Whole-Building HVAC Fault Detection and Diagnosis with the 4S3F Method
Towards Integrating Systems and Occupant Feedback

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

Publication date
2024

Document Version
Final published version

Published in
ASim2024, The 5th Asia Conference of the IBPSA

Whole-Building HVAC Fault Detection and Diagnosis with the 4S3F Method: Towards Integrating Systems and Occupant Feedback

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

[1]Department of Architectural Engineering and Technology, Delft University of Technology, Delft, Netherlands

ABSTRACT
Automated fault detection and diagnostics (FDD) can support building energy performance and predictive maintenance by leveraging the vast amounts of data generated by modern building management systems. Diagnostic Bayesian Networks (DBN) offer a particularly promising approach due to their robustness, flexibility and scalability. However, FDD applications in whole building systems are rare, as they require the integration of different building subsystems, with their own potential faults and symptoms, which increases complexity and makes the resulting DBNs system-specific. In order to overcome these limitations, the 4S3F (four symptoms and three faults) method offers a simplified, adaptable framework for FDD implementation across building systems.

In this paper, we implement the 4S3F methodology to a whole-building HVAC system in a case study office building located in the Netherlands. Our methodology uses generic, aggregated representations of individual subsystems within the building, such that FDD methods for specific subcomponents can later be incorporated where available. We first define aggregated building system groups (boiler group, chiller group, hydronic groups, ventilation groups, and end user groups) and subsequently define generic faults that can be detected with the existing sensor infrastructure. This simplified system representation is then used to define a DBN to isolate the most probable system-level faults that lead to building-level symptoms. By focusing on the whole building system, this work aims to provide the groundwork to incorporate occupant feedback and behavior in FDD.

KEYWORDS
Fault Detection and Diagnosis, Diagnostic Bayesian Networks, Whole building HVAC

INTRODUCTION
Modern building management systems (BMS) generate vast amounts of data from a large number of sensors deployed throughout the heating, ventilation and air conditioning (HVAC) system. Despite this wealth of information, however, buildings continue to waste energy due to malfunctioning components and inadequate controls, with estimates ranging from 10–20% (Taal et al. 2018) to up to 40% (Schein et al. 2006). Automated fault detection and diagnosis (FDD) offer a promising solution to this problem by leveraging these vast datasets to detect faults with physical systems, diagnose their causes and potentially provide prognostic maintenance for degrading systems (Katipamula and Brambley 2005).

The literature shows a variety of FDD methods applied to systems at various scales, including HVAC-level energy efficiency, chillers, air handling units, and sensors (Wang et al. 2022). However, most research focuses on a few individual components, with air handling units (AHU), chillers, sensors, vapor compression systems, and variable refrigerant flow systems

[*] Corresponding author email: m.a.mosteiroromero@tudelft.nl

accounting for more than 80% of published literature in the field (Chen J et al. 2022). This is due to the fact that chillers and AHUs are the energy-using components that are most likely to cause serious and costly problems (Mirnaghi and Haghighat 2020).

On the other hand, real-world HVAC systems are complex and consist of a number of subsystems that need to be operated and controlled simultaneously. FDD methods focusing on single components might thus neglect the interdependencies between different components, leading to inadequate fault diagnosis in practice (Verbert et al. 2017). For example, the impacts of a fault occurring in one subsystem may propagate to other subsystems, leading to false alarms in the FDDs for those other subsystems (Chen Y et al. 2022). Furthermore, focusing solely on components ignores the role building occupants play both as potential causes for faulty system behavior, as well as their feedback as potential symptoms of inadequate building performance. An integrated approach to HVAC system FDD is therefore necessary (Taal et al. 2018).

Among FDD methods, Diagnostic Bayesian Networks (DBN) are particularly well-suited for whole building HVAC system FDD due to their robustness, flexibility and scalability. Compared to other methods, they can address a number of different and potentially simultaneous faults (Chen J et al 2022), which are desirable characteristics for large, integrated building systems. However, their application to whole building systems has so far been limited. Verbert et al. (2017) proposed a multi-model approach accounting for both HVAC subsystem interdependencies and changing modes of operation and demonstrated it through two simulated faults. Taal and Itard (2020) developed a whole-building DBN for a case study building in the Netherlands using the four symptoms three faults (4S3F) method and demonstrated their methodology by analyzing their method's capabilities of detecting various symptoms. Chen Y. et al. (2022) developed a discrete Bayesian Network (DisBN) approach for diagnosing and isolating cross-level faults in a VAV HVAC system, focusing on nine different cross-system faults affecting the chiller and AHU systems.

This paper introduces a DBN for a whole building HVAC system using the 4S3F method introduced by Taal et al. (2018). Our methodology uses generic representations of individual subsystems within the building, such that the DBN can determine which subcomponents need to be further investigated by operators or by its own FDD methods where available. We first define aggregated building system groups (boiler group, chiller group, hydronic groups, ventilation groups, and end user groups) and subsequently define generic faults that can be detected with the existing sensor infrastructure. This simplified system representation is then used to define a DBN to isolate the most probable system-level faults that lead to building-level symptoms. The methodology is then tested through the analysis of historical data and the symptoms and faults detected by the system under different operating modes.

METHODOLOGY

In this paper, a DBN for a whole HVAC system for a case study building in Delft, Netherlands. The methodology used is loosely based on the four symptoms three faults (4S3F) approach proposed by Taal et al. (2018). Setting up a DBN model based on the 4S3F framework involves the following steps (Wang et al. 2022). First the systems and subsystems to be considered need to be selected. For this, Taal and Itard (2020) identify three system levels: the whole HVAC system; aggregated systems (generator, distributor and emitter); and subsystems consisting of trade components. Subsequently, the list of all possible symptoms that can be detected is compiled from P&IDs or other documentation. The list of all possible faults leading to those symptoms is then also derived from the P&IDs. Once all possible faults and symptoms are identified, their relationships are translated to a DBN, with which the probability of each fault occurring can be estimated at every time step based on the collected evidence of the symptoms occurring. Subsequently, a building operator can make decisions to repair or adjust operation to remove the fault.

A DBN for a whole building system can quickly become impractically large if all possible faults and symptoms are considered. In order to solve this problem, Chen Y et al. (2022) focus on some specific "cross-level" faults, which would cause fault symptoms across different components or subsystems. Verbert et al. (2017) and Taal and Itard (2020), on the other hand, used aggregated system definitions (e.g., AHU, boiler, chiller) that each contains a number of sub-components. In this paper, we take the latter approach, under the assumption that sub-components will each have their dedicated FDD approaches for further investigation of the root cause of a symptom once the fault at the component level is identified.

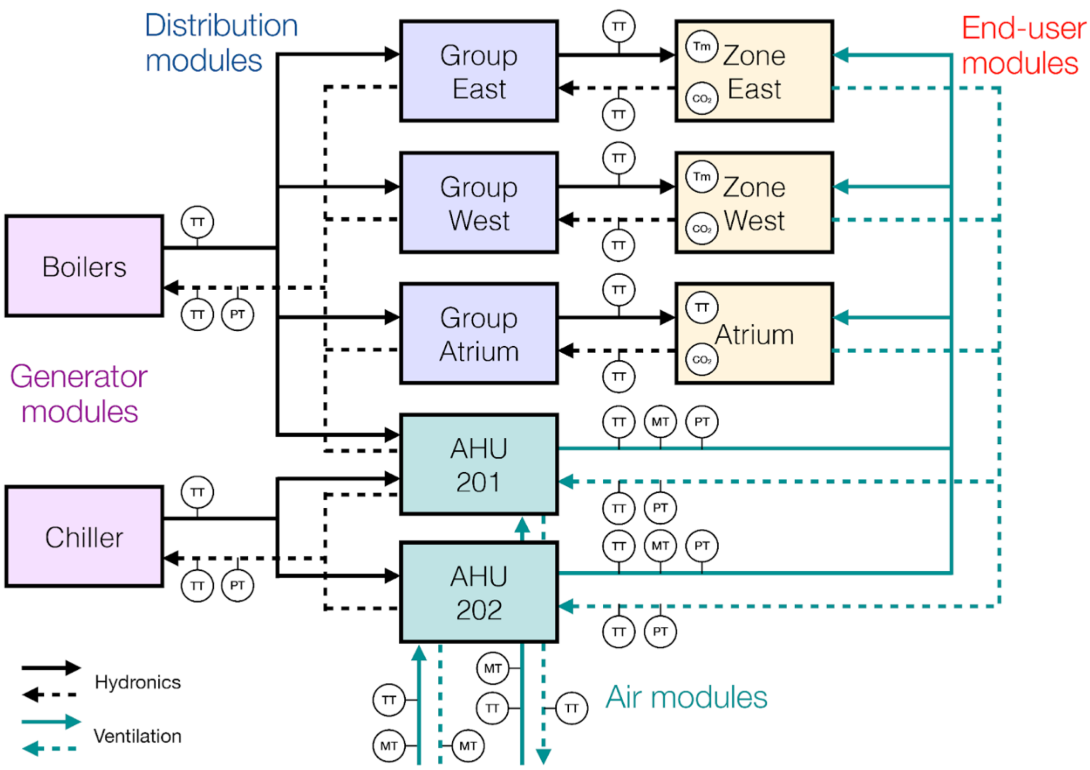

***Figure 1**. Simplified schematic representing the main aggregated systems in the building, along with the existing temperature (TT), pressure (PT), moisture (MT) and CO_2 sensors in the case study building.*

The resulting aggregated diagram for the case study building in the Netherlands is shown in Fig. 1. The case study is a seven-floor office building equipped with two boilers, one chiller and two AHUs, only one of which has a heating coil. Three distribution groups supply hot water to the radiators in three zones: East, West and Atrium. Cooling is delivered by a chiller to the AHUs, which both supply all three zones. The ventilation is controlled by CO_2 sensors in each room, and Temperature sensors have been installed across the majority of floors within each zone, enabling precise monitoring and analysis of thermal conditions.

In developing the DBN, the list of all possible faults was defined first, similar to Verbert et al. (2017). The HVAC systems are equipped with temperature, pressure and moisture sensors, but there are no flow rate sensors in the systems. Due to this, no Energy Performance or Balance symptoms can be established for the case study building (Wang et al. 2022). Component faults were defined based on the aggregated system definitions in Fig. 1, leading to generic faults such as "AHU 201 fault". Control faults were defined based on the documentation for the building automation systems. Symptoms were defined by assessing which sensors downstream from any given faulty piece of equipment would be affected by the fault. For example, a generic "AHU 202 fault" might lead to temperature and/or pressure symptoms on the supply side, temperature and/or CO_2 symptoms in the zones, and return temperature and/or pressure symptoms in the AHUs and distribution groups.

Even for aggregated building systems as implemented in this case study, the resulting DBN is complex, as shown in Fig. 2. Each aggregated group includes a corresponding control system (except for the air distribution group). The zone groups include room level manual controls, namely the ability of occupants to adjust the radiators and to open the windows. These are included in order to allow the incorporation of occupant behaviors into the diagnosis method later on. Every sensor used for symptom detection is also connected to a potential sensor bias fault. The list of symptoms considered in this DBN is summarized in Table 1.

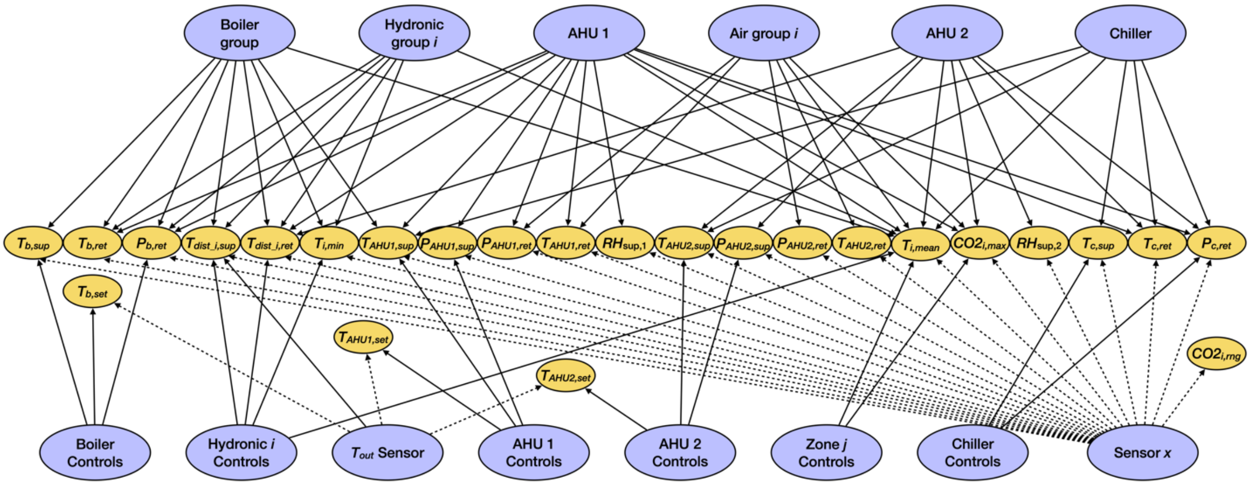

***Figure 2**. DBN for the case study HVAC system. Sensor fault edges are shown as dotted lines to improve readability. Nodes including the subscript* i *imply that there are actually three nodes: East, West, and Atrium. Subscript* j *implies two nodes: East and West. Subscript* x *replaces the name of every sensor used as a symptom.*

Having defined the DBN structure and relationships between fault and symptom nodes, the only remaining task is to assign prior probabilities to the fault nodes and conditional probability tables to the relationships between faults and symptoms. This is, however, the most difficult task for complex systems, and studies have shown that it is unreliable to directly generate the conditional probabilities for each state of the evidence node when there are more than four fault nodes (Chen Y et al. 2022). In order to reduce the number of parameters that have to be estimated, we use Noisy-OR gate nodes as done by other works in the literature (Taal and Itard 2020, Chen Y et al. 2022, Wang et al. 2024). For demonstration purposes, all prior and conditional probabilities were assumed based on expert knowledge as follows: component fault probability 2%; control fault probability 5%; sensor fault probability 2%; conditional probability (probability that fault is absent if symptom is present) 5%; and LEAK probability 5%. The sensitivity analysis carried out by Taal and Itard (2020) showed that the results of the diagnosis were adequate even if different prior and conditional probabilities were assumed. Nevertheless, the probabilities assumed for this whole building DBN may later be adjusted based on measured data and on-site experiments.

Table 1. *List of symptoms defined for the DBN.*

Variable	*Symptom description*	*Faulty state definition*
$T_{b,sup}$	Boiler supply temperature	$\lvert T_{b,sup} - T_{b,set}\rvert > \varepsilon_1$
$T_{b,set}$	Boiler setpoint temperature	$\lvert T_{b,set} - T_{b,set,calc}\rvert > \varepsilon_1$
$T_{b,ret}$	Boiler return temperature	$\lvert T_{b,sup} - T_{b,ret}\rvert > \varepsilon_3$
$P_{b,ret}$	Boiler return pressure	$P_{b,ret} \leq \varepsilon_4$
$T_{c,sup}$	Chiller supply temperature	$\lvert T_{c,sup} - T_{c,set}\rvert > \varepsilon_2$
$T_{c,ret}$	Chiller return temperature	$\lvert T_{c,set} - T_{c,set,cal}\rvert > \varepsilon_2$
ΔT_c	Chiller sensor bias (chiller off)	$\lvert T_{c,sup} - T_{c,ret}\rvert > \varepsilon_2$
$P_{c,ret}$	Chiller return pressure	$P_{b,ret} \leq \varepsilon_5$
$T_{dist,i,sup}$	Hydronic group *i* supply temp.	$\lvert T_{dist,i,sup} - T_{dist,i,set}\rvert > \varepsilon_1$
$T_{dist,i,ret}$	Hydronic group *i* return temp.	$\lvert T_{dist,i,sup} - T_{dist,i,ret}\rvert > \varepsilon_3$
$T_{n,sup}$	AHU *n* supply temperature	$\lvert T_{n,sup} - T_{n,set}\rvert > \varepsilon_2$
$T_{n,set}$	AHU *n* setpoint temperature	$\lvert T_{n,sup} - T_{n,set,calc}\rvert > \varepsilon_2$
$T_{n,ret}$	AHU *n* return temperature	$\lvert T_{n,ret} - T_{zone,i,min}\rvert > \varepsilon_2$
$P_{n,sup/set}$	AHU *n* supply/return pressure	$P_{n,sup/ret} \leq \varepsilon_n$
$T_{i,min}$	Zone *i* minimum temperature	$T_{i,min} < \varepsilon_6$
$\overline{T_i}$	Zone *i* temperature comfort range	$\overline{T_i} \in [\varepsilon_7, \varepsilon_8]$
$\overline{CO2_i}$	Zone *i* CO_2 sensor bias	$\overline{CO2_i} \in [\varepsilon_9, \varepsilon_{10}]$
$CO2_{i,max}$	Zone *i* maximum room CO_2	$CO2_{i,max} > \varepsilon_{11}$
$RH_{n,sup}$	AHU *n* relative humidity (comfort range)	$\overline{RH_{n,sup}} \in [\varepsilon_{12}, \varepsilon_{13}]$

ε_1=3K, ε_2=1K, ε_9=360 ppm, ε_{10}=3000 ppm (Taal and Itard, 2020); ε_3=20K (installation plans); ε_4=90kPa, ε_5=40kPa, ε_6=11°C, ε_{11}=1200 ppm, ε_{201}=185 Pa, ε_{202}=177 Pa (control documents); ε_7=19°C/22°C, ε_8=25°C/27°C [winter/summer], ε_{12}=30%, ε_{13}=70% (building report).

RESULTS

In order to test the proposed DBN, BMS data for a two-year period (2022-2023) was used to detect symptoms in the whole building system. The frequency of detection for every symptom considered over this time period is shown in Fig. 3. Three different symptom detection timescales were considered: sub-hourly detection (i.e., all samples in the dataset were used), hourly and yearly. Furthermore, two hourly detection cases were considered. In one, whether a symptom was present or not in a given hour was estimated based on the mode of all symptoms detected during an hour. In the other case, thresholds were used: symptoms were only considered present if they were detected for two timesteps in a row, at least three times during that hour. The latter method was also used for daily detection. The detection results show that on a daily basis, a much larger share of the samples was faulty, which is expectable since many systems are off for much of the day, and therefore no symptoms can be detected for a large number of timesteps.

The most common symptom was CO_2 measurements being outside of the acceptable range. This is due to a number of sensors on all building zones that appear to need recalibration, as they are constantly below the CO_2 concentration for outdoor air. In order to avoid excessive computational expense, CO_2 and room temperature symptoms were aggregated by zones, therefore even if just a few room CO_2 sensors need calibration, the symptom for the entire zone will be detected. Building operators would subsequently need to explore which sensors are actually faulty.

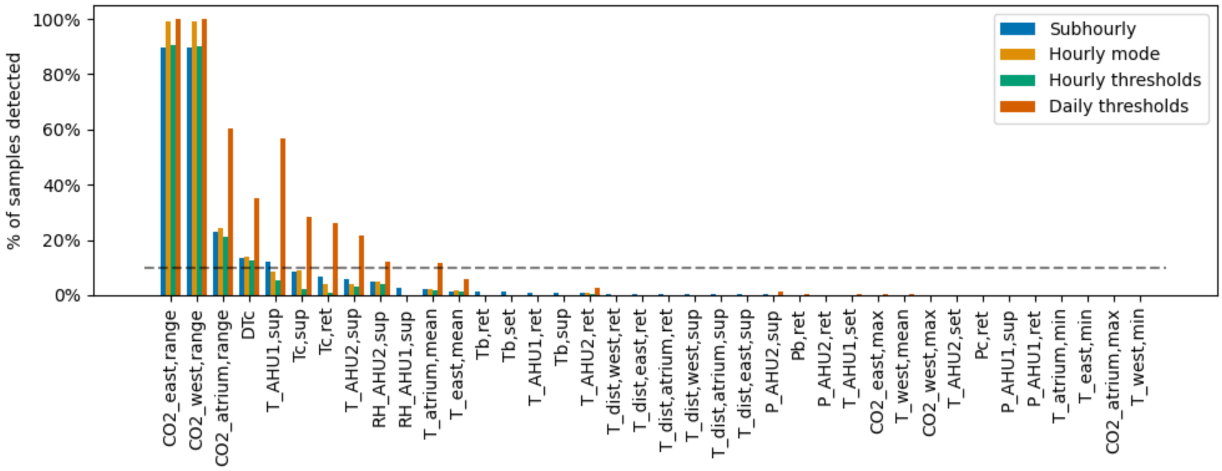

Figure 3. *Symptom detection frequency over two years for four detection timescales.*

A number of discrepancies between the building system documentation and the actual operation were also found. For example, while the nominal values for the chiller supply and return temperatures were listed as 6–7°C and 13°C, respectively, the mean and median values for the measured temperatures were 11°C and 14°C, respectively. Similarly, AHU setpoint curves appear to have been modified over time, as shown in Fig. 4, possibly in order to reduce the heating demand in winter. These discrepancies led to a large share of samples being detected as symptoms, in spite of these being the expected operating conditions at the time of the measurement. Therefore, a procedure was developed in order to first assign the current AHU setpoint curve for a given basis and then use this adjusted curve for symptom detection. While setpoint symptoms are rarely encountered, AHU supply temperature symptoms remain common. For chillers, new nominal supply and return temperatures of 11°C and 14°C were assumed, however, supply temperature symptoms remain common. On the other hand, a chiller supply and return temperature difference greater than 1°C while the chiller is off (symptom *DTc*) is detected very often, meaning that there might be biased or faulty temperature sensors in the chiller. The AHUs have no humidity control, so supply air relative humidity symptoms are also often detected.

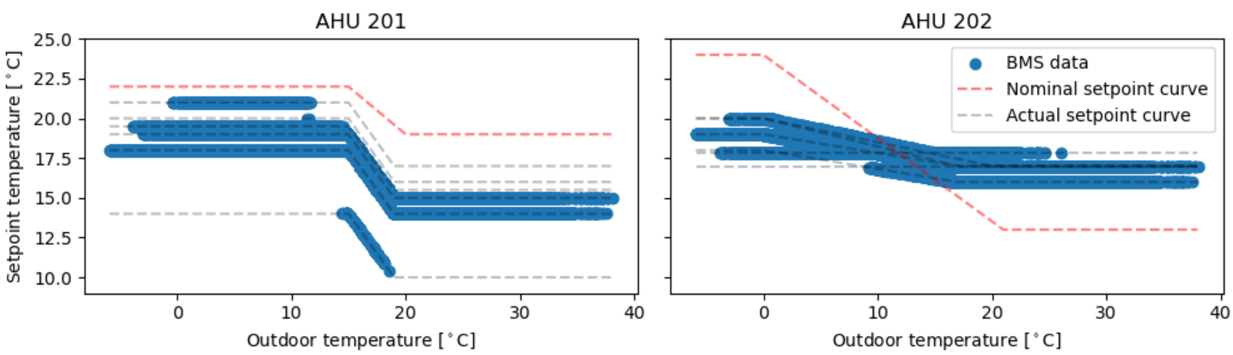

Figure 4. *Comparison between the AHU setpoint temperatures in the BMS records and the setpoint curves according to the control documents. The daily setpoint curves used during symptom detection are shown in gray.*

The final step in the FDD process is the diagnosis of the faults leading to the symptoms observed. For demonstrative purposes, we present here the results of fault detection on an hourly basis, which is a timescale short enough for building operators to take action in real-time applications, but also long enough to minimize transient effects. A summer week in 2023 was selected as an example. A posterior probability threshold of 15% was selected as done by Chen Y et al. (2022). The posterior probabilities calculated by the DBN for the week in question are shown in Fig. 5. Only faults for which the maximum posterior probability during this week exceeded 0.5% are shown. As discussed for the symptom detection step, the CO_2 sensors are consistently detected as faulty, further stressing the need for further investigation of the precise sensors that need to be calibrated again. A number of chiller-related symptoms are also detected. This once again relates to the incorrect supply temperatures observed during system operation, but also to the excessively high temperature difference between supply and return side when the chiller is not operational. Therefore, during chiller operation incorrect controls are diagnosed by the DBN as the most likely cause for discrepancy, while the return temperature sensor is detected as possibly faulty when the cooling systems are off.

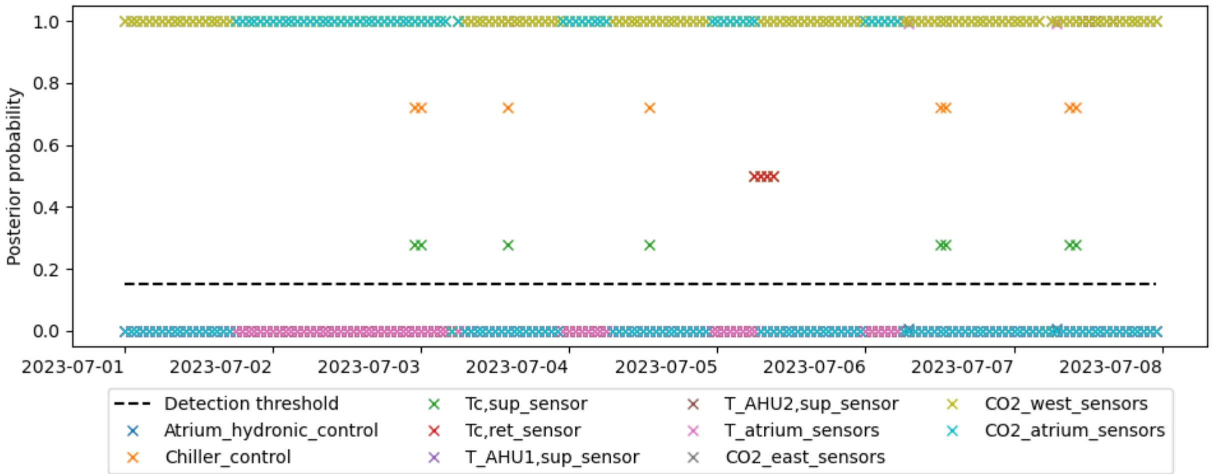

__Figure 5__. Posterior probabilities of selected faults for the first week of July 2023. Only faults with a posterior probability of at least 0.5% for any timestep are shown.

DISCUSSION AND FUTURE WORK

The DBN presented here represents a first step towards a whole building implementation of FDD. The demonstrative results presented seem to indicate that the network is able to detect the most likely faulty components at building scale, which warrant further inspection from building operators. These include both likely component degradation faults (CO_2 and chiller return temperature sensors) and operational faults likely caused by inadequate documentation of the operational strategy of the building (chiller setpoint temperatures). This underlines the need for further investigation into the actual operation of the case study building, while at the same time presenting an example of the construction of FDDs is strongly influenced by the system being investigated and the challenge of transferability.

A key aspect of the development of this DBN was the incorporation of zone-level effects and comfort symptoms in the diagnosis. A data collection campaign is currently being developed in order to collect air quality data through sensors and occupant feedback through a smartphone application in order to expand the DBN to account for end users' behaviors as potential faults in the building system and occupant feedback as possible symptoms of malfunctioning systems. While the incorporation of building occupants as a source of additional information in FDD has been proposed before (Taal and Itard 2020), no such implementation can be found in the literature. This paper therefore represents an initial step towards FDD methods that can support both building system performance and occupant comfort.

CONCLUSION AND IMPLICATIONS

A methodology to develop a DBN for a whole HVAC system was presented. The methodology is loosely based on the 4S3F method and focuses on cross-level fault diagnosis, accounting for all systems in the buildings as well as the three building zones that are served by those systems. The DBN's symptom detection capabilities were shown, which showed the building's CO_2 sensors and chiller as the most problematic systems in the building. During fault detection for a sample week in the year, the CO_2 sensors were again found to be faulty, and both the chiller controls as well as the chiller temperature sensors were detected as possibly faulty. Due to the incorporation of building zones and comfort-related symptoms in the DBN, ongoing work is being carried out to include occupant feedback and behavior as potential symptoms and faults in the building system.

ACKNOWLEDGEMENTS

This research was carried out as part of the Brains for Buildings project, sponsored by the Dutch grant program for Mission-Driven Research, Development and Innovation (MOOI), which was established by the Dutch Ministry of Economic Affairs and Climate Change and the Ministry of the Interior and Kingdom Relations and executed by RVO Netherlands Enterprise Agency. The authors would like to thank Dr. Arie Taal for his valuable suggestions in constructing the DBN.

REFERENCES

Chen J, Zhang L, Li Y, Shi Y, Gao X, and Hu, Y. 2022. A review of computing-based automated fault detection and diagnosis of heating, ventilation and air conditioning systems. *Renewable and Sustainable Energy Reviews* 161: 112395.

Chen Y, Wen J, Pradhan O, Lo LJ, and Wu T. 2022. Using discrete Bayesian networks for diagnosing and isolating cross-level faults in HVAC systems, *Applied Energy* 327: 120050.

Katipamula S. and Brambley MR. 2005. Methods for Fault Detection, Diagnostics, and Prognostics for Building Systems – A Review, Part I. *HVAC&R Research* 11(1): 3–25.

Mirnaghi M.S. and Haghighat F. 2020. Fault detection and diagnosis of large-scale HVAC systems in buildings using data-driven methods: A comprehensive review. *Energy and Buildings* 229: 110492.

Schein J, Bushby ST, Castro NS, and House JM. 2006. A rule-based fault detection method for air handling units, *Energy and Buildings.* 38(12): 1485-1492.

Taal A, Itard L, and Zeiler W. 2018. A reference architecture for the integration of automated energy performance fault diagnosis into HVAC systems, *Energy & Buildings* 179: 144–155.

Taal A and Itard L. 2020. P&ID-based symptom detection for automated energy performance diagnosis in HVAC systems, *Automation in Construction* 119: 103344.

Verbert K, Babuška R, and De Schutter B. 2017. Combining knowledge and historical data for system-level fault diagnosis of HVAC systems. *Engineering Applications of Artificial Intelligence* 59: 260–273.

Wang Z, Lu C, Taal A, Gopalan S, Mohammed K, Meijer A, and Itard L. 2024. Bayesian network-based fault detection and diagnosis of heating components in heat recovery ventilation, Proceedings of Roomvent 2024, Stockholm, pp 417.

Wang Z, Meijer A, and Itard L. 2022. 4S3F Diagnostic Bayesian network-based fault detection and diagnosis of heating components in heat recovery ventilation, Proceedings of CLIMA 2022, Rotterdam, Netherlands.