Physics-based Dynamic Bayesian Network for Fault Detection and Diagnostics in Building HVAC Systems

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ABSTRACT

Heating, ventilation and air conditioning (HVAC) systems, as key components in commercial building air conditioning systems, significantly impact indoor environmental quality and building energy efficiency. This paper focuses on developing a physics-based dynamic Bayesian network (PBDBN) that integrates a dynamic scheme for detecting and diagnosing faults in building HVAC systems. Contrary to traditional data-driven BN methods that infer structure from statistical processes, our approach constructs the BN structure grounded on physical equations, with coefficients determined through data-driven processes. Moreover, unlike reference model-based BN methods that keep the building model separate from the BN structure, our approach significantly simplifies and incorporates the building model directly into the BN structure. A detailed structure construction of the proposed PBDBN is demonstrated in this paper. The model is evaluated by injecting minor sensor faults into the HVAC system. The results show that the proposed PBDBN-FDD has significant improvements compared to the existing DBN-FDD methods.

1. INTRODUCTION

The faults in building heating, ventilation and air conditioning (HVAC) systems refer to the failures of sensors, components, controlled devices and system operations. Fault detection and diagnostics (FDD) technologies are utilized to first determine and then identify and localize these faults in buildings and therefore are critical to ensure the reliable operation and performance of buildings. With the increasing adoption of building automation systems (BAS), FDD technologies have seen significant advancements in the past decade, particularly in delivering fast, timely, and intelligent responses for building HVAC systems (Z. Chen *et al.*, 2023).

Conventional FDD approaches are based on expert rule-based (knowledge-driven) methods. Recently, the focus has shifted to model-referenced methods, data-driven methods, and hybrid methods that integrate expert knowledge, model simulation, and building operation data. However, these advanced FDD approaches, such as data-driven FDD or model-referenced FDD, demand more precise and comprehensive data support. This requirement often presents challenges in real-building applications due to incomplete information and uncertainty (Z. Chen *et al.*, 2023). Moreover, each building's unique boundary conditions, such as weather, occupancy, and internal load schedules, indicate that an FDD approach developed for one building may not be suitable for another. Furthermore, accurate FDD methods for BAS, aimed at detecting minor faults in sensors and controllers, are still limited and require further investigation. These limitations compromise the feasibility and wider applicability of advanced FDD approaches with various building HVAC systems, consequently preventing their adoption as alternatives or complements to existing rule-based FDD approaches. To enhance the robustness, accuracy, and versatility of FDD tools for CAI applications, a hybrid method that combines physical models with data-driven models presents a promising solution.

Among the various advanced FDD methods, the Bayesian Network (BN) stands out as one of the most prevalent tools. It is typically categorized as a data-driven method, as both its structure and parameters can be derived from building operation data (data-driven BN). However, the structure of a BN can also be exclusively based on expert knowledge (knowledge-based or rule-based BN). This versatility makes BN particularly effective for developing innovative FDD approaches that integrate expert knowledge, model simulation, and operational data, thereby enhancing the accuracy, efficiency, and versatility of advanced FDD systems.

Existing BN FDD models for buildings typically focus on either the component level (Xiao *et al.*, 2014) or the system level (Y. Chen *et al.*, 2022). Many of these models are developed using data-driven approaches, which share several shortcomings with general data-driven FDD methods, such as the need for extensive fault data for training, limited transferability and scalability across different building systems, challenges in detecting minor errors, and difficulties in interpreting the models in terms of their physical meaning (Z. Chen *et al.*, 2023). To reduce dependence on extensive building data, another type of BN-FDD model has been developed based on referenced building models. This approach uses a reference-building model to generate baseline values, which are then compared with monitored values; the residuals are used to detect faults (Wang *et al.*, 2021). The key advantage of this reference model-based BN is that it does not require fault data for training. However, this method demands high precision and accuracy from the reference model, and the complexity of establishing and computing these models for modern buildings with complex HVAC systems can be quite challenging, thus limiting the universality of this approach. Additionally, most recently developed BN FDD models are discrete BNs, while research on Dynamic Bayesian Networks (DBN) in building FDD remains limited (Shi *et al.*, 2018). Given the capability of DBN to identify minor but persistent errors, distinguishing minor sensor and component faults from system noise, further investigation into DBN-FDD for buildings is crucial, particularly for modern buildings integrated with BAS.

In this research, a novel BN-FDD is proposed which directly embeds the physical building model with a dynamic scheme. Unlike the data-driven BN approaches which learn the BN structure through the statistical process, this novel DBN determines the structure based on physical equations, though the coefficients in physical equations can be learned from the data-driven process. Unlike the reference model-based BN approaches which separate the building model from the BN structure, this novel DBN-FDD significantly simplifies the building model, and merges it inside the BN structure. Overall, the proposed DBN-FDD approach does not require complex building models and large amounts of data training compared with other advanced FDD. Moreover, it has the ability to detect minor sensor, controller, and component faults, and it can be readily transferred to various building systems combined with the data-driven method.

2. METHOD DESCRIPTION

2.1 PBDBN-FDD Overview

Compared with the existing BN-FDD, the proposed BN first embeds the physical building model within the BN structure, as depicted in Fig. 1. Correspondingly, the developed BN structure consists of the equation nodes representing the physical model, and the system coefficients can be estimated either by the building model or by the building operation data (data-driven), which makes this BN more flexible to be transferred to other buildings. Moreover, the sensor nodes and fault nodes are integrated with equation-based BN, which enables the BN to implement sensor bias and predict the sensor reading values based on the system states (hybrid equation-based BN). Owing to this, the proposed BN can detect and locate minor sensor faults. Furthermore, a dynamic scheme is applied in the developed BN to increase accuracy and eliminate the interference of system noises. Summarizing the above features, the proposed novel method can be refined as a physics-based dynamic Bayesian network FDD (PBDBN-FDD).

2.2 Physical Building Model

As illustrated in Section 2.1, physical models for building HVAC systems are fundamental to developing PBDBN. In this paper, the physical model is established based on a general air handling unit (AHU) of the building HVAC system working in the cooling mode, as shown in Fig. 2, where the thermal zone is modeled using thermal resistance-capacitance (RC) method, as demonstrated in Fig. 3.

Accordingly, the governing equations of the physical building model can be concisely described as

$$\mathbf{x}_{k+1} = f(\mathbf{x}_k, \mathbf{u}_k, \mathbf{d}_k), \tag{1}$$

where k and $k+1$ are the current and next time step respectively, $\mathbf{x}$ represents the system states including thermal zone temperature T_z, wall temperature T_w, return water temperature T_{rw} and supply air temperature T_{sa}. Moreover, $\mathbf{u}$ denotes the control variables such as supply water mass flow rate m_{sw}, supply air mass flow rate m_{sa}, supply water temperature T_{sw}, and fresh air ratio β. Furthermore, $\mathbf{d}$ refers to the disturbances consisting of solar heat gain Q_{rad}, internal heat gain Q_{ig} and ambient temperature T_o. Specifically, Eq. (1) can be further expressed as follows:

$$T_{z,k+1} = T_{z,k} + a_{11}T_{z,k} + a_{12}T_{w,k} + c_{11}\dot{m}_{sa,k}T_{z,k} + c_{14}\dot{m}_{sa,k}T_{sa,k} + d_{11}T_{o,k} + d_{12}Q_{rad,k} + d_{13}Q_{ig,k}, \tag{2}$$

$$T_{w,k+1} = T_{w,k} + a_{21}T_{z,k} + a_{22}T_{w,k} + d_{21}T_{o,k} + d_{22}Q_{rad,k}, \tag{3}$$

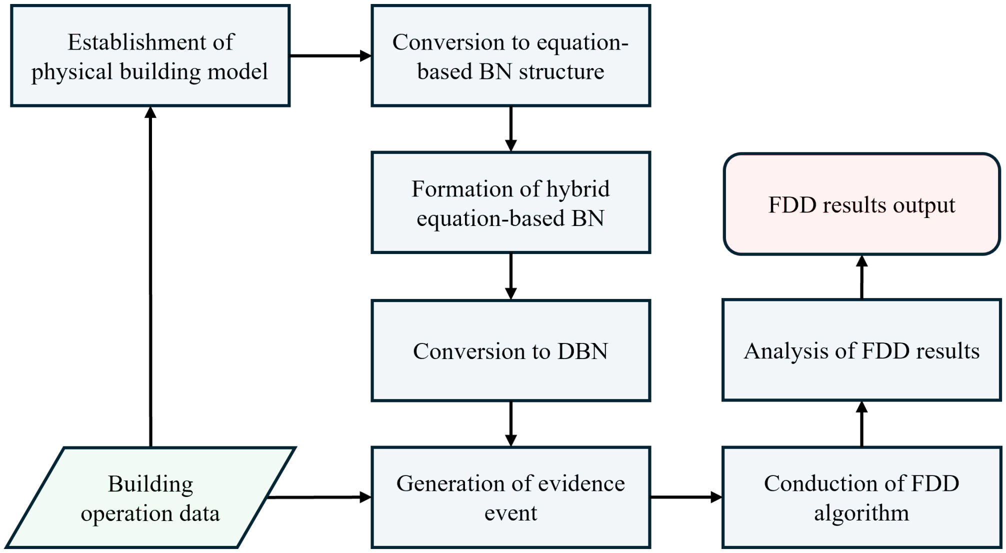

Figure 1: General method architecture of PBDBN FDD.

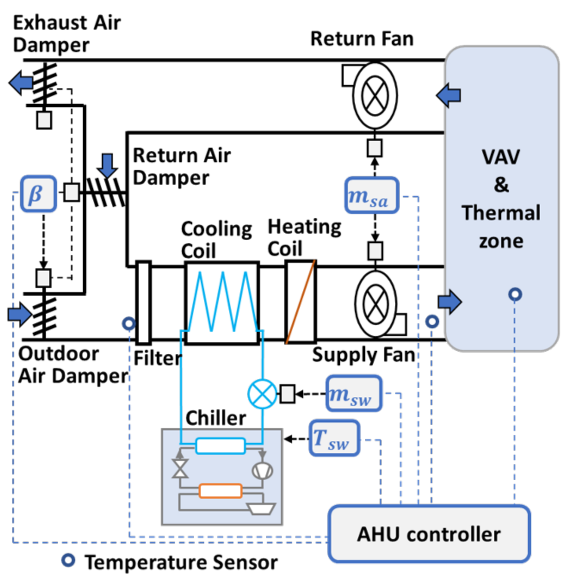

Figure 2: AHU system scheme.

$$T_{rw,k+1} = T_{rw,k} + a_{33}T_{rw,k} + a_{34}T_{sa,k} + b_{31}\dot{m}_{sw,k}(T_{sw,k} - T_{rw,k}), \tag{4}$$

$$T_{sa,k+1} = T_{sa,k} + a_{43}T_{rw,k} + a_{44}T_{sa,k} + b_{42}\dot{m}_{sa,k}\beta_k T_{o,k} + b_{43}\dot{m}_{sa,k}(1-\beta_k)T_{z,k} + c_{44}\dot{m}_{sa,k}T_{sa,k}, \tag{5}$$

where a_{ij}, b_{ij}, c_{ij} and d_{ij} are coefficients either calculated from the building system properties or trained by building operation data.

2.3 Equation-based Dynamic Bayesian Network

The interpretation of physical equations in Section 2.2 can be achieved through the equation-based BN method. According to Eq. (1), the building system states $\mathbf{x}_{k+1}$ at next time step $k+1$ can be predicted from the system states $\mathbf{x}_k$, control variables $\mathbf{u}_k$ and disturbances $\mathbf{d}_k$ at current time step k. Eqs. (2)–(5) that describing the evolution of the building system states, i.e., $\mathbf{x} = [T_z, T_w, T_{rw}, T_{sa}]$, are directly embedded into a dynamic BN structure with equation nodes

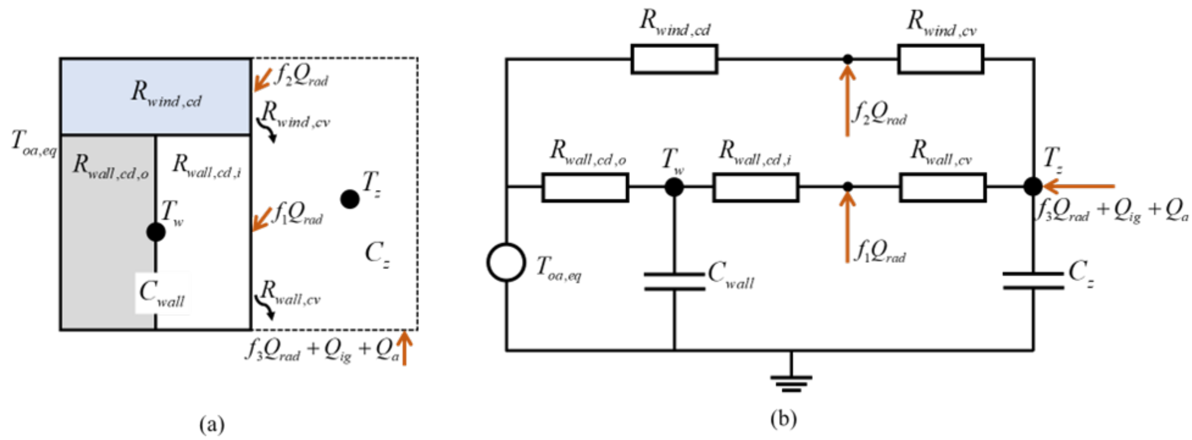

Figure 3: Thermal RC network: (a) Thermal zone window and wall model (b) Thermal RC model diagram.

denoted as blue circles. The definition of all state nodes $\mathbf{x}_{k+1}$ at time step $k+1$ can then be given as

$$\mathbf{x}_{k+1} = f(\mathbf{x}_k, \mathbf{u}_k, \mathbf{d}_k) + \mathcal{N}(0, \sigma_x^2), \tag{6}$$

where $\mathcal{N}(0, \sigma_x^2)$ is the normal distribution with mean at 0 and standard deviation σ_x for each system state. By adjusting σ_x, the normal distribution $\mathcal{N}(0, \sigma_x^2)$ can be tuned to account for the system noises.

The equation nodes transformed from the physical building model can predict the values of system states. However, to enable diagnostics of the system faults (e.g., sensor faults) based on the observations (building operation data), the BN structure should be further completed by adding equation nodes representing sensor readings and chance nodes denoting the various sensor faults. As illustrated by Fig. 4, equation nodes (dark blue) of sensors $\mathbf{S}$ and chance nodes (yellow) of sensor reading faults $\mathbf{F}$ are connected with the equation nodes of system states $\mathbf{x}$, control variables $\mathbf{u}$ and disturbances $\mathbf{d}$ for each time step. Additionally, binary chance nodes C are connected to fault nodes indicating the impact of recent calibrations on the probability of sensor faults.

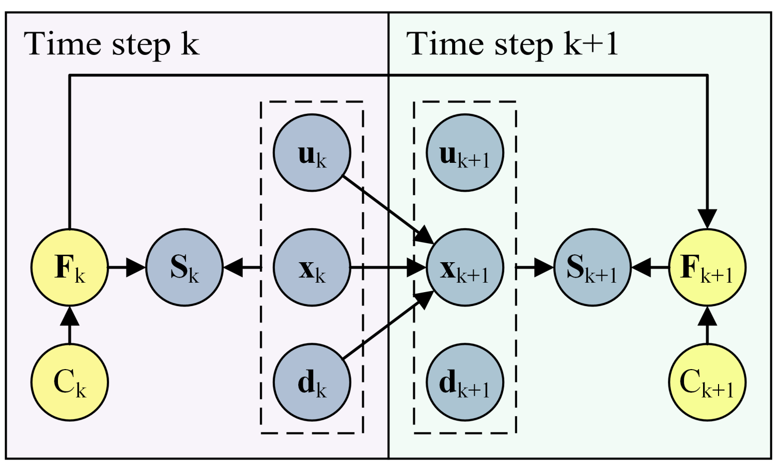

Figure 4: Hybrid equation-based dynamic Bayesian network between two-time steps k and $k+1$.

The equation nodes of sensors $\mathbf{S}$ are defined as

$$\mathbf{S} = \mathbf{x} + \mathcal{N}(0, \sigma_s^2) + f(\mathbf{F}), \tag{7}$$

where $\mathcal{N}(0, \sigma_s^2)$ is the normal distribution representing the sensor reading noises, and $f(F)$ is the conditional equation based on sensor fault nodes F, where the definition of F is provided in Table 1. Accordingly, $f(F)$ can be expressed

Table 1: Definition of sensor fault nodes **F**.

Recent calibration (node C)	Yes	No
Accurate	$P(Accurate\|Yes)$	$P(Accurate\|No)$
Extremely high (EH)	$P(EH\|Yes)$	$P(EH\|No)$
Mildly high (MH)	$P(MH\|Yes)$	$P(MH\|No)$
Extremely Low (EL)	$P(EL\|Yes)$	$P(EL\|No)$
Mildly high (ML)	$P(ML\|Yes)$	$P(ML\|No)$

as

$$f = \begin{cases} 0, & \mathbf{F} = \text{“Accurate”} \\ \mathcal{N}(\mu_{EH}, \sigma_{EH}^2), & \mathbf{F} = \text{“EH”} \\ \mathcal{N}(\mu_{MH}, \sigma_{MH}^2), & \mathbf{F} = \text{“MH”} \\ \mathcal{N}(\mu_{EL}, \sigma_{EL}^2), & \mathbf{F} = \text{“EL”} \\ \mathcal{N}(\mu_{ML}, \sigma_{ML}^2), & \mathbf{F} = \text{“ML”} \end{cases} \tag{8}$$

where the mean and standard deviation of the normal distribution at each fault state can be prescribed for each sensor.

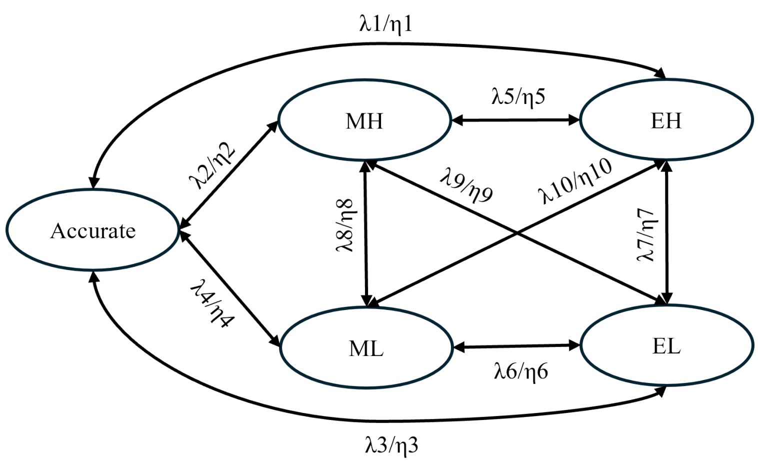

Figure 5: State transition diagram of sensor fault nodes F between two adjacent time steps k and $k + 1$.

Considering the typical sensor failure pattern, it may occur suddenly, or it may worsen gradually over time and persist until recalibrated. Therefore the relationship between the corresponding fault nodes across adjacent time steps k and $k + 1$ is connected as displayed in Fig. 4. To obtain the condition probability table (CPT) for node $\mathbf{F}_{k+1}$, the state transition relationship should be determined, as demonstrated in Fig. 5, where λ and η are transition rates between each state of fault node. Once the transition rates are set, each conditional probability of $\mathbf{F}_{k+1}$ can be calculated following the method introduced by Kohda and Cui (Kohda & Cui, 2007).

A Bayesian network that integrates equation nodes with chance nodes is categorized as a hybrid BN. To conduct the BN inference and FDD analysis, the continuous equation nodes are discretized based on the prescribed intervals and the probability for each interval is obtained utilizing stochastic sampling algorithms (Yuan & Druzdzel, 2006). Following that, the constructed hybrid BN can be converted to dynamic BN (DBN) by inheriting the same structure, discretized interval of equation nodes, and CPT of all nodes. Theoretically, the established discrete DBN can approximate the hybrid equation-based BN. By looping the developed two-time steps DBN algorithm and passing the final probabilities of the current turn to the initial probabilities of the next turn, i.e., $\mathbf{x}_{k,i} = \mathbf{x}_{k,f}$ and $\mathbf{F}_{k,i} = \mathbf{F}_{k,f}$, large amounts of building operation data can be diagnosed at a reasonable computational cost.

3. METHOD EVALUATION

To evaluate the improved PBDBN-FDD and compare it with the original DBN, the fault is injected into the sensor of supply air temperature T_{sa} of a basic AHU system, as shown in Fig. 6. The fault degree is set at 2.0 °Cand the total simulation time is 72 hours.

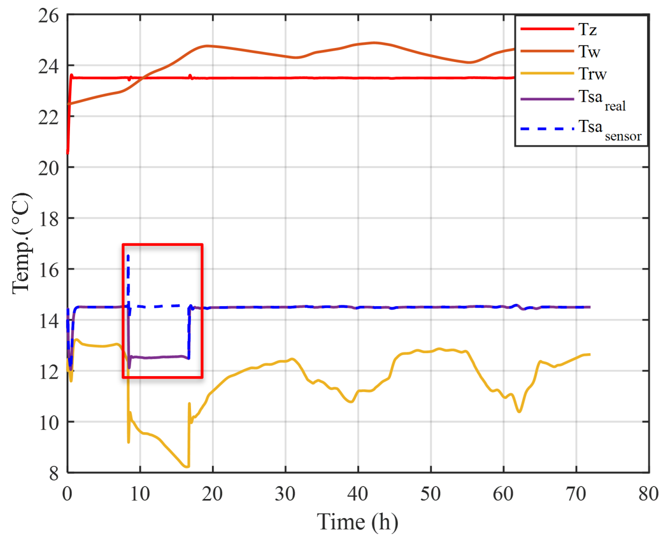

Figure 6: 2.0 °C T_{sa} sensor fault injected building simulation data.

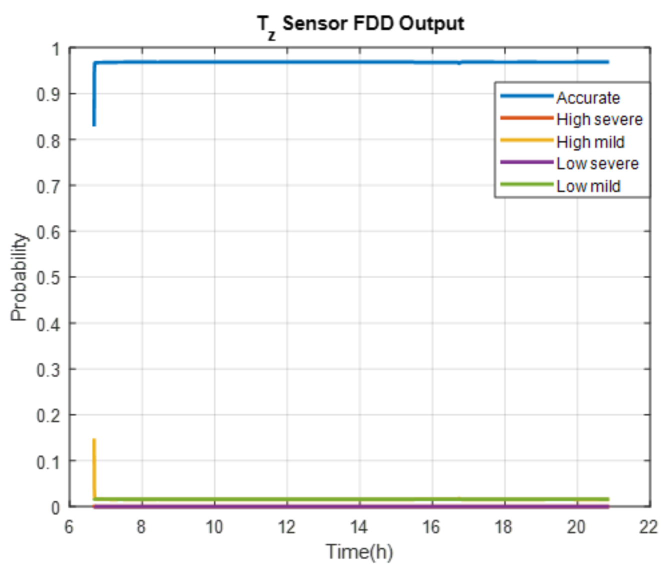

Figure 7: T_z FDD results for 2.0 °C T_{sa} sensor fault.

The FDD results from 6 hours to 22 hours for improved DBN are given in Fig. 7, Fig. 8 and Fig. 9. Fig. 7 shows the probabilities for T_z sensor fault, where the probability for accurate sensor value is maintained above 0.9, indicating that T_z sensor has a low probability of failure. Fig. 8 displays the probabilities for T_{rw} sensor fault, where the fluctuation can be observed at the time when the fault injects and ends. Nevertheless, the accurate rate of T_{rw} sensor value is maintained above 0.8 for the most of time during the fault injection period. On the contrary, the detection results in Fig. 9 reveal a 'High mild' fault in T_{sa} sensor during the fault injection, where 'High mild' indicates that the current sensor value is supposed to be slightly higher than the actual value.

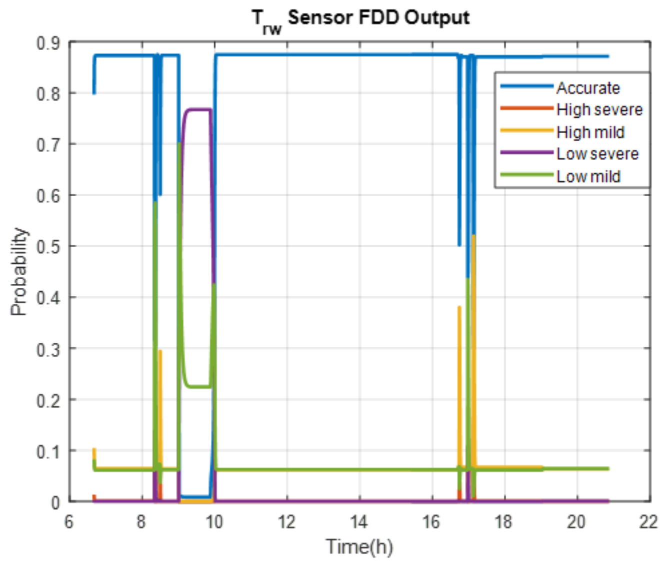

Figure 8: T_{rw} FDD results for 2.0 °C T_{sa} sensor fault.

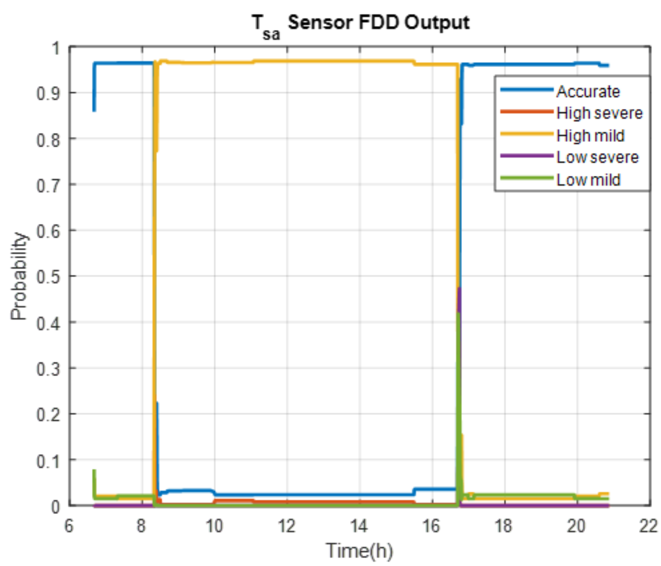

Figure 9: T_{sa} FDD results for 2.0 °C T_{sa} sensor fault.

Compared with the original DBN-FDD, the improved DBN-FDD has a better fault detection rate and stability, as indicated by Fig. 10 and Fig. 11. Fig. 10 displays the possibilities of accurate sensor value of T_{rw} for both improved DBN and original DBN. During the fault injection period (8-17 hours), the improved DBN manages to keep a relatively more stable possibility of an accurate state above 0.8 despite some fluctuations at the beginning and end of the fault injections, manifesting that the return water sensor is more likely to be accurate. Furthermore, from the comparison of FDD results for T_{sa} in Fig. 11, the fault detection for T_{sa} sensor by improved DBN is more prominent and stable than that by original DBN. Combining the information from these two figures, it is obvious that through improved PBDBN-FDD, T_{sa} sensor faults can be analyzed.

4. CONCLUSION

In this paper, a PBDBN-FDD approach is proposed to detect and locate sensor faults in HVAC systems. Compared with the original DBN-FDD in the literature, the improved DBN-FDD can better detect minor sensor faults. Moreover, it is

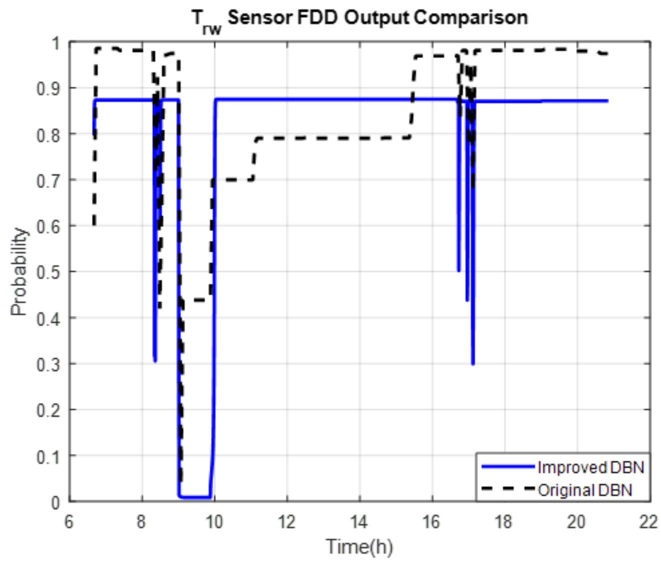

Figure 10: Comparison of T_{rw} FDD results for 2.0 °C T_{sa} sensor fault.

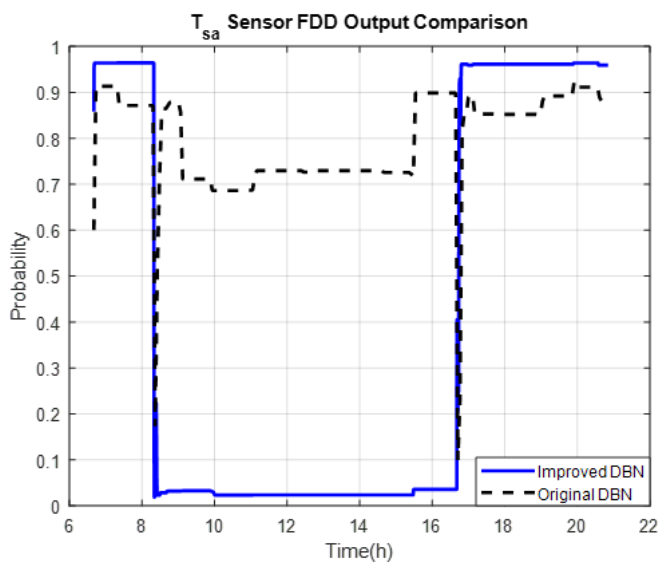

Figure 11: Comparison of T_{sa} FDD results for 2.0 °C T_{sa} sensor fault.

more efficient to process large amounts of the building operating data. In addition to improving the current developed FDD, adapting the new FDD to real building applications is crucial to this research. Therefore, the focus of future research work will be placed on the validation of the developed PBDBN-FDD with real building data.

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