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Wang, Z.; Lu, C.J.; Mosteiro-Romero, Martín; Itard, L.C.M.

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Simultaneous presents faults detection by using Diagnostic Bayesian Network in Air Handling Units

Z. Wang[1,*], C. Lu[1], M. Mosteiro-Romero[1], L. Itard[1]

[1]Faculty of Architecture and the Built Environment, Delft University of Technology, Delft, the Netherlands.

ABSTRACT

Energy waste in buildings can range from 5% to 30% due to faults and inadequate controls. To effectively mitigate energy waste and reduce maintenance costs, the development of Fault Detection and Diagnosis (FDD) algorithms for building energy systems is crucial. Diagnostic Bayesian Networks (DBNs), as graphical probability models, are particularly useful in scenarios where high-quality data is not always available. While many studies have focused on single fault detection using DBNs, the occurrence of multiple simultaneous faults is common, yet the versatility of DBNs in handling such cases is rarely explored. This study adapts a DBN, initially designed for single fault diagnosis, to perform simultaneous fault diagnosis Experiments were conducted on an air handling unit (AHU) in the Netherlands, using implemented simultaneous faults to test the model. The results suggest that the DBN can detect both single and multiple faults effectively.

KEYWORDS

Fault Detection and Diagnosis, Diagnostic Bayesian Networks, Multiple Faults Detection

INTRODUCTION

Approximately 36% of the European Union's greenhouse gas emissions are attributed to the building sector, with 75% of existing structures considered energy inefficient (IEA 2023). This highlights the urgent need to enhance energy efficiency to meet climate targets. HVAC (Heating, Ventilation, and Air Conditioning) systems, responsible for regulating temperature, air quality, and humidity, account for nearly half of a building's energy consumption (Pérez-Lombard et al. 2008). Improving HVAC system efficiency is crucial for reducing energy waste.

A key component of many HVAC systems, particularly in non-residential buildings, is the Air Handling Unit (AHU), which regulates airflow and maintains optimal indoor conditions. Inefficiencies or faults in the AHU can lead to energy waste, increased costs,

* Corresponding author email: Ziao.Wang@Tudelft.nl

and decreased occupant comfort. Consequently, the development of effective Fault Detection and Diagnosis (FDD) methods for AHUs have attracted considerable attention, with Lin et al. (Lin et al. 2020) reporting potential energy savings of 5-30% in building energy systems through the application of FDD.

Current FDD techniques, including data-driven methods like machine learning, rely heavily on large datasets for training, making them less adaptable to environments with changing fault conditions (Yan et al. 2016, Cheng et al. 2021). These approaches often require retraining, which can be time-consuming and resource-intensive. Furthermore, many methods are limited to single fault detection, whereas in practice, AHUs also experience multiple simultaneous faults, which complicates diagnosis.

To address these challenges, knowledge-based approaches, such as Bayesian networks, offer a promising alternative to data-driven methods. Bayesian networks are graphical probability models that represent the conditional dependencies between different variables, making them well-suited for fault diagnosis in complex systems like AHUs (Zhao et al. 2015, 2017). One of the key advantages of Bayesian networks is their ability to incorporate expert knowledge and prior probabilities, allowing them to function effectively even in cases where high-quality data is scarce or incomplete. This makes them particularly useful in real-world building energy systems, where sensor data may be noisy, missing, or limited.

This study focuses on the application of Diagnostic Bayesian Networks (DBNs) for detecting and diagnosing multiple simultaneous faults in AHUs. While previous studies have demonstrated the effectiveness of Bayesian networks in single fault detection (Taal and Itard 2020*a*, *b*, Wang et al. 2024), their potential for diagnosing multiple faults has remained largely unexplored. This research aims to explore the ability of DBNs to detect simultaneous faults using a model initially designed for single fault detection, without modifying the parent or child nodes.

METHODOLOGY

This study applies a DBN to detect and diagnose both single and multiple faults in an AHU, inspired by the four symptoms three faults (4S3F) approach from Taal et al.(2020*a*), modified for the specific requirements of this research. The key stages in building the DBN, as outlined by Wang et al. (2022), include analyzing the Pipe and Instrumentation Diagram (P&ID), identifying faults and symptoms, constructing the DBN, and validating it with simulated fault scenarios.

The P&ID of the AHU in Kropman (Fig. 1.), located in Breda, was reviewed. Then the Heat Recovery Wheel (HRW), Heating Coil Valve (HCV), and fan were selected due to their significant impact on the AHU's energy efficiency and operational stability.

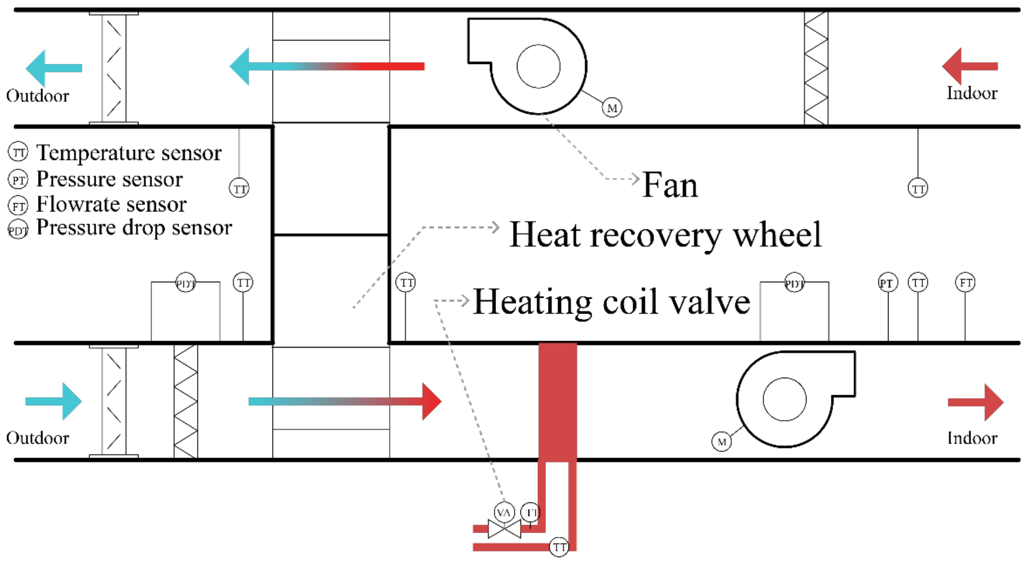

Figure 1. *P&ID of AHU in Kropman*

Following the 4S3F framework, key symptoms were mapped to the three selected faults using BMS data, control documents, and expert knowledge. These symptoms derive from deviations from predicted behavior, control setpoints, and physical imbalances.

The HCV position ($U_{\mathrm{hc,pred}}$) is predicted as a function of the setpoint temperature (T_{set}), related humidity at supply air distribution system (RH_{sad}), exhaust air temperature (T_{ea}), absolute humidity at supply air distribution system (AH_{sad}), outdoor air temperature (T_{oa}), and inlet air temperature (T_{ia}) as shown in Eq. (1):

$$U_{\mathrm{hc,pred}} = f(T_{\mathrm{set}}, T_{\mathrm{ea}}, T_{\mathrm{oa}}, RH_{\mathrm{sad}}, AH_{\mathrm{sad}}, T_{\mathrm{ia}}) \tag{1}$$

One standard deviation (σ) of the prediction model is used as a fault detection threshold.

Deviations between predicted and actual fan flowrate are used as an indicator of fan-related faults, as outlined by Zhao et al. (2017), with the fan flowrate prediction ($Q_{s,pred}$) expressed as a function of the supply fan pressure drop, as shown in Eq. (2):

$$Q_{\mathrm{s,pred}} = f(P_{\mathrm{fa}}) \tag{2}$$

Where (P_{fa}) is the supply fan pressure drop.

Table 1. summarizes the faults and Table 2. and Table 3. are their associated symptoms and variables used in symptom definition, based on the 4S3F methodology.

Table 1. *Selected faults and prior probability*

Fault	*Faulty probability*	*Normal probability*
HRW stuck	0.05	0.95

HCV stuck	0.05	0.95
Fan stuck	0.05	0.95

Table 2. *Variables used in symptoms definition*

Name of variable	*Abbreviation*	*Unit*
Supply air temperature	T_{sa}	°C
Set point temperature	T_{set}	°C
Heating coil valve openness	U_{hc}	%
Supply flowrate	$\mathrm{Q_s}$	m^3/s
Supply filter pressure drop	$\mathrm{P_f}$	Pa
supply pressure	P_{sa}	Pa
Set point pressure	P_{set}	Pa

Table 3. *Symptoms associated with faults*

Symptom	*Symptom description*	*Faulty state definition*
$\Delta U_{\mathrm{hc,pred}}$	Difference of HCV position prediction & signal	$\lvert U_{\mathrm{hc}} - U_{\mathrm{hc,pred}} \rvert > \varepsilon_{hc}$
$\Delta T_{\mathrm{s,sa}}$	Difference of setpoint & supply temperature	$\lvert T_{\mathrm{set}} - T_{\mathrm{sa}} \rvert > \varepsilon_{ts}$
η_{HRW}	HRW efficiency	$\eta_{\mathrm{hrw}} < \varepsilon_{\mathrm{hrw}}$
$\Delta Q_{\mathrm{s,pred}}$	Difference of flowrate & flowrate prediction	$\lvert Q_s - Q_{s,\mathrm{pred}} \rvert > \varepsilon_q$
ΔP_{f}	Supply filter pressure drop	$\mathrm{P_f} < \varepsilon_{\mathrm{f}}$
$\Delta P_{\mathrm{s,sa}}$	Difference of setpoint & supply pressure	$\lvert P_{\mathrm{set}} - P_{\mathrm{sa}} \rvert > \varepsilon_{ps}$
$\varepsilon_{hc}, \varepsilon_q = \sigma,\ \varepsilon_{ts} = 0.5\ °C,\ \varepsilon_{hrw} = 0.7,\ \varepsilon_{\mathrm{f}} = 60\ Pa$		

The DBN was constructed, based on the full AHU DBN initially designed for single fault detection, to assess its ability to diagnose multiple simultaneous faults. The extracted DBN includes nodes of HRW, fan, and HCV. Fig 2. illustrates the DBN structure, highlighting the relationships between faults and symptoms.

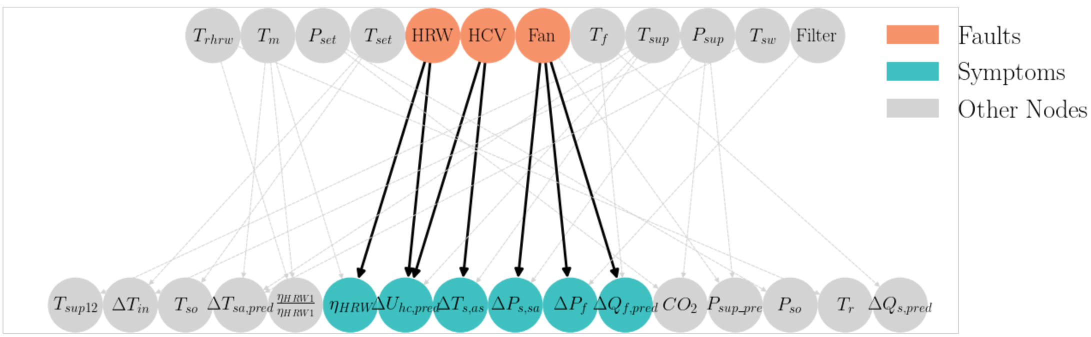

***Figure 2**. DBN structure*

The prior probability of each fault (HRW, HCV, and fan) was set to 5%, with a normal operational probability of 95%. Table 1. outlines the prior fault probabilities. Conditional probabilities were assigned using a Noisy-OR gate to simplify the process (Chen et al. 2022*a*), assuming symptom independence given the parent faults (Taal and Itard 2020*a*, Wang et al. 2022). The probability of a fault being absent when a symptom is present was set to 5%, and a no-leak probability was applied.

To validate the DBN, faults were introduced in the AHU in Kropman, including six groups of multiple faults, six single faults, and two normal operation days. The DBN's reliability was tested by comparing its diagnostics to actual faults in both single and multiple fault scenarios.

RESULTS

Fig.2. illustrates the frequency of detection for each symptom across the implemented fault cases. Each bar represents how often a particular symptom was detected, providing an overview of the system's behavior under different fault conditions.

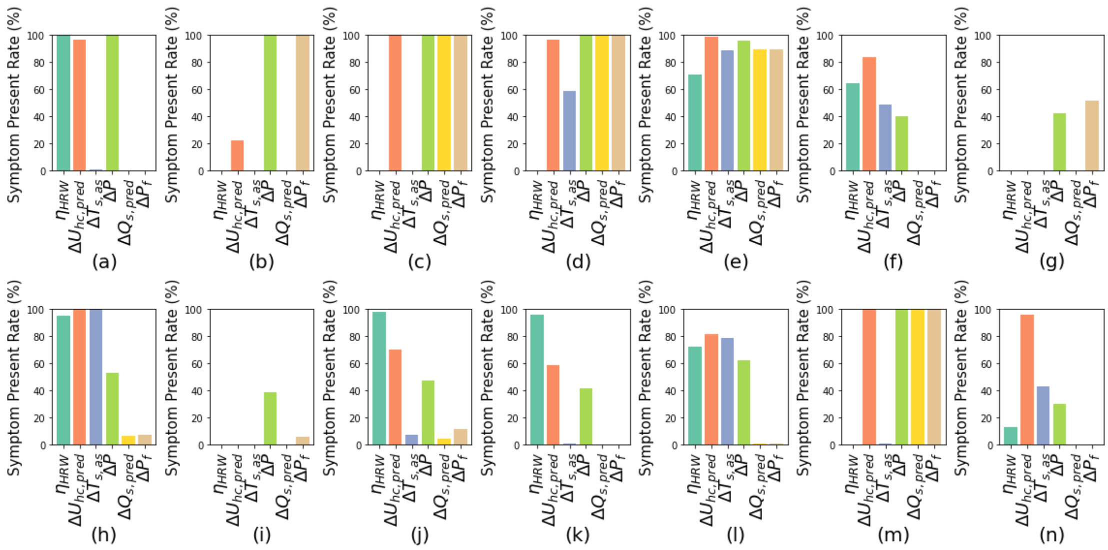

***Figure 2**. Symptom detection frequency of (a) HRW 30% & Fan 70%; (b) Fan 65% ; (c) HRW 30% & Fan 40%; (d) HCV 30% & Fan 40%; (e) HCV 70% & Fan 40%; (f) HCV 30% & HRW 70%; (g) Normal day 1; (h) HCV 30% & HRW 30%; (i) Normal day 2; (j) HRW 30%; (k) HRW 50%; (l) HCV 40%; (m) Fan40%; (n) HCV75%*

Across multiple fault cases, $\Delta U_{hc,pred}$ symptom was one of the most commonly detected, particularly in the scenarios involving HCV stuck, such as those shown in Fig. 2. (d), (e), (f), This high detection rate indicates the sensitivity of the $\Delta U_{hc,pred}$ to faults affecting the valve openness. Similarly, $\Delta Q_{s,pred}$ $symptom$ was frequently detected in fan-related fault cases such as case in Fig. 2. (d), (m).

Several anomalies in symptom detection were observed. For example, the η_{HRW} was inconsistently detected in some cases where valve faults were introduced, such as case in Fig. 2. (c). This suggests that HRW-related symptoms may not be as prominent or could be masked by other system behaviors.

Additionally, $\Delta U_{hc,pred}$ was detected in cases primarily involving HRW or fan faults, such as case in Fig. 2. (a), (c), (d), and (j), even when no direct HCV stuck fault occurred. This points to potential cross-influences between system components or issues within the prediction model.

Discrepancies were noted between system documentation, expert knowledge and actual symptom detection. For instance, in the case in Fig. 2. (a), ΔP_f symptom did not appear, despite the implementation of a fan stuck fault. In cases in Fig. 2. (l) and (e), η_{HRW} symptom appeared, even though no HRW faults were introduced. This mismatch suggests potential sensor issues or undocumented interactions between components, complicating the accuracy of symptom detection.

Table 4 shows the DBN diagnosed faults correctly or partially. Faults detected with probabilities over 15% were flagged (Chen et al. 2022*b*), but some false positives and negatives were observed and matched symptom detection results, where symptoms were either over-detected or missed.

Table 4. *Fault diagnostic result*

Fault Case	*HRW*	*HCV*	*Fan*	*Diagnostic result*
HCV 30% & Fan 40%	0.024	**0.37**	**0.89**	Successful
HCV 70% & Fan 40%	**0.30**	**0.35**	**0.84**	Partially Successful
HRW 30% & Fan 40%	0.02	0.03	**0.85**	Partially Successful
HRW 30% & Fan 70%	**0.37**	0.01	0.02	Partially Successful
HCV 30% & HRW 30%	**0.23**	**0.41**	0.06	Successful
HCV 30% & HRW 70%	**0.22**	**0.22**	0.03	Successful
Fan 40%	0.01	0.03	**0.88**	Successful
Fan 65%	0.05	0.00	**0.26**	Successful
HRW 30%	**0.31**	0.05	0.04	Successful
HRW 50%	**0.28**	0.01	0.00	Successful
HCV 40%	**0.24**	**0.33**	0.00	Partially Successful
HCV 75%	0.08	**0.26**	0.00	Successful
Normal day 1	0.00	0.00	0.01	Successful
Normal day 2	0.00	0.00	0.06	Successful

For example, in the case shown in Fig. 2. (c), the symptom η_{HRW} did not appear, despite the HRW stuck. This can be attributed to the counteracting effect of the fan speed drop, which decreased airflow and gave the HRW more time for heat exchange. Consequently, HRW efficiency increased, masking the fault. This interaction led to only a partial diagnosis, as the system did not detect the HRW's efficiency drop due to the fan's influence.

In some single fault cases, shown in Fig. 2. (n) and (m), the DBN successfully diagnosed the faults with high accuracy, indicating that the DBN is able to identify both HCV and fan issues individually. However, in more complex scenarios, particularly those involving simultaneous faults like the case shown in Fig. 2. (e), a false positive was observed. This could be due to the cross-influences between the system components, leading to either false positives or negatives in the diagnosis.

DISCUSSION

This study explored the ability of the DBN to diagnose multiple simultaneous faults in an AHU without modifying a model initially designed for single fault detection. In most cases, the DBN correctly diagnosed faults or partially identified them. However, challenges emerged when there were cross-influences between system components, sensor inaccuracies, or undocumented interactions, which sometimes led to false positives or false negatives. For example, in the case shown in Fig. 2. (c), the fan's reduced speed led to improved HRW efficiency, masking the fault and resulting in a false negative. Potential sources of error include symptom overlap, sensor misreading, and limitations within the DBN model itself. These factors affected the accuracy of the fault diagnoses, requiring further attention in future work to enhance the model's capability in dealing with complex fault interactions.

CONCLUSION

The results suggest that the DBN is capable of detecting both single and multiple faults in AHUs without modifications, though improvements are necessary to handle more complex interactions and cross-influences. Future work will focus on increasing diagnostic accuracy by introducing model improvements that account for sensor issues, cross influences, and performing additional experiments such as triple faults scenario to refine the DBN.

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