

# DEMOSA: a DT-enabled Middleware for Self-adaptive Smart Spaces

Jun Ma<sup>\*</sup>, Georgios Bouloukakis<sup>\*</sup>, Ajay Kattepur<sup>†</sup>, Roberto Yus<sup>‡</sup>, Denis Conan<sup>\*</sup>

<sup>\*</sup>Télécom SudParis, Institut Polytechnique de Paris, France

<sup>†</sup>Ericsson AI Research, India

<sup>‡</sup>Dept. of Computer Science and Electrical Engineering, University of Maryland, Baltimore County, USA  
{jun\_ma, georgios.bouloukakis, denis.conan}@telecom-sudparis.eu, ajay.kattepur@ericsson.com, ryus@umbc.edu

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## Short Description

Heating, Ventilation, and Air Conditioning (HVAC) systems account for a significant portion of energy consumption within buildings. In order to balance thermal comfort and energy savings, HVAC control strategies have been proposed. However, the strategies are static and do not take into account dynamic changes of consumers, hence creating sub-optimal outcomes. This paper proposes DEMOSA, a Digital Twin (DT)-enabled middleware for autonomous smart buildings. The DEMOSA middleware interconnects and coordinates intelligent data exchange between the building edge servers, DTs and Artificial Intelligence (AI) planning nodes in order to invoke appropriate strategies. Moreover, DEMOSA is paired with a self-adaptive mechanism that can detect the anomaly of generated planning and adaptively modify it.

## Application to the DI-Hydro Project

The DI-Hydro project aims to empower smart decision-making for hydropower plants (HPPs) through digital twins for efficiency and sustainability. DEMOSA will be integrated into the DI-Hydro project, so the following benefits will be realized:

- **Enhanced Data Integration and Real-Time Insights:** DEMOSA middleware facilitates seamless data exchange between sensors, smart devices, digital twins, and AI planning nodes. It provides real-time insights into HPPs operations and maintenance needs.
- **Improved Decision-Making and Automation:** DEMOSA uses AI Planning for real-time decision-making and self-adaptive mechanisms for building management schedules. This will be integrated with HPPs to optimize energy production downtime reduction and equipment management.
- **Scalability and Flexibility:** DEMOSA's scalable and adaptable architecture supports the expansion across multiple plants, which is suitable for the diverse operational contexts of HPPs.

# DEMSA: a DT-enabled Middleware for Self-adaptive Smart Spaces

Jun Ma<sup>1</sup>, Georgios Bouloukakis<sup>1</sup>, Ajay Kattepur<sup>2</sup> Roberto Yus<sup>3</sup> Denis Conan<sup>1</sup>  
{jun\_ma,georgios.bouloukakis,denis.conan}@telecom-sudparis.eu,ajay.kattepur@ericsson.com,ryus@umbc.edu

<sup>1</sup>Télécom SudParis, Institut Polytechnique de Paris, France

<sup>2</sup>Ericsson AI Research, India

<sup>3</sup>Dept. of Computer Science and Electrical Engineering, University of Maryland, Baltimore County, USA

## Abstract

Heating, Ventilation, and Air Conditioning (HVAC) systems account for a significant portion of energy consumption within buildings. In order to balance the effect of thermal comfort vis-a-vis energy savings, HVAC control strategies have been proposed. However, the strategies are static and do not take into account dynamic changes of consumers, hence creating sub-optimal outcomes. This paper proposes *DEMSA*, a Digital Twin (DT)-enabled middleware for the self-adaptation of smart buildings. The *DEMSA* middleware interconnects and coordinates intelligent data exchange between the building edge server, digital twin and Artificial Intelligence (AI) planning nodes in order to invoke appropriate strategies. Moreover, *DEMSA* is paired with a self-adaptive mechanism that can detect the anomaly of generated planning and adaptively modify it. This process ensures balancing building energy consumption and thermal comfort requirements, without human intervention. The *DEMSA* middleware is described over a real smart space scenario.

**Keywords:** Digital Twin, Middleware, Self-adaptive systems

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## 1 Introduction

One of the highest energy consumers in commercial buildings, with an average consumption of around 40% is the HVAC (heating, ventilation and air conditioning) system. The IEA (International Energy Agency) states that by the

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year 2050 only space cooling will account for 37% of total energy consumption worldwide [24]. Existing approaches have mostly focused on holistic comfort provision but, in most situations, people share the spaces where they live, work, or study. Given the diversity of people and their preferences, it is challenging to provide them with comfort in a shared space. Multiple challenges arise to determine the appropriate thermal comfort level of a group including how to benefit individuals, while maintaining some notion of fairness within the group. This might result in additional energy consumption costs since the HVAC settings would need to be highly dynamically adapted to offer a warmer or colder temperature depending on who is in the zone at the moment.

While dynamically adapting energy systems (HVAC, Lighting, etc.) seems a promising solution, spaces can be highly diverse and the trajectories of occupants can be different from space to space. In order to capture the uncertainty and side-effects of configuration changes within HVAC systems, Digital Twins (DT) of smart spaces have been proposed [20]. Challenges in employing DT for HVAC control include the accurate real-time representation of the building state, update of sensor information onto the DT and usage of the twin for “what if” simulations. This paper introduces the design of a *DT-enabled* middleware for the dynamic adaptation of *Edge infrastructures* in smart spaces (HVAC, IoT devices, etc.) regarding their inhabitants’ comfort profiles, climate zones, energy systems and diversity of spaces. The main contributions of this paper are:

1. A Thermal Comfort Provision system responsible for regulating temperature using diverse *strategies*.
2. A DT system for enabling “what if analysis” via a co-simulation module.
3. Temporal scheduling of Edge infrastructures for balancing thermal comfort and energy consumption.
4. A middleware architecture for self-adaptive Edge infrastructures using people and spaces’ feedback.

The rest of the paper is structured as follows. Section 2 overviews the state of the art. Section 3 presents an overview of the *DEMSA* middleware. Sections 4, 5, 6 present the core *DEMSA* entities while Section 7 demonstrates their integration using the *DEMSA* middleware. Section 8 provides an overview of the current prototype implementation. Finally, Section 9 concludes the paper.

## 2 Related Works

The provision of appropriate *thermal comfort*, which expresses satisfaction with the thermal environment, for the occupants of a building has been a well studied and popular problem in the literature. Multiple approaches have been presented to deal with the problem in a holistic way or by focusing on specific challenges in such a context [18]. However, the literature focuses on situations where the goal is to provide specific people with their desired thermal comfort. In the real world, workers share their work spaces with others. This creates an intrinsic challenge in thermal comfort provision since people in the same climate zone might have different comfort preferences. Most of the existing works focus on providing thermal comfort while ignoring energy efficiency and diverse climate zones.

Furthermore, thermal comfort preferences/sensations have been identified as a factor of several drivers [13] including: physiological (such as age, sex, body composition and fitness, metabolic rate); psychological (including effects of personal control, thermo-specific self-efficacy, personality, and anticipated cost of cooling); and contextual factors of the built environment. Different studies have shown that, for example, the elderly are more susceptible to cold [15], and people from tropical regions have a lower tolerance to the cold environment [8]. At the same time, workforce diversity has been identified as a key to improving productivity [25]. Even this lack of diversity has been noted in a recent systematic review of personal thermal comfort models [10].

For systems characterized by uncertainties and unpredictable information, traditional predictive control approaches often struggle to deliver satisfactory performance [12]. To address these shortcomings, the concept of Digital Twins (DT) has emerged as a transformative approach for enhancing efficiency and performance in the domain of smart buildings [6]. Authors in [17, 19] have explored DT models for buildings, including Building Information Modeling (BIM), Wireless Sensor Networks (WSN), Data Analytics, and Machine Learning approaches. Furthermore, several studies [11, 22] have proposed middleware solutions to enhance the accuracy, resolution, and complexity of DT.

The integration of DT with HVAC systems has been a focal point of recent research, aiming to enable real-time monitoring, predictive maintenance, and energy optimization. For instance, Agouzoul et al. [4] propose a methodology enabling continuous improvement of neural network models and energy performance of the building through DT models. Mohseni et al. [20] developed a real-time DT-based controller to measure temperature and humidity in HVAC systems. Similarly, Hosamo et al. [9] proposed a novel DT framework of HVAC systems (HVACDT) based on BIM with real-time sensor data, utilizing machine learning approaches to balance predicted percentage of dissatisfaction (PPD) on thermal comfort and energy consumption.

This paper proposes a DT-enabled middleware for self-adaptive decision making regardless of the deployed energy systems, profiles of space inhabitants and dynamic spaces.

## 3 Overview

**Motivation Scenario.** The Drahi-X Novation Center of the Institut Polytechnique de Paris (IP Paris), is a tertiary building with around 5000  $m^2$  of surface, 12 electric zones and two floors. It is equipped with IoT devices such as temperature sensors, motion detectors, smart plugs, HVAC systems, as well as small tablet devices installed in the corridors of the building. These tablets are used by building inhabitants to provide their feedback related to the current environment and their preferences (thermal comfort feedback). A Smart Building Management System (BMS) has been installed in order to control the devices and the overall HVAC system.

Inhabitants of the Drahi-X building always have certain schedules of classes and meetings related to university activities. This leads to a huge potential for enhancing occupant well-being and energy efficiency by controlling the building elements such as the HVAC and lighting systems based on such schedules. For instance, the schedules and motion detectors can be integrated together to model current and future numbers or activities of people in each room. Then, the feedback of people can be used to regulate the HVAC system with proper settings before people enter rooms. Complex strategies involving thermal comfort, fairness among inhabitants and real-time energy adaptation are not possible with current BMS.

**Challenges.** Based on the recent energy crisis and the above use case scenario, it is essential to investigate systematic solutions for balancing energy consumption and thermal comfort of their building inhabitants. However, this comes with a number of challenges as follows:

- **Dynamicity:** Balancing energy consumption and thermal comfort requires predicting the future states of building inhabitants in order to proactively regulate temperature. Such prediction can be performed using simulations. However, smart buildings evolve over time demonstrating an unpredictable environment.
- **DT Precision:** Digital Twin can be utilized for forecasting, monitoring, and analyzing building performance by integrating with simulations. This leads to a challenge to ensure the accuracy and real-time nature of the DT for creating simulations.
- **Integration Complexity:** Seamlessly integrating IoT devices and smart energy systems with simulations is a complex task. Moreover, simulators usually focus on one aspect of the building (e.g., HVAC) and thus, there is a need to synchronize multiple simulations.
- **Adaptive Regulation Strategies:** Finding a proper strategy to achieve the right balance between conserving energy and maintaining thermal comfort can

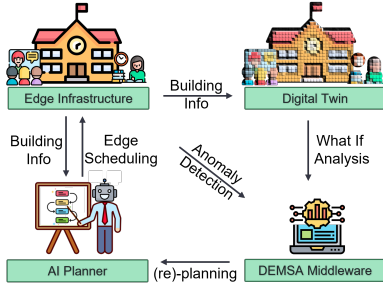


Figure 1. DEMSA Overview.

be challenging (especially in a dynamic space where building inhabitants can be variable over time).

Based on the above challenges, it is essential to introduce self-adaptive building management systems that proactively optimize the Edge infrastructure of smart buildings (HVAC, IoT, Lighting). First, a DT-enabled approach for co-simulation of different systems/aspects (HVAC, People feedback) must be introduced for “what-if-analysis”. Second, strategies to optimally balance energy consumption and thermal comfort must be leveraged. Finally, self-adaptive techniques must be integrated to monitor, analyze, and respond to dynamic conditions and occupant needs without human intervention. **DEMSA Middleware.** This paper presents DEMSA, a comprehensive system leveraging IoT-Edge infrastructures, DTs approaches via co-simulations, and automated planning techniques for self-adaptive smart buildings. DEMSA consists of the following components:

*Edge Infrastructure:* refers to the real physical environment and associated systems of the building (HVAC, IoT, etc.). It collects IoT data for monitoring the actual building environment, feeding the DT component, and controlling the smart energy applications to ensure inhabitants’ thermal comfort and energy consumption.

*DEMSA Digital Twin (DT):* is the digital replica of the physical building’s architecture, equipment, inhabitants, and real-time weather conditions. Also, it employs multiple simulation models to enhance predictions and decision-making.

*AI Planner:* takes the role of the strategist, tasked with optimizing building operations based on predefined objectives set by administrators. It solves complex planning problems to generate plans about controlling the building for different aims based on predicted future events. The semantic representation of the digital twins is used within the AI planner to generate accurate strategies.

*DEMSA Middleware:* acts as the intermediate entity responsible for data integration and coordination of interactions. The main responsibility is to synchronize co-simulations for evaluating the balance of energy consumption and thermal comfort. Furthermore, it ensures self-adaptation based on the situation of buildings by interacting with the AI Planner.

Figure 1 depicts how the above components interact with each other. The Edge Infrastructure connects with the DT providing actual building data. In addition, the DT performs

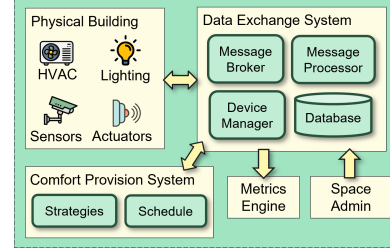


Figure 2. Edge infrastructure of Smart Spaces.

“what if analysis” procedures via co-simulations. The AI Planner also acquires the building data to build a domain model. Finally, the DEMSA Middleware acts as a guard that triggers the AI Planner to regenerate a new plan if the DT predicts a different situation in the building or detects violations of metrics. The generated plans trigger a new temporal schedule that can be applied at the Edge infrastructure. DEMSA uses the following metrics for evaluation: (i) *Energy Consumption (EC)* is the amount of energy consumed by the smart building; (ii) *Thermal Comfort (TC)* indicates how many people feel comfortable based on their feedback; and (iii) *Equality (EQ)* refers to the equality level by monitoring if the system treats individuals fairly.

## 4 Smart Buildings’ Edge Infrastructure

A smart building usually employs an Edge infrastructure for collecting, processing and exchanging data from various energy systems (HVAC, lighting systems) as well as IoT devices (sensors) and feedback from building inhabitants.

As depicted in Figure 2, we define an Edge infrastructure with five elements – *Physical Building, Data Exchange System, Comfort Provision System, Metrics Engine, and Artificial Controls*. The Edge infrastructure is based on the Publish/Subscribe (pub/sub) system which is a fundamental messaging pattern used in distributed systems to enable communication between devices and services[16]. The devices regularly publish real-time IoT data streams to the Message Broker of the Data Exchange System. The Device Manager models and provides essential information about the devices such as their location and data types. The Edge infrastructure also includes a management system that provides APIs for occupants to send feedback (thermal preferences).

A *Comfort Provision System* leverages sensors and control mechanisms to generate specific building control actions, called **strategies**, aimed to improve the performance of buildings. The Comfort Provision Systems executes different strategies over time based on the schedule provided by the AI Planner (§6). We leverage the following strategies: (1) *Majority:* is considered as a robust rule [3]. It always satisfies the majority’s feedback and maximizes the comfort level of the overall workforce regardless of energy consumption. (2) *Drift:* presented in [21], assumes inhabitants voting their sensations. If people feel quite comfortable, it applies a small *drift* towards the uncomfortable environment. This

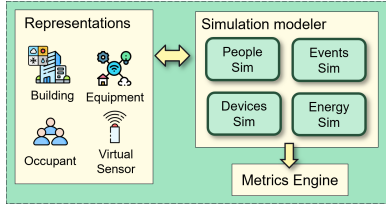


Figure 3. DEMSA DT core entities.

strategy aims to preserve energy by ensuring the environment is always between very comfortable and uncomfortable. (3) *Fairness*: by Shin et al. [7] to maintain *fairness* among the inhabitants. It fairly meets inhabitants’ requirements based on the accumulated discomfort level. This strategy fairly satisfies the inhabitants but it may consume more energy.

Satisfying inhabitants’ thermal comfort always contradicts with reducing energy consumption. Thus, there is literally no energy-efficient thermal comfort strategy. Thus, applying the right strategy at the right moment becomes crucial. AI Planning is leveraged to construct a schedule for executing these strategies, guided by scenario prediction. However, the accuracy of the prediction decays over time, which makes the selected strategy less suitable. To accommodate the imprecise predictions, we designed a *Metrics Engine* to collect information based on the requirements of building administrators. Thus, building administrators may define their requirements using the Edge infrastructure that exposes a set of APIs for data exchange with building devices and other components.

- `subscribe(topic)`: enables subscribing to topics for receiving notifications (IoT data, feedback, etc.) that are published to “topics” in the message broker.
- `update(sched)`: used to update the schedule in the Comfort Provision System.

## 5 Digital Twin for IoT-enhanced Spaces

As shown in Figure 3, our DT defines a *Simulation Modeler* for creating simulation models based on the representation of the building. Simulations of inhabitants, events, energy systems (HVAC, etc.), and IoT devices can be achieved. The simulation results can be used for predicting evaluation metrics (EC, TC, EQ). To create the DT and enable simulations, the representation of a building includes the architectural floorplan of the building, with its spatial layout, room configurations, and structural knowledge. It also incorporates comprehensive insights into the equipment deployed within the building. To facilitate interoperability between different entities, we use the NGSI-LD standard to digitize the physical building and standardize the communications. NGSI-LD provides a standardized framework for modeling and managing information about the building’s assets, simulation models, their relationship, and their properties [14].

Moreover, the representation has information about inhabitants, ensuring an understanding of their locations and activities, which is vital for optimizing occupant comfort, or

decision-making. Moreover, for the need to optimize inhabitants’ thermal comfort, including real-time weather conditions and forecasts helps comfort provision strategies adjust the HVAC systems. Our DT also defines a *Metrics Engine* which can help model those metrics that may require simulations. For example, in the building, not everyone has the time and willingness to provide their feedback. If they don’t, we can use historical data to predict their feelings, which is a primary consideration of the Metrics. Below is the list of APIs that the DT offers for integration with DEMSA:

- `get_dt_info(data_type)`: used to retrieve data related to building representations (floors, IoT devices, etc) in JSON format.
- `update_dt(data_type, value)`: used to update the values of the building representations using NGSI-LD operation.
- `get_model(sim_model)`: returns the simulation model for a specific system (HVAC) or building property (Trajectories of inhabitants).

## 6 Self-adaptive Edge using AI Planning

The primary role of the AI Planner [23] in our system is to optimize the schedule of running comfort provision strategies of the smart building by aligning it with predefined objectives. Building administrators can define various goals, such as reducing energy consumption and enhancing occupants’ thermal comfort. The AI Planner takes these goals into consideration when making decisions. The AI planning problem is usually represented by an initial state, a desired goal state, and a function to be optimized. AI planning algorithms systematically explore possible combinations of actions to discover (near)-optimal sequences that transform the initial state into the goal state while adhering to predefined constraints and optimizing the desired outcome.

To model the planning problem, we use Planning Domain Definition Language (PDDL) [2], which is a formal knowledge representation language designed to express planning models. It consists of two descriptions (i) the *domain* description that decouples the parameters of actions from specific objects, initial conditions and goals (ii) the *problem* description that instantiates a grounded problem with objects, initialization, goals and metrics. The same domain description may be paired with multiple problem instances, with varying grounded objects, initial conditions and goals.

The integration of AI planning into the smart building ecosystem brings numerous benefits. AI planning proves especially effective in the context of large-scale scheduling systems, such as smart buildings with numerous and interconnected rooms and devices. However, to fully utilize the potential of AI planning in optimizing smart buildings, the incorporation of simulations becomes necessary. Simulations allow the AI Planner to simulate the outcome of conducting a series of selections, providing a more accurate insight into

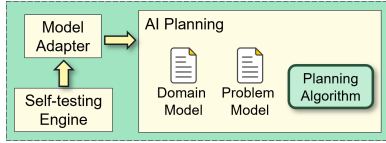


Figure 4. AI Planner entities.

the sequences. This capability provides AI planners with vertical information, enabling them to transition from a static, predefined approach to a dynamic one. As a result, the planner gains a deeper understanding of how various strategies affect the smart building’s performance, ultimately facilitating more informed and adaptive decision-making. Two examples of plans that may be generated include:

- Temporally ordered schedule that determines optimal strategy for a given monitored time period with time instances  $t_i$  and duration  $d_j$ :  
 t1: fairness strategy room1 [d1]  
 t2: drift strategy room1 [d2]  
 t3: fairness strategy room1 [d3]  
 t4: majority strategy room1 [d4]
- In addition, using the goal metric property of PDDL, weighted goals may be set to plans that optimize a combination of features related to energy efficiency.

The DT semantic representation is used to create the domain model of the AI planner. Moreover, the metrics provided by the DT for different strategies may be used to improve the planning performance via feedback. As shown in Figure 4, the *Model Adapter* is in charge of connecting the AI Planner and simulations. During the generation, the AI Planning models should be updated with simulation results. For example, results on temperatures and energy consumption caused by running strategies help the AI Planner to do further planning (re-initializing planning problem) and compute the costs. The *Model Adapter* receives the update command and asks the middleware to execute simulations, then update the models based on the result. Additionally, as discussed in §4, the schedules are not always reliable due to the incorrectness of predictions. The self-testing Engine reevaluates the precision of predictions and performance of the building regularly and regenerates schedules if necessary. The AI Planner provides the following API:

- `schedule(build_info, metrics)`: Creates a planned schedule for running strategies based on current building information and goal metrics.

## 7 DEMSA for Self-adaptive Smart Buildings

This section presents DEMSA that is responsible for data integration, co-simulation and adaptive operation of Edge infrastructures. As shown in Figure 5, DEMSA comprises two key components, the *Co-sim Middleware* and *Co-sim Driver*. The Co-sim Driver is designed for driving the co-simulations. As the AI Planner requires values for metrics (EC, TC, EQ) for generating temporal schedules, this entity connects the

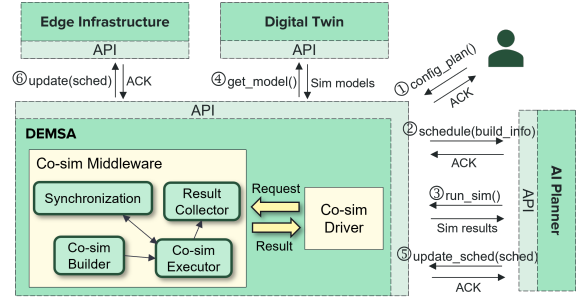


Figure 5. DEMSA Architecture.

*Model Adapter* and *Co-sim Middleware* entities by receiving a list of strategies required to be executed over time.

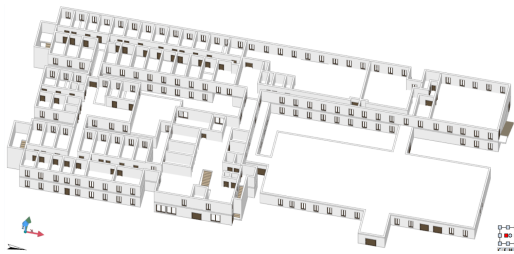
The Co-sim Middleware bridges different simulation models coming from the DT through a synchronization mechanism which is in charge of time-step coordination, and simulation control. Such synchronization enables to advance the simulation at the same speed, guaranteeing that interactions occur at the correct moments. Within the Co-sim Middleware, the Co-sim Builder is responsible for identifying and obtaining the corresponding simulation models from the DT component. Such simulation models are integrated in the *Co-sim Executor* for running the co-simulation process. Occasionally, simulators may not provide the direct information needed, necessitating the use of a *Result Collector* to pull and refine the data for the AI Planner.

As shown in Figure 5, to demonstrate the adaptability of DEMSA, consider the following scenario:

- ① Building administrators can update the smart space objectives – e.g., via `config_plan` (pattern) to set up “Low energy level, High comfort level” pattern.
- ② DEMSA sends a command to the AI Planner using `schedule(build_info, metrics)` as soon as a new temporal plan is required.
- ③ The situation of a space changes over time. To address this problem, the AI Planner received updates from the DT to re-plan temporal schedules. Here the AI Planner calls `run_sim(sim_config)` to get updates on current or future space situations.
- ④ The DT regularly updates its simulation models with information from the building representations. Then the DT uses the `get_model(sim_model)` API call to receive needed simulation models for co-simulations.
- ⑤ Over time, the AI Planner may generate temporal schedules with a sequence of strategy selections and send it DEMSA using `update_sched(sched)`.
- ⑥ Such schedules will setup and run the Edge Infrastructure using the `update(sched)` API call.

## 8 Implementation Overview

This section provides the current status of the DEMSA prototype implementation. As a real Edge infrastructure, we use the Drahi-X Novation Center of IP Paris. Access to real



**Figure 6.** Drahi-X 3D Representation.

BMS, HVAC and Lighting systems has been provided. To create a DT of Drahi-X, we have constructed a 3D model of the building in NGSi-LD format using [14] (see Figure 6). The DT uses this representation to simulate HVAC and the building’s inhabitant behavior.

For simulating HVAC, EnergyPlus [1] has been used which is an open-source tool that simulates the energy consumption caused at each room. We also used SmartSPEC [5], a smart space simulator that generates trajectories of inhabitants based on their preferences and activity schedules. To enhance its functionality, we integrated a feedback mechanism within SmartSPEC that generates inhabitants’ feedback based on the simulated indoor temperature from EnergyPlus. To synchronize these simulation tools, we developed the initial entities of the Co-Sim Middleware (see Figure 5). In particular, the EnergyPlus simulation model acquires inhabitant information from SmartSPEC for controlling and sending indoor temperatures for feedback generation.

Currently, we are developing the AI Planning component for generating optimal schedules over time to enable an adaptive Edge infrastructure of Drahi-X.

## 9 Conclusion

Strategies to control HVAC systems in buildings are ill-equipped to meet the dynamic changes in consumer topologies and requirements. In this paper, we present DEMSA, a novel approach of DT-enabled middleware for self-adaptation in smart spaces to address the balance between providing thermal comfort and energy consumption. The DEMSA middleware orchestrates Edge infrastructures, DT systems and AI planners to optimally balance comfort and energy saving. The self-adaptation of DEMSA is proposed over a real building scenario with autonomous operation. The dynamic adaptation will prove useful in multiple smart-building deployments to optimally configure HVAC systems.

Future directions include implementing the middleware over a building HVAC system to demonstrate intelligent adaptation of strategies.

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