A Survey on Semantic Modeling for Building Energy Management

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Abstract
Buildings account for a substantial portion of global energy consumption. Reducing buildings’ energy usage primarily involves obtaining data from building systems and environment, which are instrumental in assessing and optimizing the building’s performance. However, as devices from various manufacturers represent their data in unique ways, this disparity introduces challenges for semantic interoperability and creates obstacles in developing scalable building applications. This survey explores the leading semantic modeling techniques deployed for energy management in buildings. Furthermore, it aims to offer tangible use cases for applying semantic models, shedding light on the pivotal concepts and limitations intrinsic to each model. Our findings will assist researchers in discerning the appropriate circumstances and methodologies for employing these models in various use cases.

1 Introduction
Buildings are crucial for promoting sustainable resource consumption and eco-friendly environment. However, they are responsible for approximately 40% of the final energy use and 36% of the total CO\textsubscript{2} emissions in the European Union [63]. Addressing these figures involves reducing non-renewable energy consumption and enhancing buildings’ energy efficiency. The advent of voluminous data from building systems and environment has given rise to strategies aimed at improving building performance, leveraging advancements in Information and Communication Technologies (ICT) topics, such as the Internet of Things (IoT), Cyber Physical Systems (CPS), Artificial Intelligence (AI), Context-Aware Systems [83], and Semantic Web Technologies (SWT).

Building Energy Management (BEM) is the concept and practice of managing a building’s energy usage. Beyond achieving targets like energy efficiency, BEM applications also focus on occupant comfort (e.g., thermal, acoustic, lighting, and air quality), energy storage and flexibility, predictive modeling, maintenance, and fault detection.

Meeting these objectives requires a cohesive strategy that prioritizes sustainability along with occupant satisfaction. Modeling the building environment is challenging due to its complex and dynamic nature, influenced by numerous factors including building equipment and envelope, thermal conditions, weather, and occupancy activities. The lifecycle of a building is marked by three major phases: design, construction, and operation. The first two phases focus on the geometric representation of buildings, providing static information such as building orientation, building materials, and other specifications, as illustrated in Figure 1(a). However, the operational phase is dynamic, overseeing the commissioning of the building to ensure optimal performance, occupant comfort, energy consumption, and efficient energy utilization. This phase gathers dynamic data such as CO\textsubscript{2}, weather information, temperature, among others, as also depicted in Figure 1(a), which is crucial for comprehending the building’s changing environment.

Building applications for energy management are often customized due to the diversity in building types, building systems, and varying data formats. The disparity in data formats arises from the distinct protocols employed by various equipment manufacturers, which hinders the development of universally applicable energy management applications.

To circumvent this issue, semantic modeling aims to standardize data and consistent representation of entities within a domain. In the context of buildings, semantic models can streamline data queries and enable the creation of context-aware applications deployable across diverse buildings as shown in Figure 1(b). For instance, this is achieved by harnessing contextual information from semantic models, combined with AI techniques for predictive maintenance [157], fault detection and diagnosis [96], and building operation and control strategies [157].

Semantic modeling encompasses the representation of both physical and abstract concepts within the context of building operations. Physical concepts pertain to the tangible assets present in the building environment, while abstract concepts encompass ideas, principles, and processes utilized to inform the operational building state. The penetration of Building Energy Management Systems (BEMS) necessitates features such as the interoperability of systems and data, along with modeling the orchestration of computational tasks. These tasks include orchestrating key performance indicators (KPIs), assessments, and services. These features are crucial for enhancing the self-awareness and adaptability of buildings to achieve optimal operating conditions, along with the automation of computational tasks involved.

Prior efforts have aimed to represent these concepts; however, they have typically been modeled independently. For instance, consider a scenario involving a building with diverse occupants where the owners are dedicated to reducing energy consumption, lowering operational costs, and upholding tenant satisfaction. In instances where energy KPIs are modeled in isolation from assessment and services, the KPI is monitored independently, focusing on metrics such as...
energy consumption per square foot. While this approach provides insights into energy usage, it lacks context on when and how assessments are conducted and how specific building services impact energy consumption over time.

This independent modeling approach restricts the potential for leveraging data-driven analytics within the building environment, hindering the comprehensive optimization of building operations. As a solution, this paper proposes an innovative approach to interlinking these abstract concepts, forming a more comprehensive ontology. This interconnected framework enhances the applicability of context-aware applications for building energy management. This survey paper looks into the semantic models relevant to building operations to describe the critical physical and abstract concepts they encompass, shedding light on their limitations, emerging trends, and commonalities.

The primary objective of this survey is to comprehensively understand and analyze the intricacies of semantic modeling and its diverse applications in BEM, focusing on building operations. More specifically, it aims to (i) enlighten semantic modeling foundational concepts, methods, and tools; (ii) review applications that actively employed semantic modeling in BEM, noting their successes, challenges, and lessons learned; (iii) identify the best practices from the analyzed studies and provide recommendations for future implementation in similar scenarios, and (iv) highlight, based on the reviewed literature, areas where current applications might be lacking and identify opportunities for future research in this field. These efforts aim to foster a holistic understanding of the role of semantic modeling and the potential to revolutionize BEM, paving the way for more efficient, sustainable, and intelligent infrastructures.

### 2 Research Methodology

This section outlines the research questions and describes the methodology employed for selecting papers for this survey. The research questions we intend to address with this survey are as follows:

- **RQ1.** What is the need for the applications of ontologies in building operations?
- **RQ2.** What were the different ontologies used in the building operation phase?
- **RQ3.** What examples of use cases were demonstrated in building ontologies?
- **RQ4.** What are the limitations of applying the existing ontologies in building operations?

Research question RQ1 is answered in Section 3 and aims to elucidate the significance and benefits of semantic modeling in building operations. RQ2, answered in Section 4, intends to illustrate the diverse ontologies integrated into building operations. RQ3, detailed in Section 5, seeks to showcase an example of the concrete application of ontologies in building operations. Finally, RQ4 exposes in Section 6 the drawbacks of existing ontologies in building operations.

To perform a thorough literature review on semantic modeling for BEM, a strategic keyword search was initiated to identify studies that align with the objectives of this research. The refined search string employed was:

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("Semantic modeling" OR "Semantic modelling" OR "Ontology" OR "Ontological Framework" OR "Data Model") AND ("Building" OR "BEMS") AND ("KPI" OR "Key Performance Indicator") AND "Energy Management"
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This string was queried across six major databases: IEEE (27,816 results), ACM (38 results), Web Of Science (3 results), Science Direct (197 results), Scopus (129 results), and Google Scholar (830 results). In writing this survey paper, the following numbers represent papers retrieved from each database. However, these figures may vary over time. These databases were selected for their comprehensive indexing of journals with documented impact factors and their inclusion of international, multidisciplinary studies, ensuring an extensive coverage of relevant literature. The quality of the papers was determined according to the prestige of the publishing journal or conference (e.g., Scimago Journal Rank for journals and CORE rank for conferences). Studies without detailed descriptions of building ontology for the
operational phase were excluded, focusing on those including detailed semantic models pertinent to the operational phase and excluding those solely concerned with the design and construction phases. Following a rigorous evaluation based on PRISMA guidelines [116] (e.g., removing duplicate papers (5000 papers), title and abstract screening (450 papers), applying eligibility criteria), a total of 50 papers were selected for an in-depth review.

3 Context and Background

This section explores the gradual evolution of the digitization of building data from its nascent stage to its recent stage. It also discusses the essence and the adoption of semantic modeling concepts for BEM on building operations. Lastly, it details the basic semantic concepts required for ontologies to represent for BEM.

3.1 Digitization of Building Data

The inception of digitizing building data stemmed from the development of Building Information Models (BIMs). Introduced in the 1970s, BIMs have significantly shaped the Architecture, Engineering, and Construction (AEC) sector over the past few decades [138, 43]. The National Building Information Model Standard (NBIMS) defines BIMs as a “digital representation of the physical and functional attributes of a facility.” In this capacity, BIMs serve as a collaborative knowledge repository, offering valuable information about a facility that is a dependable foundation for decision-making throughout its entire lifecycle, starting from its initial stages and extending onward [22]. BIMs find predominant application during the building’s design and construction stages to foster improved stakeholder communication. These digital tools generate extensive data from the planning, design, construction, operation, maintenance, demolition/recycling processes. This data is exchanged among stakeholders to enhance the building’s energy efficiency [43, 117, 18]. However, using these tools presents a challenge due to the vast array of disparate data types that are difficult to exchange and handle, making knowledge extraction problematic for stakeholders with varying backgrounds [118].

The BIM uses a standard data model known as Industry Foundation Classes [87]. The IFC data model enables users and software providers to consistently depict building information under the defined specifications of the IFC schema. IFC is primarily employed within BIMs to facilitate data exchange among various BIM authoring tools, including Autodesk Revit.1 This data interchange can be accomplished using various file formats, including the IFC STEP Physical File Format (IFC-SPFF) defined using the EXPRESS data specification language (ISO 10303) [124], the XML file format defined using the XML Schema Definition Language (XSD) (ISO 10303-28) [90], and the Resource Description Framework (RDF) file format defined by the Web Ontology Language (OWL) for IFC (ifcOWL) [23].

Although IFC finds representation in multiple schemas, it exhibits limitations in achieving interoperability, identified as Binding, Adaptability, and Extensibility [120]. Binding emphasizes how the heterogeneous nature of IFC translation and the binding process via each BIM authoring tool can result in distorted and incomplete IFC models. Adaptability pinpoints how slow it can be to change the IFC schema. It requires different industries and companies to agree on what the IFC should look like and how it should work. Extensibility implies that the IFC schema is not accessible to add new concepts, especially for users who are not experts in the EXPRESS language used to define the IFC model. Despite these limitations, Semantic modeling through semantic web technologies offers a viable solution for facilitating interoperability in the building operational phase and overcoming the barriers of the IFC data model. This process involves adopting a linked data approach to link information from diverse domains (e.g., BIM, sensor data, simulation data) into a unified web of linked building data.

This section highlights the progressive digitization of building data, tracing its inception from its nascent stages and evolution over time. It further elucidates the technologies employed for data exchange in the building industry, accentuating their advantages and limitations. Lastly, it spotlights a prospective resolution to enhance semantic interoperability during the building operation phase, with a comprehensive exposition presented in subsequent sections.

3.2 The Advent of Semantic Modeling Technologies in Building’s Operation Phase

The building operational phase encapsulates a wealth of data from the operational systems and components, contributing to its daily functionality. Devices are employed to gather insights from the building environment, encompassing monitoring systems at both the building and urban scales. Concurrently, models of the components interact synergistically with diverse tools, such as simulations assessing building energy efficiency and occupancy levels, to aid better decision-making for the enhancement of the built environment. Hence, establishing adaptable mechanisms becomes imperative to facilitate seamless data interchange among stakeholders involved at various phases, fostering essential interoperability among data, tools, and devices.

The idea of semantic modeling via semantic web technologies aims to promote a standardized data format across diverse heterogeneous data sources. Semantic modeling embodies the substantial potential for advancing information linkage. As a result, building information can be seamlessly connected across diverse sources, comprehensible to computers, thereby enabling the execution of increasingly sophisticated tasks.

1https://www.autodesk.com/products/revit/
The IFC open data standard was converted into an OWL ontology [4, 119]. This transformation aimed to enable the incorporation of building data onto the World Wide Web Consortium (W3C) [7], thus facilitating web-based data exchanges. The IFC schema is notably intricate and encompasses an extensive array of classes and attributes, a characteristic evident in the size of the ifcOWL ontology. As a result of this intricacy, effectively querying the ifcOWL ontology poses challenges in the usability and performance of developing scalable building applications [148]. Moreover, this complexity results in difficulties when attempting to extend the ifcOWL ontology, making it challenging to introduce or alter new components without causing ripple effects across the entire structure. This lack of modularity restricts the ability to selectively choose and incorporate specific components or functionalities, limiting a pick-and-choose approach commonly desired in software development. Consequently, due to the non-modular nature of the ifcOWL ontology and its resemblance to the comprehensive IFC schema, users and developers are constrained by the predefined structure and scope of the ontology. The intricate interconnections within the ontology make it challenging to tailor the ontology to specific application requirements without considerable effort. This limitation hinders the flexibility and adaptability often sought in data modeling.

Despite the limitations associated with the ifcOWL initiative, it laid the groundwork for the emergence of the W3C Linked Building Data community and the buildingSMART Linked Building Data working group [121]. These collectives are dedicated to standardizing the presentation and interchange of building data on the internet, thereby propelling the Architecture, Engineering, Construction, and Operation (AECO) industry toward a heightened state of technological advancement. Consequently, owing to these concerted endeavors, various other undertakings strive to define a framework comprising more compact, modular, and adaptable Linked Building Data (LBD) ontologies. These ontologies aim to establish an ecosystem less reliant on IFC while encompassing similar concepts.

Semantic modeling technologies, manifested as ontologies in the context of the building operation phase, will be examined in detail within Section 4.1. This examination will encompass a comprehensive exploration of the concepts embedded in these ontologies and an in-depth analysis of their constraints.

3.3 Ontologies and Semantic Web

Semantic models, often called semantic or metadata schemas, encompass information that elucidates the description and meaning of the underlying data. These models serve as frameworks for organizing information, facilitating a more nuanced understanding of data as comprehensibility is crucial for developing intelligent building applications. These models’ complexity varies widely, and this variation is elaborated upon through a hierarchical perspective.

At the foundational level, straightforward lists of terms (e.g., types of sensors) offer basic categorizations without intricate relationships or layers of meaning. These lists contribute to a fundamental information organization but need more depth of analysis and contextual connections in more sophisticated models. Progressing along the complexity continuum reveals the emergence of taxonomies characterized by a structured approach to classification. Data organizes itself into hierarchical categories in this structure, mirroring the hierarchical control architecture observed in Heating, Ventilation, and Air-Conditioning (HVAC) systems. This refers to an organized structure that governs the operation of HVAC systems. Although taxonomies are more intricate than simple lists, their primary emphasis is categorizing rather than capturing relationships between concepts.

The pinnacle of complexity within semantic modeling is the facet of ontologies. Ontologies transcend previous levels by introducing the utilization of graph data structures. In an ontology, concepts are akin to nodes within a graph. These nodes are interconnected through graph edges, representing the relationships and associations between various concepts [156]. This interconnection allows for a more holistic representation of knowledge, capturing what concepts exist and how they are interrelated. This nuanced depiction enables a richer understanding of the context and significance of the data. Ontology is salient to support data readability and machine reasoning [24]. The W3C suggests more modular and simple data formats that can be interlinked and extended over time. Figure 2(a) shows the concept of interconnected ontologies, and it can be seen that the domain-specific ontologies can be separated as smaller graphs and linked with other ontologies. Experts widely acknowledge that various communities loosely categorize artifacts as ontologies [76]. Within information science, ontologies constitute a formalized representation of knowledge encompassing domain-specific concepts, relationships, classes, and attributes. An ontology can be defined as a method for explicitly establishing concepts, classes, objects, and their corresponding interrelations within a specified domain of interest [75]. Another definition explains ontology as a “formal, explicit specification of a shared conceptualization,” recognizing the importance of achieving a shared understanding of the knowledge represented [144].

The Semantic Web, an extension of the World Wide Web, was brought into being by formulating standards by the W3C. Its primary objective is facilitating machine-readable capabilities for internet-based data [150]. The inception of linked open data (LOD) [10] aimed to reduce obstacles in disseminating, sharing, and retrieving information online, fostering a worldwide data environment. Using this method; data must be structured via the Resource Description Framework (RDF) [39]. This concept lays the groundwork for the renowned 5-star open data [7], which means organizing data based on the RDF model and connecting it to other RDF data collections, leading to the formation of the LOD cloud. The RDF data model represents data using subject-predicate-object triple structures, as shown in Figure 2(b), which create graph patterns. An RDF triple provides a framework for illustrating things and their relationships. The predicate acts as the bridge connecting the subject and the object. Essentially, this format allows any given subject to be related to any object, indicating the nature of their relationship through the predicate. The Web of Data consists of interconnected graphs using the triple format to consistently depict information to ensure the
data is comprehensible and reusable for humans and computers.

An extra layer known as the New Generation Service Interface Linked Data (NGSI-LD) [127] can be incorporated into the ontological representation of entities in a given domain. The NGSI-LD is a way to digitally represent each entity and relationship within an ontology so that computers can read and identify it without ambiguity. This is done by assigning each entity a Uniform Resource Locator [108] (URL) / Uniform Resource Name [8] (URN) that uniquely identifies it, as shown in Figure 2(c). NGSI-LD is based on JavaScript Object Notation for Linked Data [141] (JSON-LD), which introduces the concept of the @context element to provide supplementary information allowing the computer to assimilate information with better clarity and depth. The NGSI-LD has three major building blocks: Context Broker, Context Producer and Context Consumer. The context broker enables organizations to manage and share data in real-time describing what is currently happening within their systems and organizations. The context producers allow the publication of context information, while the context consumer processes context information of interest.

The AEC domain predominantly depends on file-based exchange. While building information modeling has been embraced, its utilization during the operational phase remains relatively limited. This phenomenon owes to the intricate characteristics of the IFC standard, primarily centered on geometric representation, and its constrained capacity for effectively establishing interconnections across diverse data domains.

Several ontologies and data models have been developed recently, primarily with the support of the World W3C, to facilitate the representation of the building environment in a manner compatible with the Semantic Web. This notion encompasses the ontologies created by the W3C Linked Building Data (LBD) Community Group [43]. These ontologies draw inspiration from the IFC data model yet begin with a more straightforward and modular design. Ontologies such as Building Topology Ontology (BOT) [129], Smart Applications REFerence (SAREF) ontology [47], Semantic Sensor Network / Sensor, Observation, Sample and Actuator (SSN/SOSA) [79], Brick Schema [20], among others. Next section discusses each key ontology utilized in the building operational phase, identifying the core concepts they cover.

### 3.4 Identifying Core Concepts in Building Operational Ontologies

Concepts determine the nature of an item (its type), properties provide general details about the item, and relationships describe the item’s association with other items (its function or role in a more extensive system) [5]. Main concepts are needed to support the full functionalities of the BEM process. These concepts can include, for instance, Building, Zone, Space, Building Envelope, Control Device, Building System and Equipment, Sensor and Actuator, and Occupant, as partially identified by [126].

Buildings’ architectural and functional intricacies involve many building systems and equipment. Within these systems and structures exists a hierarchy of devices, such as sensors, actuators, and controllers. These devices are pivotal in automating and managing building operations within designated physical or virtual spaces known as zones. These zones can range from tangible spaces (e.g., rooms, floors, and staircases) to virtual segments devised for some operational need.

Building topologies and their spatial configurations are incredibly varied, encompassing structures like apartments, offices, residential buildings, among others. Consequently, it is challenging to enumerate all components in buildings, each with their unique attributes. Within this context, space refers to any tangible area within a building structure. While zones may represent a collective of these spaces or be abstract areas without physical boundaries. Moreover, the building envelope is integral to the structure’s design and function, which consists of components that demarcate indoor and outdoor environments, such as walls, doors, and windows. The external data refers to data that originates independently of the building, falling outside the scope of the building’s systems and equipment. This encompasses

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**Figure 2:** Key components of semantic data modeling and interoperability in smart environments.
data beyond the building’s control, including weather conditions, grid price signals, and other similar factors. Occupant refers to data that are used to characterize the behavior of individuals in a building, helping to discern their comfort satisfaction levels and energy usage.

Given the European Union’s emphasis on enhancing energy flexibility in buildings, semantic modeling becomes crucial for seamlessly integrating data from various energy resource entities essential to achieving this goal. This survey further assesses ontologies that encompass aspects of managing both non-renewable and renewable resources and examines their interaction with buildings to enhance energy efficiency.

Understanding these fundamental concepts is crucial when modeling the operational scenarios of buildings. These foundational ideas provide a framework to decipher the functionalities and constraints of semantic models used in building operations. By grasping these concepts, professionals can better harness these models’ potential and be aware of their inherent limitations.

4 Semantic Models

4.1 Core Semantic Models

This section focuses on semantic models and the concepts they embody within building operations. Since their inception, ontologies like BOT, SAREF, SSN/SOSA, and Brick have been embraced and put into practice through various use cases. Hence, these ontologies are subject to a more thorough discussion than others that have seen less adoption. While not extensively discussed due to its limited application in existing studies, the PH ontology is acknowledged in a comparative context, as outlined in section 5. Nonetheless, its contribution is noteworthy for introducing the innovative concept of tags, a feature incorporated into the Brick ontology. This research recognizes the existence of various data models based on XML or UML. However, these models have been excluded due to their limitations in aligning with linked data methodologies, particularly their inability to incorporate semantics into their specifications as delineated by the W3C [39, 81]. Table 2 elucidates the main (and other) ontologies discussed in this survey related to the building operational phase. These ontologies focus on various scopes, such as Smart Building, Smart Home, Smart City, Smart Device, Smart Energy, and Smart Grid. However, some of these ontologies are applied to multiple scopes. Smart building refers to buildings that can adapt to their environment by integrating various technological systems to meet the drivers for building progression: energy and efficiency, longevity, and comfort and satisfaction[21]. These buildings can be of various types, such as residential, commercial, industrial, and others. On the other hand, smart homes are confined to residential buildings equipped with smart technologies to provide tailored services for users [105]. A smart city is a well-defined geographical area that leverages the integration of high technologies such as ICT, logistics, energy production and others to support users’ overall well-being and environmental quality [34]. Smart Energy is defined as an approach that facilitates the combination of thermal, electricity and thermal grid utilizing storage technologies coordinated to attain an optimal solution for each distinctive sector and the overall energy system [102]. Smart Grid is an electricity network that efficiently delivers sustainable, economical and secure electricity supplies via the intelligent integration of all users’ actions, including generators, consumers and those that do both [151]. Smart devices are defined as those that autonomously collect data about users or their surroundings to support context awareness or guide action by providing insights into personal or environmental contexts [95].

4.1.1 BOT—Building Topology Ontology

The Building Topology Ontology (BOT) offers a streamlined and expandable framework for depicting building structures, encompassing stores, spaces, their elements, and their 3D geometrical designs. Introduced in 2019 by the Linked Building Data Community Group (LBD CG) under the W3C Consortium, BOT utilizes linked data and semantic web technologies. While lightweight, BOT helps complementing other ontologies to cover concepts in product details, sensor readings, IoT devices, intricate geometries, or project management data, thus simplifying semantic interoperability. This mechanism aids web-based data integration in the AECO sectors. Although BOT allows for representing essential building topological concepts and the relationships between its various components [128], it has not gained recognition as an official W3C standard [74].

The BOT fundamentally centers around conceptualizing buildings’ structural and spatial intricacies. This ontology examines the various configurations and organizational patterns that buildings can possess, capturing their complex spatial and relational characteristics. The primary objective of BOT is to offer a comprehensive framework to model buildings and their internal components in a structured manner, as depicted in Figure 3.

BOT comprises a class taxonomy for zones (building site, buildings, store, and spaces). In the BOT ontology, the zone class bot:Zone facilitates the nuanced representation of distinct three-dimensional volumes within a building’s topology. The conceptual framework of BOT pivots around an organized hierarchy that can nest more specific, characterized areas within these spaces. A meticulous exploration of the sub-classes provided by BOT unravels a versatile set of tools to articulate a spectrum of spaces, each carrying distant spatial functional attributes within a building’s architecture and function.

The BOT element class bot:Element represents concepts such as Envelope, Building Systems and Equipment, Control Devices, and Sensors. The incorporation of the interface class, identified as bot:Interface within BOT, provides a medium to represent spatial intersections where zones and elements converge or interact. This concept
forms a networked spatial representation wherein entities and their interfaces form a cohesive, interconnected web, enabling the representation of a building as an interlinked system of spaces and elements.

BOT establishes the relationships among instances of zones and elements based on various properties within the ontology schema. Relationships among zones, particularly those about their physical and spatial relationships, can be structured using properties like `bot:containsZone`, `bot:adjacentZone`, and `bot:hasBuilding`, among others. These properties facilitate the development of a spatially coherent model where zones are not merely isolated entities but part of an interconnected spatial ecosystem within the building structure.

BOT is a minimalist ontology aligned with other ontologies to meet the needs of building operational use cases. Thus, it cannot be used alone to semantically describe the building domain. Depending on the use case, it collaborates with other ontologies, employing ontology alignments [136].

4.1.2 SAREF — Smart Applications REFerence Ontology and its Extensions

Initiated in 2013, the SAREF ontology is a reference for IoT applications [62]. This project was a joint effort by the European Commission and the European Telecommunication Standardization Institute (ETSI) to create a unified ontology, working closely with the smart appliances industry [36]. Among a diverse array of IoT standards, platforms, and technologies spanning various sectors [49, 48], SAREF serves as a universally agreed-upon model facilitating communication between IoT devices from various producers using distinct protocols and standards [55]. ETSI presents SAREF through a sequence of technical specifications. At the time of this review, the SAREF ontology includes a foundational core ontology tailored for IoT [62] and has 12 domain-specific extensions, which covers areas like SAREF4ENER for Energy [53], SAREF4ENVI for Environment [54], SAREFBLDG for Building [51], SAREF4CITY for Smart City [57], SAREF4INMA for Industry and Manufacturing [55], SAREF4AGRI for Smart Agriculture and Food Chain [56], SAREF4AUTO for Automotive [50], SAREF4EHAW for eHealth/Ageing-well [52], SAREF4WEAR for Wearables [60], SAREF4WATR for Water [59], SAREF4LIFT for Lift [58], and the recently added SAREF4GRID for Smart Grid [61]. It also includes SAREF for Systems (SAREF4SYST), previously an extension of SAREF.

It now functions as a model for illustrating how SAREF can be extended and applied to describe diverse sets of application-specific information in various fields. In 2017, a preliminary solution using SAREF was showcased and applied to current commercial products in the energy domain [109]. Given the focus of this survey on the building domain, the discussion will center on the relevant SAREF extensions, including the core SAREF, SAREF4BLDG, SAREF4ENER, and SAREF4SYST. The SAREF4GRID ontology, having been recently released, remains unexploited in practical use-case scenarios. Consequently, a brief explanation of this ontology will be provided. The SAREF core ontology encompasses 29 classes, 35 object properties, 4 data properties, and 10 named individuals. Table 1 shows the number of classes, object properties, data properties, and named individuals for SAREF and its extensions.

At its core lies the concept of `saref:Device`, representing a tangible object capable of performing one or more `saref:Function` as shown in Figure 4. This function denotes devices’ primary roles, such as temperature regulation by a thermostat. Devices also operate in specific `saref:State`, giving insights into their current mode, like being operational or on standby.

The SAREF ontology introduces the concepts such as `saref:Command` and `saref:Service` to facilitate interactions and operations with these devices. Commands act as directives sent to devices, triggering specific actions or changes, while services encapsulate a device’s operations or capabilities. Underlying these interactions are `saref:Task`, specific sets of actions assigned to a device. An essential consideration in this ontology is the `saref:Profile`, which reflects
the behaviors concerning power or energy consumption patterns.

SAREF also focuses on procedure, command, and operation execution. The `saref:ProcedureExecution` infers the act of carrying out a procedure performed by a device. `saref:CommandExecution` illustrates the execution of a command and relates to some feature of interest aspect, where the `saref:FeatureofInterest` can be a tangible entity like temperature, and `saref:OperationExecution` depicts the execution of an operation in a network. A `saref:Commodity`,
represents the main goods or products that may be consumed, produced, or stored by some device or feature of interest such as energy. `saref:Property`, denoting specific attributes of these features. `saref:Observation` then provide quantified property values via a procedure to calculate the value of a property of a feature of interest. The SAREF documentation provides a more in-depth discussion [62].

The SAREF4BLDG is an extension of the SAREF ontology [62] dedicated to buildings that incorporate elements from the IFC and BOT. While it draws inspiration from models of building spaces and topology, its primary focus is on devices within those buildings, meaning that while it can model the physical structure of a building, its primary concern is on appliances and systems. The `s4bldg:Building` and `s4bldg:BuildingSpace` classes in SAREF4BLDG help define the physical layout and sections of a building. Generally, Zones and Spaces are terminologies used to describe specific areas within a building. The SAREF4BLDG specializes in generic device definition from `saref:Device` to include building-specific devices. Examples are boilers (`s4bldg:Boiler`) and cooling towers (`s4bldg:CoolingTower`). The SAREF4BLDG extension introduces attributes to represent the location using the W3C’s basic geo vocabulary [74]. This ensures a standardized representation of location data. The relations `s4bldg:isContainedIn` determine the physical relationships between spaces in buildings. The SAREF4BLDG ontology class represents physical objects associated with buildings and their components using `s4bldg:PhysicalObject`. Physical object refers to an umbrella of items about walls, doors, windows, beams, and potentially any tangible component within a structure.

The SAREF4SYST ontology is uniquely positioned within the SAREF framework, delineating and modeling the complex web of device relationships, emphasizing their connectivity and interaction dynamics. A noticeable hierarchy emerges within complex systems, especially in smart environments, with devices linking to form subsystems that connect to more comprehensive systems. This ontology aims to capture these relationships with precision, documenting each device’s placement and its links within a system or subsystem in detail.

SAREF4ENER is another extension of the SAREF ontology, developed in collaboration with Energy@Home [45] and EEBus [44] to facilitate seamless communication between smart appliances from different manufacturers that integrates into any energy management system at the building or in the cloud. The SAREF4ENER ontology concentrates on a specific aspect of energy management, such as demand response scenarios. Demand response, in the context of the Smart Grid, is an approach that encourages end-users or consumers to modify their usual electricity consumption patterns in response to certain triggers [139]. Within these demand response applications, the SAREF4ENER introduces the concept of a Customer Energy Manager (CEM).

The SAREF4ENER establishes concepts such as `s4ener:PowerProfile` which is a subclass of the profile class from the core SAREF `saref:Profile`. The SAREF4ENER introduces classes that are necessary for smart energy management. These classes are incorporated to schedule devices in specific modes and preferred times using power profiles to optimize energy efficiency and accommodate the customer’s preferences. Examples of these classes are `s4ener:PowerProfile`, `s4ener:AlternativeGroup`, `s4ener:Slot`, and `s4ener:PowerSequence`. A detailed examination of the SAREF4ENER structure is available within its documentation [53].

The Smart Grid Ontology extends SAREF to provide a standardized representation of general concepts for smart grid data oriented to the IoT field [61].

### 4.1.3 SSN —Semantic Sensor Network and SOSA —Sensor, Observation, Sample, and Actuator

The SSN/SOSA ontology results from the fusion of two related ontologies: SSN and SOSA. The W3C SSN Incubator Group created the SSN ontology, uniquely describing sensors regarding their capabilities, measurement processes, observations, and deployments, which aim to represent sensor-based systems [29]. They offer a robust framework for modeling various building systems and equipment. The SOSA emerged from a reconsideration of the SSN due to scope changes, shifts in the target audience, technological advancements, and lessons learned over the years [88]. Combining these two ontologies resulted in a more comprehensive ontology, as depicted in Figure 5. This combined ontology offers a semantic description of systems comprising sensors and actuators, observations, measurement procedures, the subjects, and their properties observed or acted upon, samples, and the sampling process [78].

In SSN (`ssn:System`), modelers can capture various systems and equipment present in a building, like the Air Handling Unit (AHU). Additionally, SSN includes a property class (`ssn:Property`) to delineate the intrinsic characteristics of the equipment.

SSN/SOSA goes beyond equipment representation and also encompasses control devices. Systems can implement procedures that carry out actions based on observation inputs. The core class, `ssn:Sensor`, and `sosa:Actuator`, in SSN/SOSA are vital for modeling sensor and actuator devices. The `sosa:Sensor` class, a sub-class of the SSN System, represents devices involved in or implementing a `sosa:Procedure`.

Actuators, denoted as `sosa:Actuator`, are devices used by or implementing SOSA procedures to alter the environment’s state. In SOSA, a class called `sosa:ActuatableProperty` is introduced to help modelers characterize what aspects of a `sosa:FeatureOfInterest` can be acted upon in the environment. For instance, it can represent a window’s ability to be opened and closed by an attached actuator.

Additionally, the `ssn-system:SystemProperty` class enables modelers to define characteristics that represent a system’s ability to function for its primary purpose. For instance, it depicts a sensor’s capacity to generate observations or an actuator’s capability to actuate in a given environment.
4.1.4 Brick

The Brick Schema is an open-source, semantic data modeling framework for smart buildings and building automation systems. Brick initially found its description and application within the academic community, with its first publication emerging in 2016 [2]. Brick encompasses an extensible dictionary of terms and concepts within the building domain. It is an open-source initiative that standardizes semantic descriptions of buildings’ physical, logical and virtual assets and their relationships. Brick is an ontology-based metadata schema that effectively represents buildings and their subsystems by capturing their necessary entities and relationships, described in a machine-readable format. The Brick ontology comprises five significant concepts: Entity, Tag, Class, Relationship, and Graph.

From the standpoint of brick, an entity is an abstraction of actual things in a building that can be physical, abstract, or logical. Physical entity refers to any identifiable object or substance that exists in the physical world. It has a tangible, measurable presence and can concretely interact with the physical environment. Physical entities encompass various items, such as mechanical equipment like HVAC systems, lighting systems, networked devices like electric meters, thermostats and spatial elements like rooms and floors. Virtual entities are digital constructs or representations within computer systems, software applications, or virtual environments rather than having a physical presence in the real world. Examples include temperature sensors, energy consumption of a space heater, and actuation points, which are used to observe the current state of the environment and infer changes when required. Logical entities are entities or collections of entities defined by rules. Examples are HVAC zones and lighting zones.

Tag is an attribute that characterizes an entity adopted from the project haystack [80], which is further explained in Section 4.1.5. Tags can describe physical, virtual or logical entities. For instance, the tags brick:AHU, brick:Sensor, and brick:Lighting serve as examples for physical entities. virtual entities are represented by tags such as brick:Setpoint, Energy Usage Sensor. While tags like brick:Energy Zone, HVAC Zone, exemplify logical entities.

A class represents a defined category with intentional meaning, serving as a mechanism for categorizing entities. Organized into a hierarchical structure, classes act as the types of entities, each being an instance of one or several classes. Furthermore, classes possess an array of related tags, offering valuable annotations that aid discovery. Brick exhibits a hierarchical design, where Classes and Subclasses define varying levels of detail [26]. Within the Brick model, although five classes exist, only three are predominantly used in the building domain: brick:Location, brick:Equipment, and brick:Point. The brick:Location class describes a physical or virtual space like a Zone. Moreover, this class encompasses 10 subclasses with a hierarchical subclass level. The brick:Equipment class represents devices that serve all or part of a building and has 22 subclasses. The brick:Point class describes measurements, setpoints, commands, parameters, alarm and device status from varied devices, and it consists of 6 subclasses.
A relationship delineates the specific nature of the connection between two interconnected entities. For instance, the placement of a temperature sensor within a room inside a building can be expressed through the use of `brick:hasPart` to define the relationship between the building and the room, and `brick:isPointOf` to associate the temperature sensor with the room.

Brick utilizes a directed, labelled graph to represent its structure. Figure 6 depicts a graph representation of connections between various entities within a building [103]. These entities are an AHU, two variable air volume boxes, a thermal zone identified as HVAC zone, and a set of points and rooms.

**Figure 6: Brick model representing an AHU, two VAVs, and a handful of points and rooms (image from [20]).**

The Brick ontology is built on design principles that include completeness, expressiveness, usability, consistency, and extensibility [2] [3]. Completeness is the ability of an ontology to encompass all the information required by building applications. Expressiveness indicates the ontology’s capability to represent a wide range of entities and relationships prevalent in buildings, which is crucial for crafting BEM applications. Usability suggests that the ontology ought to be straightforward and user-friendly. Consistency ensures that the modeling process remains uniform across various users when employing the ontology. Extensibility guarantees that the ontology can be effortlessly expanded to incorporate new concepts.

4.1.5 **PH — Project Haystack**

Project Haystack (PH) is a semantic data model designed to represent various equipment and their relationships within automation, control, energy, HVAC, and additional environmental systems [80]. This initiative aims to provide standardized data to facilitate a seamless exchange of information and unlock value from the vast amounts of data generated by smart devices in homes, buildings, factories, and cities.

PH associates physical objects within buildings to entities, where an entity, from PH’s perspective, represents an abstraction that could be a single site (such as a building identified by an address), a specific piece of equipment within a building (e.g., an HVAC system, an electric meter, or a variable air volume box), or a sensor point (which includes digital or analog sensors generating signals and data, e.g., temperature or pressure sensors and on/off switches).

PH is fundamentally structured around the use of tags. Each tag specifies a fact or attribute about an entity. For instance, assigning a site tag to an entity signifies that the entity is recognized as a building with an address, aligning with the definition of a site tag according to Project Haystack. It also includes over 200 tags designed to standardize the description and relationships of equipment, systems, and their associated data. This tagging system is flexible, allowing for the application of tags pertinent to particular applications relevant to specific applications.

In Project Haystack, **Site**, **equip**, and **point** are the three main tags for defining an entity. Many tag types exist, including marker, string, reference, among others. A marker tag is merely an annotation with no associated value to identify an entity type. For example, applying the **ahu** tag to an entity indicates that it is an air-handling unit. A string tag has an associated value commonly used for human-readable descriptions. A string tag is accompanied by a value, often utilized for descriptions that are readable by humans.

4.2 **Others**

This section describes other ontologies covering certain BEM areas, as shown in Table 2. Some of these ontologies leveraged existing ones by identifying specific gaps and introducing new concepts to extend them, specified in the "Uses/Extends" column. This column represents domain-specific ontologies in building operational phases used to develop new ontologies. Ontologies that did not mention if they utilized other ontologies were regarded as "None". The
number of classes provided was counted manually on those ontologies that explicitly listed them on their website. For those that did not provide this information, the Protege² was utilized to count the number of classes by passing the ontology file into the software. These ontologies can be aligned and integrated with other ontologies to cover certain building concepts. Ontology alignment refers to finding equivalent entities across two different ontologies [1]. Ontology reuse explains when an ontology is based on another, meaning it extends or derives its structure from an existing ontology [25]. While these concepts seem similar, it is important to provide a clear distinction between the two cases to comprehend when an ontology is reused or aligned with other ontologies.

RealEstateCore is an ontology tailored for smart buildings developed from well-established real estate and construction practices. It is modular, consisting of a collection of data schemas that describe concepts and relationships pertinent to the modeling of buildings and their systems, as well as data derived from these systems [153]. It supports two main use cases: energy usage analysis and optimizations, and presence analysis. Also, it promotes the interaction between smart buildings and smart cities. The ThinkHome ontology is specifically designed for smart home environments, emphasizing the management of energy supply and consumption [136]. It encompasses models that cover various aspects such as comfort, user behavior, processes, energy, devices, external influences like weather, and the building structure itself. The ThinkHome Ontology aims to create an extensive knowledge base that encapsulates all the necessary concepts to facilitate the development of energy-efficient and intelligent control mechanisms for home environments. Energy Flexibility Ontology (EFOnt) aims to serve as a standardized tool for knowledge co-development and streamlining energy flexibility-related applications [98]. It provides a standardized representation of energy flexibility resources in buildings. DogOnt ontology (modeling for Intelligent Domotic Environments) emphasizes the modeling for all devices being part of IoT inside a smart environment [15]. It encompasses a rule-based mechanism that automatically generates states and functionalities for domotic devices. Mirabel delineates how devices can express their energy flexibility by integrating the user preference with the device energy profile [152]. The ontology-based power consumption model (PowerOnt) is tailored for smart homes to represent concepts of power consumption pertinent to smart devices [16].

A smart building ontology for ambient intelligence (BonSAI) is an ontology to model aspects of service-oriented smart building system [143]. This refers to a framework where various functionalities are provided as services. These services include operations that the system can perform, inputs it can take, output it can produce, the logic it uses to process information, parameters it operates with, and the environmental conditions it monitors or controls. This ontology is based on an upper ontology named Web Ontology Language for Services (OWL-S) [106] for service description and the Context-Driven Adaptation of Mobile Services (CoDAMoS) [125], which provides services depending on the user and environmental context. The owl-s ontology is not included in Table 2 because it is an upper ontology alongside the CoDAMoS ontology as it is deprecated. SARGON (SmArt enERgy dOmain Ontology) defines semantic descriptions of the smart assets in building and smart grid and their relationships [77]. This model is based upon the SAREF4ENER ontology, extending it to include concepts relating to the distribution of electrical grid and building energy automation. Flow Systems Ontology (FSO) describes the energy and mass flow relationships between building systems such as HVAC, building components and their compositions [94]. Due to the limitations of FSO ontology to represent system components’ capacity and size-related properties, the Flow Properties Ontology (FPO) was introduced to cover those concepts [92]. Building Automation and Control Systems (BACS) represents physical devices of Building Automation Systems (BAS) and their location in the building and connection to technical equipment and appliances, alongside control behaviors [149]. BASont ontology proposed integrating device descriptions on BAS devices and functional specification with adjacent domains of BIM [123]. Smart Building ontology (SBonto) [158] focuses on smart building (private or public), which defines concepts such as device, state, architecture, environment, furniture and network. Another smart building ontology (Onto-SB) was proposed to provide a structured framework for modeling smart buildings and their environment [40]. It models various concepts, including building actors, representing the inhabitants living within the building. Also, it supports the reasoning process behind mitigating building energy consumption. The RESPOND ontology manages real-time optimal energy dispatching, considering all energy on-site. It aims to deploy an interoperable energy automation, monitoring and control solution to deliver demand response programs at a dwelling, building and district level [16]. The Smart Energy Aware System (SEAS) is an ontology designed to support the interoperability and efficiency of smart energy systems [97]. It is a structured framework that defines a common vocabulary for smart energy systems, including energy production, consumption, conservation, and efficiency concepts. It can be aligned with other domain-specific ontologies like SSN/SOSA. The Open Energy Ontology (OEO) is a domain ontology for energy system modeling and analysis [17]. The Smart Grid (SG¹) Ontology was developed to describe a prosumer-oriented smart grid to facilitate data integration and communication with buildings [72]. Another Smart Grid (SG²) Ontology was designed to describe entities and their interrelationships in smart grid systems to enable cyber attack identification [147].

An Ontology-Based Information Model for Smart Grids (SSG) was developed to enable semantic interoperability between heterogeneous smart grid components to ensure grid interactive buildings [134]. It was based on the IFC data model, mostly used in the building design phase. The Semantic Smart Grid Information Model (SSGIM) is an ontology designed to integrate essential information for demand response applications [160]. It is based on the International Electrotechnical Commission’s Common Information Model standard [28] to describe electrical equipment, DBpedia [37] to represent spatial, organization, and infrastructure concepts, and it utilizes a weather data model to

²https://protege.stanford.edu/
encompass weather-related information [19].

Table 2: An overview of the analyzed key ontologies.

<table>
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<th>Ontology</th>
<th>Ref.</th>
<th>Year</th>
<th>Uses/Extends</th>
<th>Classes</th>
<th>Formats</th>
<th>Scope</th>
<th>Main Focus</th>
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**Scopes:** Smart Device, Home, Building, City, Energy, Grid

**Formats:** T Turtle, R RDF, X XML, O OWL, J JSON-LD, N N-Triples, (3+) formats, C Closed Source

Continued on next page
### Table 2: An overview of the analyzed key ontologies. (Continued)

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**Scopes:** Smart Device, Home, Building, City, Energy, Grid  
**Formats:** Turtle, RDF, XML, OWL, JSON-LD, N-Triples, (3+) formats, Closed Source

**Table Note:** In this table, the ontology names are linked to where they are explained in more detail in the text and the numbers of classes are linked to the repositories where the ontologies are publicly available on the Internet.

The ontology created by the Smart Electric Power Alliance (SEPA) was designed for building management. It encompasses the registration of energy consumption, which serves as the foundation for Smart Grid applications. The Ontology for Energy Management Applications (OEMA) represents energy performance and contextual data from various energy domains. It is based on ThinkHome, SAREF4ENER, the prosumer smart-grid oriented ontology and an energy use ontology which is currently deprecated. The Domain Analysis-Based Global Energy Ontology (DABGEO) is the improved version of the OEMA ontology that provides adequate control to energy management applications. The DELTA ontology aims at modeling concepts relating to demand response to promote interaction between buildings and energy providers. The Smart-Grid Building Energy Management System (SG-BEMS) provides an abstraction layer that enables the semantic representation of smart grids and buildings to establish interactions for BEMS operations.

The Common Information Model (CIM) for smart grids developed by the Cerise-SG project is an ontology to represent information related to smart grids. The Ontological Solution for Energy Intelligent Management...
(OSEIM) and NewOSEIM represent objects that relate to both internal and external home environments [133, 132].
These objects can have an impact on electrical energy consumption, and they provide a reasoning mechanism to achieve intelligent energy management. A framework based on ontology was initiated for building energy management (BEM) to identify the cause of a building’s energy efficiencies and inefficiencies [101]. This framework allows for the inference of proper control strategies when necessary.

Google digital buildings represent structured information and building-installed equipment [73, 6]. The ICBMS (IoT, Cloud, Big-Data, Mobile, Security) ontology extends upon the SAREF ontology, incorporating concepts related to states, sensor measurements, and units to support building applications such as thermal comfort [89].

The Energy Management Key Performance Indicator (EM-KPI) ontology facilitates the exchange of key performance indicator information and data for districts and buildings [100]. This provides a standardized structure to compare building performance aspects to other buildings based on certain performance metrics. A KPI ontology was introduced to represent metrics associated with building renovation activities to conform to requirements of energy-efficient buildings [65]. A Performance Assessment (PF) ontology was introduced to allow building performance assessments at a granular level [30]. This stemmed from the idea of evaluating building performance to support optimization. It is based on three data models: the SSN model, the Simulation Domain Model (SimModel), a data model for the building simulation domain [112], and the ifcOwl ontology. The SimModel and ifcOwl ontology were not included in Table 2 as they are not often used in building operations. Another Building Performance Ontology (BOP) was initiated to facilitate a homogeneous data environment used by complex building performance assessments [42]. This method involved the integration of static and dynamic data points for thermal comfort analysis. The Semantic BMS (SBMS) ontology was designed to represent building automation systems and aid building operations analysis [91]. It includes a unified model called SBIM, which describes building information modeling elements and is utilized by the principal SBMS ontology.

Semantic Tools for Carbon Reduction in Urban Planning (SEMANCO) facilitates access to diverse energy-related data from various organizations, supporting the assessment of energy analysis across cities [104]. Open Automated Demand Response (OpenADR) ontology is designed to standardize the representation of demand response systems, thereby enhancing semantic interoperability within the demand response domain. [68]. The SEmantic SmArt Metering (SESAME) is an ontology-based model that enables the integration of smart metering, building and rule-based reasoning to provide energy optimization for energy consumers and providers [64]. This ontology was developed under the SESAME-S project.

Home appliance ontology encompasses the home energy management domain, and it was developed to support energy consumption performance analysis of home appliances [137]. Also, it extends the Suggested Upper Merged Ontology (SUMO), which is a generic ontology for describing a myriad of computer information processing system [111]. The ONCOM ontology introduced a wireless sensor network approach to semantically represent sensor from the sensor network to support emotional state analysis of building occupants, towards reaching adequate indoor thermal comfort [115].

The Ontology Profile (OP) ontology was developed to represent occupancy profiles in building spaces, detailing how occupant’s behavior impacts building energy [66]. Another ontology was proposed to provide a standardized representation of energy-related occupant behavior in buildings [85]. However, since this model exclusively relies on the XML and occupant behavior XML format (obXML) [84], it has not been included in Table 2.

5 Identifying Usecase Scenarios on the Application of Ontologies

This section identifies relevant use case scenarios for applying the ontology described above to diverse building applications. It will be subdivided into three categories: single, double, and multiple ontology use case scenarios.

Table 3 summarizes the use case scenarios, highlighting the ontologies utilized, the concepts covered, and the classes employed for concept representation. This summary does not consider the correspondence between classes and concepts. Yet, the review acknowledges that multiple classes might represent a single concept. Some of these ontologies used upper ontologies, which are not limited to a specific domain, to define general concepts such as time, units of measurement, and space positioning of individuals [82]. These upper ontologies will not count as complementary domain-specific models since they are general-purpose and are used across multiple domains.

5.1 Single-Ontology Use Case Scenarios

Single ontology use case scenarios refer to data-driven applications that employ a singular ontology to characterize the data and its contextual meaning. The subsequent text outlines research endeavors that utilize a single ontology for their applications.

A study focused on an in-depth analysis of physical systems within a generic zone inside a building [11]. Their primary objective was to offer a standardized depiction of the components within that system. By doing so, they aimed to facilitate simulations that accurately mirror the dynamic environment within a building, a crucial step in supporting the energy modeling processes. This, in turn, allows for rigorous ongoing commissioning of a building’s systems and creates an avenue for detecting and diagnosing faults. To achieve this, the study leaned heavily on the SAREF ontology and its two extensions; SAREF4BLDG, and SAREF4SYST. The
research demonstrated how SAREF4SYST could be employed to link data-driven models representing the dynamic behavior of SAREFBLDG components such as s4bldg:BuildingSpace, s4bldg:SpaceHeater, s4bldg:Valve, saref:Sensor, s4bldg:Controller, and s4bldg:Damper. This linkage was accomplished using the s4syst:System, s4syst:Connection, and s4syst:ConnectionPoint classes. It is worth noting that while the study’s focus was on a singular zone within a building, the authors believe that the methodologies they employed can be extrapolated and applied to entire buildings.

SAREF ontology’s validity was tested by creating two SAREF implementations in a smart home setting [154]. First, by mapping data from the smart home to a knowledge graph using SAREF. The second one explores data sharing between different devices using an interoperability framework. The validation of success occurs when all information from the data source is accurately modeled using SAREF, ensuring no loss of information. The experiment involved 33 smart devices within an unidentified smart home, with an objective to transform the data from these devices into a knowledge graph using the SAREF ontology. After eliminating redundancies, nine unique data sources remained, which included current temperature, CO2 levels, humidity, target temperature, and three distinct occupancy indicators: last-time movement, first-time movement, and the presence of occupants. The researchers executed a study to fine-tune room temperature. Of the nine devices, a thermostat and a CO2 sensor were pivotal to the experiment. These sensor data were mapped to the SAREF ontology using specific classes, such as saref:Measurement, saref:UnitOfMeasure, saref:TemperatureUnit, saref:Property, saref:FeatureOfInterest, saref:Device, saref:Task, saref:Comfort, saref:WellBeing, saref:Function, saref:SensingFunction, saref:Command, saref:State, and saref:Service. However, they incorporated the OM1.8: Unit of Measure ontology [131] as an upper ontology to instantiate the unit of measurement. For example, using om:degreeCelsius to represent temperature. Finally, the modeling of these concepts was used to facilitate the automation of room temperature to enhance user comfort.

Another data modeling application was demonstrated using the Open Power System Data (OPSD) [114] to execute data mapping [155]. This dataset comprises information from 68 devices across 11 buildings, which include three industrial buildings, two public buildings, and six residential households. The study primarily focused on data from six residential households, employing nine distinct devices that act as sensors for data extraction and mapping. The devices used are as follows:

- grid_import: Represents the energy imported from the public grid, measured in kilowatt-hour (kWh).
- grid_export: Signifies the energy exported to the public grid, quantified in kWh.
- pv: Captures the total energy generation from photovoltaic sources, gauged in kWh.
- dishwasher: Pertains to the energy consumption of the dishwasher, denoted in kWh.
- ev: Stands for the energy consumption during electric vehicle charging, presented in kWh.
- Refrigerator: Indicates the energy consumed by the refrigerator, ascertained in kWh.
- Freezer: Denotes the energy intake of the freezer, tabulated in kWh.
- Circulation_pump: Specifies the energy consumption of the circulation pump, expressed in kWh.

Although the OPSD household dataset captures information from various devices, all measurements share a standard kWh unit. Furthermore, these devices were represented using the following classes in SAREF, which includes saref:Measurement, saref:UnitOfMeasure, saref:Property, saref:PowerUnit, saref:Power, saref:FeatureOfInterest, saref:Device, saref:Meter, saref:Appliance, saref:Task, saref:MeterReading, saref:Washing, saref:WellBeing, saref:Comfort, saref:Function, and saref:MeteringFunction. They also used the OM ontology to instantiate the unit of measurement as om:kilowatt_hour. The study did not apply this data to any specific building applications. Nevertheless, this data holds potential for building applications, including energy management systems, demand response systems, predictive maintenance, and solar energy forecasting.

A study aimed to evaluate long-term thermal comfort using portable and reproducible application development techniques, leveraging a brick metadata schema and a mortar data testbed [145]. The research utilized the mortar testbed [69], encompassing over 25 buildings, to assess the generalizability of the application’s performance. The evaluation employed air temperature-based metrics, including the range outlier index, overcooling outlier index, and overheating outlier index. The study employed the brick ontology to represent building entities such as brick:Zone, brick:Room, brick:Floor, brick:AHU, brick:Variable Air Volume Box and brick:Zone Air Temperature Sensor. This ontological approach facilitated a disaggregated analytical process at the zone, room, and equipment levels, allowing for precise diagnosis of issues affecting long-term thermal comfort.

This research introduced an innovative approach to standardize the representation of building data across its entire lifecycle by employing the Brick metadata model to facilitate ongoing building maintenance [70]. Metadata from various sources, corresponding to different stages of the building’s lifecycle, were consolidated into a unified model through a central integration server using the Brick model. This model encapsulated concepts including brick:Air Handling Unit, brick:Power Meter, brick:Building Power Meter, brick:Rooftop Unit, brick:VAV, brick:Chiller, brick:Absorption Chiller, brick:Temperature Sensor, brick:Flow Sensor, brick:Return Air Flow Sensor. The classes used to represent the relationships between the concepts are: brick:hasPoint, brick:feeds,
and brick:hasPart. The study aimed to gather pertinent metadata throughout the building’s lifecycle to bolster data-driven applications.

A study assessed how effectively three metadata schemas could represent contextual, spatial, and functional connections among sensors in built environments [9]. The schemas analyzed were PH, IFC, and Semantic Sensor Web frameworks like SAREF and SSN. The evaluation involved three commercial buildings and a broad spectrum of smart building applications. The criteria for assessment included completeness, relationship-capturing ability, and flexibility. Completeness was defined as the schemas’ capacity to encompass all building sensor metadata. Furthermore, relationship capturing refers to how well the schema could depict sensor connections with other building entities, while flexibility is related to the schemas’ adaptability to new building entities.

The study incorporated a tagging mechanism, initially mapping building metadata to PH tags and creating new tags where PH was lacking. Regarding completeness, PH, IFC, and Semantic Sensor Web scored 54%, 29%, and 11%, respectively. For relationship-capturing ability, the scores were 77% for PH, 86% for IFC, and 41% for Semantic Sensor Web. However, none of the schemas effectively handled new sensor information, indicating a gap in flexibility. The study concluded that none of the investigated schemas could fully represent all tags and semantic information in buildings. It noted the excessive fragmentation of semantic web ontologies, limiting their practical application.

In response to these findings, the subsequent study with the Brick ontology sought to overcome some of these limitations [9]. While PH Haystack showed proficiency in capturing building management system datapoints with its tagging system, it lacked a formalized approach to tag usage. Brick adopted PH’s tagging system but introduced a standardized and strict tag application to characterize BMS datapoints. This approach was validated using eight applications from the previous study and applied across six different buildings. The findings revealed that the Brick ontology successfully captured 98% of data points in these buildings, demonstrating its efficacy in facilitating query processes for the required information in various applications. The brick ontology does not provide the percentage metric for flexibility. These two studies were comparative analysis of how well these metadata schemas could represent building information. However, they will not be included in Table 3 since they do not provide the specific tags and classes used to capture the BMS data points.

A study conducted an in-depth comparative analysis of ontologies to assess their suitability for semantic interoperability in demand-side management [38]. Eight distinct ontologies were meticulously evaluated based on essential concepts such as spatial information, building energy systems, control and topology, measurement setup, measurable properties, and grid interactivity. The methodological basis for this comparative study was the metadata quality metrics [113]. Each ontology was measured by its capacity to represent the vital concepts, ensuring they possessed the semantic depth necessary for delivering robust, context-aware demand-side management. Generally, this evaluation showed that none of the models could completely model all the concepts presented. However, Brick and SAREF emerged as the most suitable ontologies for covering most data needed in a demand-side management application. The authors suggest that implementing demand-side management through an ontology-based architecture can enhance energy flexibility, efficiency, operating costs, and environmental comfort by utilizing intelligent, adaptive, and responsive control strategies. This study is also excluded from Table 3 as they do not provide the classes and tags used to describe these concepts.

This research showcased the practical implementation of SAREF in mapping various devices from different manufacturers, essential for enhancing the efficiency of energy consumption and production across all household appliances through communication with a cloud-based energy management system [71]. The investigation drew from the Dutch pilot of the H2020 InterConnect project, where the energy manager served as a system for coordinating energy supply and demand, proving to be an effective instrument for analyzing and planning energy flexibility. SAREF and SAREF4ENER were employed as the benchmark frameworks to encapsulate the pertinent data from these devices. However, since the specific classes utilized were not disclosed, this analysis is not included in Table 3.

A different application of SAREF took place within a Greek pilot of the H2020 InterConnect project, aiming to convert residential buildings into smart homes through the installation of energy meters and sensors [71]. In this context, SAREF, alongside SAREF4BLDG and SAREF4ENER, served as the unified data model showcasing the smooth information exchange between four distinct service providers. Due to the absence of detailed information on the classes employed for modeling the concepts, this study has been omitted from Table 3.

### 5.2 Two-Ontology Use Case Scenarios

This identifies the use cases that incorporate the use of two separate ontologies to represent relevant building concepts. This can also be done via extension, creating a new ontology by extending and merging with another ontology to identify new concepts.

A hybrid inference system was proposed to infer indoor environmental conditions within a building [89] by processing real-time data streams sourced from a Building Automation System (BAS) located in the Researcher Hotel of Alto University, Espoo, Finland. The primary objective of the research was to assess the internal thermal comfort of individual apartments based on key parameters, including temperature, humidity, occupancy status, and CO₂ concentration. The inference system utilized a dataset of 4199 data points, encompassing various aspects such as HVAC, indoor/outdoor temperature, illuminance, and other environmental properties. To facilitate this comprehensive data analysis, the authors proposed an ontology known as the ICBMS (IoT, Cloud, Big-Data, Mobile, Security) ontology.
The ICBMS extends SAREF’s ontology via the sensor class to include sensor types and their units of measurement. It also extends SAREF’s state class to model different types of state information for a building space. The classes employed in this study include `saref:Sensor`, `saref:Device`, `icbms:CO2Sensor`, `saref:TemperatureSensor`, `saref:HumiditySensor`, `saref:State`, `icbms:ThermalComfortState`, `icbms:HotState`, `icbms:WarmState`, `icbms:SlightlyWarmState`, `icbms:NeutralState`, `icbms:SlightlyCoolState`, `icbms:CoolState`, `icbms:ColdState`, `icbms:OccupancyState`, `icbms:OccupiedState`, `icbms:VacantState`, and `saref:BuildingSpace`. The classes used to interlink these concepts are `icbms:hasThermalComfortState`, `icbms:hasOccupancyState`, `icbms:hasNumberOfPeople`, `icbms:hasObjectid`, `icbms:hasPMV`, `icbms:hasPPD`, `saref:contains`, `saref:isMeasuredIn`, `saref:hasValue`, `saref:isUsedFor`, `saref:hasModel`, and `saref:isLocatedIn`. Additionally, the ICBMS ontology incorporated upper ontologies such as Time ontology [31] and the Ontology of Units and Measure [131] to model concepts relating to time and units of measurements associated with sensor data. The study deduced thermal metrics such as Predicted Mean Vote (PMV) and Predicted Percentage Dissatisfied (PPD) [146] using sensor data stored within the ontology. This comprehensive approach aimed to enhance the building’s understanding and management of indoor environmental conditions.

Another research introduced a middleware layer designed to enrich data from building automation systems with additional semantic layers, support facility benchmarking and assess facility performance to achieve efficient, economical, and sustainable operations [91]. A novel semantic model termed the SBMS ontology, which extends the SSN ontology, is proposed to offer a more domain-specific description of building automation system data points. The underlying concept was to differentiate specific domain individuals from the more general entities described in SSN. For instance, the `ssn:FeatureOfInterest` is refined by the `sbms:FeatureOfInterest` to specifically represent sites, buildings, floors, rooms, or devices. This ontology contains a simplified model to describe BIM elements using the namespace `sbim`. The study showcases two use case scenarios focused on room environment and energy consumption analysis employing the SBMS ontology. Key classes leveraged in their analysis include `sbms:Address`, `sbms:Datapoint`, `sbms:Input`, `sbms:Property`, `sbms:FeatureOfInterest`, `sbms:SensingDevice`, `sbms:Sensing`, and `sbms:Observation`. Fundamentally, this approach seeks to equip developers with user-friendly and dynamic querying tools for BMS or BAS, supporting the development of analytical applications dedicated to building operation analysis.

A diagnostic tool guided by the air handling unit performance assessment rules was introduced to identify operational faults in ventilation units equipped with heat recovery systems [110]. Semantic modeling techniques were deployed to enhance the tool’s portability and ensure its scalability across various AHU systems. Integrating the PH and BRICK models facilitated the representation of entities associated with the AHU unit, utilizing metadata (tags) designated by human experts. For the accurate characterization of a data point, three specific tags are required: the quantity it represents, its associated location, and its regulatory role, such as a sensor or required value. This approach facilitated a comprehensive description of each data point’s diagnostic relevance.

The study underscored the limitation that neither the PH nor the Brick ontology alone could fully encapsulate the semantic data within an air conditioning system, driving the necessity for a collaborative endeavor towards developing a unified ontology. Although this work did not detail the specific tags employed for modeling entities in their case study, leading to its omission from Table 3 regarding use case scenarios, it accentuated the effectiveness of semantic modeling strategies in achieving a satisfactory detection rate across a broad spectrum of AHUs.

This study introduced an architectural methodology illustrating the integration of semantic sensor networks, semantic web technologies, and reasoning [122]. This integration aimed to facilitate the development and implementation of sophisticated models for analytical tasks, such as prediction and diagnosis, in real-world scenarios. A semantic framework was developed for fault detection and diagnosis, utilizing a diverse array of sensors within IBM’s technology campus in Dublin. A specific case study involved a single office room equipped with a temperature sensor, occupancy sensor, cooling actuator, and setpoint with the addition of a virtual sensor to derive a diagnostic model for sensor anomalies. The SSN ontology described sensor and space monitoring concepts, notably through the classes `ssn:Sensor` and `ssn:FeatureOfInterest`. However, existing limitations in modeling concepts like physical processes, which elucidate the cause-effect relationships among sensors, necessitated an extension of the SSN ontology. This extension introduced new classes with a namespace “phy”, which includes `phy:PhysicalProcess`, `phy:FeatureLink`, `phy:Anomaly`, `phy:Property`, and `phy:Cause` to encompass these concepts. The findings underscore the utilization of semantic techniques and the adapted SSN ontology in automating analytical tasks within buildings, demonstrating their capability to pinpoint causes and anomalies in building systems and devices effectively.

### 5.3 Multiple-Ontology Use Case Scenarios

Multiple ontology use case scenarios pertain to data-driven applications that employ several ontologies to depict the data underlying their analytical processes. This approach includes integrating additional ontologies to augment standalone ones, which may struggle to describe certain data elements within a building context accurately. The following text will detail studies implementing this methodology for their applications.

This work presented an ontology-based method to standardize the automatic calculation of KPIs to aid the energy evaluation of diverse buildings [159]. This method integrates building information such as BIMs, energy consumption and environmental data collected from sensors, which are classified into static and dynamic categories. They presented a case study to validate the KPI calculation approach using two office buildings in Shanghai, China. For the two buildings, sensors were installed on each floor to collect electricity consumption in total and per each item, including
lighting, sockets, and air conditioning, over a 15-minute interval.

The developed KPI ontology captures concepts essential for KPI calculations using the following classes, which include kpi:Input, kpi:Result, kpi:Formula, kpi:Parameter, and kpi:Operator. It is further enhanced by incorporating BOT and Sosa classes to encompass static and dynamic data concepts such as bot:Building, bot:Space, bot:Zone, sosa:Platform, sosa:Sensor, sosa:Observation, sosa:FeatureOfInterest and sosa:Property.

The study highlighted that collecting data for KPI calculation in an isolated manner is labor-intensive. Integrating linked data can automate and streamline this process, allowing for a more efficient and iterative approach. It was emphasized that while the type of building and the variations of sensors from a different manufacturer may influence the KPI calculations for evaluating a building’s energy performance, the analysis of the two buildings provided results that closely mirrored their actual consumption performance. This suggests that the methodology adopted can be effectively applied to evaluate other buildings within the city, indicating a scalable and adaptable approach for broader building energy assessments within the same city.

Another study examined semantic models for knowledge representation and reasoning across various building applications, which proposed a semantic infrastructure and techniques that utilize established domain-specific ontologies and upper ontologies [41]. Domain-specific ontologies, including BOT for illustrating building topology with features like bot:adjacentZone, and Brick for the representation of equipment and systems with brick:HVAC Zone, brick:Supply Air Temperature Sensor, brick:VAV, brick:AHU, brick:Cooling Valve, brick:Mixed Air Temperature Sensor, brick:Exhaust Fan were employed. The Sosa ontology was utilized to describe sensing and actuation processes with sosa:madeObservation, sosa:resultTime, and SAREF4BLDG to depict building spaces with s4bldg:BuildingSpace.

The upper ontologies supplemented this framework, with QUDT addressing units of measurement through entities like units and quantities, as well as Time Ontology [31] providing concepts such as time:TimeInterval, time:startTime, and time:endsAt. The efficacy of this method was demonstrated through the application of semantic rules designed to delineate inference mechanisms applicable to a broad spectrum of building applications, which ranged from semantic representation, fault detection, and diagnostics to spatial and temporal reasoning, as well as asset management, maintenance, and context-aware control.

A methodology for linking data was proposed to combine various data sources, supporting digital twin applications [107]. A tool was developed to enable this integration, employing multiple ontologies to characterize static and dynamic data domains. The static domain encompasses building topology, while the dynamic domain pertains to sensor data. The IFC model initially represented static building information from the design phase. However, due to its complexity, non-modular nature, and rigid schema structure [120], it was converted into the BOT ontology using the IFC-to-LBD converter [14] to address these limitations. For this research, the BOT ontology, along with three additional ontologies, were employed. The BOT detailed building topological concepts, the Brick ontology depicted dynamic data, and the Building Element Ontology (BEO) described building elements like walls, doors, and roofs. Furthermore, the Building-Related Properties (PROPS) ontology was utilized to model properties specific to building elements or equipment. The BEO and PROPS ontologies were not previously discussed because they focus on building design and construction phases. This research was applied to a real-world case at the Technical University of Crete, focusing on a three-story building with en-suite student rooms and a communal kitchen on each floor. The spaces were equipped with split air conditioners for heating and cooling, thermostats for climate control, and occupancy sensors. Key classes from the mentioned ontologies were employed to describe these building entities, including bot:Space, bot:adjacentElement, brick:Space, brick:Thermostat, brick:Zone, Zone Air Temperature Set Point, brick:timeseries, and beo:Window. This study demonstrated the effectiveness of using the linked data modeling technique as an integration approach to develop an efficient querying mechanism for retrieving static and dynamic data and potentially support various digital twin use cases in buildings.

In an extensive analysis of ontologies and metadata frameworks, the study assessed 40 different schemas, each designed for specific sectors like building design, energy modeling, and building operations [126]. Within this extensive collection, the study identified five notable ontologies for a more comprehensive evaluation. This study presents an office building with an HVAC system that serves different spaces. The aim was to model the building information using pre-existing ontologies for three use cases: energy auditing, automatic fault detection and diagnosis, and optimal control of building systems. The chosen ontologies included SAREF, SSN/SOSA, BOT, Brick, and REC. They demonstrated this experiment using an office room within an office building connected to building systems and equipment such as the HVAC. Using a single ontology to capture all the concepts needed for the aforementioned three use cases was impossible. Hence, these ontologies were combined to complement each other in areas they fail to cover. The classes utilized include: brick:VAV, core:Device, s4bldg:Flow Terminal, ssn:System, s4bldg:BuildingObject, s4bldg:BuildingSpace, bldg:VirtualBuildingComponent, brick:HVAC Zone, brick:Room, bot:Space, bldg:Office, core:Room. There are situations whereby multiple ontologies could model a concept. Hence, selection would depend on the researcher. Despite the significance of these five ontologies, the research underscored some inherent limitations in each. Across the board, these ontologies exhibited gaps or omissions in certain concepts, impacting their overall efficacy in the specified use cases. The study highlighted that while these ontologies have merits, none singularly encompasses all essential concepts. Thus, augmenting these ontologies to cater to specific applications is imperative.

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3 https://github.com/maximelefrancois86/props
This section examined the landscape of use case scenarios in ontology applications, shedding light on their relevance across various domains. A detailed analysis of the studies discussed shows that the application of ontologies offers promising prospects for addressing complex challenges and fostering semantic interoperability in BEM.

Table 3: Usecase Scenarios on the Application of Ontologies.

<table>
<thead>
<tr>
<th>Usecase</th>
<th>Concepts</th>
<th>Classes</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data Integration for building energy analysis [11]</td>
<td>Building Space, Building system and components, CO₂ sensor and controller</td>
<td>Uses SAREF, S4BLDG, S4SYST</td>
<td>SAREF ontology was incorporated to model a single zone system.</td>
</tr>
<tr>
<td>Data Integration in Smart Homes [154]</td>
<td>Current temperature, CO₂ sensor, First time movement detected, Last time movement detected, Motion detected, Presence detected, Humidity, Smart switch actuator, Target temperature</td>
<td>Uses SAREF</td>
<td>SAREF does not possess a class specifically designed to model the unit of measurement for CO₂, nor a property class for measuring CO₂ levels. Nonetheless, it can be easily extended to include these features</td>
</tr>
<tr>
<td>Data Integration with OPSD Household Data set [155]</td>
<td>Energy imported/exported from/to the public grid, Total Photovoltaic energy generation, Electric Vehicle Charging energy, Appliances and Circulation pump energy consumption</td>
<td>Uses SAREF</td>
<td>The SAREF ontology was incorporated to map building data using the OPSD Household data set</td>
</tr>
<tr>
<td>Long-term Thermal Comfort Evaluation with Brick Schema [145]</td>
<td>Air Handling Unit, Variable Air Volume box, Zone Air Temperature, Room and Floor</td>
<td>Uses Brick</td>
<td>The Brick ontology was employed to formalize specific building entities to analyze thermal comfort evaluation.</td>
</tr>
<tr>
<td>Data integration for data-driven analytics [70]</td>
<td>Building system and equipment, Data points</td>
<td>Uses Brick</td>
<td>Brick served as a unified model for integrating metadata from different data sources</td>
</tr>
<tr>
<td>Energy and Thermal Comfort Analysis [89]</td>
<td>Thermal Comfort State, Number of occupants, Occupancy State, Building Space, Humidity and CO₂ Sensor, PMV and PPD values</td>
<td>Uses ICBMS</td>
<td>ICBMS ontology extends the SAREF ontology and introduces more specific concepts relating to sensor and state information</td>
</tr>
<tr>
<td>Data integration for building operational analysis [91]</td>
<td>Data Points, Sensing, Source, Property, and Feature of Interest</td>
<td>Uses SBMS</td>
<td>The SBMS ontology represents information available for building operational analysis. It is an extension of SSN ontology introducing the concept of data points</td>
</tr>
<tr>
<td>Smart building diagnosis [122]</td>
<td>Process, Observation, Properties, Environment</td>
<td>New classes using namespace PHY</td>
<td>This custom ontology utilised the SSN ontology and extended it to model physical and cause-effect relationships between sensors to support building applications to automatically derive complex models for analytics tasks such as prediction and diagnostics.</td>
</tr>
</tbody>
</table>

Legend: saref, s4bldg, s4syst, icbes, bot, sosa, s4p, brick, sbms, ssn, phy, other

Continued on next page
This survey highlights a notable trend within the semantic modeling domain: the fragmentation of the ontology energy flexibility solutions. To establish a common practice and enhance semantic interoperability, supporting broader adoption and integration of also provide a robust and agnostic approach for extending ontologies to incorporate these concepts. This strategy aims representation of energy flexibility resources. Given the complexity of modeling all resources, this framework should comparison and scalability. This review advocates for developing an ontological framework that standardizes the contribution delegates the need for comprehensive and efficient implementation strategies [27]. Central to these strategies is proper communication and coordination among diverse distributed energy resources and energy stakeholders. In this context, semantic modeling technologies are essential for standardizing data representation across various sources related to energy flexibility. However, the application of semantic modeling, particularly in areas such as demand response, has not been thoroughly investigated. Although existing ontologies partially address these concepts, the challenge persists in comprehensively modeling the extensive range of energy flexibility resources identified in the literature [99]. These resources, each with unique physical properties, are represented through various models at differing levels of detail, often developed on an ad-hoc basis using disparate software or tools. Such models lack interoperability, complicating comparison and scalability. This review advocates for developing an ontological framework that standardizes the representation of energy flexibility resources. Given the complexity of modeling all resources, this framework should also provide a robust and agnostic approach for extending ontologies to incorporate these concepts. This strategy aims to establish a common practice and enhance semantic interoperability, supporting broader adoption and integration of energy flexibility solutions.

6 Discussion on Identified Limitations and Forthcoming Steps

This survey highlights a notable trend within the semantic modeling domain: the fragmentation of the ontology development landscape resulting from the creation of numerous smaller ontologies. Researchers often encounter situations where an existing ontology does not encompass specific entities needed for their application. They develop extensions or entirely new ontologies rather than collaborating to refine and expand the existing ontology. This practice leads to an ever-increasing number of ontologies, each with slight variations. Such proliferation could have been mitigated through enhanced collaboration and integration efforts within the ontology development community.

The survey identifies the necessity for a more unified methodology in developing ontologies. To ensure the effectiveness and utilization of these semantic tools, their extension and modification must be managed to preserve compatibility and minimize duplicate efforts. A systematic approach is required to maintain the coherence of ontologies, avoiding excessive fragmentation. This approach should involve creating systems or protocols that facilitate the efficient tracking and integration of various ontology extensions. By doing so, the ontology community can work towards a more cohesive and comprehensive, universally applicable semantic framework. For example, the Unified Medical Language System (UMLS) integrates many biomedical standards and vocabularies in the bioinformatics domain to promote the development of more interoperable and more effective biomedical information systems and services [13].

Implementing such a coordinated approach would enable the harmonious growth of ontology libraries, ensuring that they evolve in a manner that is beneficial for individual research needs and conducive to broader community goals. It would foster an environment where ontological resources are expanded, strategically refined, and aligned with existing frameworks. This, in turn, would enhance the effectiveness of ontologies in various applications, providing a robust foundation for semantic interoperability and data integration across diverse domains.

The European Union’s increasing emphasis on advancing energy flexibility within buildings to promote decarbonization delegates the need for comprehensive and efficient implementation strategies [27]. Central to these strategies is proper communication and coordination among diverse energy resources and stakeholders. In this context, semantic modeling technologies are essential for standardizing data representation across various sources related to energy flexibility. However, the application of semantic modeling, particularly in areas such as demand response, has not been thoroughly investigated. Although existing ontologies partially address these concepts, the challenge persists in comprehensively modeling the extensive range of energy flexibility resources identified in the literature [99]. These resources, each with unique physical properties, are represented through various models at differing levels of detail, often developed on an ad-hoc basis using disparate software or tools. Such models lack interoperability, complicating comparison and scalability. This review advocates for developing an ontological framework that standardizes the representation of energy flexibility resources. Given the complexity of modeling all resources, this framework should also provide a robust and agnostic approach for extending ontologies to incorporate these concepts. This strategy aims to establish a common practice and enhance semantic interoperability, supporting broader adoption and integration of energy flexibility solutions.
This survey brings to light another critical trend: the absence of a clear philosophical framework guiding the modeling of building entities with its requirements. The philosophical motivations of semantic models need to be reviewed [86]. This gap results in diverse and inconsistent methods of modeling the same concepts. Such variability undermines the fundamental purpose of semantic modeling, which is to foster a shared understanding of concepts, thereby enhancing semantic interoperability.

The lack of a unified modeling philosophy leads to ambiguity and confusion when applying ontologies. This hinders effective communication between different systems and applications. For semantic modeling to be truly effective, there must be a consensus on the principles and practices guiding the representation of entities. This would ensure that when a concept is modeled, it is done so in a manner that is universally recognizable and interpretable within the context of the building operations domain. For instance, in BEM, the concept of a zone often carries a broad definition. This can lead to varied interpretations creating ambiguity and affecting the modeling of this concept. The BOT ontology describes a zone as any entity existing within the physical world [128]. However, while the Brick ontology shares some conceptual overlap with BOT regarding zones (viewing them as combinations of physical spaces), it separates the concept between physical spaces and zones. In Brick’s framework, a zone is associated with spaces designated for specific assessments [20]. Nevertheless, the types of assessments are not confined solely to those outlined in the Brick ontology. They do not mention that a zone can be within a single physical space, as there can be a need to model such scenarios. This often leads researchers to provide their ways of modeling certain concepts based on their interpretation of how the ontology defines the concept. For example, the SAREF ontology does not explicitly define a zone class for modeling such concepts. Yet, some researchers suggest that zones can be represented using the BuildingSpace class within SAREF4BLDG [126]. This highlights the many variations in modeling certain concepts, with less specific details on how they can be modeled and applied in different scenarios. This also applies to modeling concepts relating to building systems and equipment, sensors, and actuators. A formalized way of representing concepts should be enforced to explicitly provide requirements that need to be attained to model these concepts successfully, such as clearly defining the data properties, object properties, relationships and, if needed, systems and equipment composition strategies.

Zones are a crucial basis for abstracting and covering various assessments within a specific part of a space or a larger area. Zone concepts are typically confined to the topology of buildings. Yet, they extend beyond this to function as a critical instrument for analyzing building operations during the building operational phase, which typically encompasses computing systems and IoT devices. With the ongoing evolution of these computing systems, it is challenging to find a comprehensive ontology capable of modeling the vast array of building systems and devices. While some ontologies address certain device and system concepts, limited studies focus on modeling the computational processes linked to these computing systems. Therefore, it is essential to model the information derived from these devices and systems and capture the computational tasks for conducting specific assessments within a building. These computational tasks, such as KPIs, assessments, and services, are vital for deriving functions that prompt changes in the building’s environment to meet predetermined objectives.

While individual studies have explored these concepts, they often lack an integrated approach. A limitation in current studies is that the approach for evaluation is independent for each concept, which limits the automation of energy management processes within buildings. The EM-KPI ontology, tailored for multi-level energy performance tracking, includes a standardized way of computing KPIs but falls short in linking how these KPIs are regularly assessed [100]. Also, the KPI ontology, defined for building renovation activities [65], does not align properly with the devices’ computational aspect and the associated workflows. While the PF ontology focuses on assessing KPIs (such as evaluating energy usage and thermal comfort) [30], there remains an isolation between possible services and information from the assessed KPIs.

Also, this survey has unveiled a disparity between the theoretical abundance of information surrounding these semantic models and their actual application in real-world scenarios. While both domains have recognized and extensively explored the potential of semantic modeling, there is a pressing need to bridge this knowledge with practical applications. Driving this transition would require technical advancements and the development of user-friendly platforms that seamlessly integrate these models into BEMs.

This survey aims to promote collaboration within the ontology community, develop an integrated approach for modeling computational tasks and workflows, and promote more practical applications. These efforts are intended to demonstrate the effectiveness of semantic modeling in improving BEM.

7 Conclusions

This survey thoroughly explores semantic modeling technologies within building energy management. It emphasizes the evolution and significance of semantic web technologies, particularly ontologies, and their increasing adoption by the building community, specifically focusing on their application in the building operation phase. Key concepts within the building domain were identified to gauge the capacity of these semantic models to capture relevant information. Furthermore, this survey made an in-depth discussion of five prominent ontologies applied for building operation analysis, along with other ontologies that are under utilized.

This survey outlined scenarios where single, double, and multiple ontologies are applied in diverse building application contexts. These scenarios formed the foundation for an in-depth analysis of trends, strengths, and limitations associated with semantic models and their applications. The discussion highlighted key aspects that could enhance the use of
semantic modeling in BEM applications. It underscored the imperative for increased collaboration within the ontology development community to address the issue of fragmentation and the proliferation of numerous smaller ontologies. It further discussed the urgent requirement to model a variety of distributed energy resources for energy flexibility, which can act as a crucial facilitator in achieving the energy objectives of the European Union. The survey emphasized the importance of a clearly defined philosophical approach to modeling, which would improve adaptability in representing various building concepts. It advocated for a more cohesive approach to modeling computational tasks and workflows in building operations and encouraged the practical application of these models to demonstrate their efficacy. Despite the identified challenges and limitations, the survey posited that semantic modeling possesses substantial potential to facilitate smarter, more efficient, and sustainable building operations. This aligns with global initiatives aimed at enhancing energy efficiency and environmental sustainability.

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