CHALLENGES AND CONCEPT FOR AN INTEROPERABLE DIGITAL TWIN ARCHITECTURE FOR PV-INTEGRATED HEATING NETWORKS

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Abstract

Existing data-driven approaches are not always supported, or only partly implemented, by existing tools, platforms, and services. The study focuses on proposing a novel, theoretical and general model to describe the heating network of buildings. This study will consolidate and abstract access to standardized interfaces, using a transparent interoperability mechanism, the "meta" interface, supporting translation modules to translate from different components or hardware that are commonly used in current heating networks of buildings in Europe. The ICT architecture will be based on state-of-the-art digital twin technologies and methodologies, offering a unified ecosystem for orchestrated deployment of different input/output configurations, and data flow and energy exchanges. This study will further validate the reference ICT architecture using data-driven approaches, applied in a use case that could be considered a typical low-temperature district heating network.

Keywords: building heating network, distributed renewables, data-driven, ontology, interoperability, digital twin, co-simulation

1. Introduction

Building energy networks are currently undergoing a major overhaul. The energy system is becoming increasingly distributed and reliant on intermittent energy sources (e.g. PVs). As the production of solar power is not necessarily correlated with electricity demand, a need for flexibility is emerging. One promising solution is to use renewable energy for heating purposes, considering its costs and benefits (Bloess et al., 2018). Therefore, a strong integration of thermal storages linked with Power-to-heat (P2H) devices in building heating networks, is witnessed. Simultaneously, a trend toward digitization in buildings is underway through increased device connectivity and large-scale data collection. These digital technologies promise increased observability and understanding of the underlying system, processing and optimization (Drgoňa et al., 2020; Weinberg et al., 2022).

Today, most building heating and cooling systems are operated using rule-based control (RBC) techniques. However, these traditional control systems have been proved insufficient in integrating thermal storage solutions, operating in the context of low temperature networks and are energy inefficient. In particular, this method does not take into account the thermal inertia of buildings, which is becoming fundamental in next generation systems. The reduced energy transfer capacity implies a need for longer control horizons (Weinberg et al., 2022). A proposed solution is Model Predictive Control (MPC), a control technique based on constrained optimization. It delivers energy savings of 15 % to 50 %, while improving thermal comfort (Drgoňa et al., 2020). Another advantage lies in the formulation of the cost function. There are several types of orientation for MPC formulation: economic, greenhouse gas emissions, indoor comfort, renewable energy share, integration of multiple storage and generation components, etc. (Cupeiro Figueroa et al., 2018; Figueroa et al., 2020; Weinberg et al., 2022). The objectives can be diverse, considering that the minimization of the cost function can cover anything that can be quantified mathematically in the model (Cupeiro Figueroa et al., 2018).

However, the main bottleneck in the practical implementation of MPC is to address an interface towards the

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physical installations in the targeted building, requiring the development of a model. Naturally, the quality of the MPC solution depends on the accuracy of the model, but the overall implementation of MPC is also affected by the chosen modeling approach in several ways (Clausen et al., 2021; Drgoňa et al., 2020; Sutton and Barto, 2018). Various methods have been proposed based on three different approaches: white box, black box and gray box (Zhao and Magoulès, 2012). While the former uses physical principles to determine the energy behavior of a building or a network, the second analyzes large datasets to infer the relationships in the data, while the latter is a hybrid. Physical models can provide accurate results but tend to be complex and very time-consuming (Berthou et al., 2014; Drgoňa et al., 2020; Weinberg et al., 2022; Zhao and Magoulès, 2012). To further improve the system integrations by data-driven methods and existing MPC, interoperability starts to play an essential role for, e.g., co-simulations that hybrids MPC with other machine learning frameworks. However, such approaches require first defining a high-level framework so that the digital representations/descriptions can be initiated, with a clear understanding that the target heating network are described general enough with interoperability to initiate any further modeling and controls.

A digital twin serves as a virtual mirror of a physical object or system, crafted by harnessing real-time data to reflect the physical state of the entity or system. It utilizes technologies such as machine learning to form a dynamic digital simulation model, not only capable of forecasting the current and future states of its physical counterpart but also managing data transmission between the physical and digital worlds (Lu et al., 2020). Moreover, the digital twin has been acknowledged as a strategic technology trend, with its market projected to reach 15 billion dollars by 2023, underscoring its potential impact and relevance in the future across various industries, including construction and building management (Khajavi et al., 2019).

2. Objectives and the digital twinning concept

A building heating network consists of multiple subsystems and components, depending on the size and complexity of the building energy system. Achieving interoperability among the systems and actors involved in future heating networks requires a cost-efficient solution for data harmonization, integration and sharing frameworks that can be generalized. This study develops an automatic process and reference architecture, or framework, for data integration, harmonization, and enrichment based on different data-driven approaches. As the basic layer of the information architecture of the heating network digital twin, the framework will make sure new IoT applications or HVAC components behind-the-meter or operation modeling approaches can be created following a general architecture. The framework will make it easier to connect building heating network-level devices, such as storage tanks, heat pumps, district heating, etc., to aggregation systems and operated safely for the grid and utilities with streamlined information flows.

The objective of this study is to develop a digital twin framework that integrates distributed renewables (in particular PV/T) and energy storage solutions, for modeling and optimizing the system performance in the context of building HVAC systems. This framework is intended to enable the next generation of data-driven modeling and optimization/control approaches that are emerging. The development of such a digital twin framework faces a number of challenges. First, bidirectional data transmission is crucial to ensure a smooth interface between the digital and physical worlds and facilitating not only the integration of data from the physical system in the digital twin but also the dispatch of control signals back to the physical environment. Second, the digital twin should be capable of implementing and utilizing advanced methods, especially machine learning models and algorithms, providing capabilities such as making precise predictions and optimizing control strategies. Third, simulation is inherent to our digital twin, offering a virtual mirror that accurately reflects and simulates the real physical world, thereby enabling analyses of both real-time and future states. Last but not least, we aim to address interoperability issues. Our digital twin should be capable of utilizing existing ontologies and ensure compatibility with various systems to guarantee that different systems can communicate and function synergistically, enhancing the utility and applicability of the digital twin across diverse platforms and use cases. This framework will be elaborated upon in Section 4.

3. Challenges and previous work

A digital twin framework relies on interoperability, as mentioned, which is the ability of multiple entities to communicate and cooperate. In literature many types are described, but the focus is on technical interoperability and semantic interoperability (Motie et al., 2017). This section presents a complete analysis and through literature review about such challenges from previous works.

3.1. Technical interoperability

Addresses systems connectivity (e.g. sensors, actuators), network and device representation. This type of interoperability is no longer a significant challenge thanks to standardized technologies such as BACnet and IEEE standards (Bergmann et al., 2020). For instance, High Level Architecture (HLA) is an IEEE technical architecture that provides a framework for modeling and simulation with a primary goal of facilitating reuse and interoperability among simulations. HLA standard defines run time infrastructure (RTI) allowing to run a set of independent simulators and coordinate them all, thus forming a federation (Lévesque et al., 2014). Each simulator, acting as a federate, implements an interface allowing the synchronization by communicating with a run time infrastructure (RTI). This standard consists in five parts: (1) Framework and Rules, (2) Federate Interface Specification, (3) Object Model Template Specification, (4) Federation Development and Execution Process, (5) Verification, Validation, and Accreditation (VV&A) of a Federation (Falcone and Garro, 2019):

(1) Specifies the rules that a Federate shall follow to interact.

(2) Delineates the functional interfaces between the simulation member applications and the infrastructure that enables the distributed simulation execution. This step covers the capabilities of the software infrastructure of HLA and defines the specifications between the RTI and Federates, which they use to exchange information.

(3) The Object Model Template concerns the mechanisms to specify the format of data, in terms of a hierarchy of both HLA ObjectClasses and HLA InteractionClasses, that are produced and consumed by each Federate participating in a Federation execution

(4) Outlines the procedures that developers must follow to design, develop, and execute an HLA Federation. It provides a framework into which system engineering procedures can be combined and adapted to address specific needs.

(5) Specifies the processes and procedures to design and implement VV&A for HLA Federations. Hence it ensures that the HLA Federation is properly verified, validated, and accredited.

These steps collectively provide the guidelines, specifications, and processes required to set up and execute a distributed simulation using HLA.

Functional Mock-up Interface (FMI) is an open standard designed to solve the problem of technical interoperability, launched in 2010 by a European consortium led by Dassault. FMI provides an interface between master and slaves and addresses data exchange, by ensuring that the definition of types are identical across the whole system. It is nowadays widely adopted for digital twin frameworks. FMI supports different working modes but this study's focus is on FMI for co-simulation since it allows individual Functional Mock-up Units (FMU) to use their own solver engines (Mohseni et al., 2023). In plain terms, FMUs are executables, implementing FMI standard and they consist in a ZIP file containing the required components: FMI model description as an XML-based file, the source code and eventually additional data (Falcone and Garro, 2019). However, the FMI does not include master algorithms for scheduling and execution (Motie et al., 2017; Pedersen et al., 2015). Several approaches have been proposed and will be detailed below. A limitation of the FMI is the definition of inter-model connections which must be done manually in an initialization phase. As described in (Mitterhofer et al., 2017), the correct transmission of data exchanged between simulations and its detection is proving to be a tedious and increasingly complex task, as the number of sub-systems and FMUs increases.

3.2. Semantic interoperability

Addresses the importance of structured metadata, while ensuring that the precise meaning of exchange information is unambiguously interpreted by other systems (Bergmann et al., 2020). Achieving semantic interoperability remains a major challenge and is broadly studied in the literature. Several approaches have been proposed, none of which has yet achieved consensus. In the context of building heating networks with increasingly interdependent heterogeneous systems, it is important to arrive at a structuring of metadata. One of the solutions is making use of semantic taxonomies and standardised ontologies, which act as a common dictionary to map similar contents and data points across various protocols (Bennaceur and Issarny, 2014). In the case of BEM systems, ontology modules can be divided into several layers (Lork et al., 2019):

- **Generic Ontology -** Definitions, terminologies and taxonomies that are common to every building are defined as well as general concepts and sub-concepts for the sensors and equipment.
- **Knowledge Base -** Static and dynamic data are stored in this part. Static data can include the building type (e.g. residential, office), sensor type (e.g. temperature, radiation, humidity) while the dynamic ones can be the sensed values (e.g. temperature, C02, light) or time information (e.g. day of the week, hour).
- **Interface -** Covers the communication between knowledge base and the systems.

Each layer is built on top of the previous one in that it exploits and extends it. Ontology offers semantic integration (mapping and alignment of different data models, protocols, etc.), knowledge representation (concepts, relationships, properties, rules) (D'Elia et al., 2010) and context awareness (building occupancy pattern, environmental conditions, etc.). Several ontology-based approaches have been proposed to solve the problem of semantic interoperability.

One of them consists in creating maps between schema to enable data exchange between information systems (Regueiro et al., 2017). It addresses both syntactic and semantic conflicts. A promising method for BEM systems is the mediator-based approach (Banouar and Raghay, 2016) which makes use of intermediaries (mediators or wrappers). Each of them have specific knowledge linked to a terrain, a mapping or rules. They are independent from one another, and, by receiving requests and distributing them among the heterogenous data sources, bridge the gap between different ontologies and knowledge. Request distribution can be guided by the knowledge of data integration defined in an ontology at the mediator level (Regueiro et al., 2017). The ontology is also used to verify the functional compatibility of the components before mediation (Bennaceur and Issarny, 2014). Therefore, we recognize two types of mediation (Motie et al., 2017):

- Schema mediation such as in (Renner et al., 1996) which aims to connect to schema or ontologies through successive translations.
- Context mediation as described in (Motie et al., 2017).

The manual development of those wrappers is a challenging and time-consuming task, requiring substantial effort and a deep understanding of the application domain. Hence, research efforts are moving in the direction of automation for mediators. Furthermore, automation enables seamless and spontaneous interaction between components in highly dynamic environments (Bennaceur and Issarny, 2014; Regueiro et al., 2017).

4. Proposed digital twin framework

The proposed digital twin framework should support both co-simulation, and (near) real-time control and operation planning. This study emphasizes reusability, modularity, and interoperability to address the requirements of standardization and the incorporation of domain and semantic knowledge (Wiens et al., 2021). The proposed framework solves technical interoperability issues through the FMI standard and semantic interoperability through interoperability with, e.g., Brick Schema ontology. Moreover, by selecting standardized or known tools, it greatly enhances reusability while remaining flexible and efficient. We will provide guidelines to follow for the proper development of such a digital twin starting from the co-simulation aspect and concluding with the control phase.

For the purpose of simulating and controlling the operation of a building heating network, the digital twin should be capable of modeling the flow of energy throughout the building energy system. Therefore, we propose a digital twin architecture comprising the following layers:

1. **Basic system and energy flow representation**: a graph representation of the building HVAC system and relevant parts of the building energy system, containing the key parameters of the system and energy transfer relationships between components, subsystems, and thermal zones;
2. **Ontology framework, semantic interoperability, and data exchange**: the "meta" interface interoperability mechanism for di-directional data exchange between the digital twin model and external systems and hardware components;

3. **Data-driven co-simulation and control**: integration with services and tools developed on top of the information/energy flow layers.

The two first layers are the foundational layers of the digital twin framework, and intended to be very general to further support the development of data-driven models and control algorithms. These layers are explained in more detail in the following subsections.

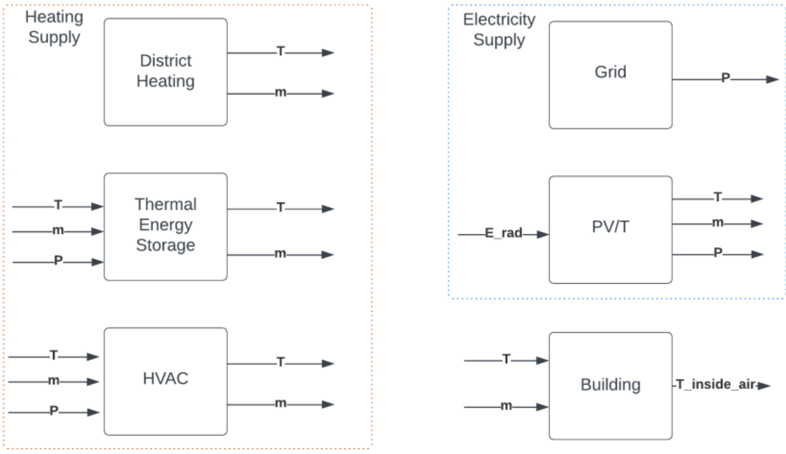

Figure 1. Basic components and inputs/outputs (ports).

4.1. Basic system and energy flow representation

As the framework presented here is intended to be general, a preliminary study has been carried out to determine the system precisely. This involved defining the relevant components and description, as well as the relevant variables and parameters required to support simulation and control of the building HVAC system. The principles of the proposed digital twin concept revolve around two notions: ***components*** and ***ports***. A component takes some *inputs* and produces some *outputs* – these are called ports, and components can be interconnected if they have matching input-output ports. Note that it is not the responsibility of this basic system representation to model the transformation of these components, but rather to model interconnections between components. The upper layers are responsible for modeling the interactions between components.

The basic ports are: 1) temperature (T); 2) mass flow (m); and 3) electric power (P), which model the internal energy flow of the HVAC system. The framework also allows for additional ports, to connect information from external systems to the digital twin – for now we have included the radiation energy. The components may maintain an internal state, which is not the same as a port, for example the temperature of a thermal zone, or other sensor measurements. The basic components are: thermal supply, power supply, and thermal zones. These can be characterized as follow: 1) a thermal supply component is characterized by having a (T, m)-output port, and includes district heating, thermal energy storage, PV/T, and HVAC components; and 2) a power supply is characterized by having a -output port, and includes the power grid, batteries, and PV. A thermal zone is an area with a single temperature setpoint and has a (T, m)-input port.

This methodology adeptly constructs subsystem ontology from an existing comprehensive building ontology, ensuring our digital twin framework is compatible with all buildings and can accurately and effectively represent the physical HVAC systems within them. The connectors represent a connection between two components, whereby some parameter determined by one component influences another component. The physical interfaces of each component have been determined and depicted in Figure 1. However, a clarification needs to be made regarding the storage systems as they are in the meantime feeding their associated aggregator and receiving energy from it. The interfaces presented here aim to be comprehensive and, therefore, by accounting for certain null flows, could represent any configuration. The same applies to Figure 2, which illustrates the isolated physical flows of each component, providing an overview of the possible connections between them.

Our framework, aims to be comprehensive and targets real implementations, to reduce the number of considered parameters without sacrificing precision and gaining computational time, is then of paramount importance. Humidity and solar radiation have joined the outdoor temperature as meteorological factors. Additionally, temporal parameters have been added, as they are inevitable to consider in particular for control perspective (Hao et al., 2023; Maljkovic and Basic, 2020; Roccatello et al., 2022).

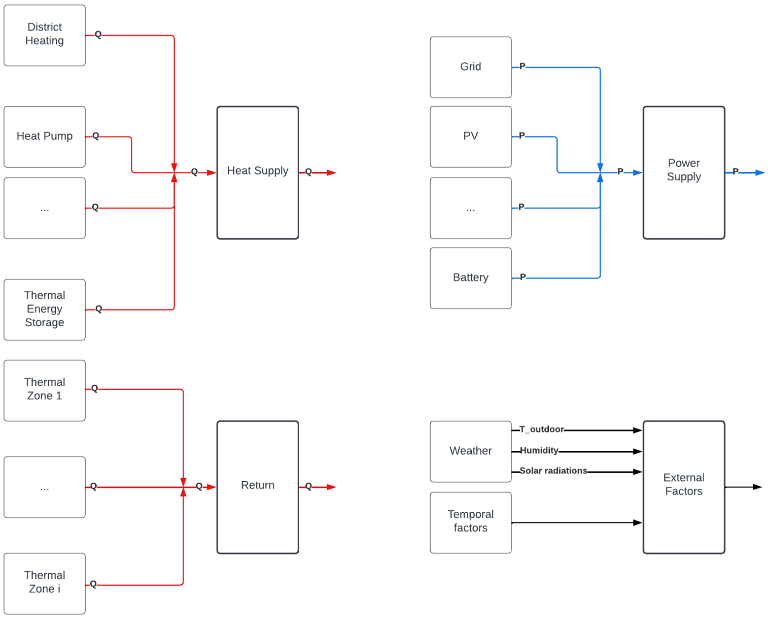

Figure 2. Basic components and inputs/outputs (ports).

4.2. Ontology framework, semantic interoperability, and data exchange

The integration of semantic and domain knowledge occurs through the REC ontology, which serves as a link between digital building representations, their control, and operation facilitated by Internet-of-Things (IoT) technologies. REC can be considered as a standard and modular schema for building knowledge graphs. Among other things, REC is based on ontology reuse, and the consortium is working on increasing the interoperability between well-established ontologies like SSN/SOSA and Brick. Such an ontology then provides a holistic description of building systems from equipment categories to measurable properties, including the integration of the sensor and actuator network. Furthermore, clear process and sampling semantics can be described, through the prism of real-estate.

Figure 3. Comprehensive Brick Schema of a Building (left) and AHU (VAV) Subsystems (right).

As the first step, the ontology framework is developed, aiming at providing assurance for digital-twin framework can semantically comprehended and engaged with the intricacies of building systems. Since these ontologies are typically comprehensive and intricate, our approach is focused on distilling only the components that align with the aims of our study. In this section, Brick Schema is used as an example to demonstrate the methodology for extracting a subsystem, such as building heating system (using mechanical ventilation), from a comprehensive existing brick schema. The process encompasses a few strategic steps. Initially, a definitive list of components within the HVAC system, such as AHU, etc., is compiled as these elements form the focal point for the subsequent extraction from the overarching schema. Using Python and SPARQL, we can design specific queries to find and pull out the relevant structure for the listed components from the overall schema, and utilize the CONSTRUCT query in SPARQL to create a new RDF graph, exclusively containing the extracted data. We can visualize or utilize it for validation for further analysis, Figure 3 (left) presents the comprehensive Brick schema from a particular building, while Figure 3 (right) showcases the extracted AHU which using variable air volume (VAV) as subsystems.

4.3. Data-driven co-simulation and control:

According to (Barbierato et al., 2022), a co-simulation framework should include the following parts:

- **a Scenario**: Contains the semantic knowledge of the considered system. It allows for the connection between Simulators and initializes all the relationships that occur between the Model Instances.
- **the Simulators**: Perform calculations based on knowledge provided by Model Instances.
- **the Model Instances**: Represent physical subsystems.
- **an Orchestrator**: Statue of data exchange and time synchronization between simulators.

The simulators and model instances are handled by the FMI standard. Each of the aforementioned components will be modeled through a data-driven approach and exported as FMUs. Consequently, the number of FMUs is not predetermined and is not intended to be so, as the case study will dictate the requirements. This will increase the co-simulation precision and enable better real-world implementation. A pronounced need for a clear and holistic system description is then appearing. Notably, these FMUs must communicate and be connected, and the multiplication of these entities considerably complicates this task. Thus, the reasoning capabilities allowed by the ontology will be harnessed. REC, enabling such a representation, will enable the formulation of SWRL rules to autonomously establish inter-FMU connections. Subsequently, these connections will be semantically valid and mirror the building's reality.

The integration of ontological knowledge into FMUs is achieved by adding an .owl file to the FMU's ZIP file at its creation. For greater flexibility, a layered approach to knowledge incorporation, as described in (Mitterhofer et al., 2017), is preferred. This provides the possibility of using the same FMU types in different contexts. Thus, at this stage, only basic properties are indicated, such as unit or quantity concepts and domain-related information, namely BEM. Thereafter, project-specific knowledge will be added, e.g. spatialization concepts. This final step will be accomplished through reasoning using the SWRL rules and a reasoner.

To address the control aspects, the termination phase of the FMI is equipped with several functions for result extraction. These provide the opportunity to implement control strategies based on the formulation of optimization problems. The constraints and objectives of this problem will depend on the user's needs and the project requirements. It will be essential to keep the objectives in mind for the control during the framework configuration stage.

Control involves providing commands to the identified and defined actuators. With the division of different components into FMUs and thus the developed models, it will be possible to propose adapted and efficient control strategies. Once the predictions and actions are determined, based on the described system, they will be re-injected into the real system. It is then possible to apply different reasoning methods to compare the actual outcomes of the control policies implemented to the expected results.

5. Use case implementation and discussions

The framework has been implemented on a use case based on the heating system of an apartment building in Testbed KTH 3.0 (and neighborhood apartments Testbed EM), located at KTH campus, Stockholm, Sweden. The case consists of a few private rooms with a shared kitchen and common area. The whole apartment is heated by ventilation, supplied by one air-handling unit (AHU) with one heating coil. The supply air can be pre-heated by a ground-source heat pump (HP) with 11 boreholes. The coil in the AHU is heated from a thermal storage unit (TES). The heat pumps also supply another TES, specifically eight domestic hot water (DHW) Tanks. For space heating (SH), the heated air goes directly to the shared spaces by 2 duct openings – one in the living room and one in the kitchen – and to 4 VAVs, one for each private room. Each VAV contains one damper that controls the airflow and one after heater in case more heating of the air is required. Figure 4 presents the schematics of the heating system of the use case. All spaces (each room, the kitchen, the living room and each bathroom) have a Temperature Sensor, a Relative Humidity Sensor, and a CO_2 sensor. In addition, over roof temperature sensors, floor temperature sensors etc. are equipped in different rooms. There are also some wall temperature sensors located between rooms and with ambient. Each room has an assigned temperature and CO_2 setpoint.

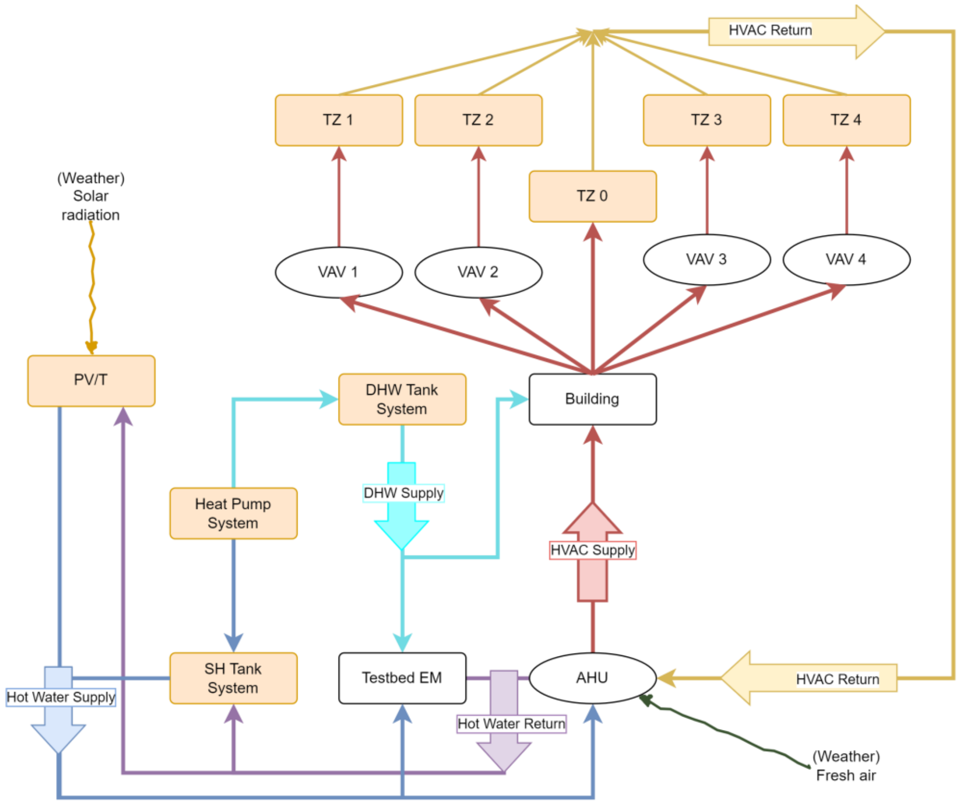

Figure 4. The heating network configuration and energy flow schematics of the suited use case.

Table 1 also presents the components, incl. photovoltaic and thermal (PV/T), that are included in the heating network, and sensing/controllable points.

Table 1: Systems and their Subsystems/Components/Points

	Subsystem	**Has Component**	**Has Point**	**Is Controlled**
PV/T System	Panels			no
	Battery System	Batteries	Storage Capacity	yes
	Ducts	Damper	Damper Setpoint	yes
HVAC	AHU	VAV		
	VAV	Damper	Damper Setpoint	Yes
		After Heater	Setpoint	yes
Space heating Tank System		Tanks (1-3)		
DHW Tank System		Tanks (1-8)		
HP System		Heat Pumps (1-3)		yes

Figure 4 represents the heating network of the selected use case, based on the minimum data and their flow needed in our framework. Red lines represent air supplied to building while the respective ones from heat recovery are represented in yellow lines. Correspondingly blue lines represent water supply while the purple ones water return. In both cases the data are either mass flow and temperature or energy, depending on the available sensors. As is the case with the electricity representation, inputs and outputs are only known to and from each system separately so supplies and returns are aggregated and then split for each system. In Table 2 we see how the data are organized in each case.

Table 2: Inputs and outputs of each system of the electricity network of the use case.

Systems	Inputs	Outputs
PV/T		Electricity Production Thermal Energy Production
Battery System	Unused PV Electricity	
SH TES		Supply Water Temperature Supply Water Flow Rate
DHW TES		Domestic Hot Water Supply
HP System	Total Electricity Used	Condenser Energy For Space Heating Condenser Energy For Domestic Hot Water
AHU	Air Intake Temperature (fresh air) Return Temperature (common) Return Air Flow Rate Supply Air Fan Power Return Air Fan Power	Supply Temperature (common) Supply Temperatures (distribution levels) Supply Air Flow Rate
Grid		Bought Electricity
Testbed KTH	Domestic Hot Water Use Electricity Used	
Other Buildings and Systems		Domestic Hot Water Use Electricity Used

For the electricity network, the building, and by extension the heating system of this study is provided with electric power not only through the grid, but also with locally generated power from PV/Ts located on the roof of neighborhood apartments. Batteries can also be potentially used as storage, where thermal energy produced is used in the preheating of the AHU, see Figure 4. In Figure 5, the electricity system data flow is adapted in the use-case. For clarification, the connections represent every useful data as described in Table 2. Every supply is aggregated and then split based on the knowledge. Dotted lines represent inherited values that are optional/customized, or in the case of the AHU it is because it is a subsystem of HVAC.

Figure 6 presents the framework as an example of how ontology can present the digital twinning of the selected heating network in the use case. Connections represented with dotted lines represent inherited relationships. On the one hand, for the sake of presenting many different interactions, the HVAC system is chosen as it has the most components and connections in our use-case. An example of a relationship that is not presented is the "isComponentOf" inherited connection, which in this case is shown only between the Dampers and HVAC, although this relationship exists between more systems, subsystems and components. Also every relationship described should automatically inherit the inverse relationship, for example every "feeds" creates an inverse direction "isFedBy”.

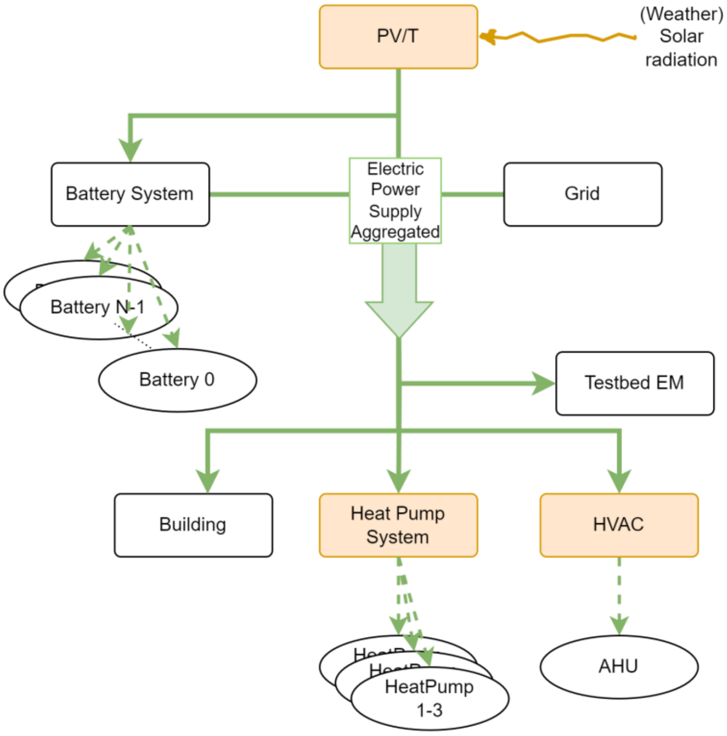

Figure 5: The electricity network configuration and energy flow schematics of the suited use case.

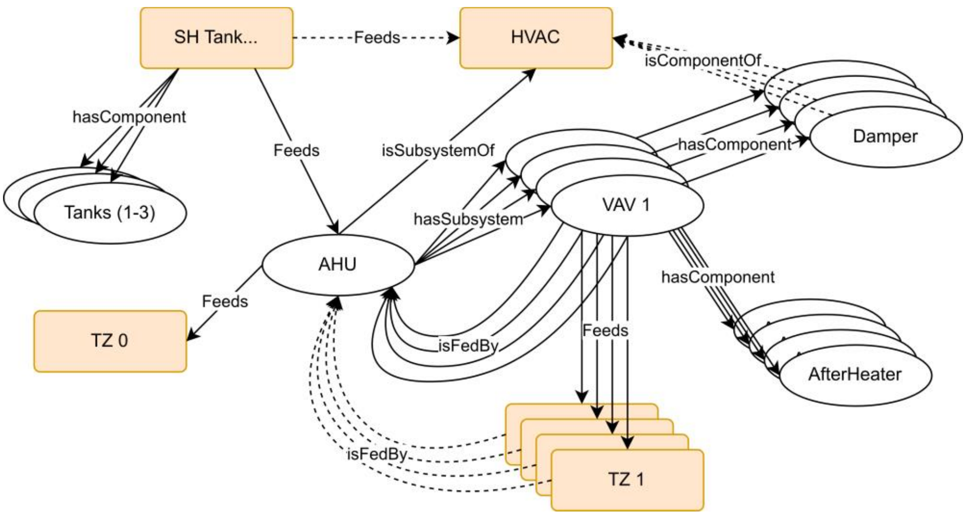

Figure 6: Example of studied ontology of the heating network of the use case.

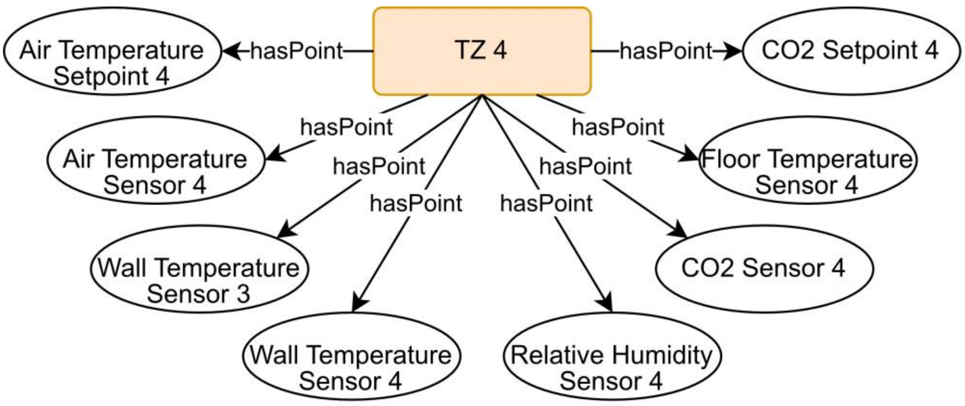

Figure 7: Thermal Zone 4 and its associated points

In this study, thermal Zones are not considered as locations, but abstract spaces/systems affected by parts of the system. Thermal Zones, as well as many other parts of the system, have their own points (sensors or actuators) and are considered through them. Thus, in this case, each room is considered a Thermal Zone because of their actuators and setpoints in the VAV. On the other hand, The shared spaces, although having many sensors have no actuator so they are all considered one Thermal Zone, namely "Thermal Zone 0". Thermal Zone 4 has a wide variety of points and its representation is hereby selected to convey some of the points of the system, as can be seen in Figure 7.

6. Conclusions

This study introduces an interoperability mechanism and a digital twin framework for simulating and controlling building HVAC systems integrating distributed renewables, and especially PV/T, and storage. In particular, it identifies the key components and subsystems, together with their key parameters and interfaces to describe the energy and information flows to support automated, data-driven co-simulation and control. To demonstrate the framework, it has been further adapted to a real building, the live-in-lab testbed at KTH. The interoperability aspects of the framework will be further developed to support IoT and BMS integration.

7. Acknowledgments

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