

## Invited Review Article

# Ontology-driven energy management in smart buildings: A comprehensive review of methodologies, tools, and challenges



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## ABSTRACT

While building energy systems (BES) increasingly rely on advanced automation, occupant-centric control, and digital twin technologies, a lack of robust semantic interoperability continues to hinder integrated, adaptive, and efficient energy management. Ontology-based approaches have emerged as a powerful solution, offering structured knowledge representation, consistent data exchange, and improved interpretability for AI-driven analytics. However, existing reviews tend to focus on subfields - such as occupant behaviour, IoT sensor data, or demand response - without providing a holistic synthesis of ontology-driven frameworks across diverse BES. In response, this study systematically reviewed 997 articles using a series of academic databases from 2011 to 2024, identifying 81 primary studies relevant to building energy analysis for comprehensive review. The results reveal that although ontologies facilitate standardised data flows and multi-agent coordination, significant gaps remain in domain coverage, alignment with emerging industry standards, and the integration of time-series data for predictive modelling. Furthermore, the interdependence of occupant comfort, multi-energy systems, and real-time decision-making has not been sufficiently addressed. This review compares commonly utilised ontological models (Brick, SAREF, SSN, and Open Energy Ontology) and proposes future directions emphasising interoperability with domain-specific data sources, bridging occupant modelling with data-driven optimisation, and leveraging digital twins for real-time operations. These findings aim to guide both academic and industry stakeholders in harnessing ontology-based methods for more intelligent, adaptive, and sustainable building environments.

## 1. Introduction

### 1.1. Motivation

Energy consumption in buildings represents a substantial share of global energy use [1]. In recent years, the integration of distributed energy resources (DER), demand response (DR), and smart grid technologies has emerged as a strategic approach to reduce environmental impact and operational costs [2]. Building energy systems (BES) play a pivotal role in this context, as they can be designed and operated to balance the shifting demands of occupants while interacting seamlessly with the larger power grid [3]. Frameworks, such as multi-agent-based approaches, allow individual residential or commercial buildings to coordinate their generation, storage, and load management activities, enhancing overall energy efficiency and strengthening the grid resilience [4]. Moreover, the adoption of internet-connected sensors and

deep learning algorithms fosters data-driven decision-making, enabling real-time monitoring and adaptive control of heating, ventilation, and air conditioning systems (HVAC) [5].

One crucial element in these advanced BES is the concept of DR, wherein end-users adjust their consumption patterns in response to real-time pricing signals or grid-wide constraints [6]. Through well-designed DR programmes, buildings can reduce peak loads or shift energy usage to off-peak times, thus alleviating stress on the grid and lowering energy expenses. Simultaneously, adaptive thermal inertia strategies allow buildings to maintain occupant comfort while shifting loads to off-peak times, thus enabling more flexible responses to fluctuations in energy supply. Another key dimension involves the development of effective energy management systems, often powered by artificial intelligence (AI), that learn occupant preferences and prioritise comfort while optimising energy usage [7]. These initiatives establish a foundation for sustainable, cost-effective, and adaptive building environments that integrate

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## Nomenclature

Abbreviation	Definition
HVAC	Heating, ventilation, and air conditioning systems
DR	Demand response
AI	Artificial intelligence
RES	Renewable energy sources
BEMS	Building energy management systems
ML	Machine learning
PV	Photovoltaic
DSM	Demand-side management
DER	Distributed energy resources
IoT	Internet of things
BIM	Building information modelling
OEO	Open energy ontology
SAREF	Smart Applications REFERENCE
OWL	Web ontology language
RDF	Resource description framework
BES	Building energy system
DT	Digital Twins
EFOnt	Energy flexibility ontology
ETSI	European Telecommunications Standards Institute
MAS	Multi-agent system
BPS	Building Performance Simulation

seamlessly with smart grids, facilitate the adoption of renewable energy sources (RES), and contribute to a more resilient and environmentally sustainable energy future.

In addition to these strategies, local cloud-based solutions can further streamline data exchange and enable real-time performance in DR scenarios, ensuring both privacy and low-latency communication within the building ecosystem [8]. By deploying user-centric energy management systems that integrate seamlessly with occupant needs, buildings can respond dynamically to utility price signals while maintaining comfortable indoor conditions [9]. Moreover, certain system designs incorporate hybrid solutions such as photovoltaic (PV)-thermal panels, thereby exploiting solar energy for both electricity and heat generation [10]. These combined technologies highlight the multiplicity of factors - ranging from occupant behaviour to advanced data analytics - that must be harmonised to achieve optimal outcomes. Consequently, BES serve not only as key enablers of grid stability but also function as active nodes for distributed generation and storage. As research and practice continue to evolve, the holistic convergence of RES, data-driven control strategies, and occupant comfort is poised to reshape building operations, resulting in more intelligent, resilient, and sustainable built environments.

Building energy management systems (BEMS) are integral to optimising energy consumption, integrating RES, and ensuring efficient building operations. However, significant challenges in data heterogeneity, interoperability, scalability, complexity, and lack of automation hinder widespread implementation [11,12]. A core difficulty is data heterogeneity as the energy sector includes diverse data sources with varying formats, protocols, and measurement standards. Distinct models (e.g. EnergyPlus, TRNSYS, neural networks) complicate data harmonisation, required for integrated energy strategies [13]. Multi-energy district systems, combining PV generation, storage, and grid interactions, exacerbate these disparities by requiring different forecasting methods [14]. Such data silos hamper seamless optimisation and decision-making. While standardised data formats, ontologies, and semantic web technologies can mitigate these issues, proprietary constraints persist [15]. Interoperability issues stem from incompatible communication protocols. Legacy building automation systems (e.g. Modbus, BACnet, KNX) conflict with modern IoT-based devices using MQTT, CoAP, and Zigbee [16], impeding coordination of energy storage, smart meters, and HVAC systems [17]. In building-to-grid interactions, the lack of com-

mon APIs limits real-time demand-side management (DSM) and data exchange among buildings, utilities, and DERs [18]. Although open-source middleware solutions and universal data models exist, adoption of standards such as IEC 61,850 and OPC UA remains slow due to legacy resistance and transition costs [15]. Scalability and complexity also pose significant barriers. As district energy systems expand, data volumes and computational demands grow exponentially [19]. Large-scale real-time optimisation requires processing high-dimensional sensor data, often causing bottlenecks [13]. Multi-energy systems introduce further complexity, requiring algorithms that balance cost, emissions, and occupant comfort [13]. Traditional time-series models can falter in dynamic environments, while deep learning approaches require extensive datasets and computing power [18]. Cloud-based and IoT-enabled BEMS also raise cybersecurity concerns [15]. Decentralised strategies, such as edge computing and federated learning, can improve scalability and resilience [20]. Finally, limited automation remains a critical shortcoming, as many BEMS continue to rely on static, rule-based strategies that fail to adapt to changing energy demands, occupancy patterns, or weather conditions [13]. Advanced control methods, including self-learning and adaptive systems that integrate real-time data and predictive analytics, promise better performance but require substantial computational resources [15]. Digital twins (DT) combine machine learning (ML) models, IoT data, and simulations for real-time optimisation, yet remain challenging to integrate with existing BEMS. Automated demand response strategies could enable buildings to adjust loads in response to electricity prices and grid conditions, though such systems are underutilised [13]. Reinforcement learning and model predictive control techniques show potential for managing HVAC, lighting, and energy storage, but implementation is limited by computational intensity and training requirements [18].

### 1.2. The role of knowledge representation and ontologies in BEMS

As energy systems grow increasingly complex, the requirement for structured and interoperable knowledge representation has become essential. With the integration of diverse data sources, devices, and technologies, traditional methods of data management can no longer support the intricacies of modern energy systems. A well-defined and standardised method for organising knowledge is crucial to ensure effective communication and integration across various systems, especially in the domain of smart buildings and grids [21]. An ontology serves as a formal and explicit framework that defines a shared understanding of a domain, structuring knowledge representation systematically. It consists of concepts, relationships, and rules that define entities within a specific context and how they interact. Ontologies are a highly effective means of addressing challenges associated with data integration, semantic interoperability, and advanced reasoning across heterogeneous systems. An ontology provides a formalised framework that defines the entities within a specific domain and their interrelationships. In the context of energy systems, ontologies enable standardised representation of components such as energy sources, devices, and operational processes, facilitating seamless data exchange and system integration. The advantages of ontologies are particularly evident in BEMS, where they support semantic interoperability, knowledge reusability, and enable automated reasoning. Semantic interoperability ensures that systems can exchange and comprehend data consistently, even when they originate from different platforms or manufacturers [22]. The reusability of ontologies allows them to be easily adapted across various applications, reducing the requirement for repeated development efforts. Furthermore, ontologies enable automated reasoning, allowing systems to make intelligent decisions based on the information they represent, such as optimising energy consumption or identifying inefficiencies [23]. When compared to traditional data models, ontologies offer a range of benefits. Unlike conventional models, which typically rely on fixed, rigid structures, ontologies allow for dynamic and adaptable knowledge representation. This flexibility makes it easier to accommodate new

**Table 1**  
Summary of related studies.

Ref.	Focus and Scope	Distinctive Contributions and Remaining Gaps (vs. This Review)
[39]	Synergies between MAS and DT for system coordination and optimization	Comprehensive on MAS-DT integration but lacks adaptive ontology framework.
[37]	Interoperability layers (technical-organizational-semantic)	Defines interoperability taxonomy but does not operationalize semantic linkages.
[38]	Urban-scale multi-energy DTs and life-cycle data integration	Focuses on data architecture and lifecycle but not multi-agent collaboration.
[36]	AI-driven metadata inference for semantic DTs interoperability	Targets automation of metadata generation, not ontology integration.
[33]	Ontology applications for battery lifecycle and system-level reasoning	Narrow focus on electrochemical systems; current review extends to systemic intelligence.
[34]	Catalogues metadata standards and semantic models for buildings	Descriptive rather than integrative; current review proposes MAS-based alignment.
[31]	Ontologies and reasoning for IEQ monitoring	Focused on occupant comfort; lacks energy optimization or multi-agent coordination.
[30]	Tools for semi-automatic ontology generation	Concentrates on tooling but not operational deployment.
[29]	Smart-city data integration and knowledge representation frameworks	Broad urban focus but limited to conceptual framework.
[28]	BIM-BAS interoperability for DSM	Strong on BIM/BAS mapping but limited AI integration.
[32]	Domain ontology for geothermal systems	Domain-specific and static; current review emphasizes dynamic multi-domain reasoning.
[40]	Ontology-assisted coordination in MAS for energy management	Provides ontology concepts but lacks integration with DT semantics.

technologies and changes in energy management practices. Additionally, ontologies support advanced features such as inference and automated decision-making, which are not possible with traditional data models [24]. In practical applications, ontologies play a key role in integrating emerging technologies such as the IoT and AI into BEMS [25]. They facilitate the integration of IoT devices, enabling real-time data collection and analysis, which powers predictive analytics. Ontologies also enable interoperability between various energy management systems, ensuring they work together effectively. Additionally, they are increasingly utilised for automated fault detection and optimisation, helping to identify problems and improve energy efficiency [26]. In summary, ontologies are a paramount tool for structuring and managing knowledge in BEMS, addressing the growing complexity of modern energy networks, and supporting the transition towards smarter, more efficient energy systems.

### 1.3. Previous reviews

Previous reviews have investigated the role of ontologies in BES, though most have focused on specific application areas or domain challenges. For example, Ma et al. [27] emphasised how ontologies in multi-agent systems (MAS) contribute to energy coordination, yet offered limited insight into occupant modelling, DT integration, or AI-driven control strategies. Another study addressed semantic interoperability for DSM, analysing data exchange between building information modelling (BIM) and building automation systems, without fully exploring broader topics such as fault detection, energy storage, or advanced learning algorithms [28]. Meanwhile, another survey on smart city ontologies highlighted synergies among energy, transportation, and infrastructure but predominately focused on city-scale frameworks rather than the building-level details of HVAC systems, occupant comfort, or energy flexibility [29]. Additionally, Pan et al. [30] discussed the benefits of toolchains and model reuse, however, the integration of ontologies with data analytics or reinforcement learning were not addressed. Further to this, [31] focused on semantic web technologies for indoor environmental quality and occupant comfort, describing how ontologies can organise sensor data, occupant preferences, and building topology but did not address grid interaction or multi-energy systems. Domain-focused ontologies have also been explored, such as those targeting ground source heat pumps [32] and battery domain interoperability [33], although these predominantly examine technical modelling rather than broader building energy management or smart grid integration. Pritoni et al. [34] examined metadata schemas and ontologies for building energy applications - covering frameworks such as SAREF, Brick, and IFC - but primarily emphasised ontology structure and data representation, with limited attention to their alignment with AI-based energy analytics. Similarly, knowledge graphs have been examined in relation to IoT and BIM data integration, focusing on data structuring but with limited discussion of applications in occupant-focused control or real-time decision making [35].

To clearly delineate the distinct scope and contributions of this review in relation to prior surveys, Table 1 provides a comparative summary of existing review studies on ontology-based building energy management. The table highlights key differences in research coverage, methodological orientation, and thematic focus, emphasising how the present work offers a broader and more integrative perspective. In particular, it underscores the novel inclusion of emerging domains such as DT integration, occupant-centric control, semantic interoperability, and AI-driven optimisation-which have received limited attention in earlier reviews.

Recent reviews have significantly advanced the discourse on semantic modeling and DTs for energy systems, offering a more integrated view of their role in achieving energy efficiency. Benfer and Müller (2024) [36] provide a comprehensive examination of semantic DT in building systems, emphasising how time-series-based metadata inference can automate ontology generation and reduce the manual effort required for semantic enrichment. Their work underlines that semantic structures, particularly ontologies, remain central to achieving interoperability across heterogeneous building automation systems, a critical step toward scalable building energy management systems. This perspective situates semantics not only as a data harmonisation tool but also as the foundation for adaptive and intelligent DTs that support continuous performance optimisation. Complementing this focus, Acharya et al. [37] present a structured framework for interoperability in DT within cyber-physical systems, delineating six interoperability levels from technical to organisational. Their synthesis identifies semantic interoperability as the pivotal enabler for cross-platform communication in edge-enabled environments. This multi-layered approach aligns closely with the requirement for standardised ontological foundations in energy-focused DTs, particularly where decentralised data sources and real-time decision-making coexist. At the urban scale, Koirala et al. [38] discuss the digitalisation of urban multi-energy systems, highlighting the integration of semantic ontologies and data management strategies across the full lifecycle of DT applications. Their findings demonstrate how ontological consistency allows energy, spatial, and operational data to be unified, supporting both lifecycle management and sectoral coupling. This perspective extends semantic modeling from individual building systems to city-wide energy infrastructures, thus expanding the contextual reach of ontology-driven frameworks for sustainable urban energy management. Parallel developments in DT theory reinforce this semantic foundation. Finally, Pretel et al. [39] explore the synergy between DT and MAS, noting that semantic ontologies facilitate autonomous coordination among agents and enable intelligent, self-adaptive behaviors in energy-oriented DT.

### 1.4. Research scope and contributions

This review aims to provide a comprehensive perspective of ontology-driven approaches across the full spectrum of BES, including IoT-based sensor integration, building-level frameworks (BEMS,

## Literature Review Databases

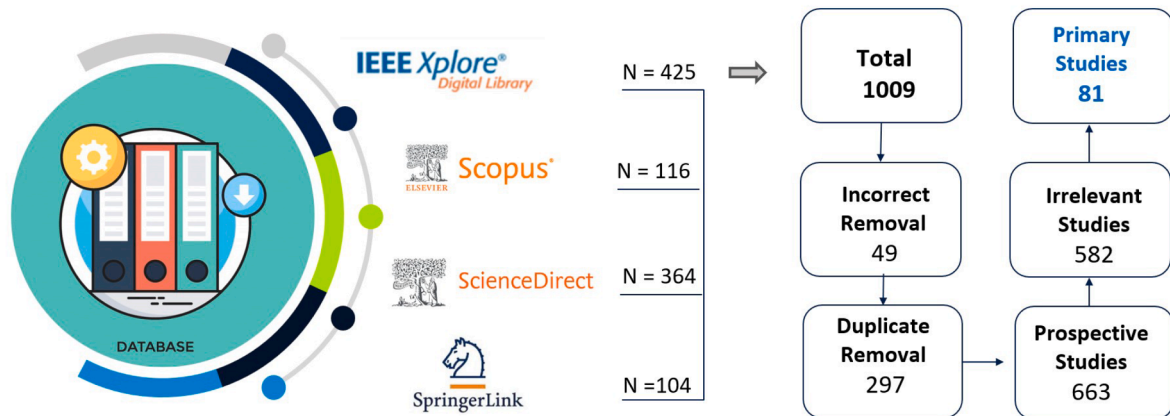


Fig. 1. Systematic literature review process.

occupant modelling, fault detection), and associated services (DR, distributed generation, multi-energy district systems). In contrast to previous reviews, which typically focus on individual components or narrow technical issues, the present work offers an integrated view, illustrating how ontologies can facilitate both cross-domain interoperability in building energy analysis and advanced computational approaches, such as AI-driven analytics and predictive control.

A systematic survey of nearly one thousand references was conducted to identify emerging themes, among which DT, AI-enhanced control mechanisms, and semantic interoperability across diverse BES were particularly salient. The review also explores how ontologies support DR programmes and energy flexibility, with special attention to occupant-driven control logic and real-time energy optimisation. Although semantic reasoning engines and ML methods are beginning to bridge operational data with higher-level contextual knowledge, notable challenges in standardisation, data harmonisation, and domain scalability remain.

In-depth comparisons of existing ontological frameworks (e.g., SAREF, Brick, SSN) and data exchange models (e.g., IFC, gbXML) form a key component of this analysis, with an emphasis on their practical limitations and potential for facilitating real-world semantic interoperability. The study highlights the requirement for further alignment between ontologies and AI-driven optimisation, as well as for the development of adaptive semantic systems that integrate time-series operational data with contextual building information. By synthesising these aspects, the review addresses crucial gaps in ontology-based building energy research, while proposing potential research directions for achieving seamless interoperability and data-driven decision support across energy domains. The consolidation of perspectives on semantic web technologies, AI-oriented control, and real-time building energy management is likely to be beneficial for both academic inquiry and industry application, underscoring the fundamental role of ontologies in next-generation energy-efficient and responsive building environments.

## 2. Literature review methodology

This research adopted a structured methodology to analyse ontologies related to energy systems, storage solutions, and grid infrastructure with particular attention paid to their use in building operations. Data gathering occurred in September 2025, drawing from four prominent databases—Scopus, IEEE Xplore, ScienceDirect, and Springer—selected for their robust coverage of energy-related scholarly work. The review in-

cludes a series of conference proceedings, and academic journal articles. The literature search was conducted from 2011 to 2024. The string used for the literature search was (ontology OR ontologies) AND (“energy system” OR “energy storage” OR “energy management”) AND building in order to encompass a broad range of ontologies in the context of building energy analysis. A total of 997 articles were identified from the four databases based on search strings. The 1009 articles were imported into the Zotero reference management software. Zotero facilitates the integration of research findings from multiple databases. A total of 346 duplicated and incorrect articles were removed, resulting in the selection of 663 prospective studies for further analysis. Subsequently, a rigorous evaluation of each study was performed and a total of 81 primary studies were identified, and the findings are presented in this review as shown in Fig. 1.

## 3. Results of the review

### 3.1. Metadata analysis and research trends

Country-wise publications are shown in Fig. 2. Approximately 67% of the primary studies were reported by EU countries, with Germany, Austria, and Portugal reporting the highest number of articles.

#### 3.1.1. Scope of research

Examining the scope of the 81 papers reveals a spread across building, grid, and device levels, with a fraction focusing on grid integration. Fig. 3 illustrates the distribution of reviewed studies according to their primary research scope. Around 60% of the reviewed studies focus on building-level issues, focusing on occupant comfort, building automation, and energy efficiency. Examples include [24], which examines loop management and parameter optimisation in cognitive control strategies, and [41], which highlights the importance of building-specific data formats for improving forecasting accuracy. Research aiming to harmonise BIM with semantic definitions features in [42], illustrating the ambition to unite design, construction, and operation data within a coherent framework.

Approximately 16% of the literature addresses device-level control and interoperability. In this category, [43] develops ontological approaches for device modelling and causal relations, while [44] focuses on establishing common data definitions for solar installations. Another 4% of the studies explores grid-level issues, as in Choi et al. [45] and Aryan et al. [46], where reliability, security, and market mechanisms

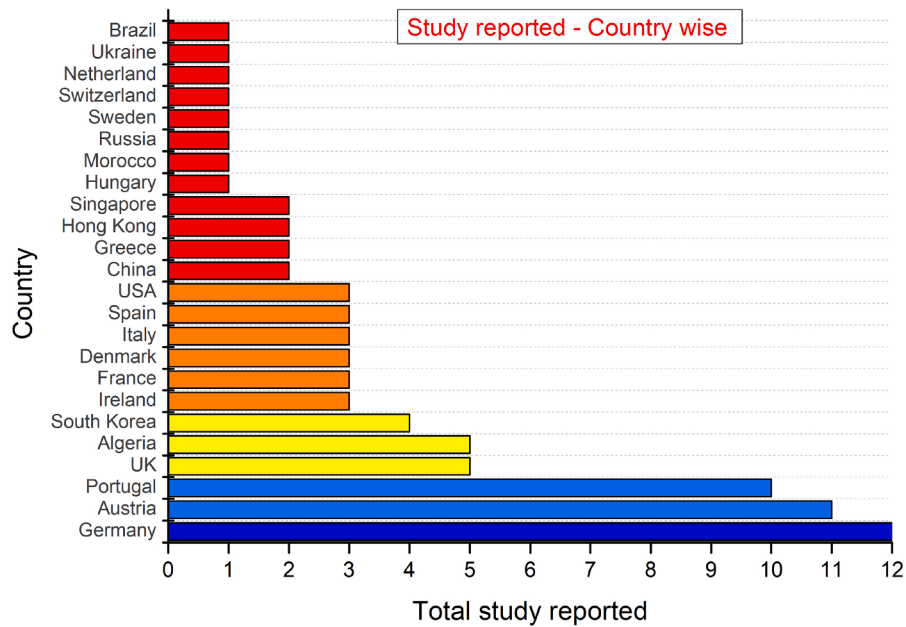


Fig. 2. Geographic distribution of the primary studies.

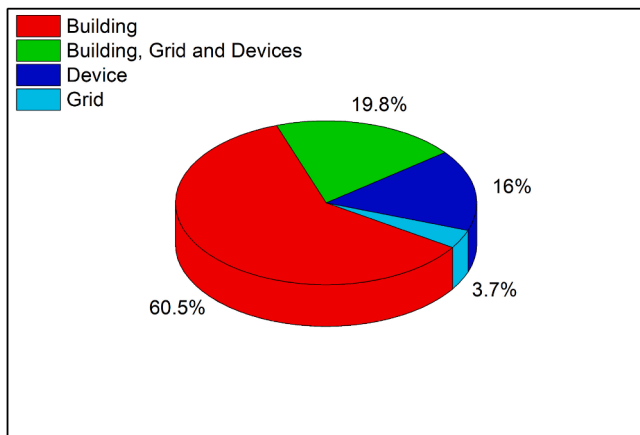


Fig. 3. Scope of study.

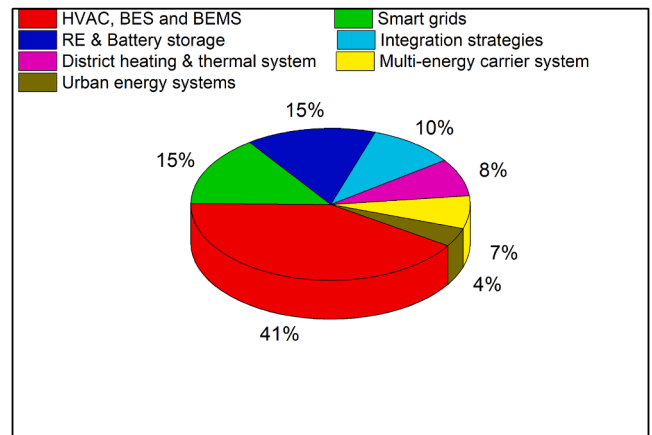


Fig. 4. Classification of studies based on energy system considered.

come to the fore. About 20% of the publications take a multi-scale perspective, bridging building, grid, and device levels to reflect the interconnected reality of modern power and thermal systems. In this context, [47] highlights the impact of building energy flexibility on grid balancing, while [48] presents a framework that accounts for goal alignment at every scale, from individual devices to the system as a whole.

This distribution illustrates how the device, building, and grid are increasingly viewed as parts of a unified ecosystem. Zhang et al. [49] and [50] suggest that semantic data models are required to harmonise the flow of information among different actors, from occupants to utility operators. As the prevalence of DERs continues to rise, research that straddles all these scales appears vital, mirroring real-world trends such as the spread of microgrids, virtual power plants, and community energy initiatives.

### 3.1.2. Energy systems considered

Across the literature, there is a wide breadth in the types of energy systems discussed, indicating a comprehensive interest in everything from micro-level device interactions to full-scale urban energy networks (Fig. 4). Approximately 15% of the papers explicitly focus on renewable energy generation such as PVs or wind turbines, often in combination

with battery storage solutions. For instance, [44] details the complexities of grid-connected PV systems, while [51] integrates solar PV and wind turbines within a microgrid environment. Close to 8% of the studies emphasise district heating, geothermal, or other thermal solutions, including [52] and [53], which examine how large-scale thermal infrastructure can supply heat more sustainably and efficiently.

A significant portion, approximately to 41%, discuss HVAC and general BES, including BEMS, lighting, occupant-centric controls, plug loads, thermostats, and shading devices. In [40], for example, the authors focus on occupant behaviour modelling in relation to multiple building subsystems. A similar attention to building zones appears in [23], illustrating how occupant preferences vary from one space to another. Meanwhile, energy storage technologies are gaining attention, with approximately 10% of the studies highlighting integration strategies, especially for building-scale battery systems or thermal energy storage. Couloumb et al. [54] discusses energy storage in conjunction with scheduling algorithms, and [55] highlights the need for improved ontology coverage of energy storage components to unify building design and operational data.

Approximately 4% of the papers, reported the studies relevant to urban energy systems. Zhang et al. [49] discussed the role of accurate

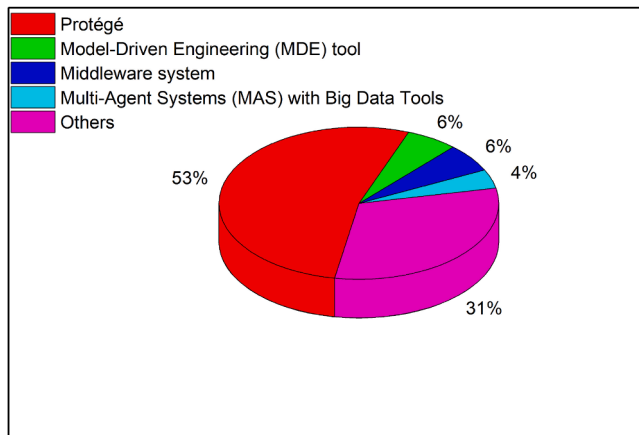


Fig. 5. Development toolkit used in the reported studies.

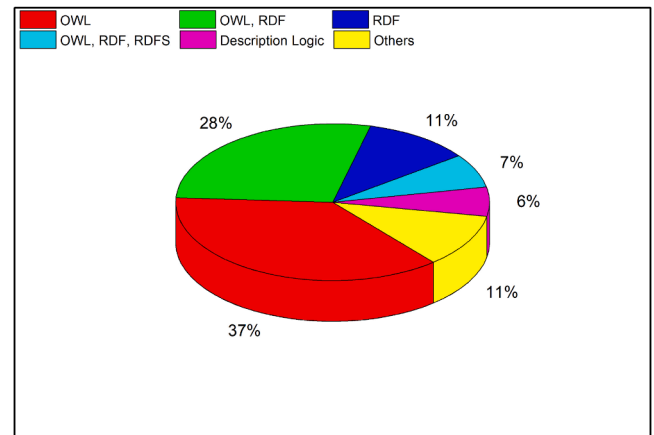


Fig. 6. Languages/syntax used in the reported studies.

heat demand forecasting in the context of evolving urban energy systems and the requirement for ongoing research and collaboration in this field. Ouhajjou et al. [56] emphasises the importance of stakeholder-oriented approach in urban energy planning, highlighting the use of advanced technologies to facilitate better communication and decision making among stakeholders. Roughly 7% of the literature addresses multi-energy carrier systems or integrated energy networks, where various forms of generation-electrical, thermal, or others-are combined in complex topologies. For instance, studies such as [57] and [58] mention the requirement for more advanced ontologies to model these interactions. Approximately 15% of the literature demonstrated the ontology application in smart grid and microgrid system. [59] considered a microgrid energy system, specifically focusing on the energy management of a microgrid on a university campus. This included distributed generation sources, energy storage, and demand response mechanisms.

### 3.1.3. Ontology toolkit and languages/syntax

Ontology toolkits are software tools that are intended to design, manage, and employ ontologies, which are formal frameworks that represent knowledge through concepts, relationships, and rules within a domain. They enable interoperability between systems, semantic reasoning, and the integration of structured data. Approximately half of the studies reported the utilisation of Protégé as the development toolkit for the ontology studies as shown in Fig. 5. Others, which likely include a variety of less common tools, make up 31% of the distribution, while model-driven engineering tools hold a 6% share.

Protégé is widely used to develop energy ontologies such as the open energy ontology (OEO). Li and Hong [47] utilised Protégé for Web Ontology Language (OWL) and the resource description framework (RDF) representations of the Energy Flexibility Ontology (EFOnt), which is utilised as a tool for enhancing the understanding and management of energy flexibility in buildings. Booshehri et al. [60] used Protégé as the development tool for the OEO for energy systems analysis. Other toolkits utilised were Model-Driven Engineering tool, TopBraid Composer, SAREF4BLDG Framework, Modelica etc. TopBraid Composer is an enterprise-oriented tool designed for organisations requiring advanced semantic modelling, data integration, and governance capabilities [61]. The SAREF4BLDG framework is a specialised extension of the SAREF (Smart Applications REFERENCE) ontology, developed by the European Telecommunications Standards Institute (ETSI). It focuses on building automation and smart building systems, offering a common language for describing devices, services, and interactions in residential, commercial, and industrial buildings SAREF4BLDG facilitates interoperability among IoT devices, such as HVAC systems, lighting, and sensors, thereby enhancing data exchange and automation within smart buildings [62].

Ontologies are formalised through specialised languages that represent knowledge in a structured and machine-readable format. As illus-

trated in Fig. 6, OWL was the most commonly used language, accounting for around 37% of all studies, followed by combination of OWL and RDF, which accounted for 28% of the studies. OWL builds on RDF to add richer semantics and reasoning capabilities. Other languages and syntax used were XML, RDFS, FIPA-ACL, etc. OWL, RDF, RDFS and Others each hold 8% of the share while Description Logic and RDF contribute 6% each.

### 3.2. Trends in existing building energy ontologies

Research on semantic modelling for building energy applications has expanded considerably in recent years, motivated by the need to address disparate data requirements, foster interoperability, and incorporate advanced analytics. A series of research efforts emphasise the reuse or extension of existing ontologies, while others propose entirely new frameworks dedicated to specific research themes such as fault detection, occupant behaviour, or grid interaction. A significant portion of the literature focuses on leveraging established ontological concepts, thereby reducing developmental overhead and creating synergy across projects. Studies by [44,63] exemplify how existing frameworks can be adapted to meet varying requirements such as indoor comfort optimisation and PV energy system integration. For instance, [63] rely on the ThinkHome ontology (itself assembled from DogOnt and BOnSAI) for structuring building data.

However, many researchers recognise that existing ontologies do not always cater to emerging requirements. Approximately 19% of the reviewed studies develop new ontologies from the ground up, aiming to represent novel concepts in energy systems. For example, [64] focuses on semantic models for fault detection, whereas [47] proposes a specialised ontology to quantify building energy flexibility. Wu et al. [65] address decentralised energy data, mapping table headers and device information into RDF triples. Such custom ontologies allow researchers to capture granular or cutting-edge concepts-flexibility metrics, advanced occupant behaviour models, or distributed energy flows-that older schemas do not fully accommodate. Other research efforts extend existing ontologies, which often appear in the form of modifications or specific sub-modules that target unique research problems. Teixeira et al. [59], for instance, integrate new rules and classes into a pre-existing framework to support MAS interoperability. Schweikert et al. [44] apply an extended approach to handle FAIR digital objects for PV data, thereby achieving robust data reusability. Overall, these studies show that while existing ontologies provide a consistent starting point, specialised expansions remain indispensable when advanced domain concepts require finer semantic granularity.

A further critical finding across the literature is that ontologies are extensively utilised for reasoning, data exchange, or simulation contexts. Several works describe how ontology-based systems facilitate

**Table 2**

Comparative overview of key ontologies (Brick, SAREF, SSN, and OEO) highlighting their domain coverage, interoperability mechanisms, and principal limitations.

Ontology	Domain Coverage	Interoperability Features	Limitations
Brick Schema	Designed for building operations; covers HVAC, lighting, equipment, sensors, and zones	Built on RDF/OWL; extends Project Haystack; aligns with ASHRAE 223P and supports semantic tagging and querying	Lacks explicit IFC alignment and building envelope representation
SAREF (and extensions: SAREF4BLDG, SAREF4ENER, etc.)	Originated for IoT and smart appliances; extended to buildings and energy domains	Maintained by ETSI; modular and extensible; reuses common IoT vocabularies and supports device-level interoperability	High-level device orientation limits detailed modeling of control logic and spatial context
SSN/SOSA (Semantic Sensor Network ontology)	W3C standard for sensors, observations, sampling, and actuators	Provides generic, extendable structure; interoperable with other RDF-based ontologies	Lightweight design requires extensions for building and energy domain specificity
OEO (Open Energy Ontology)	Broad energy domain coverage: generation, consumption, storage, and policy	Enables cross-domain data reuse and semantic alignment with other open ontologies	Less focused on building-level operational details and device semantics

semantic interoperability or advanced data analytics. For instance, [51] shows that multi-agent-based communication, supported by an ontology, can reconcile heterogeneous data sets in microgrid control. Meanwhile, [60] highlights how bridging different domain assumptions is achievable through a consistent ontological framework, which fosters cross-domain energy research. There is also a notable drive to adapt ontologies for energy management, occupant interaction, and sustainability goals. Uribe et al. [66] lay out a context-aware framework for thermal energy systems in near-zero energy buildings, while Belafi et al. [40] investigate occupant behaviour models expressed with schema formats to guide building simulation.

Considering these trends, it becomes apparent that standardisation and extension efforts are interconnected. Some research efforts focus on developing frameworks that link building energy data with broader city or environmental data, while others emphasise occupant-driven systems or advanced predictive analytics. Different aspects - ranging from occupant comfort thresholds, microgrid control, or the real-time detection of anomalies-are all integrated into knowledge representations that rely on the formal expressiveness and inference capabilities of ontology languages. To clarify the scope, interoperability capabilities, and current gaps among the most commonly referenced ontologies in building energy research, a comparative summary is provided in Table 2. This table contrasts Brick, SAREF, SSN, and the OEO in terms of their domain coverage, interoperability features, and known limitations, reflecting their respective strengths and complementarities in supporting semantic interoperability across smart building systems. The remaining sections discuss in detail how these ontologies have evolved to cover multiple application domains in the context of BES, what languages and tools they employ, and which advanced computational methods they integrate.

### 3.3. Applications of ontology-based approaches in building energy systems

This section reviews practical applications of ontology-based frameworks within building energy systems. It examines how semantic modelling has been adopted to enhance energy management, occupant behaviour representation, fault detection, demand response, and urban-scale energy coordination. The following discussion highlights the diversity of ontology use cases and their role in improving operational intelligence, interoperability, and sustainability in buildings.

#### 3.3.1. Building energy management and occupant behaviour

Ontologies in building energy research frequently address occupant-centred management, since occupant behaviour can drastically affect energy consumption in both residential and commercial settings. Semantic structures facilitate the integration of occupant factors (e.g., comfort preferences, presence patterns, usage of devices) with building automation. For instance, Belafi et al. [40] refine occupant behaviour modelling using a schema-based approach (obXML), demon-

strating that a well-structured ontology can capture a wide variety of occupant drivers and systems. This results in superior data collection and simulation practices, enabling building operators to adapt HVAC and lighting strategies. Kyselova et al. [67] showed that occupant-based forecasting can rely on semantic representations to consolidate location data and user profiles, thereby improving energy forecasting by clarifying occupant-driven patterns. Similarly, [68] note that occupant comfort parameters can be integrated into semantic knowledge graphs, so that each agent or building subsystem consistently interprets occupant comfort levels when controlling HVAC. Hamdaoui and Maach [21] developed an occupant-driven approach that outlines an ontology-based context agent acting as a mediator between occupant needs and the building management system, utilising real-time sensor data to adapt control decisions. Additionally, Uribe [66] adopts W3C standards (OWL, RDF, SPARQL) to incorporate occupant and environmental context within a near-zero energy building. This context awareness enables dynamic changes in thermal energy management whenever occupant presence or weather conditions deviate from predicted figures. Belafi et al. [40] extends occupant behaviour representation, employing XML-based metadata that can be mapped to an ontology, while including occupant schedules or preferences has also been proposed in MAS. Moghaddam [51] integrate occupant constraints into an agent negotiation process, highlighting that occupant comfort can be automatically paired with DR or cost-related objectives.

In addition to this, recent work highlights that occupant modelling has shifted from static to dynamic approaches. Rather than simply tagging occupant presence, building ontologies can encode occupant schedules, occupant comfort thresholds, and historical usage patterns. For example, [69] show how occupant-driven rules can be embedded within a broader multi-service architecture, so that occupant feedback triggers the adaptation of DR events at different levels. Occupant behaviour in some frameworks is effectively treated as a dynamic input to semantic rules that govern HVAC or lighting decisions, reinforcing occupant-centric energy optimisation. As a result, building managers can respond to occupant comfort fluctuations automatically, rather than relying on pre-programmed setpoints.

Fig. 7 illustrates an ontology-driven smart-building framework for building energy management and occupant behaviour. The diagram shows how semantic modelling supports data harmonisation between energy systems and occupant-centric factors. The ontology enables the integration of building operation data, comfort preferences, and feedback mechanisms to optimise HVAC and lighting control while maintaining user comfort. Through this structured knowledge representation, reasoning engines can infer optimal setpoints and recommend adaptive strategies for energy efficiency and occupant satisfaction.

#### 3.3.2. Fault detection, diagnostics, and predictive maintenance

Fault detection and diagnostics is another issue elaborated in the literature. Large buildings and campus-scale systems generate high

### ONTOLOGY DRIVEN SMART BUILDING: BUILDING ENERGY MANAGEMENT & OCCUPANT BEHAVIOUR

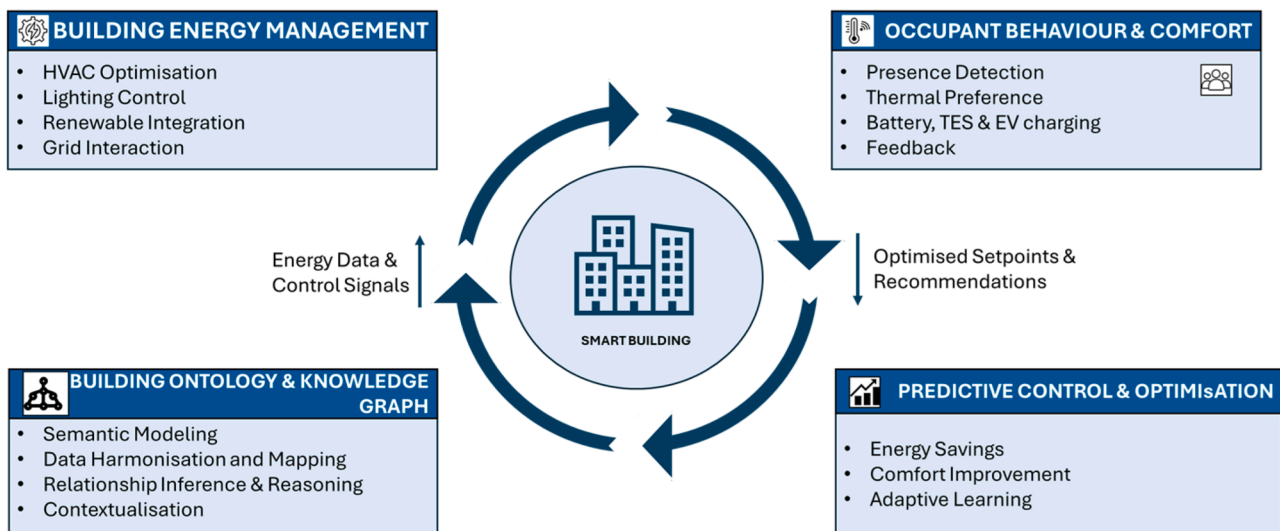


Fig. 7. Ontology-driven framework for smart building energy management and occupant behaviour, showing how semantic models integrate energy, comfort, and control data for predictive optimisation and adaptive comfort management.

volumes of sensor data, making it challenging to spot faulty equipment or anomalous operations in a timely manner. Ontology-based approaches can encode knowledge about typical operating conditions, known failure modes, and recommended corrective actions. Li et al. [64] demonstrate an OWL-based framework for automated fault detection in BES, using semantic rule reasoning combined with Z-score calculations to detect operational anomalies such as stuck dampers or inconsistent temperature readings. This approach also automatically provides interpretability, since operators can trace alerts back to explicit rules in the ontology. Gaida et al. [23] underline how semantic modelling, combined with data analytics, can detect inefficiencies and propose suitable changes to building automation configuration. By adopting rule-based inference, the system references ontological definitions of normal or optimal operating states for HVAC components. When sensor data deviates from these reference conditions, the system infers potential faults and suggests adjusting relevant parameters. Moghaddam et al. [70] likewise leverage ontology-driven knowledge to handle real-time dispatch in building and microgrid contexts, detecting anomalies that may hinder optimal scheduling.

Ontology-based predictive maintenance extends beyond real-time fault identification to anticipating future equipment failures. For example, Pruvost et al. [26] implement a knowledge graph that configures monitoring and fault-detection capabilities automatically, based on semantic metadata about building systems. In this way, the system can identify or predict anomalies by correlating building usage patterns, occupant comfort complaints, and device performance data. [67] similarly emphasise that semantic context from device-level sensors, occupant presence, and external conditions can be fused to anticipate failures. Once anomalies are identified, semantic rules or case-based reasoning modules evaluate probable causes and direct building operators to preventative measures. Such predictive maintenance is particularly valuable in large-scale settings, where the complexity of interactions between different subsystems and occupant schedules can mask the early symptoms of a fault. By merging explicit knowledge (e.g., typical setpoints, recommended operational conditions) with data-driven methods (e.g., ML, anomaly detection), ontology-based frameworks provide clarity and interpretability. Saba et al. [71] also demonstrate how a multi-agent architecture can rely on shared ontological knowledge to detect abnormal conditions, employing distributed intelligence to reduce overall building energy consumption. This approach highlights the synergy

between domain-specific semantic definitions and robust data handling for automated building management.

Fig. 8 demonstrates how ontologies can be applied to fault detection and predictive maintenance in smart buildings. Real-time sensor readings, asset metadata, and equipment histories are mapped into a building ontology and knowledge graph, providing a unified semantic structure for anomaly detection and diagnostic reasoning. The ontology supports rule-based identification of faults, root-cause analysis, and optimisation of maintenance scheduling. This cycle of data ingestion, reasoning, and feedback enables more accurate and proactive asset management.

#### 3.3.3. Energy flexibility and demand response

With the growing momentum of DR and supply-balancing programmes for buildings, research on ontologies for energy flexibility has expanded. Building energy flexibility encompasses strategies such as load shifting, storage management, and renewable integration, all of which require dynamic representations of building loads, occupant constraints, and external grid signals. Li and Hong [47] provides EFOnt to represent flexible loads, relevant key performance indicators, and building services. This ontology unifies concepts such as self-sufficiency, flexibility factor, and occupant comfort thresholds, facilitating standardised queries via SPARQL. As a result, building operators or grid coordinators can more easily negotiate DR events or plan shifting strategies. DR frequently relies on MAS, where each agent might represent a building, a group of appliances, or an aggregator. Anvari-Moghaddam et al. [51] propose an agent-based energy management system that utilises a semantic layer to handle message exchanges about occupant preferences, load constraints, and renewable generation. Ontology-based definitions of these elements help ensure consistent communication of DR event signals. Teixeira et al. [59] integrates multi-agent decision support for energy contract negotiation, showing how an ontology ensures that occupant comfort and DR constraints remain aligned across different simulation tools. Research also addresses the quantification of flexibility in building contexts. For instance, Wu et al. [65] merge household energy data with meteorological observations to predict generation and consumption patterns, enabling real-time adaptation. This approach clarifies occupant or device-level constraints using semantic categories, so that DR events can precisely target shiftable or shedable loads. These

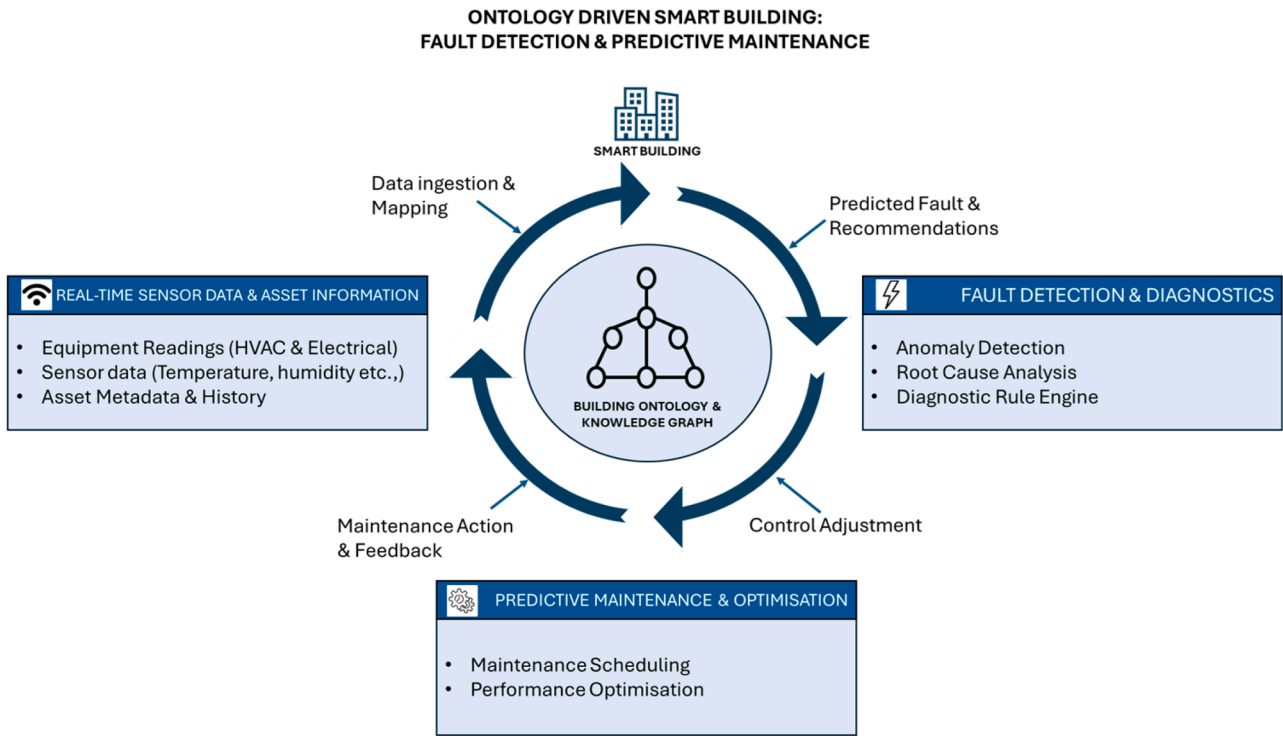


Fig. 8. Ontology-based framework for fault detection and predictive maintenance, linking real-time sensor data and asset metadata to diagnostic reasoning for anomaly detection, root-cause analysis, and maintenance optimisation.

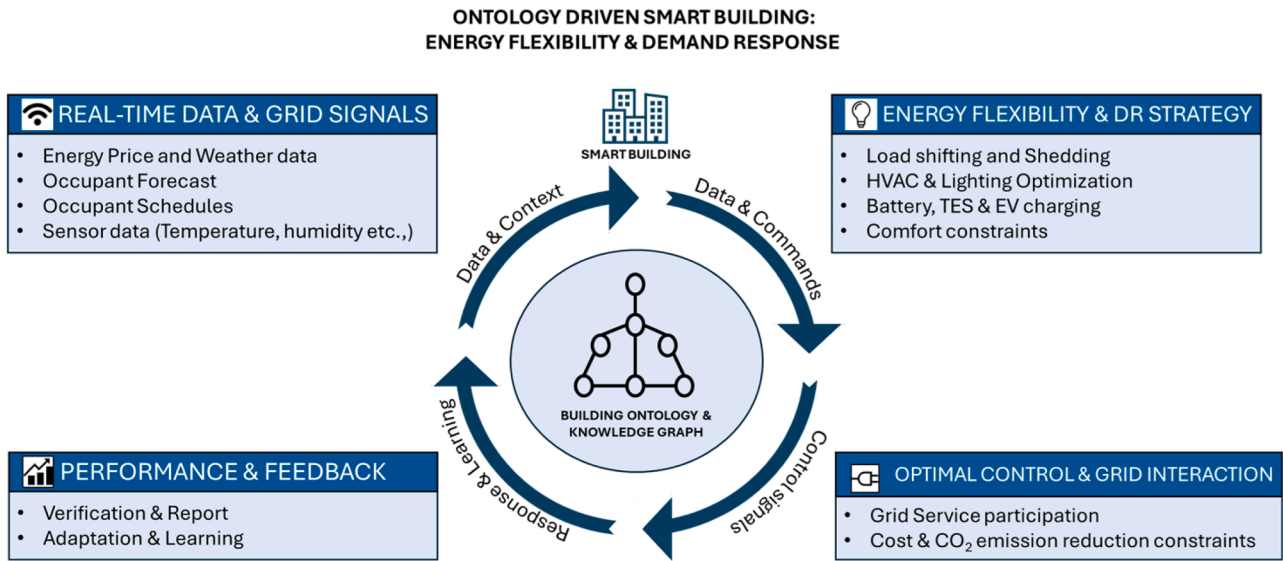


Fig. 9. Ontology-supported coordination of energy flexibility and demand response, integrating real-time data streams and control strategies to optimise load shifting, HVAC operation, and grid interaction under comfort and cost constraints.

examples show that flexible energy usage depends on consistent domain semantics, bridging occupant comfort with grid reliability requirements.

As occupant acceptance is integral to effective DR, occupant or organisational preferences must be codified in an ontology. Some frameworks specifically label occupant preferences as constraints that cannot be violated or can only be exceeded for short intervals. Others incorporate time-of-use pricing or occupant schedules as triggers for DR strategies. The ability to incorporate occupant comfort with advanced scheduling is also mentioned in [21], which integrates occupant knowledge and grid signals. When the building receives a DR event request, the ontology-based system checks occupant constraints, device-

level constraints, and cost goals before deciding whether to shift the load. Such context-aware reasoning helps ensure that occupant satisfaction remains high while participating in grid-level load adjustments.

Fig. 9 presents an ontology-based framework for energy flexibility and demand response management at the building level. The ontology captures real-time data streams such as energy prices, weather forecasts, and occupant schedules, linking them to control strategies for load shifting, HVAC optimisation, and storage operation (e.g., battery, thermal, or EV charging). By semantically relating contextual data to control commands, the system can coordinate demand response events and

### ONTOLOGY DRIVEN URBAN ENERGY SYSTEM: URBAN ENERGY SYSTEM WITH DISTRICT HEATING SYSTEM

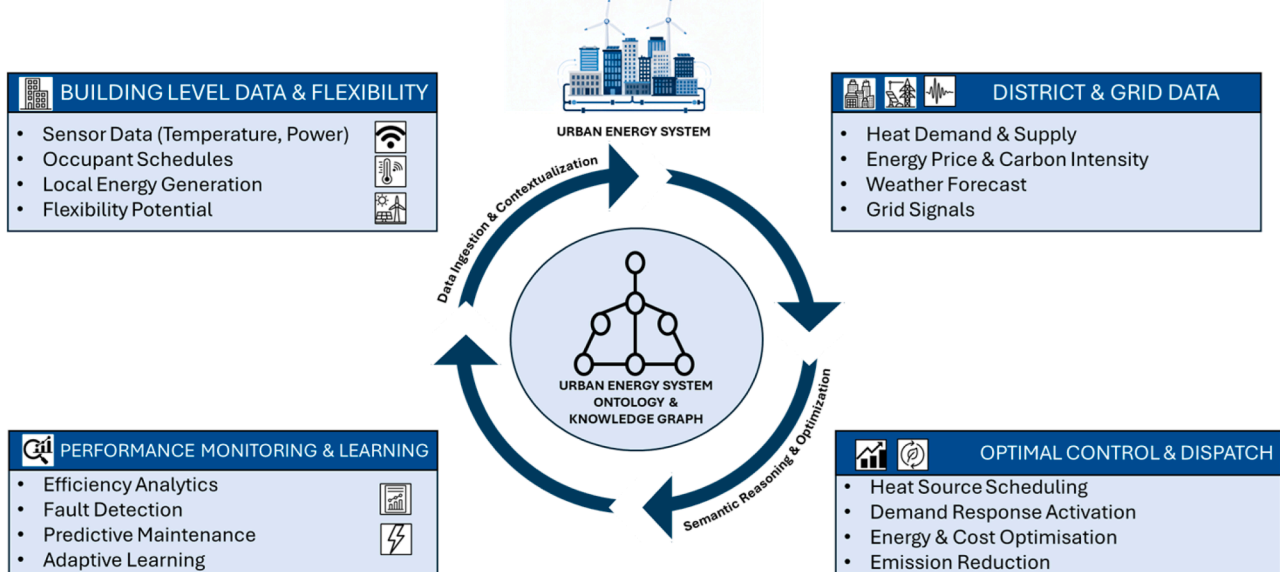


Fig. 10. Ontology-driven urban energy system integrating building-level data with district heating and grid operations, enabling semantic reasoning for coordinated scheduling, energy optimisation, and emission reduction across interconnected networks.

optimise participation in grid services while respecting comfort and cost constraints.

#### 3.3.4. Ontology-based approaches for urban energy systems and district heating

The ontological scope has also broadened to encompass city-scale energy systems and district heating or cooling networks. Urban energy planning typically involves data from multiple sources—building typologies, transport infrastructures, microgrids, policy instruments—and large numbers of stakeholders. Corrado [72] similarly illustrate a semantic approach for integrating manifold data sources in city energy analysis, bridging differences in data semantics to yield consistent urban energy models.

At the district or city scale, multi-agent approaches such as [51] show that the same semantic layers used for single-building energy management can extend to multi-building microgrids, coordinating distributed generation and storage. For full city-wide coverage, further expansions are required to capture elements such as transport networks and large infrastructure. In the domain of district heating, Li et al. [53] propose a semantic system for real-time DR. The system takes advantage of heat load forecasts, occupant comfort parameters, cost signals, and advanced control strategies within a distributed knowledge framework. Demand-side flexibility in such systems emerges from the combination of occupant constraints, building thermal capacity, and external price or carbon signals. Ontologies enable these features to be updated or replaced while retaining overall semantic integrity, which is particularly valuable for large-scale systems that can accommodate new data types or stakeholder preferences over time.

Urban DT extend the concept further, integrating real-time data from thousands of sensors and the entire building stock. Hofmeister et al. [52] discuss how knowledge-graph-based approaches integrate emission dispersion modelling, building energy analysis, and external data sources for dynamic control of district heating networks. By linking an array of domain-specific ontologies into a single dynamic knowledge graph, city operators can simulate or optimise how changes in heating generation dispatch might propagate through local buildings, occupant comfort, and greenhouse gas emissions. These city-scale semantic frameworks highlight a growing trend to handle not only building-level energy but also the synergies between energy

and local environmental factors, occupant mobility, and cross-sector interactions.

Fig. 10 depicts an ontology-driven urban-energy system integrating building-level flexibility with district-heating and grid operations. The framework links diverse data sources, including sensor readings, local generation, demand and supply information, and weather forecasts, into an urban-scale knowledge graph. Ontological reasoning supports coordination across buildings, districts, and grid layers, enabling optimal scheduling, energy-cost optimisation, and emission reduction. This illustration highlights how ontology serves as the semantic backbone for interoperability and decision-support in multi-energy urban environments.

#### 3.4. Ontology languages, syntax, tooling, and standards

The successful implementation of ontology-based energy systems depends on the availability of development tools, modelling languages, and standards that ensure semantic consistency and interoperability. This section outlines the main toolkits, frameworks, and ontology languages used in building energy research, as well as relevant standardisation initiatives that guide their adoption.

Building energy ontologies typically adopt W3C semantic web standards, with OWL and RDF featuring prominently. For instance, [64] employs OWL for fault detection via a Jena knowledge graph, while [65] represents household energy data as RDF triples linked to meteorological information. Studies such as [66] demonstrate how OWL and RDF enable context-aware systems for near-zero energy buildings. Likewise, [72] highlight that adherence to these standards promotes interoperability and leverages existing semantic web technologies such as SPARQL.

Although XML sometimes appears for data exchange or legacy bridging, RDF and OWL remain the de facto choices for expressing advanced semantic relationships. RDF provides a foundation for linking diverse resources, while OWL adds expressiveness by defining classes, properties, and constraints interpretable by reasoners such as HermiT or Pellet. Many studies rely on reasoning for automated inference about occupant comfort, equipment faults, or DR events, often using SPARQL endpoints. Protégé is a predominant tool for ontology development [40,44,47], allowing users to build and maintain OWL ontologies, alongside UML-based or spreadsheet-to-OWL approaches [44,57]. These tools help

**Table 3**

Overview of ontology languages, tools, and standards relevant to building and energy management.

Category	Representative Examples	Core Concept / Function	Distinctive Features	Application Scope in Energy/Building Systems
Ontology Languages	RDF, RDFS, OWL, SHACL	Formal frameworks to define concepts, properties, and relationships between entities	RDF: flexible graph-based representation; OWL: expressive class/property definitions and reasoning; SHACL: constraint validation for RDF graphs	Used to model building entities, devices, and their interrelations; enable semantic reasoning and interoperability across systems
Ontology Development Tools	Protégé, TopBraid Composer, VocBench, OntoStudio	Software environments for creating, editing, and validating ontologies	Offer reasoning engines, visualisation, and collaborative editing	Used to design domain ontologies (e.g., Brick, SAREF extensions) and support semantic alignment between BIM, IoT, and BEMS data models
Standards and Schemas	IFC, gbXML, Brick, Project Haystack, SAREF, BOT, SSN	Structured vocabularies and models for representing building and energy data	IFC/gbXML: geometry & BIM integration; Brick/SAREF: semantic representation of devices and functions; BOT: spatial topology; SSN: IoT sensor data	Facilitate data exchange and interoperability across BIM, BEMS, IoT, and DT platforms
Knowledge Graph Frameworks	RDF GraphDB, Neo4j, Jena	Platforms for storing and querying semantic data	Support SPARQL queries, reasoning, and linking heterogeneous datasets	Used in knowledge-based energy analytics and cross-domain data integration

domain experts unfamiliar with raw semantic syntax. Systems that integrate knowledge from standard IoT or automation vocabularies (e.g. SAREF or SSN) and convert it to energy-specific ontologies are especially useful for large-scale projects.

Various domain or cross-domain standards also appear. SAREF, initially for smart appliances, is widely used in building energy contexts, while Brick describes HVAC, lighting, and sensors. Some authors align ontologies with city or energy vocabularies, such as SEMANCO [72] or OEO [60]. SEMANCO targets city-scale data, whereas SARGON [73] focuses on smart energy domain interoperability, especially for IoT devices. SPARQL is standard for querying and reasoning over these ontologies. Zucker et al. [24] store and retrieve control strategies via SPARQL, while [47] query the EFOnt to gather building flexibility data. Some frameworks employ SWRL or SPIN for domain rules, as in [67] and [74], enabling context-awareness and occupant classification.

Because building energy data often arrives in real time, many projects integrate a semantic store (e.g. GraphDB or Apache Jena Fuseki) with big data or event-streaming platforms. Sayah et al. [75] combine Hadoop, MongoDB, and Kafka in an ontology-based system for large-scale smart city energy data, emphasising robust semantic descriptions throughout. Linking well-defined W3C standards with frameworks like Brick, SAREF, OEO, or SSN facilitates flexible, interoperable solutions that adapt to evolving technologies and occupant patterns. Table A.1 (see appendix) summarises each ontology's scope, syntax, development tools, standards, and protocols.

Table 3 presents an overview of the main ontology development tools, ontology languages, and data models or domain standards, outlining their core functions, defining characteristics, and application scopes. Complementing the table, Fig. 11 illustrates the hierarchical and semantic relationships among these components. The diagram shows how ontology development tools and applications (e.g., Protégé, VocBench, AI reasoning systems, and DTs) interact with ontology languages (such as RDF/RDFS, OWL, and SHACL), which provide the formal semantics and logic for knowledge representation and constraint validation. These ontology languages interface with data models and domain standards (e.g., IFC, gbXML, Project Haystack, Brick, SAREF, BOT, and SSN), which define the specific vocabularies and structures for representing buildings, devices, and sensors.

### 3.5. Advanced technologies and integrations

This section discusses how ontology-based frameworks enable advanced interoperability, multi-agent coordination, and digital-twin analytics. By linking semantic representations with data exchange protocols

and AI-driven control, these approaches bridge the gap between static data models and adaptive, self-learning building energy systems. The following subsections examine (i) semantic interoperability and data representation, (ii) multi-agent communication and automation, and (iii) digital-twin and AI-enabled optimisation techniques that together form the technological foundation of next-generation ontology-driven energy management.

#### 3.5.1. Ontology-based data representation and semantic interoperability

Ontology-based data representation is paramount for achieving semantic interoperability in BES, ensuring that heterogeneous data sources, such as sensors, occupant feedback, microgrid dispatch signals, use a consistent conceptual framework. Instead of scattering data across multiple unconnected databases, the ontology paradigm unifies building or city information in knowledge graphs, readily interpretable by humans and machines. Fig. 12 details the internal processes within the ontology layer. It demonstrates how heterogeneous data sources are transformed into semantically rich knowledge structures through semantic data modelling (classes, properties, and relationships) and inference and reasoning mechanisms (rule-based and advanced reasoning). These capabilities enable intelligent applications to operate autonomously while maintaining interoperability across diverse systems. For instance, Schachinger et al. [76] propose an ontology-based abstraction layer to integrate building energy management systems with the smart grid, clarifying how devices, sensors, and energy services relate in real time. Similarly, [64] rely on ontological definitions for fault detection, showing how normal ranges for temperature or device states can be encoded as classes or properties. In Wu et al. [65,77], household energy data is stored as RDF triples and linked to weather data. By systematically naming and structuring classes, properties, and relationships, the system can align usage patterns (e.g., occupant cooking events) with external conditions (e.g., temperature drops, solar irradiance). A correlation analysis in Wu et al. [65] reveals how linear relationships appear between specific device usage and temperature changes, creating deeper insights for occupant-level energy modelling. This approach is also followed by Coulomb et al. [54], who emphasise that integrating building management system data with external sources, such as billing and weather, can enhance peak shaving algorithms.

The semantic layer helps eliminate confusion over naming conventions and measurement units. Semantic interoperability underlies MAS as well. Moghaddam et al. [51] propose an agent communication language referencing domain ontologies that specify data structures for DR or occupant comfort. Each agent can interpret incoming messages unambiguously, since key terms such as “thermal comfort” or “preferred

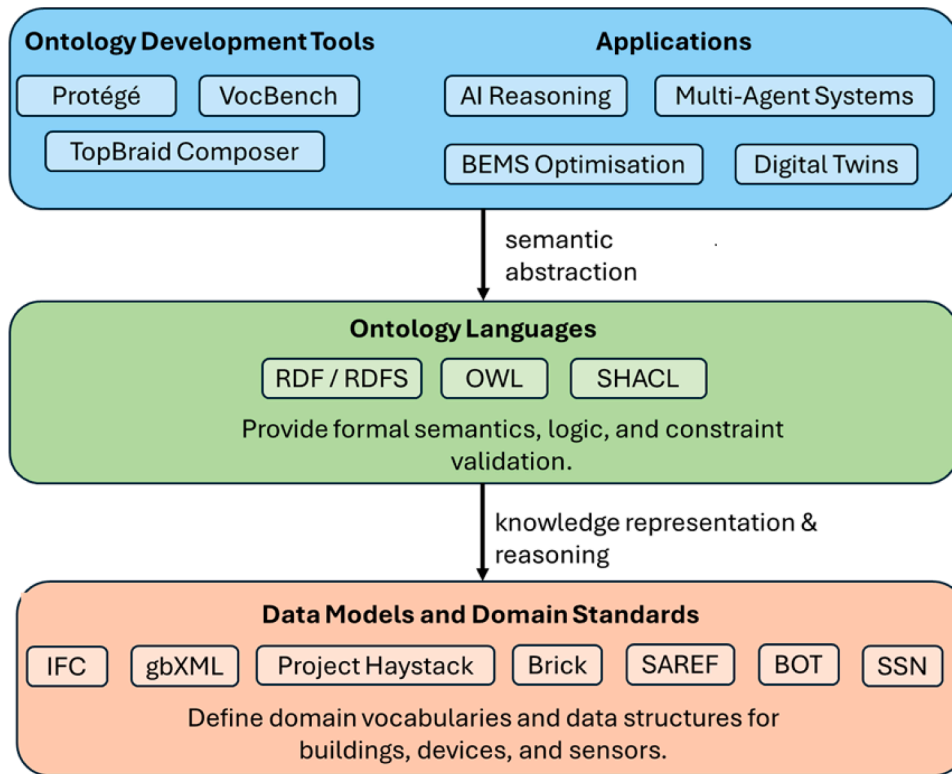


Fig. 11. Layered representation of ontology-related technologies supporting semantic interoperability in smart building energy management.

### BUILDING ENERGY ONTOLOGY IN ACTION: From heterogenous data to intelligent applications via semantic interoperability

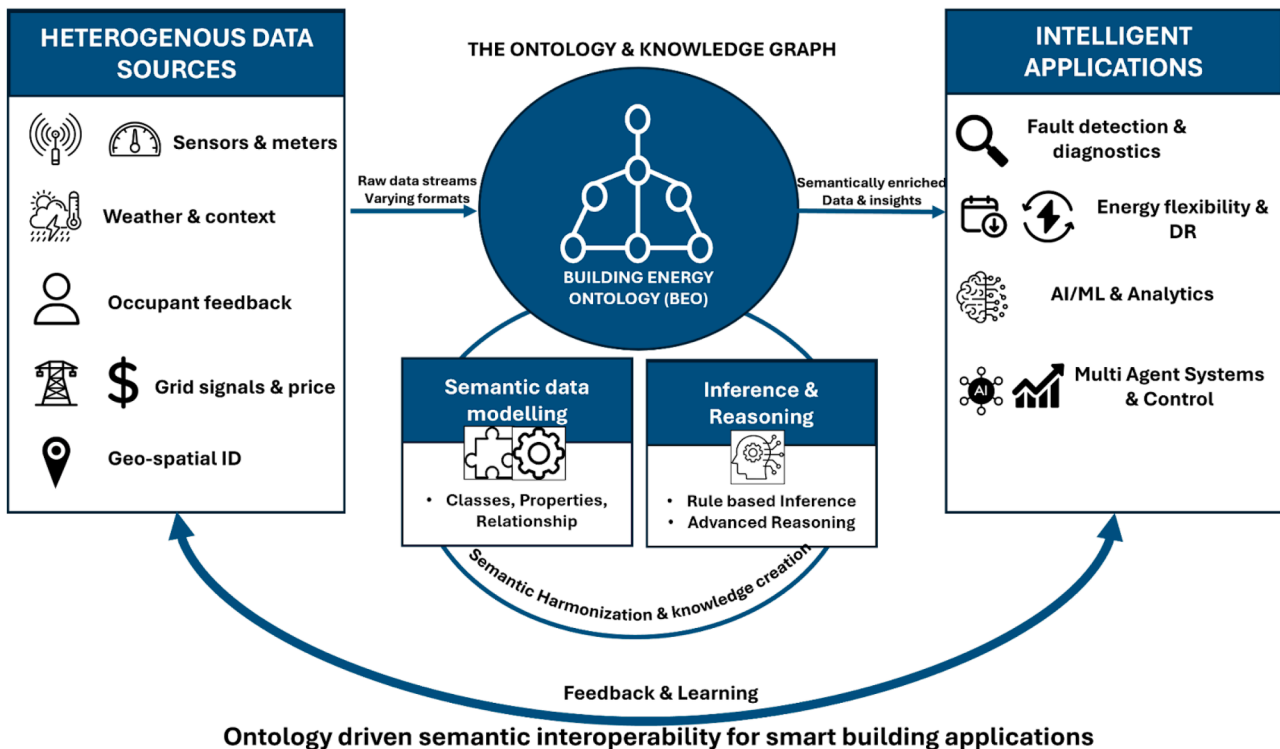


Fig. 12. Conceptual framework linking real-time building data, the Building Energy Ontology, and AI/ML applications to achieve semantic interoperability.

task scheduling” are grounded in a shared ontology. Teixeira et al. [59] extend this approach to coordinate multiple simulation tools, bridging building-level microgrid scheduling with external markets. Without a standardised ontology describing occupant loads, device constraints, or cost signals, multi-agent coordination would rely on ad-hoc definitions that hamper reusability.

Furthermore, knowledge graphs are utilised to identify relationships that are not explicitly coded in a single database. For instance, [60] shows how the OEO fosters cross-domain data reuse, enabling semantic analyses that link generation assets, consumption data, and occupant preferences. Meanwhile, [72] examines city-wide data integration, in which geospatial building footprints, occupant demographics, and building energy attributes are unified within a single semantic framework. Policymakers can accordingly query city-wide compliance with certain energy standards or identify potential retrofit targets that meet occupant density thresholds. Semantic models can further advance standardisation efforts. For instance, Wu et al (2023) [50] note that an ontology-based approach can automate building energy modelling by mapping data from external sources to the classes or individuals in an ontology. Eppy or EnergyPlus scripts rely on these definitions to generate consistent input files for simulations. Similarly, [78] extends SAREF4BLDG to accommodate dynamic behavioural models in DT. All these frameworks highlight that ontological structures serve as a universal language bridging occupant, sensor, building system, and external climate data, facilitating an ecosystem where data is discoverable, interoperable, and amenable to advanced analytics.

### 3.5.2. Semantic interoperability, multi-agent systems, and building automation

Semantic interoperability becomes especially relevant in advanced building automation systems, which rely on agent-based architectures and real-time data feedback. One of the earliest motivations for applying ontologies in multi-agent building control is that each agent typically addresses a different subsystem (lighting, HVAC, occupant comfort, or security). When these agents exchange messages about occupant preferences, cost constraints, or predicted grid signals, an ontology ensures they interpret each concept consistently. For example, [51,70] develops agent communication language protocols based on a semantic content language, while [59] leverages FIPA standards and OWL ontologies in the JADE platform to promote interoperability across energy simulation tools. Applications in building automation extend beyond scheduling or occupant-centred rule sets. Some authors use multi-agent semantic systems for complex tasks such as market bidding or aggregator-based demand response. For example, [59] outlines a multi-agent decision support system that integrates occupant loads, local generation potential, and utility signals. The approach employs semantic definitions to ensure the aggregator agent instructions align with occupant comfort preferences. Agents can also weigh occupant constraints, cost signals, or device capabilities when deciding how to respond to a load-shedding request. Further to this, Zanabria et al. [79] focus on conflict detection in battery energy storage systems for smart grids, referencing EMSOnto to unify concepts about grid services, battery states, and control constraints.

The same general principle appears in [70], where an ontology-driven approach for integrated building and microgrid ensures that occupant comfort constraints, cost objectives, and device-level constraints remain coherent across the agent society. Meanwhile, [21] details a semantic representation that helps BEMS systems negotiate with occupant-driven demands or external signals from the grid, facilitating communication in a timely, unambiguous fashion. Semantic frameworks also improve fault detection and adaptive maintenance in multi-agent building automation. For example, if one agent registers abnormal temperature readings from the HVAC subsystem, it can query the ontology to determine whether the readings align with known fault signatures. In this case, the agent triggers either a local reconfiguration or a request for human intervention. By embedding domain rules in an on-

tology, the system not only captures anomalies but also explains them in terms of domain semantics. This interpretability proves essential for building operators, who can quickly understand the rationale behind each alert. Pruvost et al. [26] highlights the potential to scale such knowledge-based approaches, automatically configuring entire recommendation systems based on an initial building description. MAS also act at a city or microgrid scale, where occupant comfort, aggregator strategies, and distributed generation must be harmonised. Santos et al. [22] address semantic communication in energy market contexts, using extended versions of existing ontologies to unify bidding, scheduling, and DR. The approach ensures that market participants, aggregator agents, and building-level controllers exchange consistent data. Where occupant comfort or device constraints factor into price-based negotiations, the ontology references occupant-based classes. This synergy of occupant, device, and market knowledge fosters real-time building automation that respects user preferences while balancing grid requirements.

Fig. 13 presents a high-level overview of how real-time data from physical buildings are structured into a building energy ontology and subsequently utilised by AI/ML algorithms, simulations, and various applications. The diagram highlights three interconnected layers: (1) the physical building and real-time data sources; (2) the ontology and knowledge graph layer that models entities, relationships, and context; and (3) AI- and simulation-driven applications that leverage semantic information for analytics, control, and optimisation.

### 3.5.3. Digital twins, AI integration, and advanced techniques in building energy ontologies

Digital twin concepts have become a central focus in research on advanced building energy ontologies. These virtual environments mirror real-world building states through sensor data, occupant usage patterns, and external signals, underpinned by ontologies capturing knowledge about building components, occupant behaviour, and environmental factors. Akroyd et al. [48] demonstrate a dynamic knowledge graph representing a building’s DT, enabling cross-domain calculations for occupant comfort or air quality. By embedding occupant patterns, device relationships, and constraints in a semantic web, the DT can process changes in real time. Recent developments refine the lifecycle accuracy of DTs through semantic-AI integration. Li et al. [80] propose an AI agent-driven virtual in-situ calibration method that embeds the Brick schema to maintain semantic alignment among physical sensors, virtual models, and HVAC components, reducing model error while keeping calibration interpretable. Lee et al. [81] extend this idea to fully autonomous construction and calibration of virtual building models using multi-agent AI within a BIM-supported ontology framework, enabling scalable deployment of DTs across building portfolios.

AI and ML integration further enhances building energy ontologies. Couloumb et al. [54] use semantic data to refine ML forecasts of building load peaks, ensuring consistent labelling of weather or occupant factors. Ni et al. [41] incorporate deep learning in a parametric DT, semantically aligning occupant or device data, thus improving predictions of density, setpoint schedules, or temperature changes. Semantic definitions also accelerate simulation-based tasks. Wu et al. [50] propose automated energy modelling with thermal zoning by mapping building data into EnergyPlus scripts via an ontology. Eckstadt et al. [82] transform Mod-elica models into knowledge graphs using MoOnt, automating BES design. Bjornskov et al. [78] integrate grey-box models into DT built on SAREF4BLDG, improving simulation and forecasting reliability through consistent parameter naming and device descriptions.

Generative AI has emerged as an interaction layer for DT ontologies. Song and Yoon [83] demonstrate an ontology-assisted GPT environment for building performance simulation, showing that structured semantic metadata preserves correctness while enabling natural-language access to airflow simulation and compliance querying within a DT ecosystem. Similarly, hybrid decision support is becoming more user-facing. McGlenn et al. [84] integrate semantic rules, ANN-GA optimisation, and a 3D building interface (BuildVis) to guide facility

## ONTOLOGY-DRIVEN DIGITAL TWIN & ADVANCED INTELLIGENCE

### A layered architecture for AI – powered smart buildings

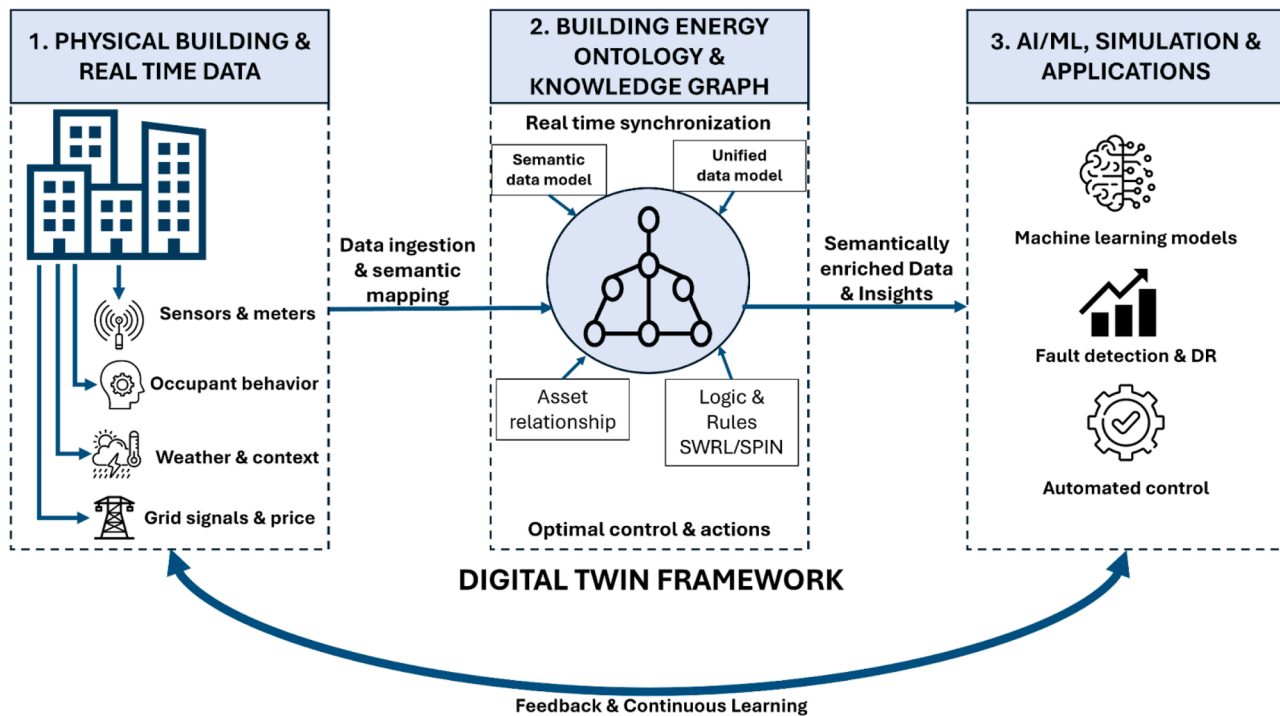


Fig. 13. Conceptual workflow linking physical building environments and real-time data with ontology-based knowledge graphs and AI/ML-driven applications.

managers through real-time energy actions. Semantic web technologies also bolster fault diagnosis and predictive maintenance. Li et al. [64] define a typical HVAC operational range in an ontology, linking occupant comfort thresholds, sensor data, and temperature limits. When anomalies arise, semantic rules interpret them as potential faults. Pruvost et al. [42] demonstrate how knowledge-based systems can recommend real-time interventions by referencing occupant or device constraints stored in the ontology. Moreover, explainability and trust in autonomous operation are receiving greater emphasis. Teixeira et al. [85] introduce a semantic rule-based framework that fuses AutoML with context-aware reasoning, ensuring decisions remain grounded in explicit occupant and system requirements while adapting in real time to evolving building states.

Interoperability continues to be fundamental for dependable DT energy analytics. Chen et al. [86] employ environment ontologies for statistical model checking in cyber-physical energy systems. Haghgoo et al. [73] present ENTIRETY, an IoT provisioning application using the SARGON ontology, which aids ML algorithms in identifying meaningful features. Complementing these efforts, Garlet et al. [87] highlight that IFC-based workflows remain prone to geometry loss and semantic inconsistencies; they identify ontology-driven rule checks and AI-assisted space classification as key enablers for robust BIM-simulation integration aligned with DT requirements.

Multi-objective optimisation frequently addresses occupant comfort, energy costs, and greenhouse gas reductions. Li et al. [53] use a semantic approach for real-time demand response in thermal grids, storing comfort thresholds as classes or properties, with ML and evolutionary algorithms managing cost or emission goals. Wu et al. [65] merge occupant data with weather inputs for local microgrid scheduling, leveraging semantic clarity for occupant constraints. Finally, large-scale and city-focused DT highlight the value of ontology-based methods. Hofmeister et al. [52] link city energy modelling with emission dispersion in The World Avatar knowledge graph, combining occupant data, building ty-

pologies, and climate factors. Corrado et al. [72] similarly fuse semantic data from multiple city domains for integrated energy planning across European sites. By translating real-time sensor updates, microgrid information, and governance inputs into a coherent ontology, these systems maintain consistent definitions of building and occupant attributes, exemplifying the robust potential of DT for holistic energy management.

## 4. Discussion

### 4.1. Limitations and challenges

The literature review reveals a array of interrelated challenges related to ontologies for energy systems. Data availability and interoperability stand out as some of the most persistent difficulties, emphasised by multiple studies that explore how heterogeneous data formats hamper the integration of innovative tools across various domains.

The integration of building-level and grid data is further complicated by the absence of common standards. Specifically, many existing ontologies are not publicly accessible, and the absence of shared vocabularies increases the effort required for semantic integration [22]. Similarly, Booshehri et al. [60] point out the difficulties brought about by siloed datasets, inconsistent terminologies, and insufficient coverage of domain concepts. Moreover, [76] and [72] note that bridging different ontological frameworks can be labour-intensive and time-consuming, especially when these frameworks evolve independently.

A second core challenge pertains to managing complex control strategies, particularly when dealing with novel automation approaches for buildings and microgrids. Anvari-Moghaddam et al. [51] raises concerns about both centralised and decentralised control architectures, suggesting that neither strategy is entirely resilient to issues related to communications overhead or network-induced delays. Similarly, Zucker et al. [63] comment on the complexity of parameterising cognitive systems in buildings, pointing to the computational burden and the

necessity of skilled experts for integration with conventional building automation systems. In [64], the difficulty of detecting faults in real time is emphasised, given that large buildings can contain countless devices and operating conditions, making it arduous to pinpoint specific root causes.

The tendency to generalise occupant behaviour in building models further complicates the issue, often resulting in suboptimal or inaccurate simulations. In Belafi et al. [40], for instance, the authors remark on the limitations of occupant behaviour models when they are applied to a wide variety of building types and climate contexts. Their observation underscores the importance of understanding local and cultural factors, as well as the requirement for incorporating social science into engineering models.

Many of these challenges are compounded by the inherent novelty and ever-evolving scope of smart energy applications. The lack of standardisation and uniform definitions for energy flexibility, for example, is singled out by [47] as a major barrier to improving building-grid integration. The absence of clear metrics or widely accepted taxonomies significantly hinders the replication and comparison of results across different projects. These complexities extend to device-level integration, with [44] highlighting the absence of consistent, widely adopted ontologies for PVs. A central concern in that study is the proliferation of distinct object classes and extensive link resolution overhead when scaling up to more complex energy systems. Schranz et al. [88] also point to interoperability issues in the FIWARE platform, showing that reliance on certain open-source configurations may inadvertently expose users to data handling challenges and unknown functional behaviours. Managing the wide variety of data from distributed energy assets, as stressed in Kyselova et al. [67], is another layer of complexity, since large volumes of data require real-time processing and high accuracy in prediction algorithms to realise the full potential of context-aware energy management. Such challenges are especially pertinent when occupant comfort and operational costs must be balanced.

Challenges related to the development of ontologies for energy-specific applications are further evidenced by works such as [57], which highlights limitations in representing function behaviours, and [73], which describes the difficulty of mapping class-based OWL structures to JSON-LD. Across these investigations, there is a recurrent mention of the shortcomings of existing modelling tools and the slow pace of adoption for advanced semantic frameworks in industrial practice. He et al. [55] highlight the shortage of domain coverage concerning energy storage systems within building ontologies, limiting the ability of designers or facilities managers to incorporate these components into an integrated environment. Similarly, [26] and [89] note that every building has its unique combination of location, equipment, and usage, resulting in laborious adaptation processes whenever new digital services or data-driven methods are introduced.

#### 4.2. Open questions and future research directions

In light of these challenges, the literature converges on several key strategies aimed at strengthening energy system design, analysis, and operation. A primary focus is on the creation, expansion, and refinement of ontologies to enhance interoperability. Studies such as [72] and [60] call for standardised vocabularies, improved documentation, and ongoing community participation. There is a drive to automate the processes of generating, validating, and updating ontologies, as reflected in Li et al. [64], where the authors propose data-driven enhancements to discover new rules for fault detection. A similar approach is followed by [58], which advocates automating causality knowledge extraction and scaling ontology-based methods to manage cascading failures in electrical grids. The overarching ambition, illustrated by [44], is to merge multiple domain ontologies into robust, all-encompassing frameworks such as the OEO.

Another research direction emphasised in the studies revolves around refining data-driven methodologies, ML techniques, and the ex-

tension of DT concepts. Akroyd et al. [48] outline how advanced scenario simulation could benefit from intelligent algorithms that align diverse system goals. In addition to this, the integration of data sources that include real-time conditions, occupant feedback, and environmental parameters is essential for creating high-fidelity building simulations [90]. By incorporating more flexible data input layers, these simulations can support predictive control and other proactive strategies. Meanwhile, [65] and [77] propose exploring semantic methods such as GeoSPARQL or temporal RDF to break down the silos between energy data and other datasets, notably in policy, climate, and market contexts.

Closely aligned with these developments is the trend towards automating and improving fault detection and diagnosis processes. For example, [64] strongly advocate linking ontological approaches with AI-based inference engines to identify the specific location of faults in real time, while [79] discusses refining integrated solutions through improved engineering tools. Other researcher efforts propose expanding knowledge bases and agent-based frameworks to encompass RES and finer-grained building usage data [54]. Additionally, more adaptive and intelligent approaches to diagnosing irregularities and managing energy services could enhance both reliability and cost-effectiveness [91].

Further research often highlights the need to address the socio-technical dimension of energy systems. For instance, Belafi et al. [40] emphasise the need for a deeper engagement with sociology and psychology to account for occupant behaviour. Similarly, Hofmeister et al. [52] consider an integrated approach by combining environmental and health impacts into a multi-objective optimisation framework for district heating networks. A similar perspective is suggested in [92], which advocates for a more efficient design process and a comprehensive suite of computational tools capable of capturing the complexity of integrated energy systems.

Developing better market mechanisms and standardised protocols is another emerging theme. For instance, [47] and [45] emphasise the necessity of improved definitions and quantification frameworks for flexibility to bridge the gap between advanced building-level control and grid interactions. The overarching objective of these works is to create transparent and economically viable pathways for both individual building owners and large utility operators, helping them meet sustainability and cost objectives.

## 5. Conclusions

This review reveals an evolving ecosystem of frameworks designed to standardise sensor data, occupant information, device semantics, and operational rules. Nevertheless, a significant research gap remains in developing comprehensive ontologies capable of robustly integrating occupant-centric modelling, time-series data, AI-based control, and multi-energy interoperability. Existing ontologies such as Brick, SAREF, SSN, and OEO address different subsets of the domain-device relationships, building descriptors, or sensor measurements, however, none comprehensively cover the full range of variables required for real-time, predictive, and occupant-responsive building operations.

A pronounced shortfall arises in harmonising occupant-related data with advanced analytics for dynamic energy flexibility. Current frameworks often treat occupant behaviour as static or loosely modelled, hindering accurate fault detection, load shifting, and distributed DR coordination. Likewise, the integration of thermal storage, RES, and emerging building technologies is still fragmented, restricting the ability of semantic systems to manage the intricate interactions involved in diverse energy assets. Moreover, fragmented data governance and a lack of consensus around key ontological entities—such as comfort thresholds, occupant profiles, and energy flexibility metrics—further aggravate interoperability challenges.

To this end, this review provides a comprehensive perspective on ontology-based building energy solutions, highlighting future research

directions: (1) the development of holistic, open ontologies that capture occupant behaviour, device constraints, and grid-level signals; (2) the extension of current schemas to include multi-energy carriers and advanced storage systems; and (3) the alignment of semantic models with AI-enabled predictive control. By clarifying these requirements and research gaps, the paper lays a foundation for researchers, practitioners, and standardisation bodies to collaborate on next-generation ontologies that underpin adaptive, scalable, and occupant-centred BES.

#### CRediT authorship contribution statement

**Adamantios Bampoulas:** Writing – review & editing, Writing – original draft, Validation, Project administration, Methodology, Formal analysis, Conceptualization; **Kaiwalya Raj:** Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Conceptualization; **Anandhi Parthiban:** Writing – original draft, Formal analysis, Conceptualization; **Mohammad Saffari:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization; **Eleni Mangina:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization.

#### Data availability

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

#### Declaration of competing interest

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

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#### Appendix A

**Table A.1**  
Summary of ontology languages/syntax, development tools, standards, and protocol/semantic tools.

Title	Ontology Developed/ Scope	Ontology Language/ Syntax	Development Tool	Ontology Standards	Protocol/ Semantic Tool
[63]	Ontology for knowledge representation in cognitive systems	OWL, RDF	Protégé	-	SPARQL
[66]	Ontology for thermal energy management	-	-	-	-
[40]	Occupant behaviour ontology (obXML)	XML	-	Functional mock-up interface (FMI)	-
[51]	Ontology-driven multi-agent EMS	-	-	-	-
[44]	PV system ontology integrated with FAIR principles	OWL	Protégé, Enterprise architect	IEC 61850, GeoJSON, SensorML	FAIR Digital Objects
[64]	Ontology for fault detection in building energy systems	OWL, RDF, RDFS	Protégé	-	-
[47]	EFOnt for energy flexibility	OWL, RDF, RDFS	Protégé	Rule interchange format	Semantic Web
[65]	Ontology for decentralised energy systems	RDF, SWRL	Protégé	W3C standards	Semantic Web, SPARQL
[68]	Interoperability ontology for energy systems	RDF, OWL	-	FIPA-ACL, SPARQL Protocol	SPARQL-Act
[57]	Energy management system ontology (EMSOnto)	-	Model-Driven Engineering Tools	IEC 61850, IEC 61499	-
[93]	IoT context ontology	-	-	-	-
[94]	Brick ontology for building management	-	-	Brick Standard	-
[88]	Minimalist ontology for district energy IoT systems	-	-	FIWARE Standards	FIWARE
[24]	Energy management ontology	-	-	-	SiMA Framework
[67]	Context-aware energy management ontology	-	-	-	-
[71]	Green smart home ontology	-	Protégé	-	UML
[52]	Dynamic knowledge graph ontology	RDF, OWL	-	-	Knowledge graph
[95]	OntoPowSys	Description Logic	-	-	TWA Framework
[54]	Multi-system semantic representation	RDF, OWL	-	W3C Standards	SPARQL
[96]	Ontology for conflict resolution	Description Logic	Model-driven engineering (MDE)	Smart grid architecture model (SGAM)	-
[73]	SARGON	RDF	Python, Flask, Docker	-	-
[46]	ExpCPS Framework	OWL	-	-	Knowledge graph algorithms
[49]	Digital transition in urban energy systems	-	-	-	-
[90]	Brick Schema	-	Modelica	ASHRAE Standard 223P	-
[97]	System ontology for building operation	-	-	BIM	-
[98]	System-agnostic model for DR interactions	OWL	TopBraid Composer	ASHRAE, BACNet, FSGIM, IEC TC57	SPARQL
[99]	Intelligent energy systems ontology (IESO)	OWL, Turtle	Protégé	OBO Foundry Principles	-
[45]	Context ontology for power equipment management	OWL	Protégé	-	-
[60]	Open energy ontology (OEO)	OWL	Protégé, GitHub	Basic formal ontology (BFO)	ROBOT
[59]	Tools control center (TOOCC) ontology	OWL	Protégé	-	SPARQL
[22]	Semantic data model for multi-agent systems	OWL, RDF	-	Foundation for intelligent physical agents (FIPA)	-
[100]	Set of ontologies for semantic interoperability	OWL	Protégé	-	-

**Table A.1**  
continued.

[101]	Case-based reasoning ontology for energy reduction	-	Protégé	-	SPARQL
[55]	Building-energy storage ontology integration (BESOI)	OWL	Protégé	Brick	Ontology matching tools
[77]	Household energy consumption ontology	RDF, RDFS, OWL	Protégé	-	Semantic web techniques
[21]	Ontology for semantic representation in smart grids	OWL, RDFS	-	-	-
[26]	Expert system ontology for building monitoring	-	-	-	-
[89]	FUSE-IT ontology for building management systems	OWL	Protégé	SSN, SAREF	-
[43]	Ontology for industrial energy systems model identification	RDF, RDFS, OWL	Protégé	-	SPARQL
[102]	E-district ontology for district energy management	RDF, OWL	Protégé	IEC 61850	Web service generator
[100]	Set of ontologies for smart grid and energy simulations	RDF, OWL	-	CIM	Multi-agent protocols
[92]	IES DT ontology	-	-	ISO standards	DT framework
[57]	EMSOnto for battery energy storage systems	Description Logics	MDE tools	IEC 61850, SGAM	Semantic reasoning
[103]	Generic model ontology for predictive control	RDF, RDFS	Cloud-based tools	-	Optimisation tools
[82]	MoOnt ontology	RDF, OWL	MoTTL transcriptor	W3C standards	-
[73]	SARGON ontology	OWL	-	SAREF (extension for energy domain)	-
[69]	Semantic services catalog ontology (SSC)	OWL-S, RDF	-	WSMO	SPARQL
[30]	Building energy ontology	OWL2, RDF	Chowlk, Protege	SAREF4ENER, SAREF4BLDG	Matching algorithms, semantic similarity -based tools
[46]	Knowledge graph for explainable CPS	-	-	-	-
[104]	Call for proposal ontology (CfP)	-	-	-	-
[48]	Dynamic knowledge graph for digital twins	Semantic Web technologies (OWL-based)	-	-	Semantic web protocols
[105]	BRICKS for building energy and security management	-	-	-	-
[42]	Semantic description for building energy systems	-	-	IFC, BOT, QUDT	Semantic web reasoning tools
[53]	Ontology for thermal grid demand management	OWL	Simulation and optimisation engine	-	-
[75]	Smart building ontology (Onto-SB)	-	Multi-agent systems (MAS) with big data tools	IFC for smart cities	Big data semantic integration tools
[50]	Ontology for building energy modeling and thermal zoning	-	BIM-to-BEM translation Tool	Industry foundation classes (IFC)	Automatic ontology translation
[78]	SAREF Ontology for building DT	-	SAREF4BLDG Framework	SAREF and SAREF4SYST standards	Semantic alignment using SAREF4SYST
[74]	Smart building ontology	RDF	-	Ontology-based knowledge representation standards	Context- awareness mechanism
[35]	Ontologies for energy efficiency decision support systems	RDF	-	Linked data standards	Knowledge graphs, SPARQL
[23]	Ontology for building automation systems (BAS)	OWL	Protégé	W3C standards for OWL	Data analytics framework with descriptive, predictive, and prescriptive analytics

**Table A.1**  
continued.

[60]	Open energy ontology (OEO)	OWL	Protégé	W3C standards for OWL	Ontology-driven energy systems analysis
[106]	Holonic energy system ontology for domestic flexibility markets	OWL	-	CIM, OpenADR, Energy@home	-
[86]	Environment ontology for CPES	OWL	-	-	UPPAL-SMC
[107]	Domo OWL ontology	OWL	Custom rule-editing environment (INTELLEMRules)	SWRL	INTELLEM
[70]	Ontology for integrated energy systems dispatch	FIPA-ACL	-	-	Multi-agent system
[108]	Ontology for renewable energy multi-source systems	-	Protégé	-	-
[56]	Ontology for stakeholder-focused urban energy planning	OWL	-	-	SPARQL
[109]	Ontology for solar hot water system optimisation	OWL, RDF	Protégé	-	SPARQL
[76]	Ontology for smart grid and building energy management	OWL, RDF	Protégé	-	Semantic Web
[91]	Domo OWL ontology	OWL	IntelliDomo	SWRL	-
[110]	Smart home energy ontology	RDF, OWL	Semantic extension of UPnP	-	Semantic extensions of UPnP
[111]	Multi-agent building automation ontology	-	-	-	-
[112]	Energy efficiency ontology	-	LinkSmart Middleware	-	LinkSmart Middleware
[72]	SEMANCO Ontology	OWL	OWL/DL- LiteA	SO/IEC FDIS 13273:2014, EN ISO 13790, EN 15316, FprEN 15603, ANSI/ASHRAE/ IESNA Standard 90.1, CEN/TR 15615, ISO/TR 16344, ISO 17742, TABULA, DATAMINE	Semantic energy information framework (SEIF)
[41]	BRICKS for building energy management	-	-	-	-
[87]	Ontology-supported IFC-based interoperability for BIM-BEPS	OWL, RDF	IFC-based frameworks, ML	IFC4, W3C	SHACL validation, ontology frameworks
[83]	GPT-driven ontology for BPS workflows	OWL, RDF	GPT, CONTAM	BIM-BPS standards	GPT interface, semantic reasoning
[80]	Ontology for DT calibration via AI agents	OWL, RDF	AI multi-agent, BIM	IFC, ISO 16739	AI communication, ontology mapping
[81]	Multi-agent ontology for DT modelling	OWL	BIM-based agent framework	IFC, ASHRAE 223P	Agent-based reasoning
[85]	Ontology- driven rule framework for energy management	OWL, SWRL	Protégé, JESS	W3C, FIPA-ACL	SPARQL, reasoning/ inference
[84]	Ontology- enabled web-based BIM system	RDF, OWL	Web-based platform, Protégé	IFC, ISO 16739	Semantic web APIs, ontology alignment

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