Continuous Calculation of Key Performance Indicators for Buildings through an Application Layer Connected to a Knowledge Graph

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Abstract
Building Energy Management Systems play a crucial role in monitoring and managing energy consumption in buildings, ensuring efficient operation and alignment with performance expectations. This paper proposes an approach comprised of an application layer that interacts with semantic technologies to calculate and analyze energy performance indicators for building energy performance monitoring. This work explores how the formal, yet flexible structure of semantic technologies can be harnessed to manage complex performance calculations efficiently and interoperable across diverse data sources. A proof-of-concept implementation demonstrates how the application layer and ontology work together to serve the calculation of energy performance indicators. These functional components are part of a modular framework designed to process inputs from data instances that are semantically linked to established domain ontologies. In this case, the Brick ontology is referenced. The application layer consists of a collection of scripts that provide instructions to handle data processing and integration of performance indicators into the knowledge graph. The aim is to minimize the amount of information needed to calculate performance indicators from a knowledge graph. Our approach supports energy performance monitoring and provides a framework to enable alignment of calculations with standards and policies, which could offer significant value to organizations and stakeholders involved in building energy management. By demonstrating how semantic technologies enable effective and interoperable energy performance monitoring, we provide a foundation for advancing sustainable building practices at scale.

Keywords
Semantic web technologies, brick ontology, building energy management systems, diagnostics, key performance indicators, real-time data processing

1. Introduction

The building sector accounts for over a third of global energy use and emissions, with growing floor area outpacing efficiency gains—hindering net-zero goals by 2050 [1]. Identifying when and where energy is used is vital for effective solutions. This requires seamless data exchange and interoperability between systems to enable real-time monitoring and control. Efficient Building Energy Management Systems (BEMS) depend on integrated data to optimize performance and guide decisions [2]. Driven by digital transformation, intelligent buildings use tools like Computer-Aided Design (CAD) and Building Information Models (BIM) for integrated design, and IoT devices for real-time performance tracking. Yet, despite growing data volumes, a lack of semantic interoperability hampers integration, scalability, and reuse across systems. To address this, semantic data models and ontologies are used to enrich sensor data with context, enabling machines to interpret, integrate, and reason across diverse datasets. This enrichment is key for the detection of energy patterns and calculation of performance indicators [3]. This paper explores an approach for deploying and

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managing semantic web technologies (SWT), including ontologies and knowledge graphs (KG), to support the handling of performance indicators within a BEMS. The core objective is to anchor the definition of these indicators to formalized concepts from established domain ontologies, thereby enabling scalable, interoperable, and machine-readable representations that facilitate consistent analysis and cross-system integration.

2. Related Work

2.1. Building and Energy Management Systems

BEMS are essential for monitoring, controlling, and optimizing building energy use. A Building Management System (BMS) focuses on operating and controlling devices and systems, while an Energy Management System (EMS) analyzes electrical distribution and provides actionable insights. While BMS ensures effective operation, EMS enhances efficiency. Combined, they form a BEMS—a comprehensive decision-support system designed to reduce energy consumption and improve occupant comfort [4]. [5] classify the methods of BEMS as passive or active. Passive methods influence user behavior through non-automated strategies, while active methods employ sensors and actuators for direct control of building systems, often using techniques such as model predictive control and fault detection and diagnosis (FDD). BEMS collect data through distributed sensors and actuators and may integrate BIM for enhanced contextualization using structured building data, such as room layout and system specification [4]. Intelligent BEMS typically include sensing technologies, control units, and user interfaces to process data, make decisions, and optimize energy usage while responding to occupants' needs [5]. User engagement and system usability are major challenges for adoption. As Hernandez et al. [6] point out, systems relying on indirect control require active user involvement, and the complexity of data-driven methods can be a barrier. To address energy performance and flexibility, BEMS increasingly integrate technologies such as cloud computing, artificial intelligence (AI), and digital twins (DT). Despite these advances, user understanding and awareness of system outputs remain limited. Design considerations are also crucial. Mischos et al. [7] emphasize that EMS should be simple, modular, and scalable from the outset to ensure long-term functionality and ease of expansion. Likewise, Hussaina et al. [4] argue that BEMS must adapt continuously to structural and operational changes, as they are not inherently self-sustaining. Lastly, de Andrade Pereira [8] highlights a major gap: the lack of interoperable and adaptable demand flexibility solutions that can function across heterogeneous systems.

2.2. Energy performance indicators as a part of BEMS

Energy performance indicators (EnPIs) are essential for assessing and optimizing building energy efficiency throughout the life cycle by measuring performance goals [9]. ISO 50006:23 provides guidelines for the creation, use, and maintenance of EnPIs, which are quantitative metrics that help identify improvements in energy management. EnPIs can be defined at various scales, from systems to entire organizations, and are used to normalize energy consumption for tracking efficiency over time and comparing across site [10]. Goldstein and Eley [11] classify EnPIs into four categories. *Asset Rating* is based on simulated performance only. *Operational Rating* uses measured energy data and compares it to typical values for similar buildings. *The O&M* Index compares metered performance to the modeled performance of the same building. The *Energy Services Index* compares the simulated energy use of the building under actual operating conditions to its simulated energy use under the standard conditions used for the Asset Rating. Among these, operational ratings are the most widely adopted as they provide a comprehensive view of performance and are relatively simple to implement. In the context of BEMS, real-time KPI calculation enables ongoing adaptation to changing operating conditions. This supports demand-side flexibility and timely responses to fluctuating energy needs [12]. For accurate evaluation and comparability, energy-related KPIs must be contextualized according to building type, use patterns, and climatic conditions [13].

2.3. Semantic Web Technologies and Ontologies

SWT formally represent and interlink data, enabling insights such as discovering hidden relationships such as the energy balance of buildings [14]. These insights rely on semantic models (or metadata schemas) that describe data meaning and structure. Semantic models vary in complexity, from glossaries and taxonomies to ontologies that use graph structures to define domain concepts, relationships, and attributes. Standards like RDF and OWL support formal ontology definitions in machine-readable triples (subject–predicate–object), while SHACL defines validation rules [3] and SPARQL enables querying RDF data. KGs integrate data and ontologies in a graph format, supporting reasoning, querying, and uncovering implicit links [15]. Costa and Sicilia [16] emphasize that standardized SWT-based representations are essential for efficient building simulations. Ontological descriptions support consistent interpretation of data across different platforms. However, Pritoni et al. [3] identify limited interoperability at the semantic layer as a key barrier, as it prevents seamless integration of interdependent software and reduces reusability across building contexts.

2.3.1. Ontologies for Building and their Energy System

As Pritoni et al. [3] note, multiple initiatives are applying Semantic Web Technologies (SWT) across different building lifecycle phases and challenges. Aniakor et al. [17] identify inconsistent data representation as a major barrier to scalable building applications. BEMS are highly individualized due to diverse building types, systems, and data formats. Ontologies help structure this complexity by contextualizing physical systems—devices, locations, and energy use patterns [18]. They can also define abstract concepts like KPIs and link them to building and energy systems. While KPIs reveal performance levels, semantics can support analysis by connecting underlying concepts. Intelligent systems should autonomously manage performance factors like technical specs, building characteristics, and energy supply. A semantic knowledge base is key for enabling automated decision-making. Building performance relies on many variables that require structured representation and reasoning. Wicaksono et al. [19] use a domain-specific ontology and rule-based inference to classify real-time device data as energy waste or anomalies, allowing dynamic responses to consumption shifts. Pauwels et al. [20] highlight the value of formal semantics in the AEC (Architecture, Engineering, and Construction) industry for evaluating system performance. SWTs offer both extensibility and interoperability by linking multiple ontologies, even when describing the same elements. Semantic descriptions in BEMS enable richer encapsulation, reducing dependency between software and knowledge bases [18]. Several ontologies have been developed and published to represent the classes and properties of BEMS. Table 1 summarizes a set of widely used ontologies covering concepts relevant to BEMS.

Table 1
Related BEMS ontologies

Ontology	**Namespace**	**Knowledge Domain**
Haystack	https://github.com/Project-Haystack (accessed on 11th November 2024)	Building Energy Management
BOT (Building Topology Ontology)	https://github.com/w3c-lbd-cg/bot (accessed on 11th November 2024)	Building Topology
BRICK Schema	https://ontology.brickschema.org/ (accessed on 11th November 2024)	Building Systems
REC (RealEstateCore)	https://doc.realestatecore.io/3.2/core.html (accessed on 11th November 2024)	Real Estate
User Behavior and Building Process Information	https://www.auto.tuwien.ac.at/downloads/ thinkhome/ontology/ProcessOntology.owl (accessed on 11th November 2024)	User Behavior
Semantic Sensor Network Ontology	http://purl.oclc.org/NET/ssnx/ssn (accessed on 11th November 2024)	Sensor Networks
SSN (Semantic Sensor Network)	https://www.w3.org/ns/ssn/ https://esipfed.github.io/stc/sweet/index.html (accessed on 11th November 2024)	Sensor Networks
SAREF (Smart Applications REFerence Ontology)	https://saref.etsi.org/saref4ener/v1.2.1/ (accessed on 11th November 2024)	Energy Management Systems

(Project) Haystack is a standardized for tagging components in EMS, offering a scalable structure and vocabulary for metadata. However, it struggles with architectural components and lack of relational expressiveness [21]. BOT provides a minimal framework for defining buildings' topological elements (storeys, spaces, components) and supports data exchange in the Architecture, Engineering, Construction, Owner, and Operation (AECOO) industry. Brick, introduced in 2016, offers a comprehensive schema for building metadata. It's expressive and user-friendly, aiding tasks like fault detection and semantic tagging in digital twins [22, 23]. Brick can also be extended to model occupant data and support rule- or mode-based systems for monitoring, fault detection, energy advice [24] [25]. REC is an OWL2-based, open-source ontology for the real estate sector that promotes interoperability and data integration in smart buildings, aiming to bridge standards while supporting sustainability and tenant well-being [26]. TU Wien developed an ontology for smart homes, emphasizing user behavior and process modelling [27]. SSN standardizes sensor descriptions and related data. Its 2017 update made it more modular and expanded terms to include sampling and actuation [28]. SAREF enables semantic interoperability for smart appliances, providing a unified framework to manage energy use and reduce market fragmentation [29].

2.3.2. Ontologies for Performance Indicators

KPIOWL is an ontology-driven approach to formalize and manage indicators of business objectives, such as performance, results, measures, goals, and relationships within a strategic framework [30]. It was applied to identify semantic discrepancies in a water management facility and defines separate classes for KPIs and time-based Key Result Indicators (KRIs). KPIOnto is another ontology that describes indicators and emphasizes explicit algebraic relationships between them [31]. Although the authors of KPIOWL considered reusing KPIOnto, they developed a new ontology due to missing key concepts and recommended future alignment. KPIOWL also defines data properties to link calculated and worst-performing KPI values. The saref4city ontology [29] and the "Key Performance Indicator Ontology" [32] also include terms to represent KPIs and their values, using one class for the KPI itself and another for its value at a specific time. Since both are part of broader ontologies for smart cities and building renovation, we developed a minimal, context-independent KPI ontology that closely follows the schema of these two models.

2.3.3. Ontologies for Energy Performance Indicators

The EM-KPI ontology aims to provide order to heterogeneity of cross-domain data exchanged during energy management at district and building levels. The modular ontology covers several master domains, including KPIs, observations, locations, infrastructure, occupants, weather and energy parameters [33, 34]. In order to achieve this, the modular ontology needs to import many different domain ontologies to represent calculation. The KPI module of the EM-KPI ontology is shown in Figure 1. The ontology links the KPI Calculation class to the *KPIEvaluatedObject* with the *hasAssociatedObject* property. Possible classes a KPI can be associated to include *District*, *Buildings* and *PowerSystemResources.*

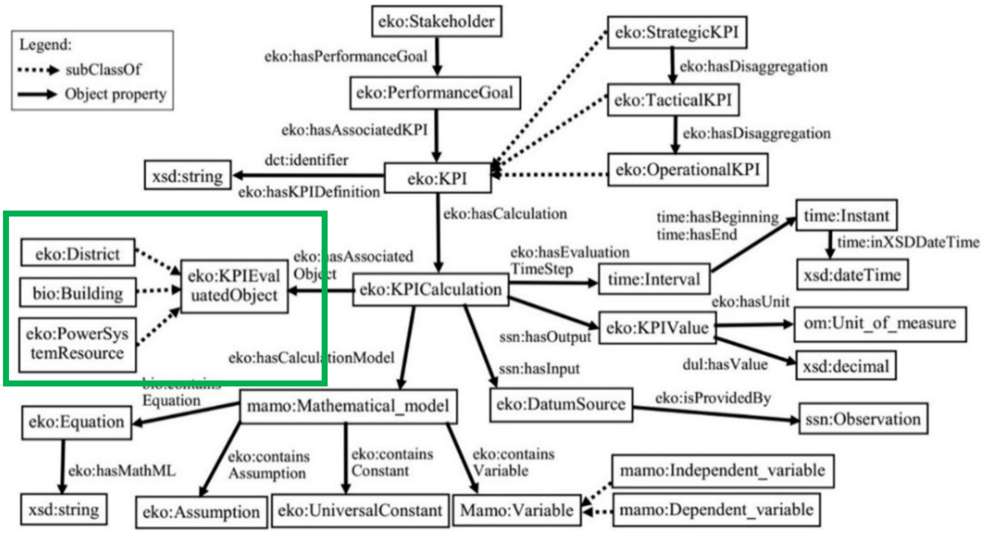

Figure 1: KPI Module of the EM-KPI ontology [33]

Using this approach, the ontology would need to be updated with the calculation and data sources whenever a new KPI is proposed. Also, keeping the ontology up to date with the latest version of the imported ontologies requires ongoing maintenance. Considering that the EM-KPI ontology was last updated in 2017[1], it appears there was no mechanism to achieve this. Because of these considerations, it is believed that representing the KPI calculation as part of the ontology is challenging to manage and inflexible to new KPIs and new sources of data. This work presents an alternative to this approach where the focus is on developing a portable application that references data confirming to any combination of ontologies within a knowledge graph. This means that the knowledge engineers can focus on using the best available ontologies to represent their physical systems and application developers and define rules to extract the required information for the BEMS and stakeholders of user interfaces designed to explore the data.

2.4. Semantic integration within BEMS

Hu et al. [35] present a conceptual framework that uses RDF, OWL ontologies, and inference rules to semantically integrate cross-domain building data into a linked dataspace. By applying reasoning to infer hidden links and implicit knowledge, the framework builds a knowledge base capable of feeding KPIs. Similarly, Zheng et al. [36] propose a data interoperability framework that connects expected and actual energy performance measurements from heterogeneous data silos by leveraging the Brick ontology and SWT to verify gaps in power usage within a building. The framework

[1] https://energy.linkeddata.es/em-kpi/ontology/index-en.html Accessed 07/04/2025

establishes standardized modeling rules, maps BEMS data to the Brick schema, and stores the unified model together with the associated time-series data in a KG. In contrast, Chiosa et al. [37] proposes a portable framework based on the Brick schema for EMIS (Energy Management Information System) application development. Their approach enables the separation of complex EMIS logic development from the time-consuming tasks of data integration and contextualization by introducing a modular, Python-based mediation layer, which they tested by deploying and adapting a machine learning-based anomaly detection application in a case study. A further development by De Andrade et al. [8] introduces an approach that not only enhances semantic integration within BEMS by aligning Brick and SAREF concepts to generate semantic models suited for demand flexibility applications but also enables the mapping of metadata from BIM and Building Automation System (BAS) sources. In detail, they introduce a modular and adaptable control platform that simplifies the development, configuration, and deployment of portable and replicable Demand Flexibility (DF) applications across diverse building contexts. Likewise, [38, 39] use SWT by applying SHACL-rules to support automated fault detection and diagnostics in BAS. Vyshnevskyy et al. [21] developed a custom semantic model for a multi-tenant BEMS, integrating not only meter data but also occupant behavior, tariff structures, and climate effects; they reference JavaScript Object Notation for Linked Data (JSON-LD) as a suitable technology for encoding heterogeneous data as linked data, offering a clean separation between the semantic layer and the presentation layer (e.g., HTML).

3. Research Objectives and Methodology

Although intelligent buildings generate large volumes of sensor data, the lack of semantic interoperability limits tools and platform integration [3]. While KPIs are key to evaluate energy performance [12], their semantic modeling and dynamic calculation is inconsistently applied across BEMS [30, 32]. Recent research highlights that semantic solutions face deployment challenges due to building-specific configuration and the absence of portable models, requiring high customization [8]. Moreover, current EnPI implementations tend to focus on operational metrics but overlook real-time data streams and contextual factors such as building type and usage patterns [13]. Responding to these gaps, this work addresses the following research question and objectives:

"*How can ontology-based application layers enable automated and adaptable KPI computation in BEMS?*"

- Establish formal links between EnPis and energy system descriptions using SWT, enabling a contextualized understanding of building performance.
- Develop an application layer that continuously calculates and updates KPI values within a KG, demonstrating the feasibility of dynamic and reusable performance monitoring.
- Demonstrate the scalability and adaptability of the approach by enabling the integration of new KPIs and energy systems without requiring major restructuring.

To achieve these goals, this research contributes a novel semantic framework that (i) unifies sensor data, metadata, and KPI logic using standard ontologies; (ii) enables continuous, explainable, and transferable performance analytics; and (iii) provides a blueprint for modular, ontology-driven extensions of BEMS platforms across multiple contexts.

This research adopts a Design Science Research (DSR) [40] approach to enable flexible and user-centered development. The methodology applied in this paper follows an iterative process consisting of four main phases:

1. **Conceptual Design**: Relevant EnPIs are selected (based on ISO50005:23) and contextualized using formal ontologies such as Brick. Semantic descriptions are used to define portable KPI templates, specifying the calculation logic, involved entities, periods, and update frequencies.

2. **Prototype Development:** An intermediate application layer is developed to manage the dynamic calculation and integration of KPI values into a KG. It processes configuration files (JSON), queries RDF triples using SPARQL, retrieves time series via REST APIs, writes computed KPI values back into the KG. In addition, a web-based dashboard is designed to enable users to interactively explore KPI values, their relationships, and associated building components through an interactive KG.

3. **Implementation and Testing:** The prototype is deployed and tested in a real-world smart building environment equipped with a high-resolution sensor network, generating operational data across various energy systems and zones.

4. **Evaluation and Refinement**: The prototype is deployed in a real-world smart building with a high-resolution sensor network generating diverse operational data.

By combining semantic modelling, real-time data processing, and interoperable configuration strategies, the proposed methodology enables the continuous and reusable calculation of KPIs across diverse building contexts without requiring monolithic or proprietary systems.

3.1. Data resources

The data used for this study come from the NEST (Next Evolution in Sustainability Building Technology) demonstrator at Empa. NEST is a modular research and innovation building in which new technologies, materials, and systems are tested under real-life conditions. Energy is supplied and controlled via a multi-energy hub so that different technology combinations and energy strategies can be evaluated. A network of 500 actuators and 1,500 sensors generates approximately 10,000 measurements per minute, which are processed by a programmable logic controller (PLC or SPS – *Speicherprogrammierbare Steuerung*), an industrial computer that controls and monitors automation processes. These values are then transmitted via an OPC-UA gateway to a time series database. The data architecture structures information hierarchically, from BIM-based building parts to systems (e.g., batteries), devices (e.g., sensors), and individual data points. The time-series database is connected to both the BIM model and a metadata graph stored in an RDF database (GraphDB). While the knowledge graph supports semantic reasoning and querying, the BIM model primarily provides spatial and geometric context, including for visualization purposes. Each object is enriched with metadata, such as unique identifiers and locations. Historical data and metadata are accessible through a REST API, and semantic mappings to the Brick schema enable SPARQL queries.

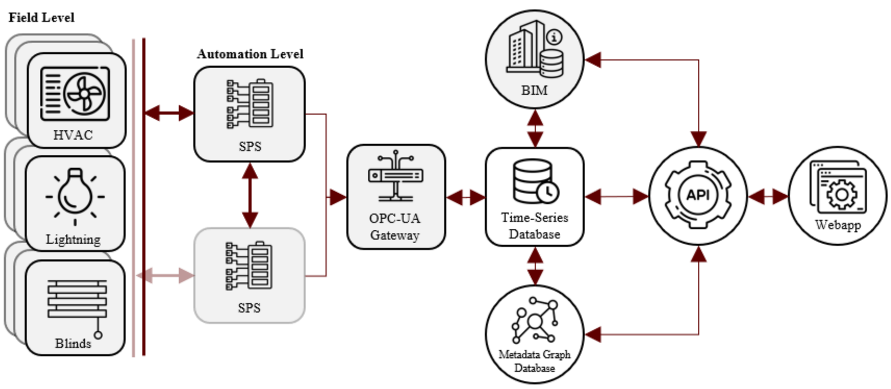

Figure 2: Data Architecture of the NEST-Demonstrator

3.2. Selection of energy performance indicators

In this proof-of-concept study, we apply the approach to calculate EnPIs following the guidelines of the ISO 50005:23 and consider *operational ratings* according to Goldstein and Eley [11]. The following KPIs in Table 2 were selected to capture both overall energy usage and specific characteristics such as energy intensity and peak loads. They provide an initial comprehensive overview of the energy performance of buildings and their metering devices and enable meaningful comparisons across time, locations, and types.

Table 2
A summary of the selected KPIs implemented in this study

KPI Name	Formula	Domain (Business Objective)	Diagnostic value
Energy Consumption	Total Equipment Energy Consumption [kWh]	Operational Rating (Comparison across equipment of different types, location, and building affiliation over time.	Identification of energy-intensive devices that influence maintenance work and decisions on device replacement.
Energy Consumption Intensity	Total Equipment Energy Consumption / Total Building Area [kWh/m^2]	Operational Rating (Comparison across equipment of different types, location, and building affiliation over time independent of building size.)	Detection of devices with proportionally high energy consumption in relation to their performance.
Space Energy Consumption	Total Building Energy Consumption [kWh]	Operational Rating (Comparison across buildings of different types, and location over time.)	Awareness of overall efficiency, energy consumption patterns and evaluation of the effectiveness of e.g. energy saving initiatives at building level.
Space Energy Consumption Intensity	Total Building Energy Consumption / Total Building Area [kWh/m^2]	Operational Rating (Comparison across buildings of different types, and location over time independent of building size.)	Localization of low-performing buildings. It facilitates benchmarking against industry standards.
Peak Power	Max. Equipment Energy Consumption [kWh]	Operational Rating (Comparison across equipment of different types, location, and buildings	Capturing peak loads Facilitates the dimensioning of electrical systems and load control strategies.

4. Results

4.1. KPI synchronization engine

At its core, the KPI synchronization engine functions as an application layer made up of a set of scripts to read and modify the contents of the knowledge graph. These scripts are responsible for managing data processing and integrating EnPIs into the KG, as illustrated in Figure 4. The process begins with the application layer retrieving and interpreting the descriptions of the desired KPIs defined using JSON-based templates. Each KPI listed in Table 2 is associated with its own template.

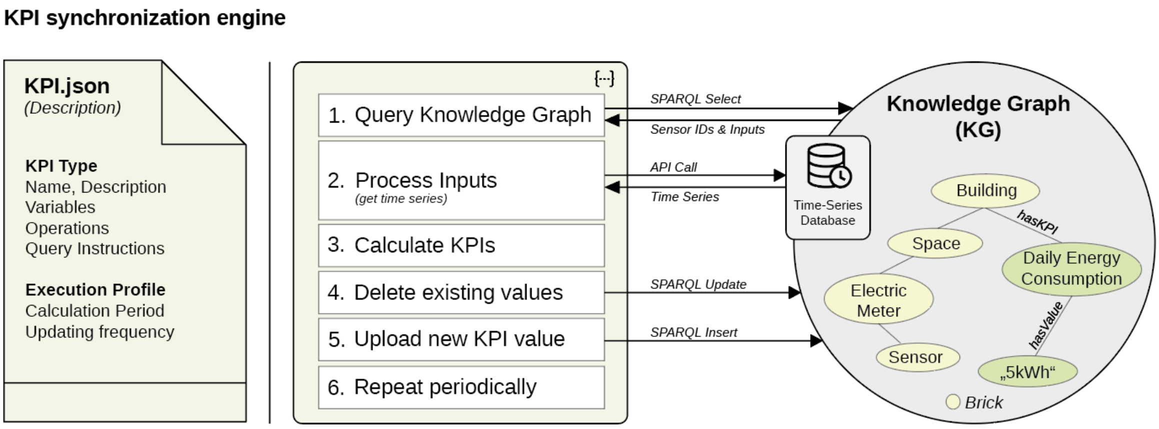

Figure 3: proposed KPI synchronization engine

Templates are structured into two main parts. The first part contains the KPI metadata, including the name of the indicator, SPARQL-based queries for retrieving necessary data from the knowledge graph, details about the required inputs, any preprocessing operations, and how the KPI should be represented. The SPARQL queries, written for the Brick schema in this case, are used to extract relevant information—typically values already stored in the graph such as room areas, other KPIs, or links to time series data residing in an external database. These queries can be adapted to work with different ontologies if needed. The only information relevant to the KPI calculation process are the values extracted from these queries. Within each template, the KPI inputs are mapped to specific variables retrieved via SPARQL, and these may include additional instructions for preprocessing. For example, a time series input might need to be reduced to its maximum value before being used in the calculation. The operations section then defines how to combine these preprocessed inputs to compute the KPI. In some cases, no further processing is required—for instance, when the KPI is simply the peak value of a time series, which is already determined during input preprocessing. An example of this structure is shown in Listing 1, which illustrates the metadata definition for the *Peak Power* KPI and its corresponding KPI type description.

```
"SPARQL Query":
"PREFIX brick:  <https://brickschema.org/schema/Brick##>
"PREFIX ref:    <https://brickschema.org/schema/Brick/ref#>
SELECT ?Meter ?Power_Sensor ?TimeseriesId ?PeakPowerStoredAt
WHERE { ?Power_Sensor a brick:Power_Sensor ;[…].}

"SPARQL Description":
"Returns Power Sensors with external references that are points of a Meter.",
 "inputs":[
        {"name": "PeakPower", "stored_at_name": "PeakPowerStoredAt", "type": "timeseries",
         "timeseries_processing_function": "get_max_value"
        }],
 "kpi_value":
        {"column_name": "PeakPower","unit": "KiloW", "associated_datetime_from_input": "PeakPower"}
        }
```

Listing 1: Excerpt of a SPARQL query using the example of the KPI Type *Peak Power*

The second part of the template defines the calculation period and update frequency, enabling flexible configuration for how often each KPI is calculated or updated. Once the application layer loads the configuration from the JSON file, it uses the embedded SPARQL queries to retrieve relevant identifiers such as sensor IDs and URIs of instances from the knowledge graph. Using these identifiers, and based on the defined calculation periods, the system fetches the associated time series data from the external database via a REST API. The KPI is then computed using this data, following the operations and functions specified in the template. The resulting KPI value is written back into the knowledge graph, replacing the previously stored value to ensure the data remains current.

4.2. Demonstration

The real-time KPI Graph is a web application designed for visualizing and analyzing KPIs calculated through the synchronization engine. It provides users with an interactive interface to explore the performance of different parts of a building through a semantic, graph-based representation. By leveraging the underlying KG, the application allows users to navigate and explore each KPI.

Users select a KPI and a specific building element (such as room, system, or device), which triggers the calculation process described in Section 4.1. The application retrieves relevant data from the KG, fetches time-series data, performs the KPI computation, and writes the results back to the graph for immediate display in the interface as shown in Figure 4. Nodes can be expanded to reveal related KPIs, devices, sensors, and spatial hierarchies, all modeled using the Brick schema. This structure supports exploration beyond individual metrics, enabling users to understand interdependencies, detect anomalies, and compare performance across different zones or equipment. For example, a user investigating Peak Power usage of an HVAC unit on the second floor selects the relevant KPI and equipment in the interface. The prototype locates the corresponding sensor in the KG, retrieves recent power data, calculates peak power value over the last 24 hours, and displays the result. The user can then expand the node to inspect related indicators such as Energy Consumption, helping to identify what may have caused the peak. By comparing similar units in other areas of the building, the user can determine whether the issue is localized or systemic, supporting timely and informed decision-making.

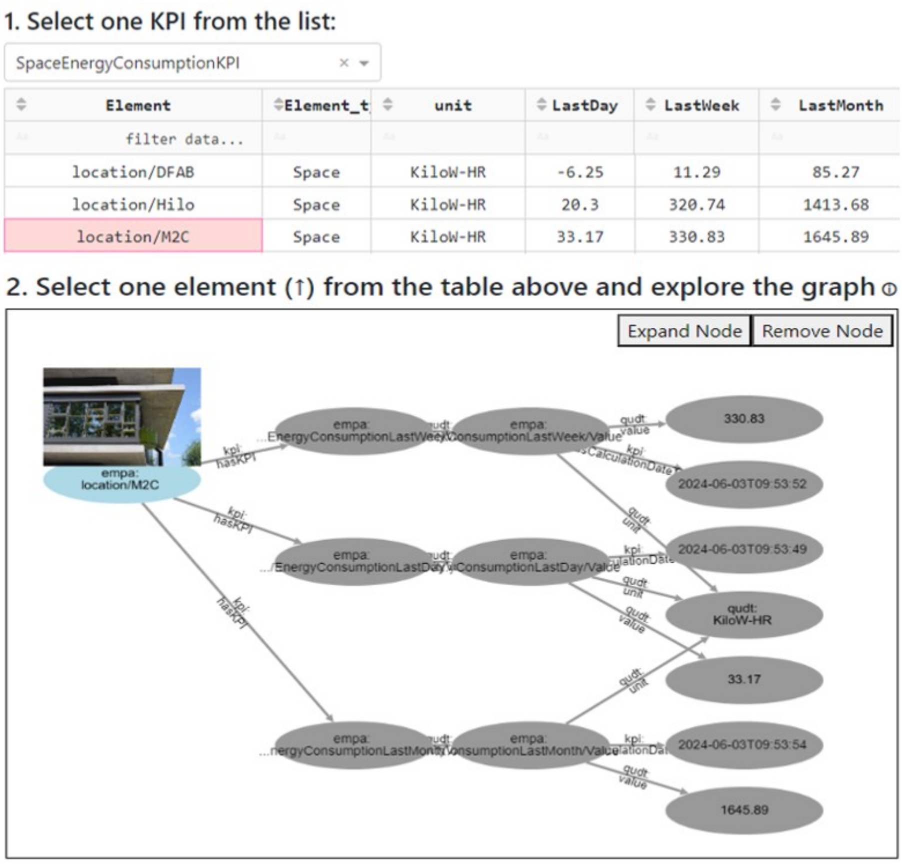

Figure 4: Real-time KPI Graph

5. Discussion

This paper proposes a lightweight and modular approach that supports the continuous calculation, integration, and visualization of KPIs in BEMS by leveraging SWT and configurable JSON files. By formalizing common EnPIs (see Table 2) with platform-independent descriptions linked to the Brick ontology, the approach facilitates portability and semantic consistency across diverse building contexts. Once a KG is in place, these KPI descriptions can be reused and adapted with minimal reconfiguration, supporting efficient and scalable deployment.

Aligned with the classification by [5], the approach corresponds to a passive BEMS, emphasizing ongoing monitoring and analytics rather than active system control. A key contribution lies in the decoupling of KPI logic from ontology structure, distinguishing this work from frameworks like KPI-Onto or EM-KPI [33] that embed logic directly within the ontology at the expense of flexibility. This separation avoids duplication across different systems (e.g., Environmental, Social, and Governance (ESG) reporting, service monitoring) and reduces misalignment by using established ontologies. The approach also overcomes some of the challenges in maintaining a global ontology that imports many sub-ontologies for the KPI calculation. The JSON provides the instructions to extract the necessary information from the graph for the calculation. It is believed that updating JSON is more manageable than maintaining an ontology, which imports multiple ontologies and contains the information necessary to perform the KPI calculation. However, the author of the JSON must be able to construct the SPARQL query to extract the relevant variables. Application developers can then focus on developing interfaces to explore the available KPIs.

The architecture also supports the modular extension beyond energy metrics to include indicators for comfort, air quality, or maintenance—addressing the growing demand for holistic building performance insights. This is important for going beyond reporting and into energy efficiency improvements: to understand how energy consumption is impacted by user requirements and by the physical functioning of the energy systems. The semantic representation enables automated validation for completeness and consistency, while the declarative structure of templates ensures maintainability and transparency. Compared to proprietary or NLP-based systems [41], this approach ensures transparency through explicit ontologies and declarative templates, improving maintainability and reuse across different buildings. It also supports recent calls for transparent benchmarking systems [12, 28] and complements modular EMIS solutions like the framework by [37], by providing a generalizable blueprint for ontology-driven KPI integration. In particular, it supports the understanding of how EnPIs are interrelated. In contrast to rule-based reasoning systems such as those presented by [35], this approach supports the flexible extension of KPIs without requiring changes to inference models, thus enhancing scalability. Furthermore, it bridges semantic monitoring with energy certification schemes such as Asset Rating, Operational Rating, and Energy Service Index [10, 11], providing a foundation for consistent, standards-aligned performance evaluation.

5.1. Conclusions

In this study, we developed an application demonstrating a practical method for calculating energy performance KPIs utilizing semantic technologies. Specifically, the application leverages a knowledge graph of building components aligned with maintained domain ontologies—in this example, the Brick ontology. This approach represents an efficient alternative to embedding all KPI-related information directly within the ontology and knowledge graph itself. Consequently, it effectively separates the roles of knowledge engineers from application developers in the context of Building Energy Management Systems, thereby promoting flexibility and maintainability. However, some customization remains necessary, particularly regarding proficiency in SPARQL queries to extract required variables from the knowledge graph. Additionally, the JSON-based communication structure provides adaptability, enabling flexibility in defining variables used for data exchange between the application and the graph. The JSON instructions encapsulate the data extraction process, while the application separately manages KPI calculations and subsequently inserts KPI instances back into the graph. This design facilitates scalability, allowing straightforward deployment across multiple buildings, provided their data adheres to the relevant ontology standards. While the method significantly simplifies system updates compared to modifying ontology structures, adjustments to JSON configurations will still be required to accommodate new KPIs or additional data streams. Future work will concentrate on enhancing and streamlining the communication mechanisms between the application and the semantic graph to further improve usability and efficiency. This example is solely based on systems that are represented by the Brick ontology, as this was the only knowledge graph available at the time. Future work could aim to continue developing the approach by working additional ontologies covering climate building operation, users and life-cycle assessment.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. ChatGPT was also used to assist the language of some sentences to improve clarity. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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