Development of FDD-ON: an Ontology for VAV HVAC System Fault Detection and Diagnostics

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Abstract

Fault detection and diagnosis (FDD) technology is essential for improving HVAC system reliability, energy efficiency, and maintenance effectiveness. However, effective deployment of FDD solutions in buildings requires structured domain knowledge that can bridge heterogeneous data sources, diverse equipment types, and varied diagnostic outputs. Limited data interpretability and interoperability within the FDD domain have led to fragmented information silos, hindering the implementation of FDD and related applications, such as the digital twin-enabled FDD frameworks and artificial intelligence (AI)-driven maintenance decision-making systems. This paper presents an FDD Ontology (FDD-ON), a modular and extensible ontology to formally represent variable air volume (VAV) HVAC system components, fault types, symptom statuses, fault impacts and associated attributes. FDD-ON integrates HVAC system FDD semantics to provide comprehensive representations of fault and symptom attributes, supported by the well-defined controlled vocabulary. Additionally, FDD-ON offers comprehensive fault, symptom, and impact libraries to capture a broad spectrum of operational abnormalities and their consequences in VAV HVAC systems. Through explicit contributing cause-fault-symptom-impact relations, FDD-ON serves as a machine-interpretable basis for querying diagnostic knowledge, mapping heterogeneous FDD outputs, and developing interoperable FDD-related applications. FDD-ON is evaluated using publicly available VAV HVAC system datasets and demonstrated through FDD development applications. Results indicate that FDD-ON provides a foundational semantic framework for advancing scalable, transparent, and interoperable FDD solutions across various applications.

Key words

Ontology, FDD, HVAC system, operation and maintenance, artificial intelligence

1. Introduction

Heating, ventilation, and air conditioning (HVAC) systems are the dominant energy consumers in buildings, accounting for approximately 38% of total building energy use in the United States [1]. In addition to their substantial energy consumption and associated utility bills, the maintenance costs for ensuring system performance and improving HVAC system reliability are enormous. For example, it is estimated that the global HVAC maintenance cost was approximately $78.5 billion in 2023 and is projected to exceed $116 billion by 2030, driven by increasing demands for energy efficiency and the adoption of digital maintenance technologies [2]. Numerous faults and malfunctions occurring in HVAC systems can significantly increase energy consumption and maintenance costs [3]. For instance, studies have estimated that 15%–30% of energy in commercial buildings is wasted due to faulty, poorly maintained, degraded, or improperly controlled HVAC equipment [4–7]. Consequently, fault detection and diagnostics (FDD) technologies have become essential for improving system reliability, enhancing operational performance, reducing energy waste and supporting efficient maintenance practices. Extensive research efforts have focused on developing advanced FDD algorithms with improved fault classification accuracy, lower false alarm rates, greater scalability, and enhanced capability to address the scarcity of labelled fault data [8–12].

Despite substantial efforts on improving FDD algorithms, relatively few studies have addressed the development of knowledge models, which can enhance the development, evaluation, and integration of FDD-related solutions, such as a digital twin (DT)-based FDD deployment, semantic FDD inference frameworks, and AI-driven maintenance decision-support systems.

The absence of such frameworks presents three key challenges that impede

(1) Lack of unified definitions of faults (or specific component malfunction), symptoms and impacts. In many FDD algorithm development, the process of FDD is to identify abnormalities or malfunctions in specific components through the manifestations of symptoms [13,14]. However, it is also reported that in FDD solutions, various symptoms and even fault impacts are classified into faults [15]. For example, in an FDD tool, an abnormal supply air flow rate in an air handling unit (AHU) is classified as a fault rather than a symptom of an underlying fault. Furthermore, an increased hot or chilled water consumption is considered as an outcome-based fault instead of a fault impact [15]. This creates ambiguity in fault definitions and hence poses challenges for establishing robust fault inference mechanisms and conducting meaningful assessments of FDD approaches.

(2) Lack of sufficient illustration of attributes associated with faults and symptoms. The attributes describe fault mechanisms, symptom characteristics, as well as the cause-and-effect relations among faults, symptoms and impacts. Therefore, attribute information significantly supports FDD algorithm development and validation, subsequent maintenance activities. For example, in most HVAC FDD algorithms, symptom patterns are only represented by the deviation levels (e.g., supply air temperature in an AHU is higher/lower than the baseline or the setpoint) to indicate certain types of faults (e.g., cooling coil valve is stuck, or heating coil valve is stuck). However, other symptom patterns such as temperature slow response or oscillation, which indicate other types of faults (e.g., cooling coil water-side fouling or cooling coil valve is hunting) are often neglected.

(3) The heterogeneous data outputs generated by FDD tools have limited interoperability, causing a significant challenge for the efficient interpretation and utilization of FDD results [16]. The outputs of existing FDD and system maintenance tools consist of a mix of predefined codes, abbreviations and natural language descriptions, resulting in a high volume of unstructured and inconsistently formatted information related to fault observations, symptom manifestations, diagnostic conclusions, and fault cause assessments. Such heterogeneity dramatically hinders the automated processing, integration and analysis of FDD related data, thereby restricting the ability to transform raw diagnostic outputs into actionable insights for evaluating system operational performance, supporting maintenance decision-making, and facilitating the closure of the fault management loop through effective corrective actions.

To address these challenges, researchers have increasingly turned to ontologies, which use formal, explicit conceptual models — to support semantic reasoning, knowledge integration, and explainable diagnostics. Ontologies provide a structured and machine-interpretable representation of domain knowledge, which is particularly valuable for integrating data-driven and AI technologies into HVAC system control and O&M. In the context of HVAC system FDD, ontologies can explicitly model HVAC equipment, components, sensors, operating states, faults, symptoms, and the cause-and-effect relationships among them.

As such, they provide consistent interpretation of heterogeneous data sources and facilitate the characterization of fault behaviors and occurrence mechanisms in different system configurations. Moreover, ontologies promote semantic interoperability and support explainable reasoning. This allows diagnostic approaches to combine rule-based logic, physics-informed relationships, and metadata-driven methods within a unified framework. These capabilities make ontologies as a foundational technology for developing interoperable, explainable, and scalable FDD ecosystems, which significantly support the entire fault management lifecycle, from FDD development, deployment and implementation to maintenance planning and corrective actions.

In this study, we develop an FDD ontology (FDD-ON), which creates a standardized structure for the classification of various types of faults and symptoms, as well as attributes associated with faults and symptoms. The FDD-ON unifies the representation of faults and symptoms among varied terminologies and vocabulary, into a relational ontology that permits inference and reasoning of the relationships among fault concepts and is optimized toward annotating HVAC faults.

The contributions of this work include:

(1) FDD-ON includes a semantic model to explicitly represent fault characteristics (i.e., fault descriptions and associated attributes), symptom characteristics (i.e., symptoms descriptions and associated attributes) and impact types, as well as their relations. The semantic model represents the complexity of fault mechanisms and symptom features in VAV HVAC systems. Consequently, it improves the understanding of fault mechanisms and enables the systematic dissemination of knowledge across diverse applications.

(2) FDD-ON provides a taxonomy framework, which classifies various fault attributes and symptom attributes. The developed taxonomies enhance information representations and efficient information management.

(3) FDD-ON provides definitions for fault natures and symptom statuses through controlled vocabulary items. Additionally, the naming convention for fault types, symptom statuses and impact types are structured through a quadrinomial nomenclature. This significantly enhances the interpretability and interoperability of faults and symptoms and facilitates the translation of FDD results into multiple applications.

(4) FDD-ON contains open source and evolving libraries for fault types, symptom statuses, and impacts, to efficiently retrieve fault types, as well as associated symptoms and impacts. Currently, 469 fault types, 468 symptom statuses, 447 impact types, which are reported in five major types of subsystems and equipment (i.e., chiller plant, boiler plant, AHU, VAV air terminal unit (ATU) and packaged rooftop unit (RTU)) in VAV HVAC systems, have been included in the libraries for fault types, symptom statuses, and impact types, respectively (Version: 2026B). The libraries will be continuously evolving, so that new types of faults and symptoms in VAV HVAC systems can be included and the community can incorporate the latest results for their applications.

The subsequent sections of the paper are organized as follows: Section 2 reviews existing works on the development of ontologies in the building sector. Section 3 illustrates the development of FDD-ON. Section 4 evaluates FDD-ON, as well as discusses the limitations and future work. Section 5 concludes this paper.

2. Literature review

To support the development of the ontology tailored to the HVAC system FDD-related applications, we reviewed existing research on the development and applications of ontologies in the building sector. The review identifies the ontology development progress and uncovers gaps in existing ontologies. Meanwhile, it helps to determine whether certain ontologies can be reused in the development of FDD-ON.

2.1 Ontology in the building sector

With the increasing deployment of sensors, automation systems, and diverse data sources in modern buildings, there is a need to efficiently integrate various data sources across various systems and applications in buildings. In the past, several protocols and standards, such as BACnet (Building Automation and Control Networks) [17], ASHRAE

(American Society of Heating, Refrigerating and Air-Conditioning Engineers) standard 205 [18,19], 232 [20], gbXML (Green Building XML schema) [21], provide standardized way to design and document data models in various formats.

Furthermore, ontologies have become foundational in addressing heterogeneity, interoperability, and semantic understanding in building systems. A major strand of research focuses on semantic integration and data interoperability. For example, Pauwels and Fierro highlighted that metadata associated with building data streams is essential for meaningful interpretation and control in smart buildings [22]. They indicated that merging model-based metadata schemas (semantics) with data-driven monitoring and control into a functional system architecture is challenging. Pritoni et al. presented a comprehensive review on metadata schemas and ontologies used for building energy systems [23]. Their work underscores the strong needs for developing harmonization and standardization of schemas to enable interoperable, usable, and maintainable building models. A brief illustration of existing ontologies or semantic models are presented below.

The Industry Foundation Classes (IFC) provides a set of definitions for classes (entities), attributes, relations, property sets and other entities to enable semantic interoperability among Building Information Model (BIM) software platforms [24]. Although the IFC ontology provides comprehensive standard representations of equipment in the HVAC domain, it lacks a representation of FDD knowledge, which needs to describe fault mechanisms and associated symptom statuses and consequent impacts in HVAC systems.

Balaji et al. introduced Brick Schema, which provides standardized, machine-readable description of various systems in buildings [25]. In Brick Schema, a class hierarchy is defined to incorporate linked entities across physical, logical and virtual assets in building systems. Relations between entities can be represented through physical connections within the system. Several research works extended or integrated Brick Schema into various applications to enhance the data interoperability within the HVAC system-related applications. For example, Luo et al. extended the Brick Schema to represent metadata of occupants [26]. Ploennigs et al. extended the Brick Schema for automated comfort diagnosis [27]. Chia et al. reported integrating the Brick Schema into the plug load control strategies for load reduction [28]. Jia et al. developed a semantic framework for evaluating chiller plant operation using the Brick ontology [29].

Project Haystack is a widely adopted metadata framework that uses standardized tags and relations to describe building assets, sensors, points, and controls [30]. It is particularly useful for addressing the inconsistent point naming conventions from different vendor-specific building automation systems (BAS) and building energy management systems (BEMS) and supporting interoperable building analytics across vendor-specific systems. Nevertheless, Project Haystack is primarily designed as a general building metadata and tagging framework rather than an HVAC FDD domain ontology. Its core vocabularies do not provide information of faults in HVAC systems. Therefore, additional FDD-specific semantic structures are needed to represent diagnostic knowledge in a reusable and machine-interpretable form.

Additionally, other researchers developed various ontologies for different applications in the building system operation and control. For example, Li et al. developed Energy Flexibility Ontology (EFOnt), which extends existing terminologies, ontologies, and schemas for building energy flexibility applications [31]. Schneider et al. developed a control ontology (CTRLont) to define the domain of control logic in BAS [32]. Qiu et al. developed Human Comfort in Building ontology to capture human experiences related to various factors in the indoor environmental quality domain so that HVAC system settings can be adjusted [33]. Rasmussen et al. developed Building Topology Ontology (BOT), which provides a high-level description of the topology of buildings including stories and spaces, the building elements, and web-friendly 3D models [34]. Tomašević et al. developed a facility ontology to model all static knowledge, including technical vendor data, proprietary data types, and communication protocols in the facility management activities of airports [35].

Overall, literature highlights the benefits of ontologies used in buildings, i.e., ontologies promote semantic interoperability across solution vendors and systems. Meanwhile, ontologies provide a foundation for advanced analytics and reasoning, and facilitate the integration of complex datasets, which is essential for scalability and robust automation in smart buildings.

2.2 Ontology for HVAC FDD

In the context of FDD, semantic ontologies can support advanced reasoning and inference-based detection [36]. However, few studies have been conducted to develop ontologies or semantic models for HVAC system FDD. Existing ontologies and semantic models aim to enable consistent data integration and automated reasoning for HVAC system FDD tasks. For example, Chen et al. developed fault taxonomy for three types of HVAC equipment, i.e., air handling unit, terminal unit and packaged roof top unit [37,38]. In the taxonomy, the authors not only developed a standardized and structured naming system to represent various fault types in various locations of a component in equipment but also the defined control vocabulary to describe fault natures in HVAC systems. However, the authors classified fault symptoms into fault types (i.e., behavior-based fault type and outcome-based fault type), leading to difficulties in the reference process and fault types.

Hwang et al. extended Brick Schema to a Fault-Symptom Brick metadata schema, namely FSBrick [39,40]. In the schema, FSBrick provides a semantic framework that links HVAC faults, symptoms, system components, and measurable points, enabling more systematic and explainable FDD results. However, the schema did neither fully capture fault mechanisms, such as contributing causes and occurrence stages, nor fault symptom characteristics, such as symptom directions and symptom patterns.

Blechmann et al. developed fault ontology for AHUs to depict part of fault characteristics such as fault occurrence locations and fault nature [41]. The effectiveness of the developed approach was demonstrated using historic operation data of a real AHU in the building. However, the authors did not completely illustrate the structure of the ontology and provide a fault type library.

Gourabpasi et al. developed an ontology for automated FDD of HVAC, namely AFDDOnto [42]. The developed AFDDOnto has two functionalities: 1) integrating BIM with BAS concepts in the form of a knowledge model to assist AFDD model development; and 2) obtaining analytic results from AFDD models to update BIM-based model for the application of DT of the facility. Although the study developed a semantic model using concepts from BIM and BAS, it lacked a detailed description of fault natures, making it hard to implement reference during the diagnosing process in FDD.

Ploennigs et al. employed semantic graphs to create the diagnostic model from data points in HVAC systems and identify potential cause-and-effect relations [43]. Although the study differentiated the fault type and associated symptoms, it did not further illustrate the inherent mechanisms of each fault type and various symptoms. Additionally, it did not propose a data format that can facilitate streamlining the data analytics in FDD solutions and CMMSs.

Mallak et al. developed a system ontology which consists of four entities or classes i.e., office building, sensory and control, symptoms and failures classes [44]. The study was demonstrated to be effective in building a diagnostic direct graphic for fault diagnosis reference. However, the study did not provide a unified and structured data format to represent the developed ontology, making it difficult for CMMSs to automatically process FDD results.

Li et al. developed a domain ontology, which included semantic rules based on the knowledge graph for building energy system fault detection [45]. Through the ontology model, fault action mechanisms can be captured based on the inference chains of the rules. While the study defined five top classes, i.e., Equipment, Sensor, Datapoint, Location and Fault to illustrate the fault detection process, it lacked detailed descriptions on fault nature and other types of measurements such as control signals and meter data to represent fault symptoms and impacts.

2.3 Limitations of existing work

From the above studies, we identified three major limitations of existing ontologies. They are:

(1) Existing ontologies or semantic models have insufficient descriptions of mechanisms and attributes of faults and symptoms in HVAC systems.

(2) Non ontologies provide an open-source fault library and symptom library that cover reported fault types in HVAC systems. This prevents ontology reusability for other application developments.

(3) Existing ontologies do not consider various applications, such as the development of maintenance decision-making systems and fault tolerant control solutions, other than FDD approach development; and hence, have weak inference capabilities to support multiple applications.

3. Methodology

In this Section, we illustrate the method framework for developing FDD-ON as illustrated in Figure 1. There have been many approaches for developing ontology for various applications in the past years, and they were reviewed and compared in [46–48]. In this study, we adopted Gruninger & Fox's methodology [49], which transforms informal scenarios into formal languages. Specifically, we propose a framework that includes five major phases including: 1) information and requirement analysis, 2) development ontology, 3) development of fault libraries, symptom libraries, and impact libraries, 3) ontology evaluation, and 5) limitation discussion and evolution. It is noted that the development of FDD-ON is an iterative process, i.e., the evaluation result of FDD-ON should feedback to step #1 to update, extend and enhance the ontology. We illustrate this methodology in the following subsections in Section 3 and Section 4, respectively.

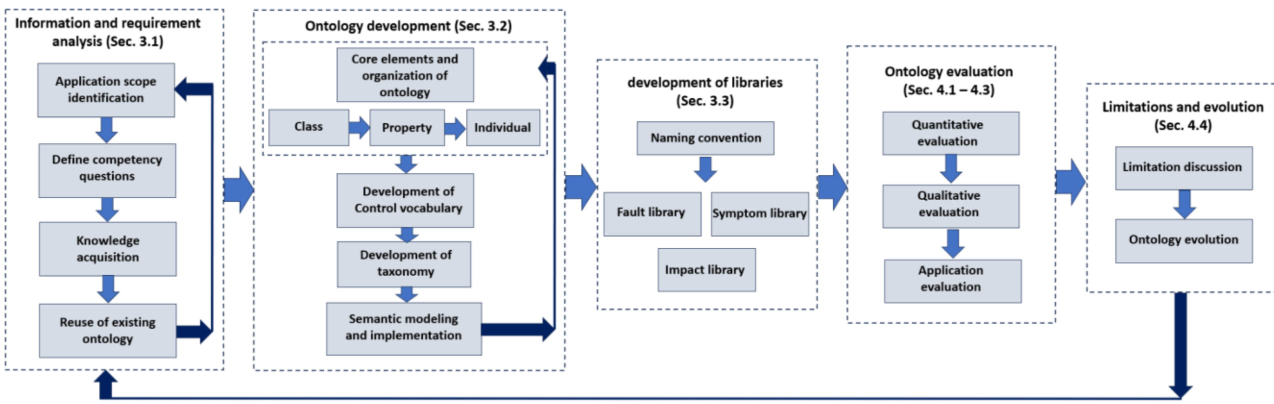


Figure 1. Methodology framework for developing FDD-ON.

3.1 Information and requirement analysis

3.1.1 Application scope identification

In this study, we identify the application scope by first constructing the knowledge structure for various applications in the FDD domain. There are six fundamental directions that the FDD area includes.

(1) Fault modeling: Fault modeling is to construct an accurate representation of occurrence mechanisms (including the fault occurrence location, and fault behaviors) of hardware faults or software faults, as well as the associated fault symptoms and impacts [50,51]. To improve fault modeling outcomes, it is needed to clearly understand fault behaviors (e.g., fault occurrence locations) and their correlations with fault symptoms (e.g., how fault severity level may affect fault symptom states and magnitudes).

(2) Fault effect and impact analysis: The fault behavior and impact analysis investigates how HVAC equipment and systems operate under faulty operations and consequently uncovers the characteristics and effects of various types of faults in the equipment and systems [3,52]. To better evaluate fault effects and impacts, it is essential to clearly scope the attributes of fault symptoms and impacts. For example, in an HVAC system, for the same type of a fault, effects and impacts vary significantly under various operational conditions. Therefore, the uncertainty of fault symptom magnitudes and impact levels should be illustrated during fault effect and impact analysis.

(3) FDD development: The development of FDD solution often includes two phases as: i) the abnormality detection process is to capture the operational abnormalities of a system or equipment; and ii) the fault diagnosis is to identify the fault location, distinguish the fault type, and estimate fault severity levels [53–55]. To enhance the development of FDD solutions, especially for the inference-driven fault diagnostics, it is needed to establish a robust understanding of the relations between faults and associated symptoms.

(4) Fault tolerant control implementation: A fault tolerant control is capable of tolerating faults in the HVAC system to improve the reliability and availability while ensuring a desirable operation performance [56–59]. When a fault occurs, the HVAC control system can isolate fault source, eliminate the fault, and is robust to mitigate fault negative impacts [60]. To develop fault tolerant control strategies, it is necessary to completely understand fault occurrence mechanisms (e.g., fault occurrence location, fault severity level and fault behaviors), as well as fault symptoms and impacts.

(5) Maintenance practice: After faults are detected and diagnosed, the facility team or technicians should address the issue, fix the faults, or plan other maintenance activities to ensure the operational performance of the HVAC system. The maintenance algorithms need to effectively support various maintenance strategies (e.g., condition-based maintenance, preventive maintenance and predictive maintenance) based on various factors such as fault behaviors, fault impact magnitude, system operation schedules and facility team arrangement [61,62]. To support HVAC system maintenance decision-making and actual maintenance work, it is required to precisely diagnose fault types, accurately estimate fault impacts and infer fault contributing causes.

(6) Fault diagnosis analysis: Fault diagnosis analysis investigates fault occurrence likelihood, fault occurrence rate, fault contributing causes in HVAC systems. It provides insight into fault occurrence distributions and patterns in different types of equipment or systems under various operational conditions. Hence, the analysis results support multiple applications such as the development of FDD approaches, equipment improvement and maintenance practices [7,63]. To perform fault occurrence analytics, it is required to obtain complete descriptive information from fault records including fault types, fault behaviors, fault impacts, and how the fault is detected and diagnosed.

3.1.2 Competency questions

Competency questions (CQs) include a set of questions stated and replied in natural language to support the development, evaluate and maintain the ontology [64]. CQs play a critical role in the development of ontology because they represent the ontology requirements [65]. After identifying the application scope, we designed seven major categories of CQs, which are used to specify ontology functional requirements and guide the development of FDD-ON as given in Table 1. Under each category of CQs, specific CQs were designed but not listed here. For example, under CQ3, a specific CQ of 'How to classify fault contributing causes was designed to enable the developers to specify the purpose and function of classifying fault contributing causes.

Table 1. List of CQs.

CQ category	CQ description
CQ1	How to define fault types and associated symptom statuses in control systems, specifically for HVAC systems in residential buildings and commercial buildings, for the purpose of sharing knowledge?
CQ2	What existing ontologies can be reused to develop the FDD ontology?
CQ3	What attributes should be included to accurately describe faults found in HVAC systems?
CQ4	What attributes should be included to accurately describe symptoms observed in HVAC systems?
CQ5	What taxonomic hierarchy can be used to accurately classify those attributes associated with fault types, symptom statuses, and impact types?
CQ6	How can the interpretability and interoperability of the fault data be enhanced to facilitate multiple applications?
CQ7	How can the HVAC system fault related data be structured and organized to address the issue of data silos?

3.1.3 Knowledge acquisition

Ontology development requires a thorough understanding of the target domain and its associated terminology through the collection and analysis of existing documents, databases, standards, expert knowledge, and relevant ontologies [66]. In this study, the knowledge acquisition process for developing FDD-ON was informed by three primary sources. First, we conducted extensive research work in several directions in the HVAC FDD area, including fault impact analysis [3,67], fault model development and fault data curation [51,68,69], physics-based and data-driven FDD approach development and deployment [8,70–74], fault tolerant control [75,76], fault prevalence and occurrence characteristics [7,63], facility maintenance [16], and data tagging and relation inference technologies used in FDD [38,77]; Secondly, we examined several commercialized FDD solutions to obtain an in-depth understanding of functionalities of the software tools [38,78]; Lastly, we incorporated insights obtained from facility operators and maintenance personnel to capture first-hand operational experiences and identify practical challenges encountered in day-to-day O&M activities.

These knowledge sources ensured that FDD-ON reflects both theoretical advancements and real-world requirements, thereby enhancing its applicability to practical HVAC FDD and maintenance scenarios.

3.1.4 Reuse of existing ontologies

In this study, we reuse some approaches and data-modeling in terms of HVAC system hierarchy and data point tagging in Project Haystack [30] and Brick Schema [25]. For example, the classification in the temperature sensor class in the Brick model was used. However, it should be noted the data point naming structure in the fault naming system was adjusted to more accurately reflect the fault and symptom mechanisms including locations, measurement types, behaviors and states. Additionally, we reused and adjusted the controlled vocabulary library and data structure that was proposed in HVAC system fault taxonomy [37]. This is because the controlled vocabulary library and the fault naming data structure developed in fault taxonomy basically capture the fault characteristics and physical configurations in HVAC systems

3.2 Development of ontology

3.2.1 Fundamentals

HVAC system FDD relies on diverse sources of information, such as operational time-series data and metadata, to support complex reasoning and cause-and-effect analyses. Based on the concept of causal chains [79,80], we developed a four-level semantic model, which characterizes the FDD inference and analytic processes, as illustrated in Figure 2. The model structures FDD knowledge and reasoning into four interconnected levels: 1) symptom detection, 2) fault diagnosis, 3) contributing cause identification, and 4) fault impact analysis.

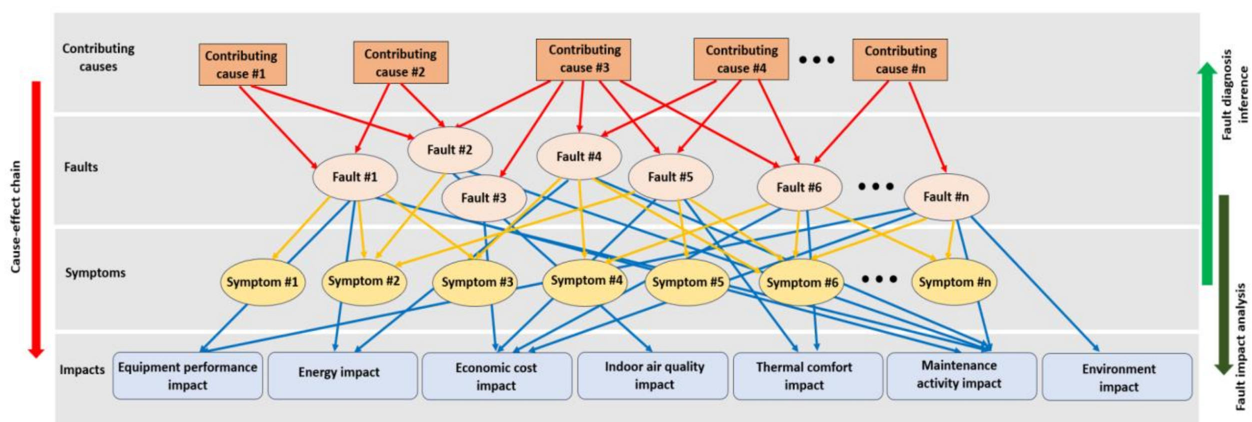


Figure 2. Four-level semantic model for FDD inference and analytics.

(1) **Symptom detection**: During system operation, symptoms are manifested as abnormal patterns in specific measurements identified by comparing the real-time interval data with predefined thresholds or expected baselines (e.g., the supply temperature is higher than expected). Accordingly, symptom detection aims to identify and flag these abnormal manifestations when thresholds are overpassed. Successfully symptom detection relies on accurately establishing performance baselines and appropriately defining detection thresholds [67,81]. Otherwise, missing detection and false alarms may occur. However, symptom manifestation in HVAC systems is often uncertain because it can be influenced by many factors such as fault severity levels, varying indoor and outdoor environmental conditions, and changes in operational sequences [82]. For instance, an AHU cooling valve stuck at a low position may not produce strong fault symptoms during the transition season, when cooling demand is less [54].

(2) **Fault diagnosis**: In FDD-ON, a fault refers to undesirable operational condition deviation from a defined operational goal, caused by non-functional component (e.g., a leaking valve), improper software settings (e.g., incorrect proportional-integral-derivative (PID) parameter setting), or ill-designed operational processes conditions (e.g., an improper sized pump). Consequently, the objective of fault diagnosis is to distinguish the abnormal operating condition in terms of both its nature and location in the system. One of the major challenges in fault diagnosis is that different faults may generate similar or overlapped symptom patterns [83,84]. For example, in an AHU, a negative bias fault in the supply air static pressure sensor and outdoor air damper stuck at a higher open position can produce similar abnormalities in supply air fan speed, fan power, and cooling coil valve position. Such symptom overlaps complicate the accurate identification of a fault.

(3) **Contributing cause identification:** Contributing causes represent the underlying conditions, actions, or environmental circumstances that lead to an occurrence of a fault. The process of uncovering fault contributing causes is to reveal the "why" or "how" behind a specific fault. The identification of contributing causes of a fault is critical to effectively carry out maintenance activities (e.g., estimate maintenance labor efforts and financial costs). For the same fault, the maintenance activities can be significantly different. For instance, for an AHU damper stuck fault, if the contributing cause of this fault is disconnected communication wires of the damper controller, then the maintenance work is to reconnect the communication wires, and there is very little maintenance financial cost associated with this maintenance activity. In contrast, if the fault is caused by a malfunctional damper actuator, component replacement may be necessary, leading to substantially higher maintenance costs and increased labor efforts.

Despite its importance, very few efforts have been made to investigate fault contributing causes in HVAC FDD. This is partly because identifying contributing causes often require complex causal reasoning and domain expertise that cannot be readily automated using existing FDD tools. In addition, records documenting fault contributing causes are rarely available in practice, making it difficult to establish systematic knowledge and standardized representations.

(4) **Fault impact analysis:** Faults occurring in specific components can propagate through HVAC systems and produce broader impacts on operational performance, energy consumption, occupant comfort, maintenance activities, and financial outcomes. Following fault diagnosis, fault impact analysis aims to quantify these consequences using various performance metrics [3]. Although the distinction between symptoms and impacts is not always explicit, symptoms generally represent observable indicators of abnormal operation, whereas impacts describe the resulting performance degradation or associated consequences. For instance, abrupt increases in power consumption or immediate reductions in cooling capacity may serve both as observable symptoms and as indicators of fault impacts. Nevertheless, fault impacts typically represent broader effects, including energy penalties, increased maintenance requirements, reduced equipment reliability, and occupant discomfort. When faults cannot be fixed rapidly, mitigating their impacts becomes essential and may require the implementation of sophisticated fault-tolerant control strategies.

In summary, the underlying cause-and-effect chain can therefore be summarized as follows: **contributing causes lead to faults, faults manifest through symptoms, and faults subsequently result in impacts**. In contrast, the FDD inference process proceeds in the reverse direction, beginning with symptom detection, followed by fault diagnosis, contributing-cause identification, and fault impact analysis. This reasoning framework provides the conceptual basis for the semantic model developed in the following sections.

3.2.2 Semantic modeling

There is a set of technologies supporting the creation of semantic models. In this study, we used RDFS (Resource Description Framework Schema) and OWL (Web Ontology Language), which are based on the World Wide Web Consortium's (W3C) standards, to develop the semantic model for data interchange on the web that allows for modeling graphs of resources over the web [85,86]. RDFS is the upgrade of Resource Description Framework (RDF), which describes resources using undirected and network graphs in the form of Triples, i.e.,three-component '*Subject-Predicate-Object*' statements which are also represented as tuples ***t***: <***s***, ***p***, **o**>.

To implement RDFS, knowledge about faults, symptoms and their relations in HVAC systems is translated into linguistic components, which are represented by logical predicates, variables, and quantifiers, to ensure the conceptualization is sound, consistent, and less ambiguous. For example, the fault and the associated fault contributing cause can be expressed in a Triple form as:

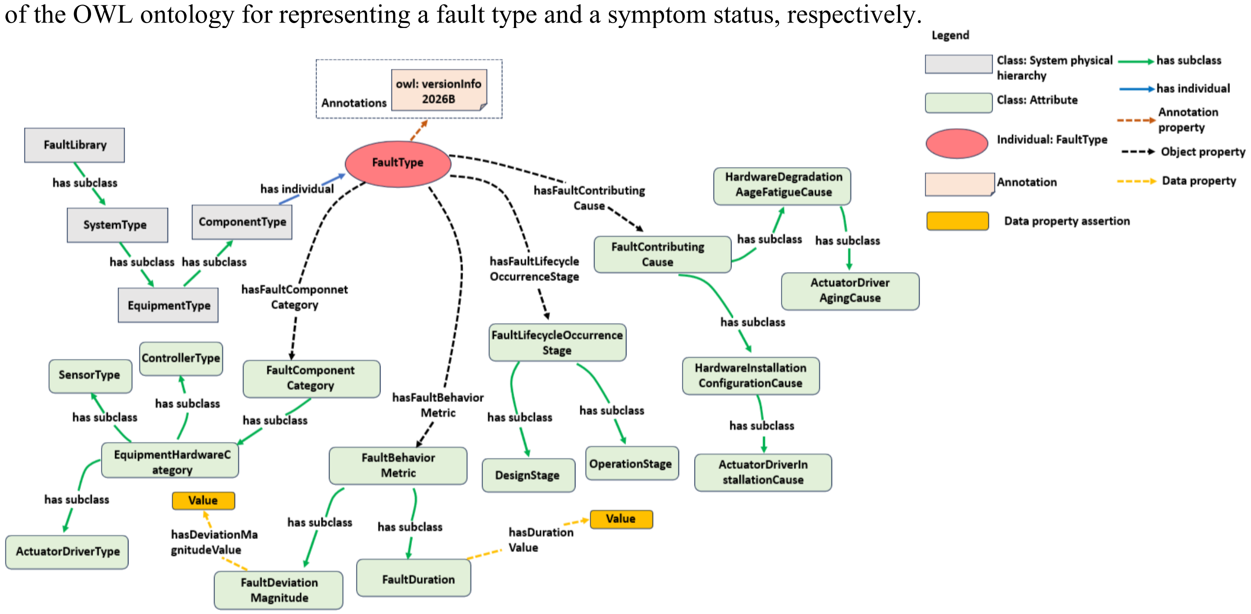
<Fault>	***<hasContributingCause>***	***<ContributingCause>***
(subject)	(predicate)	(object)

Furthermore, the fault and the associated symptoms can be expressed in a Triple form as:

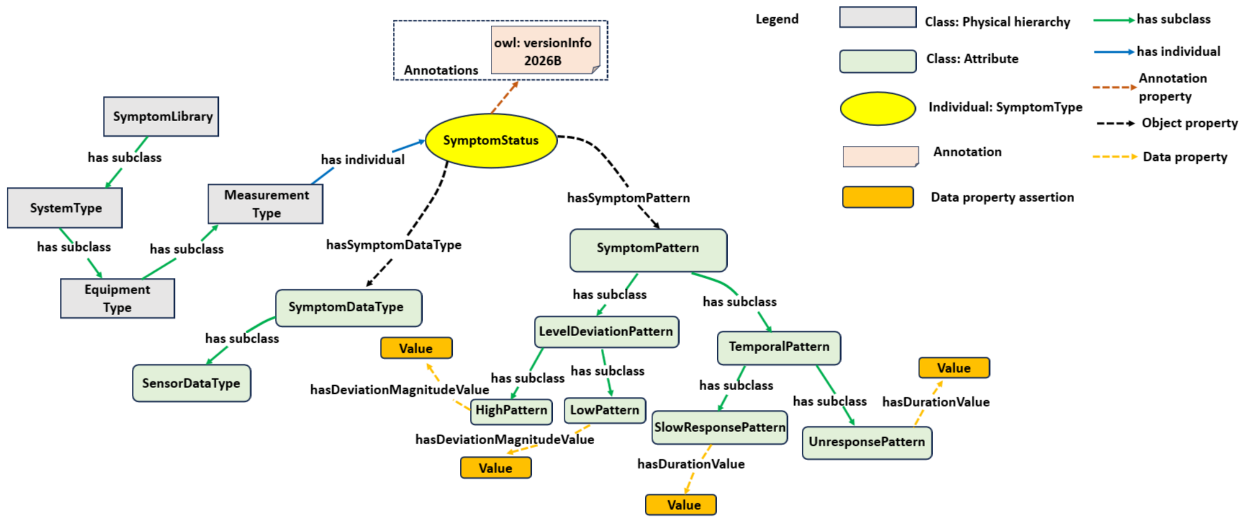
<Fault>	***<hasSymptom>***	***<Symptom>***
(subject)	(predicate)	(object)

In addition to RDFS, OWL is used to describe complex relations among the fault attribute class and the symptom attribute class. OWL is built on the top of RDFS and provides more comprehensive and complicated characteristics for creating ontologies, which require much more expressiveness than RDF and RDFS. In addition, OWL offers computational logics, namely Description Logics (DL), which facilitate advanced reasoning and data integration.

The core components of OWL include **Classes**, **Properties**, and **Individuals**. Figure 3 shows the structure examples of the OWL ontology for representing a fault type and a symptom status, respectively.



(a) A fault type and associated attributes



(b) A symptom status and associated attributes

Figure 3. The structure of FDD-ON for representing a fault type and a symptom status.

(1) **Individuals:** In OWL, individuals describe specific objects that are included in the ontology as indicated by the oval symptom in Figure 3. For example, in FDD-ON, individuals can have a specific fault type (e.g., AHU cooling coil valve leakage), or a specific symptom status (e.g., high AHU supply air temperature). In FDD-ON, fault type individuals and symptom statuses are strictly defined using the developed control vocabulary to eliminate ambiguity and enhance data interpretability as illustrated in Section 3.2.2.

(2) **Classes:** Classes categorize individuals with similar characteristics and organize them using formal descriptions in a specific domain as indicated by the rectangular block in Figure 3.

In FDD-ON, classes are built to represent two types of objects, such as i) the classes that categorize equipment, components and associated fault types and symptom statuses in the VAV HVAC systems; and ii) the classes that categorize fault attributes, symptom attributes and impact types. The classes contain single-level or multiple-level structures, which enable more granular classifications of system physical hierarchies, as well as certain attributes associated with faults and symptoms. However, it is noted that in the development of ontologies, the granularity of classes is not permanent but is determined by a potential application of the ontology.

The classes, which group similar types of equipment and components of HVAC systems, follow the physical hierarchy of the system and have three levels (i.e., sub classes) including: i) system types, ii) equipment types, and iii) component types or measurement types. For example, various types of sensors such as a discharge air temperature sensor, a relative humidity sensor, and an air flow rate sensor are categorized into the component SubClass of 'Sensor'.

In addition to the classification of physical systems, another set of classes represents similar attributes associated with a fault type or a symptom status. For instance, symptoms have an attribute set of classes, which categorize various characteristics (e.g., data types) associated with symptom statuses.

The classes are systematically structured to form the taxonomies for fault types, symptom statuses and impact types as illustrated in detail in Sections 3.2.4 to 3.2.6.

(3) **Properties: FDD-ON employs** OWL properties to link classes and individuals in the form of binary relations, which reflect the '***Predicate***' statement in RDFS. As shown in Figure 3, properties connect between classes and individuals or among individuals using arrow symbols. In FDD-ON, we employed three types of properties (the *Object Property*, the *Data Property*, and *Annotation Property*) as listed in Table 2.

Table 2. List of properties.

Property name	Property type	Characteristics	SubProperty of	Property domain	Property range
hasFaultAttribute	Object	NA	NA	NA	NA
hasFaultBehaviorMetric	Object	NA	hasFaultAttribute	FaultLibrary	FaultBehaviorMetric
hasFaultComponentCategory	Object	NA	hasFaultAttribute	FaultLibrary	FaultComponnetCategory
hasFaultLifecycleOccurrenceStage	Object	NA	hasFaultAttribute	FaultLibrary	FaultLifecycleOccurrenceStage
hasFaultContributingCause	Object	NA	hasFaultAttribute	FaultLibrary	FaultContributingCause
hasSymptomAttribute	Object	NA	NA	NA	NA
hasSymptomPattern	Object	NA	hasSymptomAttribute	SymptomLibrary	SymptomPattern
hasSymptomDataType	Object	NA	hasSymptomAttribute	SymptomLibrary	SymptomDataType
hasSymptom/isSymptomOf	Object	Inverse	NA	FaultLibrary	SymptomLibrary
hasImpactType	Object	NA	NA	NA	NA
hasImpact/isImpactOf	Object	Inverse	hasImpactType	FaultLibrary	ImpactLibrary
hasDeviationMagnitudeValue	Data	xsd:integer	NA	NA	NA
hasDurationValue	Data	xsd:integer	NA	NA	NA
hasRecurrenceIntervalValue	Data	xsd:integer	NA	NA	NA
hasFrequencyValue	Data	xsd:decimal	NA	NA	NA
hasProbabilityValue	Data	xsd:decimal	NA	NA	NA
hasStrengthennessValue	Data	xsd:string	NA	NA	NA
rdfs:label	Annotation	String	NA	NA	NA
rdfs:comment	Annotation	String	NA	NA	NA
owl:versionInfo	Annotation	xsd:integer	NA	NA	NA

The *Object Property* shows a relationship among various individuals. For example, the statement of 'a fault has an associated symptom' is defined by a property 'hasSymptom'. This property has an inverse property 'isSymptomOf', which represents that a specific symptom is linked to a fault.

The *Data Property* represents a relationship between an individual and associated data type. For instance, a quantitative symptom magnitude associated with a symptom is built through a data property, namely '*hasDeviationMagnitudeValue*'. It is noted that the data values associated with individuals should be customized in real practice to reflect real life operation of a system.

The *Annotation Property* illustrates meta-data such as the label and the ID of a specific fault type. The annotation properties have

3.2.3 Controlled vocabulary

In the HVAC FDD area, many technical terms and descriptions are used by different stakeholders to represent the same type of faults or similar symptoms [37]. This increases ambiguity and can significantly hinder the interpretability of fault information. Therefore, it is necessary to develop a set of controlled vocabulary to provide a more curated, standardized set of terms to define both the fault mode and symptom status, as well as the relationships between faults and associated symptoms in a consistent manner.

In FDD-ON, we reused and extended the controlled vocabulary list [37], which was developed to standardize the fault description. The controlled vocabulary can represent fault types and symptom statuses identified in the HVAC operations. This reduces the ambiguity and consequently, enhances the preciseness of the semantic meanings of fault types and symptom statuses, the interpretability of reporting faults and symptoms, as well as the interoperability of data across different systems. The controlled vocabularies will be encoded into a solid naming structure as illustrated in Section 3.3.

(1) Controlled vocabularies of fault types

Each fault vocabulary describes a specific fault type, which has unique occurrence mechanisms in terms of fault components, occurrence locations, and behaviors. In the study, we summarized 20 controlled vocabulary items, which qualitatively illustrate fault behaviors in the FDD-ON, as listed in Table 3.

Table 3. Controlled vocabulary list for describing fault modes.

No.	Fault type	Definition	Example component(s) in which a fault may occur
1	Bias	Sensor reading value consistently deviates from the true value, creating a persistent measurement error.	Sensor
2	Drift	Sensor reading value gradually deviates from the true value over time.	Sensor
3	Freeze	Sensor reading remains a constant value even if the true value changes.	Sensor
4	Air-side fouling	Fouling is the buildup of sediments and debris on the surface area of a coil.	Coil
5	Water-side fouling	The accumulation of unwanted deposits on the internal (water-contacting) surfaces of coils.	Coil
6	Leakage	Fluid leaks from a high-pressure region to a low-pressure region.	Coil, valve, duct, damper
7	Stuck	The actuator fails to respond to changing control signals and remains stuck at a fixed point.	Valve, damper
8	Hunting	The actuator continuously modulates back and forth, over-correcting its position while attempting to reach a stable setpoint.	Valve, damper
9	Blockage	The component is physically blocked, causing a significant increase of resistance to airflow.	Filter, vent
10	Looseness	The physical part of a system is not securely fastened, properly tensioned, or correctly seated.	Fan belt
11	Failure	The component stops work.	Compressor
12	Setting error	The parameters, control sequence, or logic in the software are wrongly set.	Schedule

13	Location error	The component is installed in the wrong place.	Discharge air temperature sensor
14	Overcharge	The fluid is overcharged.	Refrigerant
15	Undercharge	The fluid is undercharged.	Refrigerant
16	Restriction	The flow in the component (coil, tube, or pipe) is restricted, reducing the fluid flow rate.	Refrigerant circuit
17	Loss	In communication, data packages are lost.	Communication
18	Oversize	The equipment or components are oversized.	Pump
19	Undersize	The equipment or components are undersized.	Pump
20	Offline	The controller stops work.	Controller

(2) Controlled vocabularies of symptom statuses

The symptom vocabularies should accurately represent how symptoms manifest and usually indicate distinct fault types. We systematically investigated various fault symptoms and impacts reported in literature [3] and FDD software solutions [38], and then summarized 11 vocabulary items, which qualitatively describe specific fault symptom statuses in HVAC systems. The quantitative values corresponding to each status can be included under each application case. Table 4 lists the controlled vocabulary items.

Table 4. Controlled vocabulary list for describing symptom statuses.

No.	Symptom status	Definition	Example measures in which the symptom may manifest
1	High	The measured value is higher than the baseline value or the reference value.	Supply air temperature
2	Low	The measured value is lower than the baseline value or the reference value.	Supply air temperature
3	Slow response	The measured value has excessive settling time.	Chilled water supply temperature
4	Unresponse	The measured value keeps constant when it should change.	Damper position signal
5	Oscillation	The measured value has cyclical variation.	Discharge air damper control signal
6	Cycling	The measured equipment status or equipment control command signal is switched between an 'on' (logic high or 100% of the normal value) status and an 'off' status (logic low or 0% of the normal value) frequently or irregularly.	Damper position signal
7	Spike	The measured value contains a transient sharp peak.	Pump control signal
8	Step change	The measured value appears as a sudden and discrete shift from one steady level to another level.	Damper control signal
9	Intermittent	The measured value appears and disappears irregularly.	Pump control signal
10	Mismatch	The measured values are not matched.	Damper position and control signal

11	Simultaneous Occurrence	The signals can be measured at the same time, but logically they should not be measured at the same time.	Cooling valve position signal and heating valve position signal

3.2.4 Taxonomy for fault attributes

The fault attributes contain all the information that further describe fault characteristics and will be enriched by various applications. The taxonomies of fault attributes classify various fault attributes in an organized way. Currently, fault attributes are categorized into four classes as: 1) fault behavior metric; 2) component category; 3) contributing cause; and 4) lifecycle occurrence stage, as illustrated in Figure 3.

(1) Fault behavior metric

The class of fault behavior metrics defines how a fault behaves dynamically on a multi-dimensional temporal and quantitative scale, i.e., this subclass represents characteristics of the fault intensity, occurrence and evolution. Hence, this class enables an AI-driven maintenance system to quantify fault intensity, and to distinguish between transient fault and long-standing, degrading mechanical issues. It also enables the development of FDD inference approaches by providing information such as the fault occurrence likelihood. The class of fault behaviors includes four second level subclasses of behavior descriptions, as listed in Table 5.

Table 5. List of fault behavior metrics.

Subclass	Annotation	Example of mapped faults
Fault deviation magnitude	The physical severity or intensity of the fault	Cooling coil valve damper stuck at 65% position
Fault duration	The length of time that a fault condition persists in a system	Discharge air damper stuck for 170 hours
Fault occurrence frequency	The frequency that a specific fault appears within a given time period	Supply air temperature sensor bias fault occurrence at 0.01% probability
Fault recurrence interval	The time interval between two consecutive occurrences of the same fault	Outdoor air damper stuck fault recurrence interval is 15,000 hours

(2) Component category

The subclass of component categories categorizes functional components, where a fault may occur, into organized groups. In FDD-ON, the component category has three sub classes, including: 1) equipment software, 2) equipment hardware, and 3) network and communication. Under each sub class, the second-level subclasses that represent specific component types are defined, as listed in Table 6.

Table 6. List of component categories.

Subclass (component category)	Second level subclass (component type)	Example components
Equipment software	Control sequence and logic	VAV air terminal schedule setting
	Control parameter	AHU supply air fan PID parameter
Equipment hardware	Sensor	AHU supply air temperature sensor
	Actuator and driver	VAV discharge air damper

	Coil	AHU cooling coil
	Duct	AHH supply air duct
	Pipe	Chiller plant chilled water pipe
	Vent	RTU return air vent
	Power supply wire and connector	RTU condenser fan power supply wire
	Ground wire and shield	Ground wire
	Controller	AHU controller
	Fluid	Refrigerant
	Fin	Heat exchanger
	Filter	AHU supply air filter
	Controller	DDC controller
	Electrical component	Contactor
Network and communication	Network interface	Router
	Communication wire and connector	Communication wire
	Communication parameter	Network address
	Communication shield	Wire shield

(3) Contributing cause

The class of fault contributing causes categorizes the underlying factors or events that create the environment for a specific fault to occur. For instance, a damper stuck fault in an AHU can arise from multiple contributing causes, including a damper actuator power failure (e.g., power supply cause), disconnected communication wires of the damper controller (e.g., communication and network cause), and a mechanical failure of the linkage mechanism connecting the damper blades (e.g., hardware installation and configuration cause, or hardware degradation, age and fatigue cause). Without explicit representations of those contributing causes, it will be hard to enhance maintenance practice and improve equipment or system design.

In FDD-ON, we define this class as guiding FDD researchers and practitioners to carry out more investigations on understanding fault contributing causes. In the FDD-ON, the taxonomy of contributing causes are grouped into eight subclasses as listed in Table 7.

Table 7. List of contributing causes.

Subclass	Annotation	Example of mapped faults
Manufacturing and design related cause (human)	The hardware or software are improperly designed and manufactured	Pipe is oversized
Hardware installation and configuration cause (human)	The component, equipment and system hardware are improperly installed and configured	Discharge air temperature location error fault
Software programming and configuration cause (human)	The software is improperly programmed and configured	PID setting fault
Hardware degradation, age and fatigue cause	The component, equipment and system hardware are degraded, aging and fatiguing during operations	Slippery fan belt fault
Unexpected external force on hardware cause	The component, equipment and system hardware suffers unexpected external force during operations	Damper leak fault
Environmental condition cause	The operational environment causes the hardware degradation	Coil fouling fault
Power supply cause	Improper or failure power supply	Damper obstruction fault
Communication and network cause	Improper and failure communication and network due to hardware or software configuration, interference, cyberattack	Thermostat IP setting fault

(4) Lifecycle occurrence stage

The class of fault lifecycle occurrence stage attribute provides a structured temporal framework for identifying when the HVAC system' fault contributing causes originate and more importantly, when they can be systematically eliminated. By mapping fault types to these specific stages, an FDD system and AI-driven maintenance system can transition from merely detecting symptoms and diagnosing faults, to implementing targeted preventative strategies that eliminate faults at their point of origin. The sub class of attributes includes three individuals of lifecycle occurrence stage descriptions as listed in Table 8.

Table 8. List of Lifecycle occurrence stages.

Subclass	Annotation	Example of mapped fault
Design stage	The fault originates from the system design	Pipe is oversized
Installation, commissioning, and service stage	The fault originates from when the system is installed, commissioned and served	Valve leak fault
Operation stage	The fault occurs when the system operates	Coil fouling fault

3.2.5 Taxonomy of symptom attributes

The class of symptom attributes includes all the information that is required to characterize fault symptoms. The precise descriptions of symptom characteristics enable multiple applications. For example, many FDD approaches such as the rule-based approach and the Bayesian Networks approach rely on the fault symptom pattern identification to implement references of a fault. Currently, the class of symptom attributes includes two sub classes as: 1) symptom patterns, and 2) data types, as illustrated in Figure 3.

(1) Symptom pattern

Symptom patterns classify how symptom statuses are described when a fault occurs. In the development of FDD approaches, an identification and high-fidelity pattern matching fault symptom behaviors is essential to implement fault inference. Most existing FDD approaches rely on a simple steady state threshold-crossing approach to detect and diagnose faults. For example, if the supply air temperature of an AHU is constantly higher than the setpoint or the defined threshold, then a symptom (or abnormality) is detected and flagged by the FDD approach. Using this detected symptom and other symptoms, the FDD approach can infer that it is highly likely a cooling coil valve stuck fault. However, symptom behaviors can be more complex than a simple steady state threshold-crossing. Using the example above, the supply air temperature of an AHU can be oscillating, i.e., the supply air temperature may surpass the higher threshold and lower threshold frequently, indicating a fault in the controller (e.g., a PID setting fault). Very few research works have been conducted to uncover symptom patterns even though much research investigated using feature engineering approaches to extract or uncover symptom patterns [3]. Therefore, a classification of symptom patterns can enable the development of a more sophisticated, multi-dimensional pattern recognition of FDD approaches.

In FDD-ON, symptom patterns are classified into four subclasses i.e., level deviation pattern, temporal patterns, relation patterns, and statistical patterns as listed in Table 9. Under each subclass, a second level class to further describe the fault symptom patterns.

The subclass of the level deviation describes steady-state divergence, where a signal's value significantly surpasses from its expected baseline or reference values. For example, higher supply air temperature is classified into the 'High' second-level class under the 'Level deviation' subclass.

The subclass of temporal pattern characterizes the transient behavior of the symptom when fault occurs. This type of behavior captures anomalies in terms of how signal evolves over time. For instance, a slow response of a cooling coil valve position is classified into the 'Slow response' second-level class under the 'Temporal' subclass. This pattern can indicate the control parameter (i.e., the propagation gain) setting fault.

The subclass of relation pattern characterizes indicate that the symptom is described through multiple signals and manifested in terms of consistency and co-occurrence. For example, the outdoor air damper position and control signal mismatch symptom pattern uncovers an outdoor air damper stuck fault.

The subclass of statistical patterns uncovers the statistical characteristics of how symptoms manifest under specific fault types. For example, the symptom occurrence probability of discharge air temperature being too high can indicate the likelihood of the discharge air temperature abnormality under discharge air fan fault during a long-term operation [5].

Table 9. Classification of symptom patterns.

Subclass	Annotation	Sub class (second level)
Level deviation pattern	A symptom is quantified by the magnitude of deviation of measured signals from their expected values	High
		Low
Temporal pattern	A symptom is defined by the temporal dynamics of system signals, including their transient and steady-state responses	Slow response
		Unresponse
		Oscillation

		Cycling
		Spike
		Intermittent
Relation pattern	A symptom is described by relating to multiple signals and manifested in terms of consistency and co-occurrence.	Mismatch
		Simultaneous Occurrence
Statistical pattern	A symptom is defined by the statistical properties of its status, such as occurrence probability and duration.	Occurrence probability
		Continuous duration

(2) Data type

Data types indicate what type of measurement(s) is (are) used to generate a symptom. Most FDD algorithms employ sensor data, control commands and settings, and operation state data, which are directly collected in the BAS to perform FDD. Some algorithms developed virtual sensors, which create derived data to enhance FDD performance [87]. In addition to BASs, some portable equipment (e.g., infrared camera [88]), which produces the multimedia data type, are used to monitor equipment operation. Lastly, an increasing number of FDD approaches and newly developed CMMS include metadata sources, such as historical maintenance service report data and fault alarming data, to enhance the capabilities of the fault diagnostics inference [89] and support the maintenance decision-making process [16].

Hence, to promote the interpretability and interoperability of symptom data across various systems, symptoms are categorized by their underlying data types in FDD-ON. In FDD-ON, the multidimensional taxonomy includes six data types as listed in Table 10.

Table 10. Classification of data types.

Subclass	Annotation	Example of mapped symptoms
Sensor data	Data indicates sensor signals	Supply air temperature is high
Control command and setting	Data indicates from control commands and control settings in the BAS	Damper position control command is cycling
Operation state	Binary data indicates equipment operation state in the BAS	Chiller control is ON state
Text data	Text data indicates the occupant complaints; the operator notes, service logs, and system alarm descriptions	Occupant reports the zone temperature is high
Multimedia data	Data collected from multimedia devices (e.g., infrared camera) to indicate equipment operating conditions or abnormal behaviors	Discharge air fans have abnormal temperature distributions
Derived data	Data that is derived through analytics rather than directly observed	The relation of outdoor air damper position and control signal

3.2.6 Taxonomy of impact types

The class of fault impact describes equipment-level or system-level impacts due to a specific fault. Chen et al. carried out a comprehensive review on HVAC and refrigeration (HVAC&R) system fault impacts from academic literature and industrial reports [3]. They reported that faults in HVAC&R systems cause impacts on equipment performance, energy, thermal comfort, indoor air quality, economic cost, maintenance activity and environment. FDD-ON adopts the classification of impacts and summarizes them into seven impact categories (i.e., subclasses) and 17 impact types (i.e., second level subclasses) listed in Table 11. It is noted that the CO2 rate was classified into the symptom class.

Table 11. Classification of fault impacts.

Subclass (Impact category)	Second level subclass (Impact type)	Example of mapped faults
Equipment performance	COP	Refrigerant leakage
	EER	Refrigerant leakage
Energy	Electricity power	Cooling coil valve stuck
	Electricity power consumption	Cooling coil valve stuck
	Peak demand	Schedule error setting
	Gas consumption	Gas valve stuck
	Water consumption	Chilled water valve stuck
	Cooling	Chilled water valve stuck
	Heating	Heating valve stuck
Economic cost	Electricity energy consumption cost	Supply air temperature sensor bias
	Gas consumption cost	Gas valve stuck
	Water consumption cost	Chilled water valve stuck
	Maintenance money	Heating valve stuck
Indoor air quality	Outdoor air ratio	Discharge air damper stuck
Thermal comfort	Predicted percentage of dissatisfied	Discharge air damper stuck
Maintenance activity	Maintenance time	Supply air fan motor failure
Environment	Emission	Refrigerant leakage

3.2.7 Implementation of semantic modeling and ontology visualization

In this study, we translate the semantic model of FDD-ON into OWL and RDFS using Protégé software [90]. Protégé provides a GUI to allow the identification and creation of classes, class hierarchies, variables, and the relationships between classes and the properties of these relationships. Figures 4 and 5 show the developed hierarchy in the Protégé tool.

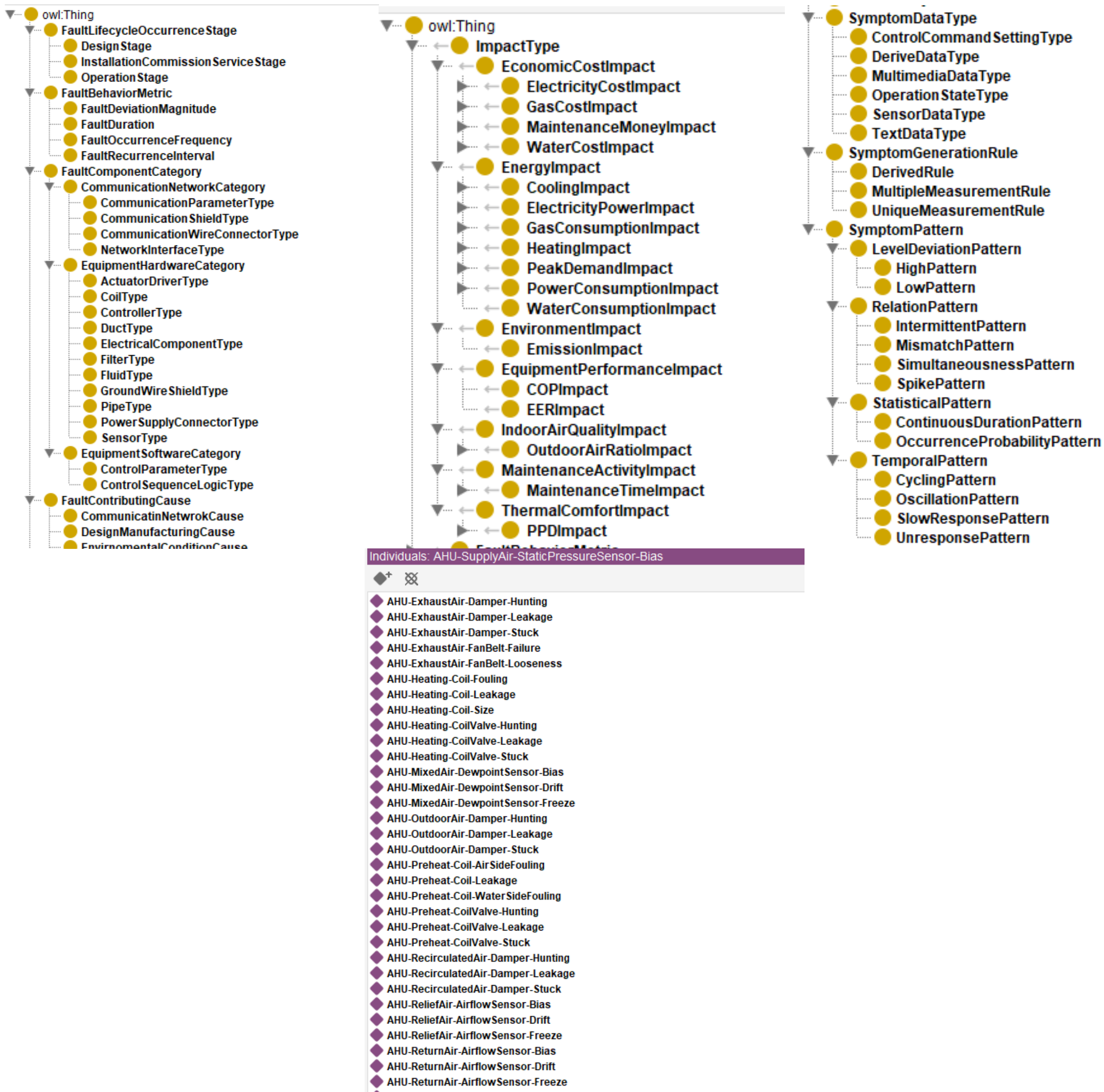


Figure 4. Example hierarchy of the classes for fault attributes, impact types, symptom attributes and individuals in the Protégé tool.

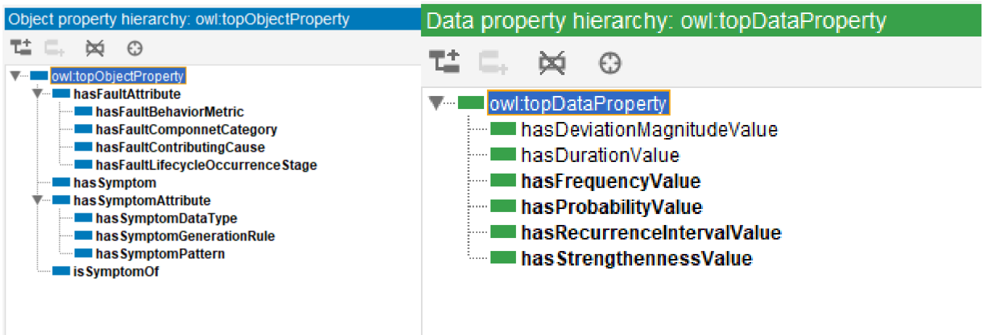


Figure 5. Example hierarchy of Properties in the Protégé tool.

Figures 6 and 7 show examples of the graphic models of the defined fault types (i.e., '*VAVATU-DischargeAir-AirflowSensor*' related faults) and symptoms (i.e., the abnormalities manifesting on the measurement of '*VAVATU-DischargeAir-Airflow*') in the FDD-ON in the fault library and symptom library. The graphic representations explicitly demonstrate fault types and associated symptoms, as well as the aligned attributes.

Under the '*VAVATU-DischargeAir-AirflowSensor*' fault subclass, it includes four specific fault types indicated by (the purple heart symbols in Figure 6: bias, drift, freeze, and error location. The fault subclass has all four types of fault behavior metric as defined in Table 5. The component where the fault occurs is the airflow sensor. So, it is classified into the '*SensorType*' under the '*EquipmentHardewareCategory*' subclass. The fault has five contributing causes: '*PowerCause*', '*DesignManfacturingCause*', '*HardwareInstallationConfigurationCause*', '*HardwareDegradationAageFatigueCause*', and '*CommunicationNetworkCause*'. The faults often occur at the installation and commission service stage and operational stage, so it is classified in the '*InstallationCommissionServiceStage*' and '*OperationStage*' in terms of fault lifecycle occurrence stage. Additionally, the faults may cause symptoms on ten measurements. They are '*VAVATU-DischargeAir-Temperature*', '*VAVATU-DischargeAir-Airflow*', '*VAVATU-DischargeAir-DamperControl*', '*VAVATU-DischargeAir-DamperPosition*', '*VAVATU-DischargeAir-Dewpoint*', '*VAVATU-Reheat-CoilValve-Control*, '*VAVATU-Reheat-CoilValve-Position*', '*VAVATU-SupplyDischargeAir-Temperture*', '*VAVATU-Thermostat-Temperature*', '*VAVATU-DischargeAir-FanSpeed*', and '*VAVATU-DischargeAir-FanSpeedControl*'. Additionally, the faults have impacts in terms of 'Cooling', 'Heating', 'ElectricityPower', 'PowerConsumptojn''ElectricityCost'

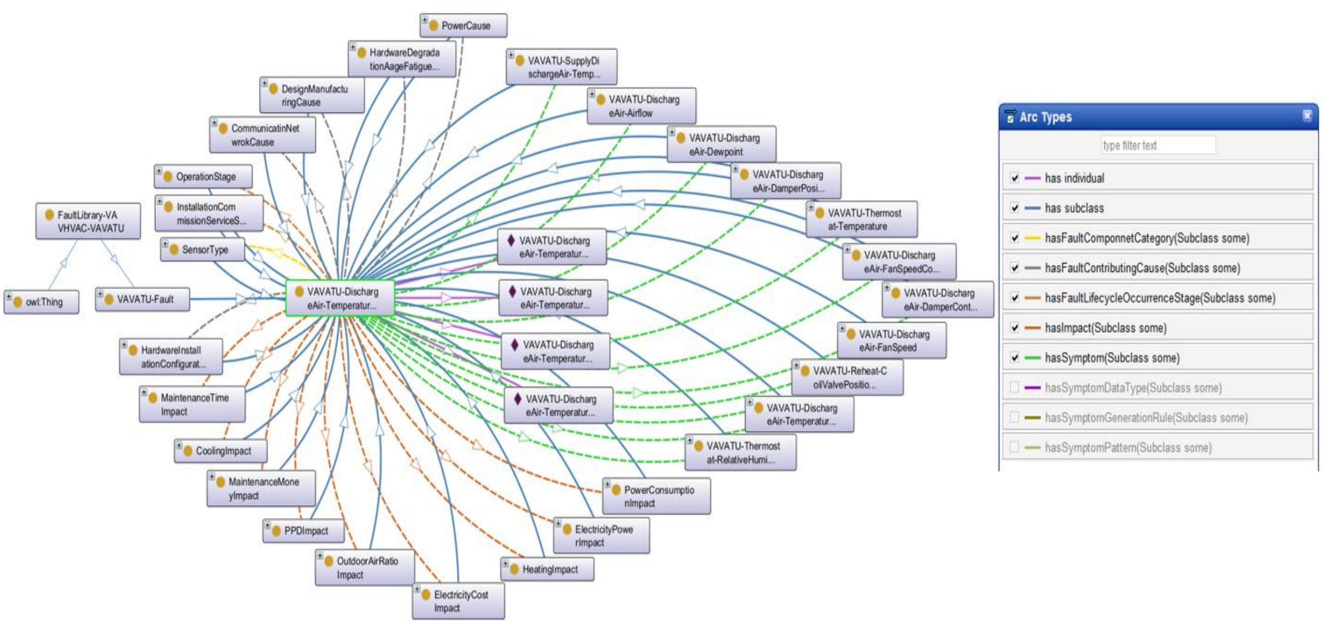


Figure 6. Example of an FDD-ON graphic model of VAV-ATU fault types (VAVATU-DischargeAir-AirflowSensor faults).

Under the VAVATU discharge air airflow abnormal symptom, it includes five specific fault statuses (i.e., high, low, un-response, oscillation and slow response). This measurement is classified into the 'SensorDataType' because the symptom is manifested by the air airflow sensor. The five statuses are classified into three patterns as 'LevelDeviationPattern', 'Temporal pattern' and 'StatisticalPatten'. The symptom is generated by a unique measurement (i.e., one sensor). The symptoms can be caused by 26 classes of faults in the VAVATUs.

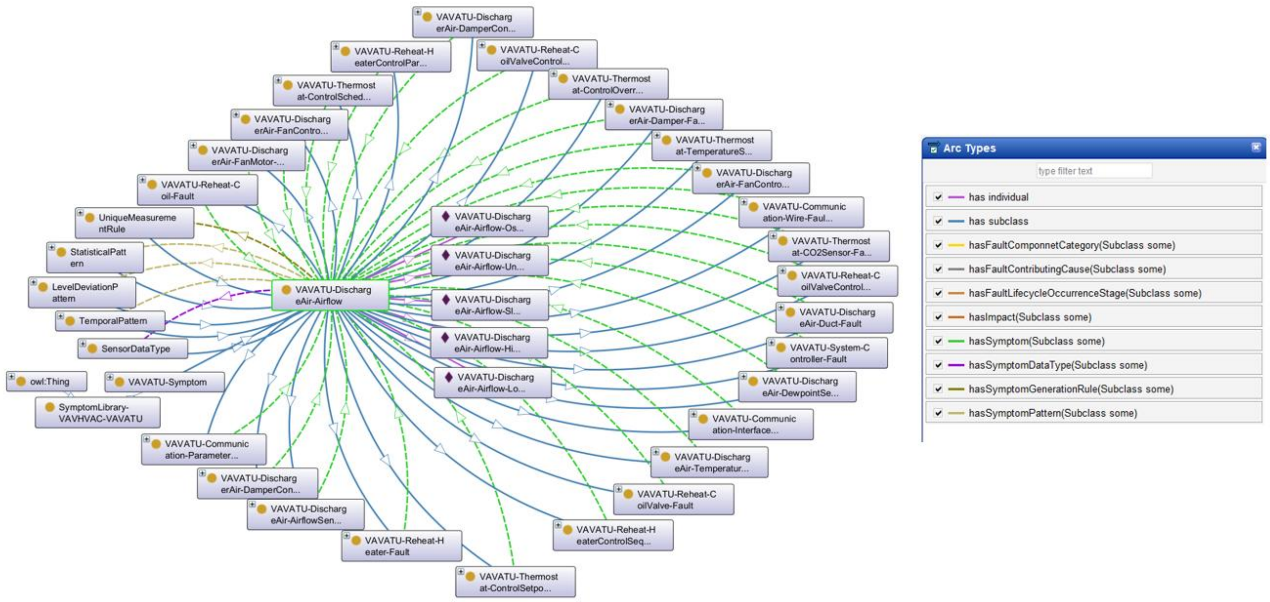


Figure 7. Example of an FDD-ON graphic model of VAV-ATU symptom statuses (VAVATU-DischargeAir-Airflow abnormal).

3.3 Development of libraries

3.3.1 Naming convention

The first step to develop the fault library and symptom library is to define naming conventions in ontology. In this study, we follow the rules to represent both a specific fault and a specific type of symptom as developed [37]. However, a major modification compared to [37] is that most behavior-based faults are defined fault symptoms to ensure a clear causal-effect relation and to guarantee robust semantic-based inference.

There are two primary considerations when developing the naming convention of fault types and symptoms.

First, the naming convention should be concise and accurate to capture the natures of fault types and symptom statuses, e.g., the equipment and component locations where a fault occurs, and the measurement types that manifest symptoms. This enhances the interpretability of the data; and hence, reduces ambiguities when developing FDD related solutions, as well as facilitating interpreting and translating FDD results into actionable maintenance activities. Therefore, In the fault names and symptom names, we try to avoid using the abbreviations of component types, locations and descriptions of fault types and symptom statuses. Instead, we only use abbreviations for equipment types, e.g., we use AHU to in the name to represent that a fault type or a symptom status is associated with an air handling unit.

Secondly, a robust naming structure should be adopted to reduce the heterogeneity of the data, and consequently increase the data interoperability, as well as efficient embedding and processing across different system environments. All fault names, symptom names and impact names are constructed into a four-section structure, namely a **quadrinomial nomenclature**. The four-section structure encodes fundamental information to illustrate a fault type, symptom status and impact type. In each section, Pascal Case notations [91] are adopted to represent specific pieces of information that are associated with characteristics of faults, symptoms and impact types. It is noted that we adopted hyphens to connect each section in the quadrinomial nomenclature because using hyphens as separators in Uniform Resource Locator (URLs) can be easily read. However, underscores can also be used to connect sections when programming the names in computer languages.

For a specific fault name, the four-section structure is constructed by: i) the equipment where the fault occurs; ii) the location of the equipment where the faulty component is located; iii) the physical component where the fault occurs; and iv) the controlled vocabulary that specifies a fault mode, respectively. Table 12 exemplifies a fault name using the defined naming convention. The full name of a damper leakage fault occurring at the outdoor air section of an AHU is hereby named as '*AHU-OutdoorAir-Damper-Leakage*'.

Table 12. Illustration of a standardized fault naming convention

Section description	**Equipment**	**Information specifying the location**	**Information specifying the component type**	**Controlled vocabulary specifying the fault mode**
Example	AHU	OutdoorAir	Damper	Leakage

Similarly, for a specific symptom name, the four-section structure encodes information, which represents i) the equipment where the fault occurs; ii) the location of the measurement where the fault symptom is measured; iii) the measure that manifests the symptom; and iv) the controlled vocabulary, specifies a symptom status. Table 13 exemplifies a symptom name using the defined naming convention. The full name of a symptom describing an AHU supply air temperature is high is hereby given as '*AHU-SupplyAir-Temperature-High*'.

Table 13. Illustration of a standardized symptom naming convention

Section description	**Equipment**	**Information specifying the location of equipment**	**Measurement type**	**Controlled vocabulary specifying the symptom status**
Example	AHU	SupplyAir	Temperature	High

The naming convention for impacts has the same three sections defined in the naming convention for the fault type, i.e., equipment type, information specifying a location of equipment, and information specifying a component type. The fourth section defines the impact type. Table 14 exemplifies a symptom name using the defined naming convention. The full name of '*AHU-SupplyAir-FanMotor-PowerConsumption*' indicates the impact of an AHU supply air fan motor in terms of power consumption.

Table 14. Illustration of a standardized symptom naming convention

Section description	**Equipment**	**Information specifying the location of equipment**	**Information specifying the component type**	**Impact type**
Example	AHU	SupplyAir	FanMotor	PowerConsumption

3.3.2 Description of libraries

FDD-ON includes three major libraries, i.e., fault library, symptom library and impact library for each type of subsystem and equipment. Currently, there are 469 fault types, 468 symptom statuses, and 447 impact types across five equipment types, which have been included in the fault libraries, symptom libraries and impact libraries, respectively. These fault types, symptom statuses and impact types have been reported in 241 specific components and 137 measures, respectively. Table 15 lists the distributions of fault types, symptom statuses, and impact types (i.e., entities) in each type of subsystem and equipment.

Table 15. Entity distributions

Equipment type	Number of component types	Number of fault types	Number of measures	Number of symptom statuses	Number of impact types
Chiller plant	42	85	25	91	82
Boiler plant	19	37	10	37	38
AHU	68	130	55	176	118
RTU	83	164	33	114	160
VAV ATU	29	537	14	50	49
Total	241	469	137	468	447

4. Evaluation and discussion

The ontology evaluation is a critical step in ontology engineering to ensure the developed model is logically sound, accurately represents the target domain, and effectively fulfills its intended application requirements [92,93]. We evaluated FDD-ON from three angles. First, we illustrate the quantitative evaluation to demonstrate the structural quality and completeness in Section 4.1. Secondly, we explain the assessment of logical consistency in Section 4.2. Thirdly, we showcase the application of FDD-ON to demonstrate its application in FDD development in Section 4.3. At the same time, we discuss the limitations in the current version of FDD-ON in Section 4.4 and we discuss the evolution directions of FDD-ON in Section 4.5.

4.1 Quantitative evaluation

4.1.1 Ontology metrics

We evaluate the structural quality by analyzing the entities used in the current version of FDD-ON, as listed in Table 16.

In the table, the axiom counts of 8,756 represents the formal statement of truth within FDD-ON by including class declarations, subclass relationships, property domains, and disjointness rules. The 6,537 logical axiom counts exclude purely structural or decorative statements (like metadata annotations, labels, and comments) and counts only the assertions that the DL reasoner evaluates to infer new knowledge. The 2,188 declaration axioms count illustrates the number of times that a brand-new entity (a new class, property, or individual) is introduced to the FDD-ON. The entity inventory (including class count, object property count and named individual count) indicates that FDD-ON consists of 775 distinct subclasses organized to represent VAV HVAC system fault types, symptom statues, impact types and associated attributes. Semantic richness is introduced via 15 object properties, 7 data properties and 1,393 individuals.

Table 16. Ontology metrics.

Name	Number of entities
Axiom	8,756
Logical axiom count	6,537
Declaration of axioms count	2,188

Class count	775
Object property count	15
Data property count	7
Individual count	1,393

4.1.2 Completeness evaluation

We evaluate the information completeness of FDD-ON by analyzing existing publicly available FDD data sets for VAV HVAC systems. The data sets were generated using real systems, lab tests and software simulations for the purpose of developing and benchmarking FDD approaches and other applications. Hence, the data sets include common fault types and measurements in VAV HVAC systems. The data sets cover the chiller plant subsystem, boiler plant subsystem, AHUs, RTUs and ATUs (including both hydronic reheat ATUs and fan power units). Table 17 lists the data mapping results.

Table 17. Data mapping analysis.

Dataset Name	Equipment type	Number of component types	Number of fault types	Pct of component type mapped	Pct of fault types mapped	Number of measurement types	Number of measurement types mapped	Pct of measurements mapped
Drexel-Nesbitt [69]	AHU	4	4	100%	100%	21	17	81%
Drexel-Nesbitt [69]	Chiller	4	4	100%	100%	25	25	100%
Drexel-Nesbitt [69]	VAV ATU	NA	NA	NA	NA	5	5	100%
ASHRAE1312 [94]	AHU	8	10	100%	100%	43	35	81%
LBNL dataset [95]	Dual duct AHU	11	16	100%	100%	54	51	94%
LBNL dataset [95]	FPU	8	10	100%	100%	16	16	100%
LBNL dataset [95,96]	RTU	11	16	100%	100%	22	21	95%
LBNL dataset [95]	Chiller plant	6	7	100%	100%	38	37	97%
LBNL dataset [95]	Boiler plant	5	5	100%	100%	13	13	100%

LBNL dataset [96]	AHU (multizone)-1	4	4	100%	100%	17	16	94%
LBNL dataset [96]	AHU (singlezone)	3	5	100%	100%	14	13	93%
LBNL dataset [95]	AHU (multizone)-2	4	5	100%	100%	25	24	96%
ORNL dataset [97]	VAV ATU	2	2	100%	100%	7	6	86%
ORNL dataset [97]	RTU	NA	NA	NA	NA	15	15	100%

It can be seen that 100% fault types in each FDD data set were mapped in the fault library of the FDD-ON. For the measurement types, the unmapped measurement types primarily consist of two types of data: 1) meter data and 2) equipment status data. Meter data were not considered in the symptom library because those data were categorized into impact types. Some equipment status data and BAS data points (e.g., the data points 'System occupancy control mode' and 'Chiller selection' in ASHRAE RP1312 dataset) were not included in the symptom library, and hence the corresponding measurements were considered as unmapped measurement types.

4.2 Qualitative evaluation

We carried out a consistency examination to assess logical expressivity. During the development of FDD-ON, DL examinations were frequently run using the Pellet plug-in in the Protégé software to ensure the DL consistency of the FDD-ON. The reasoner engine uses rules and axioms to check unsatisfiable classes (e.g., the intersection errors), property domain and range checking, and other DL errors. FDD-ON successfully passes the consistency check.

4.3 Application evaluation

4.3.1 Feature comparison

We compare the semantic modelling approach of FDD-ON with other ontologies to demonstrate the enhancement of FDD-ON in representing FDD domain knowledge and application areas.

Appendix I lists the feature comparison between FDD-ON and other ontologies in buildings to highlight the characteristics of FDD-ON. The comparison demonstrates that FDD-ON provides a more comprehensive knowledge representation for faults, symptoms and impacts in VAV HVAC systems than existing ontologies or semantic models. Therefore, the features in FDD-ON sufficiently address the CQs proposed in Section 3.1.2 and can be employed in various applications.

4.3.2 Example of an application

(1) Description of the FDD dataset

We use an FDD dataset, which was constructed by real operational data in an office building to demonstrate the application of FDD-ON. The dataset was published in [69]. In the dataset, fault inclusive data and fault free data were collected via the BAS in the Nesbitt Hall, in Philadelphia, PA, U.S. The building is a seven-story, 7,260 m^2 mixed-use commercial building. The HVAC system includes a water-cooled chiller plant subsystem and one boiler plant subsystem, which provides primary cooling, heating and domestic hot water for the building. The air distribution subsystem includes three single-duct AHUs and eighty-eight VAV ATUs to condition zones in the building's floors. The HVAC system is monitored and controlled by a BAS.

(2) Fault mapping result

The FDD dataset includes eight types of faults manually implemented in the chiller plant and AHU as listed in Table 18. The table provides the original fault descriptions, fault severity levels, fault durations, and mapped fault names in the FDD-ON fault library. It can be seen that fault descriptions are 100% mapped to fault names in FDD-ON. The two pieces of information (i.e., fault severity levels and fault durations) can be mapped into '*FaultDeviationMagnitude*' and '*FaultDuration*' in the '*FaultBehaviorMetric*' subclass in FDD-ON.

Table 18. Mapped fault types in [69].

Subsystem/ Equipment	Fault description	Fault severity	Fault duration (minutes)	Mapped fault name in FDD-ON
Chiller plant	Occupied during the unoccupied schedule; Chiller stopped earlier than scheduled; HVAC system occupied earlier than scheduled; Change weekend occupied schedule to end	NA	420; 690; 240; 80	CHILLERPLANT-Control-Schedule-SettingError
	System stopped working (Chiller off)	NA	120	CHILLERPLANT-System-Controller-Offline
	Chiller supply chilled water temperature sensor bias	−2.3°C; −1.7°C	687; 600	CHILLERPLANT-PrimaryLoopChilledWaterSupply-TemperatureSensor-Bias
	Chiller chilled water differential pressure sensor positive bias	0.69 kPa	291	CHILLERPLANT-SecondaryLoopChilledWater-DifferentialPressureSensor-Bias
AHU	AHU outdoor air damper stuck	30%; 60%; 80%, 90%; 100%	480; 600; 630; 645, 601; 541	AHU-OutdoorAir-Damper-Stuck
	AHU cooling coil valve position software override	100%	601	AHU-OutdoorAir-DamperControlSequence-SettingError
	AHU cooling coil valve stuck	80%	600	AHU-Cooling-CoilValve-Stuck
	AHU supply air temperature sensor bias	−2°C	480	AHU-SupplyAir-TemperatureSensor-Bias

(3) Symptom and impact mapping result

The FDD dataset includes more than 500 data points (measurements) collected from the BAS. The original data points cover three data types, i.e., sensor data type, control command and control setting type, and discrete operation state type. However, the measurement can also produce the derived data type after analyzing the data. For example, a symptom can be produced by comparing the outdoor air temperature and mixed air temperature when diagnosing the outdoor damper related faults [54]. Due to the length of the paper, we listed part of the mapped symptoms, as well as the corresponding data types in Table 19.

Table 19. Example of mapped symptom statuses in [69].

Data point name	Description	Mapped symptom name in FDD-ON	Data type

#drx_nsbt_chws_control/chw_flow	Sensor: Chilled water flowrate	CHILLERPLANT-PrimaryLoopChilledWaterSupply-FlowRate-High	LevelDeviation
		CHILLERPLANT-PrimaryLoopChilledWaterSupply-FlowRate-Low	LevelDeviation
		CHILLERPLANT-PrimaryLoopChilledWaterSupply-FlowRate-UnResponse	TemporalPattern
		CHILLERPLANT-PrimaryLoopChilledWaterSupply-FlowRate-Oscillation	TemporalPattern
#drx_nsbt_chws_control/chiller_status	Control chiller status	CHILLERPLANT-Chiller-ControlStatus-Mismatch	RelationPattern
#drx_nesbitt_ahu-2/sf_vfd_output/trend_log	Sensor: Supply fan speed	AHU-SupplyAir-FanSpeed-High	LevelDeviation
		AHU-SupplyAir-FanSpeed-Low	LevelDeviation
		AHU-SupplyAir-FanSpeed-Unresponse	TemporalPattern
		AHU-SupplyAir-FanSpeed-Oscillation	TemporalPattern
#drx_nesbitt_vv-1-b-2_amd33/damper_pos	Control: Damper position	VAVATU-DischargeAir-DamperControl-Mismatch	RelationPattern
		VAVATU-DischargeAir-DamperControl-Cycling	TemporalPattern

(4) Knowledge querying for FDD construction

Knowledge querying is one of the important activities when embedding ontology technologies into various applications. When developing FDD approaches, knowledge querying provides a mechanism that an AI or inference engine uses to extract context, construct cause-effect structures, and perform automated reasoning. Since ontologies have interpretable data, structured data formats, and complete relations, knowledge querying becomes efficient to leverage both explicitly stored knowledge and inferred knowledge generated by reasoners.

There are several approaches such as SPARQL (Semantic Protocol and RDF Query Language), DL Queries and Semantic Web Rule Language (SWRL) that can be used to implement semantic search and data query. The definition of query protocol of SPARQL can be found in the [98].

Figure 8 illustrates the SPARQL clause and the result after executing SPARQL search in Protégé. This shows the measurements which may manifest symptoms associated with '*AHU-SupplyAir-TemperatureSensor*' faults (including three types as bias, drift and freeze). The faults can produce symptoms on 11 measurements (i.e., symptom subclass in Figure 8(b)). Figure 9 illustrates a graphic visualization of the attributes and symptom subclasses associated with this fault subclass. It can be seen that the knowledge querying result can be used to construct certain diagnostics structures, such as rule-based methods and Bayesian Network (BN) methods, where causal-effect relations should be embedded. Additionally, DT technology can be efficiently developed with the unified and interoperable data structure provided by FDD-ON.

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>

PREFIX fdd: <http://www.semanticweb.org/y6g/ontologies/2025/FDD_ON_VAV_HVAC#>
SELECT ?symptomClass
WHERE {
 BIND(fdd:AHU-SupplyAir-TemperatureSensor-Fault AS ?faultClass)

 ?faultClass rdfs:subClassOf ?restriction .
 ?restriction rdf:type owl:Restriction .
 ?restriction owl:onProperty fdd:hasSymptom .

  { ?restriction owl:someValuesFrom ?symptomClass . }
 UNION
 { ?restriction owl:allValuesFrom ?symptomClass . }
}
```

(a) SPARQL clause

symptomClass
AHU-SupplyAir-StaticPressureSetpoint
AHU-SupplyMixAir-Temperature
AHU-SupplyAir-StaticPressure
AHU-Cooling-CoilValvePosition
AHU-Heating-CoilValvePosition
AHU-SupplyAir-Temperature
AHU-Heating-CoilFlowRate
AHU-Cooling-CoilFlowRate
AHU-Cooling-CoilLeavingTemperature
AHU-Heating-CoilLeavingTemperature
AHU-SupplyAir-TemperatureSetpoint

(b) Queried symptom subclass

Figure 8. Example of SPARQL clause and the knowledge querying result

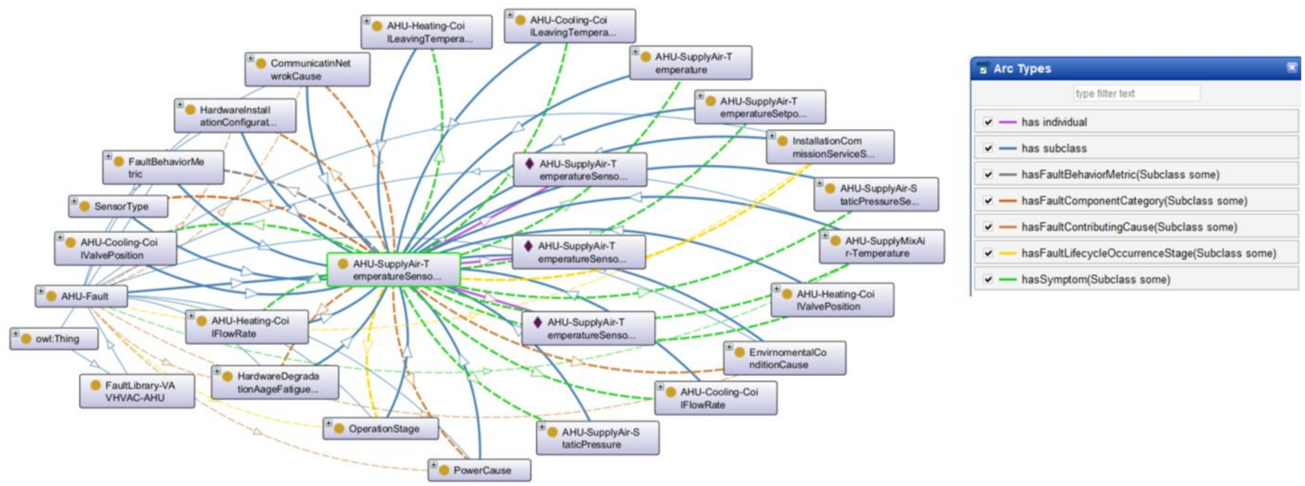


Figure 9. Graphic visualization of the attributes and symptom subclasses associated with ''*AHU-SupplyAir-TemperatureSensor*' fault subclass.

4.4 Limitations and ontology evolution

The development of ontologies is an evolving and iterative process because it requires new incoming knowledge and practical experience during practices. The current FDD-ON has two major limitations in terms of the knowledge representations and data structure as:

> (1) We only developed one-level taxonomy to categorize fault contributing causes, which may be insufficient to identify contributing causes at a more granularity level. Additionally, we did not consider the fault propagations, i.e., a fault can be a contributing cause for other types of faults. Although this simplifies the current relations between fault contributing causes and faults, it may limit more complicated analytics.
>
> (2) In the current FDD-ON, the relations between faults and symptoms, and the relations between faults and impacts are restricted to the equipment level, that's said, no cross-level casual effect relations among faults, symptoms and impacts were developed. This may limit the development of the FDD approach and perform fault impact analyses.

In addition to addressing the limitations, the research team plans to update and evolve FDD-ON from three angles.

(1) We will evolve FDD-ON by adding more equipment types, fault types, as well as associated symptoms and impacts in the HVAC systems. In addition, we will expand the representation of faults and symptoms in HVAC systems with the addition of new terms as needed for data curation and collaborative development.

(2) We will investigate more fault mechanisms and symptom statuses and then expand the controlled vocabulary list.

(3) We will study and include the knowledge related to maintenance activities into FDD-ON.

5. Conclusion

Efficient O&M for VAV HVAC systems are essential for ensuring energy efficiency, improving indoor comfort, reducing operational maintenance costs and extending equipment service lifespan. Achieving these objectives relies on the integration of multiple advanced technologies, among which, FDD plays a critical role. Successful deployment and implementation of FDD requires not only robust algorithms capable of accurately identifying abnormalities and diagnosing faults but also needs structured data representations and semantic models that support DT-based FDD applications, AI-driven maintenance decision-support systems, and fault tolerant control strategies. The integration of these technologies enables a closed-loop process that connects fault detection, diagnosis, corrective actions, and impact mitigation, thereby enhancing the overall reliability, efficiency, and sustainability of HVAC system operations. However, there is a lack of ontology targeting to cover the knowledge richness and promote FDD knowledge sharing for VAV HVAC systems in existing practice.

In this study, we develop an ontology – FDD-ON, which employs knowledge representation and semantic modeling, to enhance data interpretability and semantic interoperability, as well facilitate knowledge sharing across various applications for VAV HVAC systems. We empower FDD-ON with several novel features, aiming at providing an open source and formal ontological representation of faults and symptoms in VAV HVAC systems:

(1) We consider the requirements of multidisciplinary environments and applications, which FDD can be integrated into, when developing the four-level semantic model.

(2) We develop various taxonomies to classify various attributes associated with faults and symptoms to completely represent information at different levels related to FDD and hence enhance the semantic reasoning.

(3) We constructed an open-source fault library and a symptom library, which provide the unified definitions of fault types and associated symptom statuses in HVAC systems. Controlled vocabulary items are developed to unify the semantic representations of fault types and symptom statuses so that data interpretability can be enhanced. The standardized and structured naming conventions for fault types and symptom statuses enhance the data interoperability, making it suitable to various applications. To date, the FDD-ON includes 469 fault types and 468 symptom statuses across 241 types of components and 137 measures, as well as 447 impact types in VAV HVAC systems.

(4) We evaluate FDD-ON from multiple angles to show that the existing version of FDD-ON well captures the information in the FDD area. In addition, the nature of FDD-ON enables its evolution to address new gaps in different applications.

In the future, in addition to addressing the limitations and evolving FDD-ON as discussed, we will showcase more applications of FDD-ON in terms of DT deployment, AI-driven maintenance-supporting system development and fault tolerant control strategies.

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Nomenclature

Abbreviation

FDD	Fault detection and diagnostics
FDD-ON	Fault detection and diagnostics-Ontology
CQ	Competency question
VAV	Variable air volume
HVAC	Heating, ventilation, and air conditioning
HVAC&R	Heating, ventilation, air conditioning and refrigeration
BAS	Building automation system
CMMS	Computerized maintenance management system
O&M	Operation and maintenance
BIM	Building information model
AI	Artificial intelligence
LLM	Large language model
NLP	Natural language process
AHU	Air handling unit
ATU	Air terminal unit
RTU	Packaged rooftop unit
OWL	Web Ontology Language
W3C	World Wide Web Consortium
RDF	Resource Description Framework
RDFS	Resource Description Framework Schema
DL	Description logics
SPARQL	Semantic Protocol and RDF Query Language
BN	Bayesian Network

Appendix I

Table I.1 Feature comparison between FDD-ON and other ontologies or semantic models

Feature	**IFC [24]**	**Project Haystack [22]**	**Brick Schema [17]**	**FSBrick [29, 30]**	**AFDDOnto [32]**	**Fault taxonomy [13]**	**FDD-ON**
Model							
--Modeling approach	**Tag-based**	**Tag-based**	**Ontology-based**	**Ontology-based**	**Ontology-based**	**Tag-based**	**Ontology-based**
--Formal semantics	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
--Query language	Haxall / filters	Haxall / filters	SPARQL	SPARQL	SPARQL	Python/Filters	SPARQL
--Controlled vocabulary		**Y**	**Y**			**Y**	**Y**
Asset							
--Fault asset							
-----Fault library						**Y**	**Y**
-----Description of a fault type							**Y**
-----Information specifying the physical location at which a fault occurs					**Y**	**Y**	**Y**
-----Information specifying the component type where the fault occurs				**Y**		**Y**	**Y**
-----Information specifying the fault mode				**Y**		**Y**	**Y**
-----Information quantifying the extent of fault severity level							**Y**
-----Information specifying fault contributing causes							**Y**
--Symptom asset							
-----Symptom library						**Y**	**Y**
-----Description of a symptom type							**Y**
-----Information specifying the location of the observed symptom				**Y**			**Y**
-----Information specifying measures used to generate symptoms		**Y**	**Y**	**Y**			**Y**
-----Information specifying a symptom status				**Y**		**Y**	**Y**
--Impact asset							
-----Impact library							**Y**
Taxonomy							
--Hierarchical classification		**Y**	**Y**			**Y**	**Y**
--Data structure							
-----Structured data to represent a fault				**Y**		**Y**	**Y**
-----Structured data to represent a symptom							**Y**
--Fault attribute							
-----Classification of fault behaviors				Limited			**Y**

-----Classification of component types							**Y**
-----Classification of fault contributing causes							***Y***
-----Classification of fault lifecycle occurrence stages							**Y**
--Symptom attribute							
-----Classification of symptom data types							**Y**
-----Classification of symptom patterns							**Y**
--Impact attribute							
-----Classification of impact types							**Y**
Data relations							
--Fault and symptom relation				**Y**		**Y**	**Y**
--Fault and impact relation						**Y**	**Y**
--Fault and corresponding attributes							**Y**
--Symptom and corresponding attributes							**Y**