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Extension of the 4S3F HVAC B28 framework for identifying undefined end-user use and poor indoor climate quality

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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. However, most works on building system FDD focus on the individual component scale, neglecting the complex interactions between building systems and the cascading effects of subcomponent faults. Therefore, holistic FDD approaches that can account for all major building systems and their interactions are needed. Diagnostic Bayesian Networks (DBN) offer a particularly promising approach for whole-building FDD due to their robustness, flexibility and scalability. This paper presents a methodology for building a DBN for whole-building FDD using a combination of knowledge-based and data-driven methods, along with its testing, validation, and application in a case study office building in the Netherlands. The methodology uses aggregated representations of all major building systems to detect which faulty subcomponents need further investigation. The DBN's performance and the effects of input parameter assumptions were tested both qualitatively using historical data and quantitatively using experimental data obtained by introducing faults into the building system controls. The results using historical data demonstrate the DBN's ability to detect various faults in the building systems, raising significant issues with the building's sensor infrastructure. Despite these issues, the evaluation using experimental data showed that the DBN achieved a classification rate of 85%. Finally, the DBN was demonstrated by detecting a real-world AHU fault. This work advances the development of a validated whole-building HVAC system FDD using DBNs.

Human-informed Building Automation: Enhanced Whole-Building System FDD

Key words: Fault Detection and Diagnosis, Diagnostic Bayesian Networks, Thermal comfort, Occupant behavior

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Modern building systems generate vast sensor data for monitoring and control, yet faults in sensors, controls and documentation often undermine performance. Using Diagnostic Bayesian Networks (DBN)[1], this study demonstrates whole-building fault detection and diagnosis (FDD) in a Dutch office and explores how occupant feedback can complement unreliable sensor data for resilient building operation.

Despite the opportunities afforded by the vast amounts of data collected by modern building managements systems (BMS), the literature shows that 5–30% of energy in commercial buildings is wasted due to problems associated with controls [1]. Whole-building fault detection and diagnosis (FDD) can help reduce energy waste, improve comfort and support predictive maintenance by identifying operational faults in highly-integrated, complex building systems, and the cascading effects that arise from a fault in one component to another. Diagnostic Bayesian Networks (DBN) provide a promising solution for whole-building FDD due to their robustness to uncertainty, scalability and flexibility [2]. They have proven to be reliable at detecting cross-level faults in whole building systems [3] and able to detect control and component faults in spite of faulty sensors [4].

As part of the *Brains4Buildings* project, we have investigated DBN applications at the component to building scale. A key challenge in DBNs, however, is defining adequate baselines to different "normal" and "faulty" operation. This is typically done based on expert knowledge and building documentation,

1 A diagnostic Bayesian network method is a technique that uses a probabilistic graphical model to diagnose faults by inferring the probability of a specific fault occurring based on observed symptoms. It models the relationships between potential faults and symptoms with nodes and directed edges, allowing for a transparent and robust reasoning process under uncertainty. This approach is widely used for fault diagnosis in complex systems like building energy systems and is applicable to various industries.

however these documents might often be incomplete or outdated. Furthermore, building sensor networks can be unreliable or poorly maintained, introducing uncertainty into the FDD results. Combined, this might lead system operation to diverge from design specifications and might not match the desired indoor air quality (IAQ) during operation. Incorporating humans as sensors in whole building FDD can therefore help to maintain desired IAQ conditions [5].

This article presents the development of a DBN for whole-building FDD for an office building in the Netherlands (**Figure 1**) and its expansion to incorporate occupant feedback. In the first part of the study [6], the whole-building DBN was used to successfully identify faults during building operation, but the analysis revealed that the building's sensor infrastructure itself suffered from numerous faults. Therefore, in the second part [7], we explored how building occupants could serve as "human sensors", providing feedback on indoor environmental quality to complement unreliable sensor data for resilient building system operation. Together, these studies outline a new direction for FDD: one where occupant experience enriches data-driven fault detection, bridging the gap between building automation and the people who occupy the spaces it controls.

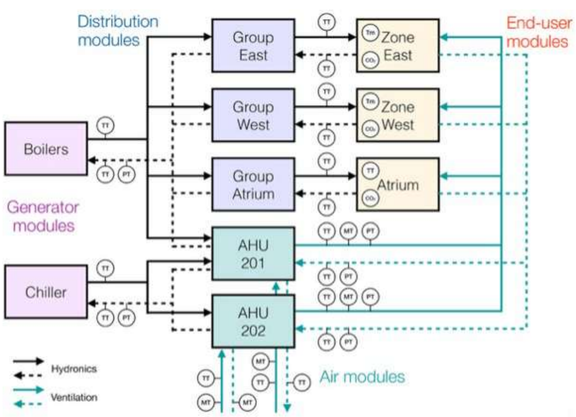

Figure 1. Simplified schematic P&ID (bottom) of the case study building.

Case Study: An Office Building in Delft

The methods were tested in a seven-floor office building equipped with two boilers, one chiller, and two AHUs supplying three thermal zones (East, West and Atrium). The system was monitored through temperature, pressure, humidity and CO_2 sensors linked to a Building Management System (BMS). In order to construct the whole-building DBN, building systems were first aggregated at the component and zone level (**Figure 2**). Generic faults to each of these components were then defined, and a list of detectable symptoms for each of these faults were defined based on the available sensor infrastructure. Although the building had extensive instrumentation, flow rate sensors were missing, such that no energy performance faults could be detected.

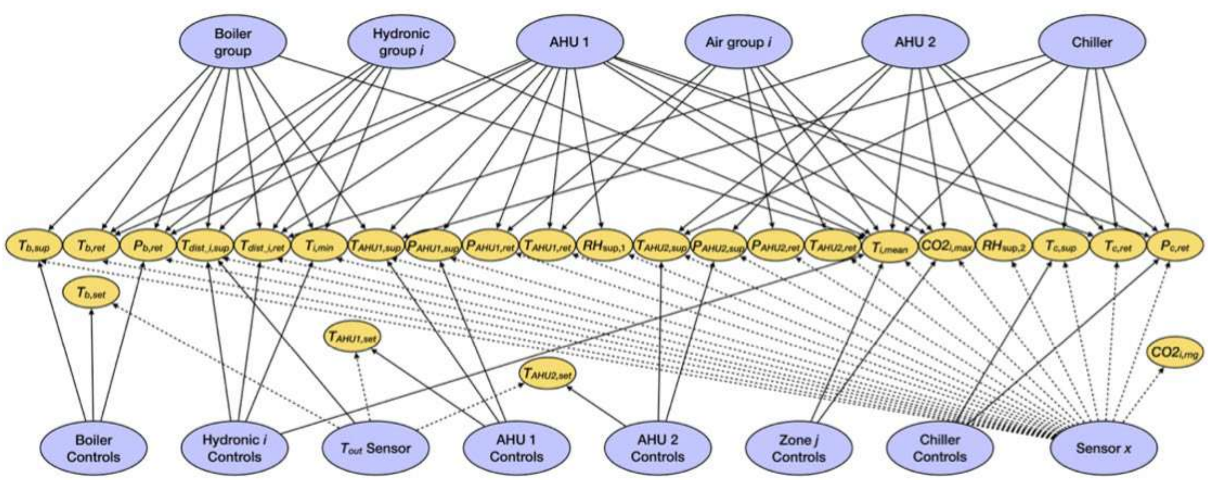

Figure 2. DBN structure for whole-building system FDD for the case study building. Sensor fault edges are shown as dotted lines to improve readability. i: East, West, and Atrium; j: East and West; x: each sensor used as a symptom.

Whole-Building DBN

The DBN structure (**Figure 2**) represents the building as a set of interconnected groups: boilers, chillers, hydronic circuits, ventilation units and thermal zones. Each group can exhibit certain symptoms (e.g., abnormal temperature differences, pressure drops, CO_2 levels out of range) that may result from different faults (e.g., component malfunction, control failure, or sensor bias). Using probabilistic reasoning, the DBN estimates which faults are most likely at any given time based on the evidence from available sensors.

Fault diagnosis based on historical BMS data

The DBN was used to detect faults in the building systems based on operational data during a period of two years (2022–2023). Fault detection results during a sample week in July 2023 are shown in **Figure 3**. The DBN was able to detect recurring anomalies, but it also exposed a recurrent issue with the building's sensors, in particular the CO_2 sensors used to control ventilation in each office. Indeed, a number of sensors were found to give readings below the outdoor CO_2 concentration of 400 ppm, which would indicate that the sensors need recalibration. Similar issues were observed in chiller temperature readings, where differences between supply and return lines were inconsistent with expected performance. Since the CO_2 sensors are used to control the building's AHUs, which in turn deliver cooling from the chiller, potential cascading faults in these AHUs were also detected.

Despite the DBN's technical robustness, the observed issues in the building's sensor infrastructure increase uncertainty in the detected faults. Furthermore, the building's ventilation systems are controlled based on the measured CO_2 concentration, issues with these sensors could contribute to poor comfort-related performance both in terms of IAQ and unmet thermal preference (TP). Indeed, over the summer of 2024 facilities management observed an increase in complaints from users. Such feedback from users can be a valuable source of information for FDD [4], allowing systems to react to user preferences even when sensor-based control strategies might be operating as intended.

Occupants as Sensors

The use of building documentation as a basis for DBN development assumes that "correct" operation means meeting predefined comfort criteria specified in the HVAC system's design documents. In practice, however, occupants' expectations may differ significantly from those assumptions and may diverge over time. Therefore, even during fault-free operation, building systems might not be able to provide for

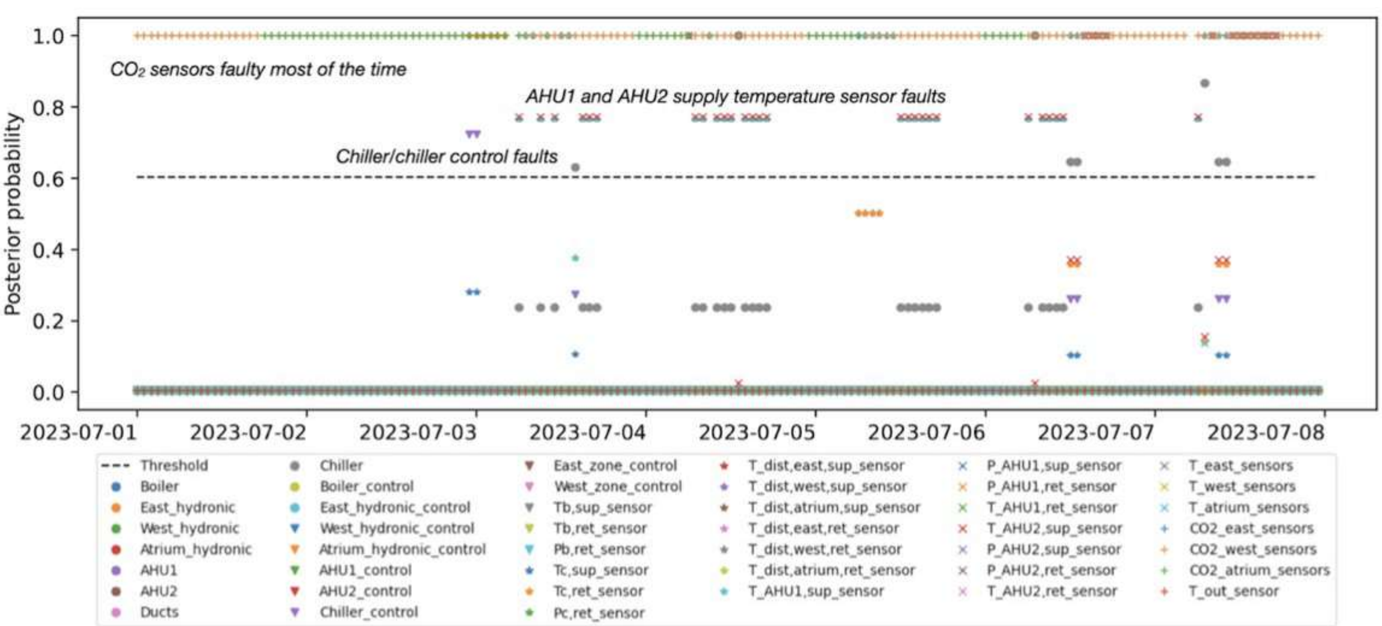

Figure 3. Fault probabilities for the first week of July 2023. Only faults with a posterior probability² of at least 50% for any timestep are shown.

2 Posterior probability is the updated probability of an event after new evidence is considered. It is calculated by using Bayes' theorem to combine a prior probability (the initial probability before evidence) with the likelihood of the evidence. This process allows for a revised, more informed probability that takes all available information into account.

user comfort, which is ultimately the goal of HVAC systems. We explored incorporating occupant feedback into our DBN approach in two ways. First, comfort feedback provides direct information on the performance of the building, as occupant discomfort is a symptom of inadequate operation. At the same time, occupant behaviors can also be faults in operation, for example if occupants leave windows open during heating season.

To explore these possibilities, we collected feedback from occupants in the same Delft office building in September and October 2024, immediately after the aforementioned complaints. Fifteen participants were recruited and asked to report their comfort and indoor environment perception using a smartphone app [8]. They could indicate whether they felt too warm or cold, perceived poor air quality, or had adjusted their windows or radiators, among other comfort-related behaviors. Each participant's office was equipped with a small set of additional sensors measuring temperature, humidity, CO_2 and occupancy every five minutes. This allowed comparison between objective environmental data and subjective feedback.

This information was incorporated into the DBN both as potential symptoms and faults in system performance, as shown in **Figure 4**. Here, only comfort related symptoms and faults are included for legibility, but every other node shown in **Figure 2** is also part of this DBN. Occupant feedback was incorporated into the DBN at three levels of additional information:

- **Case 1:** Only the original BMS data were used, with symptoms and occupant control faults aggregated by building zone.
- **Case 2:** Data from the office-level sensors were added, so that symptoms and occupant control faults are at office level.
- **Case 3:** Subjective feedback used to define comfort-related faults and self-reported window and radiator operation behaviors as office-level occupant control faults.

The integration of occupant data allows the model to reason probabilistically about whether discomfort was caused by system malfunction (e.g., AHU underperforming) or by occupant actions (e.g., an open window short-circuiting the heating).

Fault diagnosis during occupant data collection

Again, the DBN was used to assess building system faults during the period when occupant data was collected (**Figure 5**). In this section, unlike the previous one, only comfort-related symptoms are considered, although the DBN is still able to detect all other symptoms defined at building scale. In Case 1, when fault detection was only carried out using BMS data, comfort-related faults are restricted to detecting whether the expected comfort ranges are met. Likewise, only system faults can be detected at this level, and therefore the most likely causes found for CO_2- and relative humidity-related symptoms are the CO_2 sensors and AHU operation, respectively.

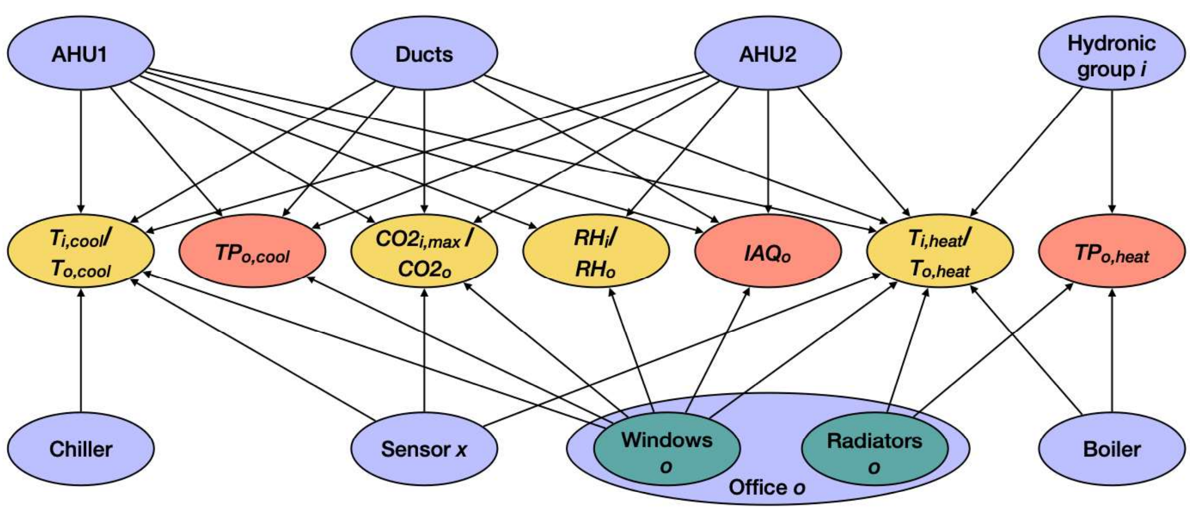

Figure 4. Simplified DBN including occupant feedback and behavior. Heating and cooling modes are shown as separate nodes. i: East, West; o: each office.

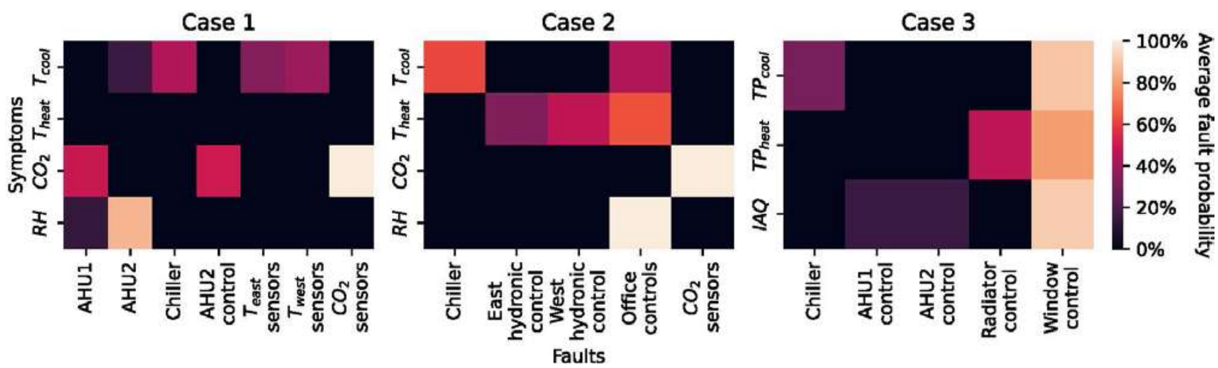

Figure 5. Average fault probability for each fault leading to a comfort-related symptom during timesteps where occupants expressed discomfort.

In Case 2, the incorporation of room-level measurements of these parameters confirms that CO_2 sensors are giving incorrect readings, but also raises occupant-related controls as a potential explanation for relative humidity symptoms. In Case 3, where occupant feedback was also incorporated, occupants' window operation actions appear as the most likely explanation for unmet TP and self-reported IAQ perception. This would seem to indicate that building systems are not able to adequately provide for occupants' subjective preferences, but users' behavior could also better support their comfort.

Conclusions

FDD can significantly contribute to resilient building operation, allowing automated response to inadequate building performance. However, FDD methods require detailed documentation, which might be missing, incomplete or outdated, as well as reliable sensing infrastructure to represent building operation. DBNs offer a promising solution to the problems raised by inadequacies in each of these, as they are able to deal with uncertainty in sensor measurements and their flexibility allows further information to be incorporated when available. However, they still require a hard definition of "normal" operation, which can be difficult to specify given personal differences in occupant preferences and their change over time. Occupant feedback can therefore help DBNs adjust to these changing preferences over time and contribute to human-in-the-loop building automation.

At the same time, it is infeasible to expect occupants to continually self-report their preferences and behaviors in the built environment, as survey fatigue will eventually cause building occupants to stop providing information over time. Therefore, in order to allow occupant preferences to continue to be represented over time, work is ongoing on the development of personalized comfort models, data-driven algorithms that predict individual comfort preferences based on previous feedback, for the case study building [8]. By incorporating these models to the whole-building DBN, comfort-related symptoms could be inferred even when no explicit feedback is available, further improving real-time fault detection.

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