Dynamic Bayesian Network-Based Fault Diagnosis for ASHRAE Guideline 36: High Performance Sequence of Operation for HVAC Systems

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ABSTRACT

A dynamic Bayesian Network (DBN) is proposed in this study to diagnose faults for building heating, ventilating, and air-conditioning (HVAC) systems that are controlled based on American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE)'s Guideline 36: High Performance Sequence of Operation for HVAC (hereinafter Guideline 36). Guideline 36 provides recommendations on supervisory-level control. HVAC systems that adopt these strategies have more comprehensive setpoint reset schedules and more advanced control logics than typical HVAC systems. It is hence of interest to understand how faults might affect the performance of HVAC systems that are controlled based on Guideline 36 and whether we can develop strategies to diagnose and isolate faults even for systems with such comprehensive control sequences. Contrarily to a Bayesian Network (BN), DBN method incorporates the temporal dependencies of fault nodes between time steps using temporal conditional probabilities. This allows fault beliefs to accumulate over time and thus improves diagnosis accuracy. In this study, the accuracy and scalability of the proposed method is evaluated using the data from a Modelica-based simulated testbed. Overall, the developed DBN shows good potential in diagnosing and isolating the root fault causes for HVAC systems that are controlled based on the Guideline 36 control sequence.

CCS CONCEPTS

Applied computing ~ Engineering

KEYWORDS

Dynamic Bayesian network, Bayesian network, fault diagnosis

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1. Introduction

Studies and field practices have shown that applying automated fault detection and diagnosis (AFDD) tools in HVAC systems, followed up with service and corrections, can help reduce the energy waste, improve occupant comfort and extend equipment lifecycle [3]. Within the AFDD framework, the process of locating and isolating the physical root cause of a fault has been challenging for HVAC systems since a detailed and accurate reasoning of the HVAC system and its control strategies is required. Among several inference and classification approaches that have been developed as fault diagnosis tools, Bayesian networks (BN) models based on the conditional probability theorem that predict the fault responses based on a set of observations have been popular for the HVAC system [6,7]

Successfully implemented BNs for fault diagnosis for different HVAC components have been reported in existing literature for both component-level and whole building fault diagnosis [4,5,8,9,10,11]. Although the existing studies demonstrate good potentials of BNs for both component-level and whole building fault diagnosis, the BN structure model used are event-based, time-invariant models (i.e., information from the previous time steps are not carried over to the next time step). Instead, a dynamic BN (DBN) model is more suitable for diagnosing faults for a continuous-time engineering system such as a building HVAC system [12]. The main advantage is that a DBN carries over past information which allows fault belief to accumulate over time. Using the past information could help eliminate measurement errors and only retain persistent faults [13]. In our earlier work [14], we conducted a systematic comparison between conventional BN and DBN by converting the existing WPM-BN model from [10] for whole building fault diagnosis. The DBN was demonstrated to be more effective in diagnosing and isolating faults when multiple and/or propagating symptoms are seen across various components or sub-systems. However, the HVAC system that has been examined by existing studies have been controlled by conventional control strategies with minimum supervisory control. It is of interest to understand, when a HVAC system adopts more advanced control strategies with varying setpoints and much more complicated subsystem interactions, whether the DBN would still be effective at diagnosing root causes of a fault.

ASHRAE Guideline 36 [17], first published in 2018, provides best-in-class HVAC sequences of operation to maximize the energy efficiency, improve system stability, enhance code compliance, and allow fault detection and diagnostics. Guideline 36 will be continuously developed with the state-of-the-art research on the high-performance sequences of operation for HVAC systems and expand the coverage to the whole building system types and configurations. Hence, HVAC systems that adopt Guideline 36 would experience much more dynamic setpoints and much more interactions among subsystems which add more challenges for fault diagnosis tools.

In this paper, the DBN structure model reported in [14] is further adapted to diagnose faults from HVAC systems that are controlled following the newest Guideline 36, in order to test the scalability of the DBN framework under different control sequences. A small-scale evaluation is performed using operation data from a virtual testbed to examine the effectiveness of the adapted DBN framework.

2. DBN for Fault Diagnosis

A BN or DBN is a probabilistic graphical model formed using causal relations. For fault diagnosis, a directed acyclic network is used in which the nodes represent the faults and symptoms (evidences) from measurements and observations, and the arcs represent the direct probabilistic dependencies among the connected nodes [4] . Details on how the BN is developed for fault diagnosis can be found in [10].

A DBN is an extension of the conventional, static BN which can represent temporal relationships of the fault and symptom nodes between different time steps. Figure 1 shows the difference between a BN and a DBN with one fault and one symptom node for n-time steps. In a static BN, the probability of a fault node *(F_{t+1})* only depends on the corresponding symptom node *(S_{t+1})*, whereas, in a DBN, the probability of node F_{t+1} depends on its symptom nodes S_{t+1} and also its own values at the previous time step F_t.

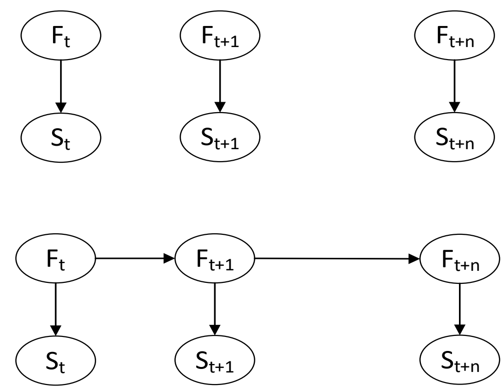

Figure 1. Schematics of a static BN (above) and a dynamic BN (below)

The additional dependency on the fault node from the previous time step requires a temporal CPT, $P(F_{t+1}|F)$, to define the relationship. The temporal CPTs carry over posterior probabilities from the previous to the current time step.

Maximum likelihood estimation (MLE) and Bayesian estimation (BE) are some of the techniques used to estimate the unknown probabilities [16]. However, utilizing statistical techniques to obtain the probability distributions is a major challenge for building system data since (i) ground truth data that confirms the root fault causes of natural-occurring faults are hard to obtain, and (ii) even if the ground truth data exists for a specific building, the probability distributions learned from specific building system data are usually not scalable to other building systems [10]. Hence, in this study, the temporal CPT are also developed using some expert knowledge and parameter sensitivity analysis.

3. Method Description

As reported in [14], the development of the DBN methodology is divided into seven steps. First, incoming snapshot data and baseline data under similar weather conditions are collected in Step 1. Following this, in Step 2, the DBN structure which includes the nodes for the fault and associated evidence, and the causal relation between them based on expert knowledge is developed. In Steps 3 and 4, various probability distributions for each fault node and evidence node, including the LEAK distribution, are calculated and assigned in the parameter model. Next, the evidence event are developed to compare the incoming snapshot data with the baseline in Step 5. An evidence event is classified to be abnormal if the incoming data is significantly different from the baseline, i.e., is higher than the statistical threshold. Based on the judgment in this step, the Bayesian inference in Step 6 is trigged, and the posterior probabilities of each fault node is calculated. Finally, the posterior probabilities are ranked, and the root fault is isolated based on pre-defined rules in Step 7.

In this study, the above-described DBN is developed for a medium-sized office building with an air handling unit that is served by a chiller. In total, 17 fault nodes which represent the faults implemented in the AHU, and 15 evidence nodes using both direct measurements and physics-based models (e.g., fan curve fits) are used to create a two-layer DBN. Table 1 list all fault nodes included in the DBN. Several common faults such as outdoor air damper stuck, cooling coil valve stuck, supply temperature bias etc. are considered. Again, the structure of the DBN is developed based on physical analysis, first-principle-models, and expert knowledge of the authors, as described in [14].

Table 1. Fault node descriptions

Fault No.	Fault Node Description
1	AHU outdoor air damper stuck higher than normal
2	AHU outdoor air damper stuck lower than normal
3	AHU cooling coil valve stuck higher than normal
4	AHU cooling coil valve stuck lower than normal
5	AHU return fan speed higher than normal
6	AHU return fan speed lower than normal
7	AHU return fan complete failure
8	AHU outdoor air damper leaking
9	AHU Air Loop Supply Duct Leakage
10	AHU Supply Air Temperature Positive Bias
11	AHU Supply Air Temperature Negative Bias
12	AHU Return Air Temperature Positive Bias
13	AHU Return Air Temperature Negative Bias
14	AHU Outdoor Air Flowrate Sensor Positive Scale Error
15	AHU Outdoor Air Flowrate Sensor Negative Scale Error
16	Chilled water differential pressure sensor positive bias
17	Chilled water differential pressure sensor negative bias

4. Method Evaluation

4.1 Description of Experimental Data

To evaluate the DBN for fault diagnosis, simulated experimental data collected from a Modelica-based simulation testbed is used. More details about the testbed and fault simulation are provided in [18].

The system is a one-floor, five-zone medium-sized office building. Heating and cooling are delivered by a single-duct VAV system. It has one AHU connected with five VAV terminal boxes serving five zones (four exterior zones, and one interior zone, respectively). The chilled water is supplied by a central chiller plant which consists of a chiller, a waterside economizer, a cooling tower, and one chilled water pump and one cooling water pump. A boiler, fed by natural gas, supplies the hot water to the AHU heating coil. The reheat in the VAV terminals is supplied by electric resistance coils.

Figure 2 illustrates the schematics of the system. The system is sized under the ASHRAE climate zone 5A Chicago, IL. Airside (AHU and VAV terminals) and waterside (chilled water loop and hot water loop) are scheduled for an automatic operation on a time-of-day basis with seven types of system operation mode according to Guideline 36, PART 5.C.6 [17].

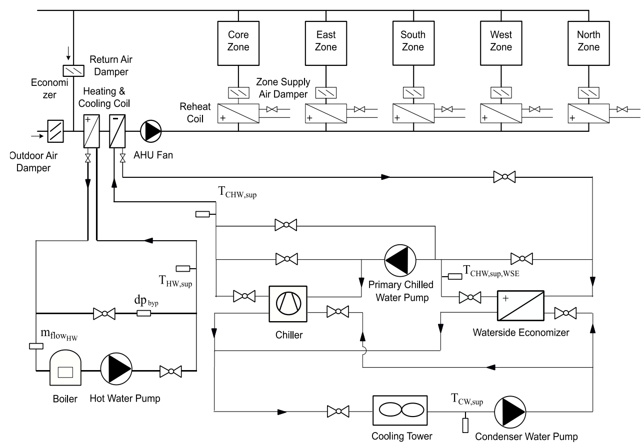

Figure 2. Schematics of the system model [18]

A total of 14 faults, which are artificially injected to the system fault model during the summer and transitional seasons as, are used to evaluate the DBN. The fault injection model is detailed in [18]. Data is collected for the period when the faults are implemented. Data that represented the baseline fault-free conditions is also collected from the simulation testbed. The baseline data is used to calculate the statistical thresholds for generating evidences in the DBN framework.

4.2 Results

The fault diagnosis results using a DBN is generated for the 15 cases. Table 2 summarizes the fault cases and the posterior probabilities of the fault identified by the DBN.

Table 2. Fault ranking for artificially injected faults

Fault Type	Posterior Probability	Diagnosis Result
AHU Cooling coil valve stuck at 0%	87%	Diagnosed
AHU Cooling coil valve stuck at 100%	63%	Misdiagnosed
AHU Cooling coil valve stuck at 15%	89%	Diagnosed

AHU Cooling coil valve stuck at 5%	88%	Diagnosed
AHU Outdoor air damper leakage of 10%	2%	No fault symptoms
AHU Outdoor air damper stuck at 0%	85%	Diagnosed
AHU Outdoor air damper stuck at 100%	71%	Diagnosed
AHU Outdoor air damper stuck at 15%	71%	Diagnosed
AHU Outdoor air damper stuck at 5%	82%	Diagnosed
Chilled water differential pressure sensor negative bias of 10 kPa	3%	No fault symptoms
Chilled water differential pressure sensor positive bias of 10 kPa	6%	No fault symptoms
AHU Air loop supply duct leakage of 20%	90%	Diagnosed
AHU Outdoor air flow rate sensor negative scale error of 30%	74%	Diagnosed
AHU Outdoor air flow rate sensor positive scale error of 30%	67%	Diagnosed

Out of the 14 cases, the DBN correctly diagnosed 10 cases, i.e., identified the root causes of the faults. For three of four remaining cases, the implemented fault did not yield any symptom which is reflected by the low posterior probability value from the DBN. The one misdiagnosed case was for the fault of cooling coil valve stuck at 100% position. Key symptoms for this fault were believed, based on physical knowledge, to be heating coil valve at a higher-than-normal value and increase in chilled water flowrate and chiller cooling. A closer manual inspection of the data revealed that the heating valve was not opened further since the boiler was prevented from turning on in the hot summer day in the simulated control logic. This caused the fault belief to be very low for the *AHU cooling coil valve stuck higher than normal* fault node since the heating coil valve was a critical symptom for this fault. Overall, the proposed framework was able to diagnose most considered faults for HVAC systems controlled by the Guideline 36 control sequences. Further improvements are needed to increase the diagnosis accuracy, especially for faults that are impacted by the boiler operation schedule.

As mentioned in our previous work in [14], the fault beliefs (posterior probabilities) obtained when using a DBN is stronger when compared to a static BN. Since a DBN allows the evidence to accumulate over time, whereas in a static BN, only evidence from a single time step is considered for inference, the fault belief is often limited to a lower value for static BN. Similar trends are seen across the fault cases evaluated in this paper.

5. Conclusions

This paper presents a DBN framework for diagnosing faults of HVAC systems that are controlled based on Guideline 36, which significantly increases the dynamics and coupling of different subsystems and hence adds challenges for fault diagnosis tools. The DBN models incorporates the temporal relationship between fault nodes in the previous time step to the current fault node using temporal conditional probabilities, contrarily to static BNs which are time-invariant models. The proposed method is evaluated using data from a simulated testbed. Causal relations between faults and their corresponding symptoms are developed using expert knowledge and observations from the data. Preliminary results show that the proposed method shows good potential in diagnosing and isolating root fault causes for HVAC system controlled by the Guideline 36 control sequences. Further study and improvements are needed to increase the diagnosis accuracy.

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REFERENCES

[1] U.E. Global Alliance for Buildings and Construction, IEA, 2018. Global Status Report 2018: Towards a zero-emission, efficient and resilient buildings and construction sector, *Glob. Status Rep*.

[2] K.W. Roth, D. Westphalen, M.Y. Feng, P. Llana, L. Quartararo, 2005. Energy Impact of Commercial Building Controls and Performance Diagnostics: Market Characterization, *Energy Impact of Building Faults and Energy Savings Potential*, U.S. Dep. Energy.

[3] M.A. Piette, S.K. Kinney, P. Haves, 2001. Analysis of an information monitoring and diagnostic system to improve building operations, *Energy Build*. DOI: https://doi.org/10.1016/S0378-7788(01)00068-8.

[4] Y. Zhao, J. Wen, S. Wang, 2015. Diagnostic Bayesian networks for diagnosing air handling units faults - Part II: Faults in coils and sensors, *Appl. Therm. Eng*. 90 (2015) 145–157. DOI: https://doi.org/10.1016/j.applthermaleng.2015.07.001.

[5] Y. Zhao, J. Wen, F. Xiao, X. Yang, S. Wang, 2017. Diagnostic Bayesian networks for diagnosing air handling units faults – part I: Faults in dampers, fans, filters and sensors, *Appl. Therm. Eng*. 111 (2017) 1272–1286. DOI: https://doi.org/10.1016/j.applthermaleng.2015.09.121.

[6] J. Pearl. 1988. *Probabilistic reasoning in intelligent systems: networks of plausible inference*, Morgan Kaufmann Publ. San Mateo, Calif.

[7] M.S. Mirnaghi, F. Haghighat, 2020. Fault detection and diagnosis of large-scale HVAC systems in buildings using data-driven methods: A comprehensive review, *Energy Build.* 229 (2020). DOI: https://doi.org/10.1016/j.enbuild.2020.110492.

[8] Y. Zhao, F. Xiao, S. Wang, 2013. An intelligent chiller fault detection and diagnosis methodology using Bayesian belief network, *Energy Build.* (2013). DOI: https://doi.org/10.1016/j.enbuild.2012.11.007.

[9] F. Xiao, Y. Zhao, J. Wen, S. Wang, 2014. Bayesian network based FDD strategy for variable air volume terminals, *Autom. Constr.* (2014). DOI: https://doi.org/10.1016/j.autcon.2013.10.019.

[10] Y. Chen, J. Wen, T. Chen, O. Pradhan, 2018. Bayesian Networks for Whole Building Level Fault Diagnosis and Isolation, *5th Int. High Perform. Build. Conf. Purdue.* (2018) 1–10.

[11] Y. Chen, J. Wen, 2017. Whole building system fault detection based on weather pattern matching and PCA method, *3rd IEEE Int. Conf. Control Sci. Syst. Eng.* (2017) 728–732. DOI: https://doi.org/10.1109/CCSSE.2017.8088030.

[12] K.P. Murphy. 2002. *Dynamic Bayesian Networks: Representation, Inference and Learning.*

[13] Z. Shi, W. O'Brien, 2018. Development of a distributed fault detection, diagnostic and evaluation framework, *ASHRAE Trans. 124* (2018). DOI: https://nrc-publications.canada.ca/eng/view/object/?id=0d09aacd-819a-4139-a25b-3dadf309e402.

[14] O. Pradhan, J. Wen, Y. Chen, T. Wu, Z. O'Neill, 2021. Dynamic Bayesian Network for Fault Diagnosis, *2021 ASHRAE Virtual Conference.*

[15] A. Zagorecki, M.J. Druzdzel, 2013. Knowledge engineering for Bayesian networks: How common are noisy-MAX distributions in practice', *IEEE Trans. Syst. Man*, (2013). DOI: https://doi.org/10.1109/TSMCA.2012.2189880.

[16] M.T. Amin, F. Khan, S. Imtiaz, 2019. Fault detection and pathway analysis using a dynamic Bayesian network, *Chem. Eng. Sci.* 195 (2019) 777–790. DOI: https://doi.org/10.1016/j.ces.2018.10.024.

[17] ASHRAE, 2018. *ASHRAE Guideling 36: High Performance Sequences of Operation for HVAC Systems*.

[18] X. Lu, Y. Fu, Z. O'Neill, J. Wen, A Holistic Fault Impact Analysis of the High-Performance Sequences of Operation for HVAC Systems: Modelica-based Case Study in a Medium-Office Building, *Energy & Buildings* (2021), doi: https://doi.org/10.1016/j.enbuild.2021.111448