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Semantic model-based large-scale deployment of AI-driven building management applications

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ABSTRACT

Digitalization and Artificial Intelligent (AI) are revolutionizing building operation management. The abundance of data generated with the digitalization of buildings in the whole lifecycle can be harnessed to enhance building operational efficiency through data-driven control and optimization applications. However, the heterogeneity of data across building datasets hampers data interactivity and interoperability, presenting obstacles to the large-scale deployment of AI-enabled data-driven solutions. A semantic model-based framework is developed to integrate multi-sources data from buildings' air-conditioning system, supporting the large-scale deployment of AI-enabled data-driven building management applications. Both static and temporal data from multi sources are stored in the database guided by the semantic model. To demonstrate the framework's effectiveness, a building cooling load prediction application is implemented and evaluated across three typical buildings. The successful deployment of the proposed semantic model-based framework demonstrates its potential for facilitating large-scale deployment of AI-enabled data-driven applications in building sector.

1. Introduction

The building sector is a significant contributor to global energy consumption and greenhouse gas emissions, directly impacting global warming. In 2021, the operation of building sector accounted for 30% of energy consumption and 27% of total energy sector emissions [1]. Therefore, building energy management plays a crucial role in the energy efficiency of buildings, as well as in the pursuit of energy conservation and carbon neutrality [2]. As part of the global effort, China aims to achieve carbon neutrality by 2060, while building sectors targeting a 50% reduction in energy consumption [3]. In Hong Kong, a typical high-intensity city, the building sector's electricity consumption accounts for approximately 90%, and the government aims to reduce energy consumption in commercial buildings by around 35% by 2035 [4].

Building automation systems (BAS), also known as building management systems (BMS), are always utilized for monitoring and controlling devices and systems in buildings to enhance comfort, safety and energy efficiency [5]. BMS systems have the capability to collect and store a substantial amount of data, as modern buildings are typically equipped with numerous metering devices and sensors. The complexity of building energy systems is increasing, and traditional rule-based control strategies often struggle to effectively manage the extensive data and information while also adapting to various working conditions and changes [6]. With the advancement of machine learning algorithms, control strategies in modern building energy system are increasingly adopting data-driven approaches, specifically based on machine learning techniques [7]. Data-driven applications have the capacity to discover and learn new knowledge from the massive data collected and stored in BMS, enabling the adjustment of control parameters and strategies to make building energy systems more intelligent, adaptive and energy-efficient [8,9].

In recent years, numerous studies have utilized massive building data to develop data-driven applications for building energy management, focusing particularly on load prediction, fault detection and diagnosis (FDD) and occupancy-related applications [6,10]. Load prediction leverages historical building operation data and climate parameters to predict cooling, heating, or electrical loads for the next few hours or days, thereby facilitating demand-side management and model predictive control [11,12]. FDD utilizes building operating parameters, equipment parameters, climate parameters, and more to detect and diagnose faults in building energy systems. Early detection of equipment faults is crucial for optimizing building energy efficiency, especially for

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energy-intensive devices such as chillers. [13]. Occupancy-related application gather occupant comfort information and indoor environment condition to optimize indoor thermal comfort, recognizing that occupant comfort is a key indicator for optimizing building air conditioning systems [14]. To effectively optimize building energy system management, research on data-driven applications necessitates the collection of extensive data from diverse sources within the building, including BIM, IoT, BMS, and others.

While data-driven approaches have proven effective, some key challenges remain. The first challenge is the heterogeneity of data from individual buildings and the variety of data types, which can hinder interactivity and interoperability [15]. BIM serves as an important tool for managing information of the construction project's lifecycle, providing a digital representation of buildings with both geometric and non-geometric attributes, including functionalities, semantics, and topological information [16–19]. Advancements in the IoT enrich building data collection, expanding beyond basic indoor environmental data such as temperature, humidity, and wind speed to encompass more complex functions like energy consumption monitoring and occupancy information [20,21]. Consequently, digital buildings now encompass not only static data (such as geometric shapes, topological structures, equipment information, and other metadata) but also temporal data (such as indoor air temperature, occupancy information, and other operational data). However, BIM models developed during the buildings design phase often become disconnected from actual operational data, and integration of sensors and devices with BIM model is infrequent. [22,23]. The lack of interoperability of BIM, BMS and IoT sensors leads to information redundancy across different systems [24]. Despite the abundance of existing data, the presence of "data silos" makes it extremely challenging across different domains, requiring expert efforts to integrate data from various sources to develop and deploy data-driven building management applications.

Another challenge is the heterogeneity in equipment and systems across buildings, which hinders the large-scale deployment of data-driven applications across buildings. Most building data-driven applications are typically developed for individual buildings and require not only expertise in data science and building science but also a comprehensive understanding of the specific configuration of each unique building [25–27]. Application developers need to not only design appropriate algorithm, but also understand which data points are available, which control points are valid, and how to access them within the specific configuration of the target building [28]. Building energy data for different buildings originates from various sensors or suppliers, is stored in different formats, and adheres to different naming standards, resulting in a complex and time-consuming process where the development and deployment of algorithms necessitate significant manual effort tailored to each specific building [29]. The heterogeneity across different buildings increases the costs of application development and hinder the large-scale deployment of data-driven building applications in building complexes.

To address the challenge of buildings heterogeneity and facilitate the large-scale deployment of data-driven building management applications, a semantic model-based framework is developed. This framework integrates data from multiple sources and supports data exchange across different format. The use of a semantic model allows for enhanced communication and coordination between different systems and devices, to some extent alleviating the data acquisition costs resulting from building heterogeneity [30,31]. For different buildings, a unified semantic model is essential for creating standardized semantic descriptions, which helps eliminate the barriers to large-scale deployment of data-driven building applications arising from inconsistent descriptions of various building resources [32]. The Brick schema, serving as a semantic model for describing building metadata, facilitates the provision of semantic descriptions for building information, making it machine-readable and enables information sharing, improves data interoperability, and improves search results [33,34]. In this study, the semantic model, guided by the Brick schema, provides a standard semantic description of the building static and temporal data, thus standardizing the acquisition of building-related data as a machine-readable process. The semantic model-based framework effectively addresses building heterogeneity, contributing the integration of data from multiple sources integration and facilitating the large-scale deployment of data-driven applications in building complexes.

The main objectives and contributions of this work are:

- Development of a flexible building management framework that supports the large-scale deployment of AI-enabled data-driven applications in various buildings.
- Integration of building static and temporal data from diverse sources into a unified framework with a semantic model.
- Enabling data-driven applications to access input parameters from semantic models in a standardized and building-independent manner.
- Facilitating the large-scale deployment of data-driven applications in different buildings, reducing application development and deployment costs.

The remainder of this paper is organized as follows. Section 2 introduces the relevant research on semantic models and their applications in the field of buildings. Section 3 describes the development method of a semantic model-based framework for large-scale deployment of AI-enabled data-driven building management applications. Section 4 demonstrates the deployment of the framework in the chiller plants of three different types of buildings. Section 5 validates the successful deployment of data-driven building applications through a building cooling load prediction application.

2. Recent development in semantic model for building energy management

2.1. Basics of semantic models

The Semantic Web is a framework that promotes common data formats, exchange protocols and vocabularies, enabling machines to autonomously understand and process the meaning of web content [35]. Originally advocated for annotating web documents in a machine-readable manner, it has since been adopted in various domains such as biology, IoT, and energy management to manage the complexity of domain information [36]. The semantic web stack, as illustrated in Fig. 1, depicts the architecture of the semantic web, and its relevant standards are outlined as follows:

- RDF: Short for "Resource Description Framework", RDF is a W3C model for data interchange on the Web, providing a linking structure for expressing relationships among entities in the form of subject-predicate-object expressions.
- SPARQL: Short for "SPARQL Protocol and RDF Query Language", SPARQL enables users to query information from databases or any data source that can be mapped to RDF.
- TTL: A syntax and file format for expressing data in the RDF data model.

As the core of the semantic web technology, ontologies consist of basic components including concepts, relations, individuals, and axioms, typically originating from different areas of expertise [38]. Numerous studies have been conducted on building-related ontologies. For building design phase, there are ontologies such as ifcOWL [39], which represents the IFC schema in OWL format, gbXML [40], primarily used for green buildings and model information exchange, and Tubes [41], utilized for high-level descriptions of building services systems. In the building operation phase, there are ontologies such as SSN/SOSA [42], which is primarily used for sensor-related information in building

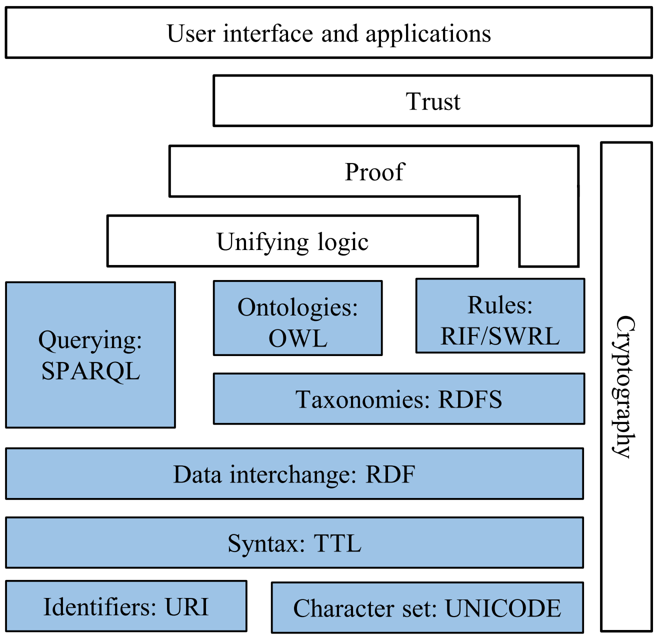


Fig. 1. Semantic web stack (adapted from [37]).

sectors, Project Haystack 4 [43], which utilizes tag sets for the hierarchical representation of building-related entities and concepts, Brick schema [33], used for describing building-related metadata, and BOT [44], used for describing building topology structures, among other relevant ontologies.

The intricate design and function of buildings necessitate the collaboration of diverse domains in creating their semantic models [45]. The remarkable extensibility of ontologies enables experts to integrate the nuanced, domain-specific ontologies they develop into a comprehensive semantic model [46,47]. Utilizing such semantic models in the management and operation of buildings represents a major advancement in the field of smart building management. These models enhance the efficiency of building system management by providing standardized, machine-readable representations of building-related data.

2.2. *Semantic model for building operation: Brick schema*

For the representation of building-related metadata in the building operation phase, the Brick schema is a prominent semantic model. Drawing inspiration from Haystack, the Brick schema utilizes a combination of entities, classes, and relationships to effectively integrate building-related metadata from various sources across the building's lifecycle [48]. It employs the RDF format to construct a directed graph that illustrates the resources within a building and their interconnections. In the Brick schema, devices, sensors, and spaces in building are represented as entities, and each entity is an instance of a class, which can be connected to other entities using relationships. These classes and properties encompass physical, logical, and virtual assets in building. Classes and subclasses are defined in an extensible hierarchical structure for describing the relationship between them (as shown in Fig. 2(a)).Fig. 2(b) provides an example of the relationships between the classes, wherein "*hasLocation*" and "*isLocationof*" are used to describe the relationship between the equipment or point and its location, and "*haspart*" and "*ispartof*" describe the subordinate relationship between equipment or system, and "*feeds*" and "*isfeedby*" are used to describe the transmission of media.

The design of the Brick schema considers the integrity of information, the expressiveness of relationships, the usability for different users, the consistency with the modelling process, and the scalability for more concepts. It is highly extensible, allowing researchers from different fields to incorporate their domain-specific knowledge into the Brick schema [50]. Existing extensions related to the Brick schema include supplementary descriptions for variable refrigerant flow systems and metadata for occupancy in buildings [48,49]. Building semantic models based on Brick schema give standardized semantic descriptions of building operation-related data, thus contributing to the advancement of smart building management.

2.3. *Application of semantic model in building management*

Semantic models have been increasingly adopted in building management-related research and applications, enabling the representation of metadata for equipment and sensors, as well as the organization of system operation data in a structed and expressive manner. For instance, Xie et al. tagged sensor entities relate to faults in building HVAC system by defining corresponding fault labels in the building semantic model [51]. Preserving knowledge in a semantically machine-readable form, this approach facilitates the fault detection and diagnosis (FDD) of building HVAC systems. Li et al. combined the ontology with semantic rules to construct the sematic model of building energy system for detecting the operational problems, control issues, equipment malfunctions, and sensor failures [52]. Additionally, Bindra et al. utilized the SPARQL query function to obtain the path and cost between points in a building by querying the building's semantic model, achieving the intelligent control of the access permission in the building [53].

As a standardize building data description model, semantic model has facilitated the development of various platforms and tools that enhance building operations and data organization. Since the inception of the Brick schema concept by Balaji et al. in 2018, they have also introduced Mortar, a platform that utilizes semantic model to describe over 90 open datasets of buildings, providing rich function descriptions for resources and subsystems with buildings [25]. Mortar has played a

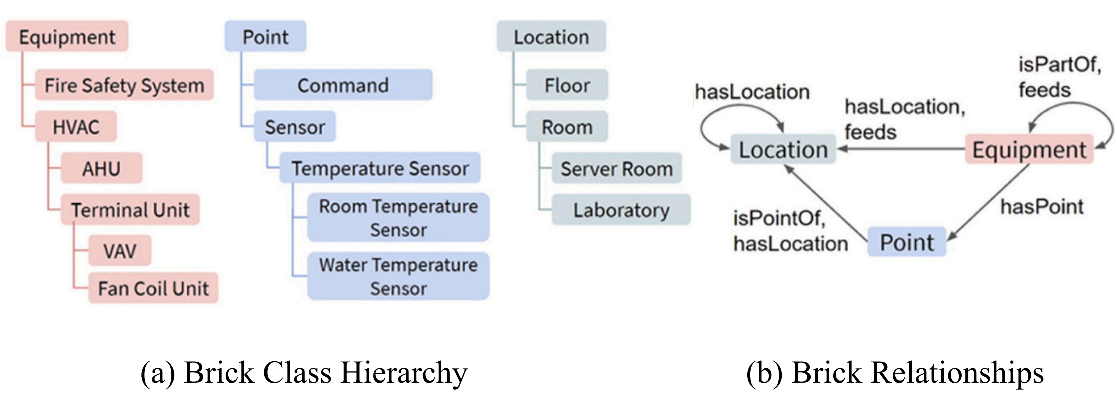


Fig. 2. Brick class hierarchy and relationships (adapted from [49]).

pivotal in developing and testing various building applications, particularly in addressing the high development costs of BMS due to the lack of standardized data representation [54]. This addressed an important issue of building data heterogeneity using semantic model. Additionally, Energon was developed by He et al. as a platform for organizing building-related data, surpassing Mortar in terms of code quantity and program construction time [29]. Furthermore, Gabrel et al. introduced the BRICKS platform, leveraging the semantic model for the intelligent management of building energy and security systems [55]. By enhancing interoperability between systems, BRICKS integrates diverse systems to achieve better system flexibility, efficiency and security [56].

Table 1 organizes existing semantic model-based building applications. Semantic models provide standardized building data descriptions and resource acquisition processes, significantly reducing the costs associated with developing and deploying data-driven building management applications. Nonetheless, most current research tends to focus on individual buildings or relies solely on open datasets from multiple buildings without implementing the framework in various real-world buildings. Furthermore, there is a notable absence of comprehensive guides detailing the process of constructing the entire framework.

Considering these issues, this study introduces a semantic model-based framework designed for the large-scale deployment of AI-enabled data-driven building management applications. The emphasis is placed on the construction of a semantic model-based framework and the development process of AI-enabled data-driven application. To demonstrate the practicality and adaptability of this framework, it has been deployed in three typical types of buildings, including an educational building, a commercial building and an official building.

3. Proposed semantic model-based framework for large-scale deployment of AI-driven building management applications

A smart building management framework is developed based on the semantic model to integrate multi-source static and temporal data in the form of standard semantic description. Under the proposed framework, the process of data acquisition for building management applications development shifts from customized collection based on single building configurations to a standardized approach that queries semantic information from building complexes. This transition reduces the cost of data acquisition process and facilitates the large-scale deployment of data-driven buildings management applications.

Fig. 3 illustrates the schematic of the proposed semantic model-based framework for large-scale deployment of AI-enabled data-driven building management applications. The proposed framework comprises three main steps: the multi-source data management, the mapping scheme, and the AI-enabled data-driven application. The multi-source data management module extracts both temporal and static data from BIM models, BMS and IoT sensors. The temporal data includes building operation data and weather condition, while the static data encompasses building system topology, equipment configuration, and location information. The extracted static data is used to build building semantic models, which are then stored in a graph database. Meanwhile the temporal data (i.e., historical, and real-time building operation data) is stored in the temporal database, guided by the building semantic models. The mapping scheme module endows the temporal data with semantic information by assigning same identifiers to temporal data points that correspond to entities within the semantic model, thereby achieving the integration of temporal and static data within a single framework. Finally, the AI-enabled data-driven application module accesses the databases and obtains the required static and temporal data by using SPARQL and FLUX query language. The queried data is then used as input for the AI engine for various applications. Details of the three modules are presented in Sections 3.1–3.3, respectively.

3.1. Semantic model-based multi-source data management

Modern buildings are complex systems that facilitate smooth operations, high energy efficiency, comfortable occupant environments, and safety based on the combination of several heterogeneous systems. The main hinder to the large-scale deployment of the AI-enabled data-driven building management applications are the multi-source heterogeneous data generated by the buildings. To solve this problem, the first module in the proposed framework, which is shown in the Fig. 4, is to collect the multi-sources data and standardize the format.

The multi-source heterogeneous data in a building can be categorized into two main types based on the characteristics from which it originates: static data (design information) from the building's BIM model, and temporal data (operational information) from the BMS system and IoT sensors.

The BIM process involves the creation and management of a digital representation that encompasses both the physical and functional characteristics of a building throughout its entire lifecycle. BIM models contain detailed information such as building geometry, spatial relationships, and component properties. COBie (Construction Operations Building Information Exchange) facilitates the immediate provision of project operation, maintenance, and management information to facility managers. The detailed information about building equipment can be effectively extracted through COBie plug-in, including system information, equipment parameters, and equipment spatial information. The extracted data, including spatial location, device name, device configuration and quantity, were organized into a table. To enhance the completeness of the model, sensor points that were not present in the BIM model were added to the table, along with the relationships between devices and sensors. Leveraging the Brick model development based on Fierro's work [57], a Python script is developed to automatically extract the information in the table to develop the semantic model of the chiller plant using the RDF format. Finally, the semantic model was stored in a graph database for further analysis and utilization.

A BMS (Building Management System) is a computer system installed in a building that facilitates communication with and control of various installations such as air conditioning, heating, ventilation, lighting, and energy supply systems. The BMS generates a significant amount of the temporal data related to building operation, which can be utilized for the development of data-driven building applications. With the rapid development of IoT technologies and devices, IoT sensors can be effortlessly installed in the building with minimal impact on the existing system to collect real-time temperature, humility, and CO_2 concentrate data. However, due to the diversity of BMS and equipment vendors in different buildings, the data transmitted by these systems often follows different protocols and formats. This creates challenges in

Table 1
Application of semantic model in building management.

Target Buildings	Semantic model construction	Ontology used	Applications	Reference
A laboratory	Manually constructed	Brick	Fault Detection and Diagnosis	[51]
An industrial building	Manually constructed	Self-built ontology	Fault Detection and Diagnosis	[52]
An office building	Manually constructed	Brick, BOT	Access control	[53]
Multiple buildings	Manually constructed	Brick	Various applications	[54]
Not specified	Manually constructed	Brick	Not specified	[29]
A business building	Not specified	Not specified	Monitoring, DR	[55,56]
Multiple buildings	Generated from BIM and BAS	Brick	Data-driven applications	This study

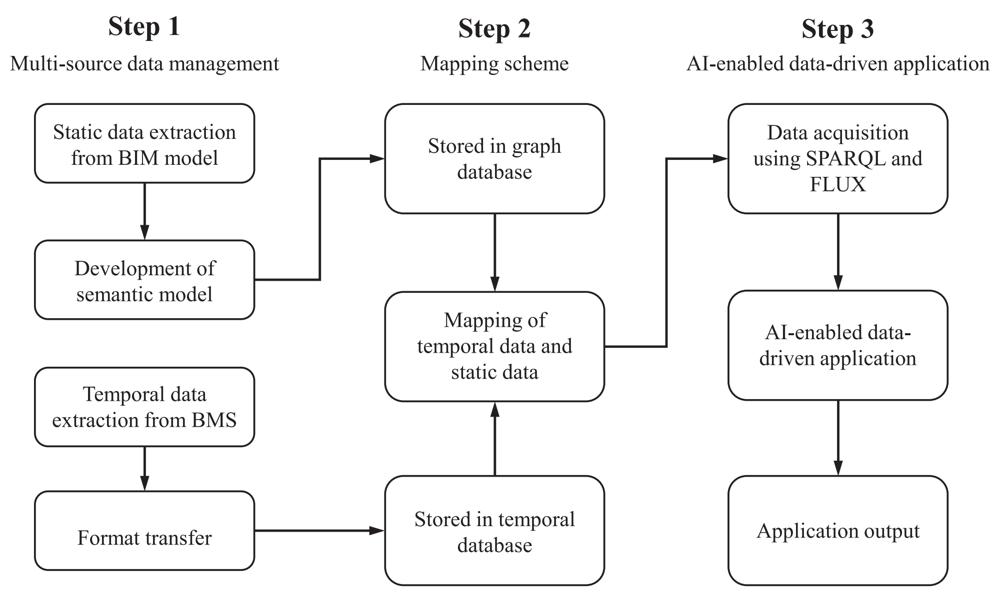


Fig. 3. Schematic of the semantic model-based framework for large-scale deployment of AI-driven building management applications.

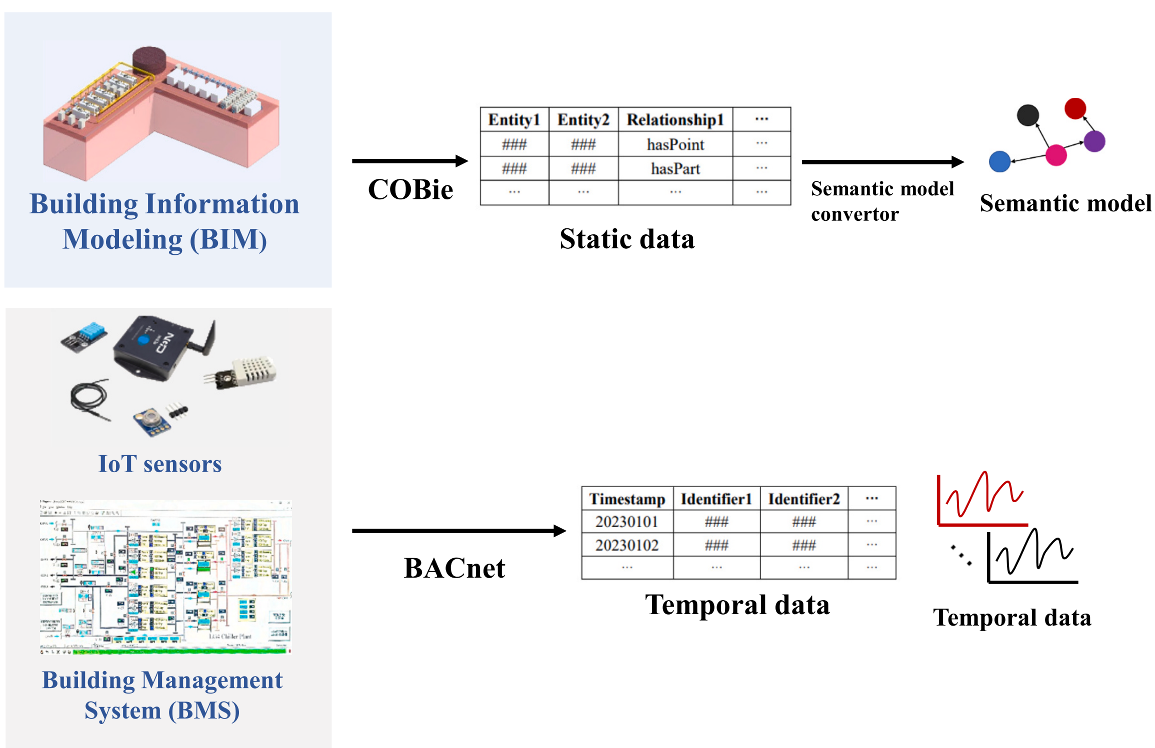


Fig. 4. Data collection and format transfer from multiple sources.

acquiring data for application development. To address this issue, the BACnet (Building Automation and Control Networks) protocol is widely utilized as a data communication protocol among various equipment, devices, and sensors to obtain real-time building operation data from the BMS and IoT sensor network. The operational data is transferred separately via the API interface and stored in a temporal database. The point name serves as the field identifier, and its corresponding value is stored as the field value. This standardized approach ensures that data from different buildings is stored in a consistent format, facilitating easier data analysis and application development.

3.2. *Mapping scheme of static/temporal data*

Once extracted from the BIM, BMS, and IoT network, the static and temporal data are stored in two separate databases, with the static data in a graph database and the temporal data in a temporal database. The formats and naming standards of the static and temporal data are different due to the different equipment and systems vendors and the absence of standard point descriptions. Therefore, an automated mapping process is design to align the two databases based on the semantic model. Fig. 5 shows the mapping scheme of the static and temporal data, ensuring semantic consistency, and enabling the effective linking and

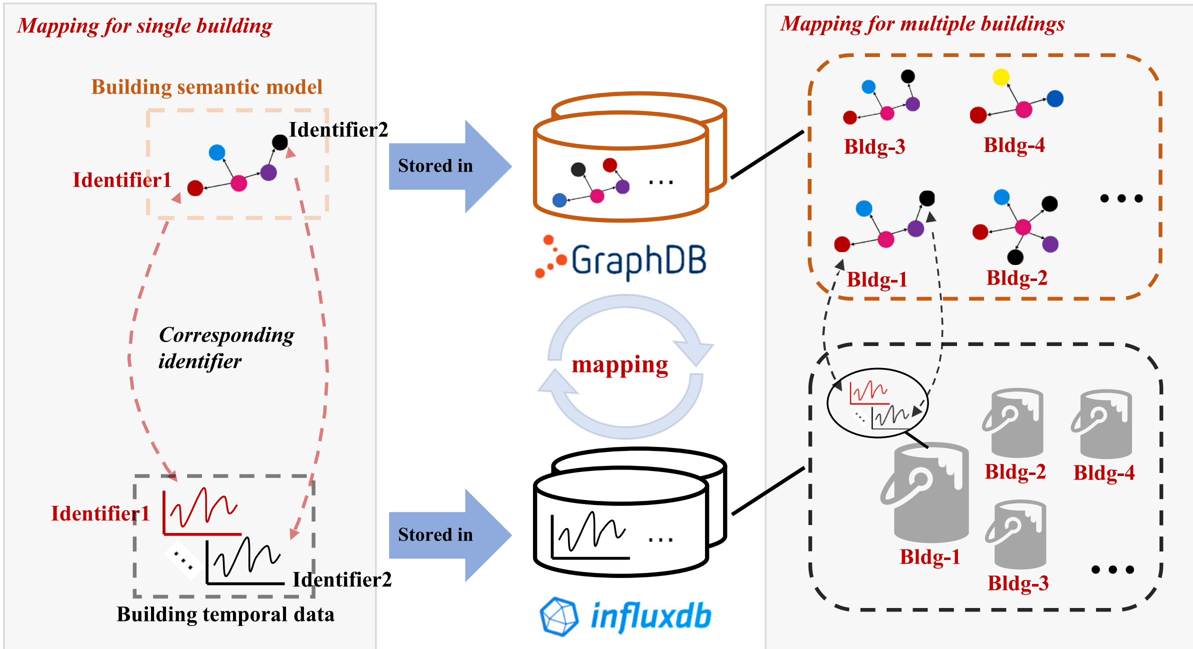


Fig. 5. Mapping scheme for spatial and temporal data.

standardized querying of the static and temporal data.

Static data extracted from BIM using the COBie plug-in is converted into RDF format semantic models and stored in a graph database for efficient querying. Temporal data, such as temperature and control signals from BMS and IoT sensors, are housed in a temporal database, which is suitable for managing large volumes and efficient retrieval of time-based building operation data.

Specifically, each temporal data point in a building is uniquely tagged with an identifier in the temporal database. In the semantic model, this identifier acts as an entity linked to its sensor entity via the "*hasTimeseriesId*" relationship, representing the temporal data point. By leveraging the "*hasTimeseriesId*" relationship in the semantic model, the temporal data stored in the temporal database can be integrated with the static data stored in the graph database. Furthermore, additional information such as the IP address of the database is also stored as an entity in the graph database.

For static and temporal data mapping in multiple buildings, each building has a semantic model stored in the graph database, while the whole corresponding temporal data for the building will be stored in a bucket in the temporal database. By combining static and temporal data in buildings using this approach, the data is given semantic meaning, ensuring the semantic consistency of building-related data across different systems and organizations. This allows static and temporal data from buildings to be stored in a standardized way under the same framework, significantly reducing the cost of data acquisition due to building heterogeneity.

3.3. AI-enabled data-driven building application

In the building sector, numerous data-driven building management applications have been developed based on building design and operational data. However, factors such as vendor differences, building heterogeneity, data availability and non-standardized metadata descriptions limit the flexibility and adaptability of the applications, often resulting in development tailored to a specific building. Applications developed in this context are challenging to directly port to other buildings, thereby presenting hinders for large-scale deployment.

The multi-source heterogeneous data generated by digital buildings present a significant challenge to the large-scale deployment of AI-enabled data-driven building applications. To address this issue, standardized data acquisition processes for building data-driven applications are crucial. Leveraging the graph database, the AI-enabled data-driven application can query and retrieve specific entities, relationships, and literals required for their operation. The query process utilizes SPARQL, allowing the definition of patterns to narrow down the set of RDF terms returned from the graph. This capability enables query authors to maintain a certain level of agnosticism towards the exact sequences of edges, enabling data acquisition in a building-agnostic manner [58].

Fig. 6 illustrates the data acquisition for AI-enabled data-driven applications in the proposed framework. The data acquisition module can access to the building semantic model using SPARQL queries generated from the data-driven model inputs. Typically, the required resources are stored as identifiers in the semantic model. The identifiers of the required resources returned by accessing the semantic model will be used to query the temporal database using the FLUX language to obtain the raw temporal data, which will then be used as input to the AI engine. In the AI engine, the raw temporal data will be sent to the data pre-processing module for data pre-processing before being utilized as inputs for training the AI model and generating the result. Ultimately, the output of the AI engine will serve as the optimal control recommendation and be sent to the building's BMS system to actualize the optimal control.

The proposed semantic model-based framework for large-scale deployment of AI-enabled data-driven applications for buildings, as introduced in the previous section, involves building semantic models to provide standardized metadata descriptions of buildings and mapping graph databases with temporal databases via identifiers. This approach overcomes obstacles to the development and deployment of building data-driven applications arising from the heterogeneous data of buildings, making large-scale deployment of AI-enabled data-driven building applications in different buildings possible.

4. Demonstration in existing buildings

To demonstrate the portability and adaptability of the proposed framework, the system is deployed in three existing buildings. The semantic models for the three sites are developed based on the extracted

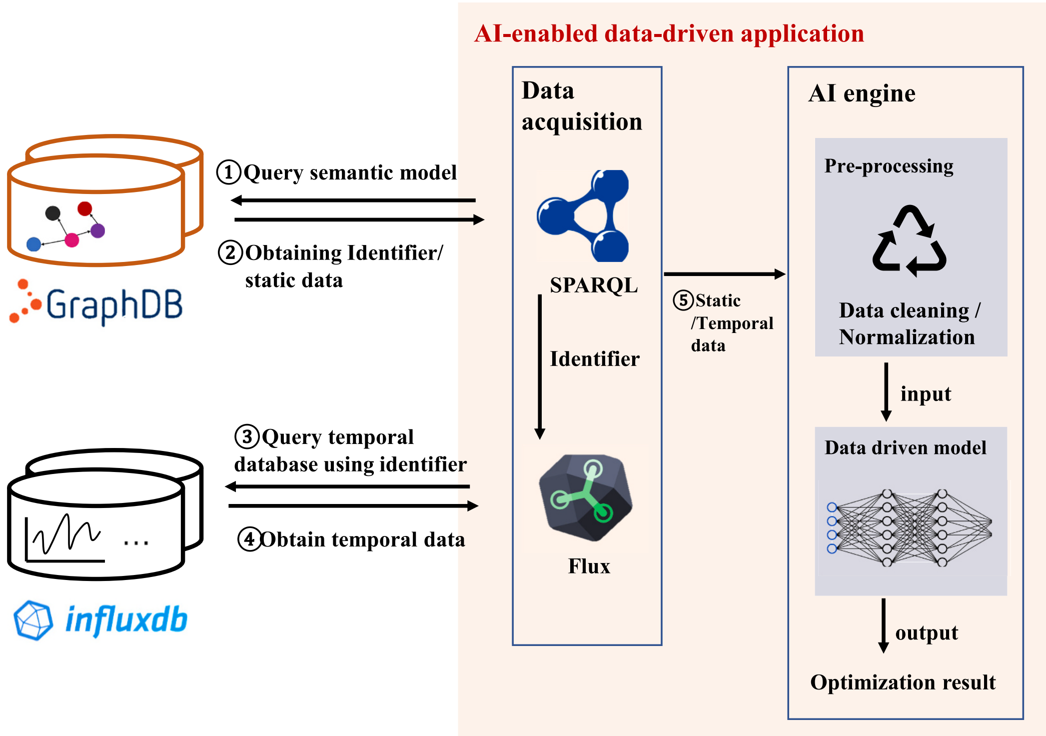


Fig. 6. Data extraction for AI-enabled data-driven application.

static data from the BIM model, while the temporal data is extracted from the BMS and IoT sensors and stored in the temporal database with the guidance of semantic models. Following the mapping process, the building cooling load prediction is utilized as a case study to assess the deployment of the proposed AI-enabled data-driven building application.

4.1. Data description of three buildings and problem statement

The study evaluates the performance of the proposed framework using data from three sites, specifically from the chiller plant rooms of three different types of buildings—an educational building, a government office building, and a commercial building. The information of these buildings is outlined in Table 2. The semantic models for the chiller plant rooms of the three sites are created by extracting the static data from the BIM models and are saved in the graph database. The temporal data of the plant room is transferred from the BMS systems to the temporal database.

The operational data of the building chiller plant HVAC system in the three different buildings mainly comprises temporal data such as chiller operation status (chilled water supply and return temperature, flow rate, cooling water supply and return temperature, flow rate, etc.), pump operation status (frequency, flow rate, etc.), cooling tower operation status (frequency, flow rate, etc.), among other aspects. An overview of the data is presented in Table 3. Due to differences in equipment and BMS suppliers across the three buildings, the naming rules for various points vary. The naming examples for the chilled water supply and return temperature of the chiller in different buildings are also shown in Table 3.

As previously described, the heterogeneity of the data from different buildings is evident from practical examples, wherein the naming rules for points with the same attribute (such as chilled water supply and return temperatures) differ completely from one building to another. The lack of standard metadata format necessitates that a developer of data-driven building applications possesses an in-depth understanding of the specific building to obtain the necessary data for training the model, resulting in elevated cost in the development of building data-driven applications. This is a key reason why existing building data-driven applications are typically developed and deployed for individual target buildings. The cost of application development and deployment stemming from building data heterogeneity can be significantly reduced with a unified framework that allows the application developer to obtain the data in a building-agnostic form. Applications developed for a single building can be more easily ported to other buildings,

Table 2
Building information.

Building	Operating time	Building area	Cooling capacity	Chiller plant configurations
Educational building	9:00 am-8:00 pm	79,670 m^2	4225 RT	8 chillers, 6 cooling towers, 18 pumps
Office building	12:00 am-12:00 am	61,804 m^2	3072 RT	4 chillers, 4 sea water exchangers, 10 pumps
Commercial building	12:00 am-12:00 am	440,000 m^2	14,702 RT	6 chillers, 6 cooling towers, 12 pumps

Table 3
Overview of data in the three different buildings.

Building	Number of points	Data period	Data interval	Point name example
Educational building	170	2020/12/08–2022/08/30	5 min	CSD WCC-1.Chilled Water Supply Temperature CSD WCC-1.Chilled Water Return Temperature
Office building	115	2021/10/16–2022/09/05	15 min	WCC01CHWSTemp WCC01CHWRTemp
Commercial building	129	2017/01/01–2018/08/31	10 min	CH01_Twevout CH01_Twevin

facilitating the large-scale deployment of AI-enabled data-driven building applications.

The proposed framework will be implemented and deployed in the aforementioned three buildings. The systems and equipment information of each building will be extracted from the corresponding BIM models, enabling the construction of a semantic model specific to each building. This semantic model will then be mapped with the operational data obtained from the BMS. To validate the scalability of the framework and demonstrate its potential for large-scale deployment, a building data-driven application will be developed based on this framework. The application will be deployed in all three buildings, allowing for comprehensive testing and evaluation across different building types. This deployment aims to showcase the framework's ability to handle diverse building environments and its potential for large-scale deployment of data-driven applications. By conducting this deployment and validation process, the study aims to assess the effectiveness, scalability, and practicality of the proposed framework across multiple buildings, ensuring its suitability for large-scale deployment and its ability to support various data-driven applications in real-world scenarios.

4.2. Framework deployment

Data-driven building applications developed within the proposed framework can indeed significantly reduce the cost of application development and facilitate deployment through the implementation of a standardized data acquisition process. To validate the feasibility of the framework, three different building chiller plant room HVAC systems were utilized, with the deployment of the proposed framework in the educational building chiller plant used as an illustrative example.

The first step involves the extraction of static and temporal data from multi-sources (BIM, BMS and IoT), and mapping them together. The static data, such as chiller type, sensor type, system information, et., is extracted from the BIM model, which was shown in Table 4. The building BIM model is shown in Fig. 7(a). This data is then used to construct the semantic model of the educational building chiller plant, which is subsequently stored in the GraphDB database. As depicted in Fig. 7, a semantic model is developed for the target chiller plant, and the static and temporal data are integrated based on the "*hasTimeseriesId*" relationship in the semantic model. Fig. 7(b) illustrates the semantic model of one chiller, with points representing different entities and lines depicting their relationships. Fig. 7(c) presents a specific segment of the model where the chiller "KC-POLYU-BCF-RF-HVAC-WCC-01" has a sensor point "POLYU-BCF-RF-WCC-01-CHWAST". The "*hasTimeseriesId*" relationship connects this measurement with the identifier "VSD WCC-1. Chilled Water Supply Temperature", indicating that the corresponding temporal data is stored in the temporal database with the same identifier.

For the temporal data, building operation information is extracted from the BMS of the educational building. This temporal data is then stored in the InfluxDB database. A total of 170 temporal data points was extracted and stored in the 'Educational Building Chiller Plant' bucket with their respective point identifiers in the BMS serving the 'field' value. Table 5 presents an example of the temporal data for certain data points related to chiller 1 of the educational building.

Table 4
Static data extracted from BIM model.

Name	TypeName	Space	Description
KC-POLYU-BCF-RF-HVAC-WCC-01	Chiller	KC-POLYU-BCF-RF	Water Cool Chiller 650RT 400 kW
KC-POLYU-BCF-RF-HVAC-ACC-01	Chiller	KC-POLYU-BCF-RF	Air Cool Chiller 325RT 328 kW
KC-POLYU-BCF-RF-HVAC-PCHWP-01	Water pump	KC-POLYU-BCF-RF	Chilled Water Pump 28 m 30 kW
KC-POLYU-BCF-RF-HVAC-CDWP-01	Water pump	KC-POLYU-BCF-RF	Condensing Water Pump 32 m 75 kW
KC-POLYU-BCF-RF-HVAC-COT-01	Cooling Tower	KC-POLYU-BCF-RF	Cooling Tower 30 kW

As shown in Table 5, each data point comprises information such as the bucket name, data point identifier, value, and timestamp. The point name is stored as an entity in the semantic model as a counterpart. This approach enables the fusion of building temporal data and static data based on the semantic model, thereby imparting semantic information to the temporal data.

Similarly, the sematic models of the other two sites are also developed, and the temporal data is extracted from the BMS separately. Following the development of the semantic model, temporal database, and mapping process, the AI-enabled data-driven application can be developed and deployed based on the proposed framework.

4.3. AI-enabled data-driven building application

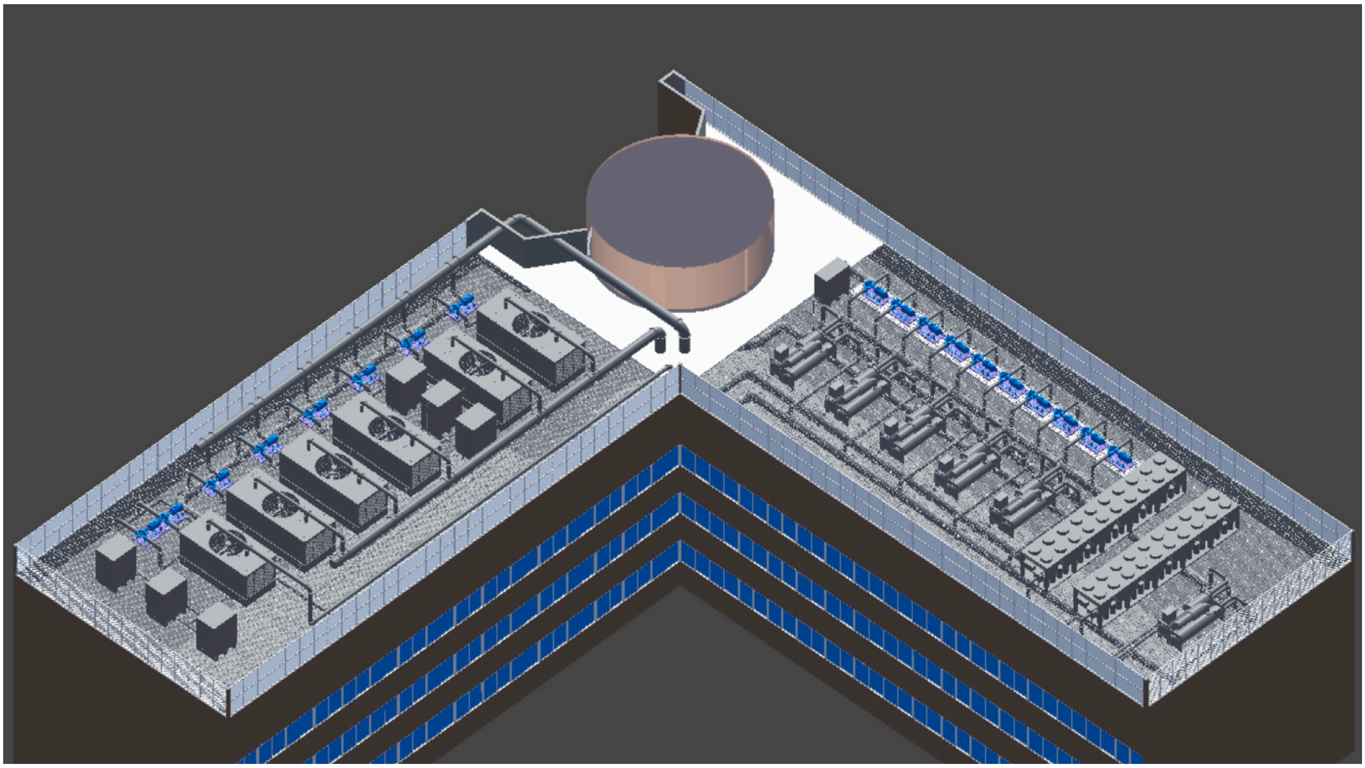
Cooling load prediction is a crucial aspect of building applications and it is often used as a case study for the development of data-driven building applications. Traditionally, when developing cooling load prediction algorithms, available data such as chilled water supply and return temperatures, outdoor air temperature and humidity is artificially identified to use as input to predict the building's cooling load. Application developed based on the proposed framework can obtain the data or information by querying the semantic model of the building using SPARQL language, rather than relying on expert knowledge to extract data from the existing BMS system. This streamlined process for data acquisition reduces costs, ultimately enabling the large-scale deployment of AI-enabled data-driven building management applications.

Fig. 8 illustrates an example of a SPARQL query for retrieving the need data identifier from the semantic model. In this query example, line 9 and line 10 demonstrate the restricted entity '*?chwst*' is derived from the temperature sensor used to measure the chilled water supply temperature, and the restricted entity '*?chwst_id*' is the identifier of the corresponded chilled water supply temperature data stored in the database. Similarly, the lines 11 to 14 indicate the identifiers of chilled water return temperature and chilled water flow. Furthermore, Line 15 restricts the result of each set of query statements belong to the same chiller.

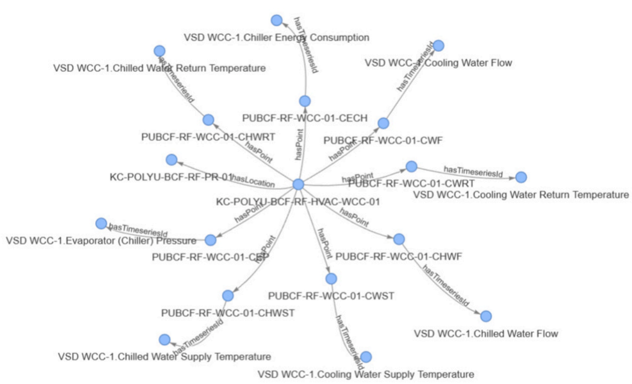
The identifiers of the chilled water supply and return temperatures, as well as the flow rates of the target chilled water plant room, obtained from the query to the semantic model, are utilized as input parameters to the FLUX query. As depicted in Fig. 9, the FLUX query is employed to access the temporal database containing the operational data of the target chiller plant room, and it allows for the determination of the interval and length of the required data.

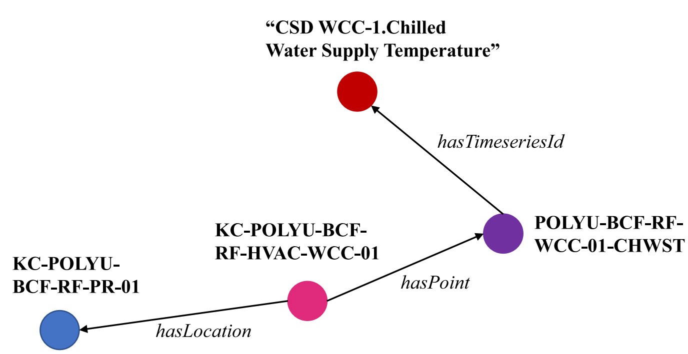
Moreover, since the location of the building is stored as an entity in the building's semantic model, it can be retrieved and utilized as identifiers for querying the InfluxDB database to obtain the corresponding weather condition, such as the outdoor air-dry bulb temperature and relativity humidity. The timestamp is then parsed into month, day and hour, and the day of the week is obtained.

The various data mentioned above extracted from the database are initially pre-processed to enhance data quality by addressing missing values and removing outliers. Given that data from BMS systems and IoT sensors typically exhibit low quality due to measurement noise, sensor faults, transmission issues, and other factors, a data pre-processing module is employed to improve data quality. To address missing values, the moving average method is utilized, while outliers are identified with domain expertise. Subsequently, min-max normalization is applied to scale the data appropriately for further analysis. As artificial neural networks are unable to directly process categorical data, they necessitate all input and output variables to be numeric. In this study, one-hot encoding is implemented to convert certain categorical variables (e.g., the day of the week and hour of the day) into a numerical format.



(a) BIM model of the educational building





(b) Semantic model of one chiller (c) Zoomed-in view of the semantic model

Fig. 7. Semantic model developed of the educational building chiller plant.

The MIMO (Multiple Input Multiple Output) method is proposed as a straightforward and efficient approach for forecasting building cooling loads for the next 24 h [8]. In terms of algorithms, the GRU (Gated Recurrent Unit) has shown its capability to achieve comparable or even superior predictive accuracy compared to LSTM (Long Short-Term Memory) and traditional RNN (Recurrent Neural Network) models, while requiring fewer computational resources [59]. Therefore, the GRU algorithm is selected for implementation in this application. The AI algorithm employed in this application utilizes a neural network architecture based on GRU-RNN. It consists of an input dimensionality of 5, a hidden layer composed of 128 neurons, and a single output.

As depicted in Fig. 10, the inputs to this model encompass the 24-h outdoor temperature, relative humidity, building cooling load, number of hours, number of months, and number of days of the week (1 for Monday, 2 for Tuesday etc.). The model's output comprises the 24-h building cooling load profile in the future.

To enhance the model for building cooling load prediction, the model incorporates the dropout and early-stopping training techniques. Dropout is a widely-used technique in the field of deep learning to fight against over-fitting. The early-stopping technique is designed to halt the training process when the accuracy of the validation data ceases to increase after a specified number of iterations, thereby expediting the training process and enhancing the efficiency of parameter adjustment. The training and testing dataset account for 70% and 30% of the entire dataset, respectively. During the model development process, 10% of the training data are randomly selected as validation data. Afterwards, a

Table 5
Temporal data stored in the temporal database.

Bucket	Field	Value	Time
Educational Building Chiller Plant	VSD WCC-1.Chilled Water Flow	93.0	2022–11-15 T07:05:00Z
Educational Building Chiller Plant	VSD WCC-1.Chilled Water Return Temperature	9.9	2022–11-15 T07:05:00Z
Educational Building Chiller Plant	VSD WCC-1.Chilled Water Supply Temperature	7.3	2022–11-15 T07:05:00Z
Educational Building Chiller Plant	VSD WCC-1.Chiller Energy Consumption	6,311,198.5	2022–11-15 T07:05:00Z
Educational Building Chiller Plant	VSD WCC-1.Compressor (Chiller) Frequency	50.0	2022–11-15 T07:05:00Z
Educational Building Chiller Plant	VSD WCC-1.Condenser (Chiller) Pressure	730.8	2022–11-15 T07:05:00Z

GRU-based RNN model is developed for 24-ahead cooling load prediction based on previous 24-h data in one-hour time interval.

5. Results and future work

5.1. Results of the sematic model-based cooling load prediction application

Following the development of semantic models for the chiller plants in three target buildings, extraction and storage of the temporal data, as well as mapping of the semantic models with the temporal data, a framework for the large-scale deployment of AI-enabled data-driven building application has been established. The efficacy of the framework is demonstrated through the implementation of a basic building cooling load prediction model.

Fig. 11 illustrates the process and results of building cooling load prediction using the proposed framework at three distinct sites. The application developer acquires the raw data from the database to train the building cooling load prediction model through AI engine, enabling the generation of load prediction results.

The first step involves utilizing the SPARQL language to obtain identifiers for the required data points and using these points to access the database to obtain raw data for training the load prediction model. Considering the characteristics of the SPARQL query, adjustments to the query for the semantic models in graph database of different target building chiller plants are solely required to change the spatial location of the chiller plant where the target chiller is situated to derive the necessary data for different sites. For instance, the query for site1 (educational building chiller plant room) is "*?chiller brick:hasLocation location:KC_POLYU*". When querying for site2 (government office building chiller plant room) or site3 (commercial building chiller plant room), the query can be modified from "*location:KC_POLYU*" to "*location:CW_QGO*" or "*location:ICC*". The data returned from the SPARQL query is depicted in the Fig. 12(a). The raw "*chwf_id*", "*chwst_id*", and "*chwet_id*" represent the identifier of chilled water flow, chilled water supply temperature, and chilled water return temperature of site1 respectively. The SPARQL query result of site2 and site3 are depicted in the Fig. 12(b) and Fig. 12(c). The identifiers obtained from the semantic models of the three sites using SPARQL are subsequently employed to query the temporal database using FLUX.

The second step involves inputting the raw data from the three different sites obtained through the data acquisition module into AI engine for automatic data cleaning, subsequently utilizing them to train the building cooling load prediction model and obtain the corresponding prediction results. The cooling load prediction result are depicted in Fig. 13. The solid line represents the true value, while the dashed line represents the prediction result of the building cooling load prediction model in the AI engine. The predicted values align closely with the true values, indicating a good fit.

Table 6 presents the prediction result of the models for different sites.

```
prefix brick: <https://brickschema.org/schema/Brick#>
prefix owl: <http://www.w3.org/2002/07/owl#>
prefix rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
prefix kcpolyu: <https://brickschema.org/schema/1.2.1/KC_POLYU_V1.1#>
select ?chwf ?chwf_id ?chwst ?chwst_id ?chwrt ?chwrt_id ?chiller ?chiller_type
where {
   ?chiller a ?chiller_type.
   ?chiller_type rdf:subClassOf brick:Chiller.
   ?chwst a brick:Chilled_Water_Supply_Temperature_Sensor.
   ?chwst brick:hastimeseriesId ?chwst_id.
   ?chwrt a brick:Chilled_Water_Return_Temperature_Sensor.
   ?chwrt brick: hastimeseriesId ?chwrt_id.
   ?chwf a brick:Chilled_Water_Flow_Sensor.
   ?chwf brick: hastimeseriesId ?chwf_id.
   ?chiller brick:hasPoint ?chwst, ?chwrt, ?chwf.
   ?chiller brick:hasLocation kcpolyu:KC-POLYU-BCF-RF-PR-01.
} limit 100
```

Fig. 8. Query semantic model for needed data identifiers using SPARQL.

```
from(bucket: "Educational Building Chiller Plant")
|> range(start: v.timeRangeStart, stop: v.timeRangeStop)
|> filter(fn: (r) => r["_field"] == "ACC-1.Chilled Water Flow)
|> aggregateWindow(every: v.windowPeriod, fn: mean, createEmpty: false)
|> yield(name: "mean")
```

Fig. 9. Query temporal data using FLUX.

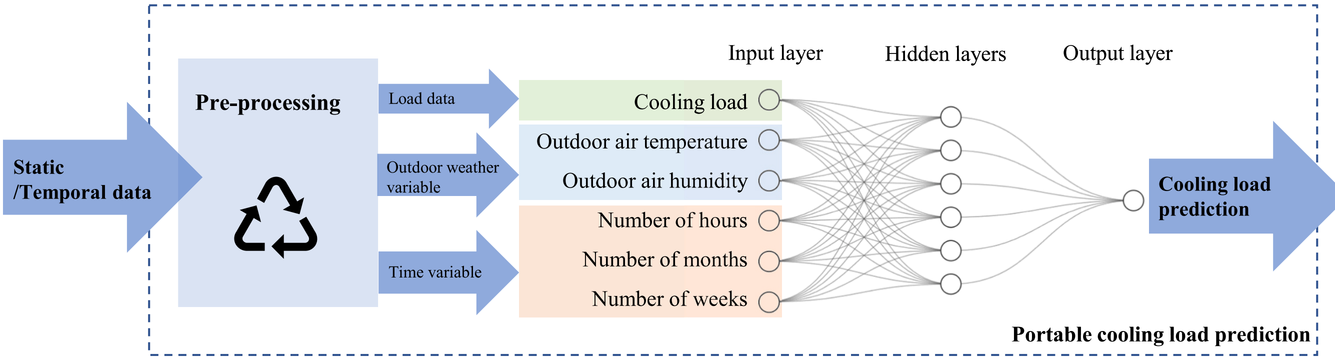


Fig. 10. Cooling load prediction model in AI engine.

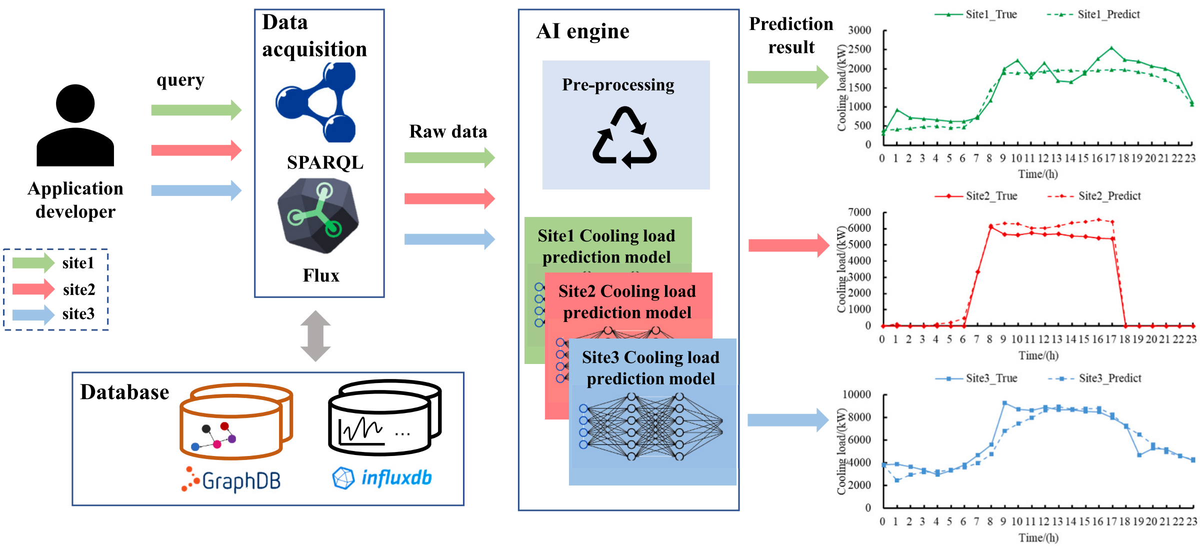


Fig. 11. Cooling load prediction in three sites under the proposed framework.

The accuracies reported were calculated for the 24-h ahead predictions in the testing dataset. Several researchers have reported that the prediction model with a CV-RMSE around 30% or less is acceptable for engineering purposes when using hourly data [60]. The CV-RMSE of the models are less than 0.20%, which means that the cooling load prediction model is available at all three different sites without significant change.

The entire process of developing and deploying a building cooling load prediction application based on the proposed framework, and obtaining the 24-h building cooling load prediction results, does not necessitate the algorithm developer to possess an in-depth and detailed understanding of the building to acquire the required data for algorithm development.

Indeed, the building data-driven applications based on the proposed framework hold applicability beyond just building cooling load prediction and offer scalability to a wider range of building energy management applications. The convenience and efficiency of data acquisition through the framework provide significant advantages compared to traditional methods. With this framework, application developers only need to know the name of the target building and can access the building semantic model and temporal database using fixed SPARQL and FLUX statements. This eliminates the need for developers to possess a comprehensive understanding of the building or rely on extensive communication with building operation and maintenance personnel to gather relevant information about the required data points.

By streamlining the data acquisition process, the framework significantly reduces the cost of data acquisition, algorithm development, and deployment. It addresses the challenge of building heterogeneity by providing a standardized approach that can be applied across different buildings. This cost reduction plays a crucial role in promoting the potential for large-scale deployment of building applications based on the framework. The convenience, efficiency, and cost reduction achieved through this streamlined approach empower application developers to focus more on the development and implementation of advanced algorithms and building energy management strategies, rather than spending excessive time and resources on data acquisition. Ultimately, this promotes the adoption and large-scale use of data-driven building applications based on the proposed framework.

5.2. Limitation and future work

The framework presented aims to integrate multi-source building data based on a semantic model and promote the large-scale deployment of AI-enabled data-driven applications. However, there are several areas for further research and improvement to enhance the framework's capabilities and address specific challenges:

For the development of the semantic model and the proposed framework, incomplete or alternative static data sources, such as buildings with incomplete BIM models or solely relying on 2D drawings, pose challenges in obtaining complete and accurate static data. Future research should focus on developing techniques to extract semantic information from these incomplete or alternative data sources, improving the adaptability of the framework. Additionally, the lack of widely accepted semantic model standards also presents a challenge in the

	chwf	chwf_id	chwst	chwst_id	chwrt	chwrt_id	chiller	chiller_type
1	kcpolyu:PUBCF-RF-ACC-01-CHWF	"ACC-1.Chilled Water Flow"	kcpolyu:PUBCF-RF-ACC-01-CHWST	"ACC-1.Chilled Water Supply Temperature"	kcpolyu:PUBCF-RF-ACC-01-CHWRT	"ACC-1.Chilled Water Return Temperature"	kcpolyu:KC-POLYU-BCF-RF-HVAC-ACC-01	brick:Air_Cooled_Chiller
2	kcpolyu:PUBCF-RF-ACC-02-CHWF	"ACC-2.Chilled Water Flow"	kcpolyu:PUBCF-RF-ACC-02-CHWST	"ACC-2.Chilled Water Supply Temperature"	kcpolyu:PUBCF-RF-ACC-02-CHWRT	"ACC-2.Chilled Water Return Temperature"	kcpolyu:KC-POLYU-BCF-RF-HVAC-ACC-02	brick:Air_Cooled_Chiller
3	kcpolyu:PUBCF-RF-WCC-01-CHWF	"VSD WCC-1.Chilled Water Flow"	kcpolyu:PUBCF-RF-WCC-01-CHWST	"VSD WCC-1.Chilled Water Supply Temperature"	kcpolyu:PUBCF-RF-WCC-01-CHWRT	"VSD WCC-1.Chilled Water Return Temperature"	kcpolyu:KC-POLYU-BCF-RF-HVAC-WCC-01	brick:CSD_Centrifugal_Chiller
4	kcpolyu:PUBCF-RF-WCC-01-CHWF	"VSD WCC-1.Chilled Water Flow"	kcpolyu:PUBCF-RF-WCC-01-CHWST	"VSD WCC-1.Chilled Water Supply Temperature"	kcpolyu:PUBCF-RF-WCC-01-CHWRT	"VSD WCC-1.Chilled Water Return Temperature"	kcpolyu:KC-POLYU-BCF-RF-HVAC-WCC-01	brick:VSD_Centrifugal_Chiller
5	kcpolyu:PUBCF-RF-WCC-02-CHWF	"VSD WCC-2.Chilled Water Flow"	kcpolyu:PUBCF-RF-WCC-02-CHWST	"VSD WCC-2.Chilled Water Supply Temperature"	kcpolyu:PUBCF-RF-WCC-02-CHWRT	"VSD WCC-2.Chilled Water Return Temperature"	kcpolyu:KC-POLYU-BCF-RF-HVAC-WCC-02	brick:VSD_Centrifugal_Chiller
6	kcpolyu:PUBCF-RF-WCC-03-CHWF	"CSD WCC-3.Chilled Water Flow"	kcpolyu:PUBCF-RF-WCC-03-CHWST	"CSD WCC-3.Chilled Water Supply Temperature"	kcpolyu:PUBCF-RF-WCC-03-CHWRT	"CSD WCC-3.Chilled Water Return Temperature"	kcpolyu:KC-POLYU-BCF-RF-HVAC-WCC-03	brick:CSD_Centrifugal_Chiller
7	kcpolyu:PUBCF-RF-WCC-04-CHWF	"CSD WCC-4.Chilled Water Flow"	kcpolyu:PUBCF-RF-WCC-04-CHWST	"CSD WCC-4.Chilled Water Supply Temperature"	kcpolyu:PUBCF-RF-WCC-04-CHWRT	"CSD WCC-4.Chilled Water Return Temperature"	kcpolyu:KC-POLYU-BCF-RF-HVAC-WCC-04	brick:CSD_Centrifugal_Chiller
8	kcpolyu:PUBCF-RF-WCC-05-CHWF	"VSD WCC-5.Chilled Water Flow"	kcpolyu:PUBCF-RF-WCC-05-CHWST	"VSD WCC-5.Chilled Water Supply Temperature"	kcpolyu:PUBCF-RF-WCC-05-CHWRT	"VSD WCC-5.Chilled Water Return Temperature"	kcpolyu:KC-POLYU-BCF-RF-HVAC-WCC-05	brick:VSD_Centrifugal_Chiller
9	kcpolyu:PUBCF-RF-WCC-06-CHWF	"VSD WCC-6.Chilled Water Flow"	kcpolyu:PUBCF-RF-WCC-06-CHWST	"VSD WCC-6.Chilled Water Supply Temperature"	kcpolyu:PUBCF-RF-WCC-06-CHWRT	"VSD WCC-6.Chilled Water Return Temperature"	kcpolyu:KC-POLYU-BCF-RF-HVAC-WCC-06	brick:VSD_Centrifugal_Chiller

(a) Site1

	chwf	chwf_id	chwst	chwst_id	chwrt	chwrt_id	chiller	chiller_type
1	cwqgo:QGO-LG4-WCC-01-CHWF	"WCC01CHWFlowRa"	cwqgo:QGO-LG4-WCC-01-CHWST	"WCC01CHWSTemp"	cwqgo:QGO-LG4-WCC-01-CHWRT	"WCC01CHWRTemp"	cwqgo:CW-QGO-NA-LG4-HVAC-WCC-01	brick:VSD_Centrifugal_Chiller
2	cwqgo:QGO-LG4-WCC-02-CHWF	"WCC02CHWFlowRa"	cwqgo:QGO-LG4-WCC-02-CHWST	"WCC02CHWSTemp"	cwqgo:QGO-LG4-WCC-02-CHWRT	"WCC02CHWRTemp"	cwqgo:CW-QGO-NA-LG4-HVAC-WCC-02	brick:VSD_Centrifugal_Chiller
3	cwqgo:QGO-LG4-WCC-03-CHWF	"WCC03CHWFlowRa"	cwqgo:QGO-LG4-WCC-03-CHWST	"WCC03CHWSTemp"	cwqgo:QGO-LG4-WCC-03-CHWRT	"WCC03CHWRTemp"	cwqgo:CW-QGO-NA-LG4-HVAC-WCC-03	brick:VSD_Centrifugal_Chiller
4	cwqgo:QGO-LG4-WCC-04-CHWF	"WCC04CHWFlowRa"	cwqgo:QGO-LG4-WCC-04-CHWST	"WCC04CHWSTemp"	cwqgo:QGO-LG4-WCC-04-CHWRT	"WCC04CHWRTemp"	cwqgo:CW-QGO-NA-LG4-HVAC-WCC-04	brick:VSD_Centrifugal_Chiller

(b) Site2

	chwf	chwf_id	chwst	chwst_id	chwrt	chwrt_id	chiller	chiller_type
1	ytmicc:ICCB1-6F-WCC-01-CHWF	"CH01_Fwev"	ytmicc:ICCB1-6F-WCC-01-CHWST	"CH01_Twevout"	ytmicc:ICCB1-6F-WCC-01-CHWRT	"CH01_Twevin"	ytmicc:YTM-ICC-B1-6F-HVAC-WCC-01	brick:VSD_Centrifugal_Chiller
2	ytmicc:ICCB1-6F-WCC-02-CHWF	"CH02_Fwev"	ytmicc:ICCB1-6F-WCC-02-CHWST	"CH02_Twevout"	ytmicc:ICCB1-6F-WCC-02-CHWRT	"CH02_Twevin"	ytmicc:YTM-ICC-B1-6F-HVAC-WCC-02	brick:VSD_Centrifugal_Chiller
3	ytmicc:ICCB1-6F-WCC-03-CHWF	"CH03_Fwev"	ytmicc:ICCB1-6F-WCC-03-CHWST	"CH03_Twevout"	ytmicc:ICCB1-6F-WCC-03-CHWRT	"CH03_Twevin"	ytmicc:YTM-ICC-B1-6F-HVAC-WCC-03	brick:VSD_Centrifugal_Chiller
4	ytmicc:ICCB1-6F-WCC-04-CHWF	"CH04_Fwev"	ytmicc:ICCB1-6F-WCC-04-CHWST	"CH04_Twevout"	ytmicc:ICCB1-6F-WCC-04-CHWRT	"CH04_Twevin"	ytmicc:YTM-ICC-B1-6F-HVAC-WCC-04	brick:VSD_Centrifugal_Chiller
5	ytmicc:ICCB1-6F-WCC-05-CHWF	"CH05_Fwev"	ytmicc:ICCB1-6F-WCC-05-CHWST	"CH05_Twevout"	ytmicc:ICCB1-6F-WCC-05-CHWRT	"CH05_Twevin"	ytmicc:YTM-ICC-B1-6F-HVAC-WCC-05	brick:VSD_Centrifugal_Chiller
6	ytmicc:ICCB1-6F-WCC-06-CHWF	"CH05_Fwev"	ytmicc:ICCB1-6F-WCC-06-CHWST	"CH05_Twevout"	ytmicc:ICCB1-6F-WCC-06-CHWRT	"CH05_Twevin"	ytmicc:YTM-ICC-B1-6F-HVAC-WCC-06	brick:VSD_Centrifugal_Chiller

(c) Site3

Fig. 12. SPARQL query result of three sites.

framework's development and deployment. The advancement of effective standards related to semantic models, such as ASHRAE Standard 223P, can facilitate the standardization and interoperability of semantic models, improve the efficiency of framework development and deployment, and facilitate the large-scale deployment of data-driven building applications.

This research demonstrates the capabilities of AI-enabled data-driven applications through a simple building cooling load prediction. However, more complex applications such as building energy flexibility analysis require additional semantic information beyond the Brick Schema. Research should investigate the extensibility of the semantic model by connecting it to other ontologies, enabling the development of richer semantic models that can support advanced applications. This would enhance the framework's versatility and ability to cater to diverse building management requirements.

Buildings undergo changes over time due to maintenance, replacements, or upgrades. Updating the semantic model to reflect these changes is crucial for accurate operation of data-driven applications. Future work should explore methods to dynamically update the semantic model in response to building element changes, ensuring its alignment with the evolving reality of the building.

Addressing these areas of research can further enhance the

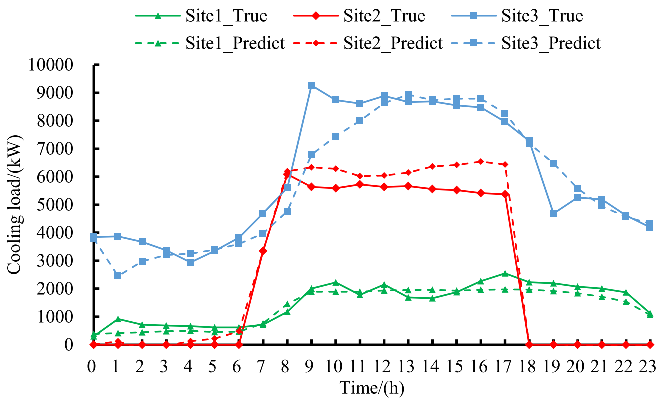


Fig. 13. 24-h ahead building cooling load predictions.

Table 6
Prediction accuracy of three sites.

	RMSE (kW)	MAE (kW)	CV-RMSE (%)
Site1	171	121	14.5
Site2	485	330	19.5
Site3	813	539	13.5

framework's capabilities, usability, and potential for large-scale deployment of AI-enabled data-driven building applications.

6. Conclusions

The challenge in the large-scale deployment of AI-enabled data-driven building management applications stems from the absences of standardization of data description and acquisition methods. The lack of standardization necessitates detailed understanding of the building's systems and data by application developers, leading to increased costs and hindering the large-scale deployment. Consequently, this paper presents a semantic model-based framework that reduces the cost of the data acquisition process, enabling the large-scale deployment of AI-enabled data-driven building management applications.

The proposed semantic model-based framework comprises of three modules: the multi-source data management module, the mapping scheme module, and the AI-enabled data-driven application module. The multi-source data management module extracts the static and temporal data from BIM, BAS and IoT sensors, which are stored in graph and temporal database with the guide of semantic models. Subsequently, the temporal data is given semantic information by mapping the static and temporal data in the mapping scheme module. Finally, the AI-enabled data-driven application module accesses the required data for model training in a standardized manner, facilitating the large-scale deployment of applications.

The proposed model development method demonstrates promising potential for the large-scale deployment of AI-enabled data-driven building management applications, despite its limitations. The framework provides a standard semantic description of building-related data, allowing applications to obtain the required data using query languages such as SPARQL and FLUX without necessitating deep knowledge of building configuration. Testing building cooling load prediction in three different buildings yields satisfactory results, indicating the effectiveness of the proposed semantic model-based framework for large-scale deployment of AI-enabled data-driven building management applications.

The extensibility of the semantic model ensures the flexibility of the framework. In today's increasingly extensive research and application of semantic models, the proposed framework can comprehensively integrate building semantic models constructed by different ontologies, enabling the effective utilization of the life-cycle building's relevant data in building energy management and promoting the development of AI-based data-driven building management applications. In the future, more intelligent automatic extraction and mapping of semantic information of building temporal data points can enhance the efficiency of establishing semantic models, thereby endorsing the widespread promotion of the framework and facilitating the large-scale deployment of AI-based data-driven building management applications, leading to more efficient building management and operation.

CRediT authorship contribution statement

Kan Xu: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Zhe Chen:** Writing – review & editing, Visualization, Conceptualization. **Fu Xiao:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization. **Jing Zhang:** Validation, Methodology, Data curation. **Hanbei Zhang:** Resources, Formal analysis, Data curation. **Tianyou Ma:** Visualization, Validation, Formal analysis, Data curation.

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.

Data availability

The authors do not have permission to share data.

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