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Building ontologies for 4-5GDHC: A critical evaluation and modeling experiments on building-side components

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A B S T R A C T

This research addresses the critical challenge of digital integration and exchange of data and information from the building side towards 4-5th generation district heating and cooling (4-5GDHC) systems, where heterogeneous data and information from distributed components hinders integration and deployment of data-driven services at scale. The study conducts a critical evaluation of six major ontologies (Brick Schema, RealEstateCore, Project Haystack, SAREF, Flow Systems Ontology, and ASHRAE Standard 223P) and performs semantic modeling experiments on key building-side components including buildings in thermal networks, thermal energy storages, heat pumps, photovoltaic-thermal systems, and waste heat recovery systems. The analysis reveals significant gaps in current ontologies for representing district-level interactions, bidirectional energy flows, and thermal storage dynamics. While existing frameworks effectively model basic building components and sensors, they lack DHC-specific terminology and cannot adequately represent prosumer relationships or complex system topologies. The paper positions ontology-based semantic models as one layer of a broader digital information infrastructure and explores how they can interface with large language models (LLMs) to streamline information interaction across building and district energy systems. This work contributes to three key advances: a comprehensive critical evaluation of existing ontologies for DHC applications, practical semantic modeling experiments demonstrating real-world applicability and limitations, and forward-looking integration frameworks combining knowledge graphs with LLMs and design metadata. The findings highlight the need for DHC-specific ontology extensions and multi-ontology integration to address the unique challenges of 4-5GDHC systems. By bridging semantic technologies and AI.

1. Introduction

Almost half of the total energy consumption within the EU is used for heat, accounting for 86% of household energy use, 76% in sectors such as commerce, services, and agriculture, and 55% in the industrial sector [1]. Decarbonizing these sectors is therefore critical to meeting the European Union's ambitious climate goals [2]. District heating and cooling (DHC) systems are central to this transition, supplying 16.9% of the EU population with heat in 2015 [3], and can reduce primary energy use and emissions while efficiently meeting building heating and cooling needs [4].

Building on this trend, 4-5GDHC systems are emerging that operate towards near-ambient temperatures [5], minimizing thermal losses and enabling the efficient use of low-exergy heat sources such as renewables and waste heat [4]. As shown in Fig. 1,

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| List of abbreviations	
Nomenclature	
4-5GDHC	4-5th Generation District Heating and Cooling
AI	Artificial Intelligence
ATES	Aquifer Thermal Energy Storage
BAS	Building Automation System
BEPS	Building Energy Performance Simulation
BMS	Building Management System
DHC	District Heating and Cooling
CHP	Combined Heat and Power
FDD	Fault Detection and Diagnosis
IEA	International Energy Agency
IFC	Industry Foundation Classes
IoT	Internet of Things
ISO	International Organization for Standardization
LLM	Large Language Model
OWL	Web Ontology Language
PV/T	Photovoltaic-Thermal
RDF	Resource Description Framework
REC	RealEstateCore
SAREF	Smart Applications REFerence
SPARQL	SPARQL Protocol and RDF Query Language
TES	Thermal Energy Storage
W3C	World Wide Web Consortium
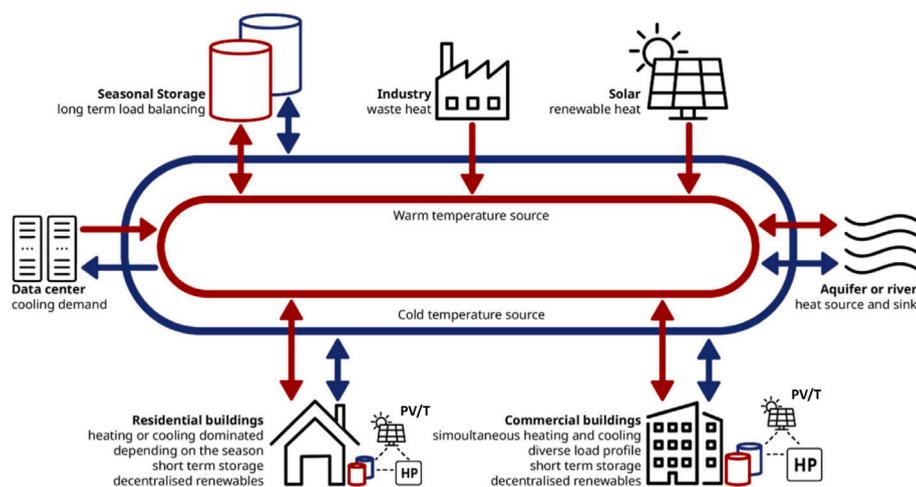
Fig. 1. Conceptual architecture of a 4-5GDHC system [11].
Source: Adapted from Renewable and sustainable energy reviews, Vol 171, Kristian Gjoka, Behzad Rismanchi, Robert H. Crawford, Fifth-generation district heating and cooling systems: A review of recent advancements and implementation barriers, Page 112997, Copyright (2023), with permission from Elsevier

these systems support bi-directional and decentralized energy flows, allowing buildings to act as both consumers and producers, which enhances system flexibility and efficiency. Core components include smart control systems, distributed thermal storage, and decentralized generation technologies such as heat pumps and solar solutions [6]. However, these integrations significantly increase system-level complexity [7]. As the volume of data and information within these systems continues to grow, adopting standardized methods for representing, communicating, and utilizing this information becomes critical to enabling scalable energy applications [8]. The call for advanced information and communication technology in the field to improve the digitalization of DHC is growing [9]. Previous studies have not fully addressed this aspect, highlighting the need for further research and development to unlock the full potential of the data and information aspects of 4-5GDHC systems [10].

2. Background

In this section, related topics relevant to this study are introduced, covering three main areas: (1) the need for digitalization in 4-5GDHC systems, (2) the concepts of semantic modeling and ontology, and how these approaches can serve as potential solutions to enhance interoperability, data integration, and operational performance in 4-5GDHC systems, and (3) detailed background on using semantic technologies to model information.

2.1. Digitalization of data and information in 4-5GDHC systems

The digitalization of data and information in DHC systems refers to the use of computer-aided and information technologies to support system-level operation and maintenance through real-time measurement data [12]. It is a prerequisite for implementing advanced control strategies that can optimize the performance of these complex systems [10]. Data exchanged among stakeholders and across building subsystems has expanded rapidly as advanced sensing, networking, communication, and control have become commonplace [13]. The scale and heterogeneity of these data highlight the need for standardized, machine-readable representations that enable semantic interoperability across vendors and sites [14].

The International Energy Agency's (IEA) DHC Annex TS4 project explored and promoted the integration of digital processes in DHC systems, together with industry professionals and researchers from nine countries [15]. The project examines how digital technologies can create new business opportunities within the DHC sector and investigates the regulatory framework surrounding data usage in these systems. The project clarified the role of digitalization in various operational and maintenance aspects of DHC systems, along with several innovative business models, supported by case studies. Building on previous efforts, the IEA DHC Annex TS9 continues working on the potential of DHC systems by promoting the integration of advanced digital processes and improving overall system efficiency and performance [16]. This initiative emphasizes the importance of data integration, breaking down silos, and enabling comprehensive communication between different domains and agents [16].

2.2. Semantic modeling and ontology: enablers of semantic interoperability

From the perspective of information science, Studer et al. defined ontology as a "formal, explicit specification of a shared conceptualization" [17]. In the context of the building and energy domain, an ontology defines a vocabulary of terms for entities (e.g., room, floor, valves, temperature sensors, radiators, pipes) and their relationships (e.g., connections, one component feeding another) [18]. The process of using such an ontology to represent a subject system is referred to as semantic modeling, which produces semantic models [8]. This formal representation of knowledge enables a shared understanding and supports reasoning over the data, facilitating semantic interoperability across different systems and applications [19]. Semantic interoperability is defined as "expressing information about things in a way that can be consistently understood by applications" [8], which is a key enabler for the scalability of applications. Ontologies have been widely adopted, forming the foundation of the modern Internet [20], and have proven essential in many other domains, such as disease ontologies [21] and marine domain ontologies [22].

In contrast to white-box and black-box modeling, which aim to describe system dynamics, semantic modeling serves a different purpose. Physical modeling (white-box) uses first-principles equations to represent dynamics explicitly. Data-driven modeling (black-box) learns patterns directly from historical data without explicit physics. Semantic modeling represents information about the system using a shared vocabulary (ontologies) that defines entities and relationships in a machine-readable form. The goal is to enable interoperability by linking operational data and control points to analytical models and applications, including physics-based and data-driven models. Fig. 2 illustrates these three approaches in building and energy systems.

The application of semantic modeling and ontology in building and energy domain is surging. Yang et al. integrate an ontology-based semantic model with model predictive control in a hospital floor that uses district heating and mechanical ventilation, standardizing heterogeneous data and auto-generating a component-based simulation inside a digital twin [23]. The study argues that coupling MPC with a semantic layer improves interoperability and scalability for building energy management [23]. Deng et al. present an ontology-based approach that integrates BIM with dynamic fire emergency management in buildings [24]. Their framework supports real-time evacuation path planning by combining semantic modeling with spatial and temporal reasoning, highlighting how ontologies extend beyond energy applications to enhance building safety and resilience through intelligent data integration. Yoon et al. propose an ontology and LLM-based digital twin framework for building operations and maintenance [25]. Their system leverages LLM-based AI agents to interact with semantic models that manage heterogeneous building data, enabling predictive analytics, adaptive control, and decision support in real time. Thomsen et al. propose ontology-based digital twins tailored for hospital building operations, enabling scenario testing and multi-objective optimization for decision-making [26]. Pereira et al. [27] introduces a semantics-driven framework that aligns Brick and SAREF ontologies to generate interoperable semantic models supporting demand flexibility applications in real buildings. By integrating BIM and BAS metadata, the framework automates model creation and enables modular, replicable deployment of demand response controls through a dedicated platform. Li et al. propose a knowledge graph approach to represent building information and operational data in a unified semantic structure [28]. Their method enables automatic reasoning and query-based analytics for building performance management, illustrating how semantic enrichment supports fault detection and energy optimization in practice.

There is a growing interest in using Modelica-based co-simulation to improve the modeling of 4-5GDHC systems, identified as a promising approach [29]. While these simulation capabilities are well established in the building energy domain, a persistent challenge lies in the labor-intensive process of preparing and integrating heterogeneous data for model creation [30]. To address
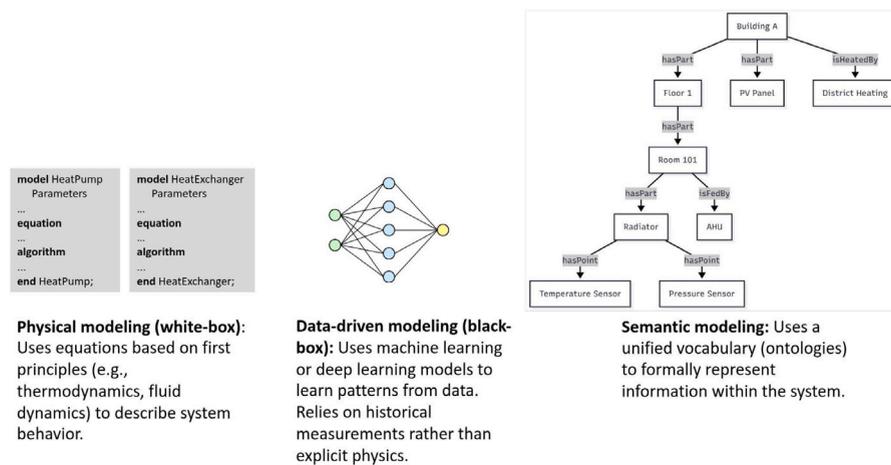
Fig. 2. Illustration of physical (white-box), data-driven (black-box), and semantic modeling approaches.

this, several studies have explored integrating ontologies with simulation workflows, particularly Modelica-based methods and co-simulation. Notable examples include Wu et al. [30], they proposed an ontology-based automatic framework for generating Building Energy Models (BEM) by integrating data from four critical sources, such as weather, building, internal heat gain, and HVAC systems, through an ontology designed to reuse and extend existing schemas, apply domain-specific design, and link with dynamic data. Mitterhofer et al. [31] developed an FMI-enabled co-simulation methodology that integrates Semantic Web Technologies and Building Information Modeling to contextualize Functional Mock-up Units (FMUs) within a common ontology, enabling automated inference of simulation topology and facilitating modular, interoperable building performance simulation. Hofmeister et al. present a framework that leverages semantic data models to achieve interoperability across heterogeneous digital twins for energy systems [32]. The approach demonstrates how linking ontologies with system simulations enables cross-domain integration and supports co-simulation scenarios that are otherwise difficult with isolated models. Hippolyte et al. investigate ontology-based interoperability between BIM and Building Energy Simulation tools, demonstrating how semantic transformations can automatically convert IFC building data into formats usable for dynamic simulation [33]. This work shows the role of ontologies in bridging design and operation stages by reducing manual modeling effort and improving consistency between BIM and energy performance analysis.

Semantic modeling using ontologies is not only capable of integrating heterogeneous data but also plays a critical role in enabling scalability. In practice, deployment costs are often dominated by bespoke integration work, particularly the curation and mapping of heterogeneous metadata from BMS [34]. Furthermore, when an application is developed for one building and then deployed in another, engineers often need to re-enter and re-map the data, creating redundancy and inefficiency [35]. When this bottleneck is removed, applications can be replicated across sites with minimal reengineering, enabling scalability. Semantic interoperability addresses this issue by providing a common, machine-readable representation of sensors, equipment, and their relationships [18]. The semantic model acts as the metadata framework that applications can query to discover resources and bind to data streams and control points using standard interfaces such as RDF and SPARQL [34]. Prior work has implemented this scalable architecture in multi-building studies, linking each entity in the semantic model to time-series archives and control endpoints, enabling applications to locate, read, and actuate without site-specific rewiring [34].

In this framing, ontology-based semantic models act as a mediation layer. Fig. 3 formalizes the interface between raw information and applications. By encoding domain concepts and relationships as graphs, it preserves meaning across systems and enables standardized queries for discovery, monitoring, and control.

2.3. Semantic tools and knowledge graphs

Resource Description Framework (RDF), developed by W3C, serves as a standard for metadata modeling and graph data exchange [36]. RDF employs a triple-based model consisting of subject–predicate–object relationships to make descriptions about resources, similar to entity-relationship diagrams in classical conceptual modeling as illustrated in Fig. 4. In the context of buildings and DHC systems, this framework can be applied to describe multiple components and their relationships. For instance, to model a radiator with a temperature sensor, an RDF triplet can be used to represent this relationship, enabling a machine-readable description of these elements and their properties. Further, Web Ontology Language (OWL) is a family of knowledge representation languages for authoring ontologies [20], built upon RDF. OWL provides formal semantics for describing concepts, relationships, and categories within a domain. Protocols such as SPARQL Protocol and RDF Query Language (SPARQL) is the standard query language for RDF, developed and endorsed by the W3C. It plays a crucial role in the Semantic Web ecosystem by enabling users to query and manipulate RDF graph-based data [37]. Take building as an example, if a building is represented as a collection of RDF triples, SPARQL can be used to formulate precise queries, such as "Get the temperature sensor in room 101 in building A". This capability allows for
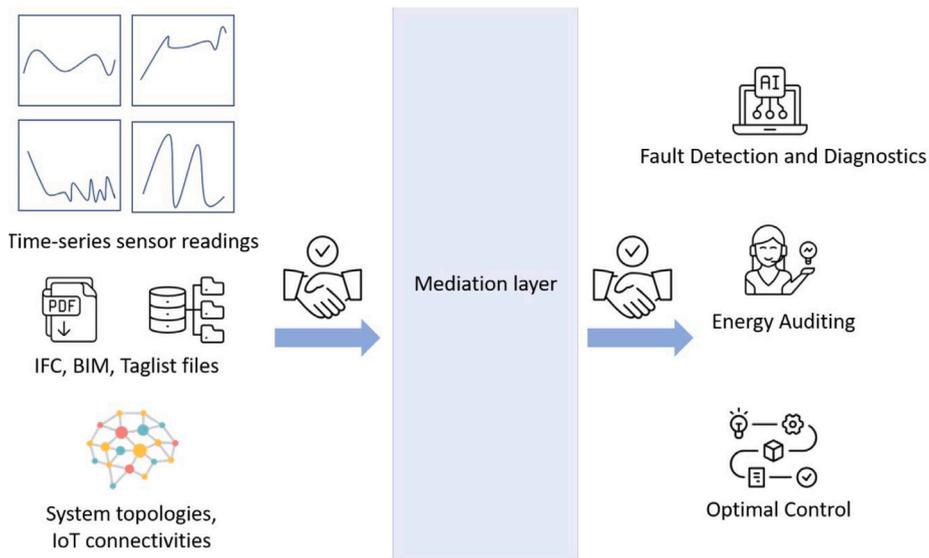
Fig. 3. Data and information - Mediation layer - Data-driven applications.
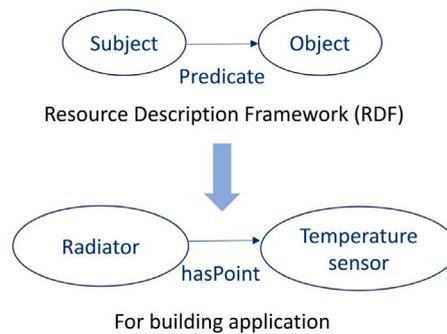

Fig. 4. RDF triplet and an example for describing building applications.

efficient retrieval and manipulation of building-related data by computer, enhancing the utility of semantic modeling in building management systems (BMS).

The graph constructed from RDF triples forms a structure that encapsulates the information of real-world systems, referred to as a knowledge graph [38]. These knowledge graphs encode the semantics of physical systems, covering data sources, connectivity, topology, and controllable points. By providing a shared vocabulary with formal relationships, they resolve the core semantic interoperability problem, enabling consistent interpretation of data across vendors and sites. As illustrated in Fig. 5, they mediate between operational data and applications and provide the semantic layer within a broader digital information infrastructure that supports the development and deployment of data-driven services.

The contributions of this work are as follows:

- It presents a critical examination of existing ontologies by summarizing their core purposes and functions, and critically evaluating their strengths and weaknesses in the context of buildings and DHC networks.
- The paper further conducts experiments by developing semantic models for a selection of systems and testing the ability of current ontologies to model the relevant data and information, providing practical insights into their real-world applicability and limitations with complete source code provided in Appendix A for further research.
- The paper explores forward-looking directions for the applications of semantic modeling in 4-5GDHC systems. These include a component-to-system approach for scalable knowledge graph construction, the integration of knowledge graphs with large language models (LLMs) to enable intelligent human-AI interaction, and the convergence of semantic models with design metadata (e.g., BIM, GIS) and energy simulation tools.
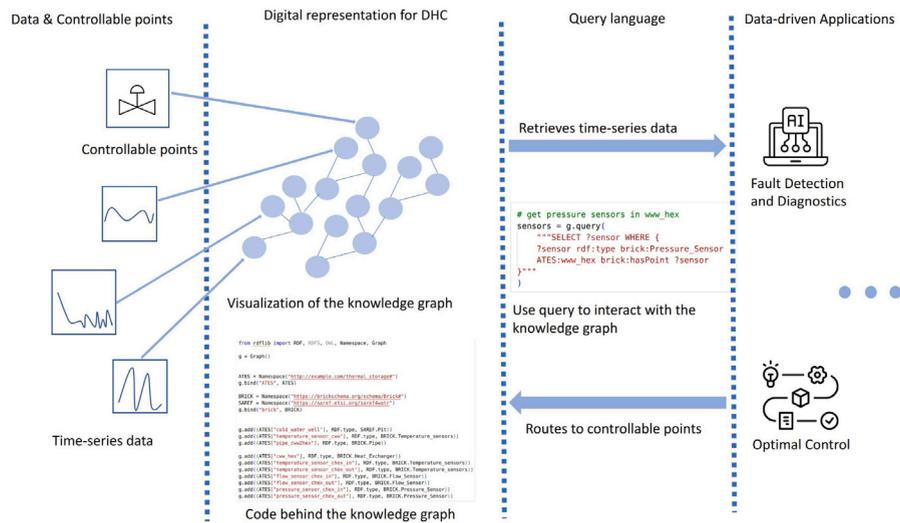
Fig. 5. How smart applications interact with knowledge graphs of DHC systems to acquire data and information, and provide control to the system.

3. General methodology

This study adopts an application-based methodology to critically examine the suitability of selected ontologies for modeling building-related demand-side components within fourth- and fifth-generation district heating and cooling (4-5GDHC) systems. The approach is designed to provide both theoretical evaluation and practical insights, ensuring that the findings are relevant for real-world deployment.

First, based on findings from prior literature, six widely referenced building ontologies were selected for their potential applicability to the representation of demand-side components and energy flows in DHC systems. The selection was guided by their coverage of building entities, interoperability with energy data models, and adoption in previous research.

Second, representative building-related components critical to 4-5GDHC operation were identified, including buildings, heat pumps, thermal energy storage units, photovoltaic/thermal (PV/T) systems, and waste heat recovery units. These components were then modeled using the formalized terms and relationship vocabularies provided by those six selected ontologies. Practical modeling experiments were conducted to test how well the ontologies could express component attributes, energy flows, and interactions with the district network.

Third, the modeling experiment results were analyzed to evaluate the ontology in terms of expressiveness, completeness, and practicality for real modeling tasks. The analysis focused on semantic consistency, coverage of key system interactions, effort required for model implementation, and potential for automated reasoning. Strengths, limitations, and gaps were presented, and actionable recommendations were derived to inform ontology selection or extension for future applications in 4-5GDHC systems.

This three-step methodology bridges conceptual analysis with hands-on modeling practice, resulting in an assessment of semantic modeling in 4-5GDHC systems using ontologies.

4. Review of existing semantic modeling practices for potential applications to DHC

In recent years, the development of ontologies for buildings has gained significant traction [18]. These ontologies aim to standardize terminology, improve interoperability, and facilitate more efficient management of complex building systems. Six ontologies reviewed in this section:

- Brick Schema
- RealEstateCore (REC)
- Project Haystack
- Smart Applications Reference Ontology (SAREF)
- Flow Systems Ontology (FSO)
- ASHRAE Standard 223P

These ontologies represent the most widely used and actively developed semantic modeling practices in the building and energy domains. While not all were originally designed for DHC, their relevance lies in their potential applicability to 4-5GDHC, particularly on the building related demand-side components where digitalization and semantic interoperability are most urgently needed.
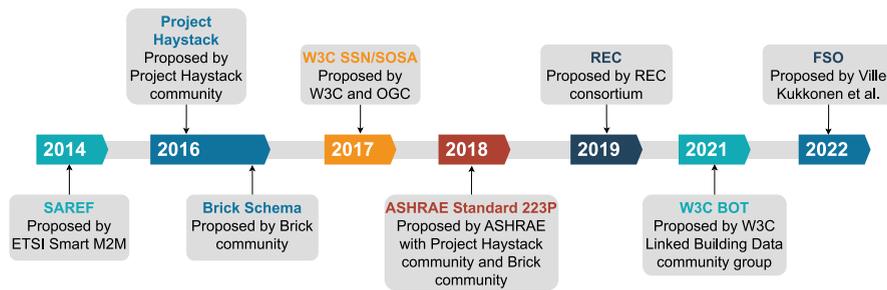
Fig. 6. Timeline of major ontologies relevant to buildings and energy field, highlighting their year of proposal and the proposing community or organization (2014–2022).
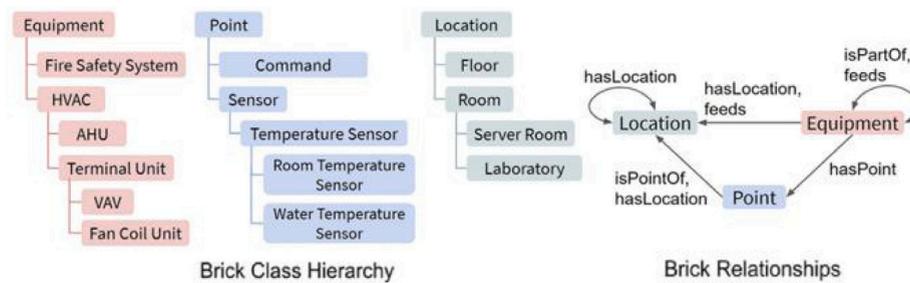

Fig. 7. Class and relationships in Brick Schema. Reprinted from Automation in Construction, Vol 139, Na Luo, Gabe Fierro, Yapan Liu, Bing Dong, Tianzhen Hong, extending brick schema to represent metadata of occupants, Page 104307, Copyright (2022), with permission from Elsevier.

The intention of this study is not to present a systematic literature review, as comprehensive ontology analysis already exists in the building and energy domains [18]. Instead, it adopts a narrative review approach, focusing on selected ontologies that are most relevant to the study's scope, those with potential applicability to building-related demand-side components in 4-5GDHC systems. The review evaluates these ontologies in terms of their strengths, limitations, and adaptability for representing DHC-specific energy flows and interactions. To provide readers with a clearer overview of how different ontologies emerged and evolved, a timeline of ontology development is shown in Fig. 6. Table 1 presents an overview of the reviewed ontologies, including their scope, key features, strengths and limitations, year of development, and responsible organization. This comparison highlights existing gaps and the potential for adapting these frameworks to better suit the requirements of DHC systems. While W3C BOT and W3C SSN/SOSA were not included in the detailed analysis due to their high-level nature, they are included in Table 1 for completeness as they represent important foundational ontologies in the building and sensor domains that researchers may encounter when exploring semantic modeling options.

The following section extends the research with an experimental application in which the reviewed ontologies are used to model selected systems, demonstrating their practical applicability and limitations in real-world semantic modeling tasks.

4.1. Brick schema

Brick Schema is an ontology for building assets that defines a dictionary of terms for physical, logical, and virtual elements within buildings, along with their interconnections, and is rooted in Project Haystack through extensive analysis of BMS data [19]. Fig. 7 illustrates the represented physical elements in buildings, such as equipment and sensors, as entities. Each entity is categorized as an instance of a specific class and can be interconnected with other entities through relationships. The model employs a flexible, extensible class hierarchy that utilizes various standard relationships, including 'hasLocation' and 'isLocationOf', 'hasPart' and 'isPartOf', as well as 'feeds' and 'isFedBy'. Brick Schema (version 1.2) is structured around four primary classes [39]:

- The Equipment class encompasses devices that provide services to all or part of a building, ranging from furnaces and boilers to air conditioners, heat pumps, and elevators.
- The Location class denotes the physical or logical placement of equipment and sensors within a building, including subclasses such as building, floor, space, and zone.
- The Measurable class is utilized to describe the quantitative and qualitative aspects of equipment and sensors.
- The Point class represents various types of data points within a building system, including sensors, setpoints, status indicators, commands, and parameters, each serving specific functions in monitoring and controlling building operations.

Table 1

Summary of ontologies for buildings in thermal networks.

Ontology	Overview	Strengths	Limitations	Year
Brick Schema	Class-based ontology for building assets, covering physical, logical, and virtual elements and their interconnections.	Robust framework for describing relationships in building systems. Highly applicable to DHC systems with comprehensive component representation.	Limited by initial focus on buildings. Lacks standardized terms for some DHC-specific elements (e.g., thermal storage, piping networks).	2016
RealEstateCore (REC)	Class-based ontology for smart building data integration, inspired by digital building representations and IoT technologies.	Ontology of agents, well-suited for describing stakeholders in DHC systems (e.g., people, companies, departments). Well-defined terms for spatial modeling and ownership.	Less developed framework for physical entities and their relationships compared to Brick Schema.	2019
Project Haystack	Open-source initiative for IoT data management in smart buildings, offering semantic modeling solutions and standardized data types.	Tagging system for flexible naming and description of components in complex systems, applicable to DHC.	Limited mechanisms for representing component connectivity and spatial relationships. May not fully capture district-level energy distribution intricacies.	2016
SAREF	Smart Applications REFerence ontology for IoT semantic interoperability, with domain-specific extensions (e.g., SAREF4BLDG, SAREF4ENER).	Comprehensive framework through multiple extensions, aligning well with multifaceted nature of DHC systems.	Complex implementation due to lack of guidelines and real-world use case samples. Integrating multiple extensions can lead to increased complexity and potential inconsistencies.	2014
Flow Systems Ontology (FSO)	Framework for describing relationships between systems and components in terms of energy and mass flows, and overall system composition.	Highly relevant for modeling DHC systems, particularly in representing material flows and piping systems. Detailed classification of distribution systems.	Lacks granularity for detailed component-level descriptions. Does not incorporate administrative or stakeholder concepts. Concerns about ongoing maintenance and development.	2022
ASHRAE Standard 223P	A standardized semantic framework to model building related metadata and control.	Comprehensive and precise approach to model hydraulic systems and controls in building systems. Potential to become an ISO standard, promoting widespread adoption. Collaborating with community-driven ontologies, such as Brick Schema and REC.	Limited set of classes compared to Brick Schema and REC, requiring extensions for district-level energy distribution. As a standard, it is challenging to update or develop incrementally.	2018
W3C BOT	A minimal, high-level ontology designed to define the core topological structure of buildings in a hierarchical structure (e.g., sites, buildings, storeys, spaces).	High extensibility, compatibility with other domain-specific ontologies (e.g., BRICK).	Provides only high-level descriptions and lacks a comprehensive set of entities for detailed modeling.	2021
W3C SSN/SOSA	Provide a framework for describing sensors, observations, actuators, and the sampling of real-world properties.	Designed for interoperability with other ontologies, and is highly extensible, allowing integration with specific domain ontologies.	High level of abstraction. Modular approach for sensor observations and actuators, not system level and application-specific.	2017

The application of Brick Schema to DHC systems presents both opportunities and challenges. On one hand, its robust framework for describing relationships and hierarchical structures of entities, sensors, and locations is highly applicable to DHC systems, which provides a detailed and standardized representation of DHC components and their interconnections. However, in DHC systems, buildings often function as simplified nodes, with heat emission systems, such as radiators, floor heating, being the most relevant building-specific components. This contrasts with Brick Schema's more detailed building-centric approach. Furthermore, Brick Schema currently lacks standardized descriptive terms for DHC elements such as thermal storage systems and the various types of hydraulic piping networks essential to DHC operations. While Brick Schema effectively captures composition and relationships, it has limitations in describing the sequenced flows within complex topologies. For example, it lacks the ability to model multiple inputs and outputs for entities like ducts or heating coils, as well as the ordered flow of media through the system—such as moving from component A to component B—which is common in DHC systems integrated with mechanical ventilation. These gaps in vocabulary and modeling capabilities highlight the need for extensions or adaptations to fully capture the unique aspects of DHC systems.

4.2. RealEstateCore

The RealEstateCore (REC) ontology is designed to facilitate data integration for building applications [40]. REC draws inspiration from various domains, including digital building representations, building systems control and operation, and emerging IoT
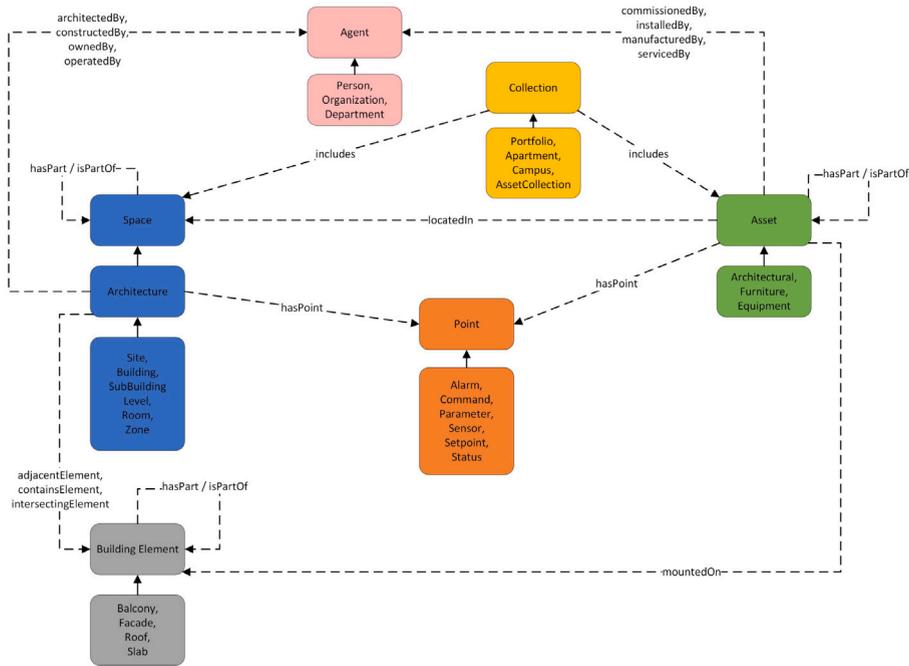
Fig. 8. REC type structure.
Source: Figure from [41] with permission.

technologies [40]. Fig. 8 provides a comprehensive type structure for representing building related data and information using REC. This structure encompasses various key elements [41], including:

- Spaces represents contiguous parts of the physical world with 3D spatial extent, ranging from Regions and Sites to Buildings, Levels, and Rooms.
- BuildingElements constitutes parts of a building's structural makeup, such as facades, walls, and slabs. Assets are objects placed within a building but not integral to its structure, including architectural elements and furniture.
- Points indicates the data production or ingestion capacity of entities, with subtypes such as Sensors, Commands, and Setpoints.
- Collections represents administrative groupings of entities treated as a unit, while Agents describe stakeholder types that can have roles or perform activities.

REC employs specific design principles to connect these types, using relationships such as 'hasPart' and 'isPartOf' for parthood, 'locatedIn' and 'isLocationOf' for spatial location, and 'includes' for administrative parthood [41]. This structured approach facilitates efficient data management in smart building applications and allows REC to interact with device configuration, observation, and actuation messages. The complete REC ontology, which imports all these modules, boasts a substantial knowledge base of 141 classes, 56 object properties, 63 data properties, and 181 individuals, making it a robust tool for representing and managing smart building data [40].

REC offers a particularly valuable aspect for DHC applications through its ontology of Agents. This feature provides a robust framework for describing the various stakeholders involved in DHC systems, which are inherently multi-stakeholder networks. The Agent class in REC, which encompasses subclasses such as People, Companies, and Departments, aligns well with the multiple roles in DHC systems. These roles include residential buildings, primary energy providers, grid operators, substation managers, and energy prosumers like industrial facilities or data centers that may generate waste heat. REC's ability to model these stakeholders and their relationships is crucial for representing the complex interactions within DHC systems.

The primary limitations of REC in this context is its less developed framework for describing the physical entities and their relationships compared to Brick Schema. While REC excels in stakeholder modeling, it lacks the granular entity-connectivity classes that Brick Schema offers for describing the technical components and their connections within DHC systems. This contrast highlights the potential benefit of integrating aspects of both REC and Brick Schema to create a more comprehensive ontology framework for DHC applications, combining REC's strength in stakeholder modeling with Brick's detailed physical system representations.

4.3. Project Haystack

Project Haystack is an open-source ontology focused on streamlining IoT data management through semantic modeling solutions for smart building systems using tags, and it serves as the foundation for Brick Schema and other tag-based ontologies [42]. Project

Haystack offers a suite of technologies for IoT data modeling, including a standardized set of data types, file formats, an HTTP API, and an ontology. The data types, referred to as "kinds", facilitate interoperable data exchange and include basic types like strings and numbers, as well as specialized types for times and dates [42]. Furthermore, the Project Haystack specifies an ontology that standardizes the modeling of common concepts in the smart building domain. This ontology includes key entities such as sites (individual buildings or equipment locations), spaces (floors, rooms, HVAC zones, etc.), equipment (physical assets like meters or air handlers), points (sensors, setpoints, or actuators), devices (microprocessor-based hardware), and weather observations. By providing this framework, Project Haystack aims to create a unified and efficient approach to handling IoT data in smart building applications, facilitating better interoperability and data management across various systems and devices.

Project Haystack offers a flexible approach to name and describe various components using tags within DHC systems. This flexibility is particularly valuable in DHC contexts, where many unique components may not be adequately described by existing ontologies. However, Project Haystack's application to DHC systems is not without limitations. While it excels at naming and tagging individual elements, it lacks robust mechanisms to represent connectivity between components, spatial relationships, and other critical aspects of DHC systems. For example, the diverse types of piping systems and their interconnections, essential to DHC operations, are not addressed in the current framework. In addition, it faces a significant challenge in standardization [43]. The lack of formal rules governing tag usage has resulted in highly customized and inconsistent implementations across different sites, making it hard to scale up the solution. These limitations underscore the need for extensions or adaptations to Project Haystack to better suit the specific requirements of DHC systems, particularly in areas of hydraulic topology, network-level interactions, and district-scale infrastructure representation.

4.4. The smart applications reference ontology

The Smart Applications REFerence (SAREF) ontology is a significant development in the field of semantic interoperability for IoT applications [44]. Initiated in 2014 as a European-level study, SAREF has evolved from its original focus on smart appliances to encompass a broad range of smart applications. SAREF is published as open standards by the ETSI Technical Committee Smart Machine-to-Machine communications (SmartM2M), aims to create a shared model of consensus that enables seamless communication between solutions from various providers across different IoT sectors [44]. SAREF contains different extensions to handle different domains, such as SAREF4BLDG for building domain and SAREF4ENER for energy domain etc. SAREF4BLDG is similar to above ontologies for buildings, it translates building device taxonomies from Industry Foundation Classes (IFC) into OWL, effectively creating a subset of the domains described in ifcOWL [45].

SAREF offers advantages for modeling DHC systems through its domain-specific extensions. Particularly relevant are SAREF4ENER for the energy domain, SAREF4BLDG for buildings, SAREF4GRID for smart grids, and SAREF4CITY, which includes concepts like districts [46]. These extensions provide an extended framework that aligns well with DHC systems, including energy distribution, building integration, grid management, and urban planning aspects. The inclusion of district-level concepts in SAREF4CITY is especially useful, as it recognizes the varying scales and administrative structures of districts across different countries and contexts [46]. However, SAREF's application to DHC modeling is not without challenges. The primary drawback is the complexity of implementation, stemming from a lack of comprehensive guidelines, code bases, or sample implementations that could serve as references for practitioners. Furthermore, accurately representing a DHC system often requires the integration of multiple SAREF extensions, which can lead to increased complexity and potential inconsistencies in the modeling process. This multi-ontology approach, while thorough, may present difficulties in creating manageable models of DHC systems, highlighting the need for more streamlined integration methods and practical implementation resources within the SAREF framework.

4.5. The flow systems ontology

The Flow Systems Ontology (FSO) is a proposed framework for describing the relationships between systems and their components in terms of energy and mass flows, as well as the overall composition of these systems [47]. This ontology aims to provide a standardized method for representing flow systems and their interactions. The FSO is designed to complement existing ontologies in the field, offering a lightweight and machine-readable approach to describing relationships between HVAC components. The ultimate goal of the FSO is to establish a common foundation for describing flow systems using linked data, see Fig. 9. This standardization is tailored to specific applications, such as hydraulic simulation tools, building energy performance simulation (BEPS), building analytics, and diagnostic systems. By providing a unified language for describing flow systems, the FSO has the potential to enhance interoperability and facilitate more efficient data exchange across various domains within building science and engineering.

FSO presents a highly relevant framework for modeling DHC systems, particularly in its approach to representing material flows and piping systems. Its strength lies in its detailed classification of distribution systems, with specific subclasses such as fso:DistributionSystem, fso:SupplySystem, and fso:ReturnSystem, which align closely with the core components of DHC systems. These classes provide a structured way to model the supply and return flows of energy and mass within the system. Furthermore, the FSO's focus on connectivity and fluid dynamics through its fso:Component and related subclasses offers a foundation for representing the physical infrastructure of DHC systems. However, the FSO has notable limitations in the context of comprehensive DHC modeling. It lacks the granularity needed to describe components such as various sensors, meters, heat exchangers, and radiators, which are often crucial for DHC system analysis and optimization. Additionally, the FSO does not incorporate administrative or stakeholder concepts, such as those found in the REC agents model, which are essential for representing the multi-stakeholder nature of DHC
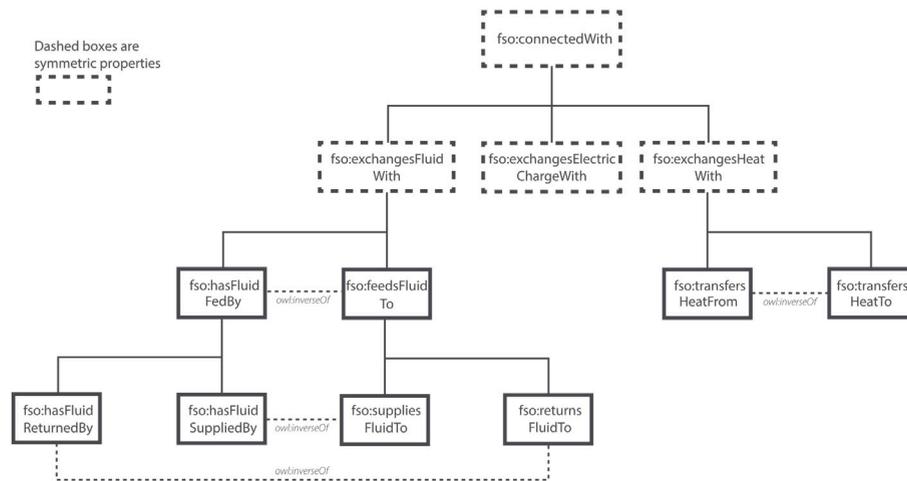
Fig. 9. Relationships for the flow of energy and matter between systems and components.
Source: Reprinted from [47] under CC BY 4.0 license.

systems. The ontology also falls short in providing the level of detail for individual entities that Brick Schema offers. A significant practical drawback is the apparent lack of ongoing maintenance and development of the FSO, which raises concerns about its adaptability to evolving DHC technologies and practices. These limitations suggest that while the FSO provides valuable concepts for flow and distribution modeling, its effective application to DHC systems would require integration with other ontologies and potentially significant extensions to address the full spectrum of DHC modeling needs.

4.6. ASHRAE standard 223P

In a move towards standardization in building semantics, three major organizations in the field, the ASHRAE BACnet committee, the Project Haystack community, and the Brick community, formed a collaborative effort in February 2018. Their goal was to integrate the tagging system of Project Haystack and the data modeling concepts of Brick Schema into a proposed new ontology, ASHRAE Standard 223P, titled "Designation and Classification of Semantic Tags for Building Data" [48]. This standard aims to provide a comprehensive dictionary of semantic tags for descriptive tagging of building data, including building automation and control systems. The collaboration seeks to create a unified, formally standardized application data modeling solution that can be implemented across various platforms and protocols [49]. This initiative is expected to enhance interoperability of semantic information in building automation. With the potential to be adopted as an ISO standard, ASHRAE Standard 223P represents a significant step towards creating a global standard that could foster a more competitive marketplace, ultimately benefiting building owners through improved engineering and automation efficiencies enabled by machine-readable semantic descriptions of data.

ASHRAE Standard 223P represents a significant advancement in semantic modeling for building systems, with potential applications to DHC systems. Its strength lies in its comprehensive approach to applying semantics to represent building systems. Unlike Brick Schema, ASHRAE 223P offers more precise modeling capabilities, particularly in representing different types of flows of media such as air in/out and water in/out. Fig. 10 illustrates this capability, showing a reheating system in ventilation where air and water flow into a heating coil and then out to ducts and dampers. This level of detail is crucial for accurately modeling the complex flows characteristic of DHC systems. The standard's focus on describing entity connections, energy and information transfer media, and system composition aligns well with the interconnected nature of DHC systems. Particularly valuable is its ability to model various levels of composition, from individual equipment components to larger systems and spaces, which could be adapted to represent the hierarchical structure of DHC systems. Furthermore, its potential to become an ISO standard suggests a path towards widespread adoption and interoperability. However, ASHRAE 223P faces several challenges in its application to DHC systems. Its extremely detailed and precise nature, while beneficial for accuracy, requires significant manual work and time investment, as well as deep domain expertise to implement correctly. The standard is still under development, with limited resources and applications available, making its immediate implementation in DHC contexts challenging. Additionally, the lack of DHC-specific examples and guidelines presents a barrier to its adoption in this field.

To summarize, this section has provided a critical review of several prominent ontologies and their potential application to DHC systems. The examined ontologies, including Brick Schema, REC, Project Haystack, SAREF, FSO, and ASHRAE Standard 223P, each offer unique strengths and perspectives on semantic modeling of complex systems. While these ontologies have made significant contributions to their respective domains, their direct application to DHC systems poses certain challenges. The building-centric focus of some ontologies, the lack of DHC-specific terminologies in others, and the varying levels of detail and scope across these frameworks highlight the complexities of adapting existing ontologies to the unique requirements of district-level energy systems. Nevertheless, the collective strengths of these ontologies present great potential for their adaptation and integration in DHC contexts.
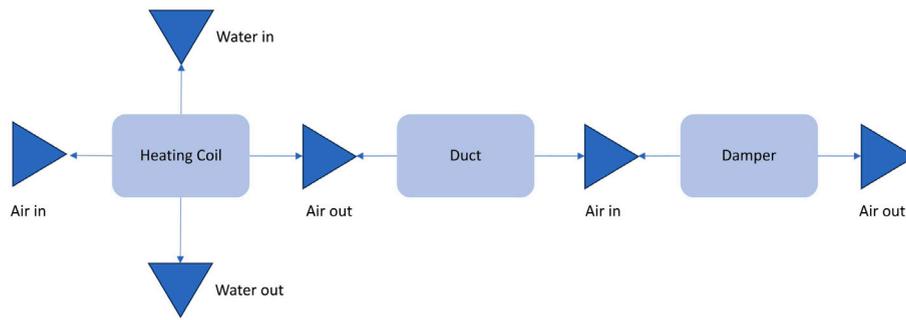
Fig. 10. Common topology for a reheating system in ventilation. ASHRAE 223P can model the flow of media such as water or air entering and exiting various components.

While considerable work remains to tailor these ontologies for comprehensive DHC modeling, their foundational concepts and structures offer a promising starting point for developing more specialized and integrated semantic frameworks for DHC systems, potentially leading to improved interoperability, efficiency, and management of these complex energy networks.

5. Evaluating ontologies for building-related 4-5GDHC components

This section presents a series of modeling experiments that apply reviewed ontologies to selected components in 4-5GDHC systems, with a specific focus on demand side/building-related systems. The aim in this section is to test how existing semantic modeling frameworks can be applied in practice to support information sharing in the context of 4-5GDHC. The resulting knowledge graphs are intended to support both the interpretation of sensor-generated time-series data and the routing of control signals to actuators, enabling smart, autonomous operation.

This application-based approach is structured in three steps to reflect the engineering guidance:

- Identify representative building-related components in 4-5GDHC systems that are critical for semantic modeling (e.g., heat pumps, thermal storage, PV/T, waste heat recovery).
- Apply current ontologies to model these components using formalized terms and relationship vocabularies.
- Critically evaluate the effectiveness and limitations of current ontologies through these modeling experiments, identifying gaps, strengths, and areas requiring extensions or integration.

Through this process, this work moves beyond theoretical review and offers practical insights on the applicability of current ontologies in real-world DHC scenarios.

5.1. Buildings with heat pumps in the thermal network

Buildings connected to DHC systems play a crucial role in the overall efficiency and performance of these systems [50], particularly in the transition towards 4-5GDHC. A critical challenge in this transition is ensuring low operating temperatures in the networks, which is often hindered by poorly controlled and operated heating systems in existing building stocks [51]. The digitalization of the demand side presents new opportunities for monitoring and improving heating system operations in buildings, potentially securing expected comfort levels with lower supply temperatures [52].

Fig. 11 illustrates a simplified configuration of a building integrated with a heat pump in a district heating system. The diagram depicts a three-floor building, with each floor containing a room equipped with a radiator for space heating and taps representing domestic hot water usage. The building's heating system is connected to the district heating network through a heat pump. It allows for efficient heat transfer and temperature management, potentially enabling the building to operate with lower-temperature district heating supply while still meeting the higher temperature demands of the building's heating and hot water systems. From the heat pump, hot water is distributed to each floor, supplying both the radiators for space heating and the taps for domestic hot water use. This configuration demonstrates how buildings in 4-5GDHC systems can utilize heat pumps to effectively bridge the gap between district-level energy distribution and individual building heating requirements.

Fig. 12 presents a simplified semantic model of a building integrated with a heat pump in a district heating network, constructed using Brick Schema. The modeling experiment reveals that Brick Schema demonstrates considerable strengths in representing various components of the building system. It effectively models sensors (such as temperature and flow sensors), radiators, heat pumps, and the spatial layout of the building including floors and rooms. The relationships between these components, such as the connection between the heat pump and radiators, are also well-represented within the Brick Schema framework. However, the experiment also uncovers significant limitations when it comes to modeling the district heating network. Notably, Brick Schema lacks specific terminologies and relationship structures to adequately represent district heating networks. This gap in the ontology becomes apparent when attempting to model the flow and media of thermal energy from the district network into the building system.
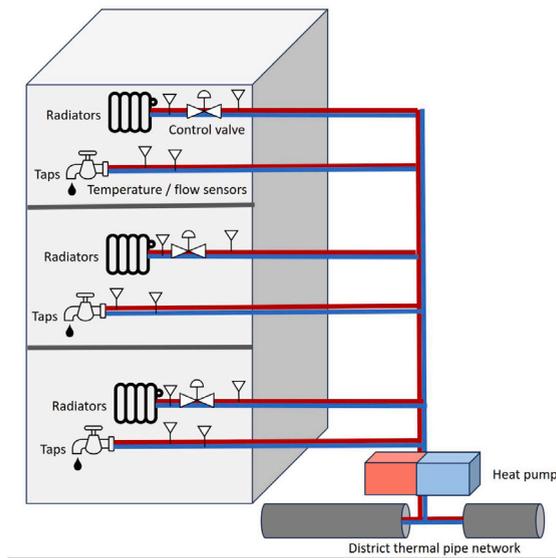
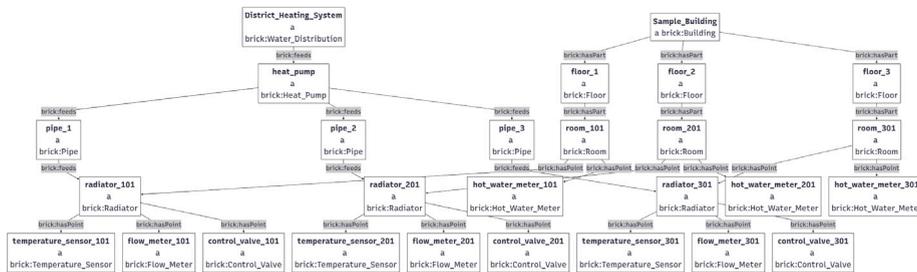**Fig. 11.** Simplified schematic diagram of a building in DHC.

Fig. 12. Knowledge graph of a building with a heat pump in DHC.

Furthermore, Brick Schema's building-centric approach does not provide sufficient constructs to represent the broader district heating network context, highlighting the need for extensions or complementary ontologies to fully capture the complexities of buildings as nodes within larger district heating systems.

5.2. Thermal energy storage

Thermal energy storage (TES) is a crucial component in 4-5GDHC systems. These systems are designed to harness and integrate renewable energy sources and reclaim waste heat. Guelpa et al. [53] conducted a comprehensive review of TES in DHC systems. They highlighted that TES systems can significantly enhance the flexibility and performance of district heating networks, enabling better integration of renewable energy sources and improving overall system efficiency. The authors reported that TES has the potential to save up to 7.8% of annual energy consumption in the European Union. In interconnected energy networks, thermal energy storage plays a vital role when they integrated with various heat generation sources and heat pumps [54], enabling sector coupling applications and flexibility services [55].

Fig. 13 illustrates a common design of a water tank-based thermal storage system. The system typically employs two main components: a high-temperature tank and a low-temperature tank, each equipped with its own heat exchanger. The high-temperature tank stores hot water, with its heat exchanger receiving steam as input. As steam flows through this exchanger, it transfers thermal energy to the water in the tank, creating a thermal energy reserve. The low-temperature tank contains cooler water, and its heat exchanger can accept either water or steam input, providing operational flexibility. Key sensors in this system play crucial roles in monitoring and controlling the storage process. Temperature sensors are installed in both tanks to continuously monitor water temperature, ensuring optimal thermal stratification and energy storage efficiency. Pressure sensors in the pipes measure system pressure, which is vital for maintaining safe operation and detecting any potential leaks or system anomalies. Flow sensors are strategically placed to measure the rate of water or steam flow through the system, providing essential data for calculating energy transfer rates and system performance. These sensors collectively provide real-time data that is critical for efficient operation, control, and optimization of the thermal storage system within the broader DHC system.
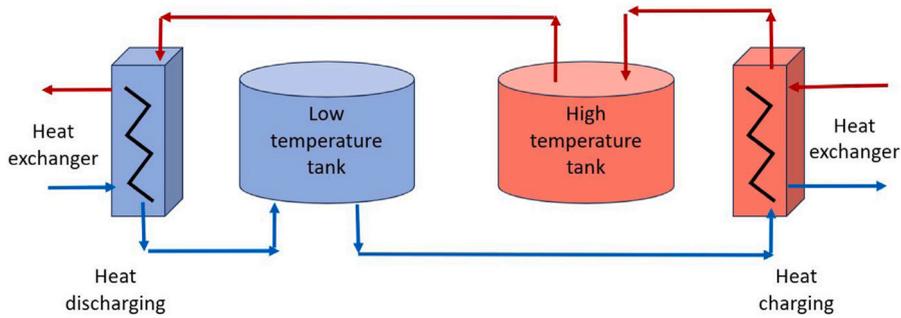
Fig. 13. Schematic system design of water tank based thermal storage.
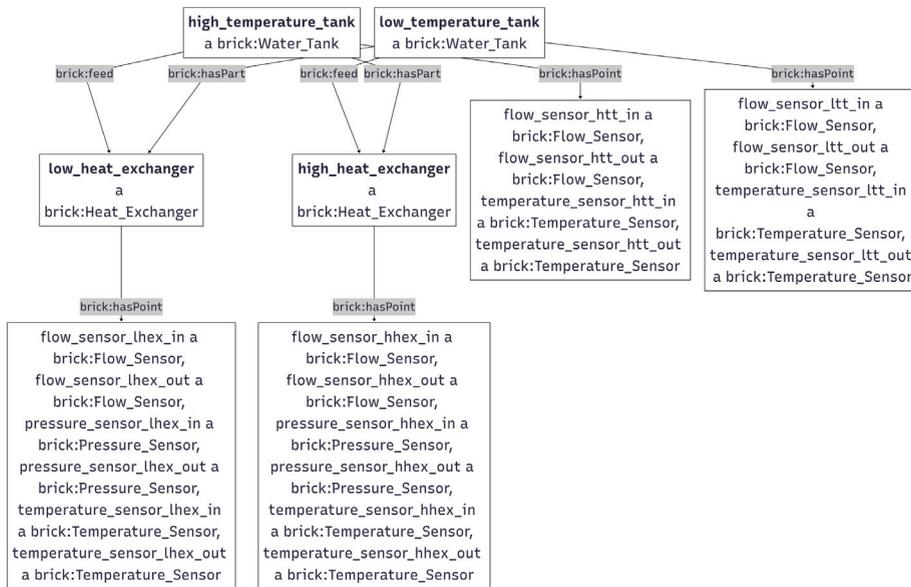
Fig. 14. Simplified knowledge graph for water tank-based thermal storage.

Fig. 14 illustrates a simplified semantic data model, focusing on controllable points and data-generating elements within the water tank-based thermal storage system. Key nodes in this graph include high-temperature and low-temperature tank entities, heat exchanger entities for each tank, and various sensor entities (temperature, pressure, and flow), with relationships such as "has_part" connecting these components. While current ontologies like Brick Schema can model basic components and their relationships, such as water storage tanks, heat exchangers, and sensors, they face limitations in fully representing thermal storage systems in DHC contexts. These limitations include a lack of specific terms for DHC thermal storage and insufficient detail for modeling water-tank thermal storage systems based on comprehensive component descriptions. Additionally, there is limited ability to represent dynamic behaviors like charging and discharging cycles, and insufficient granularity in depicting heat transfer processes. To address these shortcomings, potential improvements could involve extending existing ontologies with DHC-specific terms and relationships, developing new ontology modules focused on water tank-based thermal energy storage systems, and integrating temporal aspects to better represent system dynamics. These enhancements would significantly improve the semantic modeling capabilities for water tank-based thermal storage systems, enabling more accurate and comprehensive digital representations of these crucial DHC components.

Aquifer Thermal Energy Storage (ATES) is an innovative and energy-efficient technology that leverages natural groundwater reservoirs for thermal energy management in DHC systems. This system utilizes aquifers as a medium for storing and retrieving thermal energy, facilitating both heating and cooling applications in buildings and urban areas [56]. ATES operates by circulating groundwater between the aquifer and the surface through specially designed wells, allowing for the transfer of thermal energy. During cooling cycles, warm water is stored in the aquifer, while cold water is stored during heating cycles, creating a natural, large-scale heat exchanger. The implementation of ATES in DHC systems offers several advantages, including load balancing, peak shaving, and improved system resilience. By providing a means to store excess thermal energy during low-demand periods and retrieve it during high-demand periods, ATES helps optimize the overall efficiency of district energy systems [56].

Fig. 15. Schematic configuration of ATES.
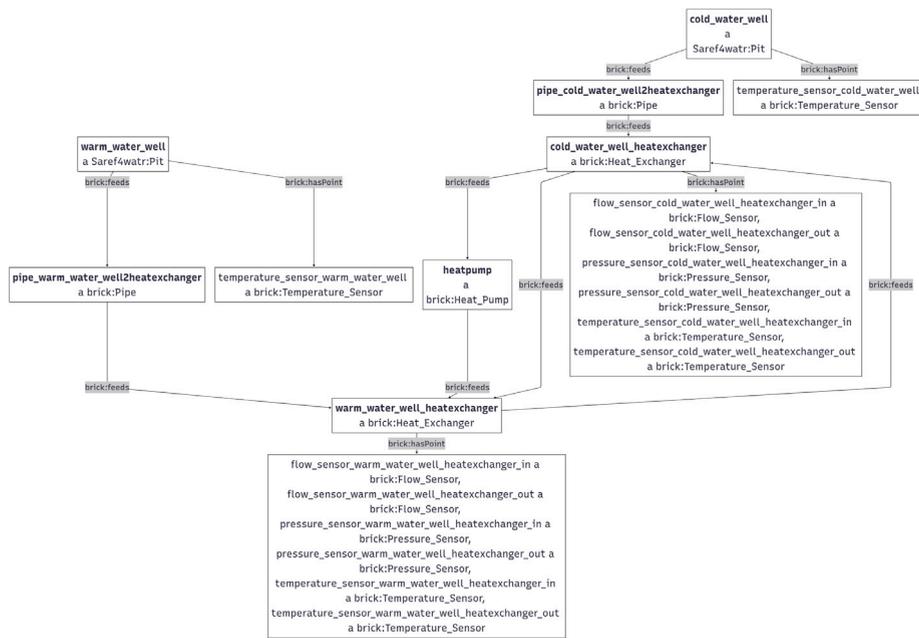
Fig. 15 illustrates a schematic configuration of a typical ATES system, which primarily consists of two wells - a cold well and a warm well - connected to heat exchangers and heat pumps. During summer, when cooling is required, cold water is extracted from the cold well and circulated through a heat exchanger, absorbing excess heat from the building or district cooling network. The warmed water is then injected into the warm well for storage. In winter, this process is reversed, with warm water extracted from the warm well, passed through the heat exchanger and heat pump to heat the building or district heating network, and the cooled water returned to the cold well. This dual-well design allows for efficient seasonal thermal energy storage and retrieval. The system is equipped with various sensors, including temperature sensors in both wells and throughout the circulation system, flow meters to measure water extraction and injection rates, pressure sensors to monitor aquifer conditions. This configuration enables ATES to significantly reduce energy requirements for heating and cooling in DHC systems, making it a valuable component in modern, sustainable urban energy infrastructures.

A simplified semantic model of the ATES system is constructed using existing ontologies, as illustrated in Fig. 16. Several key findings emerge from this modeling attempt. Firstly, basic components in this system, such as sensors, heat exchangers, and heat pumps, can be effectively described using current ontologies like Brick Schema, which is a positive aspect. However, some critical elements specific to ATES, such as the cold well and warm well, are not part of Brick Schema. Instead, the SAREF ontology extension for water, SAREF4WATR, includes the concept of a "Pit", defined as "a well or hole sunk in the ground to procure, store or drain water", which aligns closely with ATES requirements. This situation demonstrates that to comprehensively model ATES systems, it is necessary to either create extensions to existing ontologies or combine multiple ontologies. Additionally, the REC agent model provides valuable administrative information, which could be particularly useful in representing different stakeholders involved in ATES operations. This multi-ontology approach highlights the complexity of fully representing ATES systems and the need for a more integrated semantic framework that can capture all aspects of these advanced thermal storage solutions in DHC contexts.

5.3. Photovoltaic-thermal (PV/T)

The integration of renewable energy technologies into DHC systems has become increasingly crucial. PV/T systems represent a promising solution in this context, offering a dual approach to harnessing solar energy [57]. These hybrid systems combine photovoltaic cells for electricity generation with thermal collectors for heat production, addressing the limitations of traditional solar panels. While conventional photovoltaic cells can only convert a portion of the solar energy into electricity, PV/T systems capitalize on the remaining energy that would otherwise be lost as heat [58]. This type of system not only enhances overall energy efficiency but also presents unique opportunities for integration into DHC systems. By simultaneously producing electricity and thermal energy, PV/T systems can contribute to both the electrical and heating/cooling demands of district energy systems, potentially reducing reliance on fossil fuels and improving the sustainability of urban energy infrastructure.

Fig. 17 illustrates a common design of a PV/T system that could be integrated into a DHC system. The core component of this system is the PV/T collector. The PV/T collector efficiently captures sunlight, converting a portion into electricity through photovoltaic cells while also absorbing thermal energy. The thermal energy captured by the PV/T collector is typically transferred to a heat transfer fluid, often water or a specialized thermal fluid. This heated fluid is then circulated to a heat exchanger, which serves as the interface between the PV/T system and the DHC system. The heat exchanger efficiently transfers the thermal energy from the PV/T system to meet heat demand. Pumps are installed between the PV/T collector and the heat exchanger. Additionally, a control valve is incorporated into the system to regulate the flow rate of the heat transfer fluid. The PV/T system is equipped with

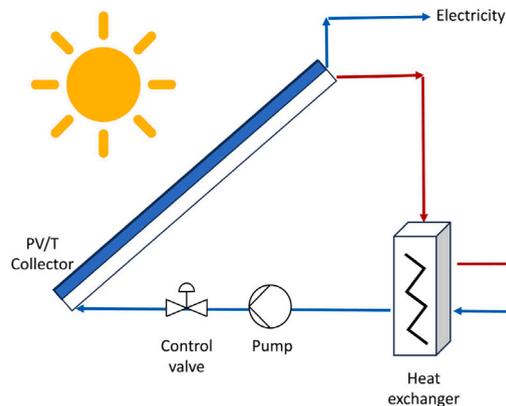**Fig. 16.** Aquifer thermal storage knowledge graph.

Fig. 17. Schematic system diagram of PV/T.

a variety of sensors to monitor and optimize its performance within the DHC system. Temperature sensors are placed at the inlet and outlet of both the PV/T collector and the heat exchanger. Flow rate sensors are installed in the fluid circulation loop to measure and control the rate of fluid flow between the PV/T collector and the heat exchanger. Additionally, solar irradiance sensors usually mounted near the PV/T collectors provide data on available solar energy and electrical sensors monitor the power output from the photovoltaic cells, offering insights into the electrical generation efficiency.

Experiments conducted to build a semantic model, as shown in Fig. 18, for PV/T systems reveal both strengths and limitations of current ontological frameworks. Findings indicate that Brick Schema provides substantial support for modeling PV/T systems, offering standardized descriptions for key components such as PV/T collectors, heat exchangers, solar irradiance sensors, and electrical sensors. This capability enables a comprehensive representation of the technical aspects of PV/T systems within DHC systems. However, the modeling attempts also uncovered significant gaps in the current work. Notably, Brick Schema lacks sufficient constructs for representing administrative information, which is crucial for modeling the governance structure of PV/T installations. For instance, there is no standardized way to represent ownership information or operational responsibilities within the current framework. This limitation becomes particularly apparent when attempting to model PV/T systems that is connected to both residential buildings and district heating networks, which is under different administrative domains. However, the REC ontology offers promising elements that could address these gaps. Specifically, REC's Agent class provides a framework for modeling Organization and Person, with Organization further subdivided into categories like Company and Department. REC also offers useful
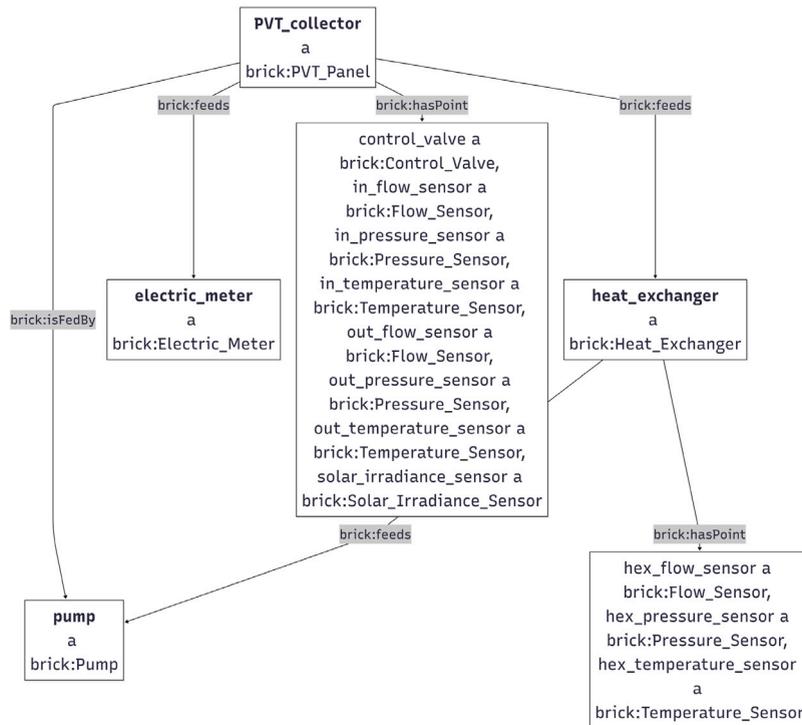
Fig. 18. Knowledge graph of a PV/T system.

properties such as 'hasMember', which indicates membership in an organization, and 'hasPart', a more generic property that can express componency relationships (e.g., departments within a corporation). These tools from REC could be effectively extended to model the complex ownership and administrative structures in DHC systems integrated with PV/T.

5.4. Waste heat recovery

Thermal energy prosumers like data centers and industrial buildings are becoming increasingly significant in DHC systems. Their integration offers the potential to contribute excess heat back into the thermal network, enhancing overall efficiency and supporting renewable energy utilization. Waste heat recovery from these sources can be integrated into DHC systems to reduce reliance on traditional heat production methods, thereby lowering operational costs and improving overall energy efficiency [59]. Data centers, in particular, generate substantial amounts of excess heat due to their high electricity consumption and cooling needs, it is possible to capture and utilize this waste heat and reuse in district heating networks [60]. This integration not only leads to cost savings but also supports the transition towards low-temperature district heating networks [61], which are more compatible with renewable energy sources and modern building standards [62]. However, the introduction of prosumers can also present challenges. For instance, their presence may cause fluctuations in differential pressure, supply temperatures, and flow velocities within the network, potentially impacting other customers connected to the same system [63].

Fig. 19 illustrates a simplified schematic of a data center connected to a DHC system. In this configuration, chilled water or another cooling medium from the district cooling network is circulated through the data center's cooling systems to absorb heat from the servers and other equipment. The warmed cooling medium, now carrying the waste heat, is then returned to the district heating network. Heat exchangers facilitate the transfer of thermal energy between the data center and the DHC system, ensuring that the waste heat is efficiently captured and utilized. Pumps are used to circulate the cooling medium, and sensors including temperature and flow meters, are placed throughout the system to monitor performance and ensure operational stability.

Creating a semantic model for the data center integrated with the DHC system, as illustrated in Fig. 20, highlights both the strengths and limitations of current ontologies like Brick Schema. While it effectively models fundamental components such as sensors, pumps, heat exchangers, and general system layouts, it lacks specific constructs for representing data center-specific elements—particularly the waste heat generated by IT workstations. Moreover, there is no standardized way within current ontologies to model the critical aspect of the data center's role as a prosumer, which is essential in 4-5GDHC systems due to their ability to enhance flexibility and efficiency through bidirectional energy flows. The absence of explicit representations for prosumers in current ontologies indicates a significant gap. Recognizing and accurately modeling thermal energy prosumers is crucial for advancing the interoperability and intelligent management of modern DHC systems. This underscores the need for extending existing ontologies or developing new semantic frameworks that can capture the unique characteristics of prosumers within DHC systems, thereby supporting the integration of decentralized energy sources and optimizing system performance.
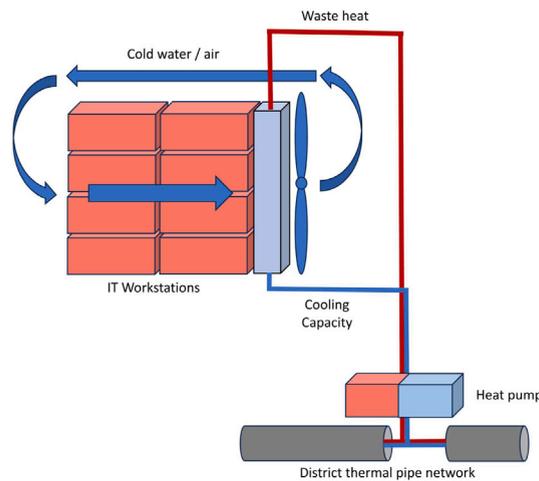
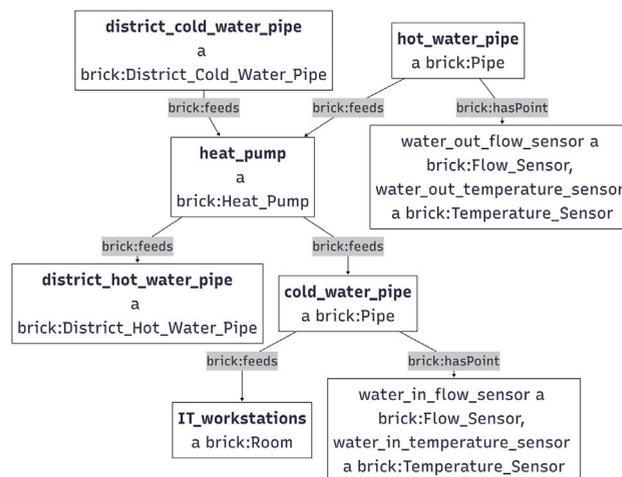**Fig. 19.** Simplified waste heat recovery from data center.

Fig. 20. Knowledge graph of a simplified data center connected to district thermal network.

6. Implications for future research

This section discusses the implications and potential advancements in semantic modeling for 4-5GDHC systems, focusing on three key areas:

- A component-to-system approach to modular construction and composition of knowledge graphs.
- The integration of knowledge graphs with LLMs.
- The convergence of design-related metadata, knowledge graphs, and energy models for lifecycle management in 4-5GDHC systems.

6.1. Components-to-system approach

The complexity of demand-side 4-5GDHC systems presents significant challenges in creating comprehensive semantic models. These systems consist of numerous components, such as different buildings, renewable energy sources, thermal storages, and heat recovery units, each with its own intricacies [6]. Constructing a complete and centralized semantic graph for the entire system is difficult, time-consuming to maintain, and challenging to update [64]. To address this issue, the study proposes a component-level approach to knowledge graph construction.
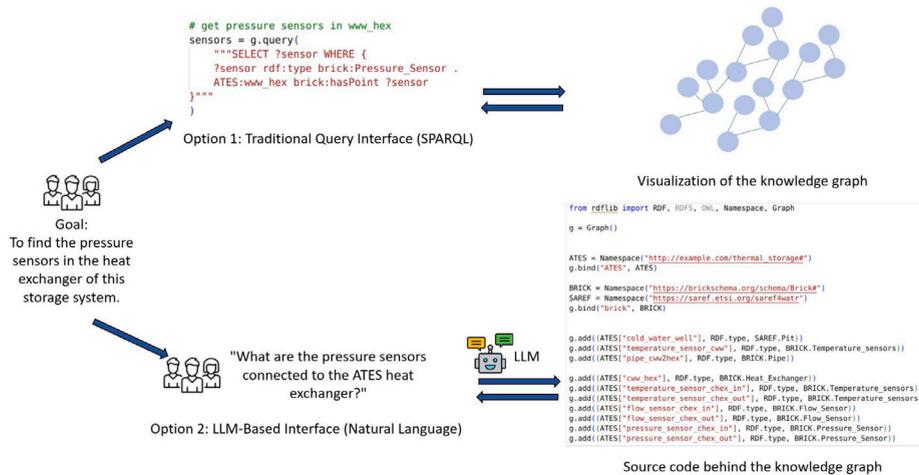
Fig. 21. Comparison between traditional SPARQL-based querying and LLM-based natural language interaction with semantic models. While SPARQL requires structured query language and technical knowledge of the ontology schema, LLMs allow users to interact with the same RDF-based knowledge graph using plain language, potentially improving accessibility and usability in real-world energy systems.

This approach takes advantage of the structure of RDF-based graphs, which support linking between different subgraphs through shared relationships and edge connections. If each component is modeled using consistent RDF-based ontologies, the resulting semantic graphs can be connected later without the need for centralized coordination or a complete system-wide model at the outset. Semantic models are developed independently for each key demand-side component, such as thermal energy storages, PV/T systems, buildings with heat pumps, and waste heat recovery systems. These individual models form modular "mini-graphs", which can be combined to represent different system-level configurations of a full DHC system. Each mini-graph acts as a building block that corresponds to a specific subsystem within the overall network. The modularity of this approach allows each mini-graph to be developed and updated independently, making the modeling process more manageable and scalable, while avoiding the complexity of constructing an entire network-level model all at once. This flexibility also enables adaptation to diverse real-world implementations. As new technologies or components are introduced, their corresponding mini-graphs can be developed and integrated into the existing framework without requiring a complete reconstruction of the model. In this way, the component-level approach provides a scalable and sustainable strategy for semantic modeling of complex 4-5GDHC systems and supports the progressive construction of system-level knowledge graphs through the integration of independently modeled components.

6.2. Knowledge graphs with large language models (LLMs)

LLMs have recently emerged as powerful, general-purpose AI systems capable of understanding and responding to a wide range of human instructions [65]. These models have shown impressive abilities across various fields, from creative writing to complex problem-solving [66], including medicine [67], finance [68], and education [69]. Their potential to transform energy management systems, especially in the context of 4-5GDHC, has not yet been fully explored. The inclusion of LLMs in this paper is motivated by two observed inefficiencies in the buildings and energy domain. First, the way engineers interact with data and information is often cumbersome and fragmented. Second, the process by which engineers and researchers use that data to create energy-related applications, such as simulations, is labor-intensive. Both tasks rely heavily on human expertise to interpret the data and require extensive manual work to prepare it for use in tools such as Modelica, Python, or TRNSYS.

A critical challenge in leveraging LLMs lies in enabling these models to comprehend and interact with the complex physical structures of DHC systems. The approach proposed in this work aims to address this challenge through the development of text-based knowledge graphs that can be processed and understood by LLMs. These semantic graphs may serve as a bridge between the linguistic capabilities of LLMs and the intricate physical components of DHC systems. By representing system components, relationships, and operational data in a format aligned with LLMs' natural language processing abilities, this approach lays the foundation for a digital information infrastructure that supports AI-driven energy management. If successful, this method could enable LLMs to efficiently query and interpret system-level semantic data, potentially transforming how complex energy networks are analyzed, controlled, and optimized.

Fig. 21 illustrates this concept by comparing traditional query-based interaction methods, such as SPARQL, with an emerging LLM-based interface that allows for natural language interaction with semantic models. While this direction is promising, further research is needed to fully assess the effectiveness, accuracy, and scalability of LLMs in real-world DHC applications.
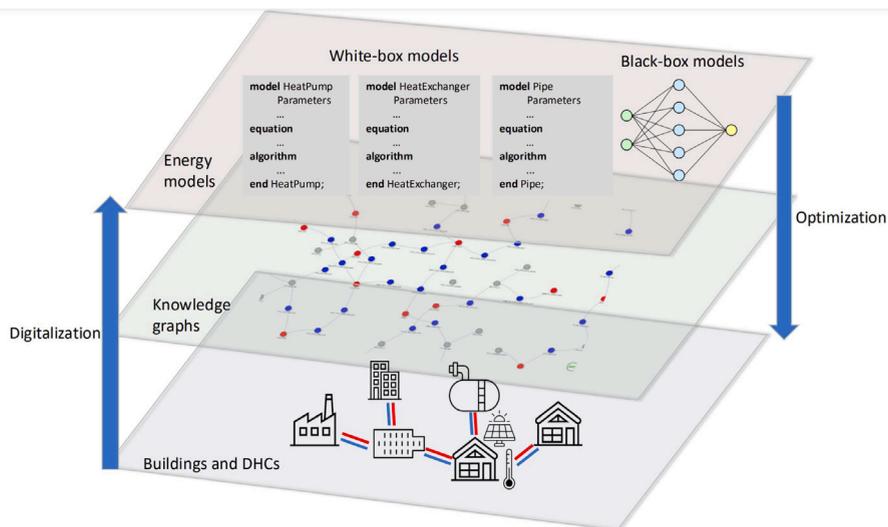
Fig. 22. Spatial models, knowledge graphs, and energy models.

6.3. Integrating design metadata, semantic modeling, and energy modeling for DHC systems

Fig. 22 illustrates the integration of design-related spatial metadata (BIMs, GIS data) of DHC, knowledge graphs, and energy models for advanced 4-5GDHC systems, from digitalization through to optimization and expansion. BIM and GIS data could be used to represent pipeline layouts, substation locations, and connectivity between network nodes. However, those models of design alone lack the ability to support the complex, data-driven interactions required for real-time operational control and predictive maintenance in DHC systems. Knowledge graphs play a critical role by enabling machine-readable representations of semantic relationships within the network, such as energy flow between substations, thermal storage units, and prosumer sites (e.g., data centers). Together, design-related models and knowledge graphs create a foundational digital bridge that could support various applications such as energy modeling simulations, network layout optimization, load balancing, and efficient integration of renewable sources.

To fully harness the potential of these technologies, knowledge graphs can act as a bridge between static spatial data and dynamic, physics-based energy models. For instance, sub-graphs of knowledge graphs could store key physical parameters of pipelines, thermal storage facilities, and heat exchangers, which can be linked to energy models like Modelica objects or black box models, to simulate temperature distribution, pressure levels, and flow dynamics in real time. This approach is particularly valuable for the modular, scalable expansion of DHC systems, where new buildings and prosumer sites can be integrated into the existing knowledge graphs. This leads to a new idea that knowledge graphs are environments that enables co-simulation.

7. Limitations

While this study provides a critical evaluation of semantic modeling for building related components in 4-5GDHC systems, it is important to acknowledge several limitations.

Firstly, although various ontologies have been discussed along with their potential integration, the practical challenges of selecting and utilizing different semantic frameworks are not fully addressed. The real-world implementation based on these ontologies may face significant hurdles that were beyond the scope of this study. Questions remain about how to effectively connect or extend ontologies like Brick Schema, REC, SAREF and ASHRAE 223P for DHC applications.

Secondly, the research primarily focused on the demand side of DHC systems, particularly on buildings and their interfaces with the district network. While this approach allowed for a detailed exploration of these components, it also meant that other important aspects of 4-5GDHC systems were not extensively covered. Specifically, large-scale renewable energy sources on the supply side, such as combined heat and power (CHP), large-scale solar installations or geothermal plants, were not thoroughly examined. However, it is worth noting that the semantic modeling approaches discussed in this paper could be potentially adapted and applied to these supply-side systems as well.

Thirdly, this study did not address the specifics of communication protocols or Internet of Things (IoT) integration. An assumption was made that data from various components could be accessed by computer systems without delving into the technical details of how this access is achieved. For instance, communication protocols like BACnet, Modbus, or KNX, which are crucial in building automation and control networks, were not discussed in detail. However, existing works have addressed this integration. For example, Duarte et al. demonstrated Brick Schema-based semantic models with BACnet and control systems in buildings [70]. This

limitation means that the practical implementation of the semantic models discussed may require additional work to integrate with existing building management systems (BMS) and IoT devices.

Lastly, the semantic modeling and knowledge graphs presented in this study are rather theoretical and based on simplified system configurations. While they provide a way for understanding and representing 4-5GDHC systems, they have not been extensively evaluated or implemented in real-world scenarios. This limitation means that practical challenges in applying these semantic models to complex, operational DHC systems remain to be fully explored.

8. Conclusions

This work makes three novel contributions to semantic modeling for 4-5GDHC systems: the first comprehensive critical evaluation of existing ontologies for DHC applications, an innovative experimental methodology combining theoretical analysis with hands-on semantic modeling, and forward-looking integration frameworks linking knowledge graphs with large language models and design metadata.

Key findings from this analysis include:

- Existing ontologies are insufficient for fully modeling DHC systems. In particular, they lack comprehensive support for some unique characteristics of 4-5GDHC systems, such as bidirectional energy flows, integration of decentralized renewable sources, and the dynamic interactions between district-level systems and prosumers. Notably, key gaps include insufficient modeling of thermal storage dynamics, stakeholder interactions, and connectivity within complex DHC systems.
- Several common DHC components can be modeled using existing ontologies, as demonstrated by this study by creating example knowledge graphs of some components in 4-5GDHC systems.
- The integration and bridging of multiple ontologies and the development of DHC-specific extensions are identified as necessary steps to create comprehensive semantic frameworks for 4-5GDHC systems.
- A promising direction lies in integrating knowledge graphs with LLMs. This synergy can redefine human–system interactions and provide a possible way for autonomous energy management.
- Knowledge graphs can play a pivotal role in providing environments or platforms that support co-simulation, bridging design-related spatial metadata with real-time energy models.

While this work has identified significant opportunities, it also highlights the need for further exploration of practical implementation challenges. The realization of semantic models in operational 4-5GDHC systems will require collaborative efforts across academia, industry, and standardization bodies.

CRediT authorship contribution statement

Zeng Peng: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Thomas Ohlson Timoudas:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Qian Wang:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization.

Declaration of generative AI use

During the preparation of this work, the author(s) used [Grammarly and ChatGPT] to improve the readability of the manuscript. After using these tools, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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.

Acknowledgments

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jobe.2025.114204.

Data availability

Data will be made available on request.

References

[1] European Commission. Joint Research Centre, European Technology Platform on Renewable Heating and Cooling (RHC-Platform), 2020–2030–2050, Common Vision for the Renewable Heating and Cooling Sector in Europe: European Technology Platform on Renewable Heating and Cooling, EUR-OP, Luxembourg, 2011.

[2] M. Jakučionytė-Skodienė, R. Krikštolaitis, G. Liobikienė, The contribution of changes in climate-friendly behaviour, climate change concern and personal responsibility to household greenhouse gas emissions: Heating/cooling and transport activities in the European Union, Energy 246 (2022) 123387.

[3] E. Smulders, H. Eijdems, D1.1 Report on Classification of DHC Networks and Control Strategies, European Union: STORM Project; 2015. D1.1, STORM Project, European Union, 2015, H2020 Grant Agreement 649743.

[4] H. Lund, P.A. Østergaard, M. Chang, S. Werner, S. Svendsen, P. Sorknæs, J.E. Thorsen, F. Hvelplund, B.O.G. Mortensen, B.V. Mathiesen, C. Bojesen, N. Duic, X. Zhang, B. Möller, The status of 4th generation district heating: Research and results, Energy 164 (2018) 147–159.

[5] P.A. Østergaard, S. Werner, A. Dyrelund, H. Lund, A. Arabkoohsar, P. Sorknæs, O. Gudmundsson, J.E. Thorsen, B.V. Mathiesen, The four generations of district cooling - A categorization of the development in district cooling from origin to future prospect, Energy 253 (2022) 124098.

[6] S. Boesten, W. Ivens, S.C. Dekker, H. Eijdems, 5th generation district heating and cooling systems as a solution for renewable urban thermal energy supply, Adv. Geosci. 49 (2019) 129–136.

[7] H. Lund, Renewable heating strategies and their consequences for storage and grid infrastructures comparing a smart grid to a smart energy systems approach, Energy 151 (2018) 94–102.

[8] H. Bergmann, C. Mosiman, A. Saha, S. Haile, W. Livingood, S. Bushby, G. Fierro, J. Bender, M. Poplawski, J. Granderson, et al., Semantic Interoperability to Enable Smart, Grid-Interactive Efficient Buildings, Lawrence Berkeley National Laboratory, 2020.

[9] S. Buffa, M. Cozzini, M. D'antoni, M. Baratieri, R. Fedrizzi, 5th generation district heating and cooling systems: A review of existing cases in Europe, Renew. Sustain. Energy Rev. 104 (2019) 504–522.

[10] D. Schmidt, Digitalization of district heating and cooling systems, Energy Rep. 7 (2021) 458–464.

[11] K. Gjoka, B. Rismanchi, R.H. Crawford, Fifth-generation district heating and cooling systems: A review of recent advancements and implementation barriers, Renew. Sustain. Energy Rev. 171 (2023) 112997.

[12] R. de Beaufort, J. Steen-Schelle, C. Johansson, R. Hellmer, M. Jungic, V. Kaasinen, M. Karstoft, A. Schache, R.R. Schmidt, P. Song, et al., Digital Roadmap for District Heating and Cooling, 2018, pp. 1–28.

[13] M. Jia, A. Komeily, Y. Wang, R.S. Srinivasan, Adopting Internet of Things for the development of smart buildings: A review of enabling technologies and applications, Autom. Constr. 101 (2019) 111–126.

[14] C. Greer, D. Wollman, D. Prochaska, P. Boynton, J. Mazer, C. Nguyen, G. FitzPatrick, T. Nelson, G. Koepke, A. Hefner Jr., V. Pillitteri, T. Brewer, N. Golmie, D. Su, A. Eustis, D. Holmberg, S. Bushby, NIST framework and roadmap for smart grid interoperability standards, release 3.0, Spec. Publ. (NIST SP) (1108r3) (2014).

[15] International Energy Agency Technology Collaboration Programme on District Heating and Cooling, Annex TS4: Digitalisation of District Heating and Cooling, IEA DHC, 2024, https://www.iea-dhc.org/the-research/annexes/2018-2024-annex-ts4. (Accessed 20 August 2024).

[16] International Energy Agency Technology Collaboration Programme on District Heating and Cooling, Annex TS9: Digitalisation of District Heating and Cooling, IEA DHC, 2024, https://www.iea-dhc.org/the-research/annexes/2024-2028-annex-ts9. (Accessed 29 November 2024).

[17] R. Studer, V.R. Benjamins, D. Fensel, Knowledge engineering: Principles and methods, Data Knowl. Eng. 25 (1–2) (1998) 161–197.

[18] M. Pritoni, D. Paine, G. Fierro, C. Mosiman, M. Poplawski, A. Saha, J. Bender, J. Granderson, Metadata schemas and ontologies for building energy applications: A critical review and use case analysis, Energies 14 (7) (2021) 2024.

[19] B. Balaji, A. Bhattacharya, G. Fierro, J. Gao, J. Gluck, D. Hong, A. Johansen, J. Koh, J. Ploennigs, Y. Agarwal, et al., Brick: Towards a unified metadata schema for buildings, in: Proceedings of the 3rd ACM International Conference on Systems for Energy-Efficient Built Environments, 2016, pp. 41–50.

[20] D.L. McGuinness, F. Van Harmelen, et al., OWL web ontology language overview, W3C Recomm. 10 (10) (2004) 2004.

[21] L.M. Schriml, C. Arze, S. Nadendla, Y.W.W. Chang, M. Mazaitis, V. Felix, G. Feng, W.A. Kibbe, Disease Ontology: a backbone for disease semantic integration, Nucleic Acids Res. 40 (D1) (2012) D940–D946.

[22] Y. Tzitzikas, C. Allocca, C. Bekiari, Y. Marketakis, P. Fafalios, M. Doerr, N. Minadakis, T. Patkos, L. Candela, Integrating heterogeneous and distributed information about marine species through a top level ontology, in: Research Conference on Metadata and Semantic Research, Springer, 2013, pp. 289–301.

[23] Y. Yang, J. Bjørnskov, M. Jradi, Optimizing HVAC systems with model predictive control: integrating ontology-based semantic models for energy efficiency and comfort, Front. Energy Res. 13 (2025) 1542107.

[24] H. Deng, Z. Fan, X. Wei, Y. Deng, An ontology-based approach to dynamic indoor fire emergency evacuation path planning with BIM integration, J. Build. Eng. 106 (2025) 112562, Available from: https://www.sciencedirect.com/science/article/pii/S2352710225007995.

[25] S. Yoon, J. Song, J. Li, Ontology-enabled AI agent-driven intelligent digital twins for building operations and maintenance, J. Build. Eng. 108 (2025) 112802, Available from: https://www.sciencedirect.com/science/article/pii/S2352710225010393.

[26] A.M. Thomsen, J. Bjørnskov, M. Jradi, Ontology-based digital twins for informed decision-making: Scenario testing and optimization in hospital building operations, J. Build. Eng. 112 (2025) 113594, Available from: https://www.sciencedirect.com/science/article/pii/S2352710225018315.

[27] F. de Andrade Pereira, K. Katsigarakis, D. Rovas, M. Pritoni, C. Shaw, L. Paul, A. Prakash, S. Martin-Toral, D. Finn, J. O'Donnell, A semantics-driven framework to enable demand flexibility control applications in real buildings, Adv. Eng. Informatics 64 (2025) 103049, Available from: https://www.sciencedirect.com/science/article/pii/S1474034624007006.

[28] Y. Li, Y. Rezgui, S. Kubicki, An intelligent semantic system for real-time demand response management of a thermal grid, Sustain. Cities Soc. 52 (2020) 101857, Available from: https://www.sciencedirect.com/science/article/pii/S2210670719316634.

[29] S. Kuntuarova, T. Licklederer, T. Huynh, D. Zinsmeister, T. Hamacher, V. Perić, Design and simulation of district heating networks: A review of modeling approaches and tools, Energy 305 (2024) 132189, Available from: https://www.sciencedirect.com/science/article/pii/S0360544224019637.

[30] Z. Wu, J.C. Cheng, Z. Wang, H.H. Kwok, An ontology-based framework for automatic building energy modeling with thermal zoning, Energy Build. 296 (2023) 113267, Available from: https://www.sciencedirect.com/science/article/pii/S0378778823004978.

[31] M. Mitterhofer, G.F. Schneider, S. Stratbücker, K. Sedlbauer, An FMI-enabled methodology for modular building performance simulation based on Semantic Web Technologies, Build. Environ. 125 (2017) 49–59, Available from: https://www.sciencedirect.com/science/article/pii/S0360132317303736.

[32] M. Hofmeister, K.F. Lee, Y.K. Tsai, M. Müller, K. Nagarajan, S. Mosbach, J. Akroyd, M. Kraft, Dynamic control of district heating networks with integrated emission modelling: A dynamic knowledge graph approach, Energy AI 17 (2024) 100376, Available from: https://www.sciencedirect.com/science/article/pii/S2666546824000429.

[33] J.L. Hippolyte, Y. Rezgui, H. Li, B. Jayan, S. Howell, Ontology-driven development of web services to support district energy applications, Autom. Constr. 86 (2018) 210–225, Available from: https://www.sciencedirect.com/science/article/pii/S0926580517308907.

[34] B. Balaji, A. Bhattacharya, G. Fierro, J. Gao, J. Gluck, D. Hong, A. Johansen, J. Koh, J. Ploennigs, Y. Agarwal, et al., Brick: Metadata schema for portable smart building applications, Appl. Energy 226 (2018) 1273–1292.

[35] R. Chiosa, M.S. Piscitelli, M. Pritoni, A. Capozzoli, A portable application framework for energy management and information systems (EMIS) solutions using brick semantic schema, Energy Build. 323 (2024) 114802, Available from: https://www.sciencedirect.com/science/article/pii/S0378778824009186.

[36] J.Z. Pan, Resource description framework, in: Handbook on Ontologies, Springer, 2009, pp. 71–90.

[37] T. Segaran, C. Evans, J. Taylor, Programming the Semantic Web: Build Flexible Applications with Graph Data, O'Reilly Media, Inc., 2009.

[38] A. Hogan, E. Blomqvist, M. Cochez, C. d'Amato, G.D. Melo, C. Gutierrez, S. Kirrane, J.E.L. Gayo, R. Navigli, S. Neumaier, et al., Knowledge graphs, ACM Comput. Surv. (Csur) 54 (4) (2021) 1–37.

[39] N. Luo, G. Fierro, Y. Liu, B. Dong, T. Hong, Extending the brick schema to represent metadata of occupants, Autom. Constr. 139 (2022) 104307.

[40] K. Hammar, E.O. Wallin, P. Karlberg, D. Hälleberg, The realestatecore ontology, in: The Semantic Web–ISWC 2019: 18th International Semantic Web Conference, Auckland, New Zealand, October 26–30, 2019, Proceedings, Part II 18, Springer, 2019, pp. 130–145.

[41] RealEstateCore, Introduction to RealEstateCore, 2023, https://www.realestatecore.io/introduction/. (Accessed 20 August 2024).

[42] Project Haystack, 2024, https://project-haystack.org/. (Accessed 18 July 2024).

[43] C. Quinn, J. McArthur, A case study comparing the completeness and expressiveness of two industry recognized ontologies, Adv. Eng. Informatics 47 (2021) 101233.

[44] R. García-Castro, M. Lefrançois, M. Poveda-Villalón, L. Daniele, The ETSI SAREF ontology for smart applications: a long path of development and evolution, Energy Smart Appl.: Appl. Methodol. Challenges (2023) 183–215.

[45] M. Poveda-Villalón, R. García-Castro, Extending the SAREF ontology for building devices and topology., in: LDAC, 2018, pp. 16–23.

[46] ETSI Technical Committee, The Smart Applications REFerence (SAREF), 2024, https://saref.etsi.org/index.html. (Accessed 20 August 2024).

[47] V. Kukkonen, A. Kücükavci, M. Seidenschnur, M.H. Rasmussen, K.M. Smith, C.A. Hviid, An ontology to support flow system descriptions from design to operation of buildings, Autom. Constr. 134 (2022) 104067.

[48] ASHRAE, ASHRAE's BACnet Committee, Project Haystack and Brick Schema Collaborating to Provide Unified Data Semantic Modeling Solution, American Society of Heating, Refrigerating and Air-Conditioning Engineers, 2018, https://www.ashrae.org/about/news/2018/ashrae-s-bacnet-committee-project-haystack-and-brick-schema-collaborating-to-provide-unified-data-semantic-modeling-solution. (Accessed 20 August 2024).

[49] ASHRAE, ASHRAE standard 223 user documentation, 2020, Available from: https://docs.open223.info/intro.html. (Accessed 20 August 2024).

[50] B. Mitterrutzner, C.Z. Callegher, R. Fraboni, E. Wilczynski, S. Pezzutto, Review of heating and cooling technologies for buildings: A techno-economic case study of eleven European countries, Energy 284 (2023) 129252.

[51] M. Tunzi, T. Benakopoulos, Q. Yang, S. Svendsen, Demand side digitalisation: A methodology using heat cost allocators and energy meters to secure low-temperature operations in existing buildings connected to district heating networks, Energy 264 (2023) 126272.

[52] E. Guelpa, V. Verda, Demand response and other demand side management techniques for district heating: A review, Energy 219 (2021) 119440.

[53] E. Guelpa, V. Verda, Thermal energy storage in district heating and cooling systems: A review, Appl. Energy 252 (2019) 113474.

[54] I. Sarbu, C. Sebarchievici, A comprehensive review of thermal energy storage, Sustainability 10 (1) (2018) 191.

[55] O. Abdur Rehman, V. Palomba, A. Frazzica, L.F. Cabeza, Enabling technologies for sector coupling: A review on the role of heat pumps and thermal energy storage, Energies 14 (24) (2021) 8195.

[56] P. Fleuchaus, B. Godschalk, I. Stober, P. Blum, Worldwide application of aquifer thermal energy storage–A review, Renew. Sustain. Energy Rev. 94 (2018) 861–876.

[57] H. Jouhara, M. Szulgowska-Zgrzywa, M. Sayegh, J. Milko, J. Danielewicz, T. Nannou, S. Lester, The performance of a heat pipe based solar PV/T roof collector and its potential contribution in district heating applications, Energy 136 (2017) 117–125, Renewable Energy and Energy Storage Systems.

[58] G. Li, S. Shittu, T.M. Diallo, M. Yu, X. Zhao, J. Ji, A review of solar photovoltaic-thermoelectric hybrid system for electricity generation, Energy 158 (2018) 41–58.

[59] M. Yuan, B. Vad Mathiesen, N. Schneider, J. Xia, W. Zheng, P. Sorknæs, H. Lund, L. Zhang, Renewable energy and waste heat recovery in district heating systems in China: A systematic review, Energy 294 (2024) 130788.

[60] M. Wahlroos, M. Pärssinen, J. Manner, S. Syri, Utilizing data center waste heat in district heating–Impacts on energy efficiency and prospects for low-temperature district heating networks, Energy 140 (2017) 1228–1238.

[61] H. Li, J. Hou, T. Hong, Y. Ding, N. Nord, Energy, economic, and environmental analysis of integration of thermal energy storage into district heating systems using waste heat from data centres, Energy 219 (2021) 119582.

[62] A. Khosravi, T. Laukkanen, V. Vuorinen, S. Syri, Waste heat recovery from a data centre and 5G smart poles for low-temperature district heating network, Energy 218 (2021) 119468.

[63] L. Brange, J. Englund, P. Lauenburg, Prosumers in district heating networks–A Swedish case study, Appl. Energy 164 (2016) 492–500.

[64] G. Fierro, A. Saha, T. Shapinsky, M. Steen, H. Eslinger, Application-driven creation of building metadata models with semantic sufficiency, in: Proceedings of the 9th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation, 2022, pp. 228–237.

[65] T. Brown, B. Mann, N. Ryder, M. Subbiah, J.D. Kaplan, P. Dhariwal, A. Neelakantan, P. Shyam, G. Sastry, A. Askell, et al., Language models are few-shot learners, Adv. Neural Inf. Process. Syst. 33 (2020) 1877–1901.

[66] J. Wei, X. Wang, D. Schuurmans, M. Bosma, F. Xia, E. Chi, Q.V. Le, D. Zhou, et al., Chain-of-thought prompting elicits reasoning in large language models, Adv. Neural Inf. Process. Syst. 35 (2022) 24824–24837.

[67] A.J. Thirunavukarasu, D.S.J. Ting, K. Elangovan, L. Gutierrez, T.F. Tan, D.S.W. Ting, Large language models in medicine, Nature Med. 29 (8) (2023) 1930–1940.

[68] Y. Li, S. Wang, H. Ding, H. Chen, Large language models in finance: A survey, in: Proceedings of the Fourth ACM International Conference on AI in Finance, 2023, pp. 374–382.

[69] E. Kasneci, K. Seßler, S. Küchemann, M. Bannert, D. Dementieva, F. Fischer, U. Gasser, G. Groh, S. Günnemann, E. Hüllermeier, et al., ChatGPT for good? On opportunities and challenges of large language models for education, Learn. Individ. Differ. 103 (2023) 102274.

[70] C. Duarte Roa, P. Raftery, A.K. Prakash, T. Peffer, Field demonstration of the brick ontology to scale up the deployment of ASHRAE guideline 36 control sequences, in: ASHRAE Annual Conference 2023, 2023.