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Bayesian Networks for Whole Building Level Fault Diagnosis and Isolation

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ABSTRACT

Buildings consume about 40% of primary energy in the U.S., and 51% of the primary energy usage in commercial buildings are consumed by heating, ventilation and air conditioning (HVAC) system. Malfunctioning sensors, components, and control systems, as well as degrading HVAC and lighting components are main the reasons for energy waste and unsatisfactory indoor environment. In building HVAC systems, faults occurring in one component or equipment can cause abnormality in other closed subsystems. Therefore, a system level fault diagnosis method is helpful to locate root-cause for such faults. Bayesian network (BN) is a prevalent tool in fault diagnosis which can handle probabilistic reasoning of uncertainty. In this paper, a two-layer Bayesian network which consists of fault layer and fault symptom layer is developed to diagnose system level faults that have an impact on multiple subsystems for building HVAC system during a cooling operation mode. Weather/schedule information based Pattern Matching (WPM) method is developed create the baseline data and to generate *LEAK* probabilities for the developed BN. BAS data from a campus building during the cooling season are collected to evaluate the effectiveness of the proposed method.

1. INTRODUCTION

Buildings are responsible for high growth of energy consumption in the world. In 2016, it was estimated that about 40% of primary energy are consumed by buildings in the U.S., and 51% of the primary energy usage in U.S. commercial buildings are consumed by heating, ventilation and air conditioning (HVAC) system as estimated in 2012 according to U.S. Environmental Information Agency (EIA, 2012) . It is well recognized that large energy waste and unsatisfactory indoor environment exist in commercial buildings due to malfunctioning sensors, components, and control systems, as well as degrading components. Studies have demonstrated that large energy saving can be achieved by automated fault detection and diagnosis (FDD) (Fernandez et al., 2010; Roth et al., 2005).

Different from component-level faults, a whole building fault refers to a fault that impacts more than one subsystems and/or has significant impact on the building energy consumption. In the past two decades, extensive work has been conducted on the development of component-level FDD methods. Since component-level FDD methods can fail to detect or give false alarms for faults that trigger abnormalities in multiple subsystems, the development of whole building FDD methods has received much attention in recent years. A top-down strategy by incorporating temporal and spatial partition was developed to detect HVAC faults across different levels (Wu et al., 2011). A SPC and Kalman filter-based method was proposed for the system-level fault detection in HVAC systems (Sun et al., 2014). A data-driven based method named weather/schedule based pattern matching and feature based Principle Component Analysis fault detection was developed and demonstrated to be effective to detect whole building faults (Chen et al., 2017). However, there generally is a lack of study that focuses on diagnosing whole building faults and isolating root causes.

In this study, a Bayesian Networks (BNs) based method is proposed to diagnose and isolate whole building faults. Bayesian Networks have been demonstrated to have excellent ability to work well under uncertainty and incomplete information (Lampis et al., 2009). In building HVAC system, there are existing studies that have adopted the BNs for component level fault diagnosis such as chiller, AHU, and VAV terminals (He et al., 2016; Xiao et al., 2014; Zhao et al., 2015; Zhao et al., 2017; Zhao et al., 2013). For example, Zhao et al., developed diagnostic BN for AHU and intelligent chiller FDD method by using a three-layer Bayesian belief network (Zhao et al., 2013). They also developed diagnostic BNs to diagnose component faults in AHU (Zhao et al., 2015; Zhao et al., 2017). Xiao et al., proposed a Bayesian network based FDD strategy for diagnosing ten typical faults of VAV terminal unit (Xiao et al., 2014). Although these studies demonstrate good potentials of BNs in component level fault diagnosis, there is a lack of study that uses BNs diagnosis methods for whole building faults where interactions exist in different sub-systems. When applying BN based fault diagnosis methods for complex building systems, the following challenges exist: 1) it is impractical to develop system-level BNs from exhausted fault data by implementing fault experiments in a real building. Hence, determining parameters (prior and conditional probabilities) are challenging; 2) due to the coupling impacts, root-cause determination and fault evidence are often more complicated for whole building faults than component-level faults; and 3) it is harder to develop baseline data models for whole building faults due to the large dimension of whole building dataset. This paper describes a BNs based method for whole building fault diagnosis and isolation. Expert and physical knowledge were used in developing BNs structure model. Weather and schedule information based Pattern Matching (WPM) method (Chen et al., 2017) which has been employed in a previously reported fault detection method is used to create a baseline data for evidence generation and to obtain *LEAK* probabilities which are needed in the BNs parameter. Whole building faults have been artificially implemented in a real campus building during the cooling season. Baseline and fault test data, collected from the real campus building, are used to evaluate the effectiveness of the proposed BNs based fault diagnosis method.

2. METHODOLOGIES

2.1 BN Structure Model Development

BNs are a powerful tool to represent the knowledge and the inference under uncertainties. A probabilistic model which reveals the causal relations between faults and symptoms can be developed through BNs. The probabilities of relations in BNs can be updated after new observations (evidence) on the system are obtained (Lampis et al., 2009). BNs model may also incorporate the system structure information (Lampis et al., 2009).

The process of developing BN structure is to generate a cause-and-effect inference. Usually, expert knowledge is used to develop the system rule which will be mapped to the BNs. During the development process, the first step is to determine the network layers according to the nature of the problem. Suggested by the literature, a two-layer of network, which include fault layer and fault symptom layer are employed to develop BNs for whole building fault diagnosis in this study.

Network nodes, including fault nodes and fault evidence node need to be identified for whole building faults. Here, a fault node represents a whole building level fault. For example, an air handling unit (AHU) outdoor air damper stuck fault (either stuck at a higher than normal or lower than normal) can be a fault node. The states of the fault node include faulty state and fault-free state. In this research, each fault node represents a specific fault type, which is different from what has been used in the literature-reported component BNs diagnosis tool (Regnier et al., 2016).

For example, an AHU outdoor air damper stuck at a higher than normal position is assigned to one fault node. While, an AHU outdoor air damper stuck at a lower than normal position is assigned to another fault node.
Evidence nodes represent observable fault symptoms. Fault symptoms typically come from two sources:

1) Concurrent relationships among measurements. For example, when AHU outdoor air damper is stuck at a 100% open position, the mixed air temperature measurement has the same value as the outdoor air temperature measurement.

2) Historical relationship between the current value of a measurement and its historical baseline value. Using the same outdoor air damper stuck at a 100% open position fault example, an additional evidence (during a cooling season) could be that the value of the cooling coil valve position is higher than its historical baseline value under similar weather conditions. In this study, a pattern matching method, i.e., the WPM method is used to generate the baseline data. Detailed information about WPM method can be found in (Chen et al., 2017).

BNs are often expressed graphically in which, arcs are connected between fault nodes and evidence nodes to represent the cause-and-effect relations between them. For example, Figure 1 shows a BN for diagnosing AHU outdoor air damper stuck at a higher than normal position fault. This fault is assigned to a fault node named as AHU-OA-DMPR-Stuck-H. The fault evidences (also known as fault symptoms) are assigned as evidence nodes including chilled water pump speed (CHW-Pump-Speed), AHU cooling valve position (AHU-CC-VLV), AHU supply air fan speed (AHU-SF-Speed), the difference of AHU mixed air temperature and outdoor air temperature (AHU-MAT-OAT), and chiller cooling energy (CHW-Cooling). These evidence nodes are connected to the fault node by adding arcs.

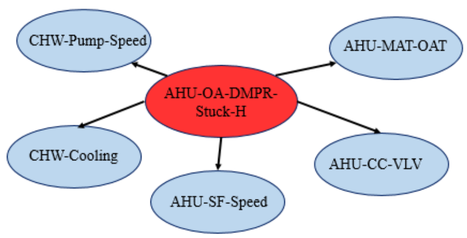

Figure 1: Example of BNs structure model

2.2 BNs Parameter Development

The second step is to identify values for the parameters (probabilities) in a BNs. The parameters of a BN reflect the quantitative relations among parent nodes and child nodes by using probability. Usually, three probabilities, i.e., *prior probabilities, conditional probabilities, and LEAK probabilities,* need to be determined when developing a BN model.

- *Prior* probability represents the frequency of a fault event may happen and needs to be assigned to the fault nodes. This probability can be obtained from expert knowledge, statistical results of system historical operation data, experimental data or simulated data.

- *Conditional* probability is the probability of a symptom event under the occurrence of a fault event. When developing a diagnostic BN, the conditional probability distributions for each evidence node are stored in conditional probability tables (CPTs) which reflect all possible combinations of states of fault nodes. The generation of CPTs can be achieved through two approaches: from expert knowledge or from the probabilistic analysis of the historical data (Xiao et al., 2014). The second approach is to use the data-driven based method or machine learning technique to obtain the probabilities.

- *LEAK* probability is the probability of the child node having a value 1 when all parent nodes are given value 0. In fault diagnosis, *LEAK* probability represents a probability when there are no faults occurring, but an evidence node demonstrates an abnormal (faulty) state.

When developing BNs parameters, one challenge is that the number of parameters for the evidence nodes grows exponentially with the increasing number of the fault node as the network structure becomes more complex. Therefore, it is unreliable to directly generate the conditional probabilities for each state of the evidence node when there are more than four fault nodes (Zagorecki et al., 2013). Therefore, canonical models such as Noisy-OR gate and Noisy-Max gate which only require a few parameters draw more attention when developing BN parameter model. The use of canonical models not only simplifies the construction of Bayesian networks and influences diagrams, but can also lead to more efficient computations (Zagorecki et al., 2013). In this study, Noisy-MAX gate is adopted to develop the BN parameters for each evidence node, and *LEAK* probabilities are determined in the Noisy-Max distribution model in this study (Zagorecki et al., 2013).

3. BNs DEVELOPED FOR WHOLE BUILDING FAULT DIAGNOSIS

3.1 Development of BNs structure model

Once the Bayesian rule sets are developed, the next step is to establish the networks. Here, GeNIe and jSMILE (Drużdżel) BNs tools developed by Pittsburg University were used to generate whole building level BN. Six whole building faults (summarized in Table 1) are considered in this study. Fault evidences, i.e., key measurements and virtual measurements (combination of measurements) used to observe a fault's symptoms, are summarized Table 2. Total ten evidence nodes are defined as E1 to E10. Figure 2 demonstrates the developed BN structure model for the whole building faults considered in Table 1 during cooling operation mode. Relationships between a fault node and its symptoms (e.g. lower/higher than normal value) in each evidence node are summarized in Table 3.

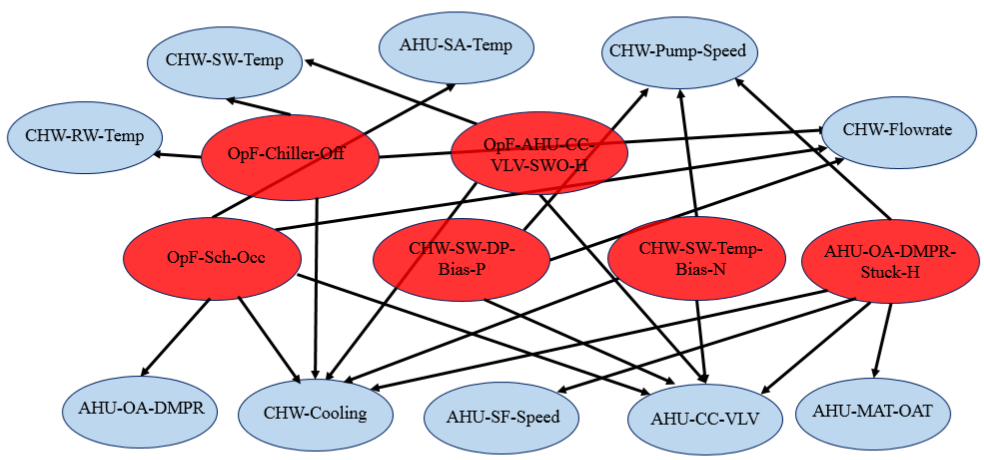

Figure 2: BN for nine whole building faults in cooling operation mode

Table 1: Whole building fault nodes list

Fault Category	Fault Name	Abbreviation
Operator Fault	Schedule fault (system is occupied while under normal operation, it should be unoccupied)	OpF-Sch-Occ
	AHU cooling coil valve control override at a higher than normal position	OpF-AHU-CC-VLV-SWO-H
	Chiller is off while under normal operation, it should be on	OpF-Chiller-Off
Primary cooling subsystem fault	Chilled water supply differential pressure sensor positive bias	CHW-SW-DP-Bias-P
	Chilled water supply temperature sensor negative bias	CHW-SW-Temp-Bias-N
Supply air subsystem fault	AHU outdoor air damper stuck at a higher than normal position	AHU-OA-DMPR-Stuck-H

Table 2: Fault evidence list

Subsystem	Evidence No.	Key Measurement and Virtual Measurement	Abbreviation
Chiller plant	E1	Chilled water supply temperature	CHW-SW-Temp
	E2	Chilled water return temperature	CHW-RW-Temp
	E3	Chilled water flowrate	CHW-Flowrate
	E4	Chiller calculation cooling	CHW-Cooling
	E5	Chiller pump speed	CHW-Pump-Speed
Supply air subsystem fault	E6	AHU outdoor air damper position	AHU-OA-DMPR
	E7	AHU cooling coil valve position	AHU-CC-VLV
	E8	AHU mixed air and outdoor air differential temperature	AHU-MAT-OAT
	E9	AHU supply air fan speed	AHU-SF-Speed
	E10	AHU supply air temperature	AHU-SA-Temp

Table 3: Fault symptom list

Fault	Fault Node	Symptom Description
1	OpF-Sch-Occ	E1(lower than normal); E2 (higher than normal); E3 (higher than normal); E6 (higher than normal); E7 (higher than normal); E4 (higher than normal); E8 (higher than normal); E9 (higher than normal); E10 (lower than normal)
2	OpF-Chiller-Off	E1 (higher than normal); E2 (higher than normal); E3 (higher than normal); E4 (higher than normal); E8 (lower than normal); E9 (higher than normal); E10 (higher than normal)
3	OpF-AHU-CC-VLV-SWO-H	E3 (higher than normal); E7 (higher than normal); E4 (higher than normal); E10 (lower than normal)
4	CHW-DP-Bias-P	E3 (lower than normal);E7 (higher than normal)
5	CHW-SW-Temp-Bias-N	E7 (higher than normal);E4 (higher than normal);E3 (higher than normal);E5 (higher than normal)
6	AHU-OA-DMPR-Stuck-H	E3 (higher than normal);E7 (higher than normal);E4 (higher than normal); E8 (lower than normal)

3.2 Development of Whole Building BNs Parameter

(1) Development of *prior* probabilities

As discussed earlier, there is a lack of understanding as how often faults occur in a building system. In this study, the values that have been reported for the component level fault diagnosis (Regnier et al., 2016) are adopted for prior probability. The prior probabilities should be updated when more system operation knowledge is obtained or statistic results can be found from the historical operation data. In this research, the fault state is divided into faulty state and fault-free state. The initial prior probabilities for each fault node are assigned as 0.01 for faulty state and 0.99 as fault-free state as shown in Table 4. These numbers indicate that we believe that for each fault, there is only 1% probability of this fault occurring.

Table 4: Prior Probability for fault node

Fault Node State	Prior Probability
Fault	0.01
Fault free	0.99

(2) Development of *conditional* probabilities

Due to the limitation of testing faults in a real building, obtaining condition probability from fault data is unrealistic. Obtaining accurate values for condition probabilities from expert knowledge is very difficult as well due to the fact that the same fault could behave slightly different in different buildings. However, expert knowledge could provide a range of condition probability for a fault and its associated fault evidences. Using the same example, when AHU outdoor air damper is stuck at a 100% open position, the fault symptoms including 1) mixed air temperature measurement has the same value as the outdoor air temperature measurement; and 2) AHU cooling coil valve has a position that is higher than normal (baseline) position). Both of these two symptoms are strong symptoms, i.e., they would occur whenever the fault occurs.

In this study, a fault evidence is firstly judged by whether it is a strong evidence or not. Three association levels, namely, strong evidence, medium evidence, and weak evidence, are used. If a fault evidence is a strong evidence, i.e., when a fault occurs, this evidence will most likely to occur, we consider that the condition probability of this evidence when a fault occurs is 90%, out of which, 45% is considered to have very sever fault symptom. In the example above, fault evidence node 1 (difference between mixed air and outdoor air temperatures) is a strong evidence and a 0.45 conditional probability is assigned to this node for a very severe fault symptom (very abnormal), a 0.45 conditional probability is assigned to this node for a sever fault symptom, and a 0.1 conditional probability is assigned to this node as a low severe fault symptom. Similar treatment is used for the other two association levels, i.e., medium association nodes and weak association nodes. Details provided in Table 5. The conditional probabilities in Table 5 can be adjusted and updated when more knowledge is obtained during the system operation. In this initial research, the conditional probabilities we use are from what have been tested in BN based component-level fault diagnosis tool (Regnier et al., 2016). Further evaluation on the conditional probabilities will be implemented in the future.

Table 5: CPT for evidence node

Association Between Evidence Node and Fault Node	Severity	Conditional Probability Under Fault
Strong Evidence	Very Serious (S-V-S)	0.45
	Serious (S-S)	0.45
	Low Serious(S-L)	0.1
Medium Evidence	Very Serious (M-V-S)	0.25
	Serious (M-S)	0.25
	Low Serious (M-S-L)	0.5
Weak Evidence	Very Serious (W-V-S)	0.05
	Serious (W-S)	0.05
	Low Serious (W-S-L)	0.9

(3) Development of *LEAK* probabilities
LEAK probability represents the probability of an evidence node to be abnormal when all of the parent fault nodes are absent (when no fault occurs). *LEAK* probabilities for each evidence node are obtained by considering the outliers in the baseline data. After comparing with the baselined data, outliers in system operation data can be categorized into three trends as positive, negative and normal. Accordingly, an outlier is defined as:

$$|x(i)-\bar{x}| > t \bullet \sigma \tag{1}$$

where $\bar{x}$ is the mean of the data sequence, σ is the standard deviation and t is the threshold.

In this study, two classes of threshold, i.e., 2σ is set for "very high/very low" and 1σ is set for "high/low" are used to differentiate two types of outlier as "very serious" and "serious".

Therefore, a *LEAK* probability can be calculated as:

$$LEAK\ Probability = \frac{Number\ of\ outlier\ data\ sample}{Total\ number\ of\ baseline\ data\ sample} \tag{2}$$

WPM method (Chen et al., 2017) is firstly used to identify baseline data that has a similar weather condition as the incoming snapshot data. The numbers of outliers in the baseline data for each snapshot window are then counted by using the pre-defined thresholds. *LEAK* probability distribution can be obtained through Equation 2.

4. FAULT TESTS

One Drexel campus building – Nesbitt Hall is chosen as the test building in this study. Nesbitt Hall is a seven-story, 78,000 square-foot mixed use building that houses offices, classrooms, laboratories, and an auditorium. This building is chosen as the test building because it has a typical HVAC system that is commonly seen in medium-sized commercial buildings, i.e., a water cooled chiller system, three variable air volume (VAV) AHU systems, and a hydronic heating system. The water cooled chiller system (primary cooling subsystem) is in the basement. One steam-to-hot-water heat exchanger subsystem located in the basement is used to provide domestic hot water and space heating needs. One air distribution subsystem which includes three AHUs and eighty-eight VAV terminal units is used to serve all seven floors. Figure 3 illustrates the HVAC system configuration in the Nesbitt Hall.
Different faults including operator fault, primary cooling subsystem fault and supply air subsystem faults were implemented during summer 2017. The operator faults include faults such as 1) “chiller is off while under normal operation, it should be on”, 2) “AHU cooling coil valve control override at a higher than normal position”, and 3) “system is occupied while under normal operation, it should be unoccupied”. Primary cooling subsystem faults include faults such as 1) “chilled water supply temperature sensor negative bias (screen reading higher than real value)”, and 2) “chilled water differential pressure sensor positive bias (screen reading higher than real value)”. Supply air subsystem faults include faults such as “AHU outdoor air damper stuck at higher than normal position”. These faults were selected because they are considered to have impacts on different subsystems or have significant impact energy consumption.

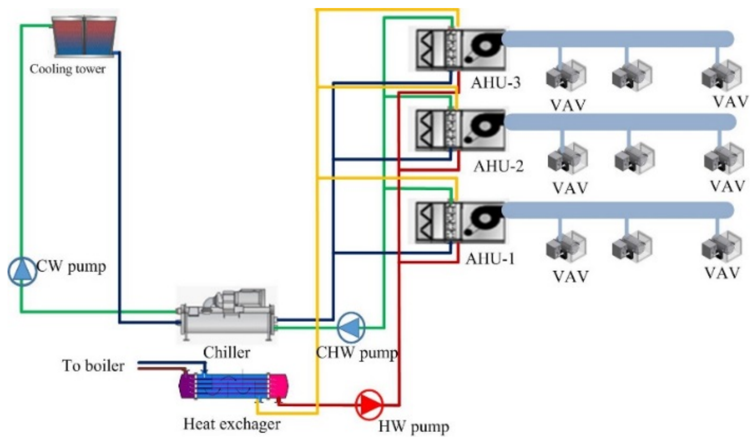

Figure 3: Whole building HVAC system configuration in the Nesbitt Hall

5. METHOD EVALUATION

5.1 Ground Truth

A thorough manual study is firstly performed to identify and tag collected building data into two states, i.e., “fault free” and “faulty”. Whole building operation is considered as “faulty”, when there are observable abnormalities found in more than two key BAS measurements (listed in Table 6). A key measurement is considered abnormal if the difference between its value and its baseline value under similar weather conditions, is larger than a threshold. The abnormality thresholds are summarized in Table 6. Notice that these thresholds are not used in our AFDD strategies but are used when we manually tag the test data for setting a “ground truth” purpose. These thresholds are selected based on 1) sensor accuracy; and 2) measurement fluctuation under normal operation.

For each “fault” case, the root-cause for the abnormality is again manually identified by observing these key BAS measurements and their baseline values. This manual process is necessary because 1) faults could naturally occurred during the test days when we did not implement a fault; 2) even a fault was artificially implemented, it may not cause any abnormality under certain operational conditions. Such data is tagged as “fault free” as the implemented fault does not trigger any observable fault symptoms. And 3) even a fault was artificially implemented, other naturally occurred faults could still occur at the same time and cause abnormality. These tagged data are served as the ground truth for the later method evaluation.

Table 6: Key BAS measurements and abnormality threshold

Sub-system	Key Measurement	Abnormality Threshold (compared with baseline)
Primary cooling sub-system (Chiller plant)	1) Chilled water supply temperature (°F)	2 °F difference
	2) Differential chilled water pressure (Psi)	0.5 Psi difference
	3) Chilled water supply pump speed (%)	5% difference
	4) Chilled water return temperature (°F)	5 °F difference
	5) Chilled water flowrate (gpm)	50 gpm difference
Air loop side sub-system (AHUs)	1) Supply air temperature (°F)	3 °F difference
	2) Supply air differential air pressure (inH2O)	0.3 inH2O difference
	3) Supply air fan speed (%)	5% difference
	4) Cooling coil valve open position (%)	15% difference
	5) Outdoor air damper open position (%)	10% difference

5.2 Fault Isolation

When posterior probability is obtained from the developed whole building BNs, the fault isolation will be conducted to determine the final fault root-cause. In this study, fault root cause is isolated by comparing the fault cause posterior probability. A fault is isolated, i.e., identified as the root-cause for an abnormality, by the following two isolation rules: 1) the posterior probability of this fault node is higher than 15%; and 2) the posterior probability of this fault node is the highest among all fault nodes and is 10% higher than the second-highest one.

5.3Method Evaluation

Firstly, an overall *LEAK* probability distribution for each fault evidence is obtained by averaging *LEAK* probability in each snapshot window from the entire baseline database. For example, for the CHW-Flowrate evidence node, when 1% data samples out of the baseline database are “Very High” outliers, i.e., the values are 2 times higher than the standard deviation according to Equation 1 and Equation 2, then, the “Very High” *LEAK* probability for this node is 1%. Table 7 summarizes all of the *LEAK* probabilities from using the WPM method for BN evidence nodes used in this study.

Table 7: *LEAK* probabilities for each measurement

Fault Evidence Node	Leak Probability				Normal
	Very High	High	Very Low	Low	
CHW-Flowrate	1.0%	1.0%	1.0%	1.0%	96.0%
CHW-SW-Temp	1.0%	1.0%	1.0%	1.0%	96.0%
CHW-RW-Temp	0.5%	0.5%	0.5%	0.5%	98.0%
CHW-Cooling	0.1%	0.1%	0.1%	0.1%	99.6%
CHW-Pump-Speed	1.0%	1.0%	1.0%	1.0%	96.0%
AHU-SA-Temp	1.0%	1.0%	1.0%	1.0%	96.0%
AHU-SF-Speed	1.0%	1.0%	1.0%	1.0%	96.0%
AHU-CC-CLC	1.0%	1.0%	1.0%	1.0%	96.0%
AHU-OA-DMPR	1.0%	1.0%	1.0%	1.0%	96.0%
AHU-MAT-OAT	1.0%	1.0%	1.0%	1.0%	96.0%

Eight fault cases which included seven artificially implemented faults and one naturally occurred fault from summer 2017 were employed to evaluate the developed BN strategy. Out of the eight fault cases, seven fault cases were successfully diagnosed. The result and all eight fault cases are shown in Table 8.

Table 8: Fault diagnosis result

Date	Fault Description	Fault Diagnosis Result
07/09/17	Chiller is off while under normal operation, it should be on	Diagnosed
07/11/17	AHU-2 OA damper stuck on 90% open (higher than normal)	Diagnosed
07/18/17	AHU-2 OA damper stuck on 100% open (higher than normal)	Diagnosed
07/22/17	Chiller DP sensor positive bias 0.2 psi	Diagnosed
08/03/17	Chiller CHWS temperature negative bias 4°F	Mis-diagnosed
08/05/17	System is occupied while under normal operation, it should be unoccupied	Diagnosed
08/11/17	AHU-2 cooling coil valve position software override at 100% open (higher than normal)	Diagnosed
09/15/17	Chiller DP sensor positive bias 0.1 psi	Diagnosed

(1) Example: successfully diagnosed fault

On July 11th 2017, a damper stuck fault (stuck at a higher than normal position) was implemented on AHU-2 from 10:00AM to 08:01PM. The stuck positions (90% open) was higher than the damper's normal position (15% open) under similar weather conditions. Under such circumstances, if the outdoor air damper is stuck at a position that is higher than normal (15% during cooling mode), cooling coil valve position will be increased to ensure the supply air temperature meet the setpoint requirement. However, in the early morning and evening hours, when outdoor enthalpy is lower than the return air enthalpy, the outdoor air damper is controlled under economizer mode to save energy. In these situations, the damper stuck fault would not yield a strong fault impact, as the stuck position is very similar to the normal damper position (under economizer mode). Figure 4 illustrates the posterior probability of different fault causes. It can be seen that AHU-OA-DMP-Stuck-H fault has the highest posterior probability compared with other fault causes. Therefore, this fault root-cause can be successfully diagnosed and isolated by the proposed BN diagnosis method.

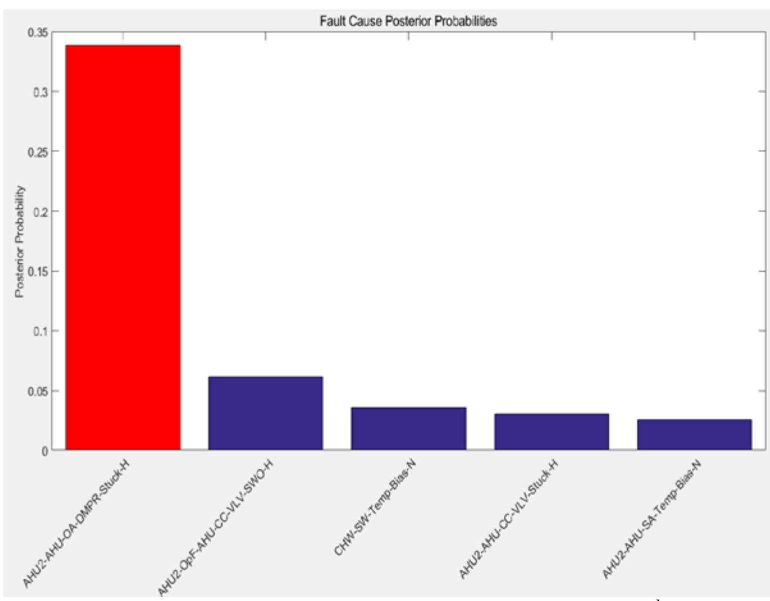

Figure 4: Ranked list of fault causes (test case in July 11th 2017)

6. CONCLUSION

In this study, a BNs based method is developed for whole building fault diagnosis. The proposed BNs include a two-layer BN structure model. Structure model is developed based on expert knowledge. Measurements from a building's automation system are used as evidence nodes. In developing BNs parameters, *prior* probabilities and *conditional* probabilities are obtained based on domain knowledge. *LEAK* probability in the BNs parameter model is obtained through historical baseline data generated by a Weather based Pattern Matching method. Posterior probabilities for fault causes are ranked to diagnose and isolate the fault root-cause. BAS data from a real campus building is used to evaluate the proposed method. The evaluation shows that BNs based method is effective to diagnose and isolate the root cause of whole building faults. Future work includes refining the BNs by using more fault test data and further developing root cause identification method.

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