Smart Data-driven Building Management Framework and Demonstration

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Abstract. The building sector holds a significant impact over global energy usage and carbon emissions, making effective building energy management vital for ensuring worldwide sustainability and meeting climate goals. In line with this objective, this study aims to develop and demonstrate an innovative smart data-driven framework for building energy management. The framework includes semantic multi-source data integration schema, AI-empowered data-driven optimization and predictive maintenance strategies, and digital twin for informative and interactive human-equipment-information building management platform. A case study was conducted in a typical chiller plant on a campus located in Hong Kong, China. The results show that the deployment of the proposed smart data-driven framework achieves chiller sequencing control in a more robust and energy-efficient manner. Specifically, the proposed control strategy achieves energy savings of 5.9% to 12.2% compared to the conventional strategy. This research represents an important step forward in the development of smarter and more sustainable building management practices, which will become increasingly critical as we strive to reduce our environmental impact and combat climate change.

Keywords: Building Energy Management, Data-driven models, Digital Twin.

1 Introduction

Improving building energy efficiency is crucial for achieving sustainable development on a global scale, given that buildings are significant energy consumers. The building sector accounts for about 30% of global energy consumption and 27% of energy-related greenhouse gas emissions [1], making it a key area for achieving climate objectives. Green buildings are crucial for decarbonization and reducing global greenhouse gas emissions. To achieve carbon neutrality, smart energy management technologies are vital to enhancing energy efficiency and intelligence in the building sector.

Today's buildings are not only energy-intensive but also data and information intensive. Data are continuously generated during the lifetime of the building, and mainly stored in Building Information Models (BIMs) and Building Automation Systems (BASs). BIMs store the static and spatial design and construction data, while BASs store the dynamic/temporal operation data. They provide a complete spatio-temporal description of a building. It is an effective way to understand and improve the building operation by analyzing and utilizing these valuable data. Numerous efforts have been made to effective data integration between BIMs and BAS, including directly linked data and ontology-linked data. Directly linked data method uses standardized naming formats such as Construction-Operations Building information exchange protocol (COBie) [2], Open Messaging Interface (O-MI) and the Open Data Format (O-DF) [3]. Ontology-linked data methods effectively store data in the data lake that is accessible through a common data management system. This method establishes a link between decoupled ontology and time-series databases, making data accessible to applications through a query process. With the development of ontology in the building sector, including Semantic Sensor Network (SSN) ontology [4], Building Automation and Control Systems (BACS) ontology [5], Building Topology Ontology (BOT) [6], ifcOWL ontology [7] and Brick Schema [8], semantic web technologies have gained popularity for integrating multi-source data due to their rich semantic description, interoperability, scalability, and query ability.

Most of the existing building energy management strategies are implemented in BAS, which are not informative, with limited visualization capability, and only support very limited and simple interactions between equipment and facility management staff. Digital Twin (DT) is considered a promising solution to address these challenges as it offers a more advanced and holistic approach to building energy management [9]. Chen et al. [10] developed a BIM-based digital twin which can improve decision-making in facility management by providing automatic scheduling of maintenance work orders. Chen et al. [11] developed a digital twin that enabled monitoring of indoor environments, indoor navigation, and predictive maintenance. By leveraging digital twin technology along with Mixed Reality (MR), IoT, Artificial Intelligence (AI), and other cutting-edge technologies, it is possible to establish an informative and interactive human-equipment-information building management platform. This platform can significantly enhance the efficiency of building operation and maintenance by creating a digital replica of the physical building and its equipment, enabling real-time monitoring and analysis of critical data.

Heating, ventilation and air conditioning (HVAC) systems often consume the most energy in buildings. Compared with conventional physics-based methods, data-driven methods require less information and understanding of buildings and their energy systems [13]. Advanced machine learning algorithms and models have achieved promising success in various applications concerning energy demand prediction [14], fault detection and diagnosis [15], energy benchmarking [16], and occupant behavior prediction [17].

This study aims to develop a smart data-driven building management framework for environmental and sustainability applications to improve building energy performance. The proposed framework includes several key components, such as developing a semantic model to integrate data from multiple sources, deploying optimization and predictive maintenance strategies empowered by AI algorithms, and developing a digital twin platform designed to manage building equipment and information comprehensively and interactively. To demonstrate the effectiveness of the proposed framework, a case study was conducted on a typical campus chiller plant.

2 Methodology

2.1 Overview of the proposed framework

Fig. 1 shows the proposed framework for smart data-driven building management.

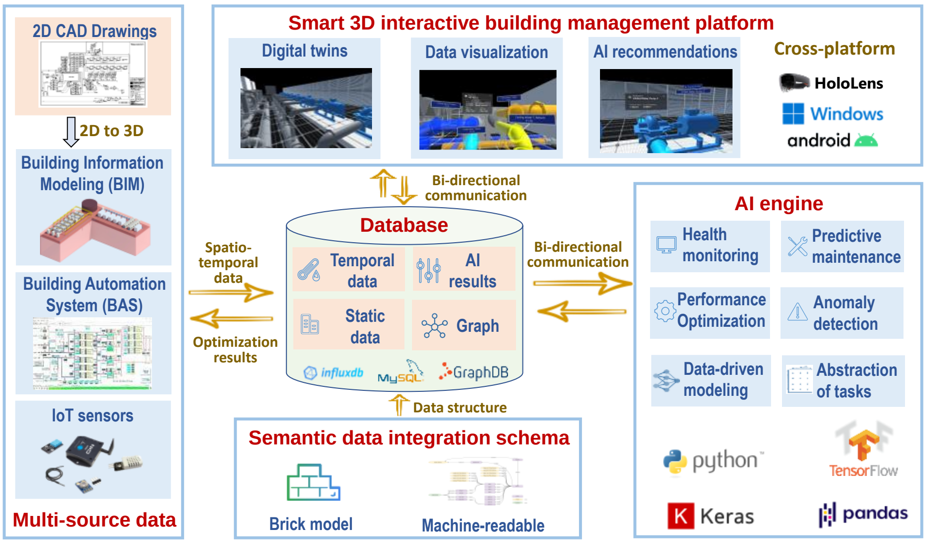


Fig. 1. Proposed framework for smart data-driven building management

Data from multiple sources across different stages of the building lifecycle are extracted and organized using a semantic model as a standardized data integration schema. These data are then stored in a database which provides real-time data to an AI engine. The AI engine is comprised of various environmental and sustainability application packages that can provide recommendations for energy savings and predictive maintenance (e.g., optimal settings, equipment warnings, etc.) to the building. These AI recommendations stored in the database will then be sent to both the smart 3D interactive building management platform for monitoring by building managers and operators, as well as the BAS for optimal control.

The combination of the semantic model, AI engine, and digital twin offers several benefits. Semantic model empowers machine-readable capabilities, enabling the AI engine and digital twin to access data in a building-independent way while maintaining semantic consistency. This facilitates intelligent analysis and decision support by comprehending and inferring data with semantic relationships and enables cost-effective deployment of AI algorithms through its flexibility and scalability. In addition, the collaboration between the AI engine and digital twin enhances operational efficiency and maintenance processes. By synchronizing the digital twin with the real system in real-time, it enables efficient and reliable monitoring, operation, and maintenance, leading to improved operational efficiency and reduced costs.

2.2 Multi-source data available in buildings

Static data. 2D drawings and 3D building information model (BIM) contain the static data at the design and construction stage. They contain primarily semantic, geometric and parametric data of building elements (e.g, wall, window, room, equipment, etc.), for example, the name, type, height, width, orientation and materials of building walls and windows, the name and location of air ducts as well as the design thermal temperature of spaces and rooms. In addition, they can also provide relationships between different building elements, for example, each VAV box entity has an association relationship with its supply duct and the room it serves.

Temporal data. Building automation system (BAS), also known as building management system (BMS), contains the temporal data at the building operation stage. Building operational data in BAS are typically multivariate time series data, including energy consumption data, operating variables (e.g., real-time indoor temperature), environmental parameters (e.g., outdoor air temperature), and miscellaneous [18]. With the radical evolution of internet of things (IoT) networks, more environmental data from IoT sensors [19] and occupant feedback [20] are also available for building operation management.

2.3 Semantic data integration schema

In this study, the static data are extracted from BIM model using the COBie plug-in in Revit software, enabling the inclusion of building elements and their relationship information to develop the building semantic model. This semantic model is then stored in a graph database, which is a specialized data management system designed for efficient storage and querying of graph data. In graph database, nodes represent the building elements, while edges represent their relationships. Properties of building elements, such as wall materials and orientations, are stored in the static database alongside their corresponding unique identifiers within the semantic model. Temporal data from the BAS and IoT sensor network are collected by Building Automation and Control Networks (BACnet) protocol. This protocol is a commonly used data communication protocol and enables data communication among various equipment, devices, and sensors. The collected temporal data are then stored in the temporal database, with each measurement assigned a unique identifier. Within the sematic model, each identifier is stored as a node and linked to the corresponding element using the “hasreferenceId” relationship to achieve spatio-temporal data integration with semantic consistency.

2.4 AI engine

The AI engine is designed to be a collection of diverse application packages focused on energy savings or predictive maintenance of buildings. These packages can provide a comprehensive view of building operations and offer recommendations for building management such as optimal control strategies, health monitoring, predictive maintenance strategies, anomaly detection, etc. This enables building managers to make informed decisions on how to optimize energy usage, reduce maintenance costs, and improve occupant comfort.

2.5 Smart 3D interactive building management platform

A digital twin-based building management platform is developed by Unity3D and can be published to cross-platform including Windows, IOS, Android and Mixed Reality devices, etc. The spatial and static data are mainly extracted from BIM for the development of digital twins. For aging buildings, preliminary BIM can be automatically recovered from 2D drawings [21] and serve as the foundation for creating a digital twin. The platform receives real-time operational data and AI recommendations from the database, which are then presented to building managers and operators for further review and analysis.

3 Case study

This section elaborates the setup and results of the case study. In section 3.1, the target chiller plant is introduced. Section 3.2 illustrates the development of the digital twin and semantic model. Section 3.3 presents the chiller sequencing results/

3.1 Introduction of the target chiller plant

The target chiller plant is located in the Hong Kong Polytechnic University. The schematic diagram of the chiller plant is shown in **Fig. 2**. The chiller plant consists of 5 water-cooled chillers (WCC1-5) rated at 650 RT (Refrigeration Tons) each, one water-cooled chiller (WCC6) rated at 325 RT, and two air-cooled chillers (ACC1-2) rated at 325 RT each. The total cooling capacity is 4,225 RT. Primary chilled water pumps (PCHWPs) are connected in parallel. PCHWP4-9 serve WCC1-5 and the others serve three 325 RT chillers. Condenser water pumps (CDWPs) 1-6 and cooling towers (CTs) 1-5 serve WCC1-5, while CDWP7-8 and CT6 serve three 325 RT chillers. PCHWPs and CDWPs are equipped with one redundant for safety. All PCHWPs, CDWPs, and CTs are operated under fixed speed, and the normal power values are listed in **Table 1**. When a chiller is staged, a set of PCHWP, CDWP, and CT will also be switched. Therefore, it is important to determine the optimal number of chillers, i.e., optimal chiller sequencing control, to reduce unnecessary energy consumption by pumps and CTs.

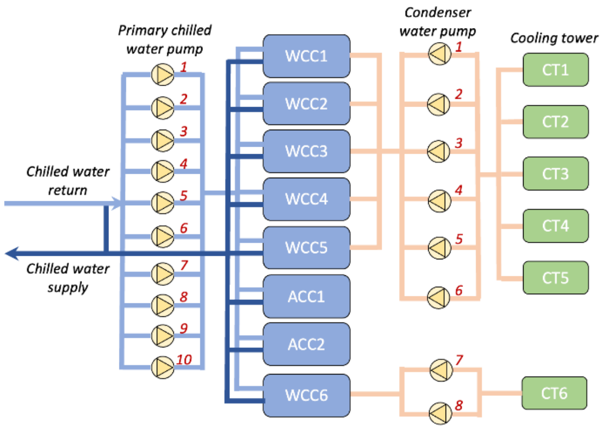


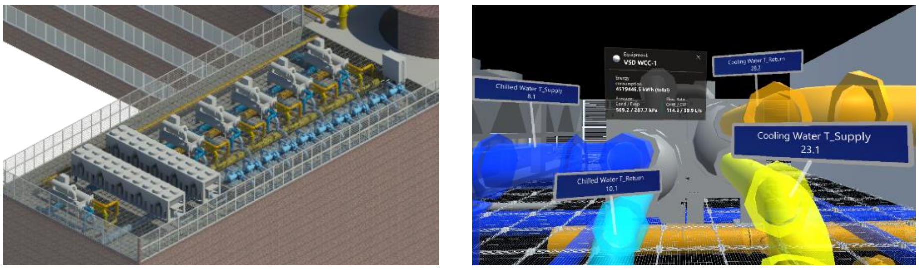
Fig. 2. Schematic diagram of the target chiller plant

Table 1. Nominal power of the equipment

Equipment	Power (kW)
PCHWP 1-3,10	30
PCHWP 4-9	55
CDWP 1-6	75
CDWP 7-8	45
CT 1-4	30
CT 5	18.5
CT 6	15

3.2 Development of digital twin and semantic model

As shown in **Fig. 3**, a digital twin is developed for the target chiller plant.

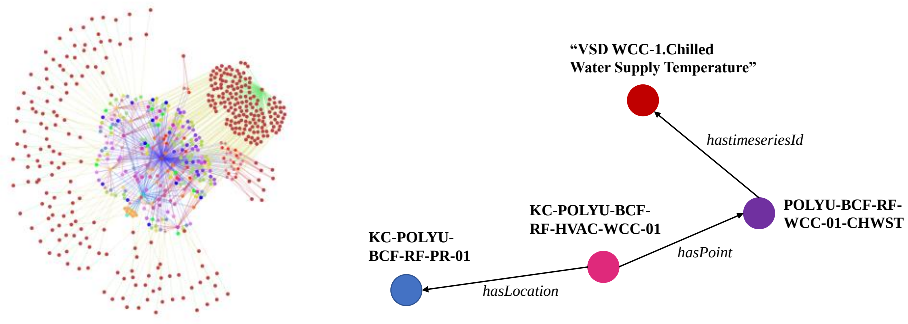


a) Overview of the digital twin   b) Real-time data visualization

Fig. 3. Digital twin developed for the target chiller plant

The necessary static data for this purpose are extracted from BIM, encompassing comprehensive details about chillers, pumps, cooling towers, pipes, and other relevant components. The temporal data are collected from the integrated database that contains operational data from BAS and IoT devices as well as AI recommendations from the AI engine.

As shown in **Fig. 4**, a semantic model is developed for the target chiller plant. The static and temporal data are integrated based on the “hastimeseriesId” relationship in the semantic model. **Fig. 4** (a) shows the entire chiller plant semantic model, with points representing different entities and lines showing their relationships. **Fig. 4** (b) demonstrates a specific part 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 point “VSD WCC-1. Chilled Water Supply Temperature”, indicating the corresponding temporal data is stored in the temporal database with the same identifier.



a) Overview of the semantic model b) Zoomed-in view of the semantic model

Fig. 4. Semantic model developed for the target chiller plant

3.3 Test of AI-enabled chiller sequencing control strategy

This study proposes and tests an AI-enabled robust chiller sequencing control strategy based on probabilistic cooling load prediction [22]. For comparison purposes, a conventional sequencing strategy widely used in building management systems was introduced, which makes sequencing decisions based on measured cooling load and chilled water supply temperature. Although effective in providing a stable and reliable cooling supply [23], unnecessary chillers may be staged by this reference control strategy because it does not consider future changes in cooling loads. The proposed strategy considers cooling load uncertainty to make sequencing actions more robust. An online risk-based actions evaluation scheme is designed to determine the number of operating chillers and assess the risks in the process and the reliability of the strategy simultaneously.

Two typical working days (Mondays) with similar outdoor air temperature and relative humidity were selected to compare the performance of two different chiller sequencing strategies. The first day, May 22nd, 2023, was used to test the conventional sequencing strategy, while the proposed sequencing strategy was tested on June 12th, 2023. The conventional strategy was built into the building energy management system. The outdoor air temperature and relative humidity were recorded, as shown in **Fig. 5**.

The outdoor temperature and relative humidity were very close in both trend and average levels. Therefore, the comparison of the sequencing strategies on these two days allows for a fair assessment of their performance.

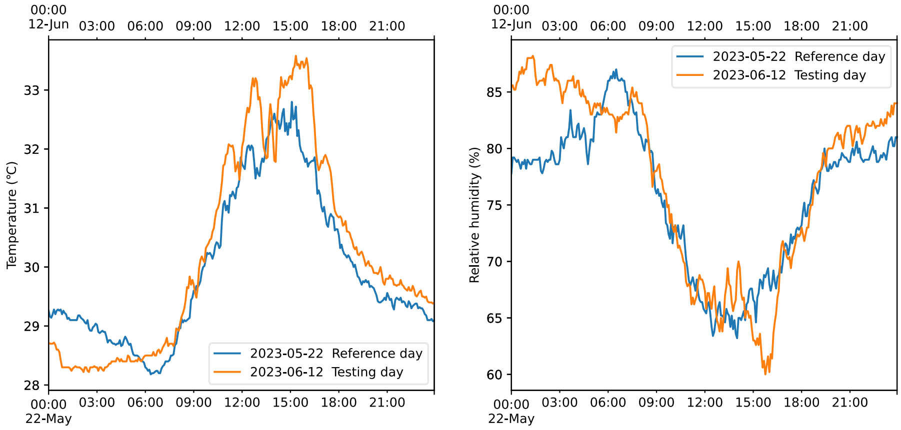
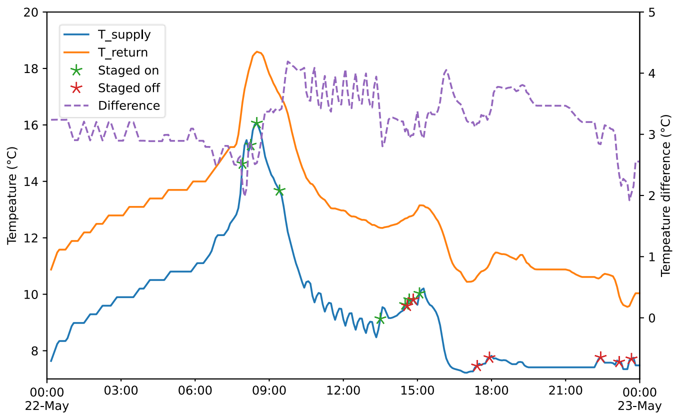


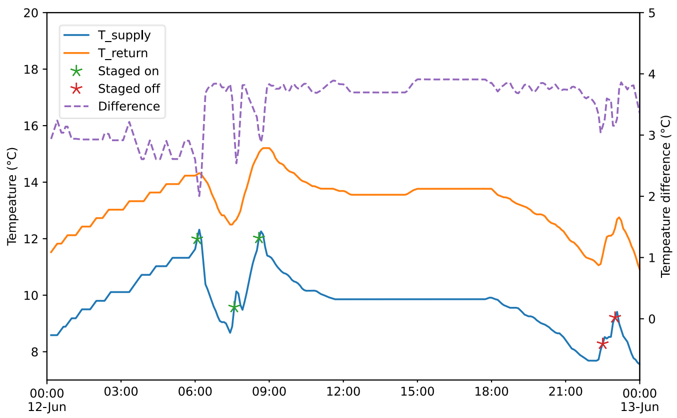
Fig. 5. Weather conditions of the two testing days

The chiller sequencing results of the conventional and proposed strategies are shown in **Fig. 6** a) and b), respectively. Two major differences can be identified. Firstly, when the conventional strategy was adopted from 8:00 am to 9:00 am, the chilled water supply temperatures were above 14 °C, leading to thermal discomfort in the occupied zones. This dissatisfaction occurred because the conventional strategy failed to provide sufficient cooling capacity when the previously unoccupied zones became occupied, after heat accumulation during midnight with only one chiller in operation. The proposed strategy, in contrast, staged on the second chiller earlier at 6:00 am and kept the chilled water supply temperature water at an acceptable level. The second difference is the temperature between the chilled water supply and the return temperature. The average temperature difference adopting the conventional strategy is only 3.2 °C, compared to the 3.5 °C adopting the proposed strategy. The low temperature difference can increase the energy consumption of pumps, resulting in decreased system performance.

The energy consumption of two testing days adopting the conventional strategy and the proposed strategy is shown in **Table 2**. Compared with the reference day, the proposed strategy achieves a 5.9% reduction in energy consumption for chillers. In terms of PCHWPs, CDWPS, and CTs, the proposed strategy leads to 12.2%, 8.9%, and 8.4% reduction in energy consumption, respectively. Overall, when comparing the total energy consumption of the two strategies, the proposed strategy saves 7.1% in energy consumption. These energy savings indicate that the proposed chiller sequencing strategy is more efficient and can help reduce energy usage in chilled water systems.



a) Conventional strategy



b) Proposed strategy

Fig. 6. Chiller sequencing results

Table 2. Comparison of energy consumption (kWh)

	Chillers	PCHWPs	CDWPs	CTs	Total
Conventional strategy	29334.8	4474.6	5878.8	2035.5	41723.7
Proposed strategy	27614.3	3927.9	5356.3	1865.5	38764.0
Energy saving (%)	5.9%	12.2%	8.9%	8.4%	7.4%

4 Conclusion

This study proposed a novel smart data-driven building management framework for environmental and sustainability applications. The proposed framework includes several key components, such as developing a semantic model to integrate data from multiple sources, deploying optimization and predictive maintenance strategies empowered by AI algorithms, and creating a digital twin platform designed to manage building equipment and information comprehensively and interactively.

The proposed framework was demonstrated in a chiller plant in Hong Kong. Through the deployment of this framework, chiller sequencing control was achieved in a robust and energy-efficient manner. The results show energy savings ranging from 5.9% to 12.2% compared to conventional strategies.

As one of the largest consumers of energy, the building sector has a significant impact on the environment and global carbon emissions. The proposed framework can be further improved and fine-tuned to better suit other types of buildings and facilities. By leveraging these technologies and strategies, substantial energy savings can be achieved, contributing to global sustainability efforts, and helping to achieve climate goals in the building sector.

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