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DOI
10.1016/j.enbuild.2025.115845

Publication date
2025

Document Version
Final published version

Published in
Energy and Buildings

Citation (APA)
Lu, C., Wang, Z., Mosteiro-Romero, M., & Itard, L. (2025). Diagnostic Bayesian network in building energy systems: Current insights, practical challenges, and future trends. *Energy and Buildings*, *341*, Article 115845. https://doi.org/10.1016/j.enbuild.2025.115845

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Energy & Buildings 341 (2025) 115845

Contents lists available at ScienceDirect

Energy & Buildings

journal homepage: www.elsevier.com/locate/enb

Diagnostic Bayesian network in building energy systems: Current insights, practical challenges, and future trends

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ARTICLE INFO

Keywords:
Diagnostic Bayesian network
Fault detection and diagnosis
Building energy systems
HVAC

ABSTRACT

Many buildings suffer from operational inefficiencies, leading to uncomfortable indoor environments, poor air quality, and significant energy waste. Developing automatic fault detection and diagnosis (FDD) tools in building energy systems is essential to mitigate these issues, reducing both energy waste and maintenance costs. Diagnostic Bayesian networks (DBNs), as probabilistic graphical models, offer a promising solution due to their interpretability, robustness to uncertainty, scalability, and flexibility. In this paper, the practical applications of DBNs for FDD in building energy systems are comprehensively reviewed. The generic modeling procedure is systematically examined and summarized, covering problem formulation, structure modeling, parameter modeling, and fault isolation and evaluation. Then, the paper provides insights into DBN modeling objectives, modeling types, diagnostic samples, and modeling software based on the 43 key relevant papers. Furthermore, the paper discusses practical challenges such as sensor configuration, baseline estimation, threshold determination, and expert knowledge integration. Finally, the recommendations are provided to guide further research, aiming to enhance DBN implementation for building energy systems in real-world scenarios, thereby supporting the transformation of the building service industry into a smart sector and ultimately improving building energy performance.

1. Introduction

1.1. Motivation

In the European Union, approximately 40 % of energy is consumed by buildings, which also account for over one-third of energy-related greenhouse gas emissions [1]. To align with the enhanced climate ambition under the European Green Deal, the revised Energy Performance of Buildings Directive aims to achieve emission reductions of at least 60 % in the building sector by 2030 compared to 2015 and to reach climate neutrality by 2050 [2]. To achieve these goals, it is essential to minimize building energy waste. Heating, ventilation, and air conditioning (HVAC) systems are the primary energy consumers in buildings and often experience diverse faults involving sensing, mechanical, and control modules [3,4]. These faults can lead to undesirable outcomes, including uncomfortable indoor environments, poor air quality, and massive energy waste [5–7]. Therefore, it is crucial to develop automatic fault detection and diagnosis (FDD) tools in building energy systems, which can effectively reduce energy waste and maintenance costs [8–10].

Abbreviations: AC, Air conditioning; AHU, Air handling unit; APAR, AHU performance assessment rules; ATES, Aquifer thermal energy storage; BIM, Building information model; BLS, Broad learning system; BMS, Building management systems; BPNN, Back-propagation neural network; CC, Cooling coil; CHS, Central heating system; COP, Coefficient of performance; CPT, Conditional probability table; CR, Classification rate; DAG, Directed acyclic graph; DBN, Diagnostic Bayesian network; EA, Exhaust air; EER, Energy efficiency ratio; EM, Expectation maximization; EP, Energy performance; ERR, Error rate; FAR, Fault alarm rate; FDD, Fault detection and diagnosis; FDR, Fault detection rate; FIR, Fault diagnosis rate; FN, False negative; FP, False positive; GA, Genetic algorithm; GSHP, Ground source heat pump; HC, Heating coil; HRW, Heat recovery wheel; HVAC, Heating, ventilation, and air-conditioning; MLE, Maximum likelihood estimation; MR, Miss rate; OA, Outside air; OAF, Outside air fraction; OS, Operational state; PA, Preheated air; P&ID, Piping & instrumentation diagram; RA, Return air; SA, Supply air; SAHP, Solar assist heat pump; SIA, Sufficient isolation accuracy; TN, True negative; TP, True positive; VAV, Variable air volume; VRF, Variable refrigerant flow; XGBoost, eXtreme gradient boosting.

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https://doi.org/10.1016/j.enbuild.2025.115845
Received 5 January 2025; Received in revised form 10 April 2025; Accepted 6 May 2025
Available online 8 May 2025
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However, developing universally applicable FDD tools remains an open issue due to the complex and time-consuming nature of the tasks, which require customization for individual building [11–13]. Over the past decades, numerous FDD tools have been developed for building energy systems, broadly classified into knowledge-based and data-driven approaches [14,15]. Fig. 1 highlights the key assessment dimensions for FDD tools in buildings: Accuracy, which is the most frequently reported metric in case studies to evaluate FDD tool performance; Generalization, which includes scalability, robustness, and transferability, ensuring diagnoses can be applied or adapted easily across different buildings, scales, and operational modes; and Trustworthiness, which addresses reliability and user confidence in the FDD tool's outcomes. When developing universally applicable FDD tools for the building industry, it is crucial to comprehensively consider these three dimensions. Moreover, there are more desirable characteristics of FDD tools that can be found in [16].

Knowledge-based approaches rely on physics rules or engineering knowledge, which can be either quantitative or qualitative [15]. These approaches have advantages in terms of trustworthiness and interpretability since they are developed based on first principles. However, their development can be tedious and time-consuming due to the requirement for a deep understanding of building energy systems. Additionally, knowledge-based approaches often suffer from low accuracy. They typically provide a binary true–false diagnosis result, which can lead to incorrect conclusions due to conflicting rules and inaccurate sensor measurements [17].

Data-driven approaches, on the other hand, are built or trained using machine learning models or multivariate statistical analysis methods, utilizing data obtained from building management systems (BMS) [18–23]. These approaches can automatically learn faulty patterns from data, eliminating the need for in-depth analysis of heat and mass transfer processes in building energy systems, and typically achieving high accuracy [24–27]. Consequently, data-driven approaches have garnered significant attention in academia, with over 70 % of studies focusing on them [15,18,28]. However, their adoption in the industry and market has been slow [29,30]. One major obstacle is the requirement for large amounts of high-quality labeled faulty data for model training [31,32], which is difficult to obtain in practice. Also, while data-driven approaches can be highly accurate for the specific building energy systems they are trained on, their interpretability, generalization to different buildings and scalability across numerous building sub-systems pose significant challenges [33–35]. These limitations hinder the development of universally applicable FDD tools in practice.

To address these issues, Diagnostic Bayesian networks (DBNs), as probabilistic graphical models, emerge as a promising solution. DBNs are robust tools for developing expert systems and have been successfully applied in various domains, including project management [36,37], safety and risk assessment [38–42], energy modeling [43], urban modeling [44], and medical diagnosis [45]. In the context of FDD in building energy systems, DBNs offer several advantages [46–48],

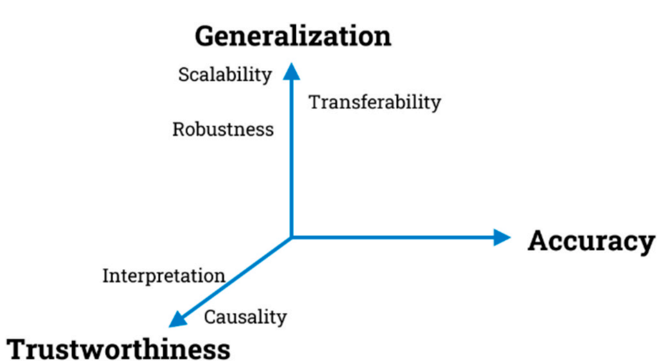

Fig. 1. Key assessment dimensions for FDD tools in buildings.

which are summarized as follows.

- Interpretability: DBNs provide good model interpretability. Their graphical structure can represent causality, and the probabilities quantify the strengths of faults and symptoms, aiding in understanding the underlying relationships. Therefore, the interpretability of DBNs enables easy adaptation to different HVAC operating conditions, system capacities, and equipment types by allowing simple modification of symptoms, thresholds, or model parameters.
- Robustness to uncertainties: DBNs can effectively handle uncertainties, incomplete, or conflicting measurements and information inherent in building energy systems.
- Scalability: DBNs have a modular architecture, which can scale well to accommodate complex building energy systems with multiple subsystems and components. As a result, DBNs can be easily scaled to include additional subsystems and new components without the need for complete retraining, unlike many purely data-driven approaches.
- Flexibility: DBNs can be either knowledge-based, incorporating expert knowledge and domain-specific rules, or data-driven, learning from experimental faulty data. This dual capability not only facilitates integration of diverse information sources but also makes DBNs particularly advantageous in scenarios with limited or partially labeled data.

Overall, DBNs align well with HVAC design and implementation practices, making them a valuable tool for researchers to investigate in developing more universally applicable FDD solutions in building energy systems.

1.2. Previous related reviews

FDD in building energy systems has received considerable attention, with many review papers published in the last five years. Frank et al. [49] assessed barriers and research challenges for automated FDD tools for small commercial buildings in the United States. They also discussed fault definition, input sample, and performance evaluation of FDD in building energy systems [50]. Torabi et al.[51] identified human errors made by technical professionals in the building industry and they also investigated FDD methods for those human errors. Shi et al. [52] reviewed various methods used by previous researchers and real-life products in a typical automatic FDD workflow, involving feature generation, fault detection, and fault diagnosis. Zhao et al. [15] comprehensively summarized artificial intelligence-based FDD methods for building energy systems, including both knowledge-based and data-driven approaches. Similarly, Chen et al. [14] and Bi et al. [28] also reviewed these approaches and further discussed the remaining challenges in terms of data and methodology. Chen et al. [18] specifically focused on data-driven approaches with discussions of modeling processes, application cases, evaluation metrics and future challenges. There are more review papers regarding FDD in building energy systems, including [13,28,53–59].

From the perspective of DBNs, Kyrimi et al. [60] reviewed Bayesian networks for application in clinical decision-support. Cai et al. [61] introduced various engineering cases using DBNs in process systems, energy systems, structural systems, manufacturing systems, and network systems. Adedipe et al. [62] summarized the use of DBNs in the wind energy industry, including wind speed forecasting, wind power generation forecasting, risk assessment, FDD, and other applications. Li et al. [47] provided a review of probabilistic graphical models-based approaches in energy systems, covering applications like reliability analysis, optimal operation, energy prediction, and FDD.

Despite these efforts, there are few reviews specifically focused on the application of DBNs in the context of FDD for building energy systems, especially regarding the modeling practice, thereby overlooking their potential. The motivation of this review paper is from two primary considerations. On the one hand, the modeling process of DBNs is flexible and complex, including its formulation, parameterization, implementation, and evaluation [63]. Without proper practice, there is a risk of misinterpreting or misusing DBN, leading to poor diagnosis and reducing credibility. On the other hand, there are unique challenges in FDD for building energy systems, such as the presence of similar HVAC components with varying configurations across different buildings, as well as the impact of diverse climate conditions. Thus, there is still a need for a systematic review that summarizes the practical applications and challenges of DBNs, which could effectively guide the development of FDD tools for building energy systems.

2. Contributions

This paper offers a systematic review of DBNs for FDD in the context of practical applications in building energy systems. The objective of this paper is to provide valuable guidance for the development of FDD tools and emphasize the potential of DBNs in developing universally applicable FDD tools for building energy systems. To provide a comprehensive overview of the existing studies in DBN for FDD in building energy systems, a four-step bibliometric analysis is conducted and the relevant publications are found though the following steps: (1) search keywords "Bayesian network; fault detection and diagnosis; building" or "Bayesian network; fault detection and diagnosis; HVAC" from Google Scholar; (2) quickly review the publications based on titles and abstracts; (3) perform an in-depth assessment of the full texts; (4) identify additional relevant studies from references. A total of 43 relevant publications have been selected for analysis and discussion. The main contributions can be summarized as follows.

- A systematic review of the applications of DBNs for FDD in building energy systems, highlighting both model developments and domain-specific implementations.
- A generic four-step DBN modeling procedure is proposed, covering problem formulation, structure modeling, parameter modeling, and fault isolation and evaluation, to offer practical guidance for researchers and practitioners.
- Modeling insights are provided, including typical diagnostic objectives, modeling types, data samples, and software tools, to inform the overall DBN implementation in building energy systems.
- Key practical challenges encountered in applying DBNs to real-world building energy systems are identified, along with actionable recommendations to guide future research and improve the robustness and applicability of FDD methods.

The rest of the paper is structured as follows. Section 2 introduces the fundamentals of DBNs. Section 3 outlines the generic modeling procedure of DBNs for FDD in building energy systems. Section 4 delves into the practical applications of DBNs from four distinct perspectives. Section 5 analyzes the practical challenges when implementing DBNs in building energy systems. Section 6 provides potential future research directions for researchers. Finally, Section 7 concludes the review.

3. Fundamentals of diagnostic Bayesian networks

A BN is a probabilistic graphical model representing a set of random variables and their conditional dependencies via a directed acyclic graph (DAG), which was first developed by Judea Pearl in 1980 s [64,65]. DBNs are a powerful tool in the field of uncertainty knowledge expression and inference [66]. There are two primary elements within the topology of a BN, i.e., the structure and parameters. The structure of a BN is a graph with the direction of the arcs, i.e., the DAG, representing a qualitative illustration of the dependencies or cause-and-effect relationships among the variables (nodes). The parameters of a DBN represent the quantitative probabilistic relationships among the variables, i.e. conditional probability tables (CPTs). Mathematically speaking, considering random variables $X_1, X_2, \cdots, X_n$, the joint probability of these variables in a BN can be expressed using the chain rule as follows.

$$P(X_1, X_2, \cdots, X_n) = \prod_{i=1}^{n} P(X_i|\text{parents}(X_i))\# \quad (1)$$

where $P(X_i|\text{parents}(X_i))$ represents the conditional probability distribution of X_i given its parent nodes in the graph.

Fig. 2 makes a simple illustration of a DBN model with four variables (nodes) in the context of FDD. Suppose that symptom A_1 could be affected by fault B_1, while symptom A_2 could be affected by both the faults B_1 and B_2. The states of these symptoms, such as *Too high*, *Too low*, *Present* or *Normal*, are observed by collecting data or measurements. Subsequently, fault states, such as 'faulty' or 'fault free', can be diagnosed by analyzing these symptom states utilizing DBNs.

4. Generic modeling procedure of diagnostic Bayesian networks in building energy systems

Based on the selected relevant studies, this section will outline the generic modeling procedure of DBNs for FDD in building energy systems. The procedure typically includes four main steps, illustrated in Fig. 3:

1) Problem formulation: this step involves understanding the components, capacities, sensors, and control in the system, identifying potential faults, and defining the symptoms of the FDD process. Hereby, the building energy systems can be conceptualized, and the FDD tasks can be formulated.
2) Structure modeling: this step involves constructing the structure of the BN model, reflecting the dependencies between the fault nodes and symptom nodes.
3) Parameter estimation: this step involves specifying the parameters of the BN model, including assigning prior probabilities and CPTs.
4) Fault isolation and evaluation: this step involves calculating the fault posterior probabilities based on observed symptoms, isolating the faults according to predefined rules, and evaluating the BN model.

If the diagnostic results are inadequate or unsatisfactory, one or multiple steps can be revised until the diagnostic results are satisfactory.

4.1. Problem formulation

As implied by its name, FDD always consists of two fundamental steps: symptom detection and fault diagnosis. When establishing a BN for FDD, it is a crucial initial step to determine the fault and symptom nodes.

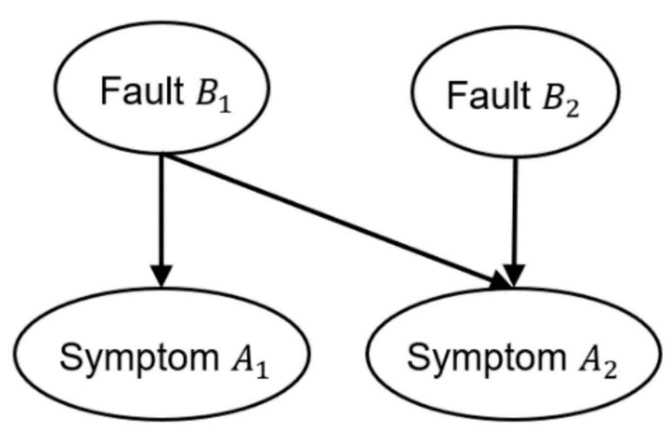

Fig. 2. Simple illustration of a BN for FDD.

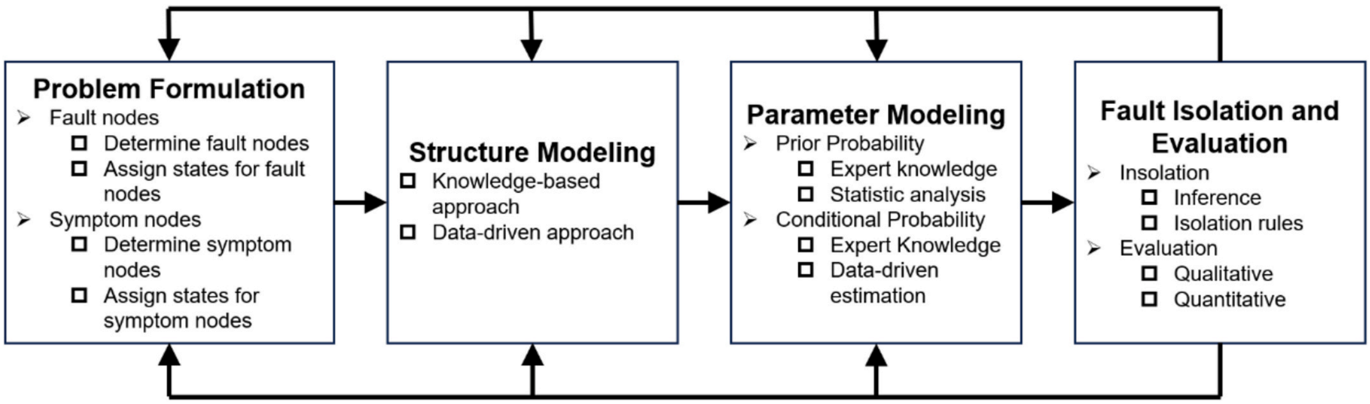

Fig. 3. The generic modeling procedure of DBNs in building energy systems.

4.1.1. *Fault nodes*

In the existing literature, the definition of "fault" encompasses various perspectives. Generally, a fault can be defined as conditions that render an element unable to perform its required function at desired levels of performance [67]. Frank et al. [50] summarized three categories of fault definition, i.e. condition-based, behavior-based, or outcome-based. These categories represent the condition or state of a physical system, by a system's undesired or improper behavior, or by a quantitative outcome's deviation from an expected value or range, respectively. In the context of building energy systems, faults can mostly be categorized into two main types: hard faults and soft faults [68]. Hard faults encompass failures of sensors, actuators, and equipment, resulting in complete or significant loss of functionality. Soft faults involve controller errors, programming mistakes, improper design, non-optimal commissioning, and inadequate preventive maintenance. The bias, drifting, and precision degradation of sensors are also considered as soft faults [69]. More systematically, Taal and Itard [46] proposed the four symptoms and three faults (4S3F) BN structure for FDD in building energy systems, illustrated in Fig. 4. The structure includes three generic types of faults, i.e. model, component, and control faults. Model faults are related to the models to estimate missing values or sensors. Component faults are related to the components and systems which do not function properly. Control faults are related to control strategies. (The corresponding symptom types will be discussed in detail in Section 3.1.2.) Furthermore, considering that fault reports are very customized and unstructured, Chen et al. [70] discussed the development of a unified taxonomy of faults in HVAC systems. They emphasized that structured and standardized fault libraries are crucial to identifying and addressing faults in HVAC systems effectively.

In practice, determining fault nodes of DBNs can be accomplished through either survey or practical experience. For instance, Zhao et al. [48] determined six typical faults in a chiller that account for a majority of the service call in the survey [72]. They also determined 28 typical faults in an AHU [73,74] based on ASHRAE Project RP-1312 [75].

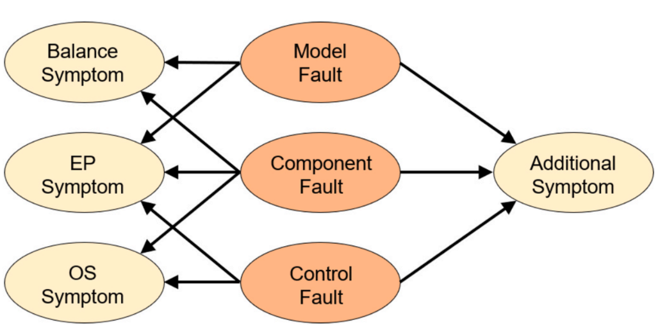

Fig. 4. Illustration of the general 4S3F BN structure [11,17,46,71].

Similarly, Wang et al. [76] determined seven faults in a chiller based on ASHRAE Project RP-1043 [77]. Chitkara [78] selected vital faults to diagnose in AHUs by conducting fault impact analysis [79,80] in a simulation environment. Cai et al. [81] imposed eight soft faults in a ground source heat pump (GSHP) system based on references and practical experience. Xiao et al. [82] utilized a BN to diagnose ten typical faults in VAV terminals, which may result in poor indoor environmental quality, energy waste, unreachable design value, and physical damages according to a comprehensive survey [83,84]. Gopalan et al. [85] conducted a fault impact analysis that considered real fault occurrence frequency data in addition to the effect of the faults on the energy performance of the building to assess their total energy impact. They found *fan stuck* and *HRW stuck* were the main faults in AHUs. These fault nodes can be defined not only at the component level but also more generally at the system level. For instance, Parhizkar et al. [86] determined four system-level faults, i.e. pump failure, burner failure, pipeline leakage, and thermal comfort failure, in a BN designed for a central heating system. Table 1 and 2 present the typical fault nodes of DBNs for AHUs and chillers in the representative studies, which are the most common components investigated in building energy systems. Notably, PA refers to preheated air in AHUs, which is also commonly known as mixed air in AHUs with a mixing box. HC fouling and CC fouling include both air-side and water-side faults [87]. Additionally, some potential faults in HVAC systems, such as Fan Outlet Blockage [88], are not listed, as the tables focus on the most common fault types identified in the selected studies.

Assigning fault intensities, or fault severities, is also crucial in DBNs. The choice of fault node states is typically influenced by the specific BMS data characteristics and the types of faults being addressed in the projects. Most studies [48,73,74] simply defined these fault nodes as binary events with two states, i.e. *Present* and *Absent*. While the presence of a fault alone is often sufficient for building managers to conduct an inspection, this approach may oversimplify the issue. Fault nodes can also have multiple states to provide more detailed and explicit information. For instance, in Xiao et al. [82], the fault node of the damper has three states, namely *Positive stuck*, *Negative stuck*, and *Fault-free*. In Zhao et al. [74], the fault node of the supply temperature sensor has five states, namely *Frozen*, *Very positive biased*, *Fairly positive biased*, *Fairly negative biased*, *Very negative biased*, and *Fault-free*. Najafi et al. [89] defined the fault nodes as representing the set of all possible faults in the AHU, including single faults and concurrent faults. They also considered the distinction between abrupt faults and degradation faults. Abrupt faults, such as stuck damper and reversed actuator, arise instantaneously and also can be thought of as binary events. Degradation faults, such as damper leakage and valve leakage, evolve over time and become progressively more severe and therefore have an associated severity state/level.

Table 1
Typical fault nodes of DBNs for AHUs in the representative studies.

Fault	[89]	[73]	[74]	[90]	[91]	[92]	[93]	[94]
OA Temperature Sensor Bias/ Frozen			√				√	
PA Temperature Sensor Bias/Frozen			√	√				
SA Temperature Sensor Bias/Frozen		√		√		√	√	
SA Pressure Sensor Bias/Frozen		√						
RA Temperature Sensor Bias/Frozen			√	√		√		
Differential Pressure Sensor for Filter Bias/Frozen		√						
OA Damper Stuck/Leaking	√	√		√	√			
RA Damper Stuck/Leaking	√	√		√				
EA Damper Stuck/Leaking	√	√			√			
HRW Stuck								√
Supply Fan at Fixed Speed /Failure		√				√		
Return Fan at Fixed Speed/Failure		√			√	√		
Filter Fouling/Broken		√				√		
Duct Leaking		√			√			
HC Valve Stuck/Leaking	√		√	√	√	√		√
CC Valve Stuck/Leaking			√	√	√	√	√	
Undersized HC			√					
Undersized CC			√					
HC Fouling	√		√			√		
CC Fouling			√	√		√		
Reduced Heating Water Pump Pressure			√					
Low Supply Heating Water Temperature			√					
Humidifier Malfunction						√		
Control faults				√			√	

Table 2
Typical fault nodes of DBNs for chillers in the representative studies.

Fault	[48,95]	[76,96–100]	[93]	[101]
Non-condensable Gas	√	√		
Refrigerant Overcharge	√	√		
Refrigerant Leakage	√	√		
Condenser Fouling	√	√		√
Reduced Condenser Water Flow Rate	√	√		
Reduced Evaporator Water Flow Rate.	√	√		
Excess Oil		√		
Chilled Water Supply Temperature Sensor Bias			√	
Chilled Water Supply Differential Pressure Sensor Bias			√	

4.1.2. Symptom nodes

Symptom nodes, also known as evidence nodes, represent relevant information and observations that can help identify and diagnose faults. Symptoms can be gathered from various sources, including building management systems (BMS), which automatically collect data, as well as manually obtained sources such as inspections and maintenance reports.

As illustrated in Fig. 4, the general 4S3F BN structure includes four generic types of symptoms, i.e. balance, energy performance (EP), operational state (OS), and additional symptoms [17]. Balance symptoms refer to the deviation of an energy, mass, or pressure balance. Efficiencies, representing heat losses in the building energy systems, are dimensionless balance indicators. For instance, outside air fraction (OAF) is a dimensionless indicator of mixing box performance in AHUs [49,69], which can be used as a symptom to diagnose a reversed actuator, outdoor air damper leakage, and return air damper leakage [65]. The heat-exchanger model based on Holmers' effectiveness number of transfer unit method [69] can be used to evaluate the heating (cooling) coil performance and to diagnose faults, such as coil fouling, valve leakage, and so on [65]. EP symptoms are related to energy performance metrics, which can be performance factors (such as coefficients of performance (COP), energy efficiency ratios (EER)), capacity indicators, and energy use outliers. OS symptoms refer to an unexpected state of some measurements, such as temperature, flow rate, pressure, and the on–off state of components. Additional symptoms can include manual tests, on-site observations, occupant complaints, and maintenance records [48,74,82]. For instance, filter maintenance service from records, and the health status of filters and ducts observed by technicians were used to diagnose the filter faults and duct leaking in AHUs [73]. Unexpected window actions could be a symptom to diagnose noise disturbance, thermal discomfort, and perceived air quality [102].

Similarly to the state assignment of the fault nodes, symptom nodes can be assigned states that are either binary or multiple. Binary symptom nodes are typically denoted as *Present* and *Absent*. Symptom nodes with multiple states represent various levels or degrees of the observation, which can help diagnose the faults more accurately, such as *Positive*, *Negative*, *Fault free,* and *Unknown*. For instance, in Li et al. [92], the symptom node of the abnormal fluid flow rate has three states, *High*, *Low*, and *Normal*, and the symptom node of the abnormal actuator feedback signal also has three states, *Maximum*, *Minimum*, and *Normal*.

On the other hand, how to define the presence/state of symptom nodes is another crucial question in DBNs for FDD. Overall, the symptom nodes can be developed using knowledge-based, data-driven, and residual-based methods [100].

- Knowledge-based symptom nodes are formed by a set of predefined rules derived from expert knowledge and experience [103,104]. For instance, AHU performance assessment rules (APAR) [105] are widely applied in DBNs to diagnose faults in AHU [73,74]. These rules establish the criteria under which symptoms are considered present or absent. These rules generally include two key parts: baselines and thresholds. Baselines represent the normal operating conditions of the HVAC system. They can be derived from several sources, including documentation and fault-free data. For instance, in Taal and Itard [71], the baselines for the efficiency of a heat exchanger and the efficiency of the thermal energy regeneration of an aquifer thermal energy storage (ATES) system were set at 87 % and 100 %, respectively, according to design specifications and Dutch regulations. Ziao et al. [73,74], estimated typical parameters as baselines using the polynomial functions and fault-free data, such as the energy consumption of fans, the differential pressure across the filter, and coil valve control signals. Chitkara [78] and Gunderi [106] utilized a machine learning method, called XGBoost (eXtreme Gradient Boosting), to predict coil valve control signals as a baseline to diagnose multiple faults in AHU. On the other hand, thresholds represent specific deviations from baselines that indicate potential faults and are typically set by experts. If a threshold is too high, only severe faults will be detected, whereas if a threshold is too low, normal variations in operating conditions may result in false diagnosis [105]. Li et al. [91] set the thresholds as three times the standard deviations of the fault-free historical data, and 99.7 % of the fault-free data would lie within the thresholds based on the *t*-student assumption.

- Data-driven symptom nodes are developed by utilizing directly measured sensor features. Data-driven methods need large volumes of data, especially faulty data, to train models. Wang et al. [98,99] proposed a novel chiller FDD method by merging distance rejection techniques into a BN. They calculated a statistical distance from a given multivariate observation to the center of a Gaussian multivariate area defined by its mean vector and covariance matrix. Then they defined a fixed control limit to decide if the observation could be accepted by the *Normal* class. Hu et al. [107] collected fault data from a variable refrigerant flow (VRF) system and selected the most sensitive sensors as the symptom nodes.
- Unlike data-driven methods that are trained directly on measured sensor data, residual-based symptom nodes are developed by considering feature residuals obtained from abstract benchmarking models. For instance, Chen et al. [93] employed a weather and schedule information-based pattern matching method to automatically create the baseline datasets for each incoming real-time snapshot data from the building systems. Consequently, BN inference and real-time diagnostics can be achieved by comparing incoming snapshot data and the baseline dataset. Wu et al. [95] utilized discretized residual variables between the measured values and baseline values of feature parameters for model training to diagnose faults in chillers. Furthermore, Wang et al. [100] proposed a generic framework to develop the residual–knowledge–data jointly driven method, which demonstrated excellent overall performance and good individual performance in chiller FDD.

4.2. Structure modeling

There are several approaches reported in constructing BN structures for FDD in building energy systems, including both knowledge-based and data-driven approaches.

The knowledge-based approach relies on analyzing cause-and-effect relationships between faults and symptoms, which can be obtained from logical analysis, first principles, fault patterns in reports, expert knowledge and experience [73,74,82,89,90,108]. More systematically, Taal et al. developed a generic reference architecture where the BN structure can be extracted from the piping & instrumentation diagrams (P&IDs) [11,12], illustrated in Fig. 5. They successfully implemented the architecture for FDD in an AHU [94,109], a demand-controlled ventilation system [46], a heating and cooling generation system [17], and a thermal energy plant that contained a gas boiler and a heat pump combined with an ATES system [71]. Gao et al. [110] defined a new control flow diagram descriptive model, which serves as a pivot language for extracting and structuring HVAC system topology descriptions, subsequently using it to build corresponding diagnostic DBNs automatically.

The data-driven approach, known as structure learning, can obtain the DBN structure from fault data when sufficient sensor data is available [112]. This approach allows DBNs to perform structural learning using score-based algorithms, which seek a DBN structure that maximizes the chosen scoring function, or constraint-based algorithms, which map out the BN structure based on conditional dependencies between pairs of variables [113]. Huang et al. [114] proposed an Eigen-Entropy-based causal learning approach for BN construction in the cross-level FDD of a medium-sized office building. In this approach, Eigen Entropy is a measure of entropy for multivariate data derived on eigenvalues extracted from the correlation magnitude matrix. Furthermore, the outcomes of structure learning can be enhanced when

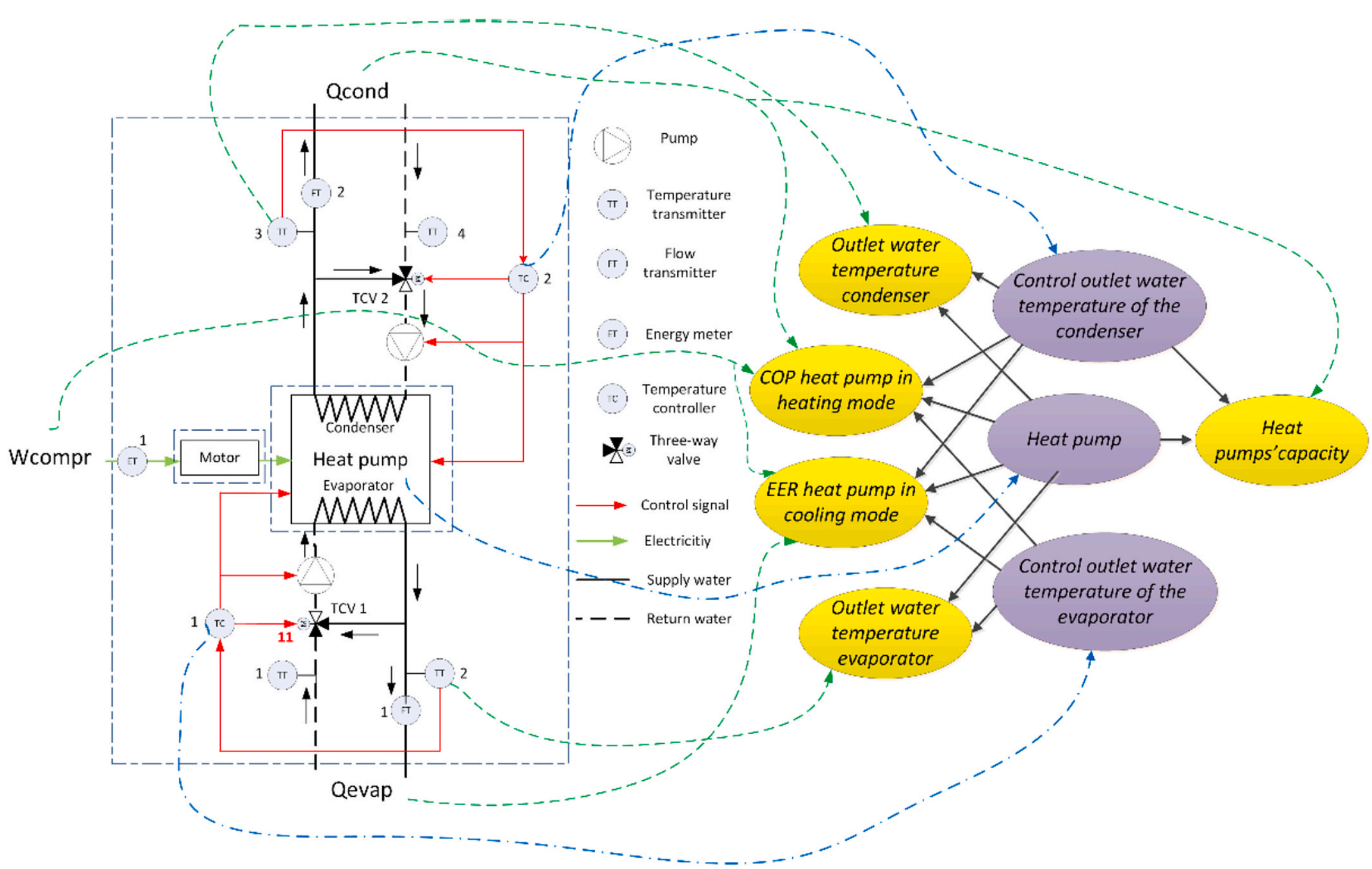

Fig. 5. The illustration of the extraction of DBNs from P&IDs of building energy systems [111].

combined with expert input. For instance, Li et al. [91] established a prior DBN structure for AHUs using expert knowledge, then they proposed an improved genetic algorithm-based approach to optimize the prior BN structure, where a hybrid scoring function was developed, incorporating the Bayesian Dirichlet Equivalent Uniform score along with a penalty term. This penalty term reflects the consistency of the DBN structure with expert knowledge.

Notably, the BN structure modeling process typically begins with the careful selection of relevant symptom nodes. Adding insignificant symptoms can increase the complexity of the BN, leading to unnecessary cost and effort while potentially reducing the diagnosis sensitivity [63]. For instance, Wang et al. [98] developed a feature selection framework to identify the retained existing features and supplemental features with high sensitivity to faults. They also proposed an enhanced BN for chiller FDD with principal component analysis to extract features [76]. Hu et al. [107] initially adopted expert knowledge and experience to select some typical characteristic features, simplifying the network and excluding some irrelevant features. Then, they used five feature selection algorithms and the BN structure for the VRF system was learned by machine learning algorithms.

4.3. Parameter modeling

The probability parameters of DBNs reflect the quantitative relations among fault nodes and symptom nodes. Both prior probabilities and conditional probabilities need to be determined during DBN modeling.

4.3.1. Prior probabilities

Prior probabilities represent the frequency of a fault event that may happen. A fault with a high prior probability is expected to occur more often than those with lower prior probabilities.

Prior probabilities can be obtained from statistical analysis and expert knowledge. There are some statistical analyses of the faults in building energy systems [4,115]. Dey and Dong [90] set up the prior probabilities for the typical faults in AHUs based on the fault occurrence survey from the International Energy Agency [116,117] and the National Institute of Standards and Technology of the United States [118]. Hu et al. [107] determined prior probabilities of the faults in VRF air conditioning systems from their frequencies, including refrigerant overcharge and refrigerant leakage. However, research into the frequency of faults in building energy systems is still insufficient, so prior probabilities are more often estimated by experts. For instance, Cai et al. [81] set the prior probabilities of all the faults in a GSHP at 2 %. Zhao et al. [73,74] estimated the fault prior probabilities of sensors in AHUs to be 4 %, while the fault prior probabilities of dampers were estimated to be higher, at 10 %. In Liu et al. [119], the prior probabilities of faults in the solar-assisted heat pump system were purely subjectively assessed by six experts. Taal and Itard [71], set the prior probabilities of component faults and control faults at 2 % and 5 % respectively based on expert knowledge.

Furthermore, there are a few studies on the sensitivity analysis of prior probabilities. Taal et al. [46,71] stated that the absolute values of the prior probabilities are not as important as their relative values. Chen [93] et al. also found that even though the average posterior probability of each fault node was changed after the prior probability was adjusted, the fault ranking results were not affected.

4.3.2. Conditional probabilities

Conditional probabilities are the likelihoods of symptoms being detected under the presence of a given fault [112]. These probabilities are usually contained in CPTs and can be obtained from either expert knowledge or data-driven parameter learning.

Expert knowledge is widely used to define conditional probabilities, particularly in practical scenarios where acquiring high-quality data is difficult. This approach has been applied in various building energy systems, including AHUs [73,74,90,94], VAV terminal units [82], chillers [48], and entire HVAC systems [17,46,71,120,121]. This requires sufficient physics analysis and domain expert knowledge to quantify the various causal relationships among faults and symptoms. In practical applications, expert knowledge of conditional probabilities can be expressed in various forms, such as specific values or fuzzy sets. For instance, Verbert et al. [108] set the conditional probability of the difference between an AHU's supply air temperature and its setpoint being *Present* as a symptom, given the fault of a stuck heating coil in the AHU, as 76 % based on expert analysis. Taal et al. [71] set the conditional probability of a symptom being present at 95 % when a fault is detected in an ATES system. Considering the fuzziness of typical expert knowledge, Chen et al. [93] defined three rough symptom levels as *Strong*, *Medium*, and *Weak*. As similar with the prior probabilities, the absolute values of the conditional probabilities are also not as important as their relative values. The nature of fault diagnosis for building energy systems makes it acceptable for such rough handling of conditional probabilities. Notably, when determining conditional probabilities in DBNs, a significant challenge is the exponential increase in the number of parameters in the CPTs as the number of parent nodes increases [112]. In practical application, developing such DBNs can be extremely challenging and time-consuming [122]. To simplify the calculation, many studies introduced the Noisy-OR gate and Noisy-Max gate to reduce the number of parameters from exponential to linear in the number of parent nodes [73,74,93,122].

Data-driven parameter learning also can be used to generate the CPTs, which can be categorized based on the data completeness. When the data is complete, maximum likelihood estimation (MLE) or Bayesian estimation [123] can be used to learn parameters. MLE is the most common learning algorithm, focusing on maximizing the likelihood function to find the most probable parameter values [124], and has been adopted to learn CPTs for FDD in chillers [96,99,125] and AHUs [91]. Hu et al. [107] adopted statistical analysis and machine learning to obtain CPTs because of the lack of expert experience and previous distributions about the VRF system. However, in practice, it is difficult to obtain complete datasets. Issues such as poor communication, sensor errors, calibration drift, and precision degradation can lead to missing values. The simplest approach to handling incomplete data is to delete the incomplete sensors, features or time steps. However, this method risks discarding valuable information, which can affect diagnostic results. Therefore, some studies tried to impute the missing values. One of the popular data imputation methods is regression. For example, backpropagation neural network (BPNN) is a powerful tool in modeling nonlinear multivariate systems. Liu et al. [119] a method for parameter learning of DBNs from incomplete data based on BPNN and MLE for fault diagnosis in a solar assisted heat pump (SAHP). Another popular data imputation method is expectation maximization (EM) [126,127]. EM is an iterative approach used for finding MLE of parameters in problems where data is incomplete. Wang et al. [128] found that, for chiller FDD, DBNs with EM-based data imputation can significantly reduce the model complexity and improve the computational efficiency and has equally high correctness rates as DBNs with BPNN-based data imputation.

4.4. Fault isolation and evaluation

After setting up the DBNs, the final step involves calculating the fault posterior probabilities based on observed symptoms, isolating the faults according to predefined rules, and evaluating the BN model.

4.4.1. Fault isolation

Based on observed symptoms, DBNs aim to isolate the most suspected faults by calculating the posterior probabilities, known as fault inference. Generally, DBN inference algorithms are categorized into exact inference and approximate inferences [112]. For complex DBNs, inference is an NP-hard problem. Considering the nature of FDD tasks in building energy systems, it is common to calculate the exact posterior probabilities of faults.

After obtaining the posterior probabilities of faults, fault isolation rules are defined for FDD tasks. Directly using the posterior to identify the root fault cause may generate errors because some faults have inherently higher prior probabilities [93]. Therefore, specific fault isolation rules are applied, particularly in single-fault scenarios. The most common isolation rules include:

- If the highest fault posterior probability exceeds a certain threshold ε_1, then the fault will be isolated.
- If the difference between the highest fault probability and the second highest one exceeds a certain threshold ε_2, then the fault with the highest posterior probability will be isolated.

where the isolation thresholds ε_1 and ε_2 can be predefined by experts and optimized during the diagnosis process. In practice, the thresholds vary in different types and scales of building energy systems. For instance, in a BN for chiller FDD, ε_1 and ε_2 were determined to be 80 % and 30 % respectively [48]. In DBNs for VAV and AHU FDD, ε_1 and ε_2 were 70 % and 30 % respectively [73,74,82]. In a BN for cross-level FDD of a whole HVAC system, ε_1 and ε_2 were 15 % and 10 % respectively [93].

Different fault isolation rules have been defined for different energy systems. In some chiller FDD tasks [76,96–100], the rules are:

- If $P(Normal|X) > P(Fault|X)$, the system will be detected as fault-free.
- If $P(F_i|X) > P(\overline{F_i}|X)$, the system will be diagnosed as the fault F_i.
- If the system is detected as faulty but not diagnosis as all the known faults, it belongs to a new type of fault.

where X represents the symptom node and F_i represents the i^{th} type of fault. These isolation rules help ensure accurate diagnosis by considering the likelihood of both known and unknown fault conditions.

4.4.2. Model evaluation

The evaluation of DBNs can be conducted through two primary approaches: qualitative and quantitative assessments.

Qualitative evaluation of DBNs involves assessing their effectiveness and soundness based on expert knowledge and judgment. One crucial aspect is evaluating the diagnostic results, where experts review the DBNs' ability to accurately identify faults based on observed symptoms, ensuring that the diagnostic results align with domain knowledge and real-world expectations [11,17,46,71]. Another important aspect is the structure and parameters of the BN, where experts assess whether the BN structure accurately represents the relationships and dependencies among nodes and whether the decision basis of diagnosing this fault is consistent with expert knowledge [91]. This evaluation ensures that the BN is both technically sound and practically useful in FDD tasks for building energy systems.

Quantitative evaluation of DBNs, on the other hand, involves the use of specific metrics to objectively measure the performance and accuracy of the network. This evaluation includes calculating metrics such as True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN), and then deriving performance metrics such as:

- False alarm rate (FAR) [76,96–100,129]: FAR is defined as the fraction of normal samples misclassified as faults among the total normal samples. The formula for calculating FAR is.

$$FAR = \frac{FP}{FP + TN} \tag{5}$$

- Miss rate (MR) [76,96–100,129]: for a given fault, MR is defined as the fraction of fault samples misclassified as normal class among all the fault samples, also known as recall. The formula for calculating MR is.

$$MR = \frac{FN}{FN + TP} \tag{6}$$

- Classification rate (CR) [76,96–100,129]: for a given class (normal or one fault), CR is defined as the fraction of the correctly classified samples among the total, also known as accuracy. The formula for calculating CR is.

$$CR = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

- Fault detection rate (FDR) [91]: FDR refers to the rate at which the fault samples are correctly detected. The formula for calculating FDR is.

$$FDR = \frac{TP}{TP + FN} \tag{8}$$

- Fault diagnosis rate (FIA) [91]: FIA refers to the rate at which faulty samples are correctly diagnosed with their specific severity levels. The formula for calculating FIA is

$$FIA = \frac{TP}{TP + FP} \tag{9}$$

where, notably, TP refers to faulty samples correctly diagnosed with the specific fault severity, and FP refers to fault-free samples incorrectly diagnosed as having a specific fault severity.

- Error rate (ERR) [91]: ERR measures the proportion of fault-free samples that are incorrectly identified as faulty, also known as False positive rate (FPR). The formula for calculating EER is.

$$EER = \frac{FP}{FP + TN} \tag{10}$$

- Sufficient isolation accuracy (SIA) [114]: SIA is a metric to measure fault isolation accuracy considering the number of symptom nodes in DBNs. The goal is to maximize SIA, indicating a robust and efficient diagnostic DBN model. Assuming there are k fault nodes and m symptom nodes, the formula for calculating SIA is.

$$SIA = \frac{1}{m} \bullet \frac{1}{k} \sum_{j=1}^{k} \frac{TP_j}{TP_j + FN_j} \tag{11}$$

5. Modeling insights

This section will discuss the practical applications of DBNs for FDD in building energy systems from four distinct perspectives: modeling objectives, modeling types, diagnostic samples, and modeling software. Based on the selected studies, Table 3 provides the representative studies of DBNs for FDD in building energy systems.

5.1. Modeling objectives

The distribution of BN modeling objectives in these selected publications is shown in Fig. 6, which summarizes the frequency of DBNs for FDD in different building energy systems.

The building energy systems can be categorized into four levels, including subcomponents, components, aggregated systems, and the total systems [11,17]. The malfunction at the subcomponent level can be a possible fault, but it will not be specified the exact location in DBNs, such as faults within fans, pumps, compressors, evaporators, or embedded controls. Considering that faults at the subcomponent level are often managed by component suppliers, they are excluded from the discussion here.

At the component level, the chiller, boiler, and pump have been

Table 3
Selected studies of BN for FDD in building energy systems.

Ref.	Year	Modeling Objective	Modeling Type	Diagnostic samples	Software
[130]	2008	Boiler	Knowledge-based	Time slice	*N/A*
[89]	2012	AHU	Knowledge-based	Time slice	*N/A*
[131]	2012	Pump	Data-driven	Time slice	*N/A*
[82]	2014	VAV terminal	Knowledge-based	Time slice	SMILE
[81]	2014	GSHP	Knowledge-based	Single instant	Netica
[119]	2015	SAHP	Hybrid	Single instant	Netica
[74]	2015	AHU	Knowledge-based	Time slice	SMILE (GeNIe)
[132]	2016	VAV terminal	Knowledge-based	Time slice	*N/A*
[90]	2016	AHU	Knowledge-based	Time slice	SMILE (GeNIe)
[96]	2016	Chiller	Data-driven	Single instant	Bayes Net Toolbox
[73]	2017	AHU	Knowledge-based	Time slice	SMILE
[108]	2017	HVAC system	Knowledge-based	Time slice	*N/A*
[99]	2017	Chiller	Hybrid	Single instant	Bayes Net Toolbox
[98]	2018	Chiller	Hybrid	Single instant	Bayes Net Toolbox
[76]	2018	Chiller	Hybrid	Single instant	Bayes Net Toolbox
[107]	2018	VRF	Hybrid	Time slice	*N/A*
[11]	2018	HVAC system	Knowledge-based	Time slice	SMILE (GeNIe)
[133]	2018	HVAC system	Knowledge-based	Time slice	SMILE (GeNIe)
[120]	2019	Whole building	Hybrid	Time slice	*N/A*
[86]	2019	CHS	Hybrid	Time slice	SMILE (GeNIe)
[129]	2019	Chiller	Hybrid	Single instant	Bayes Net Toolbox
[46]	2020	AHU + VAV	Knowledge-based	Time slice	SMILE (GeNIe)
[17]	2020	HVAC system	Knowledge-based	Time slice	SMILE (GeNIe)
[71]	2020	ATES	Knowledge-based	Time slice	SMILE (GeNIe)
[134]	2021	HVAC system	Knowledge-based	Time slice	*N/A*
[91]	2021	AHU	Hybrid	Single instant	SMILE
[128]	2021	Chiller	Hybrid	Single instant	Bayes Net Toolbox
[97]	2021	Chiller	Hybrid	Single instant	Bayes Net Toolbox
[93]	2022	HVAC system	Hybrid	Time slice	SMILE
[92]	2022	AHU	Knowledge-based	Time slice	*N/A*
[78]	2022	AHU	Hybrid	Time slice	Pomegranate
[106]	2022	AHU	Hybrid	Time slice	Pomegranate
[135]	2022	AHU	Hybrid	Time slice	Pomegranate
[102]	2022	Whole building	Knowledge-based	Time slice	SMILE (GeNIe)
[100]	2023	Chiller	Hybrid	Single instant	Bayes Net Toolbox
[101]	2023	AHU	Hybrid	Time slice	*N/A*
[121]	2023	Whole building	Hybrid	Single instant	pgmpy
[136]	2023	Household AC	Hybrid	**N/A*	SMILE (GeNIe)
[110]	2024	Whole building	Knowledge-based	Time slice	SMILE (PySMILE)
[95]	2024	Chiller	Hybrid	Single instant	SMILE (GeNIe)
[125]	2024	Chiller	Data-driven	Single instant	Bayes Net Toolbox
[94]	2024	AHU	Hybrid	Time slice	pgmpy
[114]	2024	HVAC system	Data-driven	Time slice	SMILE (GeNIe)

**N/A represents no specific mention*

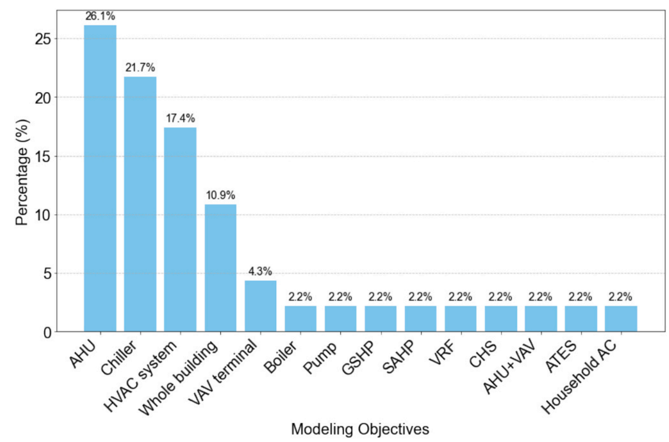

Fig. 6. Distribution of BN modeling objectives among the selected studies.

studied. Chillers are the common study system, accounting for 21.7 % of the selected studies, driven by the experimental dataset available from ASHRAE Project RP-1043 [72,77,137]. Aggregated systems are made up of individual components, including generator, hydronic, and emitter systems [71,138]. At the aggregated system level, AHUs, VAV terminals, GSHPs, and SAHPs have been studies. AHUs are the most commonly studied, accounting for 26.1 % of the selected studies, largely due to the availability of the experimental dataset from ASHRAE Project RP-1312 [75] At the total system level, FDD becomes more complex. Some studies have examined entire HVAC systems, whole building systems, and central heating systems (CHS) using DBNs. These total systems not only consider the HVAC conditions, but also the indoor environment, building envelop conditions, and overall performance [121].

5.2. Modeling types

In many papers, BN-based FDD is often classified as a knowledge-

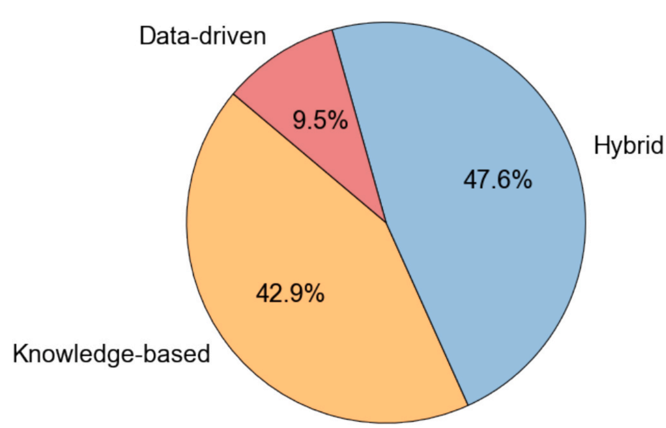

Fig. 7. Distribution of BN modeling types among the selected studies.

based approach [14,15]. However, this description is not entirely accurate since the implementation of DBNs is quite flexible. As shown in Fig. 7, the distribution of DBN modeling types in the selected publications highlights this diversity. The knowledge-based approach remains a traditional method for constructing DBNs in building energy systems, accounting for 42.9 %. It is characterized by the determination of BN structure and parameters solely based on expert knowledge. In contrast, the data-driven approach, only 9.5 % of the selected publications, determines DBN structure and parameters exclusively from data. Li et al. [91] found that generally, data-driven DBNs are more accurate than knowledge-based DBNs. However, implementing the data-driven approach requires a high-quality dataset with fault labels for each individual building or energy system, which is often challenging to obtain in practice. Table 4 provides a summary of the advantages and disadvantages of knowledge-based and data-driven DBN modeling in building energy systems.

Consequently, the hybrid approach, which combines the advantages of both knowledge-based and data-driven approaches, has become a popular choice, representing 47.6 % of the selected publications. In this approach, an initial BN is typically constructed based on expert knowledge. Subsequently, data-driven techniques are applied to enhance the BN model in the following ways:

- Data-driven baseline prediction [78,93,94,100,106,135]: Utilizing historical data to establish baseline predictions.
- Data-driven symptom selection [76,98,107,125,128,129]: Employing data-driven techniques to identify and select relevant symptoms for FDD.
- Data-driven structure optimization [91,95]: Applying algorithms to refine the BN structure based on faulty data.
- Data-driven parameter learning [91,96,98,99,110,119]: Using data to estimate and update the parameters of the BN for a more accurate representation of building energy system dynamics.

5.3. Diagnostic samples

The implementation of DBNs for FDD in building energy systems requires the systematic processing of data inputs to achieve accurate diagnostic results. Data inputs for DBNs are typically defined in two primary ways: single-instant and time-slice [50]. Fig. 8 shows the distribution of DBN diagnostic samples among the selected studies.

Table 4
The summary of the advantages and disadvantages of knowledge-based and data-driven BN modeling.

Modeling type	Advantage	Disadvantage
Knowledge-based DBN	• Tailored models that incorporate expert insight. • Independence from data. • High interpretability, as the model is built on explicit rules and expert reasoning.	• Time-consuming modeling with careful consideration of all possible factors (connections). • Subjectivity due to reliance on expert judgment. • Limited scalability to complex building energy systems with many variables (components/ subcomponents).
Data-driven DBN	• More accurate. • Ability to automatically learn DBN structure and parameters from data. • Scalability to complex systems, potentially capturing complex relationships. • Potential for continuous model adaptation as more faulty data becomes available.	• Requirement for large, high-quality datasets with fault labels. • Risk of overfitting, especially with insufficient data. • Sensitivity to data quality, which can affect model accuracy and robustness.

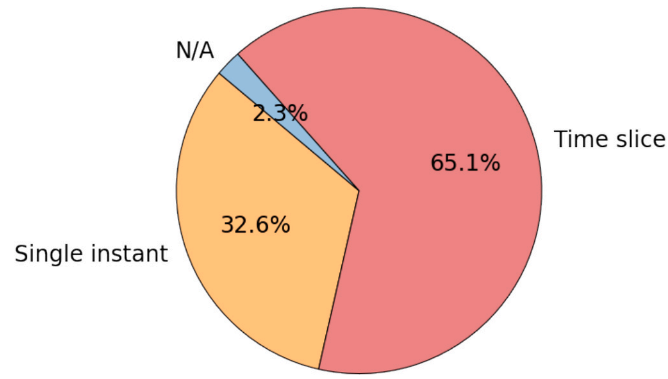

Fig. 8. The distribution of BN diagnostic samples among the selected studies.

Single-instant samples refer to capturing the state of the system at a specific moment in time, which provides a snapshot that the DBN can analyze to detect and diagnose. It is particularly effective for identifying anomalies that are evident from a single observation, such as abrupt failures or deviations from expected behavior. On the other hand, time-slice samples involve processing data over a period of time. DBNs using time-slice samples are more robust, because they are less susceptible to being affected by sensor noise, which might otherwise distort the diagnostic accuracy in single-instant samples. Moreover, by considering data over time, time-slice samples enable DBNs to analyze patterns and trends within the data. Due to the inherent delay in heat transfer processes within building energy systems, certain aspects of energy efficiency must be calculated over time rather than instantaneously [17]. This capability is also particularly valuable for detecting gradual changes or intermittent faults in building energy systems, making time-slice samples a powerful tool for predictive maintenance [101].

5.4. Modeling software

Many software packages have been developed for BN modeling, such as SMILE, Microsoft MSBNx [139], Netica, Bayes Net Toolbox, Pomegranate, AgenaRisk [140,141], HUGIN [142,143], WinBUGS [144,145]. Fig. 9 shows the distribution of BN modeling software among the selected studies. It is noteworthy that 23.26 % of the studies do not mention specific modeling software. The software packages used in those studies for FDD in building energy systems are briefly introduced in the following paragraph.

- SMILE: SMILE (Structural Modeling, Inference, and Learning Engine) is a reasoning and learning/causal discovery engine for graphical

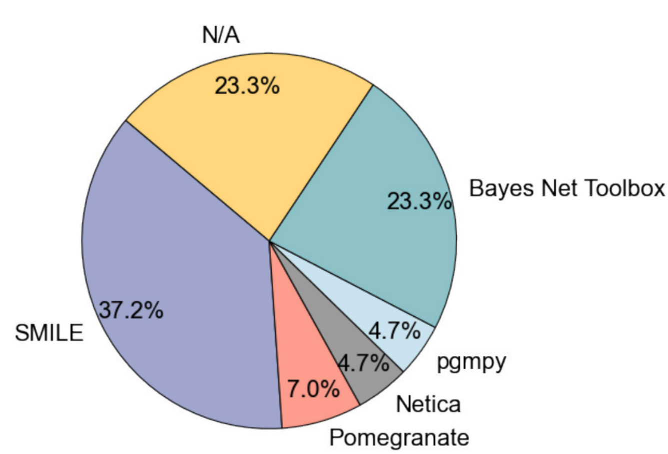

Fig. 9. Distribution of DBN modeling software among the selected studies.

models, such as Bayesian networks, influence diagrams, and structural equation models [146,147]. Written in C++, SMILE offers extensive functionality for constructing and analyzing these models. It also provides wrappers that expose its capabilities to other programming environments, including Java (jSMILE), Python (PySMILE), R (rSMILE),.NET (Smile.NET), and COM (SMILE.COM), making it accessible for integration with a wide range of applications. The popular GeNIe Modeler used in many of the selected studies is a graphical user interface to the SMILE Engine [148].
- Netica: Netica is a powerful, easy-to-use software program designed for working with belief networks and influence diagrams. It provides a comprehensive platform for entering probabilistic relationships, either manually or through equations, and includes an extensive built-in library of probabilistic and mathematical functions. One of its key features is its ability to learn probabilistic relations directly from data, even when the data set includes missing values [149,150].
- Bayes Net Toolbox: The Bayes Net Toolbox is an open-source MATLAB package for directed graphical models [151]. The toolbox supports many types of conditional probability distributions, different inference algorithms (exact and approximate), static and dynamic DBNs, and several ways for parameter and structure learning.
- Pomegranate: Pomegranate is an open-source probabilistic modeling package in Python [152]. It simplifies the process of training models by abstracting the complexities, enabling users to concentrate on defining the correct model for their specific application. Three widely used probabilistic models implemented in Pomegranate are general mixture models, hidden Markov models, and DBNs.
- pgmpy: pgmpy is a python library for working with graphical models. It allows the user to create their own graphical models and answer inference or map queries over them [153]. It includes implementation of many inference algorithms like VariableElimination, Belief Propagation, etc.

It is worth noting that SMILE and Netica are commercial software solutions that are not open-source, while Bayes Net Toolbox, Pomegranate, and pgmpy are open-source alternatives. The choice between commercial and open-source tools often depends on the specific requirements of the project, such as budget, ease of use, dependence on the vendor, and the need for proprietary features [154,155].

6. Practical challenges

This section will present the practical challenges when employing DBNs for FDD in building energy systems.

6.1. Sensor configurations

In building energy systems, sensor configurations can vary widely, ranging from redundant to standard or limited setups. Most studies are conducted in laboratories or test buildings, where sensor configurations are typically redundant, providing extensive data for analysis. There are several building standards that provide guidelines or recommendations for sensor configurations, such as “Guide H Building control systems” [156] from CIBSE (the United Kingdom), “Publicatie 31 Meetpunten en meetmethoden voor klimaatinstallaties (Publication 31 Measuring points and measuring methods for air-conditioning systems)” [157] from ISSO (the Netherlands), and “Guideline 36–2021 –- High-Performance Sequences of Operation for HVAC Systems” [158] from ASHRAE (the United State). However, in reality, building energy systems often face a stark contrast, as limited sensor configurations are far more common.

A critical practical challenge in such scenarios is the lack of sufficient sensors, which leads to unavailable symptoms in DBNs. Unlike purely data-driven methods, DBNs can still function by excluding some symptoms, though this compromises diagnostic precision. In general, sensors integrated into control loops are typically present to ensure operational functionality, but sensors dedicated to performance monitoring and fault detection are often absent. For example, Wang et al. [98] found that several critical sensors, such as those for refrigerant suction temperature, sub-cooling temperature, oil sump temperature, and oil feed pressure, were not consistently available, despite their high sensitivity to faults. Water flow rate sensors, which are crucial for diagnosing performance issues, were also rarely installed in field chillers due to their high initial costs and ongoing maintenance requirements. Similarly, in some AHUs, intermediate sensors are always missing [68], such as mixed air temperature, heating coil leaving air temperature, and cooling coil leaving air temperature. Therefore, diverse sensor configurations present significant obstacles to developing DBNs capable of supporting universally applicable FDD solutions.

6.2. Baseline estimation in symptoms

Baseline estimation is a critical step in symptom detection using DBNs, as it involves defining the expected system behavior under normal operating conditions when determining the presence/state of symptom nodes. As mentioned in section 3.1.2, establishing baselines is often not straightforward. Ideally, baselines are documented in HVAC design specifications; however, in many existing buildings, these design documents are either missing or incomplete. Furthermore, renovations and system modifications frequently render existing HVAC documentation outdated and unreliable.

The situation is further complicated by the increasing adoption of advanced HVAC control strategies in energy-flexible buildings, such as Model Predictive Controls (MPCs), which dynamically adjust system parameters in real time. While these strategies enhance system performance, they introduce variability that makes defining a consistent baseline more challenging [159]. This variability can obscure the distinction between normal and faulty system behavior, thereby complicating symptom detection and reducing the accuracy of fault diagnosis in DBNs.

6.3. Threshold determination in symptoms

Threshold is another aspect of symptom detection in DBNs. It involves defining the boundaries or deviations that distinguish normal system behavior from abnormal conditions of HVAC systems. Usually, these thresholds are established using domain knowledge and expert experience. However, several practical challenges complicate this process.

Firstly, variations in HVAC sensor installation practices can lead to inconsistent data acquisition, affecting the reliability of thresholds. Secondly, inaccurate sensor measurements, whether due to calibration issues or sensor degradation, can introduce errors, making it difficult to set accurate boundaries. Thirdly, the inability to establish robust baseline estimation, whether due to missing or outdated system documentation or limitations in the baseline estimation model itself, further undermines threshold reliability. Additionally, as mentioned in section 5.2, the adoption of advanced control strategies adds another layer of complexity. These dynamic strategies continually adjust system parameters in response to changing conditions, resulting in fluctuating operating ranges that challenge static threshold definitions.

6.4. Expert knowledge transformation

Considering the unavailability of high-quality fault datasets, integrating expert knowledge into DBNs for FDD in HVAC systems often becomes essential for symptom determination, structure modeling, and parameter modeling. However, effectively transforming expert knowledge into DBNs is inherently challenging, especially in large building energy systems. The nature of expert knowledge is often vague and imprecise, as it is derived from subjective experiences and may lack quantitative rigor. This vagueness can make it difficult to translate expert insights into clear, numerical inputs for DBNs. Additionally, different experts might have different even conflicting opinions, as experts may have differing perspectives based on their background, specialization, or interpretation of the HVAC system. For instance, Liu et al. [119] implemented fuzzy set theory to integrate six expert knowledge into DBNs for determining prior probabilities of the faults in a solar-assisted heat pump system. However, the application of such methods is still limited in scope. There remains a lack of comprehensive analysis across diverse HVAC systems, as well as insufficient exploration of other critical aspects, e.g. structure modeling and conditional probabilities, and sensitivity analysis, e.g. selection of membership functions in fuzzy theory.

Furthermore, another challenge arises when determining the states of fault nodes within the DBN. In some projects, detailed HVAC fault information may be required, which necessitates defining multiple states for each node. However, if there are too many states for each node, experts may struggle to provide accurate and effective judgments. As the number of states increases, so does the complexity of the model, leading to an exponential growth in the number of parameters. This makes assigning probabilities more challenging and less precise. Even when expert knowledge is available, it becomes difficult for experts to provide consistent and reliable input for each state. While methods such as Noisy-OR gate and Noisy-Max gate can help simplify the modeling process, they still present significant computational and modeling challenges, particularly in large, complex systems. These factors exacerbate the difficulty of effectively integrating expert knowledge into DBNs.

7. Recommendation for future research

Based on the discussion above, the following recommendations for future research are provided for enhancing the application of DBNs in FDD tasks within building energy systems.

1) Applying DBNs more extensively to building energy systems

Despite the many advantages of DBNs for FDD in building energy systems, the limited number of studies found on this topic indicates that further research is needed. Existing studies primarily focus on components like AHUs, chillers, and heat pumps. However, the integration of novel technologies, such as building-integrated photovoltaics [160–162], energy storage [163–165], and personalized coolers [166–168], introduces transformative changes to building energy systems. It is also worth noting that the growing complexity of whole-building systems and district-scale heating and cooling systems significantly increases the complexity of DBNs [169]. Furthermore, the occurrence of simultaneous faults might add additional diagnostic challenges [170]. Future research should prioritize expanding the application of DBNs to FDD tasks in these emerging building technologies and larger-scale energy systems.

2) Enhancing the transferability of DBNs across similar systems in different buildings

Currently, DBNs are often developed for specific systems and buildings, which limits their applicability across diverse configurations and installations. Taking AHUs as an example, common AHU configurations include single duct and dual duct systems, with options for constant air volume (CAV) or VAV operation. Each AHU type can have different component setups, such as single or dual fans, and may include or exclude pre-heating components and heating coils. Additionally, these systems employ various operational strategies, including different control methods for outside air dampers, supply and return fans, and supply air temperature [75]. These varying configurations significantly influence the symptoms, structure, and parameters of DBNs, highlighting the need for tailored BN models that can effectively handle the diversity and complexity of building energy systems. Enhancing the transferability of DBNs across different systems and buildings would allow for more widespread application.

3) Automatically constructing DBNs from multiple sources

The current process of constructing DBNs remains tedious and time-consuming, which presents another barrier to their widespread application. There is substantial potential to automate the construction of DBNs from building information models (BIMs) [171–173] and P&IDs [12,174–177], as these sources contain essential information about key components and their interrelationships. On the other hand, advancements in knowledge representation and machine learning offer additional pathways to automate DBN construction. Some studies [178,179] utilizing knowledge graphs have demonstrated their ability to extract and structure information to construct DBNs. Self-organizing networks, which use clustering and adaptive algorithms, have been explored for dynamically learning network structures from data [180,181]. Automating DBN construction could greatly assist HVAC engineers by streamlining the process and reducing the time and effort required. This automation would facilitate quicker and more efficient development of DBNs for FDD tasks in building energy systems.

4) Dynamic DBNs for predictive maintenance in building energy systems

Current studies mainly focus on static DBNs to diagnose faults in building energy systems. However, many faults in building HVAC systems develop gradually and can lead to significant energy waste over time. Developing dynamic DBNs can enhance predictive maintenance by modeling temporal changes and identifying faults before they become critical [101,134]. This approach supports the development of proactive maintenance and repair schedules, which is crucial for maintaining the safety, stability, and longevity of HVAC systems.

8. Conclusions

This review paper examines the practical applications of DBNs for FDD tasks in building energy systems, emphasizing their potential as a valuable tool for developing universally applicable solutions. DBNs offer several key advantages, including interpretability, robustness to uncertainties, scalability, and flexibility, making them particularly suited for addressing the complex challenges inherent in FDD tasks for building energy systems.

Based on the selected relevant publications, this paper outlines the four-step generic modeling procedure of DBNs for FDD in building energy systems, which includes problem formulation, structure modeling, parameter modeling, and fault isolation and evaluation. Then, this paper provides a discussion with respect to four key aspects: modeling objectives, modeling types, diagnostic samples, and modeling software. The main findings are as follows:

- AHUs and chillers are the most common DBN modeling objectives for FDD among building energy systems.
- Hybrid modeling approaches, integrating the advantages of both knowledge-based and data-driven approaches, have become a popular choice.
- Time-slice samples enable DBNs to analyze fault patterns and trends within the data, which is more suitable for the inherent heat and mass transfer process in building energy systems.
- A variety of DBN modeling software options are available, catering to diverse requirements and user preferences in FDD tasks.

This paper also highlights practical challenges, such as issues related to sensor configuration, baseline estimation and threshold determination in symptoms, and the transformation of vague expert knowledge into DBNs. To further advance the application of DBNs for FDD in building energy systems and facilitate their widespread adoption in the building service industry, several recommendations for future research are proposed:

- Applying DBNs more extensively to building energy systems, including novel building technologies and complex district building energy systems.
- Enhancing the ability of DBNs to generalize across similar systems in different buildings and adapt to varying system configurations, ensuring broader applicability and effectiveness.
- Automatically constructing DBNs from multiple sources, such as BIMs and P&IDs, by leveraging advanced techniques like knowledge graphs and self-organizing networks for streamlined and intelligent model generation.
- Employing dynamic DBNs for predictive maintenance, improving foresight and reliability in building energy system management.

These efforts will enhance the capability and adaptability of DBNs, paving the way for their practical implementation in real-world scenarios.

CRediT authorship contribution statement

Chujie Lu: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization. **Ziao Wang:** Writing – review & editing, Investigation. **Martín Mosteiro-Romero:** Writing – review & editing, Investigation. **Laure Itard:** Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This study is a part of the Brains4Buildings project, sponsored by the Dutch grant program for Mission-Driven Research, Development, and Innovation (MOOI), which is 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. Additionally, the authors sincerely appreciate Dr. Arie Taal for their valuable suggestions.

Data availability

No data was used for the research described in the article.

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