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WEB OF SIMULATION ONTOLOGY-DRIVEN FRAMEWORK (WOSO-DF) FOR INTEGRATING BUILDING PERFORMANCE SIMULATIONS AND IOT SYSTEMS FOR SMART ENERGY MANAGEMENT

Zehor Hounas[1,2], Maxime Lefrançois[2], Bruno Traverson[1], Antoine Acolant[1],
Hassan Sayegh[1], and Antoine Zimmermann[2]
[1]Électricité de France Recherche et Développement (EDF R&D), Palaiseau, France.
[2]Mines Saint-Etienne, Univ Clermont Auvergne, INP Clermont Auvergne,
CNRS, UMR 6158 LIMOS, F-42023, Saint-Étienne, France.

Abstract

Buildings account for a substantial share of global energy consumption, making their optimization critical for addressing climate change and rising energy demands. While IoT systems enables real-time monitoring and control, it fails to account for complex thermal dynamics. Building energy management could benefit from interoperability between IoT systems and building performance simulations. This paper demonstrates the application of the Web of Simulations Ontology (WoSO) to address this interoperability challenge in an office building located in Moret-Loing-et-Orvanne, France. The study aims to showcase a framework for applying semantic web technologies and demonstrate the benefits of simulation-IoT integration in real building systems.

Introduction

In 2023, buildings accounted for 30% of the global energy consumption, and approximately 40% in Europe and France,[1,2] positioning them as a promising response to global climate change with the ever-increasing energy demand. This makes building performance optimization a critical aspect of every phase of the building life cycle (Wang et al., 2024).

In the conceptualization and design phase, the efficiency objectives are defined. The optimization process increasingly incorporates advanced technologies such as Digital Twin, which provides a virtual representation of the building by integrating geometric data and physical parameters (Pan et al., 2023). This technology supports Building Performance Simulation (BPS), defined as the computational analysis of a building's operational performance under varying conditions, improving decision-making processes and enhancing the achievement of performance goals (Lamberts and Hensen, 2011).

Once constructed, the building enters the operational phase during which it fulfills its intended purpose. The performance of the building is assessed using Internet of Things (IoT) control systems, enabling monitoring and adjustments to ensure efficient energy management.

However, the IoT control system does not take into account all the physical phenomena occurring in the building, which are exactly what BPS model using mathematical models to simulate their dynamics.

To achieve effective collaboration, BPS and IoT systems need to interoperate as part of a building management system. This requires effective data exchange between these heterogeneous systems. The Web of Simulations Ontology (WoSO) is a core vocabulary that provides a high-level description of BPS, and target semantic interoperability with IoT systems (Hounas et al., 2024). WoSO relies on the ETSI Smart Applications REFerence ontology (Lefrançois et al., 2024) standard for IoT aspects, and on the Modelica Functional Mock-up Interface (FMI) standard specification (The Modelica Association Project FMI, 2022) to identify and describe information related to the core functionality of a simulation.

This paper introduces the Web of Simulation Ontology-Driven Framework (WoSO-DF), a semantic web-driven framework that leverages the WoSO ontology to enable interoperability between the thermal model and the IoT system of a building. WoSO-DF is demonstrated on an office building of Électricité de France (EDF) located in Moret-Loing-et-Orvanne, France, that serves as a pilot site for the European project BuildON[3]. This building is equipped with an IoT system that collects data on environmental parameters such as office temperature but cannot measure heat exchange between offices. The thermal model of the building simulates the variation of the temperature within the office over time.

The core of our proposal is a knowledge graph that effectively links IoT data with the variables of the thermal model of the EDF building. WoSO-DF highlights the significant advantages of semantic web technologies, emphasizing the utility and applicability of the WoSO ontology. By enabling seamless interoperability and enhanced integration, the framework underscores the potential of semantic web solutions to improve data-driven management and modeling in complex building systems.

[1]The European strategy for buildings, `https://france.representation.ec.europa.eu/la-strategie-europeenne-en-faveur-des-batiments_fr?prefLang=es`.

[2]Energy in buildings, `https://www.ecologie.gouv.fr/politiques-publiques/energie-batiments`

[3]BuildON Project, `https://buildon-project.eu/`, accessed: Mar. 7, 2025.

Related works

The integration of BPS and IoT systems is driven by various motivations, primarily aimed at improving the accuracy of simulation outcomes and enhancing decision-making processes within energy management systems. This requires interoperability between these heterogeneous systems. A leading interoperability standard for simulation models is FMI (The Modelica Association Project FMI, 2022; Blochwitz et al., 2011), which enables the exchange of dynamic simulation models among various tools in a standardized format, and models to be executed in different environments: in Python using libraries such as FMPy (Dassault Systèmes, 2024), pyFMI (Andersson et al., 2016) in Java using JFMI (Blochwitz et al., 2012) or using an additional interoperability layer as proposed by Hatledal et al. (2019).

Hong and Lee (2019) present the technical framework and algorithms of the inverse modeling approach, which enables the integration of large-scale IoT sensor and device data, thereby improving simulation accuracy. Liu et al. (2024) outline a methodology that leverages the convergence of IoT and Building Information Modeling (BIM), collectively enhancing the precision and responsiveness of building management systems. Nevertheless, addressing the semantic interoperability between simulation models and other applications, such as IoT applications, remains a pending challenge (Di Biccari et al., 2022; Costin and Eastman, 2019). Many researchers leverage semantic web technologies, such as ontologies, to tackle the high fragmentation of IoT systems (Esnaola-Gonzalez et al., 2020; Mohammed et al., 2021; Pan et al., 2023; García-Castro et al., 2023).

Hounas et al. (2024) proposed the Web of Simulation Ontology (WoSO) to address semantic interoperability between BPS and IoT systems, with the goal to enable effective data exchange and interaction to enhance energy efficiency in buildings. WoSO relies on the FMI standard to describe the BPS aspects (Blochwitz et al., 2011), and the Smart Applications REFerence ontology (SAREF) (García-Castro et al., 2023) to describe the IoT aspect.

The IoT system of the EDF building

The IoT system of the EDF building integrates a DAIKIN centralized heating solution powered by a heat pump. Each office is equipped with a thermostat (Figure 1(a)) for climate control that embeds a temperature sensor. The building is also equipped with a Wattsense gateway (Figure 1(b)), five Ellona IoT devices (Figure 1(c)) which embed sensors for temperature, humidity, CO2 concentration, atmospheric pressure, light intensity, vibration, and noise level. Finally, six Ethera IoT devices (Figure 1(d)) monitor indoor air quality indicators with sensors for temperature, humidity, CO2 concentration and atmospheric pressure, Nitrogen Dioxide (NO2) and Ozone (O3).

The data collected from these IoT devices is stored on three distinct IoT platforms. Data collected from the

(a) DAIKIN Thermostat (b) Wattsense gateway (c) Ellona IoT device (d) Ethera IoT device

Figure 1: IoT devices deployed in EDF building.

DAIKIN thermostat is sent through the Wattsense gateway and stored on the Wattsense platform. The Ellona and the Ethera IoT devices store data on the Ellona and Ethera platforms, respectively.

These platforms are accessible through REST APIs. The collected data are not associated with specific locations within the building. The exact locations of the IoT devices are documented in an Excel file linking each device identifier to the office in which it is located.

The IoT devices generate a substantial volume of data on a wide range of environmental indicators. Our experimentation focuses primarily on temperature as a key indicator. In addition, it includes a set of environmental indicators: humidity, CO2 concentration, and atmospheric pressure, providing a broader perspective on the variability of datasets. These parameters are particularly relevant to our study, as our experiment focuses on the thermal performance of buildings and indoor conditions. Furthermore, these indicators are among the most frequently analyzed in the building domain, underscoring their significance and utility in indoor environmental monitoring and building performance assessment.

Wattsense Platform

Each thermostat collects the temperature and returns the set-point temperature of the office it is located in and transmits them through the gateway to be stored on Wattsense platform. The gateway is also connected to the electric smart meter, which returns the global power measurement and the power measurement of the heating system, the lighting system, and the electric plug network with index readings at a frequency of 10 minutes.

Listing 1 is a snippet of the JSON file returned by the Wattsense API in response to a query for a list of devices and their measurements.[4]


```
{
"deviceId": "KOXRLN1G",
"hardwareId": "3aebae264ca33841",
"subscription": {
    "current": {},
    "next": {},
    "startDate": "2024-01-09",
    "endDate": "2025-12-11",
    "isRenewed": "True",
    "isExpired": "False"
},
"tags": {},
```


[4] All of the files from which snippets are excerpts are openly available on GitHub `https://github.com/zhounas/woso_df`

```
    "type": "TOWER",
    "activationDate": "2022-12-13T13:43:15.743Z",
    "connectivityStatus": {},
    "createdAt": "2022-12-13T13:43:15.743Z",
    "createdBy": "",
    "updatedAt": "2024-12-06T10:09:13.215Z",
    "updatedBy": "system"
}
```

Listing 1: Data returned by the Wattsense platform.

Ellona Platform

The data collected by the six Ellona IoT devices are stored on the Ellona platform. The data can be retrieved by sending a query for a list of devices and their measurements. As shown in Listing 2, the API returns data in a JSON format, but with inconsistent structure. Some entries are correctly structured, with one entry corresponding to a single device and its associated measurements along with their units. Other entries combine multiple devices and their measurements into a single entry. This inconsistency poses challenges for data parsing and analysis.

```
{ "data": {
  "devices": {
    "61163e4054ee380cbe70c89b": "POD2-00335" },
  "units": {
    "temperature": "C",
    "humidity": "%",
    "co2": "ppm",
    "barometer": "hPa",
    ...},
  "measurements": [
    {"date": "2024-12-11T09:01:00.000Z"},
    {"61163e4054ee380cbe70c89b-env_temp":
       20.5,
     "61163e4054ee380cbe70c89b-env_pres":
       1017.47998046875,
     "61163e4054ee380cbe70c89b-env_rh":
       38.70000076293945,
     "61163e4054ee380cbe70c89b-co2\_co2":
       403,
     "date": "2024-12-11T09:00:50.000Z"
    ...    },
    ...]
}
```

Listing 2: Data returned by the Ellona platform.

Ethera Platform

The Ethera Platform is a remote server for storing data collected from six devices. Each device embeds several sensors that generate a significant amount of data. The data retrieval process from the Ethera API involves a two-step procedure. Initially, a request is made to the API to return a list of available devices, Listing 3 is a snippet of the JSON returned from this call. Once the list is obtained, a second request is required to retrieve the measurements from a given device. A snippet of the response is shown in Listing 4.

```
[...
 { "bid": 9,
   "serial": "6102001000202",
   "name": "6102001000202"},
 { "bid": 10,
   "serial": "6102001000165",
   "name": "6102001000165"},
 { "bid": 11,
   "serial": "6102001000219",
   "name": "6102001000219"},
...]
```

Listing 3: List of devices returned by the Ethera platform.

```
{
'variable': {'structure': 32852,
  'source': 0,
  'id': 84,
  'name': 'Temperature',
  'unit': 'C'},
'values': [{'time': 1734166478,
    'value': 18.8}]
}
```

Listing 4: List of measurements for a device returned by the Ethera platform.

The thermal simulation of the EDF building

The simulation setup of the thermal behavior of the EDF building requires a comprehensive model representing the system under investigation, a defined scenario outlining specific operational conditions, a weather file containing historical or predicted climatic data, and temporal parameters that establish the timeline and the resolution at which the simulation will evaluate and record data.

Thermal model of the EDF building

The thermal model of the EDF building is an acausal model developed using Dymola. It uses a mathematical and computational model to simulate the thermal behavior of the entire building by breaking it down into nodes. Each node represents a zone of the building. As illustrated in Figure 2, zones can be an office, a set of adjoining offices, a hallway or a part of the hallway. The model incorporates the geometry of the building, the insulation norms, its heating system, and the boundary conditions as heat transfer. It takes as inputs the temperature of each zone, temporal parameters, and it returns different outputs. The thermal model of the building could not be included in the provided resources as it is proprietary to EDF company and restricted from disclosure.

Simulation scenario

In the context of simulations, a scenario defines the specific conditions and temporal framework under which a model operates. It typically outlines operational schedules that guide the behavior of the model over time. Defining a scenario for a simulation involves specifying the conditions and time frames that govern how the system behaves during the simulation period. The process starts by identifying key variables that influence the operation of

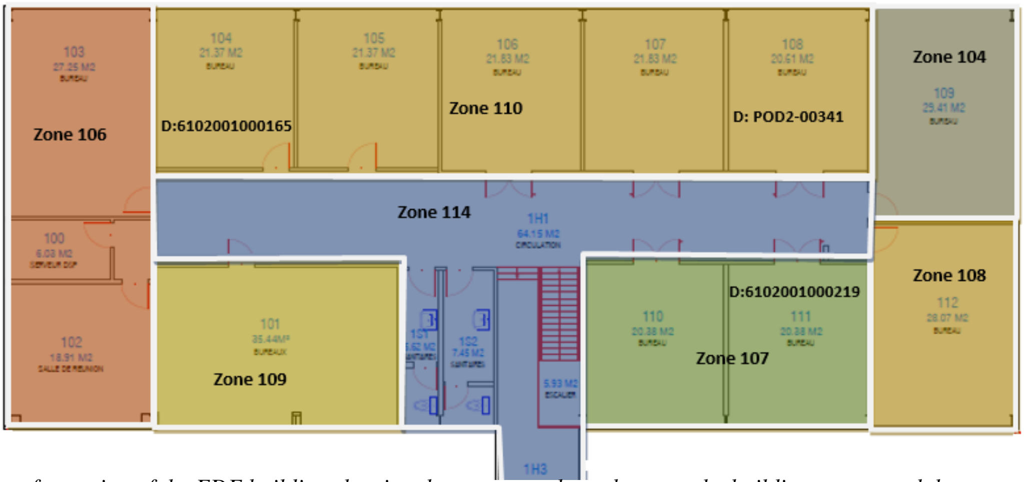

Figure 2: Plan of a section of the EDF building showing the correspondence between the building spaces and the zones of the thermal model.

the system, such as operational settings (e.g., schedules, set points). These variables are then organized into a pattern that can be applied within a coherent framework for the simulation, ensuring that they evolve consistently over time.

In our experiment, the scenario was constructed using the HelioBIM software (Bouquerel et al., 2021). We define two temperature set-points, A and B, which correspond to 20 °C and 0 °C, respectively. These set points are used to represent two distinct operational periods: S1, where the set point A (20 °C) is applied throughout the week S2, where the set point B (0 °C) is applied for another week. The scenario applies S1 from November 15 to April 15, representing heating requirements during the colder months. From April 16 to November 14, S2 is applied, as there is no cooling system to regulate higher temperatures during the warmer months. This yearly cycle is used to observe the response of the system to seasonal temperature changes.

Temporal Parameters

Temporal parameters establish the timeline and the resolution at which the simulation will evaluate and record data. Temporal parameters include simulation start and stop times, which define the overall period of interest, typically based on the intended scope of the analysis. For example, simulations aiming to capture seasonal performance variations may span multiple months, while those focused on daily energy use might cover only a 24-hour period. The output interval specifies how often simulation results are recorded, which can differ from the time-step used for calculations.

In our experiment, the simulation start time is $0day$, which means that the simulation begins on the first day of the year, January 1st and the stop time is set up to $1day$, which corresponds to the second day of the year January 2nd. The output interval is set to $1hour$. The simulation will run on 24 hours, with an interval of 1 hour.

Limitations

The IoT devices lack location data, and the information across the three IoT platforms is semantically heterogeneous, with inconsistencies in naming conventions, unit representations, and data structures. This hinders integration and necessitates standardized models for effective data harmonization and utilization. This lack of standardization in semantic and structure of the data leads to significant limitations. In addition, the storage of data on separate platforms makes it challenging to aggregate and analyze data comprehensively. Interfacing with multiple APIs adds complexity to application design, and hinders seamless integration and interoperability, requiring additional processing to unify data semantic and structures from the three platforms, and to the simulation data. The integration of the thermal simulation with the IoT system of the EDF building also presents several challenges due to limitations inherent in the thermal model:

- The thermal model is developed with a specific proprietary modeling tool, Dymola, which hinders integration with the IoT system.
- Initial conditions, such as the temperature and set-point temperature for each zone, are defined within the model and assigned default values, which limits the ability to use live data from the IoT system.
- The building model is divided into zones, each representing a set of offices, while the IoT system collects data specific to individual offices, each with a setpoint temperature and one or more temperature measurements. Due to the mismatch between model zones and IoT data, it is necessary to calculate an aggregated value for each zone based on the data from individual offices. This additional step increases the complexity of data integration and may reduce the precision of the simulation.

These limitations restrict the model's flexibility and interoperability, making it difficult to fully leverage IoT data.

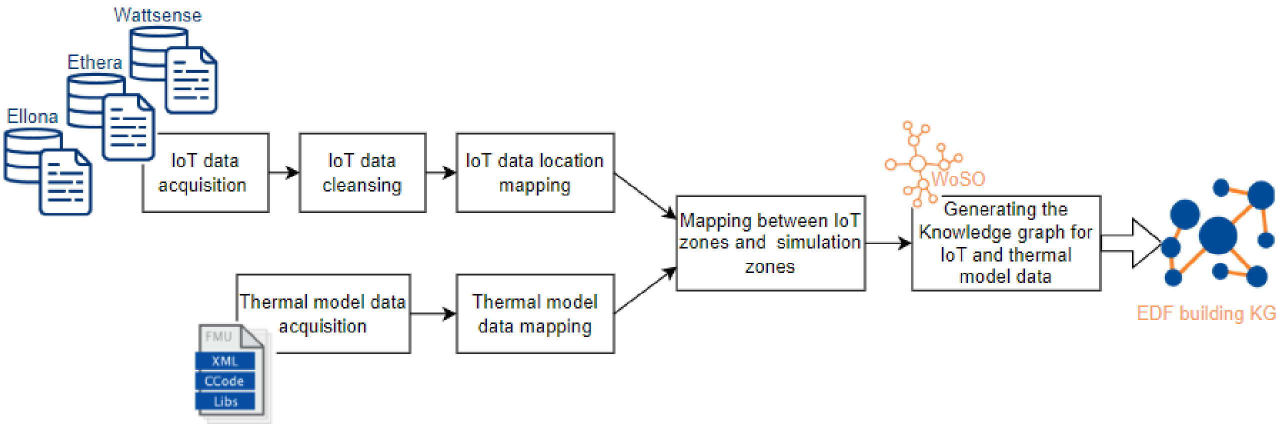

Figure 3: Process to generate the EDF building data Knowledge graph.

Methodology to generate the EDF building data knowledge graph

The objective of our experiment is to integrate the IoT system with the thermal model of the EDF building. To achieve this, we propose the WoSO-driven framework for preprocessing the data and constructing a unified knowledge graph conforming to the WoSO and the SAREF ontologies to describe the thermal model and the IoT system of EDF building, respectively.
Figure 3 provides an overview of the WoSO-DF. Subsequent subsections describe individual steps. The Python notebook that implements these steps is available on GitHub, along with the source files and step by step instructions to reproduce the eperimentation.[5]

Preprocessing the IoT data

The integration of IoT data from multiple platforms into a cohesive dataset requires preprocessing for transforming raw IoT data from the EDF building into a unified JSON file. The process involves three steps: data acquisition, data cleansing, and location mapping.

IoT data Acquisition

The acquisition of IoT data for the EDF building's smart energy management system involved the use of custom scripts designed to interface with various IoT platforms. These scripts were tailored to meet the specific authentication protocols and query requirements of each platform's API, as outlined in their respective documentation.

IoT data cleansing

The data cleansing process was undertaken to ensure consistency, accuracy, and a unified structure of the IoT data from the three platforms. First, redundant data entries were identified and removed to reduce noise and streamline the dataset. Next, naming conventions were harmonized across platforms. For instance, the identifier of the devices, referred to as device_Id in Ellona, serial in Ethera, and device in Wattsense, was standardized to a uniform naming scheme. Additionally, timestamps were converted into a consistent datetime format to ensure temporal alignment of records. The JSON structure of the data was then transformed based on the SAREF ontology. We generated a new, harmonized JSON file, providing a clean dataset.

IoT data location mapping

The data returned by the three APIs include information about the devices and the measurements they have recorded. However, it is important to note that the data does not include the location of the devices. This lack of location data makes the data unusable for our experiment. The location information is provided in an Excel file, where the devices are matched with the offices in which they are located. We first delete unnecessary information and save it as a CSV file with two columns: the IoT device identifier, and the office where the device is located. Using a Python script, we added the location information to the JSON file of the IoT data we generated in the previous step.

Preprocessing the thermal model data

The integration of the thermal model with the IoT system of the EDF building necessitates a structured approach to managing and linking simulation data. This process begins with exporting the thermal model in a standardized format to ensure compatibility and flexibility. The relevant variables are organized and mapped to their corresponding building zones, facilitating seamless interaction between the thermal model and the IoT system. The process involves two steps: data acquisition and data mapping.

Thermal model data acquisition

To ensure independence from the development tool, we export the thermal model in the Functional Mockup Unit format (FMU). Using a Python script with the FMPy library, we extract essential information about the model, including its name, version, generation tool, generation date and time, and the input, output, and parameter variables. Initially, this data is returned as an FMPy object. We then convert it into a JSON file to facilitate access and manip-

[5] WoSO-DF on GitHub – `https://github.com/zhounas/woso_df`, including the notebook EDF_building_data_KG_v1.ipynb

ulation.

Thermal model data mapping

Thermal model data mapping aims at establishing a clear correspondence between the simulation variables of the thermal model and their corresponding zones. This involved extracting zone identifiers from the provided documentation and the thermal model zone plan shown in the figure 2. We create a CSV file that associates each simulation variable with the corresponding zone. For instance: t_sp_002 is linked to zone001.

Mapping between IoT zones and simulation zones

In our study, we identified discrepancies between the zoning delimitations in the thermal model documentation and those in the building plan and the IoT documentation. To address this, we overlaid the two plans, using the documentation to correlate the thermal model zones, which could represent an office, a set of offices, or a corridor, with the corresponding IoT system zones designated for offices. We created a CSV file that includes columns for IoT zones and thermal model zones, facilitating a clear mapping between the two systems. This approach ensures accurate alignment and integration of the thermal model and the IoT data for effective interoperability.

Generating the Knowledge graph for IoT and thermal model data

To generate the EDF building data knowledge graph, we developed a Python script that utilizes the RDFLib library to create semantic representations of the integrated data. The process begins by parsing previously generated JSON files, which contain the preprocessed IoT data and the thermal model data. Additionally, the script processes CSV files that define the mappings between IoT zones and simulation zones.

The script iterates through these files to extract relevant information, such as device metadata, sensor readings, and thermal simulation variables, and maps them to the appropriate concepts defined by the SAREF and WoSO ontologies. By linking data points using ontological relationships, the script constructs a unified knowledge graph in a format that allows efficient querying and analysis.

Results

The implementation of the methodology to generate the knowledge graph for the EDF building data successfully integrated the IoT and thermal simulation data, providing a unified semantic representation. The knowledge graph links device measurements to their corresponding building zones and simulation variables. By leveraging the WoSO ontology, the graph ensures semantic consistency and facilitates efficient data querying.

To illustrate the results, Listing 5 presents a snippet of the knowledge graph we generated. This snippet focuses on the data related to Zone 107 of the EDF building, which consists of two offices: Office 110 and Office 111, as shown in Figure 2. Office 110 is equipped with an IoT device that reports the ambient temperature and a thermostat that provides both the set-point temperature and the corresponding measurement of the temperature. Office 111 contains a thermostat that returns both the set-point temperature and the ambient temperature. In addition to these data points, we retained the description of variables relevant to the thermal simulation of the EDF building, including the initial temperature of Zone 107 as well as the set-point temperature defined for the zone.

To demonstrate the effectiveness of the graph, we performed the SPARQL query in Listing 6 that aggregates the values of variables related to the same property of interest and the same feature of interest and assigns the aggregated value to the variable related to the same property of interest, where its feature of interest consists of the features of interest of the aggregated variables.

```
INSERT { ?variable woso:hasValue ?aggvalue .}
WHERE{
 {SELECT ?variable (avg(?value) AS ?aggvalue)
  WHERE{

?observation a saref:Observation ;
  saref:observes ?space_poi .

?space_poi
  a saref:PropertyOfInterest ;
  saref:hasPropertyKind ?property ;
  saref:isPropertyOfInterestOf ?space .

?propertyValue a saref:PropertyValue ;
  saref:isValueOfProperty ?space_poi ;
  saref:hasValue ?value .

?zone a saref:FeatureOfInterest ;
  saref:consistsOf ?space ;
  saref:hasPropertyOfInterest ?zone_poi .

?zone_poi a saref:PropertyOfInterest ;
  saref:hasPropertyKind ?property .

?variable woso:isRelatedTo ?zone_poi

      } GROUP BY ?variable
  }
}
```

Listing 6: Query to calculate the average of the measurement of a particular property from different devices in a particular zone and correlates these aggregated values to the input of the simulation

After running the SPARQL query on the knowledge graph, the query calculates the average of the measurements of each office of the zone 107 and attributes the value to the temperature variable of the zone 107, as shown in Listing 7.

```
@prefix rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#> .
@prefix ex: <http://example.org/iot/> .
@prefix saref: <https://saref.etsi.org/core/> .
@prefix unit: <http://qudt.org/vocab/unit/> .
@prefix woso: <https://purl.org/woso#> .
@prefix xsd: <http://www.w3.org/2001/XMLSchema#> .

ex:EDF_building_thermal_modelSimulation a woso:Simulation ;
    woso:isExecutionOf ex:EDF_building_thermal_model ;
    woso:hasInput ex:t_init_0013,
        ex:t_sp_0013;
ex:EDF_building_thermal_model woso:models ex:EDF_building ;
ex:EDF_building saref:consistsOf ex:zone107 .
ex:zone107 a saref:FeatureOfInterest ;
    saref:consistsOf ex:office110,
        ex:office111 ;
    saref:hasPropertyOfInterest <http://example.org/iot/zone107#setpoint_temperature>,
        <http://example.org/iot/zone107#temperature> .
ex:xdppivjzy2wixy6s-l1106Setpoint_temperatureValue a saref:PropertyValue ;
    saref:hasValue 19.0 ;
    saref:isMeasuredIn unit:DEG_C ;
    saref:isValueOfProperty <http://example.org/iot/office110#setpoint_temperature> .
ex:xdppivjzy2wixy6s-l1105Setpoint_temperatureValue a saref:PropertyValue ;
    saref:hasValue 21.0 ;
    saref:isMeasuredIn unit:DEG_C ;
    saref:isValueOfProperty <http://example.org/iot/office111#setpoint_temperature> .
ex:xdppivjzy2wixy6s-l1106TemperatureValue a saref:PropertyValue ;
    saref:hasValue 19.200000762939453 ;
    saref:isMeasuredIn unit:DEG_C ;
    saref:isValueOfProperty <http://example.org/iot/office110#temperature> .
ex:6102001000219TemperatureValue a saref:PropertyValue ;
    saref:hasValue 20.8 ;
    saref:isMeasuredIn unit:DEG_C ;
    saref:isValueOfProperty <http://example.org/iot/office111#temperature> .
ex:xdppivjzy2wixy6s-l1105TemperatureValue a saref:PropertyValue ;
    saref:hasValue 20.799999237060547 ;
    saref:isMeasuredIn unit:DEG_C ;
    saref:isValueOfProperty <http://example.org/iot/office111#temperature> .
```

Listing 5: snippet of the knowledge graph of the EDF building data.

```
@prefix rdf: <http://www.w3.org/1999/02/22-rdf-
    syntax-ns#> .
@prefix ex: <http://example.org/iot/> .
@prefix saref: <https://saref.etsi.org/core/> .
@prefix unit: <http://qudt.org/vocab/unit/> .
@prefix woso: <https://purl.org/woso#> .
@prefix xsd: <http://www.w3.org/2001/XMLSchema#>
     .

ex:t_init_0013 a woso:SimulationVariable ;
 woso:hasValue 20.266666666666666571927635232 ;
 woso:isRelatedToProperty <http://example.org/
     iot/zone107#temperature> .

ex:t_sp_0013 a woso:SimulationVariable ;
 woso:hasValue 20.0 ;
 woso:isRelatedToProperty <http://example.org/
     iot/zone107#setpoint_temperature> .
```

Listing 7: Snippet of the EDF data knowledge graph of zone107 after running sparql query.

Conclusion

This study presented the Web of Simulation Ontology-Driven Framework (WoSO-DF), an ontology-driven framework to integrate IoT systems and BPS for smart energy management, applied to a specific EDF office building.

The framework relies on the FMU standard format for exporting simulation models, a critical step that ensures the model's compatibility across various platforms and tools. By employing the WoSO ontology to create a unified knowledge graph, the framework maintains semantic consistency between IoT and simulation model data, thereby enhancing semantic interoperability. Additionally, the adoption of standardized data formats guarantees structural interoperability, facilitating seamless data exchange and integration across different systems.

Key steps of WoSO-DF include: 1) preprocessing IoT data, to harmonize data formats from different IoT platforms, align device metadata, and enrich it with device location information; 2) preprocessing simulation model data, to describe the simulation model, its metadata, and its simulation variables ; 3) link the IoT data and the simulation model data within a knowledge graph that conforms to the WoSO and SAREF ontologies.

WoSO-DF demonstrates the feasibility and effectiveness of harmonizing diverse data sources into a coherent and semantically rich representation. This integration supports efficient data exchange, enhances interoperability, and paves the way for advanced applications in smart energy management. In particular, advanced SPARQL queries can be executed on the resulting graph to run the simulation with live IoT data.

Future work will focus on refining the framework to accommodate additional data sources and how it improves the decision-making process for energy-efficient building operations.

References

Andersson, C., Åkesson, J., and Führer, C. (2016). PyFMI: A Python Package for Simulation of Coupled Dynamic Models with the Functional Mock-up Interface. Centre for Mathematical Sciences, Lund University Lund, Sweden.

Blochwitz, T., Otter, M., Åkesson, J., Arnold, M., Clauss, C., Elmqvist, H., Friedrich, M., Junghanns, A., Mauss, J., Neumerkel, D., et al. (2012). Functional mockup interface 2.0: The standard for tool independent exchange of simulation models. In 9th International Modelica Conference, pages 173–184. The Modelica Association.

Blochwitz, T., Otter, M., Arnold, M., Bausch, C., Clauß, C., Elmqvist, H., Junghanns, A., Mauss, J., Monteiro, M., Neidhold, T., Neumerkel, D., Olsson, H., Peetz, J.-V., and Wolf, S. (2011). The Functional Mockup Interface for tool independent exchange of simulation models. In Proceedings of the 8th International Modelica Conference; March 20th-22nd; Technical Univeristy; Dresden; Germany, pages 105—114.

Bouquerel, M., Ruben Deutz, K., Charrier, B., Duforestel, T., Rousset, M., Erich, B., Van Riessen, G.-J., and Braun, T. (2021). Application of mybem, a bim to bem platform, to a building renovation concept with solar harvesting technologies. In Building Simulation 2021, volume 17, pages 1068–1076. IBPSA.

Costin, A. and Eastman, C. (2019). Need for interoperability to enable seamless information exchanges in smart and sustainable urban systems. Journal of Computing in Civil Engineering, 33(3):04019008.

Dassault Systèmes (2024). FMPy Python library. `https://pypi.org/project/FMPy/`.

Di Biccari, C., Calcerano, F., D'Uffizi, F., Esposito, A., Campari, M., and Gigliarelli, E. (2022). Building information modeling and building performance simulation interoperability: State-of-the-art and trends in current literature. Advanced Engineering Informatics, 54:101753.

Esnaola-Gonzalez, I., Bermúdez, J., Fernandez, I., and Arnaiz, A. (2020). Ontologies for observations and actuations in buildings: A survey. Semantic Web, 11(4):593––621.

García-Castro, R., Lefrançois, M., Poveda-Villalón, M., and Daniele, L. (2023). The etsi saref ontology for smart applications: a long path of development and evolution. Energy Smart Appliances: Applications, Methodologies, and Challenges, pages 183–215.

Hatledal, L. I., Zhang, H., Styve, A., and Hovland, G. (2019). FMU-proxy: A framework for distributed access to Functional Mock-up Units. In Proceedings of the 13th International Modelica Conference, Regensburg, Germany, pages 79—86.

Hong, T. and Lee, S. H. (2019). Integrating physics-based models with sensor data: An inverse modeling approach. Building and Environment, 154:23–31.

Hounas, Z., Lefrançois, M., Zimmermann, A., and Traverson, B. (2024). Web of simulation ontology (woso): Integration of building performance simulations in iot systems. In LDAC2024-Linked Data in Architecture and Construction.

Lamberts, R. and Hensen, J. L. (2011). Building performance simulation for design and operation. Spoon Press.

Lefrançois, M., García-Castro, R., Poveda-Villalón, M., Bouter, C., Biagioni, G., Daniele, L., and Gnabasik, D. (2024). SAREF: the Smart Applications REFerence ontology. Technical Report v3.2.1, ETSI.

Liu, Z., Li, M., and Ji, W. (2024). Development and application of a digital twin model for net zero energy building operation and maintenance utilizing bim-iot integration. Energy and Buildings, page 115170.

Mohammed, M., Romli, A., and Mohamed, R. (2021). Existing semantic ontology and its challenges for enhancing interoperability in IoT environment. In 2021 International Conference on Software Engineering & Computer Systems and 4th International Conference on Computational Science and Information Management (ICSECS-ICOCSIM), pages 22–26. IEEE.

Pan, Y., Zhu, M., Lv, Y., Yang, Y., Liang, Y., Yin, R., Yang, Y., Jia, X., Wang, X., Zeng, F., et al. (2023). Building energy simulation and its application for building performance optimization: A review of methods, tools, and case studies. Advances in Applied Energy, 10:100135.

The Modelica Association Project FMI (2022). Functional Mock-up Interface specification. Technical report, MODELISAR Consortium.

Wang, X., Teigland, R., and Hollberg, A. (2024). Identifying influential architectural design variables for early-stage building sustainability optimization. Building and Environment, 252:111295.