# Enhancing Digital Continuity and Interoperability in Building Energy Management: A Digital Twin Approach with Large Language Models *

F. Ababsa, Z. Zheng, E. Yahya, E. Farazdaghi, R. El Meouche and S. Marie

***Abstract*— In the field of building energy management, the heterogeneity of data arising from the coexistence of multiple standards and ontologies, such as Building Energy Management (BEM) and Building Management Systems (BMS), presents a critical obstacle to achieving efficient, interoperable, and continuous digital twins (DTs). These systems produce disparate and often semantically incompatible data, impeding seamless integration and hindering the realization of holistic energy management strategies. To overcome these challenges, advanced data structuring and AI-based strategies are imperative to ensure semantic interoperability and uninterrupted data continuity across heterogeneous systems. This paper introduces a novel approach for constructing a unified ontology that harmonizes BEM and BMS standards, enabling the seamless fusion of their datasets within a digital twin architecture. By leveraging the capabilities of Large Language Models (LLMs), we enrich the semantic structuring process, facilitating automated and precise reconciliation of heterogeneous data sources. Experimental results underscore the viability and efficacy of the proposed methodology in maintaining robust interoperability and ensuring digital continuity, thereby enhancing the operational efficiency of digital twins for smart building energy management.**

## I. Introduction

In recent years, the management of building energy systems has become increasingly complex due to the rapid expansion of digital technologies. The convergence of Building Management Systems (BMS), Building Energy Management (BEM), and the advent of Digital Twins (DT) offer promising avenues for optimizing energy consumption and operational efficiency within buildings. Digital Twins, which serve as dynamic digital counterparts of physical systems, provide real-time insights and advanced analytics capabilities to enhance building performance and support predictive maintenance strategies [1][2]. However, despite their potential, the integration of BMS and BEM systems within Digital Twin frameworks is hindered by several challenges, including data heterogeneity, lack of interoperability, and fragmentation across multiple systems [3][4]. Building energy systems require seamless coordination between various subsystems (e.g., heating, cooling, lighting), each of which generates vast amounts of data in different formats. The complexity of managing this data often results in data silos, making it difficult to achieve a holistic view of building operations [5]. Ensuring the continuity of digital data between BMS and BEM systems is critical to overcoming these challenges. BMS systems typically control mechanical and electrical equipment in real-time, while BEM systems focus on energy modelling and simulation to optimize energy efficiency. The challenge arises from the lack of interoperability between these systems, especially when deploying Digital Twins for real-time monitoring and predictive analytics [6]. Data flows from BMS and BEM are often isolated due to the use of different data formats, leading to inefficiencies in building operations. Current frameworks frequently require manual interventions to synchronize data across these systems, which limits the potential of Digital Twins in optimizing building performance [7]. Furthermore, advancements in Large Language Models (LLMs) provide an opportunity to address these interoperability challenges by automating the structuring and mapping of heterogeneous data [5]. LLMs, through natural language processing (NLP), can automatically tag and organize data from various sources, ensuring a consistent and unified knowledge base. This approach significantly reduces the need for manual data mapping, enhancing semantic interoperability and enabling the effective implementation of Digital Twins in building energy management [8]. Moreover, semantic web technologies such as Resource Description Framework (RDF) and Web Ontology Language (OWL) have been successfully applied to BMS and BEM data to support interoperability; however, these methods often require domain-specific knowledge and extensive configuration, which limits their scalability. The originality of this work lies in proposing a novel framework that leverages LLMs for the semantic mapping of data between BMS and BEM systems, thereby ensuring digital continuity and enhancing the functionality of Digital Twins. While previous research has explored the use of semantic web technologies and ontologies for smart buildings [9], the application of LLMs to enhance data structuring and mapping within Digital Twin frameworks remains underexplored [10]. By addressing the issue of data structuring, this paper presents a scalable and adaptive solution that extends beyond traditional rule-based systems to ensure seamless data integration for energy management.

This paper is structured as follows: Section 2 provides a comprehensive review of the state of the art in BMS, BEM, and Digital Twin technologies, highlighting current interoperability challenges and the potential of LLMs in addressing them. Section 3 outlines the proposed

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methodology for using LLMs to achieve semantic interoperability, focusing on data structuring and integration across BMS and BEM systems. Section 4 presents the results of applying the framework to a case study, showcasing improvements in data continuity and operational efficiency. Section 5 concludes the paper by summarizing the findings and suggesting future research directions to further enhance the use of LLMs and Digital Twins in building energy management.

## II. Related Works

The digitization of building operations has spurred the development of Building Management Systems (BMS) and Building Energy Management Systems (BEM) to enhance energy efficiency and operational performance. BMS is primarily responsible for monitoring and controlling the core operational systems of a building, such as HVAC, lighting, and security, while BEM deals with the management of energy use and optimization through real-time data and predictive algorithms [11]. Despite their critical roles, interoperability between these systems remains a significant challenge due to the lack of standardized protocols and data models, as most BMS platforms rely on proprietary solutions [12]. A number of studies have highlighted the fragmentation of communication protocols such as BACnet, KNX, and LonWorks, which are commonly used in building automation [13]. These protocols often lack the flexibility to seamlessly exchange data across systems without extensive customization and middleware solutions. This lack of syntactic and semantic interoperability increases the cost and complexity of building integration projects. To address this, several researchers have proposed middleware-based architectures to enable communication between BMS and BEM systems, but these solutions still require manual configuration and expertise, limiting their scalability [14]. Furthermore, the emergence of Digital Twin technology has opened up new possibilities for the management of smart buildings by creating a virtual representation of physical assets that continuously updates in real-time based on sensor data [15]. The Digital Twin concept has been widely applied in sectors like manufacturing and aerospace, but its potential for building energy management is only beginning to be realized. Digital Twins provide a platform for real-time monitoring, predictive maintenance, and energy optimization, integrating data from diverse sources such as BMS, BEM, and Internet of Things (IoT) devices. However, the successful deployment of Digital Twins in the built environment is complicated by data integration challenges. For instance, BMS and BEM systems often operate in data silos, making it difficult to build a unified model that accurately reflects the building's operational state [16]. The complexity of combining data from different systems and ensuring data consistency remains a critical bottleneck. Moreover, the heterogeneous nature of building data complicates the process of building reliable predictive models, as semantic mismatches and inconsistencies between different data sources reduce the effectiveness of Digital Twins. One approach to resolving these issues is the adoption of semantic web technologies and ontologies to facilitate the standardized representation of building metadata. Ontologies like BOT (Building Topology Ontology) and IFC (Industry Foundation Classes) have been developed to standardize data models for building operations, enabling better data exchange between systems [17]. However, while these approaches have shown promise, they often require significant manual effort to configure and adapt to different building types and operational conditions. On the other hand, recent advancements in Natural Language Processing (NLP) and Large Language Models (LLMs) have provided new tools to address the interoperability challenges in building energy management systems. LLMs such as GPT-3 and T5 have demonstrated impressive capabilities in handling unstructured data and extracting semantic relationships from complex datasets. These models can be trained to recognize patterns in building operational data and automatically map them to standardized data formats, significantly reducing the manual effort required for data integration. LLMs are particularly effective at automating the process of semantic matching, where data from disparate systems is aligned with a common vocabulary or ontology. In the context of building management, LLMs can be used to match BMS data points with standardized ontologies like Brick or IFC, enabling seamless integration across systems [18]. These models can process large datasets generated by building automation systems and transform unstructured data into a structured format, making it easier to build interoperable digital twins [19]. Several recent studies have explored the application of LLMs to building energy management. For example, In [20] the authors used pre-trained language models to classify and organize data from IoT devices in smart buildings, demonstrating improved performance in real-time energy monitoring applications. Similarly, [21] applied transformer-based models to automatically tag and categorize building metadata, achieving significant reductions in the time required for manual data annotation.

Despite the promise of LLMs for improving data interoperability in BMS and BEM systems, several challenges remain. While LLMs have been shown to be effective at semantic data mapping, their implementation in real-time environments is still an emerging field. Current models require large amounts of labelled data for training, which may not always be available in building management contexts. Moreover, the scalability of these models in handling dynamic building environments where operational conditions are constantly changing needs further exploration. Future research should focus on refining LLM-based models to improve their scalability and real-time capabilities, particularly in the context of smart buildings. Additionally, the integration of LLMs with existing ontologies and semantic web frameworks will be critical for unlocking the full potential of Digital Twin technologies in building energy management. The continued development of AI-driven techniques offers exciting new possibilities for creating self-adapting building systems that can respond to changes in real-time, leading to more energy-efficient and sustainable operations.

## III. Proposed Approach

A crucial challenge in implementing DTs for energy management is the need for semantic interoperability—the ability to exchange and interpret data consistently across different systems and formats. Semantic interoperability between BMS and BEM is complicated by the heterogeneity of data sources, naming conventions, and standards employed by various building systems. For instance, the same building component might be labeled differently across systems, leading to difficulties in integrating and interpreting data in a unified manner. This lack of standardized data hinders the effective functioning of DTs, particularly when managing large, complex buildings with diverse systems and devices. To address this issue, we propose a framework that leverages Large Language Models (LLMs) for semantic data structuring and integration across BMS and BEM. By utilizing LLMs, our framework automates the tagging and standardization of BMS data points, thus facilitating the creation of an integrated, semantically interoperable Digital Twin.

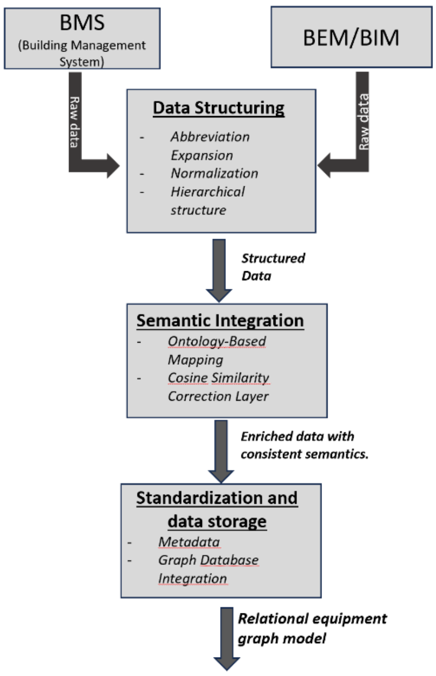


Figure 1. The proposed Framework data flow

## *A. Data structuring*

The first step in ensuring semantic interoperability is structuring raw data from BMS and BEM systems. Due to the wide variety of data points and metadata formats used by different building systems, a consistent approach is required to standardize these data points into a common format .

- Abbreviation Expansion and Normalization: Many BMS systems use proprietary abbreviations (e.g., "SP" for Setpoint or "RM" for Room) that vary across buildings. The first step involves utilizing LLMs to expand these abbreviations and normalize the data points into a standardized format. Through few-shot learning techniques, LLMs are prompted with minimal examples to recognize and expand such abbreviations automatically.

- Hierarchical Classification: Once expanded, the data points are categorized into hierarchical structures based on their functional and spatial relationships within the building (e.g., associating a "Supply Fan" with the room or floor it serves). This ensures that each data point is tagged with appropriate contextual information, further enhancing the accuracy of semantic integration.

## *B. Semantic integration*

Following the structuring of data, the next phase is the integration of BMS and BEM data into a common, semantically rich framework. This is achieved using ontologies like Brick that provide a standardized vocabulary for building systems.

- Ontology-Based Mapping: LLMs are used to map the structured BMS data points to the Brick ontology, which categorizes data into classes such as Sensors, Equipment, and Points. By leveraging the powerful language understanding capabilities of LLMs, this process is largely automated, reducing the manual effort typically required for mapping diverse building metadata into the Brick schema.

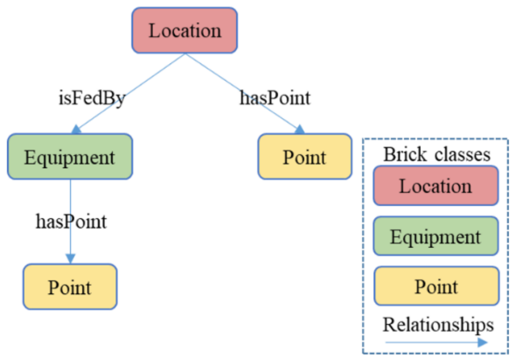


Figure 2. BRICK Ontology with three main classes : Location Equipment and Point

- Cosine Similarity Correction Layer: One challenge with using LLMs is their tendency to generate incorrect or hallucinated labels. To mitigate this issue, we introduce a correction layer that employs cosine similarity analysis on sentence embeddings. This ensures that labels generated by the LLMs are consistent with the existing ontology standards, thereby improving the accuracy and reliability of the integration process.

## *C. Standardization and Data Storage:*

The final step involves standardizing the integrated data into a format that can be utilized by various Digital Twin services such as Fault Detection and Diagnosis (FDD), Indoor Environment Monitoring (IEM), and Energy Consumption Estimation (ECE).

- Metadata Standardization: By applying the Brick ontology, the metadata from both BMS and BEM is transformed into a unified data model, which is then stored in a graph database. This enables efficient querying and retrieval of information across the building's systems.

- Graph Database Integration: The structured and standardized data is stored in a graph database that supports SPARQL queries. This allows Digital Twin applications to seamlessly access and analyse data, improving decision-making and operational efficiency.

## IV. Experimental Results

### A. Dataset Description

For the evaluation of the proposed LLM-based framework, four datasets were used:

- Soda Hall Dataset: This dataset captures HVAC and building control configurations from Soda Hall at UC Berkeley's Computer Science Department [22]. It spans approximately 110,565 square feet and includes 232 thermal zones with variable air volume (VAV) boxes. The dataset includes detailed operational parameters like temperature, energy usage, and HVAC control data, making it a valuable source for assessing building energy management
- Alpha Building Dataset: A synthetic dataset representing a mid-sized office building designed for energy simulations [23]. The dataset includes HVAC operations, lighting systems, and electrical loads across different zones. It enables detailed modelling and testing of building performance under various operational conditions
- Building 59 Dataset: Collected from a 10,400 square meter office building at Lawrence Berkeley National Laboratory [24]. The dataset spans three years and includes data from 57 thermal zones, energy consumption, and occupancy information. The dataset is useful for assessing building operational efficiency and energy usage patterns.
- IntenCity Dataset: This dataset originates from Schneider Electric's high-efficiency office building in Grenoble, which spans 27,000 square meters [25]. It integrates renewable energy sources with sophisticated HVAC systems, capturing detailed energy consumption, environmental conditions, and operational data.

### B. Setup

We applied the proposed framework to integrate BMS and BEM data using Large Language Models (LLMs) for semantic interoperability. The experimental setup involved multiple stages, leveraging advanced techniques such as prompt engineering, sentence embeddings, and an optimized workflow for data structuring and integration. Here's a breakdown of the key steps in our methodology:

*Data Preprocessing*: Data streams were collected from four datasets: Soda Hall, Alpha Building, Building 59, and IntenCity. The raw data included metadata from HVAC systems, energy consumption metrics, and environmental sensors (e.g., temperature, humidity). The primary challenge in these datasets was the inconsistency in metadata labels, due to different building management systems (BMS) and building energy management (BEM) configurations. Before applying the LLM, raw data had to be preprocessed. This phase included:

- Abbreviation Expansion: BMS datasets often contained abbreviations (e.g., "CFM" for "Cubic Feet per Minute"). Using a custom prompt, we instructed the LLM to expand these abbreviations for consistency.
- Data Normalization: Variations in naming conventions across different datasets were handled using few-shot learning and prompt engineering, ensuring the LLM could recognize equivalent terms and normalize them to standard metadata labels like those found in the BRICK schema.

*LLM-Based Structuring and Semantic Integration*: The structured dataset was processed using few-shot prompt engineering. The LLM was provided with sample building metadata along with labels based on the BRICK ontology, which defines a standardized vocabulary for building components such as sensors and equipment.

- Prompt Design: We employed a two-prompt approach: The first prompt expanded abbreviations and standardized terms. The second prompt assigned tags to data points using the BRICK schema. For example, raw entries such as CFM_SF_RM105 were expanded to Cubic Feet Per Minute, Supply Fan, Room 105 and then tagged as Supply Air Flow Sensor.
- Sentence Embedding and Correction Layer: To ensure accuracy, we applied cosine similarity between the LLM-generated labels and reference labels from the BRICK ontology. This step mitigated potential errors by adjusting any labels that deviated from standard terms.

*Workflow Execution*: The workflow was executed in the following phases:

- Abbreviation Expansion Phase: Raw BMS data points were inputted into the LLM. Through prompt-based instruction, abbreviations like CFM were expanded into their full forms.
- Preliminary Tagging Phase: The LLM tagged data points based on their functional role (e.g., identifying sensors or equipment). These labels were then checked against the BRICK ontology.
- Final Tagging Phase: Any incorrectly tagged data points were corrected using cosine similarity analysis. This ensured that the final labels adhered to the BRICK schema, which is critical for ensuring interoperability between BMS and BEM systems.

### B. Performance Evaluation

The metrics used for evaluating the model's effectiveness include precision, recall, and F1-score to assess the accuracy of labeling BMS data points across different environments.

*Few-Shot Prompt Evaluation and Results*: Using a few-shot prompt approach, the performance of the framework improved as the number of examples increased:

- With 3-shot examples, the precision improved to 77%, recall to 92%, and the F1-score reached 84%.
- The performance peaked at 9-shot examples, achieving 96% precision, 100% recall, and 98% F1-score.
- Beyond 9-shot examples, no significant improvement was observed, with 12-shot examples marking the optimal point for balancing performance and efficiency.

Figure 3 illustrates these trends, showing the sharp improvement in performance as more examples were provided, particularly with minimal prompts. This demonstrates the effectiveness of the LLM-based prompt approach in optimizing the tagging of diverse BMS points

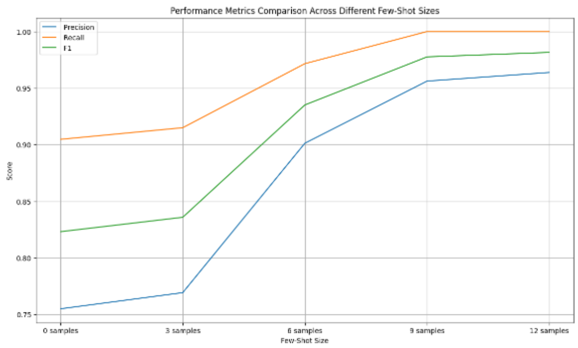


Figure 3. Performance metrics comparison across different few-shot sizes for prompt design building dataset.

*Cross-Building Generalization and Evaluation*: The trained few-shot model was tested across four different building datasets—Soda Hall, Alpha Building, Building 59, and IntenCity—to assess its generalization capabilities. The performance metrics varied slightly across buildings due to differences in naming conventions and real-world data ambiguities:

- Soda Hall yielded the best performance with a 98% F1-score, as this dataset was used for prompt design.
- Alpha Building and Building 59 saw a slight drop in F1-scores to 95%, indicating some challenges in adapting to new naming conventions, but still showcasing strong generalization capabilities.
- IntenCity showed the lowest performance with an F1-score of 92%, primarily due to naming ambiguities and more complex HVAC setups.

*Discussion*: The obtained results demonstrate the efficacy of few-shot prompt engineering combined with Large Language Models (LLMs) for tagging Building Management System (BMS) data points, particularly in the context of supporting Digital Twin frameworks. The framework's ability to maintain high performance across diverse datasets—such as Soda Hall, Alpha Building, Building 59, and IntenCity—showcases its robustness in handling variations in naming conventions and metadata formats, which are typical obstacles in BMS and Building Energy Management (BEM) system integration (Figure 4). The sensitivity of LLM outputs to prompt design was a key finding, underlining the need for well-structured and representative input prompts to guide the model towards accurate classifications. This was evident in the enhanced consistency achieved in aligning data points to the BRICK ontology, thus improving semantic interoperability. The framework proved effective in standardizing BMS metadata, which is essential for maintaining data continuity in Digital Twins and ensuring real-time monitoring and decision-making. However, the model faced challenges in handling real-world data ambiguities, as seen in the occasional mistagging of data points, particularly in datasets like Building 59. These errors were attributed to ambiguous labels and the inherent complexity of adapting theoretical models to practical scenarios. Despite these limitations, the integration of cosine similarity correction mitigated many errors, ensuring that output tags adhered closely to standardized schema labels.

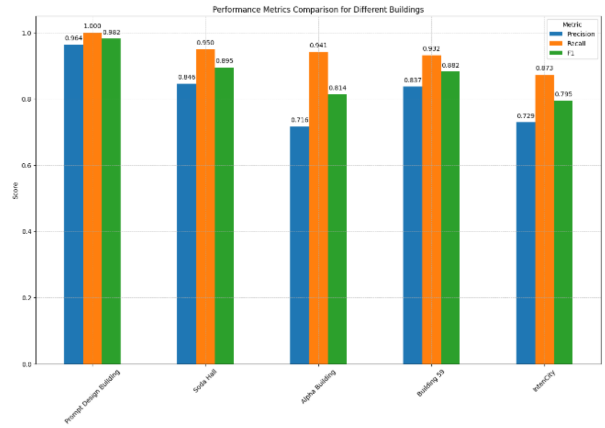


Figure 4. Performance metrics comparison across different building datasets.

## V. CONCLUSION

This research work explored the application of LLMs for tagging BMS data points to facilitate metadata standardization and semantic integration across systems. By leveraging LLMs with few-shot learning and a correction layer using sentence embeddings, we addressed key challenges in BMS data structuring and integration, reducing reliance on manual tagging and labor-intensive labeling. The framework demonstrated its potential across diverse datasets, proving particularly valuable for enabling Digital Twins in building energy management. The results showed a significant improvement in data continuity, which is crucial for maintaining accurate, real-time representations in Digital Twin models. By ensuring that BMS and BEM data is consistently structured and semantically aligned, the framework enhances the operational efficiency of Digital Twins, enabling better energy optimization, predictive maintenance, and fault detection. The successful implementation of this framework also reduces the need for frequent retraining or extensive manual input, offering a scalable solution that can be deployed across various building environments. However, the study also pointed out the need to improve the model's robustness in handling ambiguous data and hallucinations. Future work could explore the integration of Retrieval-Augmented Generation (RAG) techniques, which provide complementary contextual data to the model, further enhancing its ability to interpret and classify building data. Our study marks a significant step forward in leveraging LLMs for BMS metadata standardization,

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