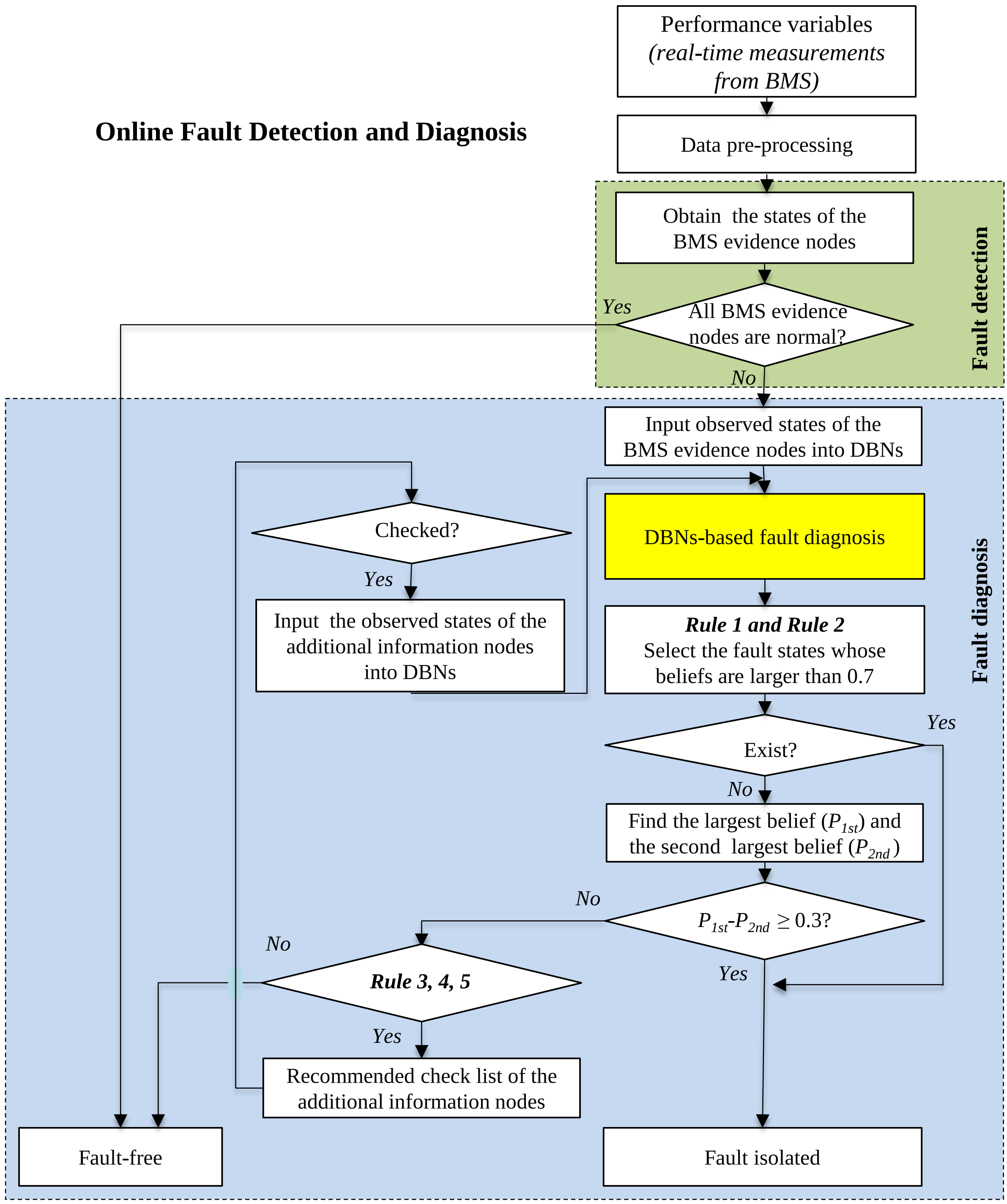

Figure 1. Flow scheme of the DBN-based AHU fault diagnosis method

There are three kinds of nodes in the DBNs, i.e. fault node, BMS evidence node and additional information node. The BMS evidence nodes represent the fault evidences that can be detected using the BMS measurements. The additional information nodes represent the evidences from on-site manual observations, active tests, or maintenance records.

3.2. Data pre-processing

The steady state filter proposed by Lee et al. is introduced here to process the measurements [37]. In the filter, the sum of the slopes of the selected variables is used as a criterion for the steady state. The slope is calculated using maximum (X_{max}), minimum (X_{min}) and mean values (X_{mean}) in a sliding window, as shown in Eq. (1).

$$S = \frac{X_{max} - X_{min}}{X_{mean}} \tag{1}$$

In this study, the common variables proposed by Li and Wen [38] are used, which include cooling/heating coil signal, supply air duct statistic pressure (P_{sa}), supply air temperature (T_{sa}) and supply fan speed N_{sf}. For each variable, current sample value and values of the five previous time steps are used to determine X_{max}, X_{min} and X_{mean}. The threshold of the slope used in this study is three times of the standard deviation of the sum of slopes using steady-state training data. The steady state training data are manually selected from the training data set. More details can be found in Lee et al. [39].

3.3. Fault detection

Fault detection is to examine whether the AHU concerned is abnormal. All of the BMS evidence nodes (refers to Section 4.1.3) summarized in Table 2 are used as fault detectors. An AHU is considered abnormal if any BMS evidence node is in fault state. As shown in Table 2, the states of the BMS evidence nodes are determined by rules using BMS measurements. The thresholds in the rules are obtained using *t*-student approach. In the *t*-student approach, the distributions of variables or deviations are assumed to be normally distributed. Confidence level of 99.73% can be obtained if the threshold is three times of standard deviation. In this study, the standard deviations are calculated using the steady-state training data in fault free conditions.

3.4. Fault diagnosis

The DBN-based fault diagnosis is to provide the most reasonable explanations for all input evidences (observed states of the evidence nodes and the additional information nodes). The outputs of the DBNs are the beliefs (posterior probabilities) of the states in fault nodes. A fault node may have more than one fault states (examples can be found in Table 1). For example, the supply air pressure (P_{sa}) frozen fault has three possible fault states, i.e. *Positive frozen* (the value of the sensor reading is frozen at a value that is higher than the set-point), *Set-point frozen* (the value of the sensor reading is frozen at the same value as the set-point) and *Negative frozen* (the value of the sensor reading is frozen at a value that is lower than the set-point). Two rules are proposed to determine the fault diagnosis results:

Rule 1: if the highest belief of a fault is larger than the threshold (e.g., 0.7), then this fault is isolated; or,

Rule 2: if the highest belief of all faults is larger than the second highest one by a threshold (e.g., 0.3), then the fault with the highest belief is isolated.

Notice that the thresholds used in *Rule 1* and *Rule 2* can later be adjusted by the building operators. It has to declare that some fault nodes have states with similar fault symptoms. For instance, all of the three frozen states of the supply air pressure (P_{sa}) sensor fault indicate the frozen fault. The sum of their beliefs is used as the belief of one fault state.

If *Rule 1* and *Rule 2* are not satisfied, it means that a fault is detected but not isolated. It might be a false alarm. For practical application, an AHU is considered to be fault free if its performance is not affected in such a case. Three variables are selected to indicate the performance since they are significant to the indoor air quality and the energy savings, i.e., P_{sa} (supply air pressure), W_{sf} (supply fan power consumption) and W_{rf} (return fan power consumption), as *Rule 3*, *Rule 4* and *Rule 5*.

Rule 3: $|P_{sa} - P_{sa,spt}| < 3*\delta_P$

Rule 4: $|W_{sf} - f(F_{sa})| < 3*\delta_{w,sf}$

Rule 5: $|W_{rf} - f(N_{rf})| < 3*\delta_{w,rf}$

Rule 3 checks whether the AHU provides a proper amount of air. *Rule 4* and *Rule 5* check whether the supply fan and the return fan run are fault free. If any of these three rules is violated, but Rule 1 and Rule 2 do not isolate the fault, a fault alarm is generated. It leaves technicians to isolate faults manually. A checklist is recommended which provides a list of faults sorted by the posterior probabilities of the additional information nodes. The checklist aims to help technicians to find faults quickly.

4. DBNs for diagnosing damper, fan, filter and sensor faults

A set of DBNs are developed to diagnose faults in a typical single duct dual fan VAV AHU as described in ASHRAE Project RP-1312 final report [38], which is also shown in Figure 2.

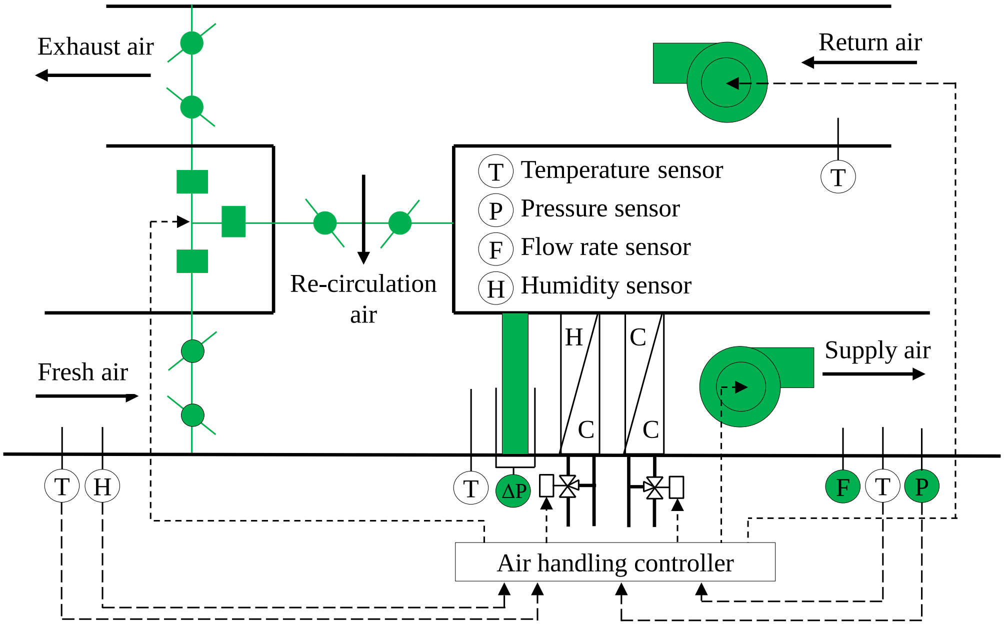

Figure 2. Schematic diagram of the AHU used in the ASHRAE Project RP-1312 and the selected measurements in this study

The AHU is controlled by conventional control sequences to provide adequate outdoor air ventilation, suitable supply air temperature, supply statistic pressure, return air flow rate, and to minimize the energy usage. There are four sequence control modes as shown in Figure 3, including:

Mode 1: Mechanical heating with minimum outdoor air

Mode 2: Economizer cooling

Mode 3: Mechanical and economizer cooling

Mode 4: Mechanical cooling with minimum outdoor air

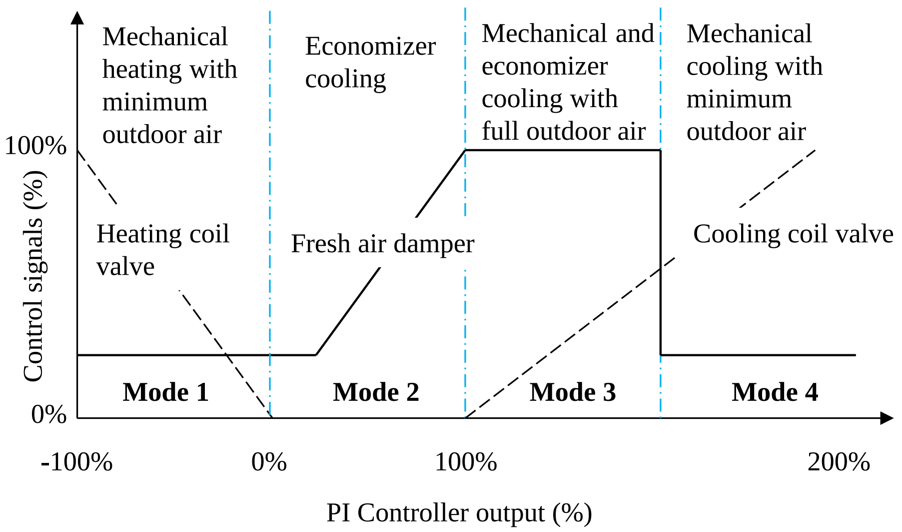

Figure 3. Split-range control strategy for supply air temperature control of a typical AHU used in the ASHRAE Project RP-1312 [38]

The minimum outdoor damper position strategy is used to control the ventilation air intake when the AHU is in Modes 1 and 4. The return fan speed is controlled to match the supply fan speed by a certain differential.

A mode detector was developed to detect current operating mode. The inputs of the detector were supply air temperature set-points ($T_{sa,spt}$), control signals of openness of valve in coiling coil (U_{cc}) and air dampers (U_{damper}). Based on these values, a set of simple rules were developed. The rules are robust to most of AHU faults. If the operating mode cannot be recognized by the rules, it is classified into Mode 5 which means failed to identify the current mode.

Mode 1: $T_{sa,spt} = T_{sa,spt,\ heating\ mode}$, $U_{damper} = U_{damper,min}$

Mode 2: $T_{sa,spt} = T_{sa,spt,\ cooling\ mode}$, $U_{damper,min} < U_{damper} < U_{damper,max}$

Mode 3: $T_{sa,spt} = T_{sa,spt,\ cooling\ mode}$, $U_{damper,min} < U_{damper} < U_{damper,max}$, $U_{cc} > U_{cc,close}$

Mode 4: $T_{sa,spt} = T_{sa,spt,\ cooling\ mode}$, $U_{damper} = U_{damper,max}$

Mode 5: if the mode cannot be identified by the above rules.

4.1. Structures of the DBNs

4.1.1. Overview

In this study, the structures of the DBNs are manually developed based on the logical analysis, first principles, fault patterns reported in the literature including ASHRAE Project RP-1020 [43], NIST 6964 [44], ASHRAE Project RP-1312 [38] and references

[2][10][11][12][13][14][15][16][17][18][21][22][37][39][42] and the knowledge/ experience of the authors who processed ASHRAE Project RP-1312.

All fault nodes are named beginning with *F* in Table 1. All BMS evidence nodes are abbreviated as *E*, as shown in Table 2. All additional information nodes are abbreviated as *M*, as shown in Table 3. In this study, it is assumed that only one fault occurs at a time.

Only common sensors are used in the DBNs, including supply duct statistic pressure (P_{sa}), differential pressure of the supply air filter (ΔP_{filter}), return air temperature (T_{ra}), outdoor air temperature (T_{oa}), mix air temperature (T_{ma}), supply fan power consumption (W_{sf}), return fan power consumption (W_{rf}), and supply air flow rate (F_{sa}). The DBNs also use the control signals and set-points that can be easily obtained from BMSs, including supply fan speed control signal (N_{sf}), return fan speed control signal (N_{rf}), supply duct statistic pressure set-point ($P_{sa,stp}$) and supply air temperature set-point ($T_{sa,stp}$).

A DBN is developed for Mode 1, 2, and 4, as shown in Figure 4. Another DBN is developed for Mode 3, as shown in Figure 5. The differences between the two DBNs are the fault symptoms of *F4* (OA damper), *F5* (RA damper) and *F8* (Return fan).

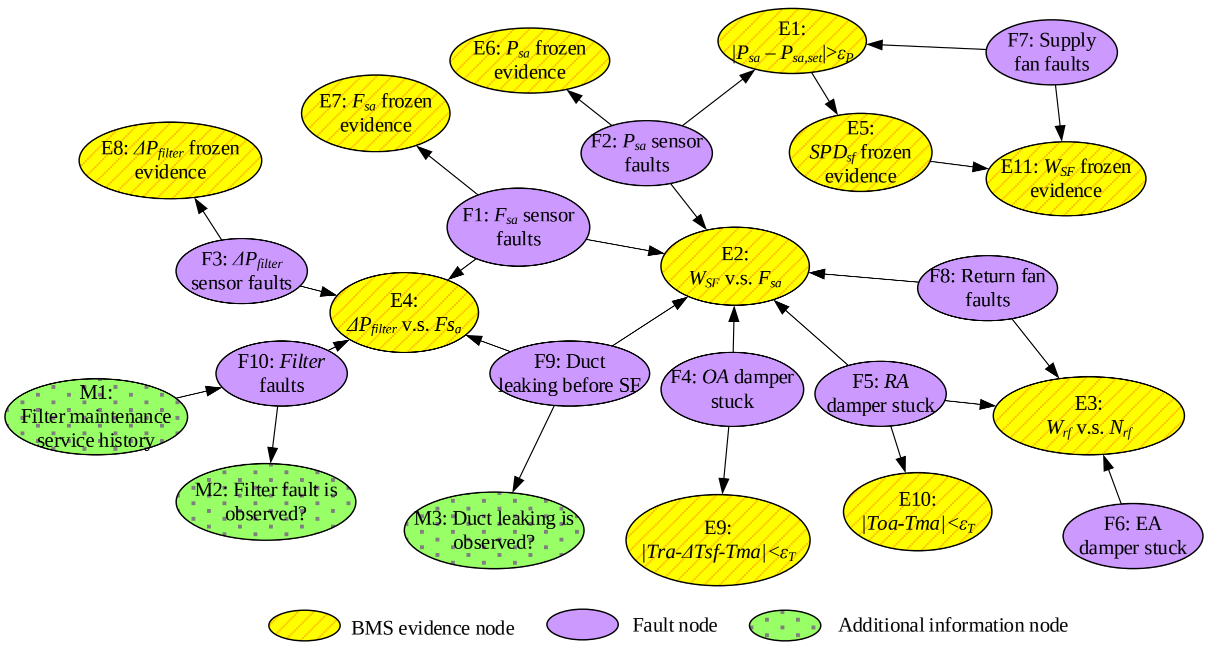

Figure 4. Diagnostic Bayesian network for AHU air side fault diagnosis in Mode 1, Mode 2 and Mode4

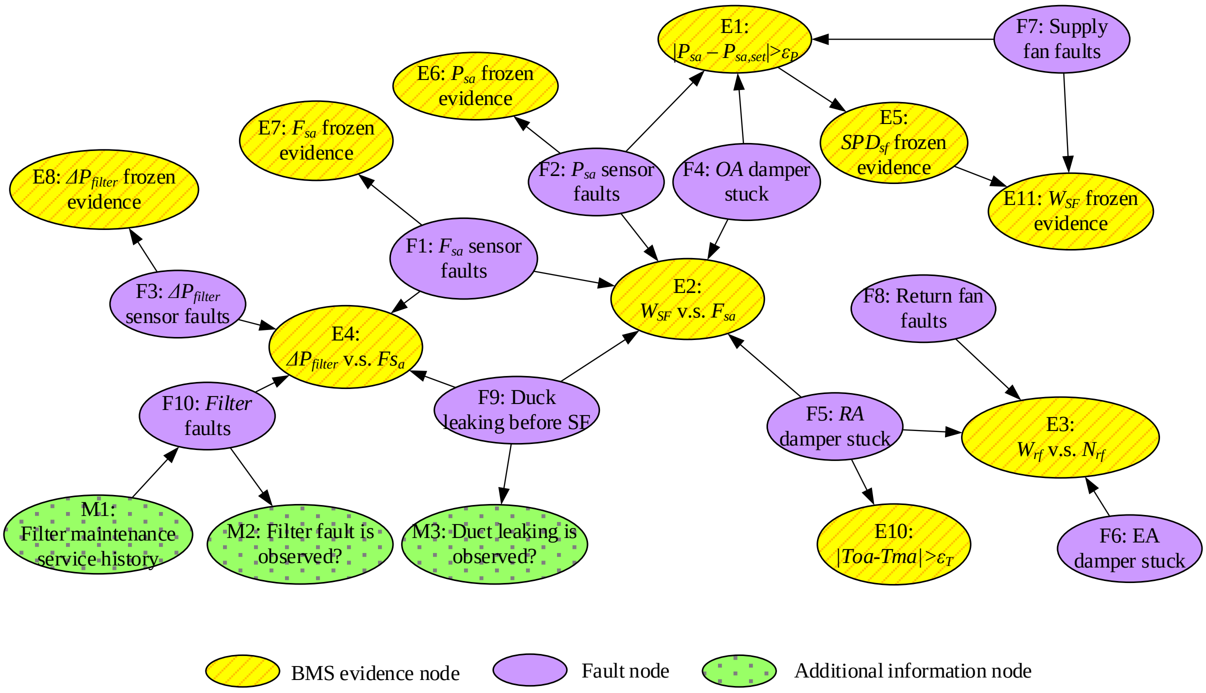

Figure 5. Diagnostic Bayesian network for AHU air side fault diagnosis in Mode 3

4.1.2. Fault nodes

In the Part I, ten typical AHU faults in dampers, fans, filters and sensors are considered in the DBNs, as listed in Table 1. Discussions about how to determine the prior probabilities refer to *Section 4.2*. The determinations of the thresholds refer to *Section 3.2*.

Table 1. Typical faults and their prior probabilities used in the Part I

Node number	Device	State of node (caused by different faults or at different fault severity level)		Prior probability
		State	Rules for defining state	
F1	Supply air flow rate sensor	*Frozen*	F_{sa} *is frozen**	0.02
		Positive biased	$F_{sa} - F_{sa,actual} > \varepsilon_F$	0.01
		Negative biased	$F_{sa} - F_{sa,actual} < -\varepsilon_F$	0.01
		Fault-free	$\lvert F_{sa} - F_{sa,actual}\rvert \leq \varepsilon_F$	0.96
F2	Supply air pressure sensor	*Positive frozen*	P_{sa} *is frozen, and* $P_{sa} > 1.1X\, P_{sa,stp}$	0.005
		Set-point frozen	P_{sa} *is frozen, and* $\lvert P_{sa} - P_{sa,stp}\rvert \leq \varepsilon_{Psa}$	0.01
		Negative frozen	P_{sa} *is frozen, and* $P_{sa} - P_{sa,stp} < -\varepsilon_{Psa}$	0.005
		Positive biased	P_{sa} *is not frozen, and* $P_{sa} - P_{sa,stp} > \varepsilon_{Psa}$	0.01

		Negative biased	P_{sa} *is not frozen, and* $P_{sa} - P_{sa,stp} < -\varepsilon_{Psa}$	0.01
		Fault-free	P_{sa} *is not frozen, and* $\lvert P_{sa} - P_{sa,stp}\rvert \leq \varepsilon_{Psa}$	0.96
F3	Differential pressure sensor for filter	*Frozen*	ΔP_{filter} *is frozen*	0.02
		Positive biased	ΔP_{filter} *is not frozen, and* $\Delta P_{filter} - \Delta P_{filter,actual} > \varepsilon_{\Delta pfilter}$	0.01
		Negative biased	ΔP_{filter} *is not frozen, and* $\Delta P_{filter} - \Delta P_{filter,actual} < -\varepsilon_{\Delta pfilter}$	0.01
		Fault-free	ΔP_{filter} *is not frozen, and* $\lvert\Delta P_{filter} - \Delta P_{filter,actual}\rvert \leq \varepsilon_{\Delta pfilter}$	0.96
F4	OA damper	*Stuck at max position*	*OAD is stuck, and* $\lvert OAD_{position,actual} - OAD_{position,max}\rvert \leq \varepsilon_{damper}$	0.04
		Stuck at partially open position	*OAD is stuck, and it is not stuck at max nor min position*	0.03
		Stuck at min position	*OAD is stuck, and* $\lvert OAD_{position,actual} - OAD_{position,min}\rvert \leq \varepsilon_{damper}$	0.03
		Fault-free	*OAD is not stuck*	0.9
F5	RA damper	*Stuck at max position*	*RAD is stuck, and* $\lvert RAD_{position,actual} - RAD_{position,max}\rvert \leq \varepsilon_{damper}$	0.04
		Stuck at partially open position	*RAD is stuck, and it is not stuck at max nor min position*	0.03
		Stuck at min position	*RAD is stuck, and* $\lvert RAD_{position,actual} - RAD_{position,min}\rvert \leq \varepsilon_{damper}$	0.03
		Fault-free	*RAD is not stuck*	0.9
F6	EA damper	*Stuck at max position*	*EAD is stuck, and* $\lvert EAD_{position,actual} - EAD_{position,max}\rvert \leq \varepsilon_{damper}$	0.04
		Stuck at partially open position	*EAD is stuck, and it is not stuck at max nor min position*	0.03
		Stuck at min position	*EAD is stuck, and* $\lvert EAD_{position,actual} - EAD_{position,min}\rvert \leq \varepsilon_{damper}$	0.03

		Fault-free	*EAD is not stuck*	0.9
F7	Supply air fan	*Complete failure*	$W_{rf} < \varepsilon_{Wsf}$	0.01
		Fixed at max SPD	*Fan runs at fixed speed, and* $\lvert N_{sf} - N_{sf,max}\rvert \leq \varepsilon_{Nsf}$	0.01
		Fixed at min SPD	*Fan runs at fixed speed, and* $\lvert N_{sf} - N_{sf,min}\rvert \leq \varepsilon_{Nsf}$	0.01
		Fixed at partial SPD	*Fan runs at fixed speed, and* $\lvert N_{sf} - N_{sf,max}\rvert > \varepsilon_{Nsf}$,*and* $\lvert N_{sf} - N_{sf,min}\rvert > \varepsilon_{Nsf}$	0.01
		Fault-free	*If above states are not observed*	0.96
F8	Return air fan	*Complete failure*	$W_{rf} < \varepsilon_{Wsf}$	0.01
		Fixed at higher SPD	*Fan runs at fixed speed, and* $N_{rf} - N_{rf,need} > \varepsilon_{Nrf}$	0.01
		Fixed at lower SPD	*Fan runs at fixed speed, and* $N_{rf} - N_{rf,need} < \varepsilon_{Nrf}$	0.01
		Fixed at expected SPD	*Fan runs at fixed speed, and* $\lvert N_{rf} - N_{rf,need}\rvert < \varepsilon_{Nrf}$	0.01
		Fault-free	*If above states are not observed*	0.96
F9	Duct before supply fan	*Leaking heavily*	$F_{sa,leaking} > 0.3*F_{sa}$	0.01
		Leaking slightly	$0.05*F_{sa} < F_{sa,leaking} \leq 0.3*F_{sa}$	0.01
		Fault-free	$F_{sa,leaking} \leq 0.05*F_{sa}$	0.98
F10	Filter	*Fouling*	$\Delta P_{filter} < 0.8*\Delta P_{filter,expected}$	0.03
		Broken	$\Delta P_{filter} > 1.2*\Delta P_{filter,expected}$	0.03
		Fault-free	*If above states are not observed*	0.94

* Sensor readings have been unchanged for δ hours (e.g. δ =2h)

4.1.3. BMS evidence nodes

The DBNs have twelve BMS evidence nodes. Rules in nodes *E6*, *E7* and *E8*, are introduced to check whether the sensor readings have been unchanged for δ hours. Rules in nodes *E5* and *E11* check the operating status of the fans. Rules in *E2*, *E1* and *E3* represents *rule 3*, *rule 4* and *rules 5* respectively.

Table 2. BMS evidence nodes

Node number	Node description	State of node (caused by fault at different severity level)	
		State	Rules to determine sate
E1	Difference between supply air pressure and its set point	*Positive*	P_{sa} - $P_{sa,stp}$ > ε_P
		Negative	P_{sa} - $P_{sa,stp}$ < -ε_P
		Fault-free	$\|P_{sa}$ - $P_{sa,spt}\|\leq \varepsilon_P$
E2	Supply fan power consumption (W_{sf}) is a polynomial function of supply air flow rate (F_{sa})	*Extremely positive*	W_{sf} - $f(F_{sa})$>3*ε_{sf}
		Positive	W_{sf} - $f(F_{sa})$>ε_{sf}
		Negative	W_{sf} - $f(F_{sa})$<-ε_{sf}
		Fault-Free	$\|W_{sf}$ - $f(F_{sa})\|\leq \varepsilon_{sf}$
E3	Return fan power consumption (W_{rf}) is a polynomial function of return fan speed (N_{rf})	*Positive*	W_{rf} - $f(N_{rf})$>ε_{rf}
		Negative	W_{rf} - $f(N_{rf})$<-ε_{rf}
		Fault-Free	$\|W_{rf}$ - $f(N_{rf})\|\leq \varepsilon_{rf}$
E4	Pressure drop across a filter (ΔP_{filter}) is a polynomial function of supply air flow rate (F_{sa})	*Positive*	ΔP_{filter} - $f(F_{sa})$>$\varepsilon_{\Delta P,filter}$
		Negative	W_{rf} - $f(N_{rf})$<-ε_{rf}, and W_{rf} is not zero
		Zero	W_{rf} = 0
		Fault-Free	$\|\Delta P_{filter}$ - $f(F_{sa})\|\leq \varepsilon_{\Delta P,filter}$
E5	Supply fan control signal	*Max value*	$\|N_{sf}$ - $N_{sf,max}\|$< ε_{Nsf}
		Min value	$\|N_{sf}$ - $N_{sf,min}\|$< ε_{Nsf}
		Partial value	*If above states are not observed*
E6	Supply air pressure reading over the past δ hours	*Frozen*	$\|P_{sa,i}$ - $P_{sa,i-n}\|$< $\varepsilon_{P,frozen}$, n=1,… δ/L. The ratio is less than θ
		Not frozen	If *Frozen* is not observed
E7	Supply air flow rate	*Frozen*	$\|F_{sa,i}$ - $F_{sa,i-n}\|$<$\varepsilon_{F,frozen}$, n=1,…

	reading over the past δ hours		δ/L. The ratio is less than θ
		Not frozen	If *Frozen* is not observed
E8	ΔP_{filter} reading over the past δ hours	*Frozen*	$\lvert \Delta P_{filter,\mathrm{i}} - \Delta P_{filter,\mathrm{i-n}} \rvert < \varepsilon_{P,frozen}$, n=1,…δ/L. The ratio is less than θ
		Not frozen	If *Present* is not observed
E9	Difference between return air and mixed air temperatures	*Negative*	$\lvert T_{ra} - T_{ma} - \Delta T_{sf} \rvert \leq \varepsilon_T$
		Positive	$\lvert T_{ra} - T_{ma} - \Delta T_{sf} \rvert > \varepsilon_T$
E10	Difference between outdoor air and mixed air temperatures	*Negative*	$\lvert T_{oa} - T_{ma} \rvert \leq \varepsilon_T$
		Positive	$\lvert T_{oa} - T_{ma} \rvert > \varepsilon_T$
E11	Supply fan power measurement (W_{sf})	*Max value*	$\lvert W_{sf} - W_{sf,max} \rvert \leq \varepsilon_{wsf}$, when *E2* is fault free
		Min value	$\lvert W_{sf} - W_{sf,min} \rvert \leq \varepsilon_{wsf}$, when *E2* is fault free
		Partial value	$W_{sf,max} + \varepsilon_{wsf} > W_{sf} > W_{sf,min} + \varepsilon_{wsf}$, when E2 is fault free
		Zero	$\lvert W_{sf} \rvert < 0.2 \cdot \varepsilon_{wsf}$, when E2 is fault free

E2 represents the relationships between the supply fan power consumption (W_{sf}) and the volumetric flow rate (F_{sa}). W_{sf} is a polynomial function of F_{sa}, as discussed in [41] and [42]. In this study, the coefficients of the function are trained using the summer fault free data collected from the ASHRAE Project RP-1312. More specifically, 2/3 of the summer fault free data (1,400 data points) are randomly selected to obtain the polynomial function between W_{sf} and F_{sa} , which is called the fan model as Eq. (2).

$$W_{sf} = 708.3 - 0.5523 * F_{sa} + 0.000424 * F_{sa} * F_{sa} \quad (2)$$

The remaining 1/3 of the summer fault free data are test data to validate the fan model. The fault data in summer experiments are used to evaluate the fault detection capacity of *E2*, as shown in Figure 6. The 'Normal' points represent the fault-free test data points.

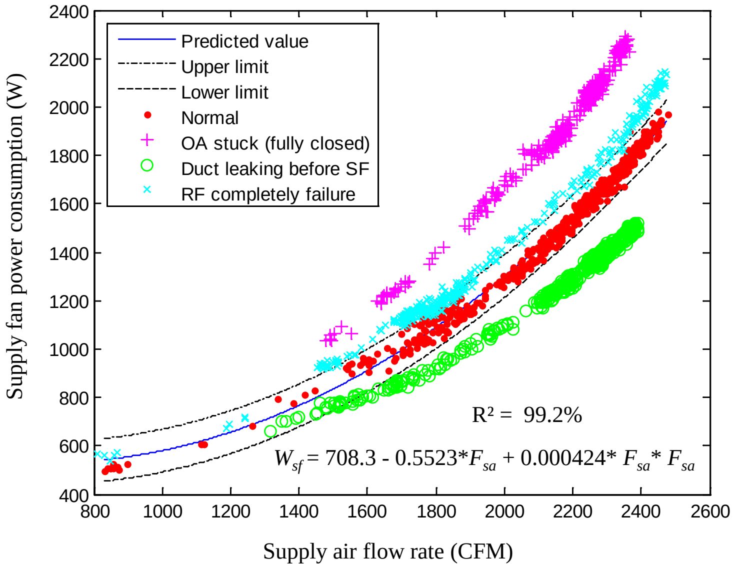

Figure 6. Relationship between W_{sf} versus F_{sa} in fault free and fault conditions using the ASHRAE RP-1312 summer data

The fan model successfully represents the relationship between W_{sf} and F_{sa}. The R-square is 99.2%. The upper limit and lower limit, which are ±3*σ to obtain a confidence level of 99.73%, are also displayed in Figure 6. σ can be calculated using the *t*-student statistic approach from the deviations between the predicted W_{sf} and the measured W_{sf} using the training data. *E2* detects fault if the deviation is out of the upper and lower limits.

Similarly, as indicated by Wen and Li [38], the differential pressure across the filter (ΔP_{filter}) has a polynomial relationship with the supply air flow rate (F_{sa}). Similar approach and data as those for the fan model are used to determine the filter model as Eq. (3).

$$\Delta P_{filter} = -15.93 + 0.000917 * F_{sa} + 0.000027 * F_{sa} * F_{sa} \quad (3)$$

The data and filter model prediction are shown in Figure 7. The 'Normal' points represent the fault-free test data points. When the filter is fouled, ΔP_{filter} is larger than predicted value by the filter model. If the filter is broken, ΔP_{filter} is smaller than the predicted value. Of course, if the supply air flow rate station (F_{sa}) is faulty, the fault symptoms could be similar to those of the filter fault. However, with the help of the evidence in *E2*, these two faults, i.e., supply air flow rate station fault (*F1*) and filter fault (*F3*) can be distinguished.

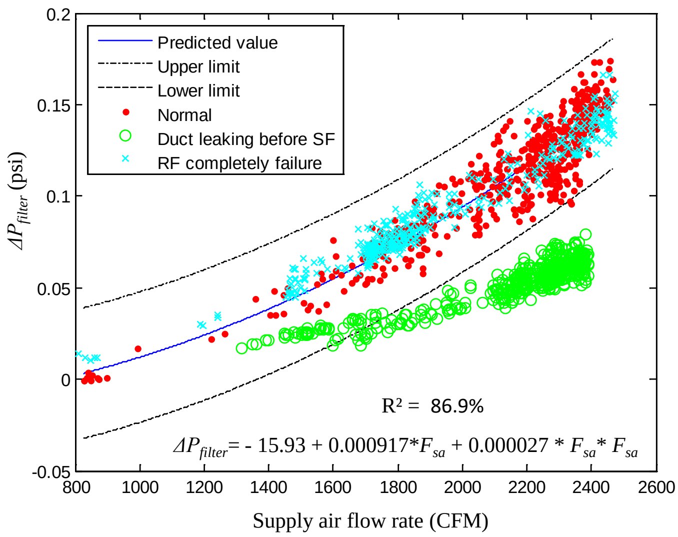

Figure 7. ΔP_{filter} versus F_{sa} in fault free and fault conditions

When the supply fan is stuck at a fixed speed, P_{sa} in general could not be maintained at the supply air pressure set-point ($P_{sa,stp}$). This symptom will then be represented in *E1* (Table 2). After a short while, the fan speed (N_{sf}) control signal will be driven to be either its maximum speed (100% in this AHU) when P_{sa} is lower than $P_{sa,stp}$ or to be its minimum speed (20% in this AHU) when P_{sa} is larger than $P_{sa,stp}$. This symptom will then be represented in *E5*. *E11* represent the symptoms when the supply fan is fixed speed or failure. If the supply fan is fixed at maximum speed, N_{sf} will be minimum and W_{sf} will be maximum. The symptom is contrast when supply fan is fixed at the minimum speed. If it is fixed at partial speed, N_{sf} will be either minimum or minimum.

The return fan has different fault symptoms from the supply air fan. N_{rf} is controlled to maintain a constant ratio of N_{sf} in the AHU concerned. It has to declare that W_{rf} depends on the resistance of the system when it runs at a fixed speed. W_{rf} would be dynamic especially at higher speed. Therefore, it cannot be used as a symptom to indicate whether W_{rf} is frozen or not. In this study, W_{rf} is considered to be a polynomial function of N_{sf} [41] by Eq. (4). Such a relationship is represented in *E3*. Validations are shown in Figure 8. The return fan failure and fixed speed faults are correctly detected. This node is not sensitive to faults of OA damper stuck at fully closed, duct leaking before supply fan and EA damper fully closed from the ASHRAE Project RP-1312 experiences.

$$W_{rf} = -263.6 + 7.984 * N_{rf} + 0.03585 * N_{rf} * N_{rf} \quad (4)$$

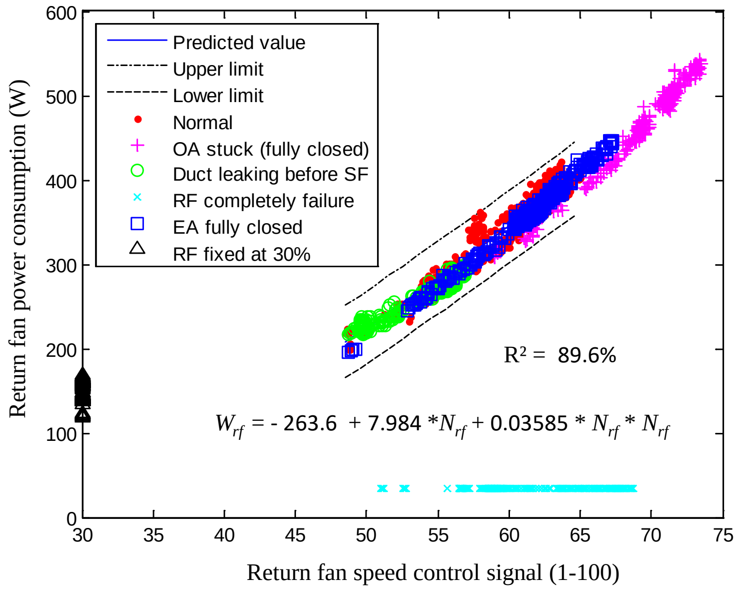

Figure 8. N_{rf} versus W_{rf} in fault free and fault conditions

The OA damper fault has different symptoms at different operating modes. In mode 1, 2 and 4, if the outdoor air damper is stuck at position near to fully closed, T_{mx} will be near to T_{ra}-ΔT_{rf} if there is no reverse flow from EA damper, as represented in *E10*. On-site tests are necessary to determine whether this symptom is adoptable in the AHU concerned. In mode 3, the RA damper is fully closed. When the OA damper is stuck at fully closed, it will be rather difficult for the supply fan to supply proper amount of air. W_{sf} will be larger than the predicted value extremely, as represented in *E2*. When the OA damper is stuck at a position near to fully open, there are no effective fault symptoms to distinguish it with other faults.

If the RA damper is stuck at fully closed position in Mode 1, Mode 2 and Mode 4, T_{mx} should be equal to T_{oa}, as represented in *E10*. If the RA damper is not fully closed in Mode 3, T_{mx} will not equal to T_{oa}. There are no unique symptoms to identify the RA damper faults when the RA damper is stuck at partial or maximum positions.

Among all evidence nodes, *E2* plays the most important role. If W_{sf} measurement is not available, N_{sf} and ΔP_{sf} can also be used in *E2*, as shown in Eq. (5) and Eq. (6) respectively. They can also effectively detect faults, as shown in Figure 9 and Figure 10 respectively.

$$N_{sf} = 61.5 - 0.004 * F_{sa} + 0.000005 * F_{sa} * F_{sa} \quad (5)$$

$$\Delta P_{sf} = 1264 + 0.244 * F_{sa} + 0.000199 * F_{sa} * F_{sa} \quad (6)$$

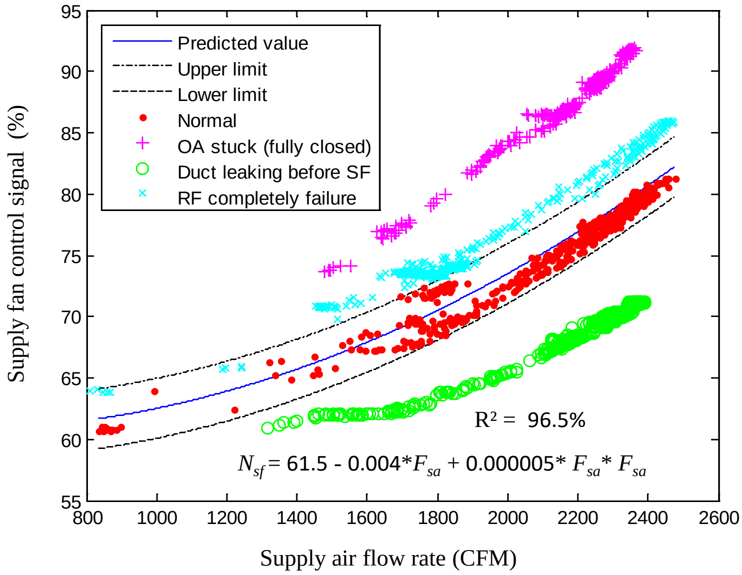

Figure 9. N_{sf} versus F_{sa} in fault free and fault conditions using the ASHRAE Project RP-1312 summer data

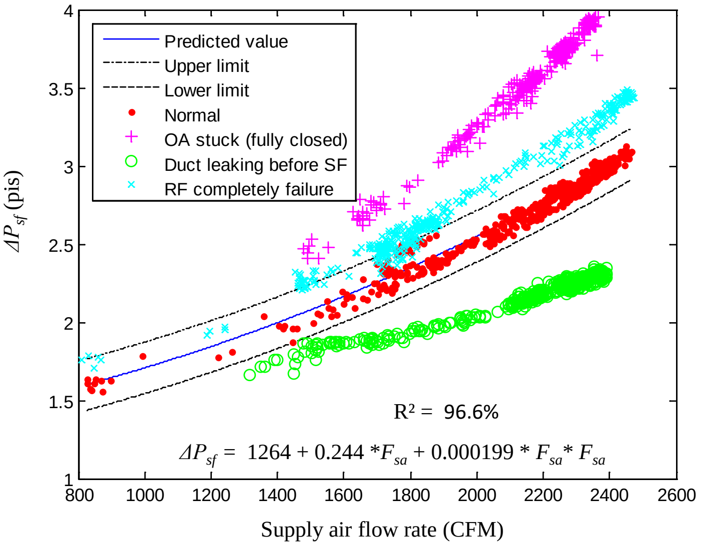

Figure 10. ΔP_{sf} versus F_{sa} in fault free and fault conditions using the ASHRAE Project RP-1312 the summer data

F_{sa} is an important measurement to isolate faults. If it is not available, *E2* is still necessary to be kept in the DBNs as an unobserved node since it is still helpful for fault diagnosis.

4.1.4. Additional information nodes

There are three additional information nodes in the DBNs, i.e. *M1*, *M2* and *M3*, as shown in Table 3. The evidences of these nodes can be observed by site investigations, manual tests and from maintenance records. These evidences, if existing, could significantly improve the fault diagnosis capacity for some faults. For instance, the duct leaking fault (*F9*) cannot be identified without the help of *M3*. If the DBNs are updated using the evidences from BMS measurements, the beliefs (posterior probabilities) of the additional information nodes actually indicate which additional information nodes are worth to be observed. The lower the belief of a fault-free state is, the more valuable that additional information node will be. For instance, if *F9* occurs, the belief of the state *No leaking* of *M3* is low, which indicates this fault is very suspected. In such a situation, the DBNs-based method will advise managers to check *M3* manually, e.g. whether the door on duct is open.

Table 3. Additional information nodes

Node number	Item	State of node in DBN	Action
M1	Filter maintenance service	*Good service*	Management records
		Poor service	
		No service	
M2	Observed fault health status of filter	*High severity level*	Observed by technicians
		Low severity level	
		No fault	
M3	Observed health status of duct	*Leaking heavily*	Observed by technicians
		Leaking slightly	
		No leaking	

4.2. Parameters of the DBNs

There are two kinds of parameters in the DBNs, i.e. prior probabilities of root nodes and conditional probabilities among parent nodes (fault nodes in most of time) and child nodes (mainly BMS evidence nodes and additional information nodes). The principles used to determine the parameters are explained in this section.

Firstly, the nodes with more than one parent node are generally set to be Noisy-MAX nodes. It helps to reduce the number of parameters significantly (more details can be found in *Section 2*). For instance, *F1* (Supply air flow rate station) and *F10* (Filter faults) are two parent nodes of *E4* (ΔP_{filter} is a polynomial function of F_{sa}). The parameters are shown in Table 4. By setting the node *E4* to be a noisy-MAX node, it is not necessary to estimate the conditional probabilities of combined states of faults, e.g. *P(E4=higher|F1=Frozen, F10=Broken).*

Table 4. Parameters of the Noisy-Max node: Examples of conditional probabilities between BMS evidence node *E4* and fault nodes *F1*, *F10*.

Parent	*F1*: F_{sa} sensor fault			*F10*: Filter fault		*Leak*
State	*Frozen*	*Positive biased*	*Negative biased*	*Fouling*	*Broken*	
Higher	0.3	0.0	0.95	0.9	0.0	0.01
Lower	0.3	0.95	0.0	0.0	0.9	0.01
Fault-Free	0.4	0.05	0.05	0.1	0.1	0.98

Secondly, a fault is divided into different faulty states in the fault node to reduce the difficulty of estimating parameters. For instance, there is a stronger relationship between *E4 = Positive* (the actual of ΔP_{filter} is larger than predicted value) and *F1 = Positive biased* (supply air flow rate station is positive biased) than that of *E4 = Positive* and *F1 = biased* (supply air flow rate station is biased but not sure the bias is positive or negative). Therefore, it is easier to estimate the parameter for *P(E4=Positive|F1=Positive biased)* than *P(E4=Positive|F1=Biased).*

Thirdly, the same type of sensors/equipment/controlled devices can be considered to have the same prior probability of fault. For example, it is reasonable to estimate that all temperature sensors have the same prior probability of frozen fault and biased fault.

In the end, the estimated parameters should be evaluated during the development processes. On the one hand, given a fault occurs through setting the fault state to be observed, the beliefs of the influenced BMS evidence nodes and additional information nodes should be the highest ones. For instance, given *F2* (Supply air pressure sensor fault) *Positive frozen*, the belief of *Frozen* state of *E6* (Supply statistic pressure reading for δ hours) should be obviously higher than any others. On the other hand, given the corresponding evidences nodes of a fault node observed, the belief of the fault should be high enough to be isolated.

In this study, the conditional probabilities are estimated by the authors mainly based on analyzing data from ASHRAE Project RP-1020 [43], NIST 6964 [44], ASHRAE Project RP-1312 [38] and literatures, first principles. For instance, Table 4 represents the conditional probabilities between *F1* (Supply air flow rate sensor fault) and *E4* (ΔP_{filter} is a polynomial function of F_{sa}). If F_{sa} is frozen, the beliefs of each state in *E4* should be almost equal in theory. Therefore, the conditional probabilities are estimated to be 0.3 (*Positive*), 0.3 (*Negative*) and 0.4 (*Fault-free*) respectively. If *F1* is *Positive biased*, it is almost for sure that *E4* will be *Negative*. The conditional probability is estimated to be 0.95.

There are very few surveys about the prior fault probabilities of AHU faults. Therefore, the parameters are also estimated by the authors. For example, the fault prior probabilities of sensors are estimated to be 0.04. The fault prior probabilities of dampers are estimated to be higher than those of sensors, i.e. 0.1.

54.3. DBNs for AHUs with other sequence control strategies

The DBNs in Figure 4 and Figure 5 are developed for the AHUs whose return fan is controlled using speed tracking strategy. There are another three common control strategies for the return fans, i.e. air flow rate matching, air flow rate differential and return fan off (or no return fan). Another two DBNs are also provided here. Figure 11 illustrates the DBN for the AHUs which adopt the air flow rate matching control strategy in Mode 1, 2 and 4. On the basis of the DBN in Figure 11, similar DBN could be developed for the AHUs which adopt the flow rate differential control strategy. Figure 12 illustrates the DBN for the AHUs without return fan in Mode 1, 2 and 4.

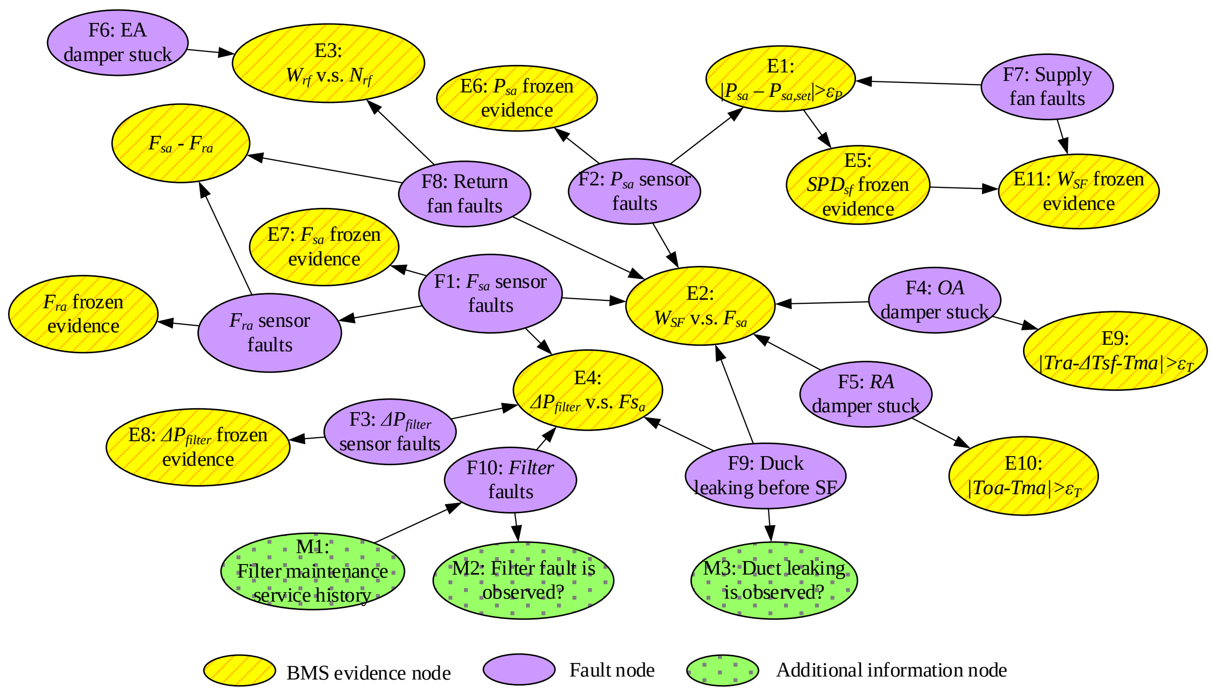

Figure 11. Diagnostic Bayesian network for AHUs using flow matching control strategy in Mode 1, 2 and 4

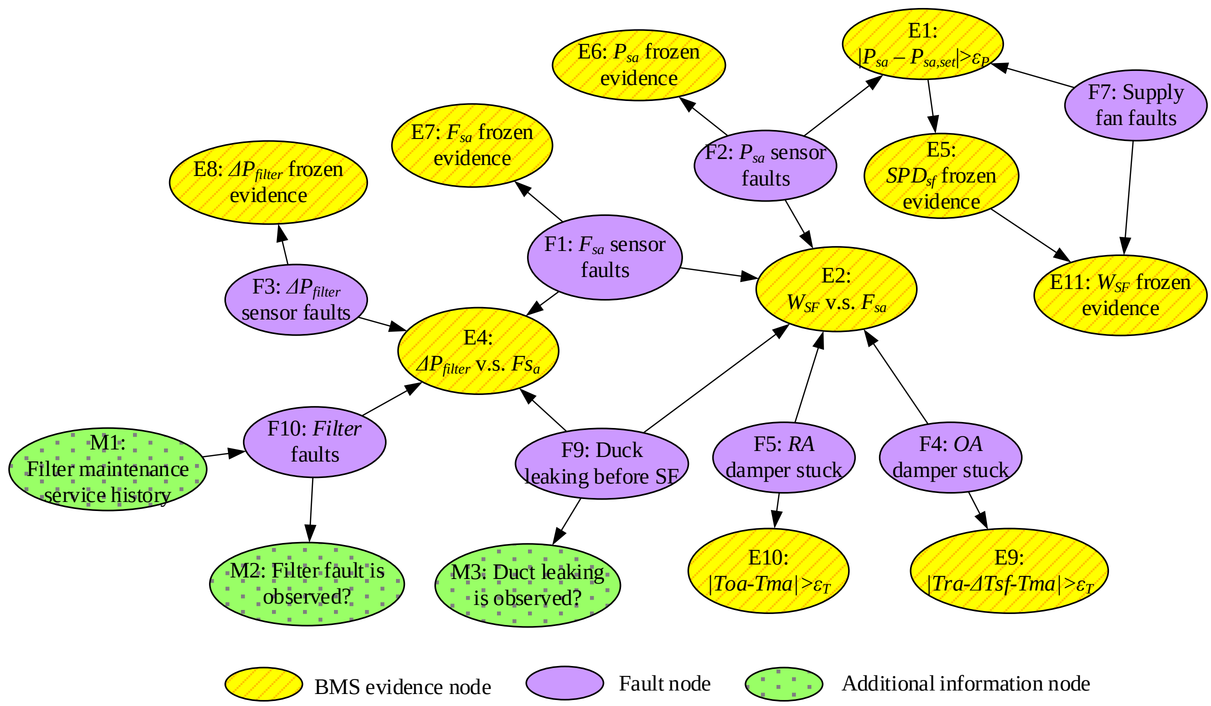

Figure 12. Diagnostic Bayesian network for AHUs without return air fan in Mode 1, 2 and 4

5. Evaluations of the method using experimental data

In this part, a DBN fault diagnosis software package is developed for the AHU concerned in this study using Visual Basic.Net (in part II, another software is developed using JAVA, which is more powerful). The Bayesian network reasoning is based on the SMILE reasoning engine for graphical probabilistic model [40]. The ASHRAE Project RP-1312 experimental data are used to validate the FDD performance of the DBNs.

5.1. Descriptions of the experimental data

In the ASHRAE Project RP-1312, the test building is the same as a typical small commercial building facing real weather conditions. The test HVAC system was operated to simulate the typical commercial building schedule, i.e., occupied from 6:00 to 18:00. The sampling interval was 1 minute.

The configurations of the AHU are as follows. The economizer control was enabled when outdoor air temperature (T_{sa}) was less than 65^oF (18.3 °C) in winter and summer, or when T_{sa} was lower than the return air temperature (T_{ra}) by 3 K in spring. Supply air set-point ($T_{sa,stp}$) was 55 ^oF (12.8 °C) in spring and summer, or 65 ^oF (18.3 °C) in winter. The speed of the supply fan was controlled to maintain the duct static pressure P_{sa} at its set-point ($P_{sa,stp}$). The return fan was controlled by the speed matching method, which maintained its speed to be 80% of the supply fan speed.

The fault type and testing schedule are as shown in the first and second columns of Table 5 (for summer tests), Table 6 (for winter tests) and Table 7 (for spring tests). The faults were implemented by manually changing hardware or software settings. Each fault was implemented over one day period. The tested faults including OA damper stuck fault (*F4*), EA damper stuck fault (*F6*), return fan faults (*F8*, fixed speed fault and complete failure fault), duct leaking before/after supply fan (*F9*) and filter fault (*F10*, block fault and broken fault).

The fault of duct leaking after supply fan was simulated by removing the duct service caps of the supply air duct that were located one foot before the supply air flow meter. The duct leaking before supply fan fault was simulated by removing the seal of AHU doors. The return fan stuck at fixed speed faults were implemented by software override the return fan speed control signal (N_{rf}) to be a fixed value.

In the DBNs, *Rule 3*, *Rule 4* and *Rule 5* are represented by *E1*, *E2* and *E3* respectively. They are effective indexes of the AHU health status. Their detection ratios are shown in Column 3, Column 4 and Column 5 respectively in Table 5 (for summer tests), Table 6 (for winter tests) and Table 7 (for spring tests). The ratios are calculated against the amount of steady-state data in a day. At each step, a fault is isolated if it satisfies *Rule 1* (threshold is 0.7) or *Rule 2* (threshold is 0.3). A fault is suspected if its highest fault belief is higher than 0.3 and lower than 0.7. In a day, a fault is successfully diagnosed if its isolation ratio is more than 30% using the test data set. It is worth noticing that the beliefs in the tables are the average values.

5.2. Evaluation Results

5.2.1. Evaluations using summer data

Table 5 shows the fault detection and diagnosis results using the summer experimental data. The DBNs are robust under fault free conditions. Fault detection results of *E1* (Column 3, how much supply air pressure is away from its set-point) show that the supply air pressure (P_{sa}) can be maintained at all time, even during the fault conditions tested in this project. Fault detection results of *E2* (Column 4, the polynomial relationship between the supply air flow rate and the supply fan power consumption) shows that the relationship between the supply air flow rate and the supply fan power consumption deviates from its fault free conditions significantly when *F9* (Leaking before SF), *F4* (stuck at min position) and *F8* (Stuck and failure) occur. Fault detection results of *E3* (Column 5, the polynomial relationship between supply fan speed and supply fan power consumption) show that the relationship between return fan speed and supply fan power consumption deviates from its fault free conditions only when return fan fault occurs.

The faults of EA damper stuck at fully open and fully close positions (*F6*) are not detected in this study since they are very insignificant [42]. All of the return fan faults (*F8*), i.e. fixed at 30% speed on Aug 22 and complete failure on Aug 23, 2007, are detected by *E2* (37% and 67% respectively) and *E3* (100%). The complete failure fault is isolated with a belief of 1.0 and ratio of 99%. The fixed speed fault is reported to be a suspected fault with belief of 0.57. It cannot be distinguished with *F6* (EA damper) for a lack of additional evidence.

It is found that the ΔP_{filter} measurements were not correct during the experiment of the outdoor air damper fully closed fault (*F4*) on Aug 26, 2007. It might be caused by *F10* (*Broken,* filter) or *F3* (*Negative biased,* differential pressure sensor for filter). Therefore, there were two faults simultaneously, i.e. *F4* and *F10*/*F3*. The DBNs are designed based on the assumption that only one fault occurs a time. However, the results are still positive. Two suspected faults are reported. The sum belief of the two fault states in *F4* (Stuck at partially open position and Stuck at min position) is 0.99 by a ratio of 88%. *F10* is also a suspected fault with a belief of 0.39 by a ratio of 91%. The belief of *F3* is lower than the threshold.

When the OA damper is stuck at 45% (Sept 5, 2007) and 55% (Sept 6, 2007) open positions, the fault symptoms are also insignificant during the testing days since these two positions are very close to the normal position (40% open). Neither of these two faults could be detected by the detection method used in this study.

When the duct is leaking before the supply fan (*F9*), the detection ratios are 90% (Sept 08, 2007) and 79% (Sept 09, 2007) by *E2* (the polynomial relationship between supply air flow rate and supply fan power consumption). However, the available information is incomplete to isolate *F9* because *M3* (Observed health status of duct) is not observed. Both *F9* and *F4* (OA damper) are suspected faults. It is because *F9* and *F4* have the same fault symptoms, i.e. *E2* is *Negative*. If additional evidence is inputted into the DBNs, i.e. *M3* is *Leaking slightly*, the belief of *F9* (*leaking fault*) will be 1.0.

Table 5. Fault detection and diagnosis results using the ASHRAE Project RP-1312 data tested in summer

AHU Fault	Test date	Detection result			FDD Result	Isolated fault		Suspected fault	
		E1	*E2*	*E3*	Detected? / Isolated?	Fault	Belief /ratio	Fault	Belief /ratio
No Fault	08/19/07	0%	0%	0%	No/NAN*	-	-	-	-
No Fault	08/25/07	0%	0%	0%	No/NAN	-	-	-	-
No Fault	09/04/07	0%	0%	0%	No/NAN	-	-	-	-
No Fault	09/10/07	5%	8%	5%	No/NAN	-	-	-	-

F6: EA Damper Stuck (Fully Open)	08/20/07	0%	8%	0%	No/NAN	-	-	-	-
F6: EA Damper Stuck (Fully Closed)	08/21/07	0%	0%	0%	No/NAN	-	-	F4	0.33/31%
F8: Return Fan at fixed speed (30%)	08/22/07	2%	37%	100%	Yes/No			F8	0.57/35%
								F6	0.43/32%
F8: Return Fan complete failure	08/23/07	0%	67%	100%	Yes/Yes	F8	1.0/99%	F5	0.57/55%
F4: OA Damper Stuck (Fully Closed)	08/26/07	5%	99%	4%	Yes/Yes**	F4	0.99/88%	F10	0.39/91%
F4: OA Damper Leak (45% Open)	09/05/07	0%	0%	0%	No/NAN	-	-	-	-
F4: OA Damper Leak (55% Open)	09/06/07	0%	11%	0%	No/NAN	-	-	-	-
F9: AHU Duct Leaking (after SF)	09/07/07	0%	9%	0%	No/NAN	-	-	-	-
F9: AHU Duct Leaking (before SF)	09/08/07	0%	90%	0%	Yes/No			F9	0.54/84%
								F4	0.46/84%
F9: AHU Duct Leaking (before SF)	09/09/07	0%	79%	0%	Yes/No			F9	0.56/71%
								F4	0.46/66%

* The fault diagnosis is not adoptable for the lack of evidences from the fault detection process.

** The ΔP_{filter} sensor was faulty during the ASHRAE Project RP-1312 experiment on Aug 26.

5.2.2. Evaluations using winter data

Table 6 shows the fault detection and diagnosis results using the ASHRAE Project RP-1312 winter experimental data. The DBNs are again robust at fault-free conditions.

During the experiments, supply air pressure sensor was accidentally faulty in some days, which caused multiple concurrent faults. The OA damper stuck at fully closed position fault (*F4*) was implemented on Jan 30 and Feb 12, 2008. The pressure sensor was faulty in these two days. The readings of the pressure senor were zero at most of the time. This pressure sensor fault (*F2*) is correctly detected by the proposed method because *E1* is *Negative* and *E6* is *Frozen*. *F2* is identified to be frozen with the belief of 0.96 and the ratio of 99%.

Similar to the FDD results in summer, the OA damper (*F4*) fault cannot be detected using the fault detection strategy when it is stuck at 52% (on Jan 31 and Feb 12, 2008) and 62% (on Feb 1, 2008). When the OA damper is stuck at 62% open on Feb 1, no abnormality is detected by *E2* (W_{sf} is a polynomial function of F_{sa}). When the same fault was implemented on Feb 15, although *E2* detects that 78% of W_{sf} are lower than expected values, it is found that W_{sf} was only lower than lower limit line for about 10% of threshold value (0.089 kW). *F5* (RA damper) is a suspected fault with a belief of 0.3 because *E10* (T_{oa}-T_{ma}) is *Negative* with a ratio of 63%. *F4* is not reported.

The EA damper stuck at fully open position fault (*F6*) on Feb 2 is still not detected nor diagnosed by the proposed method because of the insignificant fault symptoms. Unlike the FDD results in summer, *F6* is correctly detected and diagnosed with a belief of 0.54 and a ratio of 100% since this fault is detected by *E3* (W_{rf} is a polynomial function of N_{rf}) on Mode 2.

Table 6. Fault detection and diagnosis results using the ASHRAE RP-1312 data tested in winter

<table>
<tr><th rowspan="2">AHU Fault</th><th rowspan="2">Date</th><th colspan="3">Detection result</th><th>FDD Result</th><th colspan="2">Isolated fault</th><th colspan="2">Suspected fault</th></tr>
<tr><th>E1</th><th>E2</th><th>E3</th><th>Detected?/Isolated?</th><th>Fault</th><th>Belief/ratio</th><th>Fault</th><th>Belief/ratio</th></tr>
<tr><td>No Fault</td><td>1/29/08</td><td>0%</td><td>0%</td><td>0%</td><td>No/NAN</td><td>-</td><td>-</td><td>-</td><td>-</td></tr>
<tr><td>No Fault</td><td>2/16/08</td><td>0%</td><td>0%</td><td>0%</td><td>No/NAN</td><td>-</td><td>-</td><td>-</td><td>-</td></tr>
<tr><td>No Fault</td><td>2/17/08</td><td>0%</td><td>0%</td><td>0%</td><td>No/NAN</td><td>-</td><td>-</td><td>-</td><td>-</td></tr>
<tr><td rowspan="2">F4: OA Damper Stuck (Fully Closed)</td><td rowspan="2">1/30/08</td><td rowspan="2">100%</td><td rowspan="2">100%</td><td rowspan="2">0%</td><td rowspan="2">Yes/Yes*</td><td>F2</td><td>0.96/99%</td><td rowspan="2">F1</td><td rowspan="2">0.39/92%</td></tr>
<tr><td>F4</td><td>0.79/99%</td></tr>
</table>

F4: OA Damper Stuck (Fully Closed)	2/12/08	100%	100%	0%	Yes/Yes*	F2 F4	0.96/99% 0.78/99%		
F4: OA Damper Leak (52% Open)	1/31/08	6%	11%	6%	No/NAN	-	-	-	-
F4: OA Damper Leak (52% Open)	2/13/08	0%	0%	0%	No/NAN	-	-	-	-
F4: OA Damper Leak (62%Open)	2/1/08	0%	0%	0%	No/NAN	-	-	-	-
F4: OA Damper Leak (62%Open)	2/15/08	0%	78%	0%	Yes/No			F5	0.3/63%
F6: EA Damper Stuck (Fully Open)	2/2/08	0%	0%	0%	No/NAN	-	-	-	-
F6: EA Damper Stuck (Fully Closed)	2/3/08	0%	1%	100%	Yes/Yes	F6	0.50/100%		

* The pressure sensor was faulty during the ASHRAE Project RP-1312 experiment on Jan 30 and Feb 12.

5.2.3. Evaluations using spring data

Table 7 shows the fault detection and diagnosis results using the spring experimental data. During the four fault free days, there is no fault detected by E1, E2 and E3.

On May 7, 2008, when the OA stuck at fully close position fault (*F4*) was implemented, the supply air pressure (P_{sa}) sensor was also faulty (the reading was zero), similar to that on Jan 30, 2007. This day was deemed faulty by *E2* (W_{sf} is a polynomial function of F_{sa}) with 100% detection ratio. Different from the results on Jan 30, *F4* is identified with a belief of 0.98 and ratio of 99%. It is mainly because RA damper is fully closed in Mode 3. The performance of the supply fan was significantly affected since the OA damper was fully closed at the same time. The supply air pressure sensor fault (*F2*) is a suspected fault with a belief of 0.61 and a ratio of 96%. On May 8, 2008, the supply air pressure (P_{sa}) sensor was not faulty when the OA stuck at 40% close position fault (*F4*) was implemented. *F4* is correctly isolated with a belief of 0.93 and a ratio of 99%.

The EA damper stuck at fully open fault implemented on May 27, 2008 is still not detected due to a lack of significant fault symptoms. The EA damper stuck at fully closed fault (*F6*) implemented on May 10, 2008 is detected to be *Negative* by E3 (polynomial relationship between return fan power and return fan speed) with a ratio of 100%. *F6* is only a suspected fault with a belief of 0.43 and a ratio of 99% since the belief is not high enough to isolate it. It is because there is no extra evidence node to distinguish *F6* with *F8* (fixed speed fault of return air fan). Similar results are observed on May 11, 2008 when the EA damper stuck at 40% open fault (*F6*) was implemented.

The return fan complete failure fault (*F8*) implemented on May 12, 2008 is isolated with a belief of 0.68 and a ratio of 99%. The evidence from *E3* (*Zero*, W_{rf} is a polynomial function of N_{rf}) strongly supports the existence of *F4*. The faults of return fan fixed speed at 20% on May 18 and 80% on May 19 are detected by *E3* with a ratio of 100%. They are not isolated for lacking extra evidence to be distinguished with *F6* (EA stuck at fully closed fault), too.

The air filter area with 10% and 25% blocked faults (*F10*) implemented on May 22 and May 25, 2008 are detected with low ratios but not isolated. The system performance is only affected very slightly as reported by the ASHRAE Project RP-1312. For instance, the air filter area with 25% blocked fault (*F10*) is detected by *E4* (*positive*, polynomial relationship between filter pressure and supply air flow rate) with 8% detection ratio only. Although *E3* is *Positive* with 28% detection ratio, no faults is reported or suspected since their ratios are less than 30%.

Table 7. Fault detection and diagnosis results using the ASHRAE Project RP-1312 data tested in spring

AHU Fault	Test date	Detection result			FDD Result	Isolated fault		Suspected fault	
		E1	*E2*	*E3*	Detected?/Isolated?	Fault	Belief/ratio	Fault	Belief/ratio
No fault	5/2/08	2%	6%	0%	No/NAN	-	-	-	-
No fault	5/3/08	1%	0%	0%	No/NAN	-	-	-	-
No fault	5/4/08	0%	0%	0%	No/NAN	-	-	-	-
No fault	5/20/08	0%	1%	0%	No/NAN	-	-	-	-

F4: OA Damper Stuck (Fully Close)	5/7/08	100%	100%	51%	Yes/Yes*	F4	0.98/99%	F2	0.61/96%
								F5	0.44/96%
F4: OA Damper Stuck (40% open)	5/8/08	97%	100%	44%	Yes/Yes	F4	0.93/99%	F5	0.54/30%
								F8	0.32/44%
F6: EA Damper Stuck (Fully open)	5/27/08	2%	0%	0%	No/NAN	-	-	-	-
F6: EA Damper Stuck (Fully Close)	5/10/08	0%	3%	100%	Yes/No			F6	0.43/99%
F6: EA Damper Stuck (40% open)	5/11/08	1%	0%	100%	Yes/No			F6	0.49/99%
F8: Return Fan complete failure	5/12/08	0%	0%	100%	Yes/Yes	F8	1.0/99%	F4	0.3/35%
F8: Return Fan at fixed speed （20%spd）	5/18/08	0%	0%	100%	Yes/No			F6	0.48/99%
								F5	0.33/41%
F8: Return Fan at fixed speed （80%spd）	5/19/08	0%	0%	100%	Yes/No			F6	0.35/100%
								F8	0.32/99%
F10: Air filter area block fault (10%)	5/22/08	12%	18%	11%	Yes/No				
F10: Air filter area block fault (25%)	5/25/08	3%	10%	28%	Yes/No				

* The pressure sensor was faulty during the Project RP-1312 experiment on May 7.

5.2.4. Summary of the FDD results

The summary of the FDD results on the ASHRAE Project RP-1312 experimental data is shown in Table 8. Faults of three devices are isolated correctly, including OA damper fault (*F4*, fully close or stuck at partially open position in spring), EA damper fully closed fault (*F6*) in winter and return fan complete failure (*F8*). Faults in two devices, i.e., AHU duct leaking fault (*F9*) and air filter block fault (*F10*), are not detected or isolated. Some faults are not detected because they do not affect performance of AHU significantly. Some faults are detected but not isolated for the lack of information (evidences) using the BMS measurements only.

Table 8. Summary of the FDD results using the ASHRAE Project RP-1312 experimental data

Fault	Fault type	Season	FDD result	Remark
No fault	-	All	Not detected	
F4: OA Damper	Fully close	All	Isolated	
	Stuck (40% open)	Spring	Isolated	
	Leak (52% open)	Winter	Not detected	
	Leak (62% open)	Winter	Only detected	Only detected on 2/1/2008
	Leak (45%/55% Open)	Summer	Not detected	
F8: Return Fan	Fixed speed (30%)	Summer	Suspected	Information is incomplete
	Complete failure	Summer /Spring	Isolated	
	Fixed at 20% SPD	Spring	Only detected	Information is incomplete to isolate F8 with F5 and F6
	Fixed at 80% SPD	Spring	Suspected	Information is incomplete
F9: AHU Duct	Leaking (after SF)	Summer	Not detected	
	Leaking (before SF)	Summer	Suspected	Evidence from M3 is necessary.
F6: EA Damper	Stuck (Fully open)	Summer /Spring	Not detected	
	Stuck (Fully closed)	Summer	Not detected	
		Winter	Isolated	
		Spring	Suspected	Information is incomplete
	Stuck (40% open)	Spring	Suspected	Information is incomplete
F10: Air filter	Block fault (10%/25%)	Spring	Only detected	Performance of AHU is affected very slightly

5.3. Discussion

The structures of DBNs actually provide frameworks to merge all of the on-site available diagnostic information (measurements, records, observations and tests), fault detection functions (all effective functions from available publications and researches) and fault patterns (found from AHU FDD projects and available experiments). Therefore, the DBNs should be more powerful since they are based on all available knowledge about AHU FDD so far and information fusion.

The available AHU FDD methods (e.g. fault detectors and fault patterns) can be integrated into the DBNs feasibly. For instance, NIST proposed the AHU performance assessment rules (APAR) [16]. There are 28 pieces of rules which derived from mass and energy balances. Each rule is expressed as a logical statement to indicate the present of a fault. The OAF (outside air fraction) model, which are proposed by Xu et al., can be introduced to detect faults, which represent the relationship between the mixing damper position and OAF [11].

The major challenge of developing DBNs is to assign the parameters. Parameters are significant to the fault diagnosis performance. It is better to obtain them by manufactory tests or filed survey. Four principles are suggested to estimate the parameters in *Section 4.2*.

6. Conclusion

In this paper, a DBNs-based method is proposed to diagnose AHU faults. DBNs are developed for ten typical faults in fans, dampers, ducts, filters and sensors. Twelve BMS evidence nodes are used as fault detectors to represent the fault evidences from online measurements. Three additional information nodes are used to represent the evidences manually observed.

The proposed DBNs are evaluated using the ASHRAE Project RP-1312 experimental data tested in three seasons. Results show that this method is robust in fault-free conditions. The OA damper stuck fault (*F4*) can be isolated when it is stuck at partial position in spring and fully close in all seasons. Additional diagnostic information is necessary to distinguish the return fan fixed speed faults with *F6* (EA Damper stuck fault). The EA damper stuck (*F6*) is isolated when it is fully closed in winter. The return fan fault (*F8*) can be correctly isolated when the return fan is complete failure. The duct leaking fault (*F9*) is reported to be suspected fault but it cannot be isolated without the help of the evidence from an additional information node. The filter fault (*F10*, block fault) is detected but not isolated since the AHU performance was affected by this fault slightly. It is worth noting that all of these faults are almost impossible to be isolated using the conventional AHU fault diagnosis methods.

The DBNs are developed based on the assumption that only one fault occurs at a time. Evaluation results show that the DBNs can also diagnose simultaneous faults if the two faults have less common fault symptoms. The DBNs are developed for the AHU in ASHRAE Project RP-1312. They would be adoptable for AHUs of the similar mode. Revisions are necessary for AHUs of different modes.

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Nomenclature

Notation

F	air flow rate (CFM)
P	supply air pressure (PSI)
DP	pressure difference
T	temperature (^{o}F)
L	sampling interval (s)
N	fan speed control signal
W	power (W)

Subscripts

actual	actual value
damper	air damper
expect	expected value
ea	*exhaust air*
frozen	frozen fault
leaking	leaking fault
ma	mixed air
max	maximum
min	minimum
N	speed control signal (0-100%)
oa	outdoor air
ra	return air
reset	reset-point
position	position of air damper
stp	set-point
sa	supply air
supply	supply air from AHU

Greek symbols

ε	error threshold
λ	terminal damper opening (0-100%)
σ	standard deviation
ψ	currently available evidences

θ threshold