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Review

Knowledge Graphs' Ontologies and Applications for Energy Efficiency in Buildings: A Review

Filippos Lygerakis, Nikos Kampelis and Dionysia Kolokotsa *

Energy Management in the Built Environment Research Lab, Environmental Engineering School, Technical University of Crete, Technical University Campus, Kounoupidiana, GR 73100 Chania, Greece
* Correspondence: dkolokotsa@tuc.gr

Abstract: The Architecture, Engineering and Construction (AEC) industry has been utilizing Decision Support Systems (DSSs) for a long time to support energy efficiency improvements in the different phases of a building's life cycle. In this context, there has been a need for a proper means of exchanging and managing of different kinds of data (e.g., geospatial data, sensor data, 2D/3D models data, material data, schedules, regulatory, financial data) by different kinds of stakeholders and end users, i.e., planners, architects, engineers, property owners and managers. DSSs are used to support various processes inherent in the various building life cycle phases including planning, design, construction, operation and maintenance, retrofitting and demolishing. Such tools are in some cases based on established technologies such Building Information Models, Big Data analysis and other more advanced approaches, including Internet of Things applications and semantic web technologies. In this framework, semantic web technologies form the basis of a new technological paradigm, known as the knowledge graphs (KG), which is a powerful technique concerning the structured semantic representation of the elements of a building and their relationships, offering significant benefits for data exploitation in creating new knowledge. In this paper, a review of the main ontologies and applications that support the development of DSSs and decision making in the different phases of a building's life cycle is conducted. Our aim is to present a thorough analysis of the state of the art and advancements in the field, to explore key constituents and methodologies, to highlight critical aspects and characteristics, to elaborate on critical thinking and considerations, and to evaluate potential impact of KG applications towards the decision-making processes associated with the energy transition in the built environment.

Keywords: knowledge graphs; Decision Support System; semantic web; ontologies; energy efficiency; buildings

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1. Introduction

During the past decades, the Architecture, Engineering and Construction (AEC) industry has seen the utilization of digital tools for planning, designing, constructing/deconstructing, operating, maintaining and recycling buildings. These tools, which are often categorized under the generic term Decision Support Systems (DSSs), aim to help stakeholders and professionals alike to collaborate in a timely, effective and co-creative manner to avoid future issues and ensure the success of a building's energy targets [1]. In this respect, and given the present and foreseeable state of the climate crisis, the building sector is defined as being critical for the implementation and adoption of climate mitigation and energy transition measures towards the statutory framework and targets set by policy initiatives and instruments worldwide, such as the Paris Agreement and the UN SDGs [2,3]. Research in this field is constantly expanding and constitutes a vast number of applications capturing different environmental conditions and needs, case studies, technologies, methodologies, optimization targets and criteria, problem solving methods and algorithms, etc.

The main role of the DSSs is to increase efficiency and identify optimum solutions by assisting all life cycle stages [4]. This also applies when renovating existing buildings. DSSs aim to assist stakeholders to select the optimum steps, to target the best energy efficiency in a building, while taking into consideration factors such as Indoor Environmental Quality, intervention costs and the environmental impact of the construction as a whole. In order to improve the energy efficiency in a building, it is argued that there are offline and online approaches [5]. The first, the offline approach, includes discrete decision problem approaches, such as simulation-based, multi-criteria decision analysis (MCDA) and multi-objective programming (MOP) approaches. This approach targets measures such as components, materials and equipment integration, to improve energy and environmental performance, and is applied during the design or retrofit phase. One important DSS tool that is included in the offline approach is Life Cycle Analysis (LCA). LCA is used in buildings to calculate the main environmental impact of the building's components and operational energy. Simple LCA methodologies are used to support decision-making processes for building management, comparing resource efficiency for more sustainable production selection and minimization of costs and GHG emissions [6–8]. The second, the online approach, includes automation and control, and decision support. This approach utilizes real-time data to interact with setpoints, and energy management and control strategies to maximize the energy efficiency of a building during the operational phase [5]. To support the decision-making process for energy efficiency improvement, many algorithms are used for advanced control architectures, data-mining techniques and optimization processes [9]. These algorithms include artificial neural networks (ANNs), fuzzy logic (FL) modeling and evolutionary algorithms (EAs) [10,11]. ANNs imitate the human brain and, during the training process, adjust different weights to the various neurons, thus reducing the potential error. FL optimization is undertaken based on human experience. There, some rules are set and the main characteristic of FL is that there is an apportioning of the system into regions, in order to imitate the decision-making process [12]. EAs are direct parallel search techniques, which utilize greedy creation in order to decide their next steps. They are also known for their prevention of mis-convergence through built-in safeguards [13].

The main decision support tools in the AEC industry concerning buildings include BIM, Big Data analysis, IoT and semantic web technologies [4]. The utilization of digital tools is led by the need for data management, analysis and knowledge extraction in various fields [14]. Information and Communication Technologies (ICTs) drive the example of knowledge extraction from Big Data analysis in the AEC industry, where different fields exist [4]. Furthermore, the Internet of Things (IoT) also relies on information stored in BIM. The development of semantic web technologies combined with the support provided by Big Data infrastructure is leading to the semantic advance of IoT data and BIM data exchange, in addition to cloud-based analysis and storage [4].

Building Information Models (BIMs) are digital models of a built structure that use various technologies for data collection. These were first introduced in the 1970s and in the last decades have greatly influenced the AEC industry [15–18]. The National Building Information Model Standard (NBIMS) defines BIMs as a "digital representation of physical and functional characteristics of a facility. As such it serves as a shared knowledge resource for information about a facility forming a reliable basis for decisions during its life-cycle from inception onward" [19]. BIM supports data storage, management of information in a specific model, and different data exchanges between different users and different tools such as Industry Foundation Classes (IFCs) and green building XML (gbXML) [20–22]. The concept of BIM has as its main principle the continuous use of digital information throughout the life cycle of a built structure [18]. Moreover, BIM provides an effective tool for data sharing and exchange amongst various collaborating stakeholders, surpassing the document-centric method that was previously used. In addition, BIM is capable of modeling Building Automated System (BAS) devices and functions, as well as upgrading the semantic interoperability by integrating a common information model [20]. BIM is used for FM, as it is an advancement in commissioning and the operational phases of a building [23,24]. Facility managers can use BIM in operational and maintenance phases, which is an improvement from unstructured information exchange, which can result in information loss [17]. Another use of BIM is that it can be used to integrate domain knowledge and specific methodologies for intelligent applications based on automation [25]. Many data platforms have been created based on BIM systems to help the AEC industry access these more organized data [26]. Furthermore, studies have shown that data coming from several BIM models can be integrated and fully utilized when combined with semantic technologies [27]. Furthermore, it is suggested that BIM can be used in ontology-based data management and sharing [28]. Moreover, the combination of different knowledge domains and reasoning with BIM can result in a knowledge graph.

The digital twins' concept is similar to BIM, as it represents the physical structures of a building in a digital copy, but the IoT application in the former separates it from the latter. These differences between BIM and DT are also noted in a previous publication, where they are categorized based on application focus, users, supporting technology, software, stages of the life cycle and origin [29]. Data coming from sensors installed in buildings provide up-to-date information, based on the technology of the Internet of Things (IoT), which are then used to create a virtual representation of the building called a Digital Twin (DT) [30,31]. BIM is used in most cases to avoid errors during the design phase of a building, provide better communication between stakeholders, enhance construction efficiency and follow the construction's time and cost plan [32]. A DT is used to provide predictions in the maintenance phase, enhance resource efficiency, improve occupants' comfort, optimize the design of the building and communicate learnings from the building to a future one [33,34]. Moreover, the BIM's users are architects, engineers and constructors in the design and construction phase, and facility managers during the maintenance planning, and the BIM can hold useful information for the demolition processes [35–37]. DTs are mostly used by facility managers in the operational phase of the building to provide useful information to architects by pinpointing issues of the current building and avoiding them in the next one. However, more features have been explored lately.

Overall, such tools create a vast amount of data, either from procedures of planning, design, construction, operation, maintenance and destruction/recycling of buildings, or from sensors installed in the building, which are exchanged in various ways between the stakeholders and aim to improve the energy efficiency of the building [17,38,39]. One challenge related to the use of these tools is that a vast amount of different types of data, which cannot be easily traded and handled, are used for knowledge extraction by stakeholders of different backgrounds [30]. Incompatible software and proprietary information between the stakeholders are also some reasons for this issue [30]. The different types of data relate to geolocation data, 2D/3D models, plans, semantic data, system data, material data, sensor data, etc. Stakeholders vary through the different phases of a building's life cycle and can include architects, engineers, construction teams, facility managers, occupants, policymakers and governance.

The use of the semantic web, based on knowledge graphs and linked data, has been proposed and studied to support data exchange and multi-stakeholder decision-making challenges, and to achieve an improved level of communication and coordination [40]. Ontologies are at the core of semantic web design, and are characterized as formal, due to their ability to be read by machines and their explicit nature and interoperability [41].

This section briefly introduced the field's main issues and current situation. Section 2 provides information about the knowledge graphs and their connection with the DTs, in addition to the adoption of semantic web technologies and KGs to solve the stated data problem. Next, in Section 3, the methodology of this review paper is described. In Section 4, the existing ontologies for buildings are presented and, in Section 5, some of their applications are introduced. Section 6 presents a discussion based on the findings and, in Section 7, the conclusions of this paper are presented. In Appendix, Table A1 contains all the abbreviations that are mentioned in this review.

2. Knowledge Graphs

2.1. Definition

Knowledge graphs are still evolving today, yet many different attempts have been made to provide thorough and concise definitions [42,43]. According to a commonly used definition, a knowledge graph acquires and integrates information into an ontology and applies a reasoner to derive new knowledge [42]. This definition was given after research was conducted, in order to produce a working definition based on examples. As noted by Ehrlinger and Wolfram, considering that there are many diverse applications, a KG is more likely to be similar to an abstract framework than to a mathematical structure [42]. Another approach is that a knowledge graph describes real-world entities and their interrelations, organized in a graph. It does so by defining possible classes and relations of entities in a schema. In addition, it allows for other potentially interrelating arbitrary entities connection with each other, and covers various topical domains [44]. Similarly, a KG can be viewed as a graph of data intended to accumulate and convey knowledge of the real world, whose nodes represent entities of interest and whose edges represent relations between these entities [45]. Knowledge graphs were first introduced in 1973; however, they were not used in a useful way until 2012, when Google announced its KG, which was the starting point for many other companies to introduce their own [46,47]. Many applications have been developed since then and many papers have been published, all aiming at the core idea, which is to represent data using graphs in a manner to represent knowledge [48]. Graphs, contrary to a relational model or NoSQL approaches, are more coherent and direct, using edges to represent the relations between entities, and apply to various domains [45,49]. A further aspect of a graph is that it provides the creator with the ability to delay the definition of its schema. In this way, the graph is more flexible to evolve and obtain more incomplete knowledge, resulting in a continuously updated database schema, or serving under an organization or a community as an ever-evolving shared form of knowledge [48,50].

2.2. Data Graphs

One of the first principles of a KG is the graph abstraction to data. Graphs are able to create primary data graphs, be represented by data models and be processed by query languages. Modeling a graph differs in every situation, although some graph data models can be adapted and customized. For example, a directed edge-labeled graph is compiled from a set of nodes and a set of directed labeled edges that connect these nodes [51,52]. In KGs, nodes stand for entities and edges stand for the binary relations between them. This way of modeling a graph is more appropriate when adding new sources of data. The Resource Description Framework (RDF) is a model based on directed edge-labeled graphs and uses a variety of nodes [53,54]. The most important nodes are the Internationalized Resource Identifiers (IRIs), which give access to entities through the Web. Other important nodes are literals, which represent strings and other datatype values. Finally, blank nodes are used in RDF graphs, which are anonymous nodes that are not assigned an identifier. In addition to literals, Uniform Resource Identifiers (URIs) can be used to uniquely identify all nodes and edges in a graph [55]. The simplicity of an RDF is based on the triplets it consists of, which are three-part statements that represent a relationship of subject, predicate and object (Figure 1) [56].

When querying a graph, many languages have been introduced, including SPARQL for RDF graphs [57]. Graph patterns are stationed at the center of a query language, which uses the same models as the data graph that is being queried [58]. Furthermore, graph patterns also add variables as terms, which are divided into constants [58]. Next, mappings are generated from the variables and constants of the data graph; thus, the graph pattern is included in the data graph. Moreover, since a graph pattern exports a table of results, and due to the need for relational algebra to work with these tables, more complex queries are being created [58]. Another aspect of graph query languages is that navigational graph patterns add path expressions in queries. This allows the matching of arbitrary length paths between two nodes, which are expressed as a regular path and are used in graph patterns to express navigational graph patterns [58].

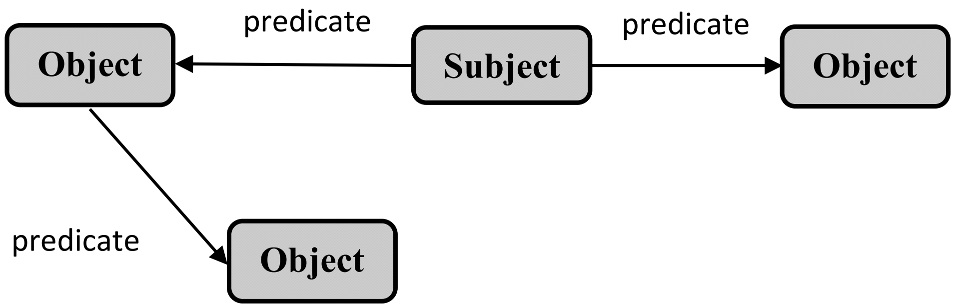

Figure 1. Structure of an RDF graph.

2.3. Deductive Knowledge

A KG can be identified as a data graph enhanced with representations of schema, identity, context, ontologies and rules [45]. Schemata are used to mark the structure and semantics that a KG will be based on. However, it has been mentioned that the definition of a schema can be delayed even after the KG's configuration [45]. One type of graph schemata is the semantic. Semantic schemata are used as a vocabulary for understanding terms used in a KG, while using these terms for reasoning the KG [45]. RDF Schema (RDFS) is an example of a semantic schema, which introduces subclasses, sub-properties, domains and ranges for the classes and properties in an RDF graph [59]. Many more details and content about the semantics of KG terms is provided by the Web Ontology Language (OWL) standard for RDF graphs [60]. Contrary to semantic schemata, validating schemata certify existing graph data, using shapes. Shapes are responsible for targeting a set of nodes in a data graph and identifying their constraints [61,62]. Both types of schemata need a domain expert to identify definitions and constraints. However, in a data graph, latent structures can be exported as an emergent schema. An emergent schema uses graphs as frameworks to separate quotient groups of nodes, while maintaining some structural properties of the graph [63,64].

It is necessary to know the meaning of the terms that are used in order to apply entailment. This is achieved using ontologies, which provide a formal depiction of the meaning of the terms. A common definition of ontologies also states that an ontology is a "formal, explicit specification of a shared conceptualization" [41]. Web Ontology Language (OWL) is recommended by the W3C and is compatible with RDF graphs [45,60]. In the process of interpretation, the data graph is changed to a domain graph. There, real-world entities and real-world connections are included and connected with the nodes and edges of the data graph, in addition to those of the domain graph, thus following the same model as the data graph [45]. Linking particular patterns in the data graph with semantic conditions results in the features of an ontology language [45]. These features result in entailments. Each axiom that is introduced from an ontology imposes some conditions on the interpretation of the graph that satisfies it, which are called graph models. One graph entails another if and only if the first is also a model of the last one or alternatively the former graph entails the latter [45]. In this context, there is not an algorithm that can decide the correct true/false answer to the question of which graph entails the other [65]. Another approach is to always halt false with the correct answer, only receiving input ontologies with specific features, and the final approach is to only reply with correct answers for any input ontology, risking never halting on some inputs [66].

2.4. Inductive Knowledge

In contrast to deductive knowledge, which follows specific logical consequences, inductive knowledge is based on generalized patterns from input observations, which are used to produce new but vague predictions. An overview of popular inductive techniques is shown in Figure 2.

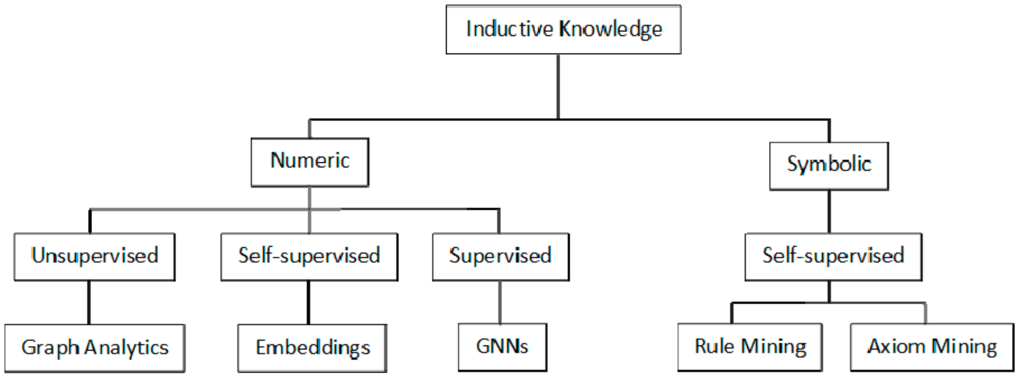

Figure 2. Conceptual overview of popular inductive techniques for knowledge.

Analytics are based on discovering, interpreting, and communicating important patterns innate to data collections. So, graph analytics are the use of analytical processes to graph data [45]. Graphs apply specific types of analytics that result in a deduction, where nodes and edges are based on the topology of the graph and gain their techniques from graph theory and network analytics [67].

Machine learning, which has made a significant amount of progress in the past few years, can be used to directly refine a KG [68]. The aim of KG embedding methods is to condense the graph in a continuous, low-dimensional vector space, where machine learning tasks can be embedded, making it possible for embeddings to execute some low-level tasks around nodes and edges [45].

Another method is to compile a custom machine learning model modified for graph-structured data, with the majority of them depending on artificial neural networks [69]. A graph neural network (GNN) compiles a neural network depending on the topology of a data graph, and is even capable of replacing algorithms [70–72].

A different method is to use symbolic learning to gain knowledge about hypotheses in a symbolic language that clarifies some positive and negative edges. These nodes are automatically produced from the KG, and the hypotheses are then used as interpretable models, capable of additional reasoning [45].

2.5. Knowledge Graphs and Digital Twins

The issue established in Section 1 referred to the need for sustainable data management and an exchange technology for buildings. DTs, described in Section 1, play the role of DSS for buildings and can integrate knowledge graphs to solve this problem. This integration is argued to be the border between the physical and cyber layers of a DT-KG architecture [73]. The connection between these two layers is the runtime data and the environmental parameters that are fed from the physical to the cyber layer. Both internal and external system parameters must be taken into consideration in such an architecture in order to either adjust them automatically, or act like a DSS and be adjusted by the user. A service interface is suggested to be used in order to access the digital models, which are synchronized with the data from the physical asset and hold a Digital Twin- Physical Asset (PA) Awareness module, which enables the ongoing parameter changes.

Furthermore, a metamodel such as an ontology is an important part of the DT-KG architecture. An ontology in such a structure establishes the static and dynamic relationships between entities, and connects them to their respective data, accessed by the physical asset. Thus, this ontology can be used to create the knowledge graph and run it with the DTs' digital data and models [73]. A proposed adoption of KGs in DTs consists of internal linking and referencing, knowledge completion, error detection, collective reasoning and semantic query, which is also supported by other papers [45,73]. After establishing the background of why KGs are important and their role in DTs and buildings, in the next section some of the most prominent ontologies based on buildings are presented, with the most important ones being explored further.

3. Methodology

The data exchange and management issue that was discussed in Section 1 is depicted in Figure 3 and functions as an overview of the work undertaken in this paper. This issue occurs among various stakeholders through the different life cycle stages of a building in the AEC industry and is proposed to be tackled with the use of DSS. The methodology that was followed is depicted in Figure 4. The different ontologies used in buildings and their applications are reviewed in this paper and categorized into design and related operational phases. The ontologies linked to the operational phase can be further classified as smart building-oriented, occupant behavior-centric, and asset management-related. The most prominent ontologies are further explored and categorized as being associated with IFC, W3C, smart buildings and occupant behavior. Next, applications are examined based on their focus on building performance improvement and facility management. Finally, conclusions are drawn based on the advantages and disadvantages of the reviewed ontology and applications. The limitations of this study and prospects are also discussed.

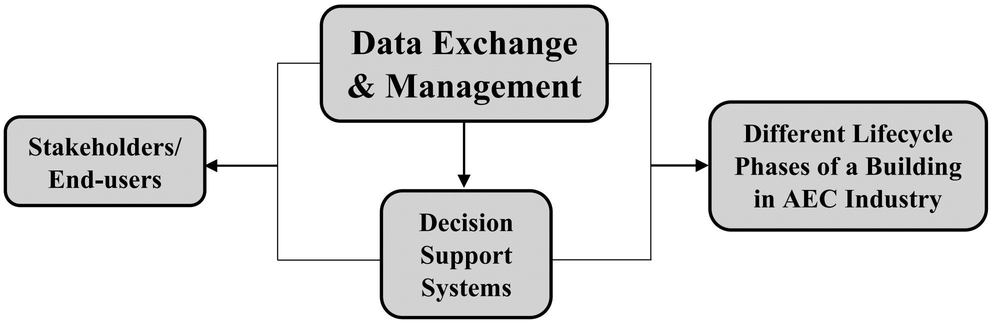

Figure 3. Data exchange and management in buildings.

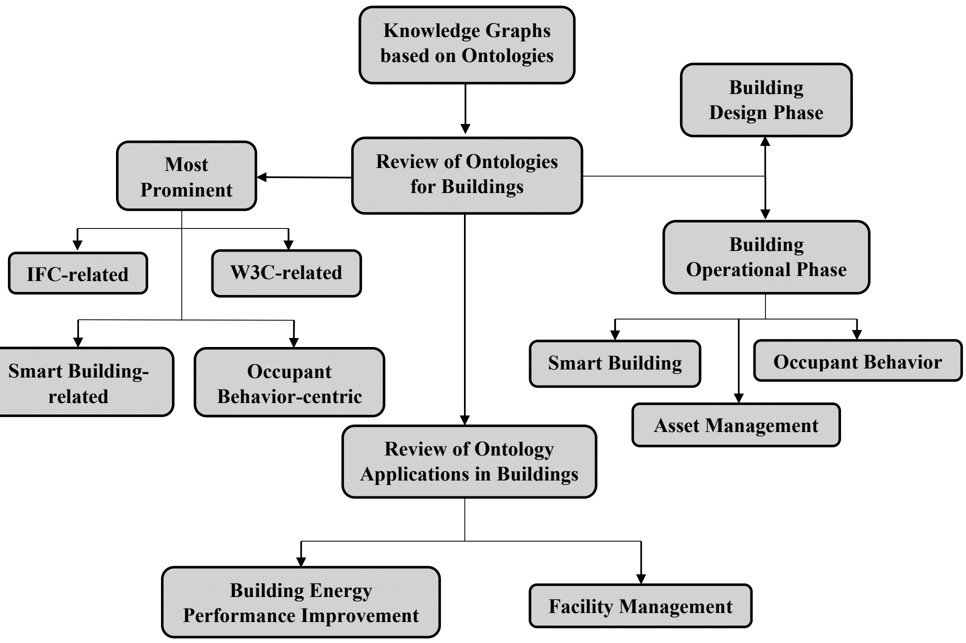

Figure 4. Methodology schema followed for the review.

4. Existing Ontologies for Buildings

In this section, the most important ontologies for buildings are introduced and categorized, according to the phase they refer to, i.e., design or operational. An in-depth analysis of some of these key ontologies is conducted as it is necessary for the objectives of the review.

4.1. Ontologies in Building Design Phase

One of the most important tools, if not the most important, that is used as a base for many ontologies is the IFC schema, which has been combined in an approach with OWL, creating the ifcOWL ontology [74,75]. ifcOWL ontology's complexion has driven the introduction of SimpleBIM, which is a much more simplified but powerful ontology [76]. These initial ontologies are further discussed in Section 4.3.1. Another ontology is Green Building XML (gbXML), for which the main scope is the information exchange between BIM and AEC analysis software [22]. With streamlining, gbXML transfers BIMs from and to AEC models, aiming to design sustainable and energy-efficient buildings [22]. Another is Tubes, which supports a high-level description of building service systems and utilizes data principles to extract their topology from IFC models [77]. Two more ontologies are SimModel Ontology and EnergyADE, which focus on exchanging energy simulation data and are an extension to CityGML [78–80].

4.2. Ontologies on Building Operational Phase

An ontology that focuses on sensor networks is Semantic Sensor Network/Sensor, Observation, Sample, and Actuator (SSN/SOSA), which is not only specific to building sensors [81]. Other ontologies, such as Web of Things Model (WoT), oneM2M BaseOntology's and One Data Model (OneDM), focus on the representation of IoT objects [82–84]. WoT is a model used to describe the virtual counterpart of physical objects in the Web of Things; oneM2M BaseOntology provides syntactic and semantic interoperability between oneM2M and external systems; and OneDM is a model used to support a common language for the Internet of Things. More ontologies that focus on smart buildings are Smart Energy Aware Systems (SEAS), ThinkHome, Building Ontology for Ambient Intelligence (BOnSAI), DogOnt, Ontology of Smart Building (SBOnto) and Smart Applications REFerence (SAREF) [85–90]. SEAS ontology represents entities in a smart building. ThinkHome is an ontology that includes concepts needed to realize energy-efficient and intelligent control mechanisms. BOnSAI is a smart building ontology for ambient intelligence, whereas DogOnt is a model for all devices being part of IoT inside a smart environment. SBOnto is a smart building ontology and SAREF matches existing assets in the smart application domain. SAREF ontology has many extensions that differentiate the classifications and concepts, which are able to be used together for a more specific approach. These extensions include SAREF4BLDG, a building domain extension. SAREF4ENER, an energy domain extension, SAREF4CITY, a smart cities domain extension, SAREF4ENVI, an environment domain extension, SAREF4INMA, an industry and manufacturing domain extension, SAREF4AGRI, a smart agriculture and food chain domain extension, SAREF4AUTO, an automotive domain extension, SAREF4EHAW, an e-health/ageing-well domain extension, SAREF4WEAR, a wearables domain extension, SAREF4WATR, a water domain extension, and SAREF4LIFT, a smart lift domain extension [90].

Next, some ontologies have building automation and monitoring as the center of their attention. These ontologies are Project Haystack 3, BASont, Project Haystack 4, HTO, Brick Schema, Google Digital Building Ontology, Semantic BMS ontology (SBMS), CTRLont and Green Button [91–99]:

- Project Haystack 3 and 4 focus on the representation of buildings entities and concepts utilizing tagsets.
- BASont focuses on building automation and monitoring.
- HTO focuses on streamlining data from IoT based on Project Haystack.

- Brick focuses on metadata and data points from building advancement and needs to be based on end-use applications.
- GDBO represents structured information about buildings and building-installed equipment.
- SBMS is a BAS-protocol-independent model of intelligent building systems, and CTRLont is a model of control logic in BAS.

Another ontology that falls in the same category is that proposed by E. Meshkova, which has as its scope the representation of relations between devices and services regarding home automation [100]. Other ontologies have a broader perspective, such as RealEstateCore (REC), Building Topology Ontology (BOT), Building Automation and Control Systems (BACS), Knowledge Model for City (KM4City) and EM-KPI Ontology [101–105]. REC focuses on usage analysis and optimization and presence analysis of a building structure; BOT focuses on the representation of physical and conceptual objects of a building and the connections between them; BACS supports the modeling control behavior in a BAS, physical devices of a BAS, and their location in the building and connection to technical equipment and appliances; KM4City is a representation model for a city and mobility; and EM-KPI focuses on the enhancement of energy management at district and building levels.

Furthermore, other ontologies target their scope towards grid-interactive efficient building applications. These ontologies are Facility Smart Grid Information Model and RESPOND [106,107]. FSGIM is an abstract information model representing a Smart Grid's perspective of a facility. RESPOND reuses BOT, SAREF and SEAS ontologies to create its ontology. Its main scope is to manage the dispatch of real-time optimal energy, considering both supply and demand, while considering all energy assets on-site [107].

Moreover, some ontologies concentrate on occupants' behavior, such as DNAs Framework (obXML), Occupancy Profile (OP) Ontology, Onto-SB and OnCom [108–111]. DNAs Framework explains that, in order to describe the impact of the behavior of occupants on energy use in building, there has to be four core components i.e., drivers, needs, actions and systems. These components interact with the outside world and the inside world as human beings [112]. Onto-SB is a human profile ontology for energy efficiency in smart buildings, OP ontology is a semantic model for occupancy profile, and OnCom is an ontology for occupant thermal comfort and energy efficiency optimization.

Finally, ontologies that emphasize asset management and audits are Building Energy Data Exchange Specification (BEDES), Virtual Buildings Information System (VBIS) and Ontology of Property Management (OPM) [113–115].

All the ontologies are gathered in Table 1, and the most prominent are discussed in Section 4.3.

Table 1. Reviewed ontologies for buildings.

Category	Name	Scope/Description	Year	Ref.
Building Design Phase	Industry Foundation Classes (IFC)	Gives spatial and other properties to every building entity	2013	[21]
	ifcOWL	Descriptive OWL representation of IFC schema	2016	[75]
	simpleBIM	Simplified version of ifcOWL	2017	[116]
	Green Building XML (gbXML)	Information exchange between BIM and Models	2000	[21]
	Tubes	High-level description of building service systems	2020	[77]
	SimModel Ontology	Exchange of energy simulation data	2014	[78]
	EnergyADE	Exchange of energy simulation data	2014	[79]

Table 1. *Cont.*

Category	Name	Scope/Description	Year	Ref.
Smart Buildings	Semantic Sensor Network/Sensor, Observation, Sample, and Actuator (SSN/SOSA)	Focuses on sensors in buildings	2011	[81]
	Web Thing Model (WoT)	Model to describe the virtual counterpart of physical objects in the Web of Things	2015	[82]
	oneM2M BaseOntology's	Provide syntactic and semantic interoperability between oneM2M and external systems	2016	[83]
	One Data Model (OneDM)	Model to support a common language for the Internet of Things	2018	[84]
	Smart Energy Aware Systems		2016	[85]
	ThinkHome	Ontology that includes concepts needed to realize energy efficient and intelligent control mechanisms	2011	[86]
	Building Ontology for Ambient Intelligence (BOnSAI)	A smart building ontology for ambient intelligence	2012	[87]
	DogOnt	Model for all devices being part of IoT inside a smart environment	2008	[88]
	Ontology of Smart Building (SBOnto)	Smart Building Ontology	2017	[89]
	Smart Applications REFerence (SAREF)	Matches existing assets in the smart applications domain	2014	[90]
	Project Haystack 3	Hierarchical representation of buildings entities and concepts utilizing tagsets	2014	[91]
	BASont	Building Automation and Monitoring	2012	[92]
	Project Haystack 4	Hierarchical representation of buildings entities and concepts utilizing tagsets	2019	[93]
	Haystack Tagging Ontology (HTO)	Streamlining Data from IoT based on Project Haystack	2016	[94]
	Brick Schema	Metadata and data points from building advancement and needs based on end-use applications	2016	[95]
	Google Digital Building Ontology	Represent structured information about buildings and building-installed equipment	2020	[96]
	Semantic BMS ontology (SBMS)	BAS-protocol-independent model of intelligent building systems	2016	[97]
	CTRLont	Model of Control Logic in Building Automation Systems	2017	[99]
	Green Button	Building Automation and Monitoring	2011	[98]
	RealEstateCore (REC)	Usage analysis and optimization and presence analysis of a building structure	2017	[101]
	Building Topology Ontology (BOT)	Representation of physical and conceptual objects of a building and the connections between them	2019	[102]
	Building Automation and Control Systems (BACS)	Supports the modeling control behavior in a BAS, physical devices of BAS and their location in the building and connection to technical equipment and appliances	2017	[103]
	Knowledge Model for City (KM4City)	Representation model for city and mobility	2014	[104]
	EM-KPI Ontology	Enhance energy management at district and building levels	2017	[105]
	Facility Smart Grid Information Model	An abstract information model of what the Smart Grid looks like from the perspective of a facility	2014	[106]
	RESPOND	Manage real-time optimal energy dispatching, considering all energy assets on site	2020	[107]

Table 1. *Cont.*

Category	Name	Scope/Description	Year	Ref.
Occupant Behavior -Centric	DNAs Framework (obXML)	Represent the impact of the behavior of occupants on the building's energy efficiency	2015	[112]
	Occupancy Profile (OP) Ontology	Semantic model for occupancy profile	2020	[109]
	Onto-SB	Human Profile Ontology for Energy Efficiency in Smart Building	2018	[110]
	OnCom	Occupant Thermal Comfort Optimization	2019	[111]
Audits and Assets Management	Building Energy Data Exchange Specification (BEDES)	Data information gathering and storing based on building's systems	2014	[113]
	Virtual Buildings Information System (VBIS)	Classifies and connects asset data sources and systems	2020	[114]
	Ontology of Property Management (OPM)	Vocabulary for modeling complex assets in a building design environment	2018	[115]

4.3. Prominent Ontologies for Buildings

4.3.1. Industry Foundation Classes (IFC) Related Ontologies

To every entity, an IFC schema gives spatial properties, and various other properties that are classified. ifcOWL is a complex ontology language, which is a translation from the IFC schema through the EXPRESS data modeling language into an OWL representation [21,75]. The complexity is shown as a property set that assigns the properties using relational nodes. Two intermediate nodes are needed to insert the name and the value of the property. The EXPRESS datatype is used to express literals. SimpleBIM is an attempt to simplify this ifcOWL as it uses the most straightforward approach. Figure 5 shows the difference between them, as they represent the same entities. SimpleBIM also uses the Turtle serialization format for RDF data models [76].

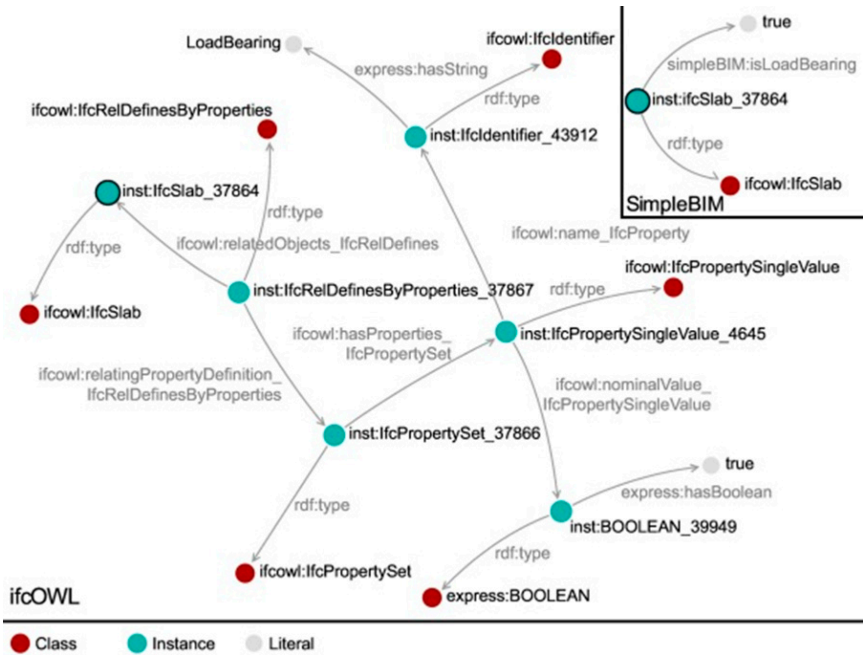

Figure 5. Visual complexity comparison of representing property assignment using ifcOWL and simpleBIM [74] (Reprinted from Elsevier Automation in Construction, Volume 108/December 2019, 102956, Mads Holten Rasmussen, Maxime Lefrançois, Pieter Pauwels, Christian Anker Hviida Jan Karlshøj, "Managing interrelated project information in AEC Knowledge Graphs", Pages No. 4 and 13, Copyright (2019), with permission from Elsevier [OR APPLICABLESOCIETY COPYRIGHT OWNER]).

4.3.2. World Wide Web Consortium (W3C) Related Ontologies and Extensions

Due to IFC's extensive use, a less complex, extensible and modular ontology was required, and hence the World Wide Web Consortium (W3C) Linked Building Data (LBD) community group was first created in order to provide solutions for these needs [117].

The main solution was Building Topology Ontology (BOT), introduced by Rasmussen in 2016. It constitutes a simple ontology based on the topology of a building and its physical and conceptual objects and the connections between them [118]. For this to happen, BOT sets some rules that subdivide the building into stories and spaces. Spaces are bound by building elements and spaces can contain building elements. It is an ontology that focuses on the building as a structure and does not cover the needs of the whole AEC domain, but can be used as a central ontology to link others [118]. As a result, BOT is a simple base ontology for building structures that can be easily connected with other ontologies to add more information, making the procedure more customizable and malleable in different situations. Having BOT as their core, many extensions to this ontology have been developed. Examples include domain ontology for building elements (BEO) and distribution elements (MEP); ontologies for damage monitoring of buildings and built structures (DOT); ontology for bridges (BrOT); a flow systems ontology (FSO); an ontology for building products (BPO); an ontology for geometry formats (FOG); an ontology for managing properties (OPM); and an ontology for managing geometry (OMG) [115,119–125]. Moreover, extension ontologies such as QUDT, SSN/SOSA, O&M and time can be combined with BOT, enabling adaptation to specific needs [81,126–128].

Ontology for Property Management (OPM), which is of great interest among the rest of the extensions, offers the vocabulary for modeling complex entities in a design environment, and was proposed by Rasmussen in 2018 [74,129]. These entities are defined as complex because they can alter through time. Their reliability can be based on assumptions and on other entities that can also change, causing an effect on them. OPM uses SEAS, schema.org and PROV-O ontologies as extensions, and can work alongside BOT, PROPS and PRODUCT ontologies of the W3C LBD Community Group [130]. To test OPM, a case study was developed to calculate the heating demand in a building through the ontology (Figure 6) [74]. An OPM-REST application on the AEC-KG was then developed as a generic approach [74]. The case study showed that OPM is a different way of working with building data and paves the way to access and utilize BIM models, exchanging information between stakeholders using the same tool [74].

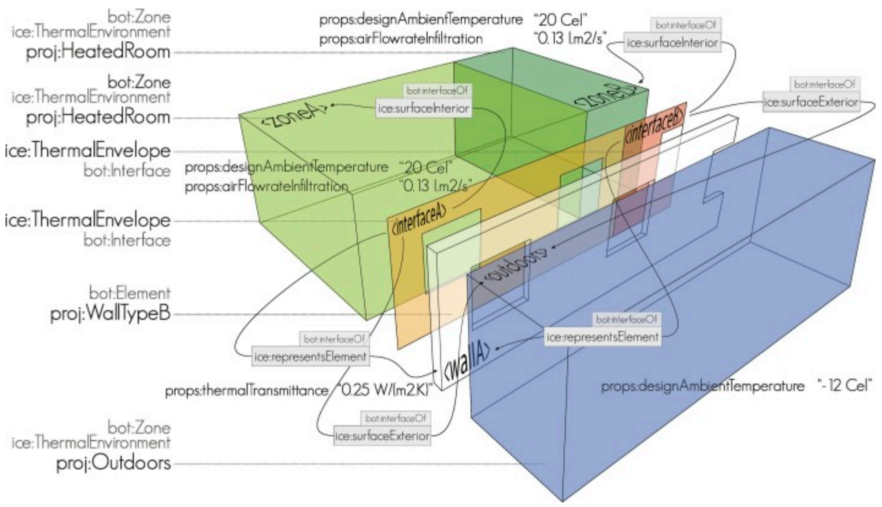

Figure 6. Visualization of the AEC-KG model for the heat-loss calculation case study [74] (Reprinted from Elsevier Automation in Construction, Volume 108/December 2019, 102956, Mads Holten Rasmussen, Maxime Lefrançois, Pieter Pauwels, Christian Anker Hviida Jan Karlshøj, "Managing interrelated project information in AEC Knowledge Graphs", Pages No. 4 and 13, Copyright (2019), with permission from Elsevier [OR APPLICABLESOCIETY COPYRIGHT OWNER]).

4.3.3. Smart Building Related Ontologies

The first smart building-related ontology to be discussed is Brick [131]. Brick's main goal is concentrated on metadata and data points from building advancement and needs. These data points are based on end-use applications and consist of the main ontology that establishes the core concepts and the connections between them, in addition to a typology that enlarges the building's concepts [95]. Brick is a schema that addresses the problem of heterogeneity of building representation, and adds a quick and non-costly reaction to energy efficiency measures [132]. The concept of tags is adopted, based on Project Haystack, to add a more flexible means to annotate metadata. Then, these tags are altered with an ontology that boosts its concepts, creating a framework that establishes hierarchies, relationships and properties that are mandatory for building metadata [95,133]. Furthermore, using an ontology provides the schema with the ability to manipulate the metadata using common tools. In the Brick schema, the tagset concept is introduced, which groups tags with similar properties [132]. In Figure 7, the information concepts and the relationship to a data point are shown. Relationships are qualities that connect a point with other classes, with the major classes being the Location, the Equipment and the Measurements, also shown in Figure 8, as well as their subclasses Figure 9 depicts the example building. Base on this building, Figure 10 shows the relationships of it and it is understood that it represents an early visual of a KG. Brick models are making it easier to represent some subsystems in buildings, as they bypass their complex and heterogeneous character, and support the composition and hierarchies in the building [95]. Furthermore, Brick also stands out due to its ability to access open reference implementations on existing buildings, in order to authenticate the effectiveness of the solution [95].

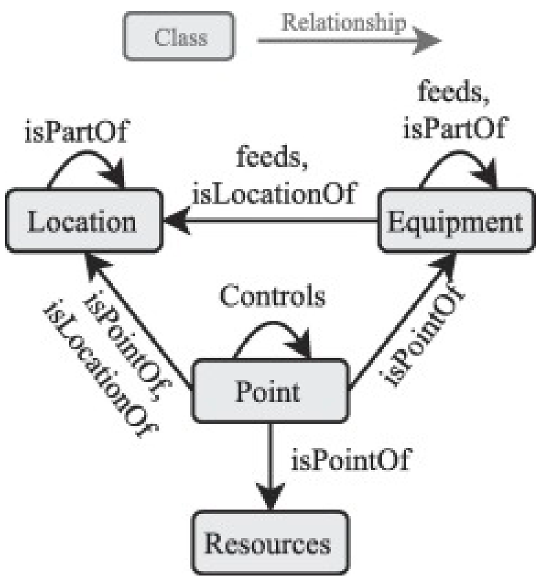

Figure 7. Information concepts in Brick and their relationship to a data point [132] (Reprinted from Elsevier Applied Volume 226, Bharathan Balaji, Arka Bhattacharya, Gabriel Fierro, Jingkun Gao, Joshua Gluck, Dezhi Hong, Aslak Johansen, Jason Koh, Joern Ploennigs, Yuvraj Agarwal, Mario Bergés, David Culler, Rajesh K. Gupta, Mikkel Baun Kjærgaard, Mani Srivastava, Kamin Whitehouse, Brick: Metadata schema for portable smart building applications, Pages No. 1273–1292, Copyright (2018), with permission from Elsevier [OR APPLICABLESOCIETY COPYRIGHT OWNER]).

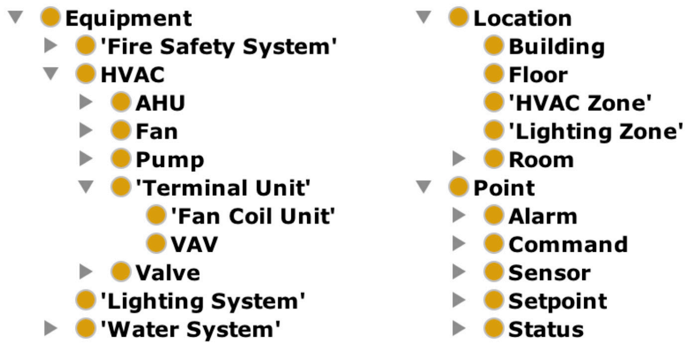

Figure 8. A subset of the Brick class hierarchy [132] (Reprinted from Elsevier Applied Volume 226, Bharathan Balaji, Arka Bhattacharya, Gabriel Fierro, Jingkun Gao, Joshua Gluck, Dezhi Hong, Aslak Johansen, Jason Koh, Joern Ploennigs, Yuvraj Agarwal, Mario Bergés, David Culler, Rajesh K. Gupta, Mikkel Baun Kjærgaard, Mani Srivastava, Kamin Whitehouse, Brick: Metadata schema for portable smart building applications, Pages No. 1273–1292, Copyright (2018), with permission from Elsevier [OR APPLICABLESOCIETY COPYRIGHT OWNER]).

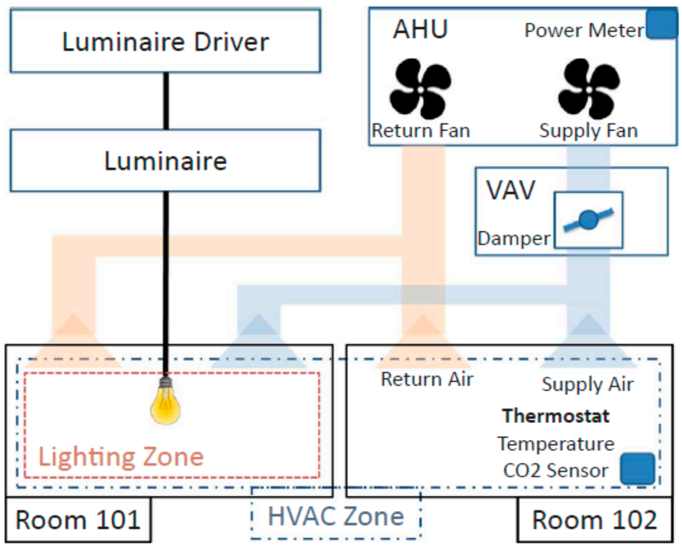

Figure 9. A simple example building that highlights the components to be modeled in a building schema [132] (Reprinted from Elsevier Applied Volume 226, Bharathan Balaji, Arka Bhattacharya, Gabriel Fierro, Jingkun Gao, Joshua Gluck, Dezhi Hong, Aslak Johansen, Jason Koh, Joern Ploennigs, Yuvraj Agarwal, Mario Bergés, David Culler, Rajesh K. Gupta, Mikkel Baun Kjærgaard, Mani Srivastava, Kamin Whitehouse, Brick: Metadata schema for portable smart building applications, Pages No. 1273–1292, Copyright (2018), with permission from Elsevier [OR APPLICABLESOCIETY COPYRIGHT OWNER]).

Haystack Tagging Ontology (HTO) is an "open-source initiative to streamline working with data from the Internet of Things", based on Haystack [94]. Haystack is responsible for terminology and instance data representation. Its primary purpose is semantic data representation using depositories of name and value relations [134]. These names are called Tags and are used to describe instance data. The name–value pairs mentioned previously are called Defs, and the repositories are called libraries, where a group of them is utilized to describe instance data [134]. HTO is based on Haystack and utilizes semantic web technologies and organizes the tags' usage in parallel to enriching the current ontology [120]. HTO's structure is similar to the Brick ontology, and consists of site, equipment and points classes, which are also connected with an external weather class [19]. The tags are utilized to connect properties and product classes with any entity in the building structure [19].

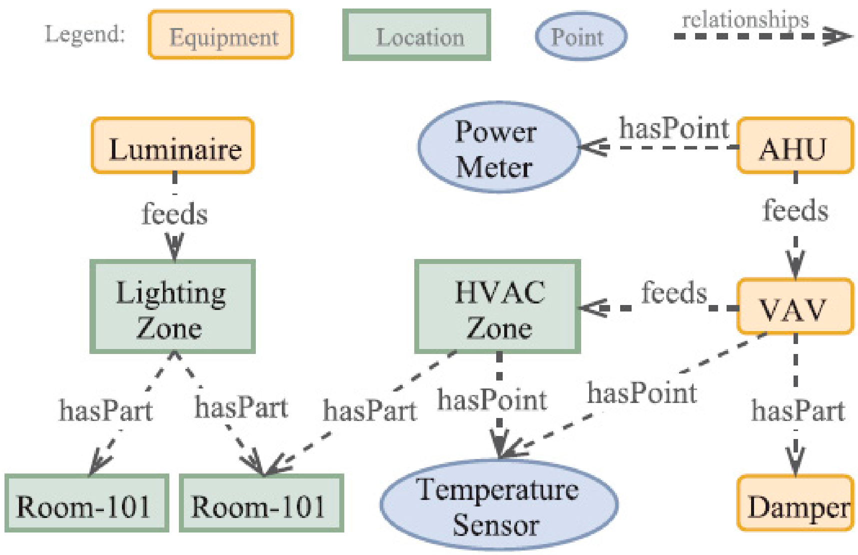

Figure 10. Brick classes and relationships for a subset of the example building in Figure 9 [132] (Reprinted from Elsevier Applied Volume 226, Bharathan Balaji, Arka Bhattacharya, Gabriel Fierro, Jingkun Gao, Joshua Gluck, Dezhi Hong, Aslak Johansen, Jason Koh, Joern Ploennigs, Yuvraj Agarwal, Mario Bergés, David Culler, Rajesh K. Gupta, Mikkel Baun Kjærgaard, Mani Srivastava, Kamin Whitehouse, Brick: Metadata schema for portable smart building applications, Pages No. 1273–1292, Copyright (2018), with permission from Elsevier [OR APPLICABLESOCIETY COPYRIGHT OWNER]).

Another important ontology is SAREF, which is "a tangible object designed to accomplish a particular task in households, common public buildings or offices and in order to accomplish this task, the device performs one or more functions" [98]. SAREF4Building Ontology is an extension of SAREF, and is an ontology similar to BOT; however, the former includes sites, stories and a class of devices, whereas the latter does not [121].

The last ontology to be mentioned is Real Estate Core Ontology (REC), which has as its main role energy usage analysis and optimization, and the presence analysis of a building structure [135]. The ontology is based on two main and four secondary modules. The two main modules include the metadata and the core. The metadata module contains annotation properties, used for ontology documentation. The core module gathers high- level classes and properties that are frequently reused in REC modules. In addition, the core module imports the metadata module. Energy usage analysis and optimization refer to the fact that a facility that is more sustainable and planned energy usage is automatically applied. REC can support a BMS in different ways [115]. One is by controlling and analyzing energy usage by locating broken or misaligned sensors and by altering the HVAC and lighting system to the users' needs. Moreover, support can be given by anticipating future needs and loads and using thermo-dynamic effects. Presence analysis refers to the ability of the system to detect occupancy in the building. This detection is achieved with measurements such as the actual number of people in different rooms, the people flows in a building and the activity of these people [115]. REC's structure is close to that of BOT and SAREF4Building, except for some classes and a difference in component classification [13].

4.3.4. Occupant Behavior Related Ontologies

DNAs Framework is a powerful approach to represent the impact of occupants' behavior on the building's energy efficiency [112]. It separates that impact into four components, i.e., drivers, needs, actions and systems, which comprise the outside and inside world (see Figure 11). Drivers are the environmental elements that impact the occupants' psychological or physical needs in the inside world. The categories of this topology include building (component, properties, location), occupant (attributes, attitudes, location, state), environment (climate, indoor, outdoor, weather), system (properties, state) and time (day, week, month) (Figure 12). Needs refer to the physical and non-physical necessities to satisfy the occupants in the inside world. Physical needs refer to biological needs (food, drink, bathroom, hygiene, sleep) and the need for comfort (thermal, acoustic, visual, IAQ) (Figure 13). Actions refer to the interactions between the occupant and the systems or activities in which an occupant can participate to change environmental comfort. These actions are interactions with the systems, movement, and reporting discomfort or inaction. Finally, systems refer to equipment or mechanisms an occupant can interact with to change environmental comfort (Figure 14). These systems are windows, shades/blinds, lights, thermostats, space, equipment, clothing and prompts/feedback (Figure 15). The overall field of DNAs Framework's applications addresses questions regarding the types of behaviors it covers, why this framework is valuable, in which types of buildings it can be applied, who can use it, when it can be used and how it can represent energy-related behavior (Figure 16).

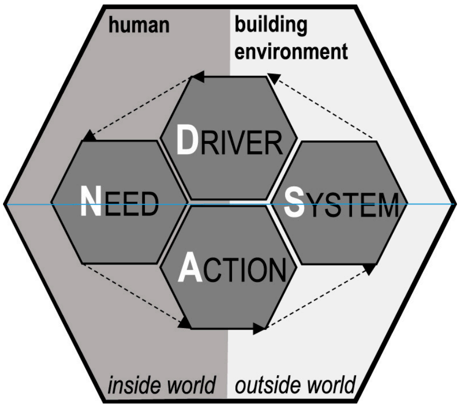

Figure 11. DNAs Framework Components [112] (Reprinted from Elsevier Building and Environment, Volume 92, Tianzhen Hong, Simona D'Oca, William J.N. Turner, Sarah C. Taylor-Lange, An ontology to represent energy-related occupant behavior in buildings. Part I: Introduction to the DNAs framework, Pages No. 764–777, Copyright (2015), with permission from Elsevier [OR APPLICABLESOCIETY COPYRIGHT OWNER]).

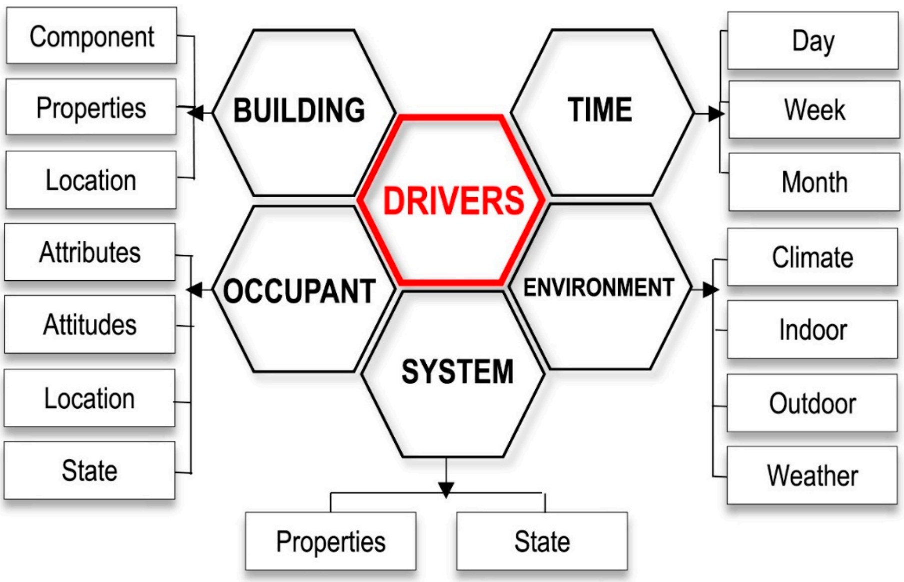

Figure 12. Drivers that impact energy-related occupant behavior [112] (Reprinted from Elsevier Building and Environment, Volume 92, Tianzhen Hong, Simona D'Oca, William J.N. Turner, Sarah C. Taylor-Lange, An ontology to represent energy-related occupant behavior in buildings. Part I: Introduction to the DNAs framework, Pages No. 764–777, Copyright (2015), with permission from Elsevier [OR APPLICABLESOCIETY COPYRIGHT OWNER]).

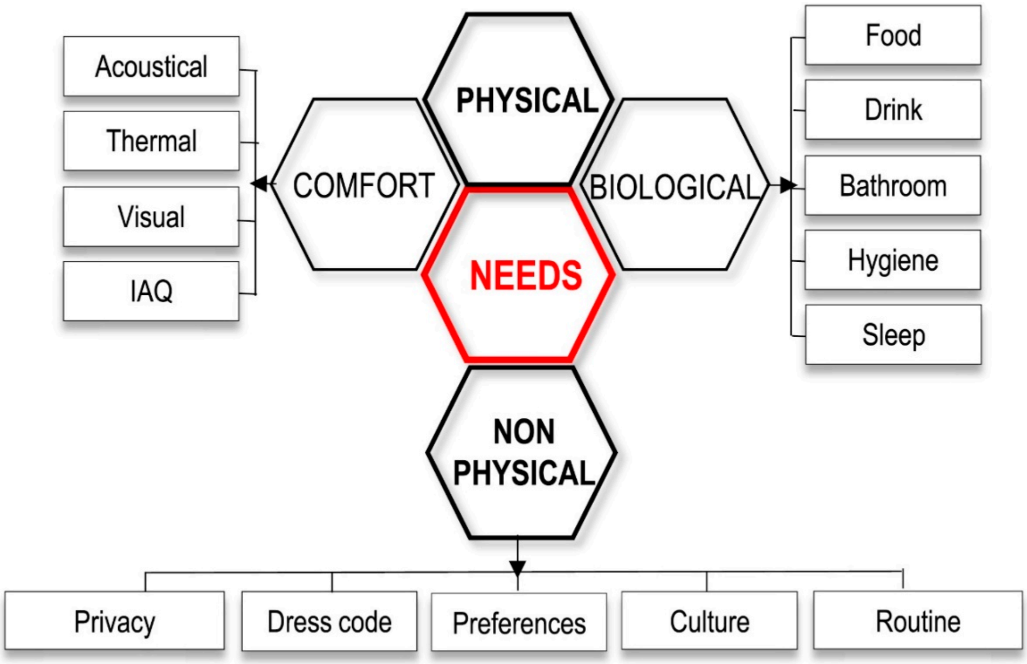

Figure 13. Needs of occupants that can impact the building energy use [112] (Reprinted from Elsevier Building and Environment, Volume 92, Tianzhen Hong, Simona D'Oca, William J.N. Turner, Sarah C. Taylor-Lange, An ontology to represent energy-related occupant behavior in buildings. Part I: Introduction to the DNAs framework, Pages No. 764–777, Copyright (2015), with permission from Elsevier [OR APPLICABLESOCIETY COPYRIGHT OWNER]).

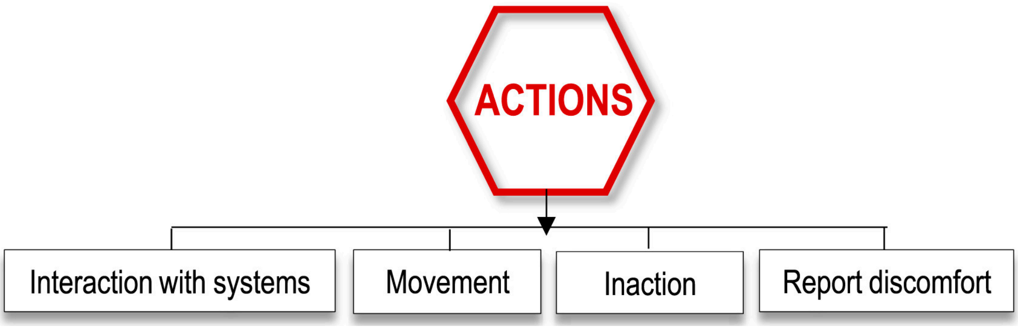

Figure 14. Actions taken by occupants to cover their needs [112] (Reprinted from Elsevier Building and Environment, Volume 92, Tianzhen Hong, Simona D'Oca, William J.N. Turner, Sarah C. Taylor-Lange, An ontology to represent energy-related occupant behavior in buildings. Part I: Introduction to the DNAs framework, Pages No. 764–777, Copyright (2015), with permission from Elsevier [OR APPLICABLESOCIETY COPYRIGHT OWNER]).

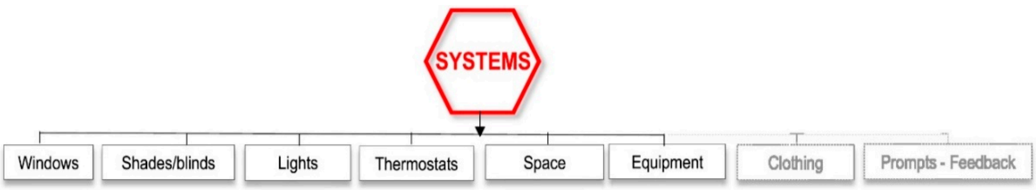

Figure 15. Systems that an occupant can interact with and change the building energy usage [112] (Reprinted from Elsevier Building and Environment, Volume 92, Tianzhen Hong, Simona D'Oca, William J.N. Turner, Sarah C. Taylor-Lange, An ontology to represent energy-related occupant behavior in buildings. Part I: Introduction to the DNAs framework, Pages No. 764–777, Copyright (2015), with permission from Elsevier [OR APPLICABLESOCIETY COPYRIGHT OWNER]).

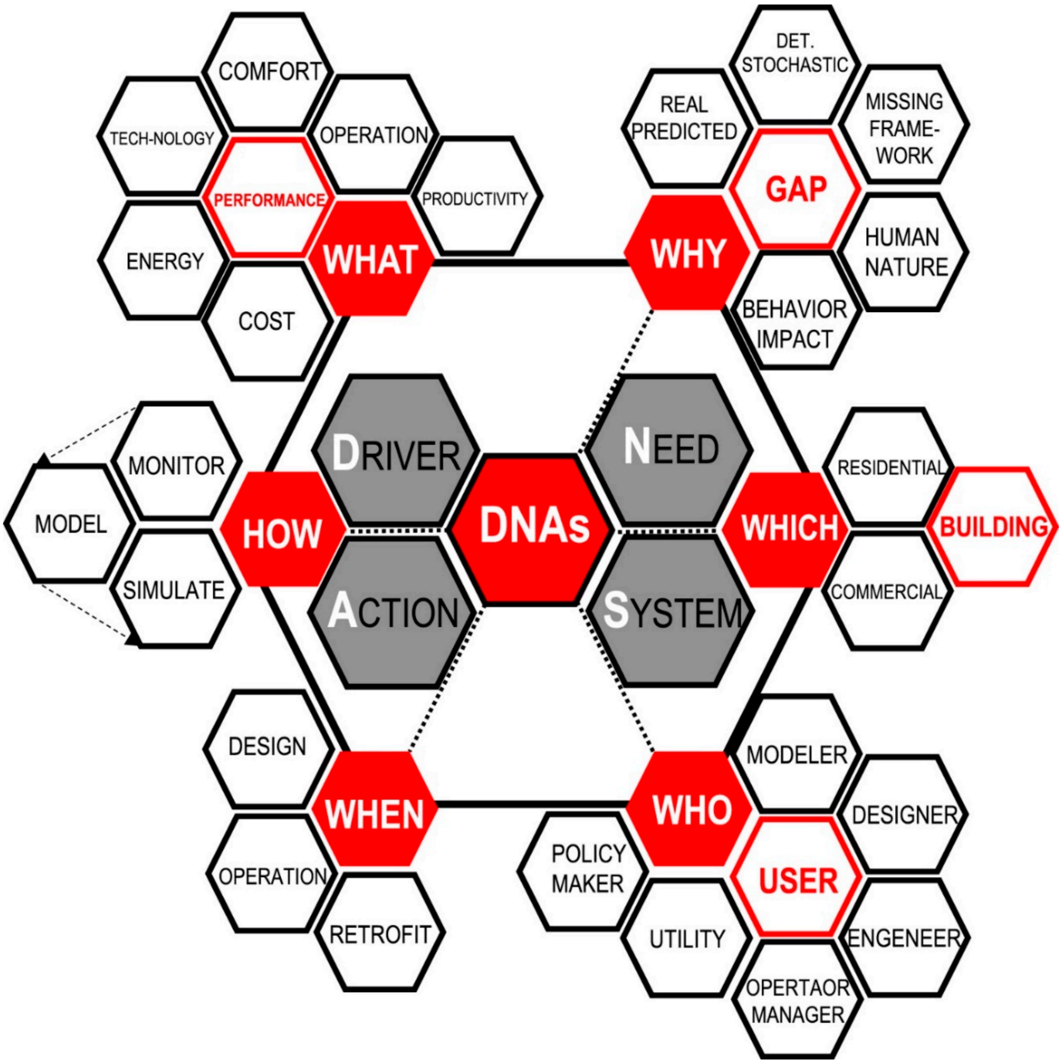

Figure 16. DNAs Framework Applications [112] (Reprinted from Elsevier Building and Environment, Volume 92, Tianzhen Hong, Simona D'Oca, William J.N. Turner, Sarah C. Taylor-Lange, An ontology to represent energy-related occupant behavior in buildings. Part I: Introduction to the DNAs framework, Pages No. 764–777, Copyright (2015), with permission from Elsevier [OR APPLICABLESOCIETY COPYRIGHT OWNER]).

obXML is an attempt to implement DNAs Framework in the form of an XML schema, which resulted in a successful schema [94]. In its success, the obXML schema can describe occupant behavior in a structured way, to researchers and different stakeholders. Moreover, the schema provides a platform to describe the occupant behavior and assess the reaction between occupant behavior and building energy modeling. Furthermore, its design means it can be easily adapted and modified to include more elements in the schema. The DNAs framework is implemented in the obXML schema, linking three core elements which refer to the Building, the Occupants and the Behaviors. In addition to these core elements are the elements of Time of Day and Seasons. obXML has in its core DNAs Framework. obXML's trees categorize the core elements and the drivers, needs, actions and systems [136]. In Figure 17, an example of applying priority indicators for possible multiple actions taken in a Drivers–Needs–Actions–System framework is shown [136]. In this example, the indoor air temperature overheating is the driver and the thermal comfort is the need. Moreover, the three actions to choose from are to close the blinds, turn on the HVAC, or open the window, and the system that it reacts with is the HVAC system.

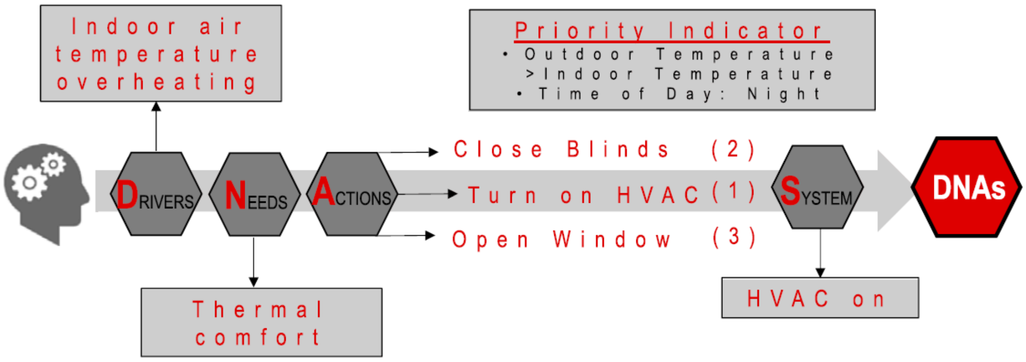

Figure 17. Example of priority indicators in DNAs Framework [136] (Reprinted from Elsevier Building and Environment, Volume 94, Part 1, Tianzhen Hong, Simona D'Oca, Sarah C. Taylor-Lange, William J.N. Turner, Yixing Chen, Stefano P. Corgnati, An ontology to represent energy-related occupant behavior in buildings. Part II: Implementation of the DNAS framework using an XML schema, Pages No. 196–205, Copyright (2015), with permission from Elsevier [OR APPLICABLESOCIETY COPYRIGHT OWNER]).

Next, another powerful ontology that considers human behavior is Onto-SB, which is a domain ontology for smart buildings [110]. This ontology considers factors of a smart building, namely humans, environment, services, devices, places, context-awareness, energy sources, profiles, etc. One of the core concepts of this ontology is the building concept. The building concept includes relationships with other concepts such as location, environmental parameters, actors and energy sources. Moreover, the activity concept is important and is divided into scheduled and inferred activities that a human can do in a smart building. Consequently, the human concept is also important for this ontology and includes characteristics such as name, age, weight, height and gender. Many concepts are also connected to the human profile, to create a better representation of the human concept in a smart building. This is rooted in the fact that human needs are responsible for the comfort in the building, which alters the energy consumption. The actors' concept is another and represents the residents of the smart building. The residents are divided into groups (family, friends, brothers, etc.) and individuals (Human and Nonhuman (pet, robot)) categories. This concept is connected with others, such as the human profile. Moreover, there is a service concept, which is connected with the appliances and devices concepts and has a type, grounding and model. This concept relates directly to the appliance that the user made the decision about. Furthermore, there is the time concept, which is divided into three classes, namely time-temporal, time-instant and time-interval. These classes include characteristics of time (hour, minute, second). Next, the concept of environmental parameters is also important and every location in a smart building is connected with that concept. Another important concept is the appliance concept. It includes categories of different devices, sensors and actuators. All three of these are connected with their location, the service they provide and the properties (ID, type, values, protocol) that defines them. The source concept is also a core concept and refers to the energy sources (renewable and nonrenewable) that can exist in a smart building. Finally, the place concept has a key role and represents different places in a smart building. This concept connects places with appliances, actors and the environment. It is also divided into indoor and outdoor places. Many other concepts are included in this ontology, but these are mostly the concepts that interact with human behavior.

5. Applications of Ontologies in Buildings

In this section, some applications of the ontologies reviewed in Section 4, as well as their reuse to create new applications, are presented. First, applications focusing on building performance improvement are discussed, followed by applications that target the facility management perspective.

Using KPIs to assess a building's performance is common and that is why some ontologies have been taken that into consideration. The first to be discussed was introduced by Corry et al. [137]. In it, ifcOWL, SimModel and SSN ontologies are reused to create an architecture that focuses on reducing the performance gap between the real and simulated data. This case study considered the simulated and measured KPIs in order to assess the thermal comfort conditions and the HVAC system performance. These considerations were supported by the selected ontologies. However, this architecture did not manage real-time data streaming. Hu et al. [138] took the previous work one step further by creating an ontology-based architecture, which was based on two algorithms. The first gathers and prepares data streaming from various sources and the second calculates the building performance. Furthermore, a case study was examined with the use of the RDF schema and SPARQL query language integrated with OpenMath and Linked Data. The difference between these two cases is that the first did not use real-time data, whereas the second did. It was proved in the second case that it is essential to use real-time data, as it supports various procedures throughout the building's life cycle. An ontology-based architecture that focused on performance tracking at building and district levels was developed by Li et al. [139], and tested in a case study of a microgrid comprising 19 solar houses. This architecture consisted of the ifcOWL ontology, the SimModel ontology, for creating an XML-based building simulation model (to be used in EnergyPlus and OpenStudio), and the SSN ontology, which was used for semantically integrating sensor data [137–139]. In addition, an ontology-based architecture for building energy savings was proposed by Han et al. [140], which included the RDF schema, D2RQ ontology translator, OWLIM-RDF database and EnergyPlus as a simulation tool [141,142]. The scope of the case study that was conducted was to identify any energy waste in the office zone. In the same context, InterfaceOnto was proposed by Kadolsky et al. [143]. Its main scope is to support the selection of efficient and best-cost HVAC systems. In addition, it focuses on the evaluation and prioritization of energy performance values (cooling/heating) consumption, through a platform called MonitoringLab. The case study aimed at the design phase, while the operational phase needs to be further researched. A more occupant-centric ontology is OPTIMUS, which is used in an architecture to target the occupants in a building and makes suggestions to reduce building energy by their behavior [144]. Two case studies were explored, where the first used the architecture to provide solutions for energy reduction and increased comfort based on the building's assessment; in the second, the architecture was applied in a lab in Athens where the building's energy was reduced relative to the year before the ontology was applied. The obFMU tool is a modeling tool that takes into consideration occupant behavior, as it is based on DNAs framework and obXML schema, which were discussed in Section 4.3.4 [145]. Moreover, these tools contain a co-simulation interface, a data model and solvers. Three examples were examined, where the first coupled obFMU with EnergyPlus to model occupant behavior lighting control; the second modeled the occupant behavior window action; and the last modeled HVAC control. Onto-SB ontology was used in another work, where an intelligent context-awareness Building Energy Management System was proposed [146]. The scope of this mechanism is to reduce building energy consumption by having occupant behavior changes as a top priority and covering their thermal comfort needs. Their case study is a residential building with four people, where they apply distinctive characteristics. After they integrate the proposed mechanism, they achieve a 40% reduction in energy consumption. Furthermore, Onto-SB ontology is also used in an approach where the main scope is the efficient control of appliances and devices in smart buildings, targeting the occupants' comfort and energy consumption reduction [147]. Two experiments were conducted. The first aimed to reduce the energy consumption by altering different characteristics in the scenario and the second tried to make the simulation process quicker. Another occupant behavior-centric ontology is OnCom, which combines a wireless sensor network and an emotional state analysis from occupants to calibrate indoor thermal comfort [111]. A case study was conducted that tested eleven participants with different characteristics. Each participant responded to the system's actions in a different situation with respect to the indoor thermal comfort. The results showed that the majority of users agreed with the system's decisions.

In another work, gbXML was used in an attempt to create a BIM-based system that automatically associates and updates thermal property measurements with BIM elements in a gbXML schema [148]. Based on two case studies, this application showed that the proposed method minimizes the gap between architectural information in BIM and the real data used for energy performance simulation. Furthermore, another work used a gbXML schema to convert semantic information from raw point cloud data and use it in energy simulation tools [149]. The applications were made in five existing buildings (three residential and two bank buildings) and, although some errors occurred, the overall integration was successful. Similar work also used a gbXML framework to store data from big buildings, such as factories, in gbXML format, to make it easier to import them into simulation tools [150].

Another work was proposed by Bottaccioli, where an ontology was created by reusing existing ontologies [151]. The architecture that was based on this ontology has the scope of providing modification options to facility managers. These options are addressed to the building, facility or energy managers. In addition, they include real-time visualization tools for energy consumption information and simulation of temperature trends, in addition to energy consumption tools. Moreover, the managers can access and assess the performance efficiency of the building, the users' energy behaviors and feasible refurbishment measures. The case study in this situation was conducted in an educational building and was able to apply real-time data in building energy simulation modifications. EESPA ontology is another approach, which combines SSN/SONA and BOT ontologies, in order to create semantic relationships between BMS data and building spaces [152]. The case study in this paper was performed on an educational building and supported its data analysis, although the lack of real-time data was found to be a challenge in HVAC system control. Another work that used BIM and BMS data connected with the semantic web in order to assist facility managers is ESIM ontology, but did not provide a case study [153].

Due to the problematic nature of creating ontologies that reuse a lot of complex existing ontologies, Uribe et al. [154] proposed a simpler ontology to be used in a context-awareness architecture for managing thermal energy in nZEBs. This ontology manages sensors and knowledge-based information in an nZEB. A case study based on this architecture was conducted, showing that SPARQL and Semantic Web Rule Language were compatible with decision making in this building. Similar to this simplification, the BACS ontology was proposed, based on EXPRESS, OSPH, SSN/SOSA, BOT and FSM ontologies, among others [155]. These ontologies were reevaluated instead of just being reused. The case study that was conducted for this work included a room and the automated control of the windows' shades using SPARQL queries.

In another approach, an ontology called SPORTE2 was created, which combined an artificial neural network, genetic optimization algorithm, real-time sensors, actuator data and SWRL rules to optimize the performance in a swimming pool [156]. Having as each base the machine-readable semantics, Schachinger and Kastner put forward a similar work with SPORTE2, with a common scope to optimize building energy [157]. As the core of the ontology, both approaches had real-time sensors, numerical methods and actuators, which integrated online simulation to improve building performance.

Having examined some notable applications of ontologies in buildings, other review papers are brought into the spotlight. Bergmann et al. [158] gathered the scope from different ontologies, including IFC, Brick, Project Haystack and other ontologies, having in mind the energy efficient buildings. In another review, Benndorf et al. [20] focused on semantic interoperability, fault detection and predictive control for energy performance optimization in buildings. Moreover, a survey on information modeling and ontologies in building automation was conducted by Butzin et al. [159]. Pritoni et al. [160] conducted a review of metadata schemas and ontologies for building energy applications. Finally, Gilani et al. [161] proposed a review of ontologies within the domain of smart and ongoing commissioning. Table 2 includes all the applications of ontologies in buildings that were presented in this section.

Table 2. Applications of ontologies in buildings.

Category	Scope	Architecture Used	Case Study	Year	Ref.
Energy Performance Improvement	Reduce the performance gap between the real and simulated data	ifcOWL, SimModel, SSN and custom	Use of simulated and measured KPIs to assess the thermal comfort conditions and the HVAC system performance	2015	[137]
	Gather and prepare data streaming from various sources and calculate the building performance	RDF schema and custom ontology	Energy Performance assessment using real-time data streaming in a university building, assessed by building managers and engineers	2017	[138]
	Performance tracking at building and district level	ifcOWL, SimModel and SSN ontology	Nineteen solar houses microgrid	2019	[139]
	Building energy savings	RDF schema	Identify any energy waste in an office zone	2015	[140]
	Support of the selection for efficient and best-cost HVAC systems/the evaluation and prioritization of energy performance values (cooling/heating) consumption	InterfaceOnto	Design phase of an office building	2015	[143]
	Optimize the energy performance	SPORTE2	Building Energy Performance Optimization of a swimming pool using ANN, Genetic Algorithms, real-time sensors and SWRL rules	2014	[156]
	Optimization problem generation on minimizing comfort dissatisfaction of building users regarding specific parameters and minimizing costs of energy consumption	Custom Ontology	Two office rooms are used to evaluate the scope of the ontology	2017	[157]
Data Injection	Creation of a BIM-based system that automatically associates and updates thermal property measurements with BIM elements in a gbXML schema	gbXML	Two case studies that the method they proposed minimizes the gap between architectural information in BIM and the real data for energy performance simulation	2015	[148]
	Use of gbXML schema to convert semantic information coming from raw point cloud data and use it into energy simulation tools	gbXML	Five existing buildings (three residential and two bank buildings)	2015	[149]
	Use of gbXML framework to store data from big buildings, like factories, in gbXML format, to make it easier to import into simulation tools	gbXML	University's manufacturing facility	2018	[150]
Facility Management	Provide modification options to facility managers	gbXML, EnergyPlus	Educational building application of real-time data in building energy simulation modifications	2017	[151]
	Creation of semantic relationships between BMS data and building spaces	SSN/SONA and BOT ontologies	Educational building support of data analysis, lacking real-time data that was found to be a challenge in HVAC system control	2018	[152]
	BIM and BMS data connected with the semantic web to assist facility managers	-	-	2018	[153]

Table 2. *Cont.*

Category	Scope	Architecture Used	Case Study	Year	Ref.
Occupant Behavior-Centric	Targets the occupants in a building and makes suggestions to reduce building energy by their behavior	OPTIMUS, SSN/SONA, Urban Energy Ontology	Use of ontology to provide solutions in energy reduction and comfort increase based on the building's assessment/application of ontology in a lab in Athens where the building's energy was reduced in contrary to the year before the ontology was applied	2018	[144]
	Modeling tool that takes into consideration occupant behavior	obFMU/DNAs, EnergyPlus	Coupled obFMU with EnergyPlus to model occupant behavior lighting control, to model occupant behavior window action and to model HVAC control	2016	[145]
	Reduce building energy consumption by having as top priority occupant behavior changes and covering their thermal comfort needs	Onto-SB	Residential building with four people, where they apply distinctive characteristics and after they integrate the mechanism that is proposed they conclude with a 40% energy consumption reduction	2019	[146]
	Efficient control of appliances and devices in smart buildings, targeting the occupants' comfort and energy consumption reduction	Onto-SB	Reduce the energy consumption by altering distinctive characteristics in the scenario and make the simulation process quicker	2020	[147]
	Combination of a wireless sensor network and an emotional state analysis from occupants to calibrate indoor thermal comfort	OnCom	Assessing eleven participants with distinctive characteristics and each one responds to the system's actions in a different situation with respect to the indoor thermal comfort and the results showed that the mean of users agreed with the system's decisions	2019	[111]
Decrease in Reused Ontologies	Context-awareness architecture for managing thermal energy in nZEBs	OWL, SWRL	Showing that SPARQL and Semantic Web Rule Language were compatible with decision making in a building	2017	[154]
	Supports the modeling control behavior in a BAS, physical devices of BAS and their location in the building and connection to technical equipment and appliances	BACS, EXPRESS, OSPH, SSN/SOSA, BOT and FSM	Inclusion of a room and the automated control of the windows' shades using SPARQL queries	2017	[155]

6. Discussion

Based on the research, it understood that the applications of knowledge graphs for energy efficiency improvements are focused on the design and operational phases of the building. However, many of them do not consider the whole building, but rather a small zone or system. On the other hand, several of them were considered powerful enough to cover various concepts and classifications in their core. By doing so, they provide a more comprehensive approach to a building's life cycle, considering both different kinds of data and various stakeholders and end users. Based on this, the literature that was reviewed showed the potential of using knowledge graphs as a part of a wider architecture, to exchange and manage information and to structure and connect the different concepts in a building's life cycle. An important role in these attempts was played by the data from the buildings' sensors. It is supported that real-time data streaming in the knowledge graphs resulted in quicker and more accurate results, which can also be useful in later assessment.

Furthermore, most applications reused different existing ontologies, in order to apply different and more specific features in a novel approach. This situation benefits both the combined approach and the existing ontology. This is because the latter provides implemented knowledge to the former, and the former advances the knowledge provided by the latter. In addition, the frequent use of ontologies in knowledge graph applications across buildings and facilities creates a better understanding and replication potential in different projects.

Next, ontologies that take into consideration the stakeholders and end users provide an improved approach for the entire architecture of knowledge graph application. This is due to the connection between the human aspect and the rest of the building's entities. Specifically, integrating the human aspect in a knowledge graph application leads to a more interactive decision making. That is also supported by functionalities such as advanced monitoring, feedback mechanisms, optimization and control. A similar perspective is followed for the occupant behavior-centric ontologies, which take into consideration the occupant's needs, actions and habits, and correlates them with the energy consumption and thermal comfort in a building. Taking into consideration the users' behavior in a building's operational phase leads to a more comprehensive ontology and a more complete DSS.

The development of KGs is considered a significant step forward due to their inherent structural and functional characteristics. The hierarchical architecture in KGs essentially translates to the fact that each subject or object is unambiguously defined in terms of its scope and location. This is particularly important since it deals with certain drawbacks associated with data handling in otherwise advanced and dynamic databases, whereby such clarity is not offered. Furthermore, the use of semantics via ontologies provides a major breakthrough. This is because data are universally defined and leave no space for interpretation or assumptions about the type of data or metrics used.

In addition, KGs are an interesting approach as a unifying framework in which various non-homogenous data from various sources can be linked in a dynamic form. Then, these linked data can be exploited by providing a number of services such as visualization, monitoring, data analysis, automated control, simulation and machine learning. In this framework, new architectures can evolve to take advantage of the new era of Big Data, IoT and the semantic web. As a result, they support the development of advanced tools for energy efficiency in buildings, neighborhoods and cities.

KGs can provide the foundation for emerging advanced decision support services such as those that can be provided via DTs, which present several advantages compared to other less advanced support systems and improve not only the analytic capabilities offered, but also assist in the visualization, interpretation and understanding of data analytics. In this sense, KGs are foreseen to provide the means for more effective and reliable decision support services to be built, thus improving collaborative decision making for energy efficiency in buildings.

Moreover, KGs are the state of the art in providing the backbone structure for the implementation of dynamic platforms and systems that can offer advanced real-time prediction and optimization services based on AI and ML. The robust structure and semantic capabilities of KG-based systems and services are vital attributes enabling transparency, traceability, interoperability and usability.

The use of KG as a backbone for the creation of decision support services rests on the notion that data across the physical, social and natural domains will become increasingly available. KGs used in such DSSs will boost the efforts for buildings renovations and smart energy management across various spatial and temporal scales. However, there are challenges associated with the fact that such data-based knowledge generation and informed decisions span various domains. These domains include business, urban services, energy and mobility, and are characterized by multiple interdependencies. Identifying interdependencies is critical to ensure that decision making in one domain takes into consideration all key parameters and constraints of interconnected domains.

7. Conclusions

The work in this review tried to address the problem of data exchange and management throughout the different phases of a building's life cycle and between the different stakeholders that are included in it. This data exchange and management originates from the need for the improvement in the energy efficiency in buildings. The solution to the problem is based on the application of the semantic web utilizing the knowledge graphs, which include ontologies in their core structure. Thus, different ontologies that focus on the different phases of a building's life cycle, proposed in recent years, were reviewed and discussed. The ontologies were categorized into design phase-related and operational phase-related sectors, with the latter including smart building, occupants' behavior and asset management. These ontologies are gathered in Table 1, and the most prominent and complete are discussed in Section 4.3. They are separated into four categories. The first relates to IFC-associated ontologies, which include ifcOWL and simpleBIM. The second relates to W3C-associated ontologies, which include BOT, and its extensions, and OPM. The third relates to smart building-associated ontologies, which include Brick, Project Haystack/HTO, SAREF and REC. The final category relates to occupant behavior-associated ontologies, which includes DNAs and Onto-SB. Next, applications of these ontologies were examined, in addition to their reuse and adaptation, which mainly focus on building performance improvement and facility management.

This study's limitations relate to the fact that most ontologies do not have a real-life application in a building, but are rather examples of its possible use; this reflects the early stage of the ontologies. Moreover, some applications are focused mostly on the design phase of a building or its early operation. More applications need to be implemented in real buildings. Time also needs to be spent for stakeholders to use these DSSs in real conditions, and provide feedback on the operational and maintenance phases of a building's life cycle.

Future work can utilize KGs to support decision making in all life cycle stages of a building, neighborhood or district. In addition, future work on KGs can include structuring and managing different BIM and sensor data to derive new knowledge regarding the optimum selection of possible application scenarios. By doing so, they would target the improvement of building energy efficiency and the minimization of environmental impacts.

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Appendix A

Table A1. Abbreviation list.

AEC	Architecture, Engineering and Construction
DSS	Decision Support System
IoT	Internet of Things
KG	Knowledge Graph
UN	United Nations

Table A1. *Cont.*

SDG	Sustainable Development Goal
MCDA	Multi-Criteria Decision Analysis
MOP	Multi-Objective Programming
LCA	Life Cycle Analysis
ANN	Artificial Neural Network
FL	Fuzzy Logic
EA	Evolutionary Algorithms
ICT	Information and Communication Technologies
BIM	Building Information Models
NBIMS	National Building Information Model Standard
IFC	Industry Foundation Classes
gbXML	green building XML
BAS	Building Automated Systems
FM	Facility Management
DT	Digital Twin
RDF	Resource Description Framework
IRIs	Internationalized Resource Identifiers
URIs	Uniform Resource Identifiers
RDFS	Resource Description Framework Schema
OWL	Web Ontology Language
W3C	World Wide Web Consortium
GNN	Graph Neural Network
PA	Physical Asset
WoT	Web of Things
OneDM	One Data Model
SEAS	Smart Energy Aware Systems
BOnSAI	Building Ontology for Ambient Intelligence
SBOnto	Smart Building Ontology
SAREF	Smart Applications REFerence
SBMS	Semantic Building Management System
HTO	Haystack Tagging Ontology
GDBO	Google Digital Building Ontology
REC	Real Estate Core
BOT	Building Topology Ontology
BACS	Building Automation and Control Systems
KM4City	Knowledge Model for City
FSGIM	Facility Smart Grid Information Model
DNAs	Drivers Needs Actions & systems
OP	Occupancy Profile
BEDES	Building Energy Data Exchange Specification
VBIS	Virtual Buildings Information System

Table A1. *Cont.*

OPM	Ontology of Property Management
LBD	Linked Building Data
BEO	Building Elements Ontology
FSO	Flow System Ontology
BPO	Building Products Ontology
FOG	Geometry Formats Ontology
OPM	Ontology for Property Management
OMG	Ontology for Managing Geometry
IAQ	Indoor Air Quality
KPI	Key Performance Indicator

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