

Operational Semantic Digital Twins for Grid-Interactive Residential Buildings:  
Application to Experimental Houses with Integrated Photovoltaics and Battery Storage

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A Thesis

In the Department

of

Building, Civil and Environmental Engineering

Presented in Partial Fulfillment of the Requirements

for the Degree of

Doctor of Philosophy (Building Engineering) at

Concordia University

Montréal, Québec, Canada

October, 2025

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**CONCORDIA UNIVERSITY**  
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## **Abstract**

### **Operational Semantic Digital Twins for Grid-Interactive Residential Buildings: Application to Experimental Houses with Integrated Photovoltaics and Battery Storage**

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**Concordia University, 2025**

Buildings are evolving from passive consumers into grid-interactive agents capable of providing demand-side flexibility, a cornerstone for achieving renewable integration and system reliability. Delivering such building-to-grid services requires supervisory control frameworks that combine predictive algorithms with interoperable, machine-readable infrastructures. Yet, current automation systems remain fragmented across proprietary platforms, while most digital twin applications focus on monitoring and visualization rather than predictive control. In parallel, model-based predictive control (MPC) has proven effective in coordinating distributed energy resources (DERs) but is rarely integrated with semantic digital twins (SDTs), leaving a critical gap between semantic interoperability and optimal operational planning.

This thesis introduces a methodological framework for developing operational SDTs that embed ontological reasoning directly into supervisory MPC. The framework progresses from data acquisition and entity structuring to layered semantic modeling, knowledge graph generation and validation, and integration with predictive control. A central contribution is the Resistance-Capacitance Ontology (RCOnt), which semantically formalizes grey-box thermal RC networks for control-oriented applications. The SDT framework integrates Brick Schema, ASHRAE Standard 223P, Energy Flexibility Ontology, and RCont, binding semantic entities to live telemetry streams and enabling query-driven discovery, model retrieval, and automated supervisory and local equipment control configuration.

The methodology is applied and validated in Hydro-Québec’s Experimental Houses for Building Energetics, two identical, instrumented residential testbeds relying solely on electricity as the energy carrier, equipped with rooftop photovoltaics, battery storage, and smart thermostats. Economic MPC for tariff-responsive load shifting achieves 35–75% reductions in electricity costs while maintaining indoor air temperature predominantly within  $\pm 1$  °C of the reference setpoint.

Heuristic MPC for post-outage cold load pickup mitigation reduces rebound demand by approximately 50%, with only a modest extension of thermal recovery time. Replication across houses demonstrates the transferability of the architecture, indicating the potential for scalability, as semantic abstraction enables reproducible, vendor-agnostic supervisory control for residential buildings with DERs.

This thesis establishes SDTs as a practical foundation for scalable grid service orchestration by integrating semantic modeling, physics-based representations, and predictive control within a single operational workflow. The results demonstrate that embedding semantics into supervisory MPC not only enhances interoperability and automation but also provides a transferable pathway for enabling real-time flexibility services in future grid-interactive buildings.

## Acknowledgements

I would like to express my gratitude to my supervisors, Dr. Athienitis and Dr. Delcroix, for their support throughout the course of my doctoral studies. Their supervision has been instrumental in shaping the direction and quality of my research. I am thankful for the opportunity to access world-class experimental facilities and real-world case studies under their supervision. I also gratefully acknowledge the invaluable opportunities they provided for disseminating my work at esteemed national and international conferences and meetings.

I extend my gratitude to colleagues at Concordia's Centre for Zero Energy Building Studies for their intellectual exchange, particularly my mentors, Dr. Rao, Dr. Dermardiros, Dr. Morovat, and Dr. Vallianos, whose insight has greatly enriched my academic growth.

Finally, I wish to express my heartfelt appreciation to my family for their support, patience, and encouragement throughout this journey.

I acknowledge the following sources of financial support throughout the course of my doctoral studies: the doctoral research scholarship from the Fonds de Recherche du Québec – Nature et Technologies, a Mitacs Business Strategy Internship, a Mitacs Accelerate Program Internship, the Concordia International Tuition Award of Excellence, the Concordia Merit Scholarship, and support from the NSERC/Hydro-Québec Industrial Research Chair in Optimized Operation and Energy Efficiency: Towards High Performance Buildings.

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## Nomenclature

| Symbol /<br>Acronym | Definition                                                                | Unit             |
|---------------------|---------------------------------------------------------------------------|------------------|
| $\alpha$            | Solar aperture                                                            | m <sup>2</sup>   |
| $\varepsilon$       | Tolerance range for indoor air temperature deviations                     | °C               |
| $\delta t$          | Time-step duration                                                        | s                |
| $\theta$            | Parameter set                                                             | —                |
| $\mathbf{u}$        | Admissible control input set                                              | —                |
| $\mathbf{x}$        | Admissible state set                                                      | —                |
| $\mathbf{y}$        | Admissible output set                                                     | —                |
| ASHRAE              | American Society of Heating, Refrigerating and Air-Conditioning Engineers | —                |
| BaU                 | Business-as-Usual                                                         | —                |
| B2G                 | Building-to-Grid                                                          | —                |
| BEFI                | Building Energy Flexibility Index                                         | —                |
| C                   | Capacitance                                                               | J/°C             |
| CH                  | Control Horizon                                                           | —                |
| CLPU                | Cold Load Pickup                                                          | —                |
| DER                 | Distributed Energy Resources                                              | —                |
| DR                  | Demand-side Response                                                      | —                |
| E                   | Energy                                                                    | J                |
| EBC                 | Energy in Buildings and Communities                                       | —                |
| EHBE                | Experimental House for Building Energetics                                | —                |
| elec                | Electric / Electricity                                                    | —                |
| env                 | Thermal mass or envelope node                                             | —                |
| $f(\cdot)$          | State update function                                                     | —                |
| FDD                 | Fault Detection and Diagnosis                                             | —                |
| flex                | Flexible                                                                  | —                |
| G                   | Effective irradiance                                                      | W/m <sup>2</sup> |
| GDB                 | Graph Database                                                            | —                |
| GEB                 | Grid-Interactive Efficient Buildings                                      | —                |
| GHG                 | Greenhouse Gas Emissions                                                  | —                |
| GHI                 | Global Horizontal Irradiance                                              | W/m <sup>2</sup> |
| $g(\cdot)$          | Output function                                                           | —                |
| IEA                 | International Energy Agency                                               | —                |
| IFC                 | Industry Foundation Classes                                               | —                |
| IoT                 | Internet of Things                                                        | —                |

| <b>Symbol /<br/>Acronym</b> | <b>Definition</b>                              | <b>Unit</b> |
|-----------------------------|------------------------------------------------|-------------|
| k                           | Current time step                              | —           |
| MPC                         | Model Predictive Control                       | —           |
| MPPT                        | Maximum Power Point Tracking                   | —           |
| N                           | Total number of data points                    | —           |
| OSTI                        | Office of Scientific and Technical Information | —           |
| out                         | Outdoor                                        | —           |
| OWL                         | Web Ontology Language                          | —           |
| P                           | Power                                          | W           |
| PH                          | Prediction Horizon                             | steps       |
| PV                          | Photovoltaic                                   | —           |
| Q                           | Heat flow                                      | W           |
| QUDT                        | Quantities, Units, Dimensions and Types        | —           |
| R                           | Resistance                                     | °C/W        |
| RC                          | Resistance–Capacitance                         | —           |
| RDF                         | Resource Description Framework                 | —           |
| ref                         | Reference                                      | —           |
| s / srv                     | Service                                        | —           |
| SAREF                       | Smart Appliances REference ontology            | —           |
| SDT                         | Semantic Digital Twin                          | —           |
| set                         | Setpoint                                       | —           |
| SHACL                       | Shapes Constraint Language                     | —           |
| SIMEB                       | Simulation Énergétique des Bâtiments           | —           |
| SoC                         | State of Charge                                | —           |
| SPARQL                      | SPARQL Protocol and RDF Query Language         | —           |
| T                           | Temperature                                    | °C          |
| TES                         | Thermal Energy Storage                         | —           |
| therm                       | Thermal                                        | —           |
| ToU                         | Time-of-Use                                    | —           |
| TSDB                        | Time-Series Database                           | —           |
| V2B                         | Vehicle-to-Building                            | —           |
| $\eta$                      | Efficiency                                     | —           |

# 1. Introduction

## 1.1 Problem Statement and Motivation

The energy landscape is undergoing a profound structural transformation. The grid is becoming increasingly dynamic and decentralized, driven by rapid electrification—primarily through the adoption of electric vehicles (EVs) and heat pumps—as well as the accelerated integration of distributed energy resources (DERs) to meet urgent global decarbonization targets (Damianakis et al., 2023). Within this context, demand-side energy flexibility has emerged as a critical capability, enabling buildings to modulate short-term energy demand and generation in response to climatic conditions, occupant needs, and grid signals without compromising comfort or system integrity (Li & Hong, 2022). This energy flexibility underpins demand-side management (DSM), contributing to grid stability during peak periods, while also facilitating renewable integration and enabling a cleaner generation mix (D’Ettorre et al., 2022). Consequently, buildings are poised to transition from passive consumers to grid-interactive agents, capable of responding to time-varying signals in alignment with emerging grid needs.

In practice, Building-to-Grid (B2G) services establish the qualitative purpose, operational requirements, and contractual mechanisms that govern how buildings and their on-site resources—such as controllable loads, distributed generation, and dispatchable storage—are utilized to interact with the power system and monetized through structured market or program participation (Rahimi & Ipakchi, 2016). These services translate potential flexibility into actionable contributions by modulating energy consumption and production to support grid objectives and enhance overall system stability and resilience. Their scope spans a wide spectrum, including frequency regulation, voltage regulation, spinning reserves, ramping support, and demand response strategies such as peak shaving, load shifting, and rapid curtailment. Each operates over distinct temporal and spatial scales, ranging from sub-second frequency response to multi-hour demand adjustments, and from individual feeders to bulk power system markets (Stanelyte et al., 2022). Effective implementation requires well-defined parameters—such as response time, duration, magnitude, and verification protocols—together with constraint-aware, predictive supervisory control frameworks (Adham et al., 2025).

The effective delivery of grid services at scale requires orchestrating building subsystems and control strategies within a unified, semantic, and machine-interpretable digital infrastructure—one that enables automated reasoning, seamless interoperability, and query-driven coordination of both physical systems and virtual services (Bjørnskov & Jradi, 2023; Guo & Lv, 2022). Yet in practice, building automation and energy management systems remain highly fragmented and vertically siloed, with sensor data streams, control logic, and performance feedback dispersed across heterogeneous, vendor-specific platforms (Taboada-Orozco et al., 2024). This fragmentation undermines interoperability, obstructs optimization, and severely limits the automation and scalability of real-time grid services (Pritoni et al., 2024).

Traditional building information modeling (BIM) standards—such as Industry Foundation Classes (ISO, 2018), Green Building XML (gbXML, 2020), and CityGML (OGC, 2021)—represent building geometry, materials, and design intent. While these schemas provide structured and interoperable representations well-suited for design-phase and as-built documentation, they offer limited support for operational monitoring, dynamic control integration, or real-time decision support (Boje et al., 2020).

Advancements in digitalization—particularly in the Internet of Things (IoT), cloud computing, and big data analytics—are now transforming building operation and maintenance, highlighting the need for data models that go beyond static design representations (Poyyamozi et al., 2024). In this context, semantic technologies such as ontologies, standards, and communication protocols have emerged to extend conventional BIM by incorporating live operational data and formalized descriptions of system behavior. These technologies formally define building devices, zones, control logic, and system interdependencies, establishing a shared and extensible vocabulary for describing system structure and function (Benfer & Müller, 2024). Their representations are encoded in machine-interpretable formats such as the Resource Description Framework (RDF; W3C, 2014) and the Web Ontology Language (OWL; W3C, 2012), providing a foundation for transparent navigation and semantic interpretation of building data.

Examples include Brick Schema, which provides a structured ontology for representing subsystems and their interrelationships (Balaji et al., 2018); ASHRAE Standard 223P, which standardizes metadata for operational data exchange and integration (ASHRAE, 2022); and

SAREF, which supports cross-domain IoT device interoperability (ETSI, 2020). Additionally, domain-specific ontologies such as Energy Flexibility Ontology (EFOnt; Li & Hong, 2022) model flexibility characteristics of energy systems for DSM applications. Complementing these semantic approaches, communication protocols such as ANSI/ASHRAE Standard 135 (ASHRAE, 2020), commonly known as BACnet, facilitate standardized data exchange and device interoperability within building automation systems, while Guideline 36 (ASHRAE, 2021) and the emerging Standard 231P (ASHRAE, 2023) formalize machine-readable sequences of operation and control logic. Collectively, these frameworks establish a machine-interpretable and scalable digital foundation that enables flexible, grid-interactive operation. In parallel, semantic modeling supports rule-based validation of system relationships, enabling reliable automated reasoning and flexible, query-driven coordination (Pauwels & Terkaj, 2016). When coupled with live telemetry, these formalized models provide interoperable infrastructures that support real-time monitoring and grid services (Li & Hong, 2022).

Despite recent conceptual advances, most digital twin applications in building operation still rely on proprietary architectures, custom APIs, and ad hoc data models, which restrict interoperability, obscure semantics, and hinder scalability across diverse platforms, vendors, and building configurations (Fuller et al., 2020). In response, semantic digital twins (SDTs) have emerged as a paradigm shift in operational building intelligence. By introducing formalized ontologies and interoperable data structures, SDTs address many of the shortcomings of conventional digital twins. However, their current implementations remain limited in scope, with a primary focus on monitoring and visualization rather than enabling advanced control integration for optimal grid-interactive operation (Bäcklund et al., 2024). The integration of SDTs with predictive supervisory control frameworks remains underdeveloped, particularly in residential contexts, yet bridging this gap is essential to unlock their full potential for delivering real-time grid services. Addressing this challenge defines the central focus of this thesis, and the corresponding research objectives are outlined in Section 1.2.

## **1.2 Research Objectives**

Addressing the underdeveloped integration of SDTs with predictive supervisory control frameworks—particularly in residential contexts—this thesis develops and demonstrates a layered

semantic digital twinning framework explicitly designed to enable supervisory model-based predictive control (MPC) for grid services. The framework is implemented and validated in two grid-connected single-family research houses owned by Hydro-Québec, equipped with rooftop photovoltaics (PV), battery storage, and commercial smart home infrastructure. Its architecture supports real-time telemetry, online model calibration, predictive optimization, and closed-loop actuation, thereby maintaining a continuous feedback loop between the physical environment and its semantic twin. The overarching aim is to establish the feasibility, effectiveness, and scalability of operational SDTs as an enabling infrastructure for flexibility-oriented supervisory control. To achieve this aim, the research is structured around the following objectives:

**Objective 1 — Critically review the state of the art in operational SDTs and MPC for grid service delivery.**

- **Approach:** Synthesize findings from the literature on semantic interoperability, control integration, and real-world MPC deployments, identifying technical gaps in scalability, adaptability, and orchestration of grid services.
- **Contribution:** Provide a structured review that establishes the research problem and justifies the integration of operational SDTs with supervisory MPC in building-to-grid applications.

**Objective 2 — Develop the Resistance-Capacitance Ontology (RCOnt): an ontology for formalizing and integrating control-oriented modeling in SDTs.**

- **Approach:** Identify conceptual and operational requirements for representing archetype grey-box thermal RC network models in semantic frameworks. Develop RCOnt by defining classes, properties, and relationships for thermal nodes, resistances, capacitances, solar apertures, and model–zone mappings, ensuring alignment with existing ontologies. Implement the ontology in RDF/OWL, integrate it into the layered SDT architecture, and validate its suitability for real-time supervisory control through Shapes Constraint Language (SHACL; W3C, 2017) validation constraints and interoperability testing.
- **Contribution:** Deliver a publicly available ontology that formalizes and integrates archetype grey-box thermal RC network models within building control workflows.

**Objective 3 — Design a layered operational SDT for real-time supervisory control.**

- **Approach:** Integrate multiple ontology layers—including Brick Schema, ASHRAE Standard 223P, EFOnt, and RCOnt—to represent building systems, device metadata, flexibility characteristics, and physics-based models within a unified semantic framework. Bind semantic entities to real-time telemetry and actuation points, and develop query templates that automate device discovery, retrieve flexibility parameters, and assemble control problem definitions from the semantic graph. Integrate a general MPC formulation with the SDT for automated retrieval of model parameters, constraints, and system associations, enabling dynamic model–system alignment without hard-coded mappings.
- **Contribution:** Deliver an operational SDT that embeds formalized annotations for physics-based thermal modeling and supports live supervisory control execution in a semantic web environment, enabling declarative, vendor-agnostic configuration and a knowledge-driven, service-oriented MPC implementation.

**Objective 4 — Deploy and demonstrate the transferability of the layered SDT methodology in a real-world testbed.**

- **Approach:** Implement the developed methodology in a highly instrumented testbed equipped with DERs, using commercial smart home infrastructure and IoT pipelines for live data ingestion and actuation. Employ MPC to deliver grid services through optimal coordination of distributed resources. Deploy the semantic model originally developed for a reference building to an identical, equivalently instrumented building without modifying the core ontology, control logic, or mapping pipeline—requiring only minimal configuration changes to telemetry endpoints and control routing.
- **Contribution:** Deploy the layered SDT integrated with supervisory MPC in a real-world testbed, and demonstrate its transferability to similarly instrumented environments with minimal reengineering as a practical pathway for grid service orchestration.

Collectively, these objectives establish a validated and modular framework for supervisory control grounded in operational semantic digital twinning, enabling reproducible deployment of real-time MPC strategies for grid service delivery on commercial hardware and open-source platforms through the seamless integration of semantic modeling, predictive control, and operational execution within a unified, interoperable architecture.

### 1.3 Thesis Structure

This thesis is organized into five chapters that collectively advance the development, implementation, and validation of operational SDTs for supervisory MPC in residential buildings equipped with DERs.

**Chapter 1 – Introduction:** This chapter establishes the motivation and problem statement by situating buildings within the evolving energy landscape of electrification, decarbonization, and digitalization. It introduces the concept of grid services and highlights the limitations of fragmented automation systems. The chapter outlines the potential of semantic digital twinning and MPC as complementary enablers of operational energy flexibility, identifies the research gap at their intersection, and articulates the research objectives.

**Chapter 2 – Literature Review:** This chapter reviews the foundations of energy flexibility, predictive control, and semantic digital twinning. It reviews international initiatives and KPIs that formalize and quantify flexibility, and evaluates building energy modeling approaches, emphasizing grey-box thermal RC networks as practical enablers of supervisory MPC. The discussion then examines MPC applications in load shifting, DER coordination, and ancillary services, highlighting both demonstrated potential and barriers to large-scale deployment. The chapter further analyzes operational SDTs, tracing their progression from monitoring and diagnostics toward interoperability and emerging roles in control, with particular attention to frameworks such as Brick Schema, ASHRAE Standard 223P, and EFOnt. It concludes by identifying critical gaps that directly motivate the objectives of this thesis.

**Chapter 3 – Methodology:** This chapter presents the methodological framework for developing operational SDTs. It outlines the semantic twinning pipeline, moving from data acquisition and entity structuring to multi-layer semantic modeling, graph generation, validation, and implementation in graph databases (GDBs). Particular emphasis is placed on RCOnt, an ontology that formalizes thermal RC networks for integration into SDTs. The chapter further describes the binding of semantic entities to time-series telemetry and the formulation of general MPC strategies for grid services, establishing a reproducible workflow for semantic supervisory control.

**Chapter 4 – Case Study:** This chapter applies and validates the proposed methodology in two experimental houses. It first describes the testbed infrastructure, including IoT sensing, DERs, and smart thermostats. Control-oriented models for indoor thermal dynamics and battery state of charge are then developed, semantically encoded within the layered SDT, and used to showcase two supervisory MPC applications: (1) economic MPC for tariff-responsive load shifting and (2) heuristic MPC for post-outage rebound demand mitigation. The chapter concludes by demonstrating transferability across identical residential testbeds. The content of this chapter is derived from the following peer-reviewed journal articles:

1. **Abtahi, M.**, Athienitis, A., & Delcroix, B. (2021). Control-oriented thermal network models for predictive load management in Canadian houses with on-site solar electricity generation: application to a research house. *Journal of Building Performance Simulation*, 15(4), 536–552. <https://doi.org/10.1080/19401493.2021.1998223>.
2. **Abtahi, M.**, Athienitis, A. K., & Delcroix, B. (2023). Archetype Building Energy Models for Residential Sector: Importance of Uncontrolled Inputs in Predictive Control and Energy Flexibility. *Journal of Physics: Conference Series*, 2654(1), 012058. <https://doi.org/10.1088/1742-6596/2654/1/012058>.
3. Vallianos, C., **Abtahi, M.**, Athienitis, A., Delcroix, B., & Rueda, L. (2023). Online model-based predictive control with smart thermostats: application to an experimental house in Québec. *Journal of Building Performance Simulation*, 17(1), 94–110. <https://doi.org/10.1080/19401493.2023.2243602>.
4. **Abtahi, M.**, Athienitis, A., & Delcroix, B. (2024). Predictive heating load management and energy flexibility analysis in residential sector using an archetype gray-box modeling approach: Application to an experimental house in Québec. *Journal of Building Physics*, 48(3), 442–466. <https://doi.org/10.1177/17442591241267833>.
5. **Abtahi, M.**, Rueda, L., Delcroix, B., & Athienitis, A. (2025). Semantic Digital Twinning for Cost-Optimal HVAC Operation: Real-Time Application to a House with Smart Thermostats and PV/Battery under a Time-of-Use Tariff. *Energy and Buildings*, 343, 115938. <https://doi.org/10.1016/j.enbuild.2025.115938>.

6. **Abtahi, M.,** Vallianos, C., Rueda, L., Delcroix, B., & Athienitis, A. (n.d.). Field Demonstration of Tariff-Responsive Load Shifting and Post-Outage Cold Load Pickup Mitigation in Québec. Manuscript submitted for publication in Sustainable Energy, Grids and Networks.

**Chapter 5 – Conclusions:** This chapter synthesizes the contributions of the thesis, highlighting how the developed framework bridges semantic interoperability with predictive supervisory control. It encompasses both theoretical and practical advances, including the development of RCOnt, the layered SDT architecture, and field demonstrations in residential testbeds. Practical and methodological limitations—such as the absence of occupants in the testbeds, reliance on stable ontologies, and the conditional nature of transferability beyond identical buildings—are also acknowledged. Finally, future research directions are outlined, focusing on automated semantic alignment, occupant-centric modeling, adaptive comfort metrics, and uncertainty-aware supervisory MPC as pathways toward scalable deployment and resilient building–grid integration.

## **2. Literature Review**

### **2.1 Introduction**

Recent years have witnessed an accelerated convergence of decarbonization policies, electrification trends, and digital innovations, fundamentally reshaping how buildings interact with energy systems. Rather than operating as isolated, passive consumers, buildings are increasingly positioned as active participants capable of modulating their demand and generation in response to grid needs, price signals, and environmental objectives.

Several international research initiatives have substantially contributed to the conceptualization and practical demonstration of pathways toward flexible building operation. Notably, the International Energy Agency's Energy in Buildings and Communities (IEA-EBC) Annexes 67 (Jensen et al., 2017), 81 (IEA-EBC, n.d.-a), 82 (IEA-EBC, n.d.-b), 84 (IEA-EBC, n.d.-c), and 96 (IEA-EBC, n.d.-d), together with the U.S. Department of Energy's Grid-Interactive Efficient Buildings (GEB) program (Satchwell et al., 2021), have advanced the formalization of demand-side flexibility principles, the design of interoperable control architectures, and the testing of scalable solutions across diverse building typologies and climatic regions.

The scalable and coordinated provision of grid services requires structured digital representations of buildings and their on-site resources, together with advanced supervisory control strategies that align flexibility activation with clearly defined service purposes, operational requirements, and contractual mechanisms. The following sections examine these interrelated domains, tracing their conceptual foundations, highlighting recent advancements, and evaluating their potential for integration within grid-interactive buildings.

### **2.2 Energy Flexibility Key Performance Indicators**

A central challenge in operationalizing grid services lies in moving from qualitative notions of flexibility to measurable and verifiable quantities. To address this, researchers have developed key performance indicators (KPIs) that quantify the magnitude, responsiveness, efficiency, and cost-effectiveness of flexibility. These indicators enable consistent assessment across building typologies, technologies, and market contexts, providing a common basis for comparing potential

flexibility resources and for structuring contractual agreements with aggregators or system operators. In effect, KPIs serve as the bridge between theoretical flexibility potential and actionable service delivery, offering metrics that support both technical evaluation and market integration (Li et al., 2023).

Methodological efforts to formalize flexibility assessment have emphasized the importance of systematic procedures. O’Connell et al. (2019), for example, proposed a four-step framework: (1) system and load identification, (2) flexibility characterization, (3) scenario modeling to visualize the impact on demand profiles, and (4) KPI-based labeling to facilitate contract negotiations between building operators, aggregators, and utilities. This structured approach underscores the role of KPIs not only as evaluative tools but also as instruments of communication between technical stakeholders and market actors. Furthermore, scalability and ease of implementation are critical considerations, as assessment methods must be applicable across large building portfolios without prohibitive data or computational requirements.

Experimental studies have complemented methodological advances by testing KPI frameworks under real-world conditions. Finck et al. (2020) demonstrated such an approach in a detached house in Amstelveen, the Netherlands, where occupant behavior and the dynamic response of the heating system were explicitly considered. Flexibility was quantified across three principal domains: (1) energy and power, capturing instantaneous demand and supply adjustments during flexibility events; (2) energy efficiency, assessing the utilization of system resources such as heat pumps and thermal storage; and (3) energy costs, reflecting the economic implications of flexibility activation in power markets. This categorization proved effective in clarifying the multidimensional nature of flexibility, enabling assessment of not only its technical availability but also its economic and operational consequences.

Li et al. (2023) advanced this line of research by systematically categorizing KPIs for evaluating operational flexibility across four dimensions: (1) computational complexity, (2) temporal and spatial resolution, (3) stakeholder relevance, and (4) underlying data requirements. This classification makes explicit the trade-offs between the precision of flexibility quantification and the feasibility of implementation for different stakeholders.

While KPIs provide essential metrics for assessing flexibility potential, operational readiness, and performance across diverse strategies and market contexts, they remain inherently evaluative rather than prescriptive. They indicate the extent of flexibility a building can offer but not the mechanisms by which it should be mobilized in real time. Their practical value therefore lies in integration with supervisory control frameworks that reconcile KPI targets with predictive modeling, operational constraints, and market requirements. At the same time, KPIs serve broader functions by quantifying deviations from baseline demand for system operators and aggregators, and by informing retrofit and design decisions through the identification of technologies with the greatest flexibility potential. In this way, they operate as a convergence point between building physics, control theory, and market design, ensuring that flexibility resources can be mobilized in practice as effectively as they are conceptualized in theory.

### **2.3 Building Energy Modeling for Model-based Predictive Control**

Building energy modeling is essential to operationalizing flexibility, providing the predictive backbone required for supervisory strategies such as MPC. While KPIs quantify the potential of buildings to provide grid services, accurate models are needed to translate this potential into real-time decision-making by forecasting thermal dynamics, energy flows, and system responses. Three principal approaches have been developed in the literature: (1) physics-driven (white-box) models, based on first-principles descriptions of mass and energy conservation and heat transfer, which explicitly represent building geometry, materials, and HVAC systems; (2) data-driven (black-box) models, which rely exclusively on statistical and machine learning techniques, with little or no explicit representation of the underlying physics; and (3) hybrid (grey-box) models, which simplify the physical description into reduced-order forms while identifying key parameters directly from measurements (Li et al., 2021).

White-box models, implemented in simulation tools such as EnergyPlus and TRNSYS, remain the gold standard for detailed design and retrofit analysis. However, their use in MPC is constrained by intensive data requirements, reliance on expert modeling skills, and the need for exhaustive calibration (Bamdad et al., 2023). Moreover, they often assume knowledge about building characteristics that is not practically available, leading to parameter uncertainty and reduced operational applicability (Candanedo et al., 2022). At the other end of the spectrum, black-

box models—such as autoregressive techniques, neural networks, or Gaussian processes—can be trained directly on measured data with limited expert intervention (Maddalena et al., 2020). While highly accurate within the training domain, they often lack extrapolation capability across unobserved operating conditions, seasons, or building typologies (Afram et al., 2017). As such, black-box models may inherently yield suboptimal behaviors, reflecting the limitations of the historical control strategies on which they were trained (Afram & Janabi-Sharifi, 2014).

Grey-box models strike a balance by embedding simplified yet physically interpretable structures and by requiring only modest calibration data (Arendt et al., 2018). They are more robust than black-box models when applied outside the training range, and they are substantially easier to set up than detailed white-box formulations (Afroz et al., 2018). For these reasons, grey-box formulations are widely recognized as the most suitable candidates for MPC and energy flexibility analysis in real-time applications (Harish & Kumar, 2016; Wang & Chen, 2019). Grey-box modeling is not an oversimplification but a careful abstraction that preserves only the dominant dynamics. Common simplifications include (1) linearization of heat transfer coefficients, (2) temporal discretization, and (3) spatial reduction through zoning (Athienitis & O’Brien, 2015). Essentially, the ideal grey-box model is the simplest possible formulation that captures the dominant thermal patterns in measured data (Bacher & Madsen, 2011).

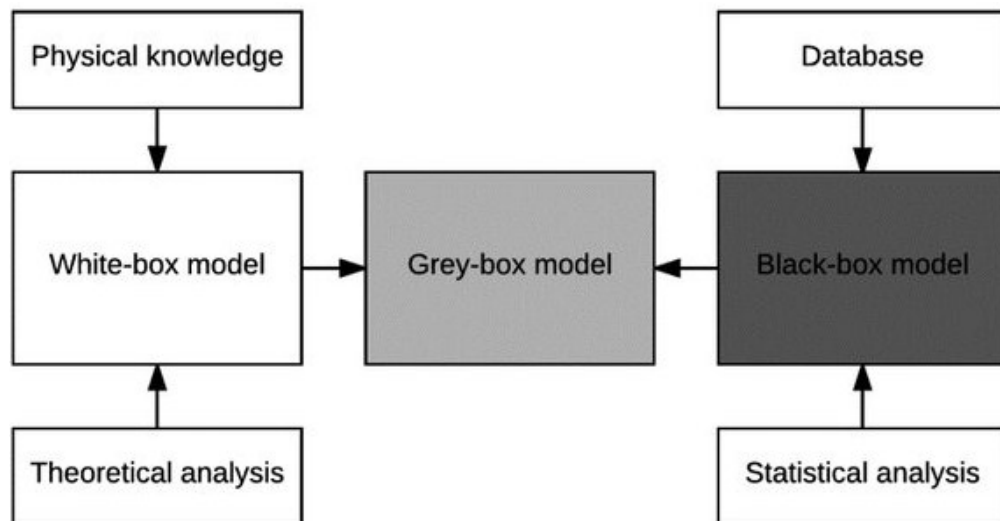


Figure 2.1 Conceptual categorization of principal modeling approaches (Duun-Henriksen et al., 2013).

Within building energy modeling, thermal RC networks have emerged as the standard representation of grey-box models. In such networks, heat transfer is modeled as exchanges between lumped thermal capacitances (nodes) connected by thermal resistances, driven by inputs that may be either controlled (e.g., HVAC operation) or uncontrolled (e.g., solar and internal gains). Determining the appropriate model structure—specifically, the number of capacitances (order) and the placement of resistances (paths)—is a critical step that directly affects the model’s structural identifiability (Agbi et al., 2012). Overly simple models risk failing to capture thermal inertia across multiple zones, whereas high-order models may become over-parameterized, leading to parameter redundancy, where multiple parameter sets yield equivalent system responses (Brastein et al., 2018).

Two main approaches exist for defining thermal RC networks structures. Heuristic approaches configure the structure of thermal RC networks to represent one or a limited number of zones, with the model order and dominant heat exchange paths determined either by established zoning archetypes such as 1R1C or 3R2C (Fonti et al., 2017; Harb et al., 2016; John et al., 2018; Žáčková et al., 2014) or by case-specific observations and expert judgment. As an example of the latter approach, Abtahi et al. (2021) compared two zoning strategies for residential buildings with smart thermostats: zoning by floor (6R3C), where each floor is treated as a separate thermal zone represented by a lumped capacitance, and zoning by orientation (7R3C), where north- and south-facing rooms are modeled as distinct zones to mitigate overheating in sun-exposed spaces during clear days with significant solar gains.

Automated approaches, in contrast, attempt to derive the most definitive structure through iteration and evaluation. Bacher and Madsen (2011) proposed a forward-selection procedure that incrementally compares increasingly complex structures to a baseline model, validated against experimental data. Prívarová et al. (2012) developed a two-stage framework, first identifying the most relevant inputs and then determining the optimal model order, tested with surrogate data from TRNSYS. Wang et al. (2019) introduced a pruning-based method that begins with a complex structure and iteratively removes parameters based on asymptotic confidence intervals, validated with data from a low-energy house. More recently, Leprince et al. (2022) presented a methodology for automatically selecting the best model structure from a predefined library, while Vallianos et al. (2022) demonstrated a multi-zone model generation method that dynamically adds or removes

parameters to derive accurate structures directly from smart thermostat data in experimental houses.

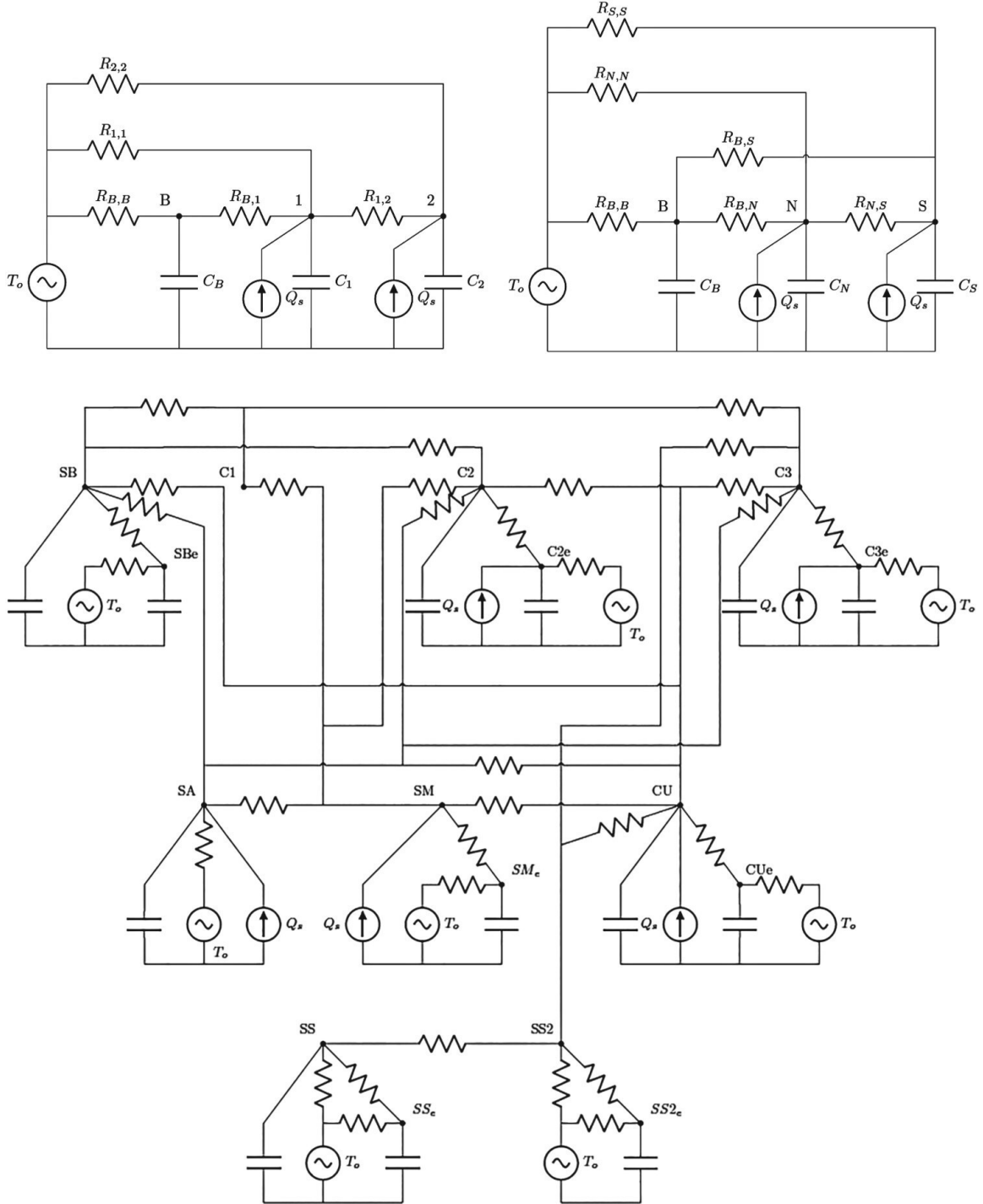


Figure 2.2 Heuristic (Abtahi et al., 2021) and automated (Vallianos et al., 2022) thermal RC network structures at different resolutions for capturing indoor air temperature dynamics in a two-story house with a basement: zoning by floor (6R3C, top left), zoning by orientation

(7R3C, top right), and automatically derived 13th-order multi-zone model (bottom). Nodes B, 1, and 2 represent the basement, first, and second floors, respectively; N and S denote north- and south-facing zones. Heating sources from electric baseboard heaters are omitted for clarity.

Building on these developments, Candanedo et al. (2022) defined control-oriented archetype models (CAMs) as low-order thermal RC networks that abstract the essential dynamics of common building or zone typologies. CAMs balance model fidelity with computational efficiency, providing sufficient accuracy for short-term supervisory control while remaining lightweight enough for real-time MPC implementation. Vallianos et al. (2023) compared heuristic low-order CAMs with automated multi-zone CAMs in an online economic MPC framework. Their findings indicated that heuristic CAMs, while faster to construct and calibrate, demand greater effort in data preprocessing and aggregation. In contrast, automated multi-zone CAMs enable direct calibration from raw thermostat data but introduce substantially higher computational burdens, particularly as the model timestep decreases.

Overall, building energy models—especially grey-box thermal RC networks—constitute the computational backbone of MPC in buildings. By combining physical interpretability with feasible calibration and manageable computational effort, they provide a practical foundation for operational energy flexibility. Crucially, the selection of model structure determines not only the accuracy of system representation but also the tractability of optimization, thereby shaping the effectiveness and scalability of building-to-grid service delivery.

## **2.4 Model-based Predictive Control for Grid Services**

MPC has emerged as a leading strategy for aligning building flexibility with grid service requirements. It solves a receding-horizon optimization problem that incorporates forecasts of system dynamics (states), uncontrolled inputs (disturbances), and operational constraints to generate an optimal control input trajectory (Drgoňa et al., 2020). Its ability to co-optimize multiple objectives—such as energy cost, occupant comfort, and service compliance—makes it particularly well-suited to the dynamic and multi-timescale nature of grid-interactive operation (Freund & Schmitz, 2021). Although early MPC studies primarily focused on minimizing operational costs, greenhouse gas (GHG) emissions, or maintaining thermal comfort—often

without explicit consideration of grid-level coordination—an expanding body of research now demonstrates its effectiveness in delivering reliable and quantifiable B2G services that directly support grid resilience and decarbonization. The remainder of this section reviews recent MPC frameworks that explicitly target service provision and grid responsiveness.

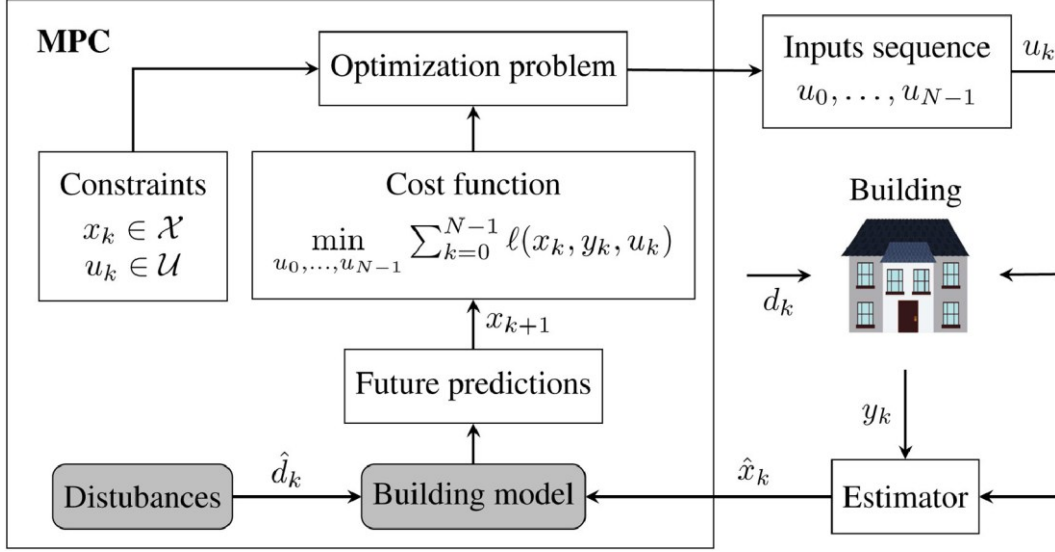


Figure 2.3 Schematic representation of the standard closed-loop system for building control with MPC and state estimator (Drgoňa et al., 2020).

MPC has shown considerable promise in demand-side response (DR) applications by leveraging the intrinsic inertia of building systems—specifically their thermal and electrical storage capacities—to modulate energy demand in a grid-responsive manner. By anticipating future system states, MPC can proactively shift loads without compromising occupant comfort, enabling buildings to absorb fluctuations in supply or cost through preconditioning strategies (Oliveira Panão et al., 2019; Johra et al., 2019). This capability is especially beneficial in thermally massive buildings or those equipped with thermal energy storage (TES), where the ability to plan the charging and discharging of thermal energy provides a powerful mechanism for shaping load profiles in response to expected tariffs or grid signals. In this context, MPC facilitates more effective DR participation, particularly for systems with slow dynamic responses such as space heating or large HVAC systems.

Furthermore, the growing electrification of heating and transportation—driven by the adoption of heat pumps and EVs—has amplified the need for building-level DR strategies that can relieve

pressure on local distribution networks (Padovani et al., 2021; Ravi & Aziz, 2022). MPC's predictive horizon and constraint-handling capabilities make it particularly well-suited for navigating this complexity. Beyond temporal load shifting, MPC has also been proposed for managing transactive interactions with the grid, in which energy consumption decisions are dynamically adjusted in response to pricing signals or market incentives (Denholm & Hand, 2011).

One of the most well-established applications of MPC in grid-interactive buildings is cost minimization through load shifting under Time-of-Use (ToU) electricity tariffs. MPC enables the optimal scheduling of flexible loads—such as HVAC systems, thermal energy storage, and batteries—to exploit periods of lower electricity prices and avoid peak pricing windows. Typical strategies include preheating or precooling spaces during off-peak hours or charging storage systems overnight for discharge during high-price periods. These predictive capabilities allow buildings to participate in demand response programs while maintaining occupant comfort and system constraints. For instance, Van Cutsem et al. (2019) demonstrated that an economic MPC controller designed under commercial ToU tariffs enabled effective load shifting without increasing overall energy use compared to a rule-based baseline. Zhou and Zheng (2020) implemented a data-driven hybrid MPC strategy in a high-rise office building and reported a 60% reduction in peak grid import—down from 500 kW—through optimal preconditioning and load adjustment. Similarly, Tarragona et al. (2020) showed that applying MPC to a residential heating system equipped with PV, a heat pump, and thermal storage yielded energy cost savings of up to 58% compared to conventional control. In another study, Cao et al. (2019) demonstrated how MPC-managed thermal energy storage in commercial buildings could simultaneously buffer temperature fluctuations and enable cost-effective participation in DR programs. Vallianos et al. (2023) further demonstrated the effectiveness of MPC for residential load shifting under Québec's dynamic ToU tariff using an experimental house equipped with smart thermostats. The controller successfully preheated the building before morning and evening peak periods, reducing electricity costs by up to 55% and high-price energy consumption by 71% compared to a reactive baseline. Together, these studies confirm MPC's role as a key enabling technology for tariff-responsive load shifting in flexible buildings.

Beyond tariff-based load shifting, MPC has demonstrated significant potential in orchestrating DERs such as PV generation, battery storage, EVs, and thermal energy storage to improve

renewable energy utilization and overall system efficiency. By forecasting generation profiles and dynamically coordinating flexible loads, MPC enables buildings to increase self-consumption of on-site renewable energy and reduce curtailment. Zhan et al. (2023), for example, implemented MPC in a net-zero energy office building and achieved a 19% improvement in PV self-consumption and a 10% gain in building self-sufficiency relative to baseline control. Kuboth et al. (2019) applied MPC to a residential energy system integrating PV, battery storage, a heat pump, and thermal storage, reporting an 11.6% reduction in annual operational costs. These savings were attributed to improved DER coordination, reduced auxiliary heating, and enhanced heat pump efficiency. Tarragona et al. (2020) similarly showed that MPC-based scheduling of a heat pump and TES under variable solar availability led to substantial energy cost savings while reducing excess PV export. In more complex multi-energy systems, MPC has also been shown to coordinate thermal and electrical storage synergistically. Song and Zhou (2023) demonstrated this approach by prioritizing surplus solar power for charging thermal storage, thereby reducing battery cycling. This strategy not only enhanced renewable electricity utilization but also extended battery lifespan and improved economic outcomes, with up to 19% cost savings reported in a solar-powered building microgrid. Such studies highlight MPC's unique ability to integrate forecasting, system constraints, and performance trade-offs, making it a powerful tool for DER coordination and renewable energy integration in grid-interactive buildings.

In addition to building-level demand flexibility, MPC has increasingly been applied to coordinate ancillary services and optimize the performance of building clusters in participation with electricity markets. These services include frequency regulation, ramping support, and cooperative bidding strategies that extend beyond individual energy cost reduction. Zhou et al. (2024) applied stochastic MPC to a microgrid comprising an office building with renewable generation and EV charging infrastructure. Their controller dynamically coordinated building loads and vehicle-to-building (V2B) interactions to mitigate renewable intermittency and provide frequency regulation services. Importantly, the study demonstrated that the optimal charging strategy varied depending on the control objective, thereby highlighting MPC's capacity to balance trade-offs among energy cost, emissions, and flexibility provision. At a larger scale, Tang and Wang (2022) proposed a multi-level MPC framework for non-residential building clusters aimed at market participation and fair profit allocation. Their approach quantified flexibility at the individual building level and implemented coordinated bidding strategies across the cluster using

cooperative game theory. The framework achieved up to 20.4% daily electricity cost reductions while ensuring equitable profit distribution among participants with heterogeneous flexibility profiles. Collectively, these studies emphasize the scalability of MPC not only for managing building-level flexibility but also for enabling coordinated control and market-based interaction at the community or campus level, thereby facilitating participation in ancillary service markets.

Despite its demonstrated potential for enabling grid-interactive and flexible building operation, the widespread deployment of MPC remains constrained by several technical, infrastructural, and operational challenges. First, integration with existing building systems is limited by the scarcity of commercially viable control hardware and software that are compatible with legacy infrastructure and standardized communication protocols (Afram & Janabi-Sharifi, 2014). Second, the development of accurate yet tractable control-oriented models continues to be a major bottleneck, as such models must balance prediction fidelity, computational feasibility, and interpretability—an effort that often consumes the majority of an MPC deployment project (Drgoňa et al., 2020). Third, the lack of automated workflows for controller configuration, calibration, and fault management complicates large-scale implementation and inhibits plug-and-play scalability. Finally, many MPC studies remain confined to idealized simulation environments, limiting their applicability and generalizability to real-world settings.

These challenges underscore the persistent gap between pilot demonstrations of MPC and its deployment at scale, namely the absence of a structured, interoperable, and machine-readable infrastructure capable of unifying heterogeneous data sources, enforcing standardized semantics, and supporting live data ingestion, continuous model adaptation, and real-time actuation across diverse building contexts. Operational semantic digital twinning—a paradigm explored in the following section—addresses this gap by embedding building systems within a semantic framework that establishes transparent linkages between physical assets, data streams, and control models. By enabling semantic interoperability, it reduces integration barriers with legacy infrastructure, while its support for automated reasoning and workflow generation facilitates scalable, resilient, and continuously adaptive MPC deployment.

## 2.5 Operational Semantic Digital Twinning

As buildings evolve into active participants in grid-interactive energy systems, their ability to respond to external signals and deliver demand-side services increasingly hinges on how effectively their internal systems are modeled, monitored, and coordinated. Traditional building automation architectures remain siloed and fragmented, lacking the interoperability, transparency, and automation required for intelligent service delivery at scale (Benfer & Müller, 2024). To overcome these limitations, operational semantic digital twinning has emerged as a paradigm that embeds ontological models directly into the live operation of building systems. In contrast to static semantic layers used primarily for offline documentation, operational SDTs actively support real-time functions such as data navigation, fault detection and diagnosis, multi-system integration, and closed-loop supervisory control. By establishing machine-readable representations of systems, their interdependencies, and associated control logic, semantic twins enable unified reasoning across heterogeneous data streams and automation layers.

One foundational strategy for semantic digital twinning involves inferring metadata directly from time-series data to bootstrap or augment ontological models such as Brick Schema. In legacy buildings where semantic labeling is absent, supervised and unsupervised learning methods have been employed to classify sensor types and generate semantic graphs from raw data. For example, Hong et al. (2015) applied a decision tree classifier to distinguish between temperature, humidity, and CO<sub>2</sub> sensors based solely on signal characteristics such as variance, periodicity, and autocorrelation. Building on this idea, Shi et al. (2019) evaluated clustering techniques and time-series features to infer point types in commercial buildings, demonstrating that unsupervised methods such as hierarchical clustering and Gaussian mixture models could effectively recover semantic attributes—including sensor function and system association—at scale. These approaches enabled the dynamic construction of semantic structures that capture relationships such as `hasPoint` or `feeds`, thus automating the onboarding of semantic twins in retrofit contexts (Benfer & Müller, 2024).

ASHRAE has played a central role in advancing interoperability in building automation through a complementary suite of standards. The ANSI/ASHRAE Standard 135 (BACnet) defines the communication protocols and object-oriented structures that remain the dominant basis for device

interoperability, now augmented by BACnet Secure Connect for encrypted exchanges (Fisher, 2020). To address the absence of standardized control logic, Guideline 36 formalizes high-performance sequences of operation for HVAC systems, and the emerging Standard 231P extends this effort by specifying a machine-readable Control Description Language (CDL) that enables control logic to be exchanged, simulated, and verified in digital form (Wetter et al., 2022). Complementing these, Standard 223P introduces a semantic framework for representing building systems and their data, harmonizing prior schemas such as Project Haystack and Brick to provide machine-interpretable metadata across domains. Collectively, these standards embody an orthogonalization of concerns—separating communication, control, and semantics—that establishes a layered foundation for scalable, interoperable, and plug-and-play building operation.

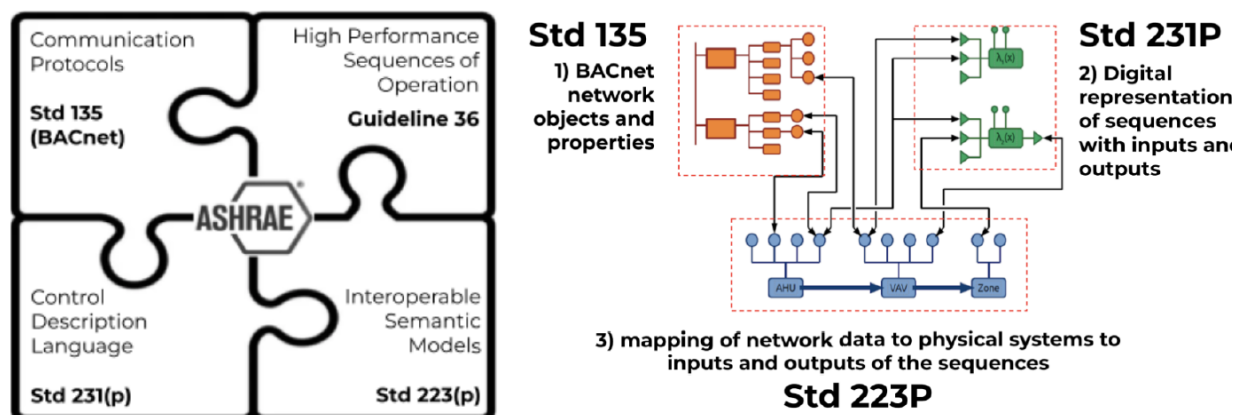


Figure 2.4 Synergistic ASHRAE standards and guidelines supporting the digitization of controls and analytics (left), and the integration of concepts across these standards (right) (Pritoni et al., 2024).

Building on these emerging standardization efforts, semantic frameworks such as the Brick Schema provide a robust foundation for real-time monitoring, data interpretation, and operational transparency. Instead of static or hardcoded mappings, these ontological models support dynamic navigation of building telemetry through structured, queryable representations. In a seminal deployment, Balaji et al. (2016) annotated sensor and actuator metadata across five university buildings using Brick Schema, facilitating real-time SPARQL Protocol and RDF Query Language (SPARQL; W3C, 2008) queries to extract data by type, location, and system affiliation. This approach significantly reduced the engineering overhead required to implement analytics across diverse building topologies. Building on this paradigm, Wang et al. (2018) proposed a semi-

automated approach to populate Brick models using pattern recognition and point metadata extraction. Their work emphasized the need for scalable point mapping methods to support large-scale commissioning and integration of building control systems. These contributions demonstrate that ontology-driven monitoring not only enhances transparency and interoperability but also accelerates analytics deployment, supports dynamic schema evolution, and enables semantic filtering—capabilities that are essential for grid-interactive building operation.

Advancements in semantic digital twinning have significantly transformed fault detection and diagnosis (FDD) in building operations by embedding reasoning mechanisms into the detection workflow. As reviewed by Hodavand et al. (2023), a growing body of research integrates ontological models into digital twins to enhance FDD scalability, interpretability, and automation. These approaches formalize system knowledge and operational rules, enabling fault identification not only through raw data anomalies but also by tracing causal and spatial relationships within the building context. Li et al. (2022) exemplify this direction by introducing a semantic model-based FDD framework that encodes prior expert knowledge in an ontology and activates reusable semantic rules over a dynamic knowledge graph. Their method detects control failures, sensor faults, and equipment malfunctions with high interpretability and adaptability, leveraging the evolving graph to automatically contextualize new data. Complementing this, Xie et al. (2023) developed a digital twin-based FDD process in which semantic representations of HVAC components are linked to rule-based and statistical detection routines. Their framework supports continuous system monitoring, fault propagation analysis, and cross-system inference, demonstrating the role of SDTs as active diagnostic agents rather than passive replicas. These FDD frameworks underscore the value of semantic digital twinning in enabling adaptive, transparent, and context-aware diagnostics—facilitating faster root-cause identification and enhancing flexibility across diverse environments (Benfer & Müller, 2024).

Beyond individual buildings, SDTs play a critical role in achieving interoperability across fragmented systems, platforms, and data representations. Vittori et al. (2023) introduced a BIM-to-Brick framework that leverages graph modeling to align spatial and IoT/BMS semantics, thereby enabling bidirectional interoperability between building information models and real-time operational data. Their approach enables seamless transitions between static building design data and dynamic telemetry, forming a unified knowledge base for downstream applications such as

control and diagnostics. Complementing this, Lork et al. (2019) developed an ontology-driven energy management framework that integrates IoT data streams and building automation signals within a modular semantic architecture. Their framework supports dynamic benchmarking, real-time inference, and context-aware control decisions—without the need for manual point mapping or vendor-specific customization. These studies demonstrate that semantic integration layers enable plug-and-play scalability, support multi-system coordination, and establish a foundation for distributed control and grid-interactive services.

While most applications of semantic digital twinning have focused on monitoring, diagnostics, and system integration, emerging research explores their direct integration into control processes. In these advanced cases, ontological models function not merely as metadata scaffolds but as active components within the control loop—supporting inference, reconfiguration, and scalable deployment of control strategies. Ramanathan and Mayer (2024) proposed a physics-infused digital twin architecture that leverages semantic reasoning and SPARQL queries to automate the deployment of reusable MPC templates to specific building systems. By aligning programmatic control logic with semantically defined equipment and spatial hierarchies, their framework inferred suitable control mappings for 34 air handling units across multiple sites. In parallel, Prakash et al. (2024) evaluated the adequacy of existing ontologies—such as Brick Schema, SAREF, and ASHRAE Standard 223P—in representing the semantic constructs needed to support MPC, highlighting critical gaps in control-specific descriptors and inferencing capabilities. Together, these studies signal the prospective integration of SDTs into supervisory control frameworks, thereby enhancing interpretability and scalability in grid-interactive building environments.

In sum, operational semantic digital twinning has evolved from a conceptual modeling paradigm into a practical foundation for real-time building intelligence. By embedding ontological reasoning across critical functions—including metadata inference, monitoring, fault diagnosis, semantic interoperability, and control—SDTs provide a unified infrastructure that fulfills the responsiveness and scalability required for effective interaction with the grid. However, despite this progress, integration into supervisory control frameworks remains at an early stage, and the potential to systematically orchestrate grid services at scale has not yet been realized. Building on

the preceding review, the next subsection highlights the critical research gaps and shows how the objectives in Chapter 1 are designed to address them systematically.

## 2.6 Research Gaps and Thesis Objectives

Delivering grid services at scale requires interoperable, machine-readable supervisory control frameworks that embed optimal and predictive algorithms. Yet widespread deployment remains constrained by persistent barriers—chief among them the fragmentation of building automation and energy management systems. Sensor data, control logic, and performance feedback are frequently dispersed across heterogeneous, vendor-specific platforms, producing vertically siloed architectures that obstruct interoperability and coordinated optimization. Integration with legacy infrastructure further amplifies these obstacles, as much existing hardware and software lack compatibility with standardized communication protocols. Taken together, these limitations curtail the scalability, adaptability, and reliability of supervisory control frameworks, impeding consistent delivery of grid services across diverse building typologies.

In response, semantic digital twinning has evolved beyond static design representations to provide structured, machine-readable models of building systems, their interdependencies, and associated operational control logic. By embedding ontological reasoning into live workflows, SDTs enable automated data integration, semantic interoperability, and dynamic alignment between control models and physical assets—establishing a unified digital substrate for scalable, predictive supervisory control. In parallel, MPC has demonstrated strong potential to align building flexibility with grid-service requirements, including tariff-responsive load shifting, DER coordination, and ancillary services. However, despite these complementary strengths, the integration of SDTs with supervisory MPC remains limited—especially in residential contexts—with most implementations emphasizing monitoring, diagnostics, and static integration rather than active, service-oriented control.

In view of this background, four interrelated research gaps can be distinguished from the literature, each directly addressed by the research objectives introduced in Chapter 1:

**Gap 1 — Fragmented understanding of operational SDTs for control integration:** Some studies in the literature demonstrate the promise of semantic interoperability for monitoring and

diagnostics, yet systematic evaluation of SDTs as enablers of supervisory control is largely absent. Few studies explicitly connect semantic models with predictive optimization frameworks, and those that do remain at an exploratory stage. Objective 1 addresses this gap by critically reviewing operational SDTs and MPC deployments, synthesizing findings on interoperability, control integration, and scalability, and establishing the rationale for combining SDTs with supervisory MPC.

**Gap 2 — Underdeveloped semantic formalization for control-oriented thermal RC modeling:** While grey-box thermal RC networks are widely recognized as practical models for MPC, no ontology currently exists to represent such archetypes within semantic frameworks to link devices, DERs, and thermal zones with local and supervisory control algorithms. As a result, control workflows remain reliant on ad hoc or simulation-based representations that lack interoperability, repeatability, and semantic transparency. Objective 2 addresses this gap through the development of RCOnt, which formalizes thermal RC network structures and validates their integration into SDTs for supervisory control.

**Gap 3 — Constrained SDT architectures for predictive supervisory control:** Ontologies such as Brick Schema, ASHRAE Standard 223P, and EFOnt capture distinct facets of building systems, yet no integrated architecture currently binds them into a cohesive semantic framework aligned with live telemetry and supervisory predictive control across system, zone, and building levels. This limitation prevents automated reasoning, query-driven assembly of control problems, and scalable deployment of MPC strategies. Objective 3 addresses this gap by designing a layered SDT framework that integrates multiple ontologies—including the newly developed RCOnt—into a unified, operationally bound architecture that directly supports declarative supervisory MPC.

**Gap 4 — Limited real-world validation of transferable SDT architectures supporting supervisory MPC in residential contexts:** While simulations and isolated demonstrations highlight the potential of MPC, only a limited number of studies have validated the transferability and scalability potential of semantic supervisory control under real operating conditions. This limitation reduces confidence in its practical deployment for grid service orchestration. Objective 4 addresses this gap by deploying the layered SDT in two grid-connected single-family houses equipped with rooftop PV, battery storage, and commercial smart home infrastructure, thereby

demonstrating portability across identical testbeds with minimal reconfiguration effort and validating replicability under real-world conditions.

The identified gaps reveal the absence of a cohesive framework that integrates semantic modeling, physics-based representations, and predictive supervisory control into practical, scalable applications. Addressing these gaps constitutes the central contribution of this thesis. The following chapter presents the methodological framework developed to implement the proposed objectives.

### 3. Methodology

#### 3.1 Introduction

Data exists along a semantic continuum, evolving from unstructured raw values to fully formalized ontological representations. In grid-interactive buildings, this continuum underpins interoperability, automated reasoning, and intelligent control within cyber-physical environments. At its foundational level lies raw data, which typically comprises protocol-level or API-derived numerical readings devoid of contextual meaning. For instance, a BACnet point reporting `AnalogInput = 21.0`, or an unlabeled payload containing a temperature value, provides no information regarding the device that produced the value, its physical location, or its operational role within the building system. Such data, while flexible in its raw form, remains semantically opaque and is only actionable when system designers or operators possess prior knowledge of its provenance and functional purpose.

To address the semantic insufficiencies of raw data, building automation platforms introduce structured abstractions known as hard-typed entities, which represent devices, sensors, and actuators with defined attributes and expected behaviour, categorizing each under specific domains and types. For example, a thermostat is represented as a `climate` entity with attributes such as `current_temperature` and `hvac_modes`. This structured representation ensures predictable behaviour and valid data formats, and facilitates local automation logic. However, despite these benefits, hard-typed entities remain platform-dependent constructs; they lack universal meaning beyond the originating platform’s context, impeding cross-platform interoperability and limiting their direct utility for semantic reasoning, knowledge integration, or control applications external to the native platform.

The highest degree of semantic formalization is achieved through the application of ontologies which provide shared vocabularies and formally define relationships among building concepts, equipment, spaces, zones, sensors, and actuators. Ontologies enable the construction of semantic knowledge graphs that support advanced functionalities, including SPARQL querying, SHACL validation, and automated reasoning across heterogeneous building systems. These knowledge graphs can be serialized in multiple formats—such as RDF/XML, JSON-LD, and Turtle—each offering distinct trade-offs in readability, interoperability, and computational efficiency. Among

these, Terse RDF Triple Language (Turtle; W3C, 2014) provides a compact, human-readable syntax that enables software agents to interpret, integrate, and query building data, as shown in the example below:

```
@prefix : <http://example.org/building#> .
@prefix brick: <https://brickschema.org/schema/1.1/Brick#> .
@prefix sh: <http://www.w3.org/ns/shacl#> .

#####
# RDF Graph Declaration
#####

# Defines Room_101 as an instance of brick:Room, with an associated
temperature sensor.

:Room_101 a brick:Room ;
    brick:hasPoint :TempSensor_101 .

# Defines TempSensor_101 as an instance of brick:Temperature_Sensor,
measuring Air Temperature,
# and located within Room_101.

:TempSensor_101 a brick:Temperature_Sensor ;
    brick:measures brick:Air_Temperature ;
    brick:isLocatedIn :Room_101 .

#####
# SHACL Shapes Declaration
#####

# Shape constraint for Room entities, requiring at least one hasPoint
property.

brick:RoomShape a sh:NodeShape ;
    sh:targetClass brick:Room ;
    sh:property [
        sh:path brick:hasPoint ;
        sh:minCount 1 ;
```

```

    ] .

# Shape constraint for Temperature Sensor entities, requiring that they
measure Air Temperature.

brick:TempSensorShape a sh:NodeShape ;
    sh:targetClass brick:Temperature_Sensor ;
    sh:property [
        sh:path brick:measures ;
        sh:hasValue brick:Air_Temperature ;
    ] .

#####
# Python SHACL Validation Script
#####

from rdflib import Graph
from pyshacl import validate

# Load data graph containing RDF triples for building entities.
data_graph = Graph()
data_graph.parse("example_building.ttl", format="turtle")

# Load shapes graph containing SHACL validation constraints.
shapes_graph = Graph()
shapes_graph.parse("example_shapes.ttl", format="turtle")

# Run SHACL validation to verify graph compliance with schema constraints.
results = validate(
    data_graph,
    shacl_graph=shapes_graph,
    inference='rdfs',
    debug=False
)

# Extract validation results.
conforms, results_graph, results_text = results

```

Figure 3.1 depicts an RDF knowledge graph in which `Room_101` is defined as a `brick:Room` with an associated `brick:Temperature_Sensor`. The sensor is linked to the room through the `brick:hasPoint` property, measures `brick:Air_Temperature`, and is explicitly located in the room via `brick:isLocatedIn`. SHACL shapes enforce schema compliance by requiring that rooms include at least one associated point and that temperature sensors measure air temperature, ensuring ontological validity prior to operational deployment.

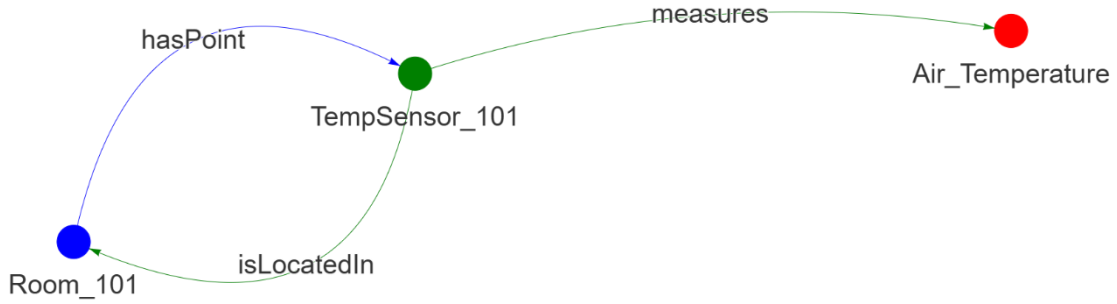


Figure 3.1 RDF semantic knowledge graph with SHACL validation constraints.

This abstraction supports diverse use cases, such as discovering unmonitored thermal zones, combining measurements from multiple sensors to estimate an effective zone temperature, aggregating several zones, and orchestrating B2G services at the zone or building level. Critically, the transition from raw data to ontological representations follows a bottom-up process: physical devices generate raw data, integration platforms abstract this data into hard-typed entities, and semantic mappings further elevate it into ontological classes, enabling system-wide interoperability, formal reasoning, and intelligent control. Building on this principle, the semantic digital twinning pipeline developed in this research transforms the raw and hard-typed data of grid-interactive buildings into semantically annotated, interoperable representations that support reasoning, control, and service delivery through the following consecutive steps:

1. **Data Acquisition:** The first step involves extracting a list of all building entities from the monitoring and control platform. This includes retrieving both raw protocol-level data and hard-typed entity abstractions such as climate devices, sensors, and actuators. The purpose is to create a complete inventory of building systems and data points, providing the necessary

inputs for subsequent semantic modeling. Comprehensive data acquisition is critical to avoid semantic gaps that could compromise reasoning and control processes.

2. **Semantic Modeling:** The second step maps building entities to multiple ontologies to create a layered, machine-interpretable representation of the building. The ontologies applied in this research include Brick Schema for structural and functional modeling, ASHRAE Standard 223P for standardized device-level metadata, EFOnt for flexibility annotations, and RCOnt (Abtahi, 2025) for thermal RC model representations. Brick Schema defines spaces, equipment, sensors, and their interrelationships, forming the structural backbone of the semantic model. ASHRAE Standard 223P complements this by aligning device types and properties with emerging interoperability standards. EFOnt introduces flexibility-relevant annotations, specifying the controllability, influence scope, and potential grid service roles of each entity. Finally, RCOnt, developed as part of this research and made publicly available, extends the semantic model to include thermal RC representations necessary for control-oriented applications. It defines classes such as RC models, thermal nodes (air and envelope), resistances, capacitances, and solar apertures, along with their structural and numerical properties. This enables a formal description of thermal dynamics within building zones, supporting MPC strategies. Additionally, entities are semantically linked to their associated time-series data streams using reference properties, enabling integration of static ontological representations with dynamic operational measurements. This binding synchronizes each entity's abstract class definition with its real-time telemetry, thereby supporting query-driven analytics, temporal reasoning, and closed-loop control applications. This layered semantic modeling approach enables each ontology to contribute within its domain of expertise, producing an integrated digital representation that facilitates scalable B2G service delivery.
3. **Graph Operationalization:** The final step entails creating the semantic knowledge graph by generating RDF triples for each mapped entity, capturing their classes, properties, and interrelationships as defined by the layered ontologies. This process involves serializing the semantic model into a structured graph format, where each node represents an entity or concept, and each edge encodes a relationship or property linkage. Once generated, the knowledge graph undergoes rigorous validation using SHACL to ensure that it conforms to the structural and semantic constraints imposed by the applied ontologies. Specifically, this

validation process checks for correct class usage, required property presence, domain and range consistency, and adherence to cardinality restrictions. It is a critical step to guarantee that the knowledge graph is logically coherent, thereby preventing errors that could propagate into downstream applications such as automated reasoning, control algorithms, or service orchestration queries. Following validation, the graph is ingested into a GDB, where it serves as the operational backend of the SDT, enabling formal querying with SPARQL, automated reasoning, and integration with service orchestration engines. A validated and operationalized knowledge graph thus forms the foundation for reliable SDT-driven operations within grid-interactive buildings.

Grid services are encoded as SPARQL query templates, executable against the operationalized semantic graph. This enables dynamic instantiation to identify available systems, retrieve flexibility attributes, generate appropriate control actions, and update the graph based on execution outcomes to maintain alignment with the building’s operational state. Furthermore, the SDT facilitates integration with advanced control strategies, enabling closed-loop operations optimized for cost savings, occupant comfort, and operational constraints. This ensures that control processes remain context-aware and aligned with building capabilities, occupant needs, and grid requirements. The following sections outline the methodological pipeline developed in this research to operationalize SDTs for delivering B2G services.

## **3.2 Data Acquisition**

Data acquisition is the foundational step in semantic digital twinning, creating a comprehensive inventory of building entities. It leverages programmatic querying of the monitoring and control platform, coupled with systematic categorization scripts, to retrieve and structure the current states of all registered entities into a machine-readable dataset. The resulting representation provides a reliable basis for ontology mapping and knowledge graph construction.

### **3.2.1 Entity Retrieval**

The retrieval procedure is implemented using RESTful API requests authenticated via secure tokens, to extract a machine-readable dataset that encapsulates each entity’s unique identifier, current state, and attribute metadata. The extracted dataset typically consists of heterogeneous data

points spanning multiple domains, including climate systems, sensors, actuators, binary switches, environmental measurements, and metadata services. For example, raw API responses include structured JSON objects containing fields such as `entity_id`, `state`, and `attributes` (e.g., temperature units, device class, friendly name, or supported features). Each entity’s data is timestamped to ensure traceability and temporal consistency for subsequent semantic modeling and control operations.

### **3.2.2 Entity Categorization and Structuring**

Following retrieval, a categorization process is applied to organize the entities into logical domain groups based on their functional and operational characteristics. This involves parsing each entity’s identifier to extract its domain prefix (e.g., “climate”, “sensor”, “switch”) and grouping entities accordingly. Such categorization is critical for facilitating efficient semantic mapping, as it pre-classifies entities into types aligned with ontology classes and reduces computational complexity in later annotation processes.

For instance, climate entities can be directly mapped to HVAC zone controllers, while sensor entities are linked to their corresponding measurement classes and properties within ontologies such as Brick Schema or ASHRAE Standard 223P. Moreover, the structuring process preserves key attribute metadata for each entity, including unit of measurement, device class, and operational parameters, ensuring no semantic information is lost during extraction. The categorized and structured dataset is then stored as a hierarchical JSON file, maintaining the domain-based grouping to enable seamless downstream integration with semantic modeling scripts and knowledge graph generation pipelines.

## **3.3 Semantic Modeling**

Semantic modeling transforms the structured and categorized building entity data into a formal digital representation that underpins reasoning, interoperability, and control. This process builds upon the acquired entity dataset to assign classes, properties, annotations, and time-series links that collectively define the SDT. The layered ontological annotation approach implemented in this research ensures modularity, extensibility, and conceptual clarity across the pipeline, culminating in a dynamic, operationally integrated knowledge graph.

### 3.3.1 Annotation Layer 1: Brick Schema

The first ontology applied is Brick Schema, which provides a structured vocabulary to model the physical and functional composition of buildings. In this research, Brick Schema is used to represent spaces (e.g., rooms, floors), equipment (e.g., thermostats, HVAC systems), and points (e.g., temperature sensors, power meters), alongside their interrelationships. For example, a thermostat entity is mapped as a `brick:Thermostat` class, linked via `brick:isLocatedIn` to its room, and connected to the temperature sensor it controls via `brick:hasPoint`.

This enables the construction of a topologically and functionally coherent building graph, supporting queries such as “Which thermostatically controlled zones lack CO<sub>2</sub> sensors?” or “List all temperature sensors on the second floor.” The use of Brick thus establishes the structural backbone of the SDT, ensuring consistency and machine-readability of building system definitions.

### 3.3.2 Annotation Layer 2: ASHRAE Standard 223P

Secondly, ASHRAE Standard 223P is integrated to enrich the semantic model with device-level metadata and interoperability classifications. While Brick Schema focuses on structural and relational definitions, ASHRAE Standard 223P standardizes device descriptions across platforms by defining classes, properties, and operational characteristics. In this research, each entity is mapped to its corresponding ASHRAE Standard 223P class to align its metadata with an emerging universal schema, facilitating data exchange across building management systems, grid services, and vendor-neutral platforms.

For instance, an electric heater mapped as a `brick:Heating_Equipment` is further assigned its ASHRAE Standard 223P equivalent class, such as `223P:ElectricResistanceHeater`, specifying attributes like power ratings, operational limits, and thermal output characteristics in a standardized format. This semantic augmentation ensures interoperability and enhances the SDT’s capability to integrate with external services, regulatory frameworks, and market platforms in future applications.

### 3.3.3 Annotation Layer 3: EFont

Thirdly, EFont is used to annotate entities with energy flexibility attributes that are critical for grid-interactive applications. It provides a standardized vocabulary for characterizing, quantifying, and operationalizing energy flexibility within grid-interactive efficient buildings. EFont extends prior semantic enrichment by defining key properties for each entity, including controllability, scope of influence, and relevance to grid service objectives.

These definitions support automated reasoning processes to identify flexibility assets for service activation. For example, a `brick:Heating_Equipment` entity mapped as a `223P:ElectricResistanceHeater` is annotated with `efont:hasControllabilityType` and `efont:hasInfluenceScope` to indicate its modulating or binary switching capability and its impact on thermal comfort, respectively. This enables queries such as: “Retrieve all devices capable of load shifting in thermal zones with occupancy constraints.”

### 3.3.4 Annotation Layer 4: RCont

Finally, RCont is introduced as the last ontological layer, representing an original contribution of this thesis. It extends the semantic model to formally describe thermal RC models for control-oriented applications. RCont defines `rcont:RCModel` as the root class representing a zone-level RC model, comprising thermal nodes (`rcont:Node`) such as `rcont:AirNode` for indoor air temperature and `rcont:EnvelopeNode` for envelope thermal mass. The classes `rcont:RValue` and `rcont:CValue` represent thermal resistance (K/W) and capacitance (J/K) components, respectively, enabling semantic encoding of heat transfer and storage parameters, while `rcont:SolarAperture` captures effective solar gain areas in square metres. If available, it may be further subdivided by orientation.

Modeling semantics are encoded through object properties. `rcont:modelsZone` links each RC model to its corresponding HVAC zone (referencing Brick classes), while `rcont:hasInput` and `rcont:hasState` associate models with external inputs (e.g., outdoor temperature) and measurable state variables (e.g., indoor temperature). Structural relationships are defined using properties such as `rcont:hasNode` to associate nodes with models, `rcont:hasResistance` and `rcont:hasCapacitance` to attach R and C components, and `rcont:hasSolarAperture` to

include solar gain effects. The `rcont:connects` property is used to specify node connectivity for each resistance, applied twice to indicate both ends of the thermal path. The `rcont:belongsToNode` property links capacitance and solar aperture components to the nodes they are physically associated with, anchoring these parameters within the thermal network structure.

Parameter values are captured through both datatype and object properties: `rcont:numericValue` stores the decimal magnitude of each resistance, capacitance, or solar aperture, while `rcont:unit` references the appropriate class from the Quantity, Unit, Dimension, and Type (QUDT) ontology to maintain unit consistency and ensure semantic integration with quantitative datasets. Finally, the annotation property `rcont:governingEquation` provides textual references to the governing thermodynamic equations underlying each RC model, facilitating documentation and linkage to control algorithm formulations such as MPC.

RCOnt enables the semantic representation of thermal dynamics for simulation and MPC, extending the SDT beyond static or device-centric models to incorporate physics-based operational representations essential for advanced control applications. The formal specification of RCOnt—including its classes, properties, and annotations—is provided in Appendix A.

### 3.3.5 Time-Series Binding

The final step in semantic modeling integrates each entity with its corresponding time-series data streams to operationalize the SDT for live telemetry and historical analytics. This is achieved by assigning reference properties, such as `ref:hasExternalReference`, to each semantic entity, creating explicit links to its measurement records in time-series databases (TSDBs) or monitoring system endpoints. Such integration binds each entity’s ontological classification to its dynamic operational profile, transforming the knowledge graph from a static representation into a continuously updated SDT capable of supporting temporally informed reasoning, predictive analytics, and real-time control tasks. For example, an indoor temperature sensor is annotated with a `ref:hasExternalReference` triple pointing to its associated TSDB containing timestamped temperature readings at defined intervals. This linkage allows queries to extract temperature trajectories filtered by semantic attributes (e.g., zone, equipment type) for advanced applications. Technically, such integration supports multiple downstream functionalities. For instance, in MPC,

the semantic pointer enables automatic retrieval of the latest state measurements as input to state estimation or optimization algorithms. In anomaly detection, SPARQL queries can extract historical temperature data linked to specific zones to identify deviations from learned baseline models. In flexibility assessment, semantic filtering combined with time-series analysis can identify controllable devices with sufficient load profiles and temporal flexibility characteristics to participate in demand-side services. Overall, the time-series data binding ensures that the SDT remains continuously synchronized with the building’s evolving operational state, enabling data-driven applications that combine semantic reasoning with quantitative temporal analysis for robust, context-aware grid-interactive control.

### **3.4 Graph Operationalization**

The final step of the semantic digital twinning pipeline involves constructing the knowledge graph, validating its structural and semantic correctness, and operationalizing it for downstream querying and control applications.

#### **3.4.1 Graph Generation**

Graph generation involves the transformation of the semantically annotated building dataset into an RDF-based knowledge graph. For each mapped entity, RDF triples are generated to encode its ontological class membership, attribute properties, and interrelationships with other entities. In this representation, entities are instantiated as graph nodes identified by globally unique URIs, while datatype and object properties are encoded as directed edges linking nodes or assigning literal values. The generated RDF model is serialized using the Turtle format due to its syntactic compactness, human readability, and compatibility with standard semantic web tools and GDB. This structured serialization ensures that each semantic statement is formally encoded, supporting subsequent parsing, validation, and graph traversal.

#### **3.4.2 Graph Validation**

Once generated, the knowledge graph undergoes rigorous validation using SHACL. It ensures compliance with the structural and semantic constraints imposed by the integrated ontologies. Specifically, SHACL validation performs (1) class verification, ensuring that each entity conforms to its declared ontology class definitions; (2) property requirement checks, confirming that all

mandatory relationships and data fields are instantiated as specified; (3) domain and range consistency validation, verifying that property links connect valid, ontology-defined classes; (4) cardinality restriction enforcement, ensuring that properties occur within allowed minimum and maximum counts. Such validation is critical to guarantee that the knowledge graph remains logically coherent, structurally sound, and semantically compliant. Ensuring this integrity prevents schema violations from propagating into downstream processes, which could otherwise compromise reasoning outputs, control algorithms, or service orchestration.

### **3.4.3 Graph Ingestion**

Following successful validation, the RDF graph is ingested into a GDB, which serves as the operational backend of the semantic digital twin. The GDB provisions a SPARQL endpoint, enabling external software agents to retrieve structured information in real time, traverse graph structures to interpret semantic relationships, and instantiate service activation templates. Ingestion does not alter the semantic content of the graph; rather, it makes the model accessible within a scalable infrastructure. As a backend, the GDB allows diverse stakeholders—such as aggregators, grid service platforms, and control engines—to execute queries for decision support and integrate building knowledge into their workflows without requiring direct access to raw data sources or local automation systems.

In summary, graph generation, validation, and operationalization transform the layered semantic model into an operational SDT ready for deployment, integrating structural definitions, standardized device metadata, energy flexibility annotations, thermal dynamic models, and live telemetry links into a unified representation. The validated and operationalized graph thus forms a reliable semantic backbone to support flexibility orchestration. However, while the SDT provides a formalized and queryable representation of the building, delivering B2G services requires a scalable and general control framework capable of computing near-optimal future actions. The following section focuses on the formulation of a model-based predictive controller designed to enable such service delivery.

### 3.5 MPC Formulation for B2G Services

To coordinate heterogeneous subsystems for B2G service delivery, the supervisory control framework in grid-interactive buildings must capture the dual nature of energy flexibility—(1) external service provision and (2) maintenance of internal operational requirements—to achieve an optimal balance between these two objectives. The fundamental mechanism enabling such services is the modulation of the building’s net electrical exchange with the grid. This modulation is realized through control actions such as HVAC setpoint adjustments, battery dispatch, and DER curtailments, which collectively shape the building’s net exchange profile over time.

B2G services differ substantially in their temporal resolutions and operational objectives. For instance, load shifting reshapes demand profiles over several hours or an entire day to reduce energy costs or peak demand, whereas frequency regulation operates at sub-minute timescales, requiring rapid bidirectional power adjustments to stabilize grid frequency. To systematically coordinate these services within grid-interactive building operations, the supervisory control framework—here implemented as MPC—must jointly optimize external service delivery and internal performance, subject to system dynamics and operational constraints. While the temporal and operational characteristics of each B2G service define its specific formulation, the control variables consistently remain the building’s internal actuators that influence net electrical exchange. Consequently, a general service-oriented MPC formulation can accommodate diverse B2G applications by defining appropriate objectives, prediction horizons, and constraints, while accounting for key differences in (1) service initiation timing and duration, (2) required modulation rate, and (3) target-tracking precision.

A general MPC formulation comprises two primary sets of objective terms. The first corresponds to service-oriented KPIs, which quantify how effectively a building supports external service objectives, such as tracking a target power profile or following a price signal. The second corresponds to internal requirement KPIs, which penalize deviations in internal states and outputs—such as battery state of charge (SoC), equipment thermal conditions, and indoor comfort variables (temperature, CO<sub>2</sub> lighting)—from their reference trajectories. Internal requirements that can tolerate temporary deviations are incorporated as soft constraints, allowing limited violations

when beneficial for service delivery, while hard constraints are reserved for safety-critical limits, such as actuator bounds or system capacities.

Equation 3.1 presents the general service-oriented MPC formulation developed in this study, with each symbol and term defined in Table 3.1. A corresponding SPARQL query and the full MPC implementation code are provided in Appendix B to demonstrate how semantic information retrieved from the SDT is used to automatically generate and execute the MPC formulation. Through this integration, ontological representations—such as zones, equipment classes, and entity relationships—are dynamically linked with their associated data and parameters, allowing the MPC problem to be instantiated automatically for different buildings and service contexts. This semantic linkage ensures that the formulation remains generalizable, scalable, and adaptable across diverse B2G applications, thereby facilitating coordinated service delivery between orchestrators and grid-interactive buildings while maintaining internal operational feasibility.

$$U^* = \arg \min_U \sum_{k=0}^{PH-1} [\omega_s^k \phi_s(y^k, y_{srv}^k) + \omega_i^k \phi_i(x^k, x_{ref}^k, y^k, y_{ref}^k)] \quad 3.1$$

subject to:

$$x^{k+1} = f(x^k, u^k, d^k),$$

$$y^k = g(x^k, u^k, d^k),$$

$$u^k \in \mathcal{U}, x^k \in \mathcal{X}, y^k \in \mathcal{Y}.$$

| Table 3.1 Description of symbols and terms in the general MPC formulation. |                                                                                                                                                    |
|----------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------|
| Symbol / Term                                                              | Description                                                                                                                                        |
| $U^*$                                                                      | The optimal control input sequence representing the set of future actions computed to minimize the objective function over the prediction horizon. |
| $PH$                                                                       | The prediction horizon, defined as the total number of discrete time steps considered in the optimization problem.                                 |
| $\omega_s^k$                                                               | The weighting factor applied at each time step $k$ to prioritize the contribution of the service-oriented objective in the optimization.           |
| $\phi_s(y^k, y_{srv}^k)$                                                   | The B2G service effectiveness KPI that quantifies how well the predicted output $y^k$ follows the service target $y_{srv}^k$ .                     |
| $\omega_i^k$                                                               | The weighting factor applied at each time step $k$ to prioritize the contribution of internal requirements in the objective function.              |

| Table 3.1 Description of symbols and terms in the general MPC formulation. |                                                                                                                                                                                            |
|----------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Symbol / Term                                                              | Description                                                                                                                                                                                |
| $\phi_i(x^k, x_{ref}^k, y^k, y_{ref}^k)$                                   | The internal requirements KPI that penalizes deviations of states and outputs from their reference trajectories to ensure operational feasibility, equipment safety, and occupant comfort. |
| $x^k$                                                                      | The system state vector at time step $k$ , representing internal states such as thermal conditions or battery state of charge.                                                             |
| $u^k$                                                                      | The control input vector at time step $k$ , representing the decision variables applied to the system, such as HVAC setpoints or battery dispatch commands.                                |
| $u^k$                                                                      | The disturbance vector at time step $k$ , capturing exogenous inputs that affect system dynamics, such as weather conditions or occupancy.                                                 |
| $y^k$                                                                      | The output vector at time step $k$ , representing measured or estimated outputs such as indoor air temperature or net electrical exchange.                                                 |
| $x^{k+1} = f(x^k, u^k, d^k)$                                               | The state update equation defining how system states evolve over time based on current states, control inputs, and disturbances.                                                           |
| $y^k = g(x^k, u^k, d^k)$                                                   | The output equation that maps system states, control inputs, and disturbances to measurable outputs.                                                                                       |
| $\mathcal{U}$                                                              | The set of admissible control input values defining operational constraints for inputs.                                                                                                    |
| $\mathcal{X}$                                                              | The set of admissible state values defining feasible and safe operating ranges for system states.                                                                                          |
| $\mathcal{Y}$                                                              | The set of admissible output values defining acceptable ranges to maintain comfort and operational standards.                                                                              |

This general MPC structure is subsequently applied in Chapter 4 to implement two distinct B2G services: tariff-responsive load shifting and post-outage CLPU mitigation.

### 3.6 Conclusions

This chapter presented the methodological framework developed to enable operational semantic digital twinning and service-oriented MPC formulation for grid-interactive buildings. The proposed pipeline integrates systematic data acquisition, multi-layered semantic modeling, RDF graph generation, validation, and ingestion into a unified SDT that supports advanced supervisory control and query-driven B2G services. The general MPC formulation, underpinned by semantic integration and automated entity retrieval, establishes a scalable optimization

framework that jointly balances external service objectives with internal operational requirements. This approach ensures effective B2G service delivery while preserving occupant comfort, equipment safety, and operational feasibility across diverse building contexts. The next chapter applies this methodology in a case study to demonstrate its practical implementation, performance, and potential to enhance real-world grid-interactive building operation.

## 4. Case Study: Application to Two Unoccupied Research Houses

### 4.1 Introduction

Québec is Canada’s largest province by land area, spanning over 1.5 million square kilometers, with a population projected to exceed 9.1 million by the end of 2025 (Institut de la statistique du Québec, 2024). According to the updated Köppen-Geiger climate classification (Peel et al., 2007), Québec features three distinct climate regions, summarized in Table 4.1.

Table 4.1 Québec’s climate regions and characteristics based on the updated Köppen-Geiger climate classification (Peel et al., 2007).

| Regions                           | Latitude      | Characteristics   | Summers                            | Winters                                         |
|-----------------------------------|---------------|-------------------|------------------------------------|-------------------------------------------------|
| Southern and south-western Québec | 45 °N - 51 °N | Humid continental | warm to occasionally hot and humid | cold and snowy                                  |
| Central Québec                    | 51 °N - 58 °N | Subarctic         | short and warm                     | long, very cold and snowy                       |
| Northern Québec                   | 58 °N ≤       | Arctic            | very short and cool                | very long, extremely cold and covered with snow |

More than 80% of the province’s population resides within a corridor approximately 300 km long and 100 km wide, extending from Greater Montréal—the province’s most populous metropolitan area—to Québec City, the provincial capital, both of which experience a humid continental climate (Institut de la statistique du Québec, 2024). The remaining population lives in scattered communities under subarctic and arctic climates, engaging primarily in activities such as forestry, fishing, and mining (Britannica, n.d.). Figure 4.1 illustrates Québec’s territorial extent, major cities, and administrative boundaries (Natural Resources Canada, 2024).

Characterizing representative weather patterns alongside the grid’s load composition is essential for assessing the range and temporal characteristics of B2G services required to maintain grid stability and enhance long-term energy resilience. Identifying typical climatic conditions enables a systematic understanding of how temperature and solar variability influence building demand, distributed generation, and grid stress events. Such characterization also supports the

design and optimal operation of control strategies by reducing problem dimensionality and thereby narrowing the decision space.



Figure 4.1 Map of Québec showing provincial territory, administrative boundaries, and major urban centers (Natural Resources Canada, 2024).

To characterize typical weather conditions in the province’s most populated corridor, the Hartigan-Wong K-means clustering algorithm (Hartigan & Wong, 1979) is applied to historical weather data collected in Trois-Rivières—located near the geographic centre of the corridor—spanning the period from November 2015 to November 2023. This classification process identifies distinct daily profiles of ambient air temperature and solar radiation for typical cold and very cold

days in southern and south-western Québec. The historical weather dataset is obtained from the Simulation Énergétique des Bâtiments (SIMEB) database (SIMEB, 2023), which provides hourly measurements of ambient air temperature and global horizontal irradiance (GHI) from multiple weather stations across Québec. For use in this study, hourly values are interpolated to 15-minute intervals using linear interpolation for temperature and backward filling for irradiance. The clustering results are presented in Figure 4.2. The top-left panel shows the classification of daily ambient air temperature profiles into distinct clusters, with the subsequent panels illustrating their monthly distributions. The bottom row provides analogous results for GHI.

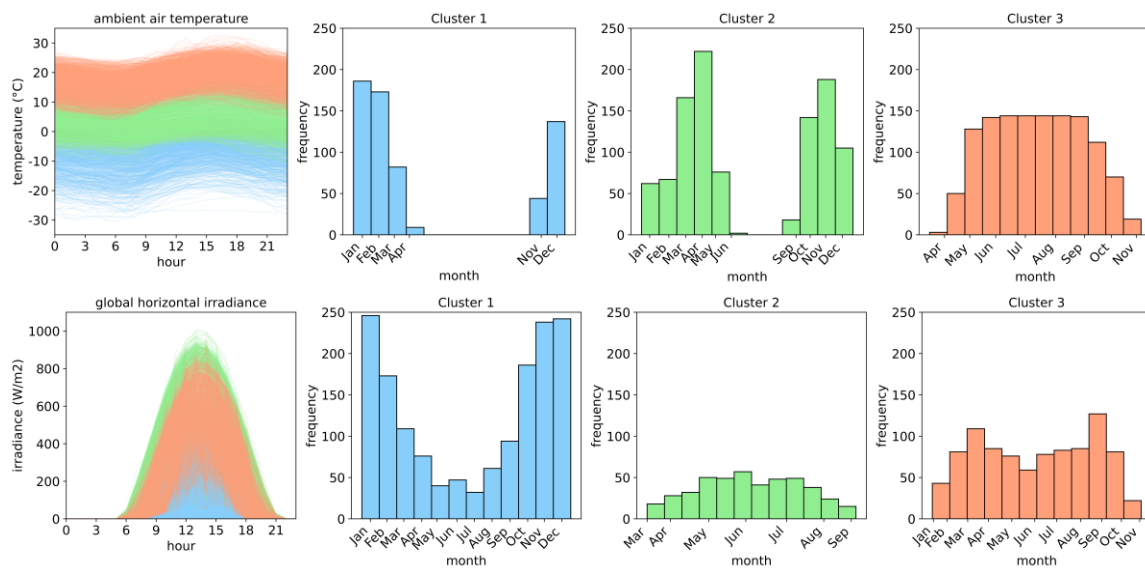


Figure 4.2 K-means clustering of historical weather data for Trois-Rivières (2015–2023)

In Québec, nearly two-thirds of households rely on electric baseboard heaters (58%) or electric radiant heating (7%) as their primary heating systems (Statistics Canada, 2023). This heavy dependence on electricity for space heating renders the grid particularly vulnerable during the heating season. Extreme winter days are consistently marked by sharp morning and evening heating peaks, widespread simultaneous activation of electric heating systems, and reduced solar irradiance due to cloud cover or snow accumulation. These conditions impose significant stress on the electrical grid, particularly during weekday hours preceding and following typical work schedules (Whitmore & Pineau, 2023).

To manage peak demand, Hydro-Québec has implemented a DR program that combines a static ToU tariff—Rate Flex D—with a smart home advisory service, Hilo (Pelletier & Faruqui, 2022). Under this program, customers pay a fixed access fee of 44.810 ¢/day year-round, with seasonal energy pricing. From April to November, the first 40 kWh consumed each day are billed at 6.704 ¢/kWh, with any excess charged at 10.342 ¢/kWh. During the winter period (December to March), these rates drop to 4.719 ¢/kWh and 8.116 ¢/kWh, respectively—except during designated peak demand events, when the rate increases sharply to 55.132 ¢/kWh. These events typically occur on weekday mornings (6:00–9:00) and evenings (16:00–20:00), with approximately 25–35 activations per winter season (Hydro-Québec, n.d.). This pricing structure is designed to incentivize load shifting, thereby reducing peak demand and alleviating stress on the grid.

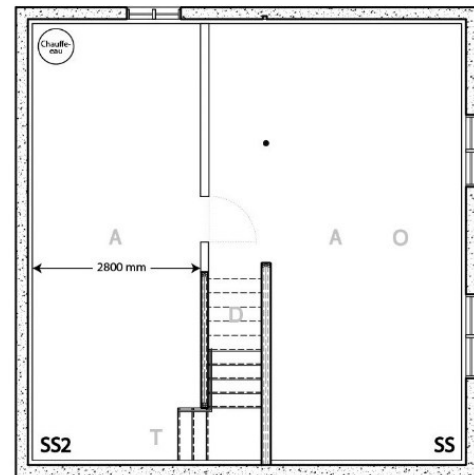
However, Québec’s heavy reliance on electric heating also introduces critical challenges for grid resilience, particularly during extreme weather events such as ice storms. These events have historically caused extensive damage to power infrastructure and led to prolonged outages. For example, the 1998 ice storm resulted in approximately \$6 billion in damages, left millions without electricity, and required Hydro-Québec to replace over 110,000 components, including transmission towers and distribution poles (Hydro-Québec, 2018; National Weather Service, 2008). In the aftermath of such disruptions, cold load pickup (CLPU) poses a significant operational risk.

CLPU refers to the significant surge in demand as large numbers of consumers simultaneously restart electric devices after an outage or a reduced demand period (e.g., nighttime), producing electrical currents that substantially exceed normal operating levels (Hachmann et al., 2022; McDonald & Bruning, 1979). This phenomenon can overwhelm distribution infrastructure, induce voltage drops, and trigger protective load shedding, thereby risking cascading failures and widespread blackouts. Given the vital importance of electric heating for occupant safety during sub-zero temperatures, the accurate estimation and proactive mitigation of CLPU are essential for preserving grid stability, enabling timely service restoration, and minimizing socio-economic losses. CLPU mitigation is crucial to enhancing both operational reliability and long-term resilience within Québec’s evolving energy landscape.

Against this backdrop, Québec presents a particularly relevant context for investigating how semantic digital twinning can support and scale the integration of control strategies and distributed energy systems for the delivery of grid services. To this end, the present study employs an unoccupied residential testbed equipped with embedded sensors, controllable subsystems, and a robust IoT-based infrastructure—with a specific focus on electric space heating as the primary source of flexibility—for real-time monitoring and actuation. This environment provides a controlled platform for experimenting with scalable energy management solutions tailored to the province’s climate, grid structure, and load composition.

## 4.2 Experimental House for Building Energetics

The Experimental House for Building Energetics (EHBE) is an unoccupied, two-storey residential testbed, owned by Hydro-Québec in Shawinigan, Québec, and relying solely on electricity as its energy carrier. It represents a typical Québec home constructed post-1980 and has a footprint of 60 m<sup>2</sup>. The first floor comprises a living room, kitchen, dining area, and powder room, while the second floor includes three bedrooms and a bathroom. The house also features an excavated basement and an attached garage. Each room is equipped with a smart thermostat-controlled electric baseboard heater. The building is additionally outfitted with a 5-kW rooftop PV array and a 5-kW/10-kWh lithium-ion battery, forming a grid-connected residential energy system.



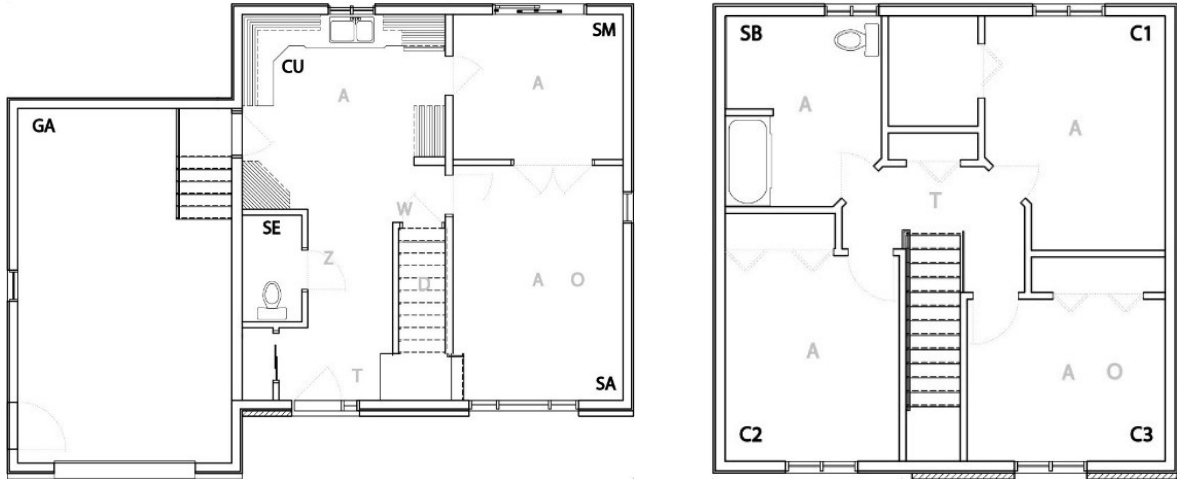


Figure 4.3 Photo of one of the two experimental houses equipped with rooftop PV (top left) and corresponding floor plans showing the basement (top right), first floor (bottom left), and second floor (bottom right).

Figure 4.3 illustrates the physical layout of the house, and Table 4.2 provides a summary of the heating zones along with their respective baseboard capacities.

| Abbreviation | Room        | Location     | Installed heating capacity (kW) |
|--------------|-------------|--------------|---------------------------------|
| SS           | Basement 1  | Basement     | 2                               |
| SS2          | Basement 2  | Basement     | 2                               |
| CU           | Kitchen     | First Floor  | 1.5                             |
| SM           | Dining Room | First Floor  | 1.25                            |
| SA           | Living Room | First Floor  | 1.5                             |
| SE           | Bathroom 1  | First Floor  | -                               |
| C1           | Bedroom 1   | Second Floor | 1.25                            |
| C2           | Bedroom 2   | Second Floor | 1.25                            |
| C3           | Bedroom 3   | Second Floor | 1.25                            |
| SB           | Bathroom 2  | Second Floor | 1                               |
| Total        | -           | -            | 13                              |

Real-time synchronization between the physical environment and its digital representation is achieved through continuous telemetry from heterogeneous devices across the building's IoT network. To operationalize this synchronization, the EHBE employs a robust infrastructure that supports seamless data acquisition, storage, and control. Measurements are recorded at a 1-minute

resolution—with no known sensor or communication uncertainty—and include indoor air temperature, thermostat setpoints, electric heating input, on-site solar generation, and battery charge/discharge power.

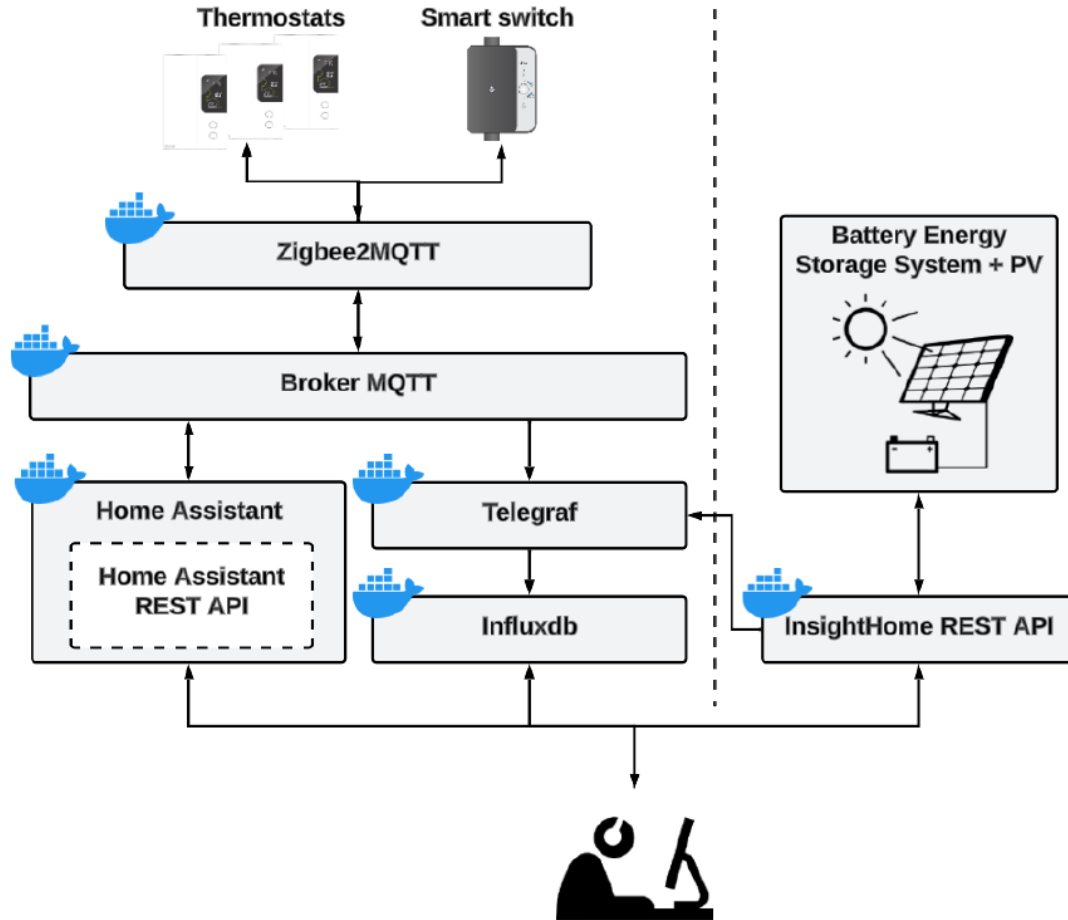


Figure 4.4 EHBE IoT network architecture: the integration of Zigbee-enabled thermostats and switches via Zigbee2MQTT, centralized data aggregation through an MQTT broker, and time-series storage in InfluxDB.

A Raspberry Pi 4 functions as the local edge device, coordinating data acquisition across the EHBE’s IoT network. Communication with smart thermostats and switches is facilitated through Zigbee2MQTT, which bridges Zigbee-enabled devices to an MQTT broker for reliable message handling and synchronization. The resulting data streams are parsed by a Telegraf agent and stored in an InfluxDB instance—owned and maintained by Hydro-Québec—to support real-time querying and long-term retention. Monitoring and control are facilitated through two RESTful APIs: the Home Assistant API, which coordinates thermostat communication, heating control, and

general device orchestration within the local network; and the InsightHome API, which enables access to telemetry and dispatch controls for the PV-battery system (Abtahi et al., 2025). Figure 4.4 depicts the software architecture and data flow within the local IoT network, while Figure 4.5 illustrates the PV-battery system configuration, managed by Schneider Electric’s XW Pro platform.

## DC-Coupling System with Single Inverter

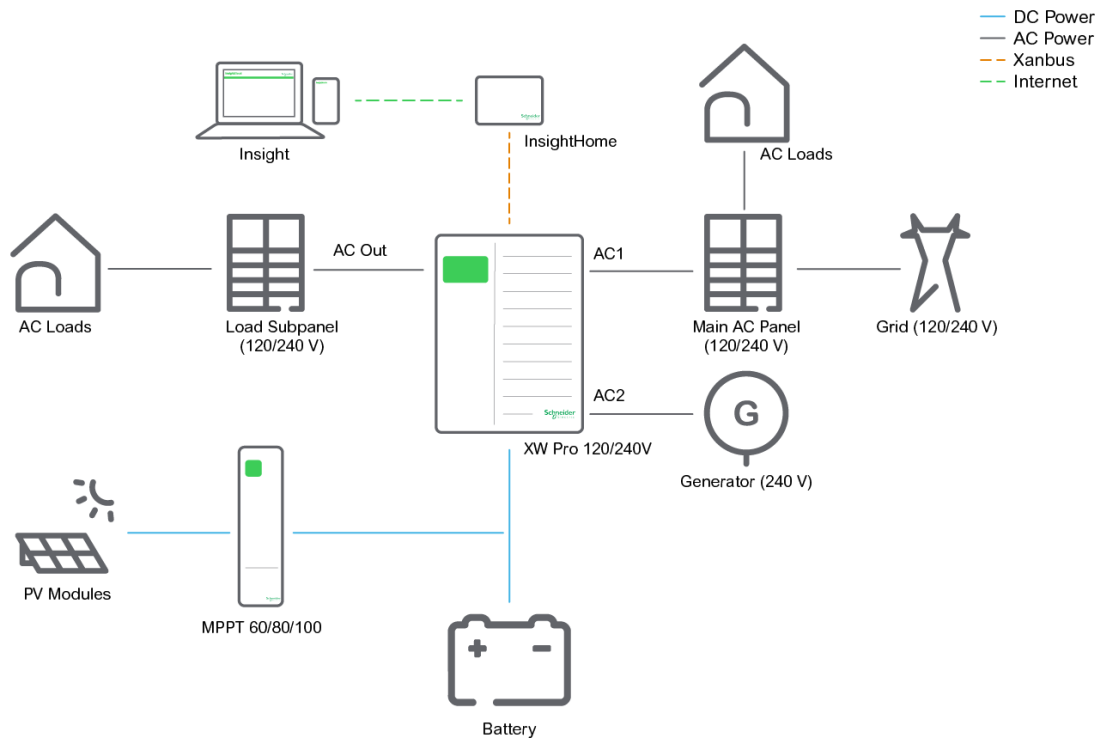


Figure 4.5 EHBE PV-battery system configuration: the DC-coupled configuration with a single inverter (XW Pro 120/240V), maximum power point tracking (MPPT) charger, and integration with the main panel, load subpanel, grid, and optional generator.

Beyond its typical construction, the EHBE provides a controlled environment for testing real-time control strategies and system integration. Its high-resolution sensing infrastructure, interoperable APIs, and DERs enable semantic digital twinning and support experimentation with scalable grid services for cold-climate residential contexts.

### 4.3 Control-Oriented Models for Indoor Thermal and Battery SoC Dynamics

This section presents the archetype models used to enable model-based predictive control within the semantic digital twinning framework. These models form the core of the control-oriented abstraction implemented at the EHBE and are specifically tailored to support real-time decision-making. They capture the dominant dynamics of indoor air temperature and battery energy storage, enabling effective optimization under varying environmental and operational conditions.

To predict indoor air temperature in the building, an archetype grey-box model was developed using a heuristic zoning-by-floor approach, in which each floor is treated as a distinct thermal zone comprising two lumped capacitances: one representing the short-term thermal inertia of indoor air and the other capturing the long-term inertia of the building envelope (Abtahi et al., 2024). This configuration—illustrated in Figure 4.6 and detailed in Table 4.3—is informed by prior findings showing that aggregating these capacitances tends to underestimate the thermal lag between air and envelope responses, particularly under free-floating conditions (Vallianos et al., 2023).

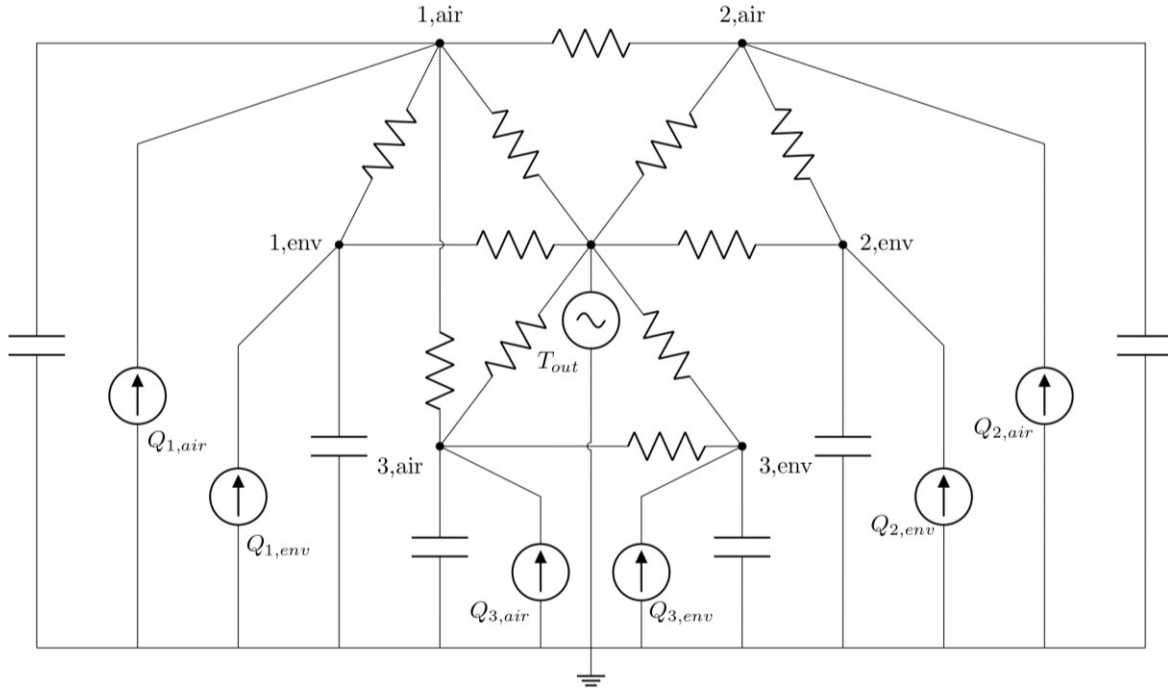


Figure 4.6 Archetype grey-box model developed for EHBE: 11R6C network with zoning-by-floor heuristic.

Table 4.3 Archetype grey-box model developed for EHBE: node descriptions, interconnections, and associated heat sources.

| Node (n) | Description                      | Adjacent nodes (m)  | Heat sources                  |
|----------|----------------------------------|---------------------|-------------------------------|
| 1,air    | 1st-floor indoor air             | 1,env and 2,air.    | Electric heating, Solar gains |
| 2,air    | 2nd-floor indoor air             | 2,env and 1,air     | Electric heating, Solar gains |
| 3,air    | Basement indoor air              | 3,env and 1,air     | Electric heating, Solar gains |
| 1,env    | 1st-floor effective thermal mass | 1,air               | Solar gains                   |
| 2,env    | 2nd-floor effective thermal mass | 2,air               | Solar gains                   |
| 3,env    | Basement effective thermal mass  | 3,air               | Solar gains                   |
| Tout     | Ambient air temperature          | All the other nodes | -                             |

Model parameters are identified by minimizing the multi-step-ahead prediction error, as defined in Equation 4.1. At each time-step  $k$ , the model forecasts indoor temperatures over the PH, using its own prior predictions to simulate subsequent steps—that is, the predicted value at  $k+1$  is used to compute the prediction for  $k+2$ , and so on. In this formulation,  $T^{(k+j)}$  denotes the measured indoor air temperature, and  $\hat{T}^{(k+j|k)}$  is the predicted temperature based on available information up to the current time-step. This formulation estimates the indoor thermal response based on key physical parameters, i.e., thermal capacitances, thermal resistances, and node-specific inputs including controlled electric heating, and uncontrolled solar gains filtered through effective solar apertures. A complete description of the variables and parameters in Equation 4.1 is provided in Table 4.4.

$$\theta^* = \arg \min_{\theta=\{R_{n,m}, C_n, \alpha_n\}} \left\| \sum_{k=0}^{N-PH-1} \sum_{j=0}^{PH} (T^{(k+j)} - \hat{T}^{(k+j|k)}(\theta)) \right\|_2 \quad 4.1$$

subject to:

$$\begin{aligned} \hat{T}_n^{(k+j|k)}(\theta) &= \hat{T}_n^{(k+j-1|k)}(\theta) + \sum_{m \neq T_{out}} \frac{\delta t}{R_{n,m} C_n} \left( \hat{T}_m^{(k+j-1|k)}(\theta) - \right. \\ &\quad \left. \hat{T}_n^{(k+j-1|k)}(\theta) \right) + \frac{\delta t}{R_{n,out} C_n} \left( T_{out}^{(k+j-1)} - \hat{T}_n^{(k+j-1|k)}(\theta) \right) + \\ &\quad \frac{\delta t}{C_n \eta_{e,n}} P_{heat,n}^{(k+j-1)} + \frac{\alpha_n \delta t}{C_n} G_n^{(k+j-1)}, \\ \underline{\theta} &< \theta^* < \bar{\theta}, \end{aligned}$$

$$\delta t \leq \min \left( \frac{C_n}{\sum m_{R_{n,m}}} \right).$$

| Table 4.4 Description of symbols and terms in the thermal RC model formulation. |                                                                                                               |
|---------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------|
| Symbol / Term                                                                   | Description                                                                                                   |
| $T^{(k+j)}$                                                                     | Measured indoor air temperature at future time step $k + j$ .                                                 |
| $\theta$                                                                        | Parameter set including thermal resistances $R_{n,m}$ , capacitances $C_n$ , and solar apertures $\alpha_n$ . |
| $C_n$                                                                           | Thermal capacitance of node $n$ (J/°C).                                                                       |
| $R_{n,m}$                                                                       | Thermal resistance between node $n$ and adjacent node $m$ (°C/W).                                             |
| $\delta t$                                                                      | Discretization timestep (s).                                                                                  |
| $G_n$                                                                           | Effective solar irradiance incident on node $n$ (W/m <sup>2</sup> ).                                          |
| $\alpha_n$                                                                      | Effective solar aperture of node $n$ (m <sup>2</sup> ).                                                       |
| $\eta_{e,n}$                                                                    | Efficiency of electric heating at node $n$ (assumed to be 1).                                                 |
| $P_{heat,n}$                                                                    | Electric heating power input at node $n$ (W).                                                                 |
| $T_{out}$                                                                       | Ambient air temperature (°C).                                                                                 |
| $\theta^*$                                                                      | Validated parameter set minimizing prediction error.                                                          |
| $\underline{\theta}, \bar{\theta}$                                              | Lower and upper bounds for the estimated parameters.                                                          |

A control-oriented model of battery dynamics is essential for forecasting and managing SoC in real time, enabling effective coordination with PV generation (when available) and electric heating demands under varying system integration levels and dynamic operating conditions. The evolution of the battery SoC is governed by the discrete-time formulation shown in Equation 4.2. This model assumes ideal coulombic efficiency and neglects degradation and thermal effects for simplicity, which is appropriate for short-term predictive control. The resulting SoC trajectory is used both to enforce operational constraints and to optimize dispatch as part of the economic MPC formulation. A complete description of the variables and parameters in Equation 4.2 is provided in Table 4.5.

$$SoC^{(k+1)} = SoC^{(k)} + \frac{\delta t}{E_{batt}} P_{batt}^{(k)} \quad 4.2$$

| Table 4.5 Description of symbols and terms in the battery SoC model. |                                                                                 |
|----------------------------------------------------------------------|---------------------------------------------------------------------------------|
| Symbol / Term                                                        | Description                                                                     |
| $SoC^{(k)}$                                                          | Normalized battery state of charge at time step $k$ , bounded within $[0, 1]$ . |

| Table 4.5 Description of symbols and terms in the battery SoC model. |                                                                                      |
|----------------------------------------------------------------------|--------------------------------------------------------------------------------------|
| Symbol / Term                                                        | Description                                                                          |
| $SoC^{(k+1)}$                                                        | Battery state of charge at the next time step $k + 1$ .                              |
| $P_{batt}^{(k)}$                                                     | Battery power at time step $k$ ; positive for charging, negative for discharging (W) |
| $\bar{E}_{batt}$                                                     | Nominal energy capacity of the battery (J).                                          |
| $\delta t$                                                           | Discretization timestep (s).                                                         |

These control-oriented models capture the building’s thermal and electrical inertia through simplified formulations. By representing the dominant dynamics of indoor temperature evolution and battery storage, they enable real-time optimization of heating and dispatch strategies under varying operating conditions. Their integration within the semantic digital twinning framework supports automated control synthesis, as developed in the following section.

#### 4.4 Semantic Digital Twinning for EHBE

This section implements the semantic digital twinning methodology presented in Chapter 3 to construct a fully operational knowledge graph for EHBE. Leveraging real-time telemetry from its sensing and control infrastructure, a comprehensive semantic model is generated by layering Brick Schema, ASHRAE Standard 223P, EFOnt, and RCOnt annotations over the building’s structured entity inventory. The resulting RDF knowledge graph captures the spatial, functional, and control relationships across building zones and equipment, while embedding thermal model parameters and flexibility attributes necessary for service orchestration. This SDT provides the unified abstraction layer required to enable query-driven reasoning, automated control formulation, and dynamic alignment between building state and grid service requirements.

The semantic three-dimensional space of the EHBE is structured into three primary thermal zones—Basement, First Floor, and Second Floor—reflecting the heuristic zoning-by-floor approach adopted in the archetype grey-box model (Section 4.3). This modeling strategy treats each floor as a distinct thermal volume for predicting dynamic energy balance in MPC. Within each floor, individual `brick:HVAC_Zone` instances represent specific conditioned spaces, semantically grouped under their corresponding `brick:Floor` and ultimately under the parent

brick:Building. This hierarchical representation provides the foundational layer for integrating control devices, sensor telemetry, and semantic annotations in subsequent steps of the digital twin.

```
@prefix brick: <https://brickschema.org/schema/1.3/Brick#> .
@prefix 223p: <https://ashrae.org/223p#> .
@prefix efont: <http://www.energyefficiencyontology.org/efont#> .
@prefix shacl: <http://www.w3.org/ns/shacl#> .
@prefix xsd: <http://www.w3.org/2001/XMLSchema#> .
@prefix rcont: <https://matinabtahi.github.io/ODT/RCont#> .
@prefix qudt: <http://qudt.org/schema/qudt/> .
@prefix unit: <http://qudt.org/vocab/unit/> .
@prefix xsd: <http://www.w3.org/2001/XMLSchema#> .
@prefix timeseries: <https://example.org/timeseries#> .
@prefix ex: <https://example.org/ehbe#> .

#####
# Building Structure
#####

### --- Building ---
ex:EHBE a brick:Building .

### --- Basement ---
ex:Basement a brick:Floor ;
    brick:isPartOf ex:EHBE ;
    brick:hasPart ex:Zone_SS, ex:Zone_SS2 .

ex:Zone_SS a brick:HVAC_Zone ;
    brick:isPartOf ex:Basement .

ex:Zone_SS2 a brick:HVAC_Zone ;
    brick:isPartOf ex:Basement .

### --- First Floor ---
ex:FirstFloor a brick:Floor ;
    brick:isPartOf ex:EHBE ;
    brick:hasPart ex:Zone_CU, ex:Zone_SM, ex:Zone_SA, ex:Zone_SE .
```

```

ex:Zone_CU a brick:HVAC_Zone ;
    brick:isPartOf ex:FirstFloor .

ex:Zone_SM a brick:HVAC_Zone ;
    brick:isPartOf ex:FirstFloor .

ex:Zone_SA a brick:HVAC_Zone ;
    brick:isPartOf ex:FirstFloor .

ex:Zone_SE a brick:HVAC_Zone ;
    brick:isPartOf ex:FirstFloor .

### --- Second Floor ---
ex:SecondFloor a brick:Floor ;
    brick:isPartOf ex:EHBE ;
    brick:hasPart ex:Zone_C1, ex:Zone_C2, ex:Zone_C3, ex:Zone_SB .

ex:Zone_C1 a brick:HVAC_Zone ;
    brick:isPartOf ex:SecondFloor .

ex:Zone_C2 a brick:HVAC_Zone ;
    brick:isPartOf ex:SecondFloor .

ex:Zone_C3 a brick:HVAC_Zone ;
    brick:isPartOf ex:SecondFloor .

ex:Zone_SB a brick:HVAC_Zone ;

    brick:isPartOf ex:SecondFloor .

```

Building upon the structured spatial hierarchy, this section semantically formalizes the complete zone-level infrastructure for control, sensing, and actuation across all defined `brick:HVAC_Zone` instances in the EHBE. Each zone is equipped with four core components: a `brick:Thermostat` for control interface, a `brick:Temperature_Sensor` to monitor indoor conditions, a `brick:Energy_Sensor` to track heating energy consumption, and a `brick:Electric_Baseboard_Heater` as the primary actuation mechanism. These entities are

instantiated using aligned class references from Brick Schema, ASHRAE Standard 223P, and EFont, enabling interoperability and semantic consistency across the SDT.

To support dual-mode operation and flexibility analysis, each zone is further assigned two distinct temperature control trajectories. The first, encoded as `ex:RefHeatingSetpoint_<ZONE>` and `ex:RefCoolingSetpoint_<ZONE>`, represents a reference schedule reflecting business-as-usual (BaU) occupant behavior and is annotated with `efont:canBeModeledBy efont:ReferenceSchedule`. The second, `ex:FlxHeatingSetpoint_<ZONE>` and `ex:FlxCoolingSetpoint_<ZONE>`, denotes the optimal setpoints generated by a model predictive controller, annotated with `efont:canBeModeledBy efont:OptimizationModel`. This dual-setpoint framework enables formal representation of override-based control strategies without compromising ontology integrity.

All components are annotated with `efont:hasScope efont:DeviceLevelApplication` and `efont:hasInfluenceOn efont:ThermalQuality` to explicitly situate their operational context and thermodynamic relevance. This structured semantic modeling supports precise telemetry alignment, enables automated reasoning for energy flexibility assessment, and lays the groundwork for real-time optimal control.

```
#####
# Zonal Control, Sensing, and Actuation Devices
#####

ZONES = [Zone_SS, Zone_SS2, Zone_CU, Zone_SM, Zone_SA, Zone_SE, Zone_C1,
Zone_C2, Zone_C3, Zone_SB]

HEATER_CAPACITIES = {"Zone_SS": 2000.0, "Zone_SS2": 2000.0, "Zone_CU":
1500.0, "Zone_SM": 1250.0, "Zone_SA": 1500.0, "Zone_SE": 500.0, "Zone_C1":
1250.0, "Zone_C2": 1250.0, "Zone_C3": 1250.0, "Zone_SB": 1000.0}

for ZONE in ZONES:

    CAP = HEATER_CAPACITIES[ZONE]

### --- Thermostats ---
```

```

    ex:Thermostat_{ZONE} a brick:Thermostat, 223p:Thermostat,
efont:PowerAdjustableSystem ;
    brick:hasLocation ex:{ZONE} ;
    efont:hasScope efont:DeviceLevelApplication ;
    efont:hasInfluenceOn efont:ThermalQuality .

### --- Temperature Sensors ---
    ex:TempSensor_{ZONE} a brick:Temperature_Sensor, 223p:TemperatureSensor,
efont:Sensor ;
    brick:hasLocation ex:{ZONE} ;
    brick:measures brick:Temperature ;
    efont:hasScope efont:DeviceLevelApplication ;
    efont:hasInfluenceOn efont:ThermalQuality .

### --- Energy Sensors ---
    ex:EnergySensor_{ZONE} a brick:Energy_Sensor, 223p:EnergySensor,
efont:Sensor ;
    brick:hasLocation ex:{ZONE} ;
    brick:measures brick:Energy ;
    efont:hasScope efont:DeviceLevelApplication .

### --- Electric Baseboard Heaters ---
    ex:Heater_{ZONE} a brick:Electric_Baseboard_Heater,
223p:ElectricHeatingCoil, 223p:ElectricSpaceHeater, efont:DispatchableLoad,
efont:ControllableLoad ;
    brick:hasLocation ex:{ZONE} ;
    brick:hasRatedCapacity "{CAP}"^^xsd:float ;
    efont:hasScope efont:DeviceLevelApplication ;
    efont:hasInfluenceOn efont:ThermalQuality .

### --- Reference Heating Setpoint ---
    ex:RefHeatingSetpoint_{ZONE} a brick:Heating_Setpoint,
223p:TemperatureSetpoint, efont:ControlSignal ;
    brick:hasLocation ex:<ZONE> ;
    brick:measures brick:Temperature ;
    efont:hasScope efont:DeviceLevelApplication ;
    efont:hasInfluenceOn efont:ThermalQuality ;
    efont:canBeModeledBy efont:ReferenceSchedule .

```

```

### --- Flexible Heating Setpoint ---
ex:FlxHeatingSetpoint_<ZONE> a brick:Heating_Setpoint,
223p:TemperatureSetpoint, efont:ControlSignal ;
    brick:hasLocation ex:<ZONE> ;
    brick:measures brick:Temperature ;
    efont:hasScope efont:DeviceLevelApplication ;
    efont:hasInfluenceOn efont:ThermalQuality ;
    efont:canBeModeledBy efont:OptimizationModel .

### --- Reference Cooling Setpoint ---
ex:RefCoolingSetpoint_<ZONE> a brick:Cooling_Setpoint,
223p:TemperatureSetpoint, efont:ControlSignal ;
    brick:hasLocation ex:<ZONE> ;
    brick:measures brick:Temperature ;
    efont:hasScope efont:DeviceLevelApplication ;
    efont:hasInfluenceOn efont:ThermalQuality ;
    efont:canBeModeledBy efont:ReferenceSchedule .

### --- Flexible Cooling Setpoint ---
ex:FlxCoolingSetpoint_<ZONE> a brick:Cooling_Setpoint,
223p:TemperatureSetpoint, efont:ControlSignal ;
    brick:hasLocation ex:<ZONE> ;
    brick:measures brick:Temperature ;
    efont:hasScope efont:DeviceLevelApplication ;
    efont:hasInfluenceOn efont:ThermalQuality ;

    efont:canBeModeledBy efont:OptimizationModel .

```

DERs are semantically represented using standardized ontologies to enable their integration into flexibility assessment and control frameworks. The PV system is instantiated as a `brick:Photovoltaic_System` and further characterized by `223p:PhotovoltaicArray` and `efont:NondispatchableEnergyGenerator`, thereby formalizing its physical presence, generation type, and non-dispatchable nature. Its rated power is declared via `brick:hasRatedPower`, while real-time power output is linked to an `ex:SolarPV_Output` instance of `brick:Electrical_Power_Sensor`, semantically anchoring the PV system's telemetry stream. The PV array's operational dependency on ambient solar conditions is expressed

through `223p:hasIrradianceInput`, which binds it to a collocated `brick:Irradiance_Sensor`. Although the PV system cannot be directly controlled, its output is projected using an `efont:GenerationProfile` derived from external forecasts—enabling anticipatory coordination in optimization routines. The profile is modeled with `efont:profileSource "forecast"` and linked to `efont:EP_GeneratorPhotovoltaic`, ensuring model traceability within the flexibility stack.

In parallel, the battery energy storage system is modeled as a `brick:Battery`, enriched with `223p:BatteryStorage` and `efont:ElectricityStorage` to capture its physical, operational, and flexibility-relevant semantics. The battery’s rated energy capacity is defined through `brick:hasRatedCapacity`, while its bidirectional interface with the electrical system is expressed using distinct current and power sensors (`brick:Electrical_Current_Sensor` and `brick:Electrical_Power_Sensor`) attached via `brick:hasInput` and `brick:hasOutput`. Operational state tracking is realized using `223p:hasOperationalState`, while dispatchability is explicitly annotated through `efont:hasDispatchability` `efont:Dispatchable`, signaling its eligibility for real-time control. Crucially, the battery’s role in flexibility provision is captured using `efont:hasFlexibilityMargin`, quantifying up-shift and down-shift power capacities, and `efont:hasStateVariable` referencing an `efont:StateOfCharge` linked to a percentage sensor. This entire system is semantically bound to `efont:EP_ElectricLoadCenterStorageBattery`, enabling alignment with simulation and optimization environments. These formal representations render DER behavior machine-interpretable and directly actionable within semantic control pipelines.

```
#####
# Distributed Energy Resources (DERs)
#####

### --- Photovoltaic (PV) System ---
ex:SolarPV a brick:Photovoltaic_System, 223p:PhotovoltaicArray,
efont:NondispatchableEnergyGenerator ;
    brick:hasLocation ex:EHBE ;
    brick:hasRatedPower "5000.0"^^xsd:float ;
    brick:hasOutput ex:SolarPV_Output ;
    223p:hasIrradianceInput ex:IrradianceSensor ;
```

```

    efont:hasScope efont:BuildingLevelApplication ;
    efont:hasInfluenceOn efont:EnergyBalance ;
    efont:hasGenerationProfile ex:SolarPV_Profile ;
    efont:canBeModeledBy efont:EP_GeneratorPhotovoltaic .

ex:SolarPV_Output a brick:Electrical_Power_Sensor ;
    brick:isPointOf ex:SolarPV .

ex:IrradianceSensor a brick:Irradiance_Sensor ;
    brick:hasLocation ex:EHBE .

ex:SolarPV_Profile a efont:GenerationProfile ;
    efont:profileSource "forecast" .

### --- Battery Energy Storage System ---
ex:Battery a brick:Battery, 223p:BatteryStorage, efont:ElectricityStorage ;
    brick:hasLocation ex:EHBE ;
    brick:hasRatedCapacity "10000.0"^^xsd:float ;
    brick:hasInput ex:Battery_Input ;
    brick:hasOutput ex:Battery_Output ;
    223p:hasOperationalState ex:BatteryState ;
    efont:hasScope efont:BuildingLevelApplication ;
    efont:hasDispatchability efont:Dispatchable ;
    efont:hasInfluenceOn efont:EnergyBalance, efont:ElectricQuality ;
    efont:hasFlexibilityMargin ex:BatteryFlex ;
    efont:hasStateVariable ex:BatterySoC ;
    efont:canBeModeledBy efont:EP_ElectricLoadCenterStorageBattery .

ex:Battery_Input a brick:Electrical_Current_Sensor ;
    brick:isPointOf ex:Battery .

ex:Battery_Output a brick:Electrical_Power_Sensor ;
    brick:isPointOf ex:Battery .

ex:BatteryState a 223p:OperationalState ;
    223p:stateValue "idle" .

ex:BatteryFlex a efont:FlexibilityMargin ;

```

```

    efont:upShift "2500.0"^^xsd:float ;
    efont:downShift "2500.0"^^xsd:float .

ex:BatterySoC a efont:StateOfCharge ;
    brick:hasLocation ex:Battery ;

    brick:measures brick:Percentage .

```

Environmental and external boundary conditions are semantically encoded in the SDT to ensure accurate thermal modeling and context-aware control. Ambient air temperature and GHI are instantiated using `brick:Temperature_Sensor` and `brick:Luminance_Sensor`, respectively, and further classified via `223p:OutdoorAirTemperatureSensor` and `223p:SolarIrradianceSensor`. These sensors are annotated with the `efont:Sensor` role and scoped at the device level, with explicit influence on `efont:ThermalQuality` and `efont:EnergyBalance`.

To support economically adaptive control, a time-varying electricity tariff signal is represented as a `brick:Price_Sensor` and `efont:Signal`, labeled “Rate-FlexD” and tagged with `efont:hasInfluenceOn efont:EnergyCost`. Forecasted environmental inputs are also formalized: a `223p:Forecast` entity models the weather prediction service and is semantically linked to its source via `efont:canBeModeledBy efont:ExternalWeatherForecastAPI`. In parallel, a predictive control signal representing PV generation is declared as an `efont:ControlSignal`, enabling anticipatory battery dispatch and load scheduling through `efont:ForecastBasedGenerationModel`.

These annotations enable the SDT to incorporate forward-looking, exogenous variables into real-time reasoning workflows, thereby improving the alignment between building operation and external signals.

```

#####
# Environmental and External Context Sensors
#####

### --- Outdoor Air Temperature ---

```

```

    ex:OutdoorTempSensor a brick:Temperature_Sensor,
223p:OutdoorAirTemperatureSensor, efont:Sensor ;
    brick:hasLocation ex:Outside ;
    brick:measures brick:Temperature ;
    efont:hasScope efont:DeviceLevelApplication ;
    efont:hasInfluenceOn efont:ThermalQuality .

### --- Global Horizontal Irradiance (GHI) ---
    ex:GHISensor a brick:Luminance_Sensor, 223p:SolarIrradianceSensor,
efont:Sensor ;
    brick:hasLocation ex:Outside ;
    brick:measures brick:Luminance ;
    efont:hasScope efont:DeviceLevelApplication ;
    efont:hasInfluenceOn efont:EnergyBalance .

### --- Electricity Tariff Signal (Rate-FlexD) ---
    ex:PriceSignal a brick:Price_Sensor, 223p:ElectricityTariffSignal,
efont:Signal ;
    efont:hasScope efont:BuildingLevelApplication ;
    efont:hasInfluenceOn efont:EnergyCost ;
    rdfs:label "Rate-FlexD" .

### --- Weather Forecast ---
    ex:WeatherForecast a 223p:Forecast, efont:ForecastModel ;
    efont:hasScope efont:BuildingLevelApplication ;
    efont:canBeModeledBy efont:ExternalWeatherForecastAPI .

### --- Forecasted Generation Profile (PV) ---
    ex:PVForecastProfile a efont:ControlSignal ;
    efont:hasScope efont:BuildingLevelApplication ;
    efont:hasInfluenceOn efont:EnergyBalance ;

    efont:canBeModeledBy efont:ForecastBasedGenerationModel .

```

The SDT leverages RCont to semantically instantiate the thermal RC network introduced in Section 4.3. Each of the three thermal zones—Basement, First Floor, and Second Floor—is modeled using two lumped nodes: an `AirNode` representing the short-term dynamics of indoor air, and an `EnvelopeNode` capturing the longer-term thermal inertia of the building mass.

Inter-nodal heat transfer is described using `rcont:RValue` resistances. Air-to-envelope connections represent intra-zone thermal exchange, air-to-air resistances link adjacent floors to capture inter-zone dynamics, and envelope/air-to-ambient resistances connect each node to an external node ( $T_{out}$ ), which semantically references the ambient temperature sensor via `brick:isPointOf`. Each air and envelope node is also assigned a `rcont:SolarAperture` to represent solar exposure, linked to the GHI sensor defined earlier.

To incorporate measured and actuated variables into the model, floor-level aggregates are constructed using `brick:aggregates`. Real-time heater energy inputs are calculated by summing the energy sensors of all constituent HVAC zones, while average indoor air temperatures are derived from aggregated zone-level temperature sensors. These are linked to the RC model through `rcont:hasInput`, while `rcont:hasState` connects the observed temperature variables.

This semantic representation establishes a machine-interpretable model within the SDT, enabling its integration with predictive control algorithms and ensuring consistency between real-time data streams and control actions.

```
#####
# RC Model (RCont)
#####

### --- Aggregated Temperature Sensors ---
ex:TempSensor_Basement a brick:Temperature_Sensor ;
    brick:isPointOf ex:Basement ;
    brick:aggregates ex:TempSensor_Zone_SS, ex:TempSensor_Zone_SS2 .

ex:TempSensor_First a brick:Temperature_Sensor ;
    brick:isPointOf ex:FirstFloor ;
    brick:aggregates ex:TempSensor_Zone_CU, ex:TempSensor_Zone_SM,
                    ex:TempSensor_Zone_SA, ex:TempSensor_Zone_SE .

ex:TempSensor_Second a brick:Temperature_Sensor ;
    brick:isPointOf ex:SecondFloor ;
    brick:aggregates ex:TempSensor_Zone_C1, ex:TempSensor_Zone_C2,
                    ex:TempSensor_Zone_C3, ex:TempSensor_Zone_SB .
```

```

### --- Aggregated Heater Energy Inputs ---
ex:HeaterInput_Basement a brick:Energy_Sensor ;
    brick:isPointOf ex:Basement ;
    brick:aggregates ex:EnergySensor_Zone_SS, ex:EnergySensor_Zone_SS2 .

ex:HeaterInput_First a brick:Energy_Sensor ;
    brick:isPointOf ex:FirstFloor ;
    brick:aggregates ex:EnergySensor_Zone_CU, ex:EnergySensor_Zone_SM,
        ex:EnergySensor_Zone_SA, ex:EnergySensor_Zone_SE .

ex:HeaterInput_Second a brick:Energy_Sensor ;
    brick:isPointOf ex:SecondFloor ;
    brick:aggregates ex:EnergySensor_Zone_C1, ex:EnergySensor_Zone_C2,
        ex:EnergySensor_Zone_C3, ex:EnergySensor_Zone_SB .

### --- Model Structure ---
ex:EHBE_RCModel a rcont:RCModel ;
    rcont:modelsZone ex:Basement, ex:FirstFloor, ex:SecondFloor ;
    rcont:hasNode
        ex:Air_Basement, ex:Env_Basement,
        ex:Air_First, ex:Env_First,
        ex:Air_Second, ex:Env_Second,
        ex:Tout ;
    rcont:hasCapacitance
        ex:C_Air_Basement, ex:C_Env_Basement,
        ex:C_Air_First, ex:C_Env_First,
        ex:C_Air_Second, ex:C_Env_Second ;
    rcont:hasResistance
        ex:R_AirEnv_Basement, ex:R_AirEnv_First, ex:R_AirEnv_Second,
        ex:R_Air_Basement_First, ex:R_Air_First_Second,
        ex:R_AirOut_Basement, ex:R_EnvOut_Basement,
        ex:R_AirOut_First, ex:R_EnvOut_First,
        ex:R_AirOut_Second, ex:R_EnvOut_Second ;
    rcont:hasSolarAperture
        ex:SolarAir_Basement, ex:SolarEnv_Basement,
        ex:SolarAir_First, ex:SolarEnv_First,
        ex:SolarAir_Second, ex:SolarEnv_Second ;

```

```

    rcont:hasInput
        ex:OutdoorTempSensor, ex:GHISensor,
        ex:HeaterInput_Basement, ex:HeaterInput_First,
ex:HeaterInput_Second ;
    rcont:hasState ex:TempSensor_Basement, ex:TempSensor_First,
ex:TempSensor_Second ;

```

```

### --- Nodes and Capacitances ---

```

```

# Basement

```

```

ex:Air_Basement a rcont:AirNode .
ex:Env_Basement a rcont:EnvelopeNode .

```

```

ex:C_Air_Basement a rcont:CValue ;
    rcont:belongsToNode ex:Air_Basement ;
    rcont:unit unit:J .

```

```

ex:C_Env_Basement a rcont:CValue ;
    rcont:belongsToNode ex:Env_Basement ;
    rcont:unit unit:J-PER-K .

```

```

# First Floor

```

```

ex:Air_First a rcont:AirNode .
ex:Env_First a rcont:EnvelopeNode .

```

```

ex:C_Air_First a rcont:CValue ;
    rcont:belongsToNode ex:Air_First ;
    rcont:unit unit:J-PER-K .

```

```

ex:C_Env_First a rcont:CValue ;
    rcont:belongsToNode ex:Env_First ;
    rcont:unit unit:J-PER-K .

```

```

# Second Floor

```

```

ex:Air_Second a rcont:AirNode .
ex:Env_Second a rcont:EnvelopeNode .

```

```

ex:C_Air_Second a rcont:CValue ;
    rcont:belongsToNode ex:Air_Second ;

```

```

    rcont:unit unit:J-PER-K .

ex:C_Env_Second a rcont:CValue ;
    rcont:belongsToNode ex:Env_Second ;
    rcont:unit unit:J-PER-K .

# Outdoor node
ex:Tout a rcont:Node ;
    brick:isPointOf ex:OutdoorTempSensor .

### --- Resistances ---
ex:R_AirEnv_Basement a rcont:RValue ;
    rcont:connects ex:Air_Basement, ex:Env_Basement ;
    rcont:unit unit:K-PER-W .

ex:R_AirEnv_First a rcont:RValue ;
    rcont:connects ex:Air_First, ex:Env_First ;
    rcont:unit unit:K-PER-W .

ex:R_AirEnv_Second a rcont:RValue ;
    rcont:connects ex:Air_Second, ex:Env_Second ;
    rcont:unit unit:K-PER-W .

ex:R_Air_Basement_First a rcont:RValue ;
    rcont:connects ex:Air_Basement, ex:Air_First ;
    rcont:unit unit:K-PER-W .

ex:R_Air_First_Second a rcont:RValue ;
    rcont:connects ex:Air_First, ex:Air_Second ;
    rcont:unit unit:K-PER-W .

ex:R_AirOut_Basement a rcont:RValue ;
    rcont:connects ex:Air_Basement, ex:Tout ;
    rcont:unit unit:K-PER-W .

ex:R_EnvOut_Basement a rcont:RValue ;
    rcont:connects ex:Env_Basement, ex:Tout ;

```

```

    rcont:unit unit:K-PER-W .

ex:R_AirOut_First a rcont:RValue ;
    rcont:connects ex:Air_First, ex:Tout ;
    rcont:unit unit:K-PER-W .

ex:R_EnvOut_First a rcont:RValue ;
    rcont:connects ex:Env_First, ex:Tout ;
    rcont:unit unit:K-PER-W .

ex:R_AirOut_Second a rcont:RValue ;
    rcont:connects ex:Air_Second, ex:Tout ;
    rcont:unit unit:K-PER-W .

ex:R_EnvOut_Second a rcont:RValue ;
    rcont:connects ex:Env_Second, ex:Tout ;
    rcont:unit unit:K-PER-W .

### --- Solar Apertures ---
ex:SolarAir_Basement a rcont:SolarAperture ;
    rcont:belongsToNode ex:Air_Basement ;
    rcont:unit unit:M2 .

ex:SolarAir_First a rcont:SolarAperture ;
    rcont:belongsToNode ex:Air_First ;
    rcont:unit unit:M2 .

ex:SolarAir_Second a rcont:SolarAperture ;
    rcont:belongsToNode ex:Air_Second ;
    rcont:unit unit:M2 .

ex:SolarEnv_Basement a rcont:SolarAperture ;
    rcont:belongsToNode ex:Env_Basement ;
    rcont:unit unit:M2 .

ex:SolarEnv_First a rcont:SolarAperture ;
    rcont:belongsToNode ex:Env_First ;
    rcont:unit unit:M2 .

```

```

ex:SolarEnv_Second a rcont:SolarAperture ;
    rcont:belongsToNode ex:Env_Second ;

    rcont:unit unit:M2 .

```

To enable seamless integration between semantic models and dynamic telemetry, the SDT establishes formal bindings between ontological entities and their associated time series data streams using the `timeseries:hasTimeseries` predicate. These bindings provide a machine-interpretable mechanism for linking static knowledge representations with continuously evolving observations and control signals. At a structural level, any entity that produces or consumes data—such as sensors, actuators, forecasts, or DERs—is annotated with a reference to its corresponding time series identifier. This design supports consistent alignment between the semantic layer and the underlying time-series infrastructure, enabling unified access to both metadata and measurements. The resulting architecture allows real-time data to be queried directly from within the knowledge graph, facilitates time-aware reasoning and control, and ensures that all semantic components remain synchronized with the operational state of the system. In practice, the data streams are ingested via a Telegraf agent and stored in an InfluxDB instance managed by Hydro-Québec, supporting scalable, high-frequency data collection for both real-time and historical analysis.

```

#####
# Timeseries Bindings
#####

### --- Zone-Level Sensors and Actuators ---
ZONES = [Zone_SS, Zone_SS2, Zone_CU, Zone_SM, Zone_SA, Zone_SE, Zone_C1,
Zone_C2, Zone_C3, Zone_SB]

for ZONE in ZONES:
ex:TempSensor_{ZONE} timeseries:hasTimeseries ex:TS_Temp_{ZONE} .
ex:EnergySensor_{ZONE} timeseries:hasTimeseries ex:TS_Energy_{ZONE} .

### --- Environmental and External Context ---
ex:OutdoorTempSensor timeseries:hasTimeseries ex:TS_Temp_Outdoor .
ex:GHISensor timeseries:hasTimeseries ex:TS_GHI .

```

```

ex:PriceSignal timeseries:hasTimeseries ex:TS_PriceSignal .
ex:WeatherForecast timeseries:hasTimeseries ex:TS_WeatherForecast .
ex:PVForecastProfile timeseries:hasTimeseries ex:TS_PVForecast .

### --- DERs ---
ex:SolarPV_Output timeseries:hasTimeseries ex:TS_PV_Output .
ex:Battery_Input timeseries:hasTimeseries ex:TS_Battery_Input .
ex:Battery_Output timeseries:hasTimeseries ex:TS_Battery_Output .

ex:BatterySoC timeseries:hasTimeseries ex:TS_Battery_SoC .

```

Figure 4.7<sup>1</sup> serializes the SDT as an RDF knowledge graph integrating Brick Schema, ASHRAE Standard 223P, EFont, and RCont to unify structural, physical, and control-layer semantics, forming the machine-interpretable foundation for real-time data integration and B2G service delivery.

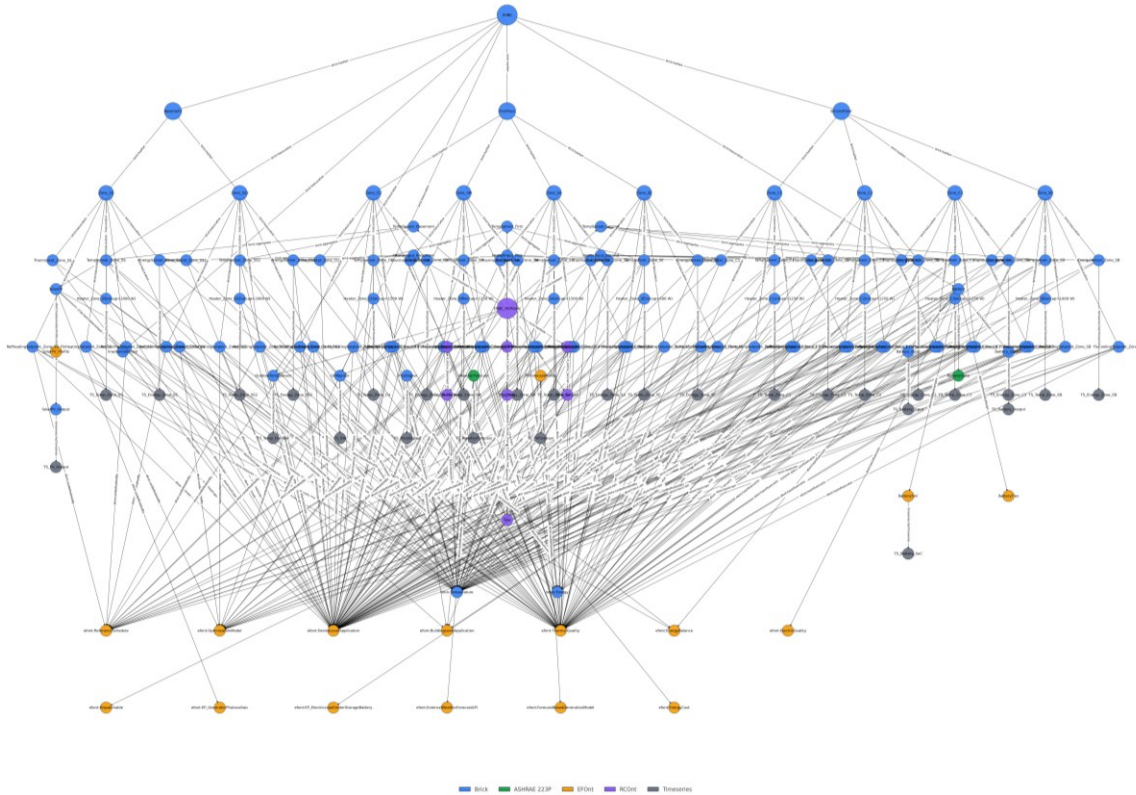


Figure 4.7 EHBE knowledge graph integrating Brick Schema, ASHRAE Standard 223P, EFont, and RCont.

<sup>1</sup> This figure presents the overall structure and information categorization logic of the RDF knowledge graph; detailed inspection of individual entities or relationships is beyond the intended scope of this visualization.

Graph traversal within the SDT enables structured navigation across multiple layers, including spatial hierarchy, device behavior, control logic, and thermal dynamics. By leveraging the inherent connectivity of RDF graphs, traversals can be initiated from any semantically defined entity—such as a temperature sensor, a thermostat, or an RC model node—and extended through well-defined predicates (e.g., `brick:isPartOf`, `brick:hasLocation`, `rcont:modelsZone`, `efont:hasInfluenceOn`) to retrieve relevant contextual, structural, or behavioral information. For example, a query starting from a thermostat can determine its physical deployment via `brick:hasLocation`, ascend to its parent `brick:HVAC_Zone`, and subsequently to the encompassing `brick:Floor`, which is linked to the corresponding thermal RC model through `rcont:modelsZone`. This hierarchical navigation enables reasoning engines to locate where in the thermal network the control device applies, which state variables it influences, and which measurements are required for closed-loop validation—thereby supporting context-aware, interpretable control.

Moreover, this capability facilitates seamless integration across previously siloed domains, such as sensing, actuation, and energy modeling. For instance, beginning from any `rcont:Node` (e.g., `ex:Air_First`), one can discover all associated thermal parameters and operational signals by following semantic links such as `rcont:hasCapacitance`, `rcont:hasResistance`, `rcont:hasSolarAperture`, `rcont:hasInput`, and `rcont:hasState`. These links extend to time-series data streams via `timeseries:hasTimeseries`, enabling predictive algorithms to retrieve live measurements and forecasts without requiring hardcoded data pipelines. The result is a fully declarative and machine-interpretable control environment, where operational logic, physical dependencies, and control targets are resolved through ontological relationships. This graph-based architecture ensures modularity, scalability, and adaptability, empowering the SDT to evolve alongside the building’s infrastructure and service requirements while maintaining semantic coherence across all layers.

To conclude, this section integrated structural, physical, and control-layer semantics into a unified, machine-interpretable knowledge graph, thereby establishing the foundation for real-time interoperability and B2G service delivery. Building on this foundation, the next section evaluates the EHBE’s ability to deliver load shifting under Hydro-Québec’s residential ToU tariff. By

leveraging the semantic twin to coordinate forecasts, comfort constraints, and system behavior, the goal is to demonstrate how the building reshapes its load profile to reduce electricity costs while contributing to grid stability during peak periods.

#### **4.5 Economic MPC for Tariff-Responsive Load Shifting**

ToU pricing structures are among the most widely implemented mechanisms to enable demand-side flexibility in the residential sector. By varying electricity rates across predefined periods, ToU tariffs incentivize consumers to shift controllable loads away from peak demand windows, thereby alleviating grid stress and enhancing its operational efficiency. Under Hydro-Québec’s Rate Flex D—where electricity rates increase substantially during designated morning and evening peak periods—buildings with electric heating and DERs offer significant potential for cost-effective load shifting.

This section presents the implementation of an economic MPC formulation designed to minimize electricity cost under Hydro-Québec’s Rate Flex D by reshaping the net electrical heating load profile of the EHBE. The controller leverages the building’s thermal and electrical inertia to deliver cost-optimal load shifting services, while maintaining indoor temperatures within predefined comfort bounds and ensuring compliance with battery operating constraints. This implementation demonstrates how semantically structured building representations can support real-time, cost-optimal control decisions in response to dynamic pricing signals. As such, it provides a concrete use case for predictive control in grid-interactive residential buildings and contributes to the broader goal of operational flexibility in cold-climate contexts.

##### **4.5.1 Formulation**

This section presents the economic MPC formulation developed to optimally coordinate electric heating setpoints and battery dispatch at EHBE in response to forecasts of weather conditions, PV generation, and time-varying electricity prices under Rate Flex D. As a special case of the general service-oriented formulation introduced in Section 3.1, the controller minimizes a composite cost function over a finite PH, balancing electricity costs with penalties for deviating from the reference setpoint.

In this formulation, the monetary cost associated with electricity imported from the grid quantifies the effectiveness of tariff-responsive load shifting. By reshaping the net load profile to avoid peak-rate periods, the controller modulates demand in alignment with grid objectives—treating cost minimization as a proxy for service performance. The internal requirements term penalizes deviations from the heating setpoint, aiming to maintain thermal comfort within acceptable bounds. However, it should be explicitly noted that the scope of thermal comfort extends beyond this term; the formulation only penalizes deviations from the specified setpoint, not the full range of comfort conditions. Equation 4.3 presents the cost function minimized by the controller in this formulation.

$$U^* = \arg \min_U \sum_{k=0}^{PH-1} [\pi_{elec}^k (P_{grid}^k \cdot \delta t) + \pi_{therm}^k (\lambda_{set}^k \cdot \delta t)] \quad 4.3$$

*subject to:*

$$P_{grid} = P_{heat} + P_{batt} - P_{pv},$$

$$\lambda_{set} = |T_{set} - \hat{T}(\theta^*)|,$$

$$\pi_{therm} = \begin{cases} 0; & \hat{T}(\theta^*) \in [T_{set} - \underline{\varepsilon}, T_{set} + \overline{\varepsilon}] \\ \omega_{\lambda} \cdot \pi_{elec}; & otherwise \end{cases},$$

$$U = \{T_{set,MPC}, P_{batt}\},$$

$$\underline{U} < U^* < \overline{U}.$$

The controller's decision variables are the heating setpoints ( $T_{set,MPC}$ ) and, when applicable, the battery dispatch power. The net grid exchange ( $P_{grid}$ ) is defined as the sum of electric heating demand ( $P_{heat}$ ) and battery dispatch ( $P_{batt}$ ), minus PV generation ( $P_{pv}$ ). The formulation accommodates varying levels of system integration; in the absence of PV or battery systems, the corresponding terms are omitted from the cost and constraint expressions. The reference heating setpoint ( $T_{set}$ ) represents the occupant-defined target, while  $\hat{T}(\theta^*)$  denotes the predicted indoor temperature, obtained from the validated archetype grey-box model introduced in Section 4.3. The deviation from this setpoint is captured by  $\lambda_{set}$ , which is penalized whenever it exceeds a predefined threshold.

The coefficient  $\pi_{elec}$  in this formulation represents the ToU electricity price signal. A scalar multiple,  $\omega_{\lambda} \cdot \pi_{elec}$ , governs the trade-off between electricity cost and deviations from the reference setpoint, where  $\omega_{\lambda}$  is a user-defined weighting factor that adjusts the controller's tolerance for the

latter. This design choice facilitates intuitive tuning, supports transferability across buildings and occupant profiles, and ensures that each term in the objective function is weighted in proportion to its practical impact. Soft constraints are applied to indoor air temperature to reflect the behavioral expectations of residential DR programs, which tolerate brief and bounded deviations from the reference setpoint when economically justified. The penalization logic is piecewise: no penalty is incurred when the predicted temperature remains within the tolerance band  $[T_{\text{set}} - \underline{\epsilon}, T_{\text{set}} + \bar{\epsilon}]$ , and a linear penalty proportional to  $\lambda_{\text{set}}$  is applied otherwise. Unlike hard constraints, which may render the optimization problem infeasible under restrictive conditions—such as insufficient PV generation or limited battery availability—soft constraints enhance solver convergence by transforming strict feasibility conditions into penalized objectives that tolerate gradual violations.

The controller’s behaviour is governed by the relative magnitudes of the two cost components in the objective function, modulated through the interpretable weighting factor  $\omega_{\lambda}$ . When  $P_{\text{grid}} \gg \omega_{\lambda} \cdot \lambda_{\text{set}}$ , energy cost dominates, and the controller may tolerate larger deviations from the reference setpoint to reduce consumption. Conversely, when  $P_{\text{grid}} \ll \omega_{\lambda} \cdot \lambda_{\text{set}}$ , strict tracking of the reference setpoint is prioritized, even at the expense of increased electricity use. Finally, when both terms are of comparable scale, a balanced trade-off is achieved. Thus,  $\omega_{\lambda}$  plays a critical role in shaping the solver’s behaviour, as it directly influences how the controller computes near-optimal future control actions based on the trade-off between electricity cost and setpoint deviation. Higher values of  $\omega_{\lambda}$  prioritize strict adherence to the reference setpoint, whereas lower values allow greater tolerance for deviation when it leads to economic benefit.

#### 4.5.2 Implementation

To evaluate the real-time performance of the proposed economic MPC formulation for tariff-responsive load shifting, a series of operational scenarios was deployed at the EHBE. Each scenario incrementally introduced new layers of control or system integration, progressing from reactive thermostat operation (baseline) to real-time optimal setpoint adjustment, and ultimately to full coordination with on-site PV and battery systems. This structured layering enables a practical assessment of how deeper levels of integration enhance residential energy flexibility.

Scenarios were executed across multiple winter periods, naturally capturing variability in ambient air temperature and solar irradiance. Rather than normalizing inputs, this variability was

deliberately preserved to reflect the stochastic nature of real-world operation. The aim was not to evaluate performance under uniform conditions, but to assess the controller’s adaptability across different integration levels and environmental contexts. This approach aligns with the core principle of semantic digital twinning—structuring physical system knowledge, live telemetry, and control-relevant context to enable informed decision-making under uncertainty. Consequently, the focus of performance evaluation was placed on robustness and responsiveness, rather than strict comparability between scenarios. The three scenarios are summarized below, each corresponding to a distinct level of control deployment and system coordination:

1. The first scenario, referred to as the Reference Scenario, reflects BaU operation with no MPC implementation or PV/battery integration. It captures the reactive behaviour of conventional thermostats operating on fixed setpoint schedules, without predictive intelligence or external coordination. Conducted over 14 non-consecutive days (February 6–16 and February 24–27, 2024, excluding February 14), this scenario serves as a contextual baseline, not for direct comparison, but for interpreting the flexibility potential unlocked by progressively integrated control strategies in the following scenarios.
2. The second scenario, Flexible Scenario 1, introduces real-time setpoint optimization while maintaining the same physical infrastructure. Conducted over a continuous 7-day period (February 17–23, 2024), this scenario isolates the impact of integrating dynamic setpoint modulation and assesses the extent to which it can reduce electricity costs while ensuring indoor temperatures remain within predefined comfort bounds.
3. The third scenario, Flexible Scenario 2, extends the previous configuration by incorporating on-site PV generation and battery storage into the control framework. Conducted over a continuous 7-day period (March 1 to 7, 2024), this scenario evaluates the joint optimization of setpoint trajectories and battery dispatch to enhance PV self-consumption, shift load to lower-cost periods, and reduce grid dependency. It reflects the compound flexibility that emerges from the real-time coordination of building’s thermal and electrical inertia.

Figure 4.8 presents the hourly distributions of ambient air temperature and GHI for each scenario. The boxplots illustrate median values, interquartile ranges, and intra-day variability in environmental conditions across all days in each scenario.

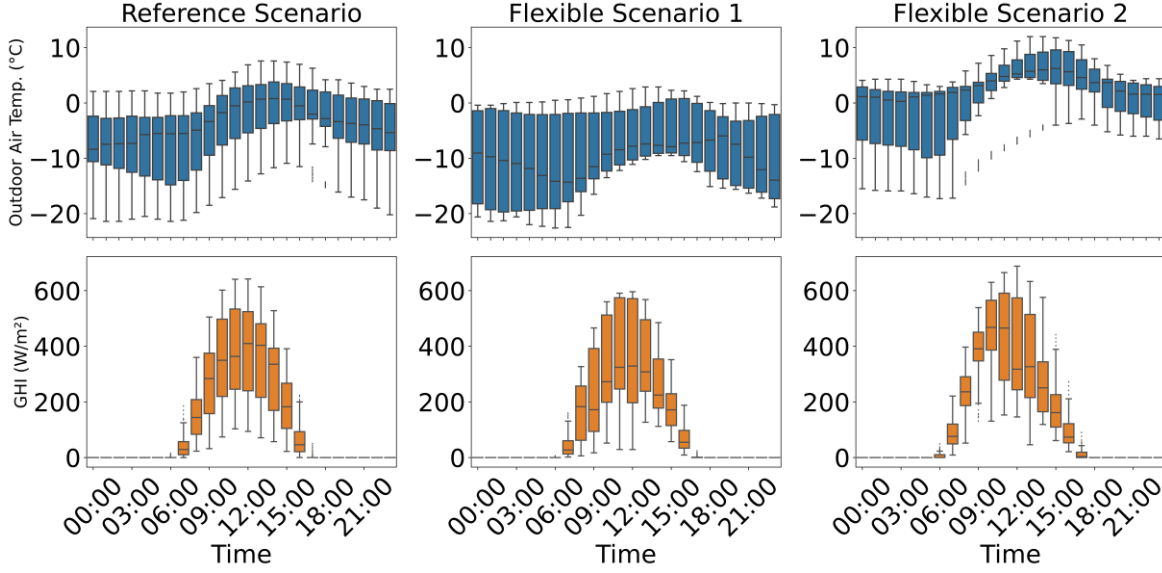


Figure 4.8 Hourly distribution of ambient air temperature (top) and GHI (bottom) across all days for the Reference Scenario, Flexible Scenario 1, and Flexible Scenario 2.

The proposed economic MPC formulation relies on a set of hyperparameters that govern its performance under real-world operating conditions. These parameters are selected based on empirical evidence, heuristic insights, and case-specific constraints, aiming to balance control performance with practical feasibility. The PH is set to 24 hours, while the CH is fixed at 3 hours. This 3-hour CH reflects a practical constraint imposed by data availability: the Solcast API (Solcast, n.d.)—used to retrieve site-specific weather and solar forecasts—offers only eight free forecast calls per day, thereby defining a 3-hour update cadence. This regular interval also facilitates reproducibility in post-experiment analysis, as it simplifies the alignment of input data, control outputs, and measured system responses across different experiments, making it easier to isolate the impact of control decisions from external variability. Although an adaptive CH—triggered by prediction error thresholds—was considered, it would result in irregular update intervals and complicate the data pipeline.

Model calibration is performed at the beginning of each CH to mitigate parameter drift and preserve fidelity in the face of changing external conditions. This process is fully automated and integrated within the semantic digital twinning framework, enabling real-time recursive parameter adaptation. Each calibration step uses the most recent measurements—including indoor air temperature, electric heating input, ambient air temperature, and solar irradiance—to update model

parameters. As the archetype grey-box model used here incorporates unobserved states—i.e., the temperature of the effective thermal mass in each floor—a rolling window of recent measurements is used to initialize these hidden states at the start of each CH, leveraging the most recently calibrated model along with electric heating input, ambient temperature, and solar irradiance data. Although measurements are recorded and stored at 1-minute intervals, both the archetype thermal RC model and the predictive control algorithm operate with a 5-minute discretization timestep ( $\delta t = 300$  s). This resolution is chosen to balance numerical stability and computational efficiency, and aligns with established practices in grey-box modeling of building thermal dynamics (Abtahi et al., 2024).

Daily reference setpoint profiles are derived from an empirical study of 300 smart thermostats in the Trois-Rivières region, which identifies consistent occupant behaviour patterns (Henao et al., 2018). Setpoint changes most frequently occur between 5:00–6:00 for morning set-ups, at 8:00 for morning set-backs, between 16:00–17:00 for evening set-ups, and at 22:00 for evening set-backs. The most common heating setpoint is 21 °C. Accordingly, the daily reference setpoint profile for the first and second floors is defined with a high of 21 °C and a low of 19 °C, with transitions at 5:00, 8:00, 17:00, and 22:00, respectively. The basement maintains a constant setpoint of 18 °C. Deviations on the upper floors are penalized when the indoor air temperature falls below the reference or exceeds it by more than 3 °C, while the tolerance in the basement is symmetric at  $\pm 2$  °C around the reference setpoint.

In accordance with Hydro-Québec’s Rate Flex D structure, electricity exports are not remunerated but instead credited in kilowatt-hours. Consequently, the unit price  $\pi_{\text{elec}}$  is set to 0 ¢/kWh during export periods and to the applicable Rate Flex D price during import. This pricing logic encourages self-consumption, as the controller derives no economic benefit from exporting surplus electricity. The weighting factor  $\omega_\lambda$  is empirically tuned to ensure that space heating costs (in \$) and deviations from the reference setpoint (in °C·h) contribute comparably to the optimization process. During peak pricing periods,  $\omega_\lambda$  is set to 5, meaning that the controller treats 1 °C·h of setpoint deviation as equivalent in cost to 5 kWh of electricity import. In off-peak periods,  $\omega_\lambda$  is increased to 55 to reflect the lower marginal cost of electricity and to discourage unnecessary thermal deviations. When exporting,  $\omega_\lambda$  is further increased to 75, compensating for the lack of economic incentive associated with grid exports.

Finally, the battery SoC is constrained between 10% and 90% to preserve long-term health and ensure reliable system operation. Table 4.6 summarizes the key hyperparameters governing the real-time implementation of the proposed economic MPC formulation.

| Table 4.6 Summary of operational hyperparameters used in real-time implementation of the proposed economic MPC for tariff-responsive load shifting. |                                                    |
|-----------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------|
| Hyperparameter                                                                                                                                      | Value / Description                                |
| PH                                                                                                                                                  | 24 hours                                           |
| CH                                                                                                                                                  | 3 hours (aligned with free weather API call limit) |
| $\delta t$                                                                                                                                          | 5 minutes                                          |
| Model Calibration Frequency                                                                                                                         | 3 hours (aligned with CH)                          |
| Setpoint Profile - Upper Floors                                                                                                                     | 21 °C (morning/evening), 19 °C (midday/night)      |
| Setpoint Profile - Basement                                                                                                                         | Constant 18 °C                                     |
| Tolerance - Upper Floors                                                                                                                            | Asymmetric [0, +3 °C] around setpoint              |
| Tolerance - Basement                                                                                                                                | Symmetric $\pm 2$ °C around setpoint               |
| $\pi_{elec}$                                                                                                                                        | Rate Flex-D price (import), 0 ¢/kWh (export)       |
| $\omega_{\lambda}$                                                                                                                                  | 5 (peak), 55 (off-peak), 75 (export)               |
| Battery SoC Limits                                                                                                                                  | Hard-constrained to [10%, 90%]                     |

### 4.5.3 Results

This section presents and interprets the results of the real-time implementation of the proposed economic MPC formulation, using a set of indicators to evaluate energy flexibility across the tested scenarios. Aligned with the target grid service—load shifting under a ToU tariff—the primary objective is to assess how effectively the building modulates electric heating loads while balancing electricity costs and adherence to thermal setpoints. From the grid’s perspective, the focus is on reducing demand during peak periods, necessitating indicators that capture both the direction and magnitude of net load shifting, while from the occupant’s perspective, the focus is on minimizing electricity costs with minimal deviation from temperature preferences. The following indicators reflect these complementary objectives and are used to evaluate flexibility performance across scenarios with varying levels of control and system integration:

1. **Cost Saving (%)**: This indicator quantifies the relative reduction in electricity import costs achieved by the flexible scenario compared to the reference scenario over a defined period. It is computed as the difference in total cost divided by the reference cost. A positive value

indicates that the flexible scenario reduced costs—typically by shifting demand to off-peak hours or increasing on-site generation—whereas a negative value implies higher costs under the flexible strategy.

2. **Average Setpoint Deviation (°C):** This indicator quantifies the average deviation of indoor air temperature from the reference setpoint over a defined period, calculated as temperature minus setpoint. A positive value indicates that the indoor air temperature was, on average, above the reference, while a negative value reflects temperatures below it. The magnitude represents the degree of divergence from preferred conditions accepted to meet operational objectives.
3. **Relative Demand Shift (unitless):** This indicator quantifies the proportional change in average net grid demand between the flexible and reference scenarios. It is calculated as the difference between average net demand in the flexible scenario and that in the reference, normalized by the reference demand—i.e.,  $(\text{flexible} - \text{reference}) / \text{reference}$ . A positive value suggests increased grid import under the flexible strategy, potentially due to low electricity prices or in anticipation of future peak periods. A negative value indicates reduced grid import, consistent with effective load shifting or enhanced self-consumption. Increasingly negative values may reflect net export or greater deviation from preferred setpoints. This single metric captures both the direction and relative magnitude of load shifting, providing a concise measure of energy flexibility from the grid’s perspective.

These indicators quantify selected aspects of tariff-responsive energy flexibility that are most relevant to the priorities of both the grid and the building. While they do not capture the full spectrum of flexibility attributes, their formulation emphasizes interpretability and computational efficiency, making them well suited for evaluation within a semantic digital twinning framework. In addition, they support pairwise comparisons across scenarios with varying control strategies and system configurations, enabling structured assessment of incremental enhancements.

To establish a baseline for evaluation, a representative 24-hour profile was constructed by averaging the daily net grid demand trajectories from the Reference Scenario. This weather-agnostic benchmark ( $P_{\text{ref}}$ ) provides a static reference for comparing both flexible scenarios. Based on this profile, the corresponding daily heating cost was computed, yielding a static cost baseline ( $C_{\text{ref}}$ ). Both the reference demand profile and resulting cost are inherently tied to the predefined

reference setpoint schedule. While these baselines enable consistent computation of the KPIs introduced earlier, their absolute values would vary under different setpoint assumptions. Subsequent analysis focuses on the performance of the two flexible scenarios. Flexible Scenario 1 integrates real-time optimal setpoint adjustments, while Flexible Scenario 2 extends this configuration by optimally coordinating PV generation and battery storage. For each day in both scenarios, the resulting demand and cost trajectories are evaluated against the static reference profile and cost, enabling a comparative assessment of the incremental benefits achieved through multi-layer integration.

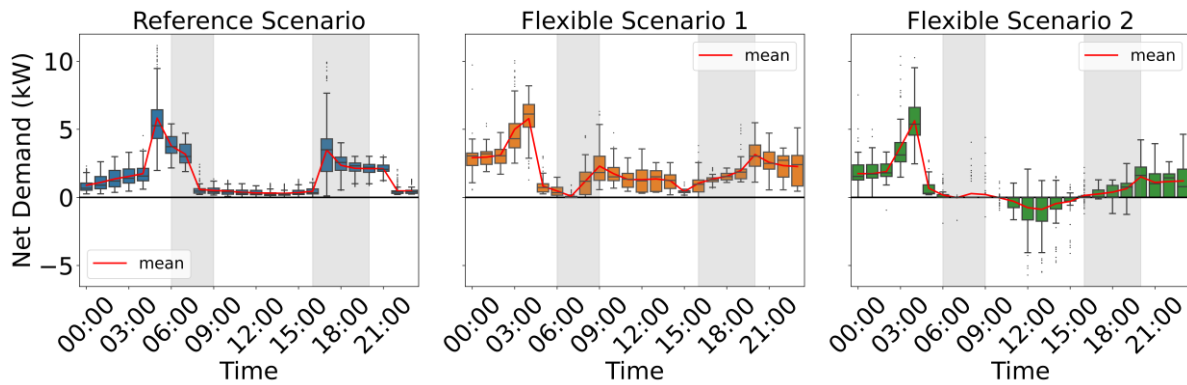


Figure 4.9 Hourly distribution of net grid demand across all days for the Reference Scenario, Flexible Scenario 1, and Flexible Scenario 2.

Figure 4.9 illustrates the distribution of daily net grid demand across the three scenarios using boxplots, which capture the median, interquartile range, and overall variability of hourly values. The red line denotes the mean daily profile for each scenario, with the Reference Scenario mean (Figure 4.9, left) serving as the static baseline for comparison. Shaded regions highlight the morning (06:00–09:00) and evening (16:00–20:00) peak periods.

To quantify economic performance, the static baseline cost is computed at 9.8 \$/day, with a 95% confidence interval of 8.0 to 11.7 \$/day, reflecting variability due to outdoor conditions. Table 4.7 consolidates daily grid import costs across all scenarios, enabling comparison of the flexible strategies against this benchmark. In Flexible Scenario 1, real-time setpoint optimization reduces costs on all days, with daily savings ranging from 8.2% to 55.1% and an average reduction of 34.7%. In Flexible Scenario 2, the optimal coordination of PV generation and battery storage

provides an additional layer of flexibility, achieving an average cost reduction of 78.4% and generating 25.3 kWh of export credits over the evaluation period.

Table 4.7 Daily grid import costs for space heating under the Reference Scenario, Flexible Scenario 1, and Flexible Scenario 2.

| Date       | Scenario   | Cost (\$) | Baseline Cost (\$) | Cost Saving (%) | Export Credit (kWh) |
|------------|------------|-----------|--------------------|-----------------|---------------------|
| 2024-02-06 | Reference  | 9.7       |                    |                 |                     |
| 2024-02-07 | Reference  | 13.6      |                    |                 |                     |
| 2024-02-08 | Reference  | 10.9      |                    |                 |                     |
| 2024-02-09 | Reference  | 10.3      |                    |                 |                     |
| 2024-02-10 | Reference  | 8.5       |                    |                 |                     |
| 2024-02-11 | Reference  | 8.6       |                    |                 |                     |
| 2024-02-12 | Reference  | 5.5       |                    |                 |                     |
| 2024-02-13 | Reference  | 10.5      |                    |                 |                     |
| 2024-02-15 | Reference  | 11.5      |                    |                 |                     |
| 2024-02-16 | Reference  | 10.5      |                    |                 |                     |
| 2024-02-24 | Reference  | 11.9      |                    |                 |                     |
| 2024-02-25 | Reference  | 14.0      |                    |                 |                     |
| 2024-02-26 | Reference  | 6.2       |                    |                 |                     |
| 2024-02-27 | Reference  | 5.7       |                    |                 |                     |
| 2024-02-17 | Flexible 1 | 6.2       | 9.8                | 36.7            |                     |
| 2024-02-18 | Flexible 1 | 9.0       | 9.8                | 8.2             |                     |
| 2024-02-19 | Flexible 1 | 6.7       | 9.8                | 31.6            |                     |
| 2024-02-20 | Flexible 1 | 7.4       | 9.8                | 24.5            |                     |
| 2024-02-21 | Flexible 1 | 6.6       | 9.8                | 32.7            |                     |
| 2024-02-22 | Flexible 1 | 4.5       | 9.8                | 54.1            |                     |
| 2024-02-23 | Flexible 1 | 4.4       | 9.8                | 55.1            |                     |
| 2024-03-01 | Flexible 2 | 4.2       | 9.8                | 57.1            | 4.8                 |
| 2024-03-02 | Flexible 2 | 3.8       | 9.8                | 61.2            | 0.2                 |
| 2024-03-03 | Flexible 2 | 1.0       | 9.8                | 89.8            | 0.2                 |
| 2024-03-04 | Flexible 2 | 2.0       | 9.8                | 79.6            | 0.1                 |
| 2024-03-05 | Flexible 2 | 0.6       | 9.8                | 93.9            | 7.2                 |
| 2024-03-06 | Flexible 2 | 2.5       | 9.8                | 74.5            | 0.6                 |
| 2024-03-07 | Flexible 2 | 0.7       | 9.8                | 92.9            | 12.2                |

Beyond economic performance, adopting flexibility measures also influences indoor air temperature trajectories. Figure 4.10 presents the hourly distribution of setpoint deviations—

defined as the difference between indoor air temperature and the reference heating setpoint—for each floor and scenario. This thermal analysis complements the financial results in Table 4.7 by evaluating the extent and nature of comfort trade-offs across the building. Across all scenarios, indoor temperatures generally remain within the prescribed tolerance ranges ( $\pm 2^\circ\text{C}$  in the basement and up to  $+3^\circ\text{C}$  on the upper floors), as shown by the shaded green bands. In the Reference Scenario, deviations primarily stem from solar gains in the afternoon—amplified by the house’s southwest-facing orientation—and the limitations of reactive control during peak periods. The result is moderate positive deviation, particularly on the upper floors.

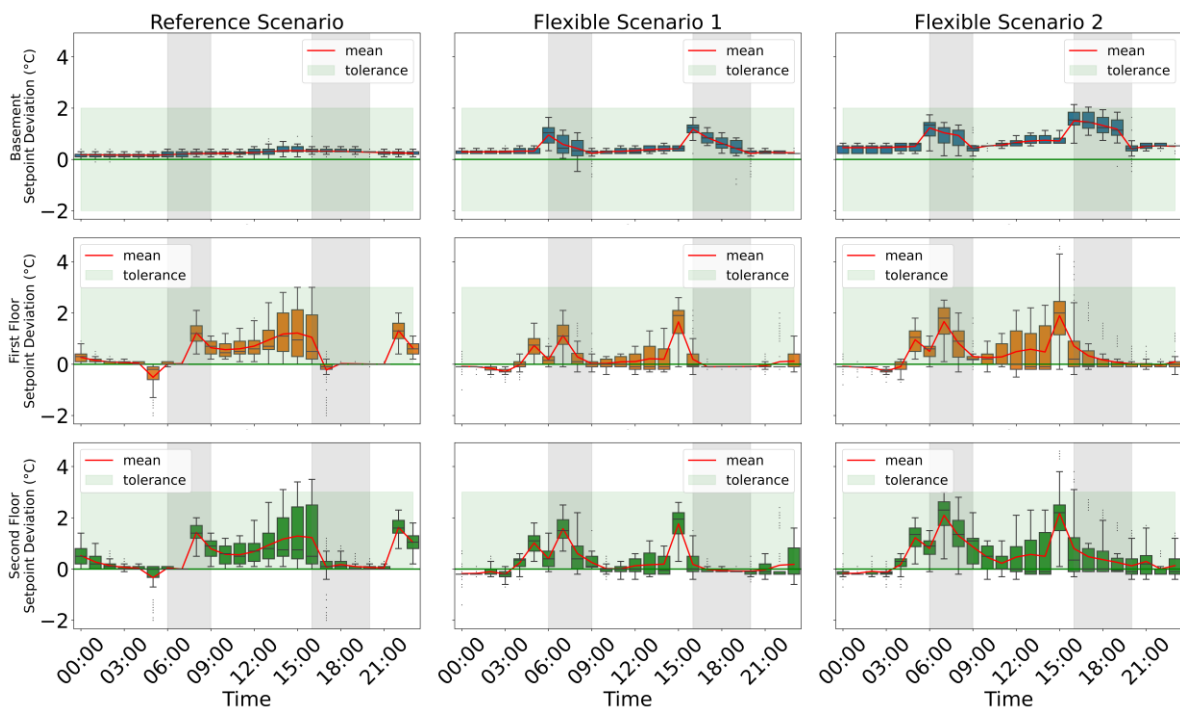


Figure 4.10 Hourly distribution of setpoint deviations (indoor air temperature minus reference heating setpoint) across all days for the Reference Scenario, Flexible Scenario 1, and Flexible Scenario 2.

Flexible Scenario 1 maintains indoor temperatures close to the reference setpoints, particularly on the upper floors. The mean setpoint deviation is  $0.16^\circ\text{C}$  on the first floor and  $0.25^\circ\text{C}$  on the second floor. The interquartile range spans from  $-0.1^\circ\text{C}$  to  $0.3^\circ\text{C}$  on the first floor and from  $-0.2^\circ\text{C}$  to  $0.4^\circ\text{C}$  on the second floor, indicating tight clustering around the setpoints. The basement shows a slightly higher mean deviation of  $0.43^\circ\text{C}$ , with an interquartile range from  $0.23^\circ\text{C}$  to  $0.53^\circ\text{C}$ —still well within the  $\pm 2^\circ\text{C}$  tolerance band.

Flexible Scenario 2 is associated with larger deviations, particularly in the basement, where the mean deviation reaches  $0.74^{\circ}\text{C}$  and the interquartile range extends from  $0.53^{\circ}\text{C}$  to  $0.94^{\circ}\text{C}$ . The first and second floors show mean deviations of  $0.37^{\circ}\text{C}$  and  $0.53^{\circ}\text{C}$ , with interquartile ranges from  $-0.1^{\circ}\text{C}$  to  $0.7^{\circ}\text{C}$  and  $-0.1^{\circ}\text{C}$  to  $1.1^{\circ}\text{C}$ , respectively. These wider deviations likely reflect increased use of thermal flexibility, though they cannot be directly attributed to the control strategy due to differences in environmental conditions across the evaluation periods. Across all floors, deviations remain within predefined tolerance limits.

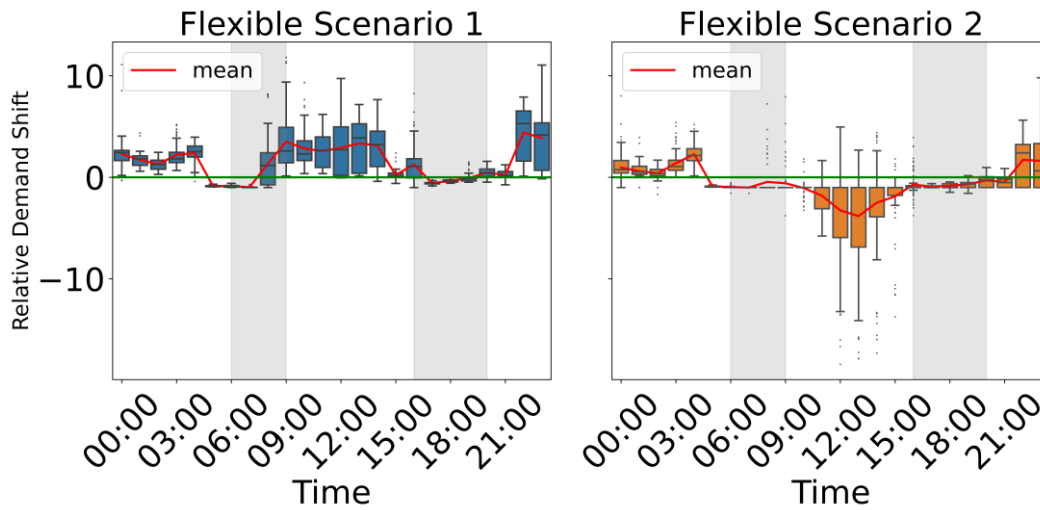


Figure 4.11 Hourly distribution of relative demand shift (with respect to the Reference Scenario) across all days for Flexible Scenario 1 and Flexible Scenario 2.

While cost savings and low average setpoint deviation were prioritized at the building level, the flexible scenarios also delivered the intended grid service incentivized by ToU pricing—namely, load shifting from peak to off-peak periods. Figure 4.11 illustrates the hourly distribution of relative demand shift, defined as the normalized difference between net power imported in the flexible scenarios and the reference scenario. Positive values reflect increased grid reliance—typically during off-peak periods—while negative values indicate effective load reduction or self-consumption enhancement. To assess the impact of the proposed economic MPC on load shifting, average net demand differences and relative demand shift were computed across five predefined daily periods aligned with the ToU pricing structure: early morning (00:00–06:00), morning peak (06:00–09:00), midday off-peak (09:00–16:00), evening peak (16:00–20:00), and late evening (20:00–24:00).

Table 4.8 Average net grid demand difference (kW) between the Flexible Scenarios and the Reference Scenario across defined daily periods.

| Date       | Scenario   | 000-6:00 | 6:00-9:00 | 9:00-16:00 | 16:00-20:00 | 16:00-24:00 |
|------------|------------|----------|-----------|------------|-------------|-------------|
| 2024-02-17 | Flexible 1 | 1.1      | -2.2      | 1.0        | -0.6        | 1.9         |
| 2024-02-18 | Flexible 1 | 1.8      | -1.6      | 2.0        | 0.0         | 1.6         |
| 2024-02-19 | Flexible 1 | 1.2      | -1.9      | 0.6        | -0.5        | 1.9         |
| 2024-02-20 | Flexible 1 | 1.8      | -1.3      | 0.7        | -0.9        | 2.2         |
| 2024-02-21 | Flexible 1 | 1.9      | -1.6      | 0.6        | -0.8        | 1.2         |
| 2024-02-22 | Flexible 1 | 0.7      | -2.4      | 1.3        | -0.9        | -0.2        |
| 2024-02-23 | Flexible 1 | 1.0      | -2.5      | 0.9        | -0.9        | 0.4         |
| 2024-03-01 | Flexible 2 | 1.5      | -1.6      | -0.9       | -1.7        | 1.3         |
| 2024-03-02 | Flexible 2 | 1.1      | -2.4      | -0.2       | -1.1        | 0.6         |
| 2024-03-03 | Flexible 2 | 0.3      | -2.5      | -0.4       | -2.0        | -0.5        |
| 2024-03-04 | Flexible 2 | 0.6      | -2.5      | -0.4       | -1.7        | 0.4         |
| 2024-03-05 | Flexible 2 | 0.2      | -2.5      | -1.4       | -2.2        | -1.3        |
| 2024-03-06 | Flexible 2 | -0.6     | -2.5      | 0.2        | -1.4        | 0.4         |
| 2024-03-07 | Flexible 2 | 0.3      | -2.6      | -2.1       | -2.1        | -1.3        |

Table 4.9 Relative demand shift (unitless) for Flexible Scenarios across defined daily periods.

| Date       | Scenario   | 000-6:00 | 6:00-9:00 | 9:00-16:00 | 16:00-20:00 | 16:00-24:00 |
|------------|------------|----------|-----------|------------|-------------|-------------|
| 2024-02-17 | Flexible 1 | 1.4      | -0.5      | 2.8        | -0.1        | 3.3         |
| 2024-02-18 | Flexible 1 | 1.8      | 0.2       | 5.3        | 0.8         | 2.8         |
| 2024-02-19 | Flexible 1 | 1.3      | 0.0       | 1.5        | 0.2         | 3.2         |
| 2024-02-20 | Flexible 1 | 1.8      | 0.6       | 1.6        | -0.3        | 3.7         |
| 2024-02-21 | Flexible 1 | 1.9      | 0.2       | 1.5        | 0.0         | 2.2         |
| 2024-02-22 | Flexible 1 | 1.0      | -0.8      | 3.5        | 0.0         | 0.3         |
| 2024-02-23 | Flexible 1 | 1.4      | -1.0      | 2.4        | -0.1        | 0.4         |
| 2024-03-01 | Flexible 2 | 1.5      | 0.4       | -2.7       | -0.7        | 2.5         |
| 2024-03-02 | Flexible 2 | 1.3      | -1.0      | -0.6       | -0.2        | 1.5         |
| 2024-03-03 | Flexible 2 | 0.7      | -1.0      | -1.0       | -1.0        | -0.1        |
| 2024-03-04 | Flexible 2 | 1.0      | -1.0      | -1.0       | -0.8        | 1.3         |
| 2024-03-05 | Flexible 2 | 0.6      | -1.0      | -4.0       | -1.2        | -1.0        |
| 2024-03-06 | Flexible 2 | -0.1     | -1.0      | 0.6        | -0.7        | 1.3         |
| 2024-03-07 | Flexible 2 | 0.6      | -1.0      | -6.3       | -1.1        | -1.0        |

Flexible Scenario 1, which integrated predictive setpoint control, demonstrates clear upward shifts in demand during off-peak hours. As shown in Table 4.8, average net import increases reach

up to +1.9 kW in the early morning and +2.0 kW in the late evening, indicating effective preheating during low-cost periods. Morning and evening peak intervals exhibit consistent demand reductions (−1.3 kW to −2.5 kW), suggesting that the controller successfully limited import during high-price hours without inducing excessive rebound effects. These dynamics are further reflected in Table 4.9, where relative demand shift values during off-peak windows reach up to +5.3, confirming deliberate load advancement. Over the evaluation period, Flexible Scenario 1 consumed approximately 84 kWh more than the reference, highlighting a trade-off in which increased total import enabled improved economic operation.

Flexible Scenario 2, which additionally integrated the optimal coordination of PV generation and battery dispatch, exhibits a markedly different load profile. While early-morning demand shifts remain slightly positive (+0.6 to +1.5 kW), all other periods show net reductions—most notably between 09:00 and 16:00, where average differences reach as low as −2.1 kW. The normalized relative shift during this midday window reaches −6.3, the most pronounced across all scenarios and periods, indicating aggressive curtailment enabled by local generation and storage. This strategy not only minimized grid import during peak pricing intervals but also reduced total consumption: Flexible Scenario 2 achieved a net reduction of 115 kWh compared to the reference scenario, delivering both economic and grid-supporting benefits.

These findings underscore how each scenario tailored its response to ToU price signals. Scenario 1 prioritized cost minimization through pre-emptive load advancement, while Scenario 2 leveraged PV integration and battery dispatch for deeper midday curtailment. Both strategies contributed to a flatter load profile, aligning consumption with periods of lower grid stress and delivering the type of load shifting incentivized by ToU pricing structures.

While load shifting primarily targets peak demand reduction under normal grid conditions, additional services are required to strengthen system resilience during rare but disruptive events such as prolonged outages. The next section focuses on post-outage CLPU mitigation—a critical service aimed at alleviating the surge in heating demand that occurs when power is restored. Leveraging the same SDT, this use case demonstrates how heuristic control strategies can pre-emptively reshape thermal states to stagger recovery loads and enhance grid stability during restoration events.

## 4.6 Heuristic MPC for Post-Outage CLPU Mitigation

Post-outage recovery events present a distinct challenge for electric utilities, particularly in cold climates where prolonged outages during winter can cause indoor temperatures to drop significantly. Upon restoration, electric heating systems tend to activate simultaneously, resulting in a surge in demand—known as CLPU. This phenomenon not only stresses grid assets but also risks secondary outages if not properly managed.

This section presents the implementation of a heuristic MPC formulation designed to mitigate CLPU at EHBE by reshaping the net electrical heating load profile during the outage recovery period. The controller evaluates predefined DER coordination plans over the outage and recovery horizon, selecting between alternatives that prioritize either rebound load minimization or setpoint tracking fidelity. This approach enables the post-outage heating load to be staggered and smoothed without relying on outage forecasts or continuous optimization. This implementation demonstrates how semantically structured building representations can support real-time scenario evaluation and rule-based load recovery strategies following grid disruptions. As such, it provides a concrete use case for predictive control in grid-interactive residential buildings and contributes to the broader goal of operational resilience in cold-climate contexts.

Heuristic MPC is a control approach that retains the predictive structure and receding horizon framework of standard MPC but replaces continuous numerical optimization with scenario-based decision-making. Unlike traditional MPC, which operates over a continuous or finely discretized action space and computes control inputs by solving an optimization problem, heuristic MPC restricts the action space to a limited set of predefined and interpretable control strategies—such as setpoint schedules, staged power levels, or mode transitions. These discrete alternatives are simulated over the PH using system forecasts, and the best-performing one is selected based on evaluation metrics. This approach simplifies tuning, enables real-time implementation under constrained computational resources, and is well suited for control problems involving categorical actions or limited observability.

#### 4.6.1 Formulation

This section presents the heuristic MPC formulation used to evaluate predefined post-outage recovery strategies for electric space heating at EHBE. Each candidate strategy defines a full DER coordination plan over the outage and recovery horizon and is assessed using system forecasts of ambient conditions and thermal state. As a special case of the general service-oriented framework introduced in Section 3.1, the formulation quantifies the trade-off between rebound mitigation and comfort preservation over a finite PH using a composite cost function, enabling interpretable comparison without requiring continuous optimization.

In this specific formulation, the cumulative grid import following service restoration serves as a proxy for CLPU severity and is used to assess the ability of each predefined strategy to mitigate rebound stress on the grid. By coordinating the timing of DER deployment, each plan reshapes the recovery load curve to varying degrees, either concentrating or staggering the return of electric heating demand. The internal requirements component of the evaluation reflects thermal comfort degradation by quantifying the absolute deviation from the reference heating setpoint. While this measure captures the magnitude of thermal departure, it does not represent the full experiential scope of discomfort during outages. Equation 4.4 defines the shared cost structure used to evaluate competing recovery strategies based on these two objectives: grid support and thermal restoration.

$$J = \sum_{k=0}^{PH-1} [\pi_{elec}^k (P_{grid}^k \cdot \delta t) + \pi_{therm}^k (\lambda_{set}^k \cdot \delta t)] \quad 4.4$$

subject to:

$$P_{grid} = \begin{cases} 0; & \text{during outage} \\ P_{heat} + P_{batt} - P_{pv}; & \text{otherwise} \end{cases}$$

$$\lambda_{set} = |T_{set} - \hat{T}(\theta^*)|.$$

The formulation presented in Equation 4.4 provides a structured means of comparing predefined recovery strategies based on two competing objectives: limiting grid import during the rebound phase and preserving thermal comfort during and after the outage. The heating setpoint remains fixed at the occupant-defined reference value, and no continuous control signals are computed online. Instead, each candidate plan defines a complete trajectory for DER usage across the outage and recovery horizon. The net grid exchange is conditionally defined: zero during the outage period and equal to the sum of heating load and battery dispatch minus PV generation

during recovery. This structure accommodates varying levels of system integration, but in the context of CLPU mitigation, it is primarily used to evaluate coordinated DER deployment strategies.

The predicted indoor temperature,  $\hat{T}(\theta^*)$ , is computed using the archetype grey-box model introduced in Section 4.3 and compared to the fixed reference setpoint to calculate  $\lambda_{\text{set}}$ , the absolute temperature deviation at each timestep. This term reflects comfort degradation during both the outage and recovery phases and serves as a metric for evaluating occupant-centric performance. All deviations are accumulated continuously from the start of the outage until the indoor air temperature returns to the reference setpoint during recovery.

The coefficients  $\pi_{\text{elec}}$  and  $\pi_{\text{therm}}$  are unitless weights that govern the relative emphasis placed on the two objectives. Specifically,  $\pi_{\text{elec}}$  modulates the importance of suppressing post-outage grid import, while  $\pi_{\text{therm}}$  adjusts the weight given to preserving thermal comfort. The ratio  $\pi_{\text{elec}}/\pi_{\text{therm}}$  functions as a tunable parameter that determines the evaluation bias: high ratios prioritize strategies that conserve DERs for recovery, while low ratios favor immediate DER deployment to maintain indoor temperature during the outage. This structure enables interpretable comparisons across a discrete set of plans, reflecting different service priorities without requiring fine-grained actuation or numerical optimization.

Rather than minimizing an objective function over a continuous decision space, heuristic MPC applies the structure of Equation 4.4 to score alternative recovery strategies. Each plan is simulated over the PH using forecast data, and the evaluation reflects how well it balances rebound mitigation and thermal restoration. In this context, the cost function does not drive real-time control but instead enables a consistent, scenario-based framework for selecting among predefined strategies aligned with grid or occupant priorities.

#### 4.6.2 Implementation

To evaluate the real-time performance of the proposed heuristic MPC formulation for CLPU mitigation, nine pre-scheduled grid outages were experimentally conducted at the EHBE. Each event imposed a 24-hour pre-scheduled grid outage during which thermostatically controlled space heating was unavailable from the grid, followed by an active recovery phase. Predefined DER

coordination strategies were executed in each case and evaluated over the PH using system forecasts. Rather than computing optimal control inputs online, heuristic MPC selects from a fixed set of interpretable, rule-based recovery plans based on their predicted performance under real-world conditions. This experimental structure preserved the predictive nature of MPC while enabling fast, scenario-based decision-making without requiring online numerical optimization.

The experimental outages were distributed across December 2023 and January 2024 to capture the effects of extremely cold weather and variable solar conditions. Each event was spaced sufficiently apart to allow the building’s effective thermal mass to reset, ensuring independent evaluation of each recovery strategy. Rather than enforcing uniform external conditions, this variability was deliberately preserved to reflect the stochastic nature of real-world outages and recoveries. The objective was not to ensure strict comparability across events, but to evaluate how predefined recovery strategies perform under diverse operational contexts. This approach aligns with the core objective of semantic digital twinning—structuring physical system knowledge and telemetry to support robust, context-aware control. Accordingly, the evaluation emphasized the relative effectiveness and resilience of each strategy in managing post-outage recovery, rather than absolute performance normalization. The two evaluated strategies are summarized below as the Reference and Flexible scenarios, each reflecting a distinct philosophy of DER coordination and rebound mitigation:

1. The first scenario, referred to as the Reference Scenario, reflects the BaU recovery plan and is simulated for use as a comparative reference. This rule-based strategy prioritizes occupant comfort by deploying all available DERs immediately during the outage. When PV generation is available, it is used to meet the heating demand, with any excess directed toward battery charging. In periods of insufficient PV, the battery discharges to maintain indoor temperature, provided its SoC remains above the lower limit. No coordination logic is applied for post-outage recovery, and all systems resume full operation as soon as grid power returns. This plan reflects intuitive, comfort-first behavior commonly embedded in autonomous islanded heating or storage systems and serves to characterize BaU rebound dynamics. This control logic is simulated as a rule-based procedure, as formalized in Algorithm 4.1 (top).

---

**Algorithm 1** Reference Scenario

---

**Input:**  $P_{\text{heat}}, P_{\text{PV}}, \text{SoC}$ **Output:** Power allocation to heating, battery, and grid

```
1: while Power outage or recovery phase do
2:   Supply heaters with  $\min(P_{\text{heat}}, P_{\text{PV}})$ 
3:    $P_{\text{surplus}} \leftarrow P_{\text{PV}} - P_{\text{heat}}$ 
4:   if  $P_{\text{surplus}} > 0$  and  $\text{SoC} < 1.0$  then
5:     Charge battery with  $\min\left(P_{\text{surplus}}, P_{\text{batt,max}}, \frac{(1 - \text{SoC})E_{\text{batt,max}}}{\delta t}\right)$ 
6:   else if  $P_{\text{surplus}} < 0$  and  $\text{SoC} > 0$  then
7:      $P_{\text{deficit}} \leftarrow -P_{\text{surplus}}$ 
8:     Discharge battery with  $\min\left(P_{\text{deficit}}, P_{\text{batt,max}}, \frac{\text{SoC} \cdot E_{\text{batt,max}}}{\delta t}\right)$ 
9:   end if
10:  if Recovery phase and  $P_{\text{heat}} > P_{\text{PV}} + P_{\text{batt}}$  then
11:    Import  $P_{\text{grid}} \leftarrow P_{\text{heat}} - P_{\text{PV}} + P_{\text{batt}}$ 
12:  end if
13: end while
```

---

---

**Algorithm 2** Flexible Scenario

---

**Input:**  $P_{\text{heat}}, P_{\text{PV}}, \text{SoC}$ **Output:** Power allocation to heating, battery, and grid

```
1: while Power outage do
2:   if  $P_{\text{PV}} > 0$  and  $\text{SoC} < 1.0$  then
3:     Suspend heating ( $P_{\text{heat}} = 0$ )
4:     Charge battery with  $\min\left(P_{\text{PV}}, P_{\text{batt,max}}, \frac{(1 - \text{SoC})E_{\text{batt,max}}}{\delta t}\right)$ 
5:   else if  $P_{\text{PV}} > 0$  and  $\text{SoC} = 1.0$  then
6:     Supply heaters with  $P_{\text{PV}}$ 
7:   end if
8: end while
9: while Recovery phase do
10:  Supply heaters with  $\min(P_{\text{heat}}, P_{\text{PV}})$ 
11:   $P_{\text{surplus}} \leftarrow P_{\text{PV}} - P_{\text{heat}}$ 
12:  if  $P_{\text{surplus}} > 0$  and  $\text{SoC} < 1.0$  then
13:    Charge battery with  $\min\left(P_{\text{surplus}}, P_{\text{batt,max}}, \frac{(1 - \text{SoC})E_{\text{batt,max}}}{\delta t}\right)$ 
14:  else if  $P_{\text{surplus}} < 0$  and  $\text{SoC} > 0$  then
15:     $P_{\text{deficit}} \leftarrow -P_{\text{surplus}}$ 
16:    Discharge battery with  $\min\left(P_{\text{deficit}}, P_{\text{batt,max}}, \frac{\text{SoC} \cdot E_{\text{batt,max}}}{\delta t}\right)$ 
17:  end if
18:  if  $P_{\text{heat}} > P_{\text{PV}} + P_{\text{batt}}$  then
19:    Import  $P_{\text{grid}} \leftarrow P_{\text{heat}} - P_{\text{PV}} + P_{\text{batt}}$ 
20:  end if
21: end while
```

---

Algorithm 4.1. Rule-based control logic for the Reference (top) and Flexible (bottom) scenarios within the heuristic MPC framework for post-outage CLPU mitigation.

2. The second scenario, referred to as the Flexible Scenario, was implemented and validated at the EHBE. It operates on a predefined plan that deliberately withholds DER usage during the outage to conserve resources for recovery. PV generation charges the battery when possible, but no heating loads are served unless PV power would otherwise be curtailed. Battery discharge is also prohibited during the outage. Upon grid restoration, both battery and PV are used to actively shape the recovery curve, limiting the magnitude and simultaneity of post-

outage demand. This plan allows brief, controlled thermal discomfort to substantially mitigate rebound effects by staggering load recovery, relying solely on predefined logic without requiring online computation or reconfiguration. This control logic is implemented as a rule-based procedure, as formalized in Algorithm 4.1 (bottom).

Both strategies are evaluated using the composite cost structure in Equation 4.4, representing the two extremes of the  $\pi_{\text{elec}}/\pi_{\text{therm}}$  spectrum: the BaU plan reflects a comfort-first approach with  $\pi_{\text{elec}} \ll \pi_{\text{therm}}$ , while the Flexible plan reflects a grid-supportive strategy with  $\pi_{\text{elec}} \gg \pi_{\text{therm}}$ .

Figure 4.12 presents the time series of ambient air temperature and GHI over the experimental period from December 24, 2023, to January 11, 2024. Each grey-shaded region corresponds to one of the nine pre-scheduled grid outage events. These environmental conditions directly influence indoor thermal dynamics and PV generation, motivating the need for heuristic control strategies assessed in the subsequent sections.

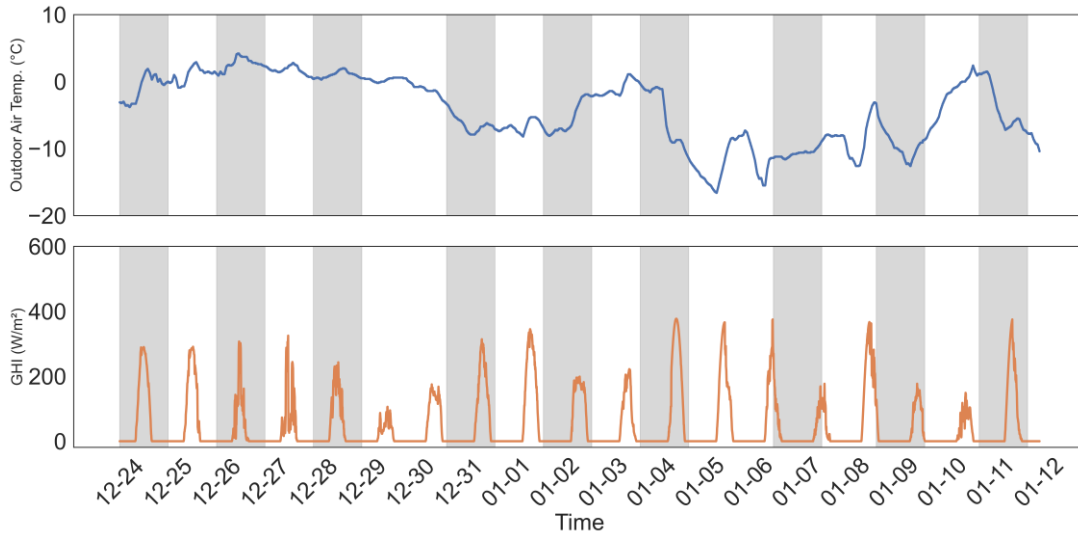


Figure 4.12 Time series of ambient air temperature (top) and GHI (bottom) over the experimental period.

Table 4.10 also summarizes the timing and configuration of these outage events conducted at EHBE. To exploit ontology-driven prioritization, each HVAC zone is semantically annotated with a priority level using `efont:hasPriorityLevel`. This enables the controller to differentiate between critical and non-critical thermal zones and sequence their recovery accordingly. In the

final three events, this lightweight annotation is applied to enable targeted comfort preservation and mitigate rebound simultaneity without increasing control complexity. Zones annotated with `efont:hasPriorityLevel "High"`—denoting essential occupancy or elevated thermal sensitivity—resume heating immediately after grid restoration, while non-critical zones remain inactive during an initial delay period. This zone-level prioritization activates recovery sequentially, demonstrating how semantic annotations can be operationalized to stagger demand recovery and mitigate CLPU.

Table 4.10 Timing and configuration of pre-scheduled grid outage events at EHBE, including zone-level prioritization strategies.

| Outage Event | Start            | End              | Semantic Zone Prioritization |
|--------------|------------------|------------------|------------------------------|
| 1            | 2023-12-24 00:00 | 2023-12-25 00:00 |                              |
| 2            | 2023-12-26 00:00 | 2023-12-27 00:00 |                              |
| 3            | 2023-12-28 00:00 | 2023-12-29 00:00 |                              |
| 4            | 2023-12-30 18:00 | 2023-12-31 18:00 |                              |
| 5            | 2024-01-01 18:00 | 2024-01-02 18:00 |                              |
| 6            | 2024-01-03 18:00 | 2024-01-04 18:00 |                              |
| 7            | 2024-01-06 12:00 | 2024-01-07 12:00 | Basement                     |
| 8            | 2024-01-08 15:00 | 2024-01-09 15:00 | Firs floor                   |
| 9            | 2024-01-10 18:00 | 2024-01-11 18:00 | Second Floor                 |

The proposed heuristic MPC formulation relies on a set of hyperparameters designed to ensure practical feasibility and interpretability in real-world deployment. These parameters are selected based on empirical evidence, heuristic insights, and case-specific constraints, aiming to balance control performance with practical feasibility.

The PH is scenario-dependent and extends adaptively until indoor air temperatures across all prioritized zones return to their reference setpoints following grid restoration. Consequently, PH duration varies across events, capturing differences in environmental conditions, DER availability, and building thermal inertia. The CH is identical to the PH in this formulation, as strategy selection is performed once, ahead of execution, using full-horizon simulation. While sub-horizon updates were considered, re-simulating mid-recovery provides little added value: unlike conventional MPC, this heuristic structure does not recalculate control actions in response to evolving uncertainty but instead evaluates fixed plans prospectively. This design simplifies implementation

and ensures full reproducibility in post-experiment analysis by aligning simulation inputs, recovery outcomes, and measured system responses across different events.

Model calibration is performed once, at the beginning of the simulation, to initialize parameters using the most current system conditions. This step is fully automated and integrated within the semantic digital twinning framework, enabling accurate scenario simulation without requiring online adaptation. Calibration uses the most recent measurements—including indoor air temperature, electric heating input, ambient temperature, and solar irradiance—to update model parameters. As the archetype grey-box model used here incorporates unobserved states—i.e., the temperature of the effective thermal mass on each floor—a fixed window of recent data is used to initialize these hidden states at the start of the simulation, leveraging the calibrated model along with electric heating input, ambient temperature, and solar irradiance measurements. Although measurements are recorded and stored at 1-minute intervals, both the archetype thermal RC model and the strategy simulation logic operate with a 5-minute discretization timestep ( $\delta t = 300$  s). This resolution balances numerical stability and computational efficiency and aligns with established practices in grey-box modeling of building thermal dynamics (Abtahi et al., 2024).

For both scenarios, the reference setpoint is predefined and fixed at 21 °C, reflecting the most common heating preference observed in Québec households. Deviations from this reference are used solely to quantify thermal rebound magnitude following the outage. The battery SoC is allowed to vary between 0% and 100% throughout the simulation. This relaxed constraint aligns with the service objective of maximizing post-outage flexibility. Under CLPU conditions, reserving 10–20% of storage capacity may hinder the ability to shape the recovery load; therefore, full capacity utilization is permitted to enable more aggressive demand reshaping. Table 4.11 summarizes the key hyperparameters governing the real-time implementation of the proposed heuristic MPC formulation.

Table 4.11 Summary of operational hyperparameters used in real-time implementation of the proposed heuristic MPC for post-outage CLPU mitigation.

| Hyperparameter              | Value / Description                                            |
|-----------------------------|----------------------------------------------------------------|
| PH                          | Adaptive (ends upon restoration of prioritized zones)          |
| CH                          | Equal to PH (simulation executed once prior to plan selection) |
| $\delta t$                  | 5 minutes                                                      |
| Model Calibration Frequency | Once (aligned with CH)                                         |

|                    |                                |
|--------------------|--------------------------------|
| Setpoint Profile   | Constant 21 °C                 |
| Battery SoC Limits | Hard-constrained to [0%, 100%] |

### 4.6.3 Results

This section presents and interprets the results of the real-time implementation of the proposed heuristic MPC formulation for post-outage CLPU mitigation, using a set of indicators to evaluate the effectiveness of different recovery strategies. Aligned with the target grid service—limiting rebound demand following outages—the primary objective is to assess how well the building moderates its net electrical load during the critical recovery phase, while balancing occupant comfort and internal thermal restoration. From the grid’s perspective, the emphasis is on mitigating the severity and simultaneity of load resurgence, necessitating indicators that quantify both the peak magnitude and temporal concentration of post-outage demand. From the occupant’s perspective, the goal is to ensure adequate thermal recovery without excessive discomfort, as characterized by metrics reflecting temperature deviations from the reference setpoint and recovery duration. The following indicators address these complementary priorities and are used to compare flexibility outcomes across rule-based scenarios with differing degrees of DER coordination and semantic control integration:

1. **Average Setpoint Deviation (°C):** This indicator quantifies the average deviation of indoor air temperature from the reference setpoint over a defined period, calculated as temperature minus setpoint. A positive value indicates that the indoor air temperature was, on average, above the reference, while a negative value reflects temperatures below it. The magnitude represents the degree of divergence from preferred conditions accepted to meet operational objectives.
2. **Thermal Recovery Time (h/min.):** This indicator quantifies the duration required for all critical zones to thermally recover following grid restoration. It captures the temporal aspect of thermal restoration and is defined as the interval from the end of the outage to the point in time at which all semantically prioritized zones reach their respective setpoints. Shorter recovery times indicate faster restoration and potentially higher occupant comfort in essential areas, whereas longer durations typically reflect deferred heating—a strategy used in flexible scenarios to

stagger demand and mitigate rebound severity. Thus, thermal recovery time highlights the inherent trade-off between grid support and comfort restoration in CLPU mitigation strategies.

3. **Average Rebound Power (kW):** This indicator quantifies the mean net electrical power imported from the grid during the thermal recovery period. It is calculated as the total rebound energy (kWh) divided by the thermal recovery time (h), yielding a normalized measure of rebound intensity in kilowatts. This normalization by recovery time ensures comparability between scenarios with different restoration speeds, allowing the metric to reflect rebound severity independent of the total recovery duration. Higher average rebound power indicates greater grid import during recovery, whereas lower values reflect diminished net demand—often achieved through effective DER coordination or a more gradual, staged approach to thermal restoration.

These indicators quantify key aspects of post-outage energy flexibility most relevant to both grid and building priorities. While they do not represent the complete spectrum of thermal resilience or occupant comfort, their design emphasizes clarity, comparability, and minimal computational overhead, making them well suited for real-time evaluation within a semantic digital twinning framework. Furthermore, they enable consistent pairwise comparisons across recovery strategies with varying degrees of DER coordination and semantic control integration, thereby supporting a structured analysis of flexibility gains under grid-disruptive conditions.

Figure 4.13 and Table 4.12 present the measured PV generation and battery SoC time series for the nine pre-scheduled Flexible Scenario events, covering the 24-hour outage period highlighted in red, followed by a six-hour post-outage window, within which the thermal recovery time—the interval until all critical zones reach their setpoints—is highlighted in green. In all events, the battery starts at 0 % SoC, reflecting the predefined control plan that prohibits discharge during the outage to preserve energy for recovery.

PV generation varies across events due to differences in weather conditions and outage start times. In higher-irradiance cases (Events 1, 4, 6, and 9), the battery charges steadily during the outage, with SoC rising above 80 % prior to restoration. Event 6 is the only case in which PV generation fully charges the battery, initiating a 1 h 50 min period of excess generation redirected to space heating—demonstrating the strategy’s capacity to utilize surplus energy for preheating

when both storage and critical load requirements are satisfied. In lower-irradiance cases (Events 2, 3, 7, and 8), battery SoC at the start of recovery remains below 50 %, limiting the duration of space heating without grid import. Event 7 is the only case with meaningful PV support during recovery (1.6 kWh), whereas all other recoveries rely almost entirely on stored energy.

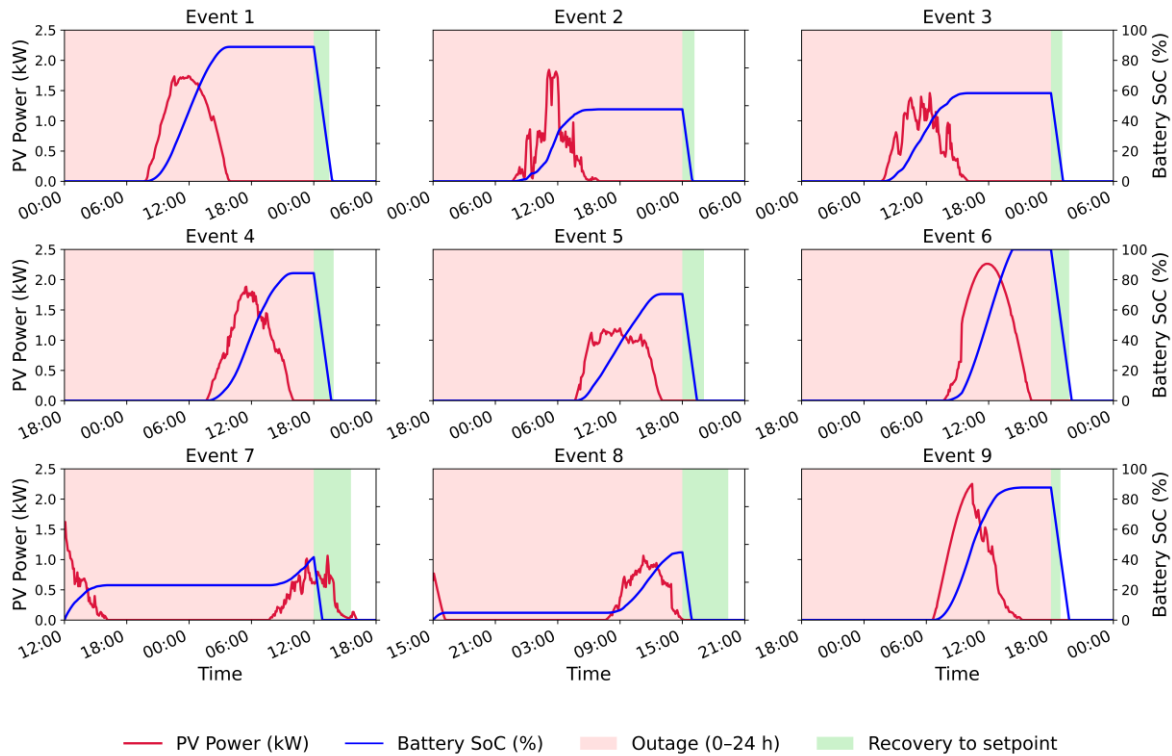


Figure 4.13 Time series of measured PV generation and battery SoC under the Flexible Scenario across the outage events.

Table 4.12 Total PV generation during the outage and recovery windows, and battery SoC at the onset of the recovery window, under the Flexible Scenario across the outage events.

| Outage Event | Total PV Generation - Outage Window (kWh) | Battery SoC at Onset of Recovery (%) | Total PV Generation - Recovery Window (kWh) |
|--------------|-------------------------------------------|--------------------------------------|---------------------------------------------|
| 1            | 8.9                                       | 88.9                                 | 0.0                                         |
| 2            | 4.8                                       | 47.6                                 | 0.0                                         |
| 3            | 5.8                                       | 58.3                                 | 0.0                                         |
| 4            | 8.4                                       | 84.3                                 | 0.0                                         |
| 5            | 7.1                                       | 70.5                                 | 0.0                                         |
| 6            | 11.3                                      | 100.0                                | 0.0                                         |
| 7            | 4.1                                       | 41.2                                 | 1.6                                         |
| 8            | 4.5                                       | 44.5                                 | 0.0                                         |

|   |     |      |     |
|---|-----|------|-----|
| 9 | 8.8 | 87.6 | 0.0 |
|---|-----|------|-----|

Observations from Figure 4.14 and Table 4.12 indicate that a battery SoC exceeding 80 % at the point of restoration consistently provides greater flexibility to shape the rebound profile, even in the absence of PV generation during recovery. They also demonstrate that excess PV generation during outages, although uncommon under winter conditions, can be leveraged for targeted preheating when both storage capacity and critical load requirements are met. Collectively, these findings confirm that, under real-world operating conditions, the Flexible Scenario adheres to its predefined DER coordination plan—charging the battery during outages and withholding discharge until restoration—yielding measurable reductions in rebound intensity while preserving the ability to meet post-outage requirements within available generation and storage capacity.

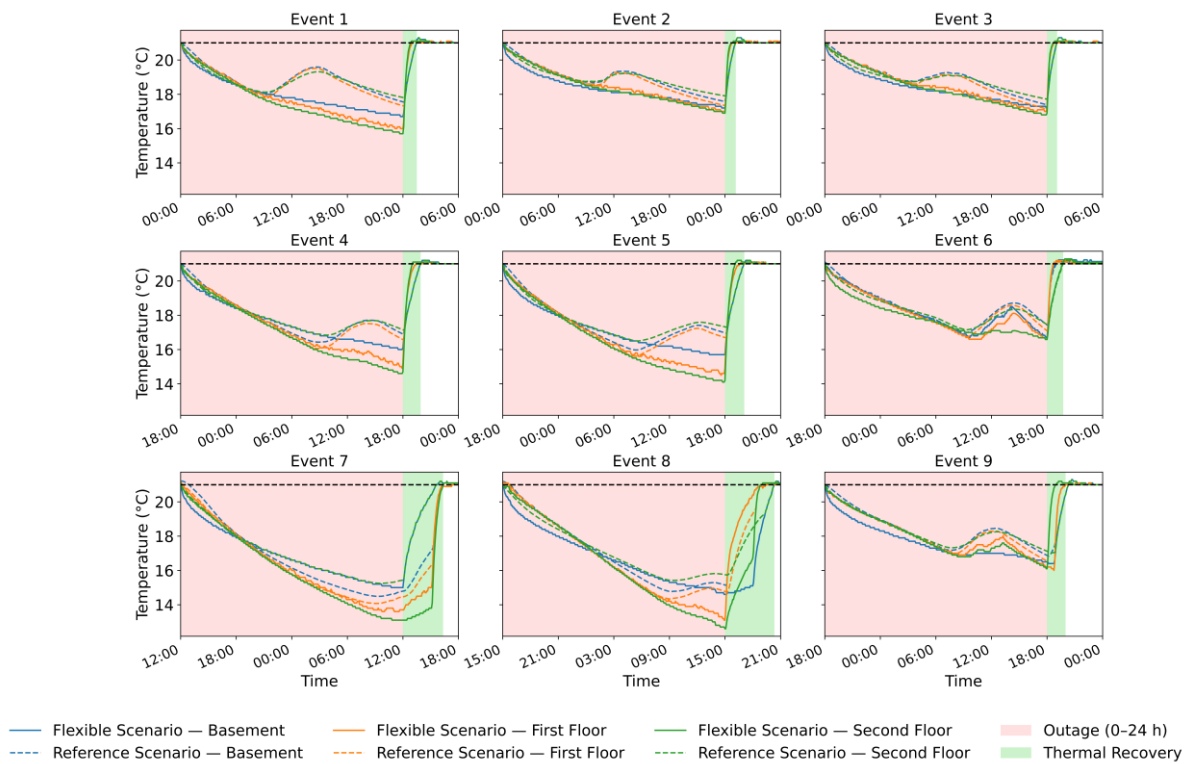


Figure 4.14 Time series of floor-level indoor air temperatures under the Reference Scenario (simulated) and the Flexible Scenario (measured) across the outage events.

Figure 4.14 presents floor-level indoor air temperature time series for the Reference Scenario (simulated) and the Flexible Scenario (measured) across the outage events. Each subplot spans the

24-hour outage period highlighted in red, followed by a six-hour post-outage window, within which the thermal recovery time is highlighted in green. As expected from the control logic, indoor air temperatures are consistently higher under the Reference Scenario, reflecting the contribution of on-site PV generation to space heating. In contrast, the Flexible Scenario withholds heating unless PV generation would otherwise be curtailed, resulting in lower indoor air temperatures across most events. A notable exception occurs in Event 6, where PV generation fully charges the battery before grid restoration, with the surplus redirected to space heating, yielding Flexible Scenario temperatures that closely approach—and in the basement, slightly exceed—those of the Reference Scenario.

Table 4.13 further presents the floor-level indoor air temperature at the onset of recovery (i.e., the instant of grid restoration). The largest divergences appear in Events 4, 5, and 8, where constrained solar availability limits the Flexible plan, resulting in upper-floor temperature deficits exceeding 2 °C relative to the Reference. More moderate gaps are observed in Events 2, 3, and 9, where available PV generation helps narrow inter-scenario differences. Floor-level patterns are also consistent: basements typically retain higher start-of-recovery temperatures than upper floors, reflecting lower envelope losses, whereas the second floor most often records the lowest temperatures at recovery onset due to its greater exposure to the roof and external walls.

Table 4.13 Floor-level indoor air temperatures (°C) at the onset of recovery (instant of grid restoration) for the Reference and Flexible Scenarios across the outage events.

| Outage Event | Reference - First Floor | Flexible - First Floor | Reference - Second Floor | Flexible - Second Floor | Reference - Basement | Flexible - Basement |
|--------------|-------------------------|------------------------|--------------------------|-------------------------|----------------------|---------------------|
| 1            | 17.6                    | 16.0                   | 17.3                     | 15.7                    | 17.8                 | 16.7                |
| 2            | 17.6                    | 17.0                   | 17.4                     | 16.9                    | 17.9                 | 17.2                |
| 3            | 17.4                    | 17.0                   | 17.2                     | 16.8                    | 17.7                 | 17.2                |
| 4            | 16.9                    | 14.9                   | 16.6                     | 14.6                    | 17.2                 | 16.0                |
| 5            | 17.0                    | 14.6                   | 16.7                     | 14.1                    | 17.3                 | 15.7                |
| 6            | 17.5                    | 16.7                   | 17.1                     | 16.6                    | 15.5                 | 17.3                |
| 7            | 14.8                    | 13.7                   | 14.5                     | 13.1                    | 15.1                 | 15.0                |
| 8            | 15.2                    | 13.1                   | 14.8                     | 12.7                    | 15.8                 | 14.6                |
| 9            | 16.9                    | 16.2                   | 16.6                     | 16.1                    | 17.1                 | 16.5                |

Table 4.14 indicates that the Flexible Scenario consistently exhibits higher average setpoint deviations during outages and longer recovery times compared to the Reference Scenario. Averaged across all events, the critical zone deviation increases from 3.0 °C to 3.5 °C, reflecting the strategy of withholding heating unless PV generation would otherwise be curtailed. Thermal recovery time also extends, increasing on average from 82 minutes in the Reference Scenario to 94 minutes in the Flexible Scenario. The most pronounced extensions occur in Events 5 and 8, where thermal recovery times increase by 20 and 15 minutes, respectively, likely influenced by the interplay between solar availability and the sequencing of heating recovery. Overall, these differences remain modest: recovery time is extended by only about 14.9 %, indicating that rebound reduction can be achieved without substantially delaying the restoration of setpoints.

Table 4.14 Critical zone average setpoint deviation (°C) during the outage period and thermal recovery time (min.) under the Reference and Flexible Scenarios across outage events.

| Outage Event | Reference - Average Setpoint Deviation (°C) | Flexible - Average Setpoint Deviation (°C) | Reference - Thermal Recovery Time (min.) | Flexible - Thermal Recovery Time (min.) |
|--------------|---------------------------------------------|--------------------------------------------|------------------------------------------|-----------------------------------------|
| 1            | 2.2                                         | 3.2                                        | 50                                       | 70                                      |
| 2            | 2.1                                         | 2.6                                        | 45                                       | 55                                      |
| 3            | 2.1                                         | 2.6                                        | 45                                       | 50                                      |
| 4            | 3.2                                         | 3.7                                        | 80                                       | 95                                      |
| 5            | 3.5                                         | 4.2                                        | 85                                       | 105                                     |
| 6            | 2.6                                         | 3.0                                        | 65                                       | 80                                      |
| 7            | 4.3                                         | 4.6                                        | 175                                      | 180                                     |
| 8            | 4.0                                         | 4.4                                        | 160                                      | 175                                     |
| 9            | 2.7                                         | 3.1                                        | 35                                       | 40                                      |

Table 4.15 Critical zone total recovery energy imported from the grid (kWh) and average rebound power (kW) under the Reference and Flexible Scenarios across outage events.

| Outage Event | Reference - Recovery Energy Imported (kWh) | Flexible - Recovery Energy Imported (kWh) | Reference - Average Rebound Power (kW) | Flexible - Average Rebound Power (kW) |
|--------------|--------------------------------------------|-------------------------------------------|----------------------------------------|---------------------------------------|
| 1            | 7.9                                        | 2.7                                       | 8.6                                    | 2.3                                   |
| 2            | 5.9                                        | 4.0                                       | 7.9                                    | 4.4                                   |
| 3            | 6.1                                        | 2.8                                       | 8.1                                    | 3.4                                   |
| 4            | 13.0                                       | 8.7                                       | 9.7                                    | 5.5                                   |
| 5            | 13.7                                       | 12.0                                      | 9.7                                    | 6.9                                   |

|   |      |      |     |     |
|---|------|------|-----|-----|
| 6 | 8.2  | 2.3  | 7.6 | 1.7 |
| 7 | 11.3 | 7.9  | 3.9 | 2.6 |
| 8 | 14.2 | 11.4 | 5.3 | 3.9 |
| 9 | 2.7  | 0.0  | 4.7 | 0.0 |

Building on the results for average setpoint deviation and thermal recovery time, Table 4.15 shows that the Flexible Scenario substantially reduces grid imports during recovery. On a per-event basis, recovery energy imported from the grid decreases by an average of 46.6 % relative to the Reference Scenario. The reduction in rebound power is even more pronounced, averaging 53.4 % and declining from 7.3 kW to 3.4 kW, as staged reheating effectively suppresses peak imports. The strongest gains appear in Event 6, where deploying a fully charged battery results in a 71.9 % reduction in recovery energy and a 77.6 % reduction in rebound power, while in Event 9 grid imports during recovery are completely eliminated. Even in Events 5 and 8, where recovery times are among the longest (Table 4.14), the Flexible Scenario still delivers 12.4–19.7 % reductions in recovery energy, confirming that the strategy remains effective under less favorable outage conditions.

Considered together, Tables 4.14 and 4.15 demonstrate that the heuristic MPC consistently mitigates post-outage CLPU while maintaining indoor air temperatures within acceptable bounds. The Flexible Scenario leads to slightly larger setpoint deviations and marginally longer thermal recovery times, yet without compromising the restoration of critical zones. The extent of CLPU mitigation is closely linked to DER availability, with higher PV contributions and battery charge enabling the most pronounced reductions, while even less favorable events continue to yield measurable improvements.

#### 4.7 Transferability

The SDT framework was developed and validated at EHBE 1 in winter 2024, establishing a robust semantic model that integrates Brick Schema, ASHRAE Standard 223P, EFOnt, and RCont ontological layers. To evaluate transferability, the framework was replicated in an adjacent residential building (EHBE 2) in winter 2025, reusing the original SDT with only minimal modifications. As EHBE 2 mirrors EHBE 1 in physical layout, HVAC systems, sensor–actuator

infrastructure, and DERs—including PV and battery storage—it provides an ideal testbed for assessing the practical transferability of the semantic framework across equivalent physical assets.

The complete semantic knowledge graph—including zone definitions, device types, functional annotations, and SHACL validation rules—is instantiated at EHBE 2 without any structural modifications. Such seamless transferability is possible because the semantic abstraction generalizes the underlying physical systems independently of specific device identifiers or implementation nuances. Replicating the SDT within EHBE 2 requires only minimal procedural adjustments: (1) updating the time-series bindings to reference the dedicated InfluxDB endpoint for EHBE 2’s telemetry data, and (2) modifying the IP address of the local edge device responsible for real-time actuation commands. These straightforward configuration changes effectively redirect the data ingestion and control pathways while fully preserving the integrity, coherence, and completeness of the semantic model initially developed for EHBE 1.

The direct reuse of SPARQL query templates, RDF-based reasoning processes, and the supervisory control framework further highlights the modularity and efficiency of the SDT’s design. This replication clearly demonstrates transferability, as semantic abstraction of physical assets substantially reduces the effort traditionally associated with implementing digital twins. Moreover, it indicates the potential for scalability by enabling reproducible and vendor-agnostic supervisory control across residential buildings with DERs.

## **4.8 Conclusions**

This chapter has demonstrated the implementation of the SDT framework in Hydro-Québec’s EHBE testbeds, providing a rigorous evaluation of advanced grid service delivery and confirming its architectural transferability. The results demonstrate that the integration of SDTs with supervisory MPC strategies enables cost-optimal load shifting in response to ToU tariffs and achieves effective post-outage CLPU mitigation during severe winter conditions, further highlighting the capacity of SDTs to deliver grid services while also facilitating streamlined deployment across buildings with identical physical and infrastructural characteristics. The following chapter summarizes the main contributions and experimental findings, discusses the principal limitations of this study and its methodology, and outlines key directions for future

research. These reflections are intended to contextualize the present results and to guide future research advancing scalable solutions for grid-interactive buildings.

## 5. Conclusions

The following chapter summarizes the main contributions and experimental findings, discusses the principal limitations of this study and its methodology, and outlines key directions for future research. These reflections are intended to contextualize the present results and to guide future research advancing scalable solutions for grid-interactive buildings.

### 5.1 Summary of Contributions

This thesis addressed critical gaps at the intersection of semantic digital twinning and predictive supervisory control for grid-interactive buildings. The principal contributions, aligned with the original research objectives, are summarized as follows:

1. Comprehensive review of SDTs and MPC for building-to-grid service delivery: The thesis presented a critical review of the state of the art in operational SDTs and MPC, synthesizing developments in semantic interoperability, control integration, and real-world MPC deployments. This review established the technical and methodological challenges—particularly in scalability, adaptability, and grid service orchestration—and defined the rationale for integrating operational SDTs with supervisory MPC frameworks in building-to-grid applications.
2. Development and public release of RCOnt for semantic thermal modeling: A novel ontology, RCOnt, was developed and released to formalize the representation and integration of control-oriented thermal RC models within SDTs. RCOnt defined the necessary classes and properties for capturing the structure and parameters of archetype grey-box models, including nodes, resistances, capacitances, and solar apertures, and was aligned with established ontologies. The ontology was implemented in RDF/OWL, validated through SHACL constraints, and successfully integrated into the operational SDT stack to support real-time supervisory control. This open resource established a semantic foundation for unifying thermal modeling and control workflows.
3. Design and real-time operationalization of a layered SDT for supervisory control: The research developed a layered, operational SDT by integrating Brick Schema, ASHRAE Standard 223P,

EFOnt, and RCOnt within a unified semantic framework. Semantic entities were dynamically mapped to real-time telemetry, model parameters, and control endpoints. The SDT enabled automated device discovery, extraction of flexibility attributes, and assembly of control definitions via SPARQL queries. This approach supported declarative, vendor-agnostic control execution through an MPC framework that retrieved all necessary constraints and associations from the semantic graph, eliminating hard-coded mappings. The SDT architecture was deployed on commercial smart home infrastructure, demonstrating the feasibility of a natively semantic, service-oriented MPC stack for residential energy management.

4. Experimental demonstration of transferable and potentially scalable building-to-grid service delivery: The SDT framework was implemented in Hydro-Québec’s EHBE testbeds, two physically identical, highly instrumented residential buildings. The experiments validated that integrating SDTs with supervisory MPC enables the delivery of grid services that are particularly critical in Québec’s energy context:
  - Tariff-responsive load shifting: Economic MPC was tested for tariff-responsive load shifting under Rate Flex D through two scenario-based experiments. In Flexible Scenario 1, real-time thermostat setpoint optimization delivered average cost savings of 35 % during a February week, with daily reductions ranging from 8–55 %. The strategy advanced heating into low-tariff hours, increasing imports by about +2 kW in early morning and evening periods while cutting peak-hour imports by up to –2.5 kW. This resulted in deliberate load shifting toward off-peak periods, reflected in relative demand shift values up to +5.3, though total consumption increased by 84 kWh relative to the reference. In Flexible Scenario 2, the framework was extended to include on-site PV and battery storage during a March week, achieving average cost savings of 78 %, a net import reduction of 115 kWh, and 25 kWh of exports. Midday curtailment reached –2.1 kW on average between 09:00 and 16:00, corresponding to a normalized shift of –6.3. Across both cases, indoor air temperature were maintained predominantly within  $\pm 1$  °C of the reference setpoint, with Scenario 1 showing minimal deviation from setpoints and Scenario 2 exhibiting broader but still permissible variation. Together, the results demonstrate that predictive control can shift heating loads to low-tariff windows, and that

coupling with PV-battery optimal coordination further enhances both cost efficiency and grid support.

- **Post-outage CLPU mitigation:** Heuristic MPC was tested for post-outage CLPU mitigation across nine pre-scheduled events. Relative to the Reference Scenario, the Flexible Scenario reduced average rebound power from 7.3 kW to 3.4 kW (−53 %) and recovery energy from 83.0 kWh to 51.8 kWh (−47 %). Critical-zone average setpoint deviation increased marginally, from 3.0 °C to 3.5 °C, with thermal recovery time extending from 82 to 94 minutes (+15 %). The strongest gains occur when a fully charged battery is deployed, resulting in a 72 % reduction in recovery energy and a 78 % reduction in rebound power, and in one such case grid imports during recovery are eliminated entirely. Even under the longest recovery durations observed, the Flexible Scenario still delivers 12–20 % reductions in imported energy, underscoring the robustness of rebound mitigation across diverse outage conditions.
- **Transferability and scalability:** The SDT architecture, initially developed for EHBE 1, was replicated in EHBE 2 without modifications to the semantic model, control logic, or mapping pipeline, requiring only minor reconfiguration of telemetry and control endpoints. This validated the architectural transferability of the framework with minimal engineering overhead and highlighted its scalability potential, as semantic abstraction enables reproducible, vendor-agnostic supervisory control across residential buildings with DERs.
- **Advancement of semantic interoperability:** The layered approach, coupled with semi-automated entity mapping and SHACL-based validation, established a transferable methodology for interoperable digital twinning and control across residential buildings, with direct contributions to the development of ASHRAE Standard 223P.

Collectively, these contributions delivered and validated a modular, reproducible framework for real-time supervisory control of grid-interactive buildings based on operational semantic digital twinning. The results advanced the state of the art in semantic modeling, predictive control, and operational execution, offering a clear pathway for scalable, interoperable, and service-oriented integration of building flexibility with evolving grid requirements.

## 5.2 Limitations and Future Work

While this study demonstrates significant contributions, especially the architectural transferability of the developed SDT framework, it also entails practical and methodological limitations that must be acknowledged.

The EHBE testbeds are unoccupied residential buildings equipped with advanced instrumentation and sophisticated IoT infrastructure. While such controlled conditions facilitate the deployment of operational SDTs integrated with supervisory MPC, they differ from real-world residential settings, where occupant interactions with HVAC systems, lighting, appliances, and other devices introduce unpredictable dynamics. This gap is reinforced by the current SDT framework, which does not incorporate occupant feedback loops, user preferences, or manual override behaviors, thereby limiting its ability to accommodate interventions common in practice. Moreover, thermal performance is evaluated using average setpoint deviation—defined as the absolute difference from a reference setpoint—as a control-oriented benchmark rather than a comfort metric. Although useful for comparing predictive control strategies, this indicator oversimplifies indoor thermal dynamics by neglecting subjective experiences, adaptive comfort responses, and individual sensitivities, providing a consistent but inherently constrained perspective on thermal conditions.

Although the transferability of the SDT framework was validated through replication between identical residential buildings, this outcome is contingent on exact parity in physical layout, HVAC systems, sensor–actuator infrastructure, and DER configurations. In real-world contexts, where buildings differ in layout, HVAC design, DER capacities, and IoT integration, replication would likely require more extensive semantic reconfiguration than the minimal procedural adjustments demonstrated here. This challenge is compounded by the framework’s reliance on stable, well-defined ontologies (Brick Schema, ASHRAE Standard 223P, EFOnt, and RCOnt). While this research achieved partial automation of ontology mappings, the process still demands substantial domain expertise and manual oversight, and the lack of widely available, fully automated semantic alignment methods continues to limit scalability, underscoring the need for further research and standardization.

These limitations highlight critical directions for future research, particularly the transition from controlled testbeds to occupied, heterogeneous, and operationally complex real-world settings. Addressing these constraints—through automated semantic mapping, occupancy modeling, and adaptive comfort metrics—is essential for advancing the SDT framework toward scalable deployment and resilient building–grid integration.

Future work should prioritize the development of robust, scalable methods for automated or semi-automated semantic alignment across diverse building typologies, system architectures, and device ontologies. Leveraging data-driven techniques, machine learning, and ontology-matching approaches can reduce manual effort and enhance the scalability of SDT deployments. Complementing these advances, continued contributions to the standardization of building ontologies, data exchange protocols, and semantic annotation schemas are essential. Promoting open-source tools, interoperable platforms, and reproducible research practices will further accelerate adoption and innovation at the building–grid interface.

Future research should extend occupant-centric modeling by embedding behavioral dynamics, comfort preferences, adaptive routines, and real-time feedback within the SDT framework to capture internal gains and interactions that strengthen the ecological validity of predictive control. Building on this foundation, the supervisory control framework should be extended with adaptive, learning-based, and uncertainty-aware MPC methods capable of adjusting dynamically to unforeseen events, forecast errors, and evolving system parameters. Embedding probabilistic forecasts, ensemble weather and DER predictions, and uncertainty quantification into both MPC formulations and SDT reasoning layers will strengthen robustness and resilience, enabling control strategies that adapt online while hedging against volatility to ensure reliable grid service delivery.

Together, these research directions outline a pathway for evolving semantic digital twinning from controlled testbeds toward practical, field-deployed infrastructures that support reliable building–grid integration.

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## Appendix A: RCOnt

```
@prefix owl: <http://www.w3.org/2002/07/owl#> .
@prefix rdfs: <http://www.w3.org/2000/01/rdf-schema#> .
@prefix qudt: <http://qudt.org/schema/qudt/> .
@prefix unit: <http://qudt.org/vocab/unit/> .
@prefix xsd: <http://www.w3.org/2001/XMLSchema#> .

#####
# Ontology Declaration
#####

<https://matinabtahi.github.io/OperationalDigitalTwinning/RCOnt> a
owl:Ontology ;
    rdfs:label "RC Ontology" ;
    rdfs:comment "A semantic ontology to describe thermal RC models for
simulation and model-based predictive control in buildings. Includes air and
envelope nodes, resistances, capacitances, solar aperture, governing
dynamics, and alignment with building zones." .

#####
### Core Classes
#####

rcont:RCModel a owl:Class ;
    rdfs:label "RC Model" ;
    rdfs:comment "A thermal RC model describing the dynamic energy balance
of a zone." .

rcont:Node a owl:Class ;
    rdfs:label "Thermal Node" ;
    rdfs:comment "A thermal node, such as indoor air, envelope wall mass,
etc." .

rcont:AirNode a owl:Class ;
    rdfs:subClassOf rcont:Node ;
    rdfs:label "Air Node" ;
    rdfs:comment "Represents the air temperature node in a thermal zone." .
```

```

rcont:EnvelopeNode a owl:Class ;
  rdfs:subClassOf rcont:Node ;
  rdfs:label "Envelope Node" ;
  rdfs:comment "Represents thermal mass of the envelope, interacting with
the air node via R/C components." .

```

```

rcont:RValue a owl:Class ;
  rdfs:label "Thermal Resistance" ;
  rdfs:comment "Represents thermal resistance (K/W) between nodes." .

```

```

rcont:CValue a owl:Class ;
  rdfs:label "Thermal Capacitance" ;
  rdfs:comment "Represents thermal capacitance (J/K) of a node." .

```

```

rcont:SolarAperture a owl:Class ;
  rdfs:label "Solar Aperture" ;
  rdfs:comment "Represents the effective solar gain surface area (in
m²)." .

```

```

#####
### Modeling Semantics
#####

```

```

rcont:modelsZone a owl:ObjectProperty ;
  rdfs:domain rcont:RCModel ;
  rdfs:range <https://brickschema.org/schema/1.1/Brick#HVAC_Zone> ;
  rdfs:label "models Zone" ;
  rdfs:comment "Connects the RC model to the Brick HVAC zone it
represents." .

```

```

rcont:hasInput a owl:ObjectProperty ;
  rdfs:domain rcont:RCModel ;
  rdfs:range <https://brickschema.org/schema/1.1/Brick#Point> ;
  rdfs:label "has Input" ;
  rdfs:comment "Associates the RC model with external inputs such as
outdoor temperature, heating power, or solar irradiance." .

```

```

rcont:hasState a owl:ObjectProperty ;
    rdfs:domain rcont:RCModel ;
    rdfs:range <https://brickschema.org/schema/1.1/Brick#Point> ;
    rdfs:label "has State" ;
    rdfs:comment "Associates the RC model with a measurable state variable,
e.g., indoor air temperature." .

```

```

#####
### Structural Properties
#####

```

```

rcont:hasNode a owl:ObjectProperty ;
    rdfs:domain rcont:RCModel ;
    rdfs:range rcont:Node ;
    rdfs:label "has Node" .

```

```

rcont:hasResistance a owl:ObjectProperty ;
    rdfs:domain rcont:RCModel ;
    rdfs:range rcont:RValue ;
    rdfs:label "has Resistance" .

```

```

rcont:hasCapacitance a owl:ObjectProperty ;
    rdfs:domain rcont:RCModel ;
    rdfs:range rcont:CValue ;
    rdfs:label "has Capacitance" .

```

```

rcont:hasSolarAperture a owl:ObjectProperty ;
    rdfs:domain rcont:RCModel ;
    rdfs:range rcont:SolarAperture ;
    rdfs:label "has Solar Aperture" .

```

```

rcont:connects a owl:ObjectProperty ;
    rdfs:domain rcont:RValue ;
    rdfs:range rcont:Node ;
    rdfs:label "connects" ;
    rdfs:comment "Used twice per R to indicate both ends of the
connection." .

```

```

rcont:belongsToNode a owl:ObjectProperty ;
    rdfs:domain [ owl:unionOf (rcont:CValue rcont:SolarAperture) ] ;
    rdfs:range rcont:Node ;
    rdfs:label "belongs to Node" ;
    rdfs:comment "Indicates the node holding thermal capacity or receiving
solar gains." .

```

```

#####
### Value Properties
#####

```

```

rcont:numericValue a owl:DatatypeProperty ;
    rdfs:domain [ owl:unionOf (rcont:RValue rcont:CValue
rcont:SolarAperture) ] ;
    rdfs:range xsd:decimal ;
    rdfs:label "numeric value" .

```

```

rcont:unit a owl:ObjectProperty ;
    rdfs:domain [ owl:unionOf (rcont:RValue rcont:CValue
rcont:SolarAperture) ] ;
    rdfs:range qudt:Unit ;
    rdfs:label "unit" .

```

```

#####
### Annotation
#####

```

```

rcont:governingEquation a owl:AnnotationProperty ;
    rdfs:label "governing equation" ;
    rdfs:comment "Textual reference to the governing physical dynamics."

```

## Appendix B: SPARQL Query Template and MPC Implementation Code

```
PREFIX brick: <https://brickschema.org/schema/1.1/Brick#>
PREFIX efont: <https://w3id.org/def/efont#>
PREFIX sh: <http://www.w3.org/ns/shacl#>
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX qudt: <http://qudt.org/schema/qudt/>
PREFIX sdt: <http://example.org/sdt#>

SELECT DISTINCT ?zone ?equipment ?input ?state ?output ?serviceTarget
?parameter ?value ?unit ?disturbance ?hasConstraint
WHERE {
    # Zones of control
    ?zone rdf:type brick:HVAC_Zone .

    # Equipment associated with each zone
    ?equipment brick:isLocatedIn ?zone ;
        rdf:type ?equipmentType .

    # Control inputs (Brick + EFont)
    OPTIONAL {
        ?input brick:isPointOf ?equipment ;
            rdf:type brick:Command .
    }
    OPTIONAL {
        ?input rdf:type efont:ControlInput ;
            efont:hasInfluenceOn ?equipment .
    }

    # State variables (Brick + EFont)
    OPTIONAL {
        ?state brick:isPointOf ?equipment ;
            rdf:type brick:Sensor .
    }
    OPTIONAL {
        ?state rdf:type efont:StateVariable ;
            efont:hasScope ?equipment .
    }
}
```

```

}

# Output variables (Brick + EFont)
OPTIONAL {
    ?output brick:isPointOf ?equipment ;
        rdf:type brick:Sensor .
}

OPTIONAL {
    ?output rdf:type efont:OutputVariable ;
        efont:hasScope ?zone .
}

# Service targets (Brick + EFont)
OPTIONAL {
    ?output brick:hasServiceTarget ?serviceTarget .
}

OPTIONAL {
    ?serviceTarget rdf:type efont:ServiceLevel ;
        efont:hasTargetOf ?output .
}

# Physical parameters (for RC modeling, etc.)
OPTIONAL {
    ?parameter brick:isParameterOf ?equipment ;
        qudt:numericValue ?value ;
        qudt:unit ?unit .
}

# Disturbances (e.g., weather, occupancy)
OPTIONAL {
    ?disturbance rdf:type efont:Disturbance ;
        efont:hasInfluenceOn ?zone .
}

# Optional: SHACL constraints
OPTIONAL {
    ?shape sh:targetClass ?target ;
        sh:property ?propShape .
}

```

```

        ?target rdfs:subClassOf* ?equipmentType .
        ?propShape sh:path ?hasConstraint .
    }
}.

### MPC
# -*- coding: utf-8 -*-
"""
Title: MPC-Based Setpoint Scheduling and Data Integration (Sanitized)
Author: matinabtahi
Affiliation: Concordia University / Hydro-Québec LTE
License: For academic reproduction; credentials must be provided via
environment/config.

Notes:
- All credentials, IPs, and URLs are read from environment variables.
- Internal/private IPs removed; use CONFIG_* vars below.
- Minor fixes:
    (a) aggregate_data(..., model="orientation") 'North' group corrected to
match disaggregate_setpoints
    (b) explicit timezone is America/Toronto for clarity
    (c) added safe solver fallback if GUROBI unavailable
"""

import os
import io
import socket
import pathlib
import warnings
import requests
import numpy as np
import pandas as pd
import cvxpy as cp
from influxdb_client import InfluxDBClient
from influxdb_client.client.warnings import MissingPivotFunction
import pysftp

warnings.simplefilter("ignore", MissingPivotFunction)

```

```

# ----- Configuration via environment -----
-----

# InfluxDB
INFLUX_URL = os.getenv("CONFIG_INFLUX_URL", "https://<influx-host>:8086")
INFLUX_TOKEN = os.getenv("CONFIG_INFLUX_TOKEN", "")
INFLUX_BUCKET = os.getenv("CONFIG_INFLUX_BUCKET", "MEEB1")
INFLUX_ORG = os.getenv("CONFIG_INFLUX_ORG", "LTE")

# Weather
SOLCAST_URL = os.getenv("CONFIG_SOLCAST_URL", "")          # e.g.,
https://api.solcast.com.au/...
SOLCAST_KEY = os.getenv("CONFIG_SOLCAST_KEY", "")
OWM_HISTORY_URL = os.getenv("CONFIG_OWM_HISTORY_URL",
"https://history.openweathermap.org/data/2.5/history/city")
OWM_KEY = os.getenv("CONFIG_OWM_KEY", "")

# SFTP Target (Raspberry Pi or Edge Gateway)
SFTP_HOST = os.getenv("CONFIG_SFTP_HOST", "")
SFTP_PORT = int(os.getenv("CONFIG_SFTP_PORT", "22"))
SFTP_USER = os.getenv("CONFIG_SFTP_USER", "pi")
SFTP_PASS = os.getenv("CONFIG_SFTP_PASS", "")
SFTP_DEST = os.getenv("CONFIG_SFTP_DEST",
"/home/pi/sharepoint_IoT/scheduler/mpcResults.csv")

# General
LOCAL_TZ = "America/Toronto"
RESULTS_DIR = pathlib.Path("./MPC_results")
SETPOINTS_DIR = pathlib.Path("./Setpoints")
SOLAR_DIR = pathlib.Path("./Solar")

# ----- Database fetch -----
def fetch_from_database(start_date: pd.Timestamp, end_date: pd.Timestamp) -
> pd.DataFrame:
    """Fetch historical data from InfluxDB and return a tidy long-format
    DataFrame."""
    # Ensure UTC for the Flux range
    start_utc = start_date.tz_convert("UTC").strftime("%Y-%m-%dT%H:%M:%SZ")

```

```

end_utc = end_date.tz_convert("UTC").strftime("%Y-%m-%dT%H:%M:%SZ")

query = (
    f'from(bucket: "{INFLUX_BUCKET}") '
    f' |> range(start: {start_utc}, stop: {end_utc}) '
    ' |> filter(fn: (r) => r["_measurement"] == "Heating_System") '
    ' |> aggregateWindow(every: 1m, fn: mean, createEmpty: false) '
)

with InfluxDBClient(url=INFLUX_URL, token=INFLUX_TOKEN, org=INFLUX_ORG)
as client:
    df = client.query_api().query_data_frame(query=query)

    df = df.loc[:, ["_time", "_value", "_field", "topic"]].rename(
        columns={"_time": "Time", "_value": "Value", "_field": "Variable",
"topic": "Zone"}
    )
    df = df.set_index("Time")
    df.index = df.index.tz_convert(LOCAL_TZ)

    # Normalize variable and zone labels
    var_map = {
        "current": "current",
        "energy": "energy",
        "linkquality": "linkQuality",
        "local_temperature": "temperature",
        "occupied_heating_setpoint": "setpoint",
        "pi_heating_demand": "heatingPct",
        "voltage": "voltage",
    }

    df["Variable"] = df["Variable"].map(var_map)
    df["Zone"] = df["Zone"].str.rsplit("/").str[1]
    return df

def get_historical_data(start_date: pd.Timestamp, end_date: pd.Timestamp,
savefile: pathlib.Path | None = None) -> pd.DataFrame:
    """Cache-aware retrieval of InfluxDB timeseries."""

```

```

        start_date = start_date.tz_localize(LOCAL_TZ) if start_date.tzinfo is
None else start_date.tz_convert(LOCAL_TZ)
        end_date = end_date.tz_localize(LOCAL_TZ) if end_date.tzinfo is None
else end_date.tz_convert(LOCAL_TZ)

    if savefile and savefile.exists():
        saved = pd.read_csv(savefile, index_col="Time", parse_dates=True)
        saved.index = saved.index.tz_localize("UTC").tz_convert(LOCAL_TZ)
    if saved.index.tz is None else saved.index.tz_convert(LOCAL_TZ)

    new_index = pd.date_range(start_date, end_date, freq="1T",
tz=LOCAL_TZ)
    newest_saved = saved.index.max()
    if (new_index.max() - newest_saved) > pd.Timedelta(minutes=1):
        # fetch only the missing tail
        to_fetch = new_index[newest_saved < new_index]
        new_data = fetch_from_database(to_fetch[0], to_fetch[-1])
        data = pd.concat([saved, new_data]).sort_index()
        data.to_csv(savefile)
    else:
        # just trim to requested end
        data =
saved.loc[saved.index.intersection(pd.date_range(saved.index[0], end_date,
freq="1T", tz=LOCAL_TZ)), :]
        return data

    data = fetch_from_database(start_date, end_date)
    if savefile:
        data.to_csv(savefile)
    return data

# ----- Weather forecast (Solcast + OWM history) -----
-----

def get_weather_forecast() -> pd.DataFrame | None:
    """Fetch 7-day forecast (Solcast) and store newest snapshot; return key
variables at 15-min."""
    # throttle downloads to every 4 hours
    need_fetch = True

```

```

if SOLAR_DIR.exists():
    existing = [p.stem for p in SOLAR_DIR.rglob("*.csv")]
    if existing:
        newest = pd.to_datetime(existing, format="%Y-%m-%dT%H-%M").max()

        if (pd.Timestamp.now(tz=LOCAL_TZ) - newest) <=
pd.Timedelta(hours=4):
            need_fetch = False
            file_to_read = newest.strftime("%Y-%m-%dT%H-%M")

    if need_fetch:
        SOLAR_DIR.mkdir(parents=True, exist_ok=True)
        if not (SOLCAST_URL and SOLCAST_KEY):
            raise RuntimeError("Solcast URL/API key not configured
(CONFIG_SOLCAST_URL, CONFIG_SOLCAST_KEY).")

        resp = requests.get(SOLCAST_URL, params={"format": "csv",
"api_key": SOLCAST_KEY}, timeout=30)
        if resp.status_code != 200:
            raise RuntimeError(f"Solcast download failed:
{resp.status_code} - {resp.text[:200]}")

        df = pd.read_csv(io.StringIO(resp.text))
        # Build index from Solcast period_end; align to 30 min trailing
        idx = pd.date_range(df.loc[df.index[0], "period_end"],
df.loc[df.index[-1], "period_end"], freq="30T")
        idx = (idx.tz_convert(LOCAL_TZ) - pd.Timedelta(minutes=30)) if
idx.tz is not None else (idx.tz_localize("UTC").tz_convert(LOCAL_TZ) -
pd.Timedelta(minutes=30))
        df.index = idx

        df = df.loc[:, ["ghi", "ghi90", "ghi10", "ebh", "dni", "dni90",
"dni10", "dhi", "air_temp"]]
        air = df[["air_temp"]].resample("15T").interpolate("linear")
        solar =
df.drop(columns=["air_temp"]).resample("15T").interpolate("pad") / 1000.0 #
W/m2 -> kW/m2 if desired
        out = pd.concat([air, solar], axis=1)

```

```

        snap = SOLAR_DIR / f"{out.index[0].strftime('%Y-%m-%dT%H-%M')}.csv"
        out.to_csv(snap)
        return out.loc[:, ["air_temp", "ghi", "ghi10", "ghi90"]]

    # read the latest stored snapshot
    df = pd.read_csv(SOLAR_DIR / f"{file_to_read}.csv", index_col=0,
parse_dates=True)
    df.index = df.index.tz_localize("UTC").tz_convert(LOCAL_TZ) if
df.index.tz is None else df.index.tz_convert(LOCAL_TZ)
    return df.loc[:, ["air_temp", "ghi", "ghi10", "ghi90"]]

# ----- Helper transforms -----
def resample_data(data: pd.DataFrame) -> tuple[pd.DataFrame, pd.DataFrame]:
    """Return 15-min temperature and heating from raw InfluxDB export."""
    temp = data.loc[data.Variable == "temperature"].pivot(columns="Zone",
values="Value")
    temp =
temp.resample("1T").interpolate("linear").resample("15T").asfreq()
    temp = temp.loc[:, temp.columns.difference(["Garage", "Bathroom_1F"])]

    energy = data.loc[data.Variable == "energy"].pivot(columns="Zone",
values="Value")
    energy =
energy.resample("1T").interpolate("pad").resample("15T").asfreq()
    energy = energy.diff() * 3600 / 900 # Wh per 15 min
    energy = energy.loc[:, energy.columns.difference(["Garage",
"Bathroom_1F"])]

    hpc = data.loc[data.Variable == "heatingPct"].pivot(columns="Zone",
values="Value")
    hpc = hpc.resample("1T").interpolate("pad").resample("15T").mean()
    hpc = hpc.loc[:, hpc.columns.difference(["Garage", "Bathroom_1F"])]
    # Nameplate powers [W] for each remaining zone (order must match
columns)
    rated_W = np.array([1000, 1250, 1250, 1250, 1250, 1500, 1500, 2000,
2000], dtype=float)
    hpc_kWh = hpc * rated_W / 100.0 / 1000.0 # fraction * W -> kW

```

```

        energy.loc[:, "Bedroom_SE_2F"] = hpc_kWh.loc[:, "Bedroom_SE_2F"] #
backfill if energy missing
        return temp, energy

def create_setpoints() -> pd.DataFrame:
    """Daily schedule: 19°C baseline; 21°C morning/evening blocks."""
    labels = [
        "Bathroom_NW_2F", "Bedroom_NE_2F", "Bedroom_SE_2F",
"Bedroom_SW_2F",
        "Dining_Room_1F", "Kitchen_1F", "Living_Room_1F",
"Underground_Tech_N", "Underground_Tech_S",
    ]
    idx = pd.date_range(pd.Timestamp.now(tz=LOCAL_TZ).date(),
                        pd.Timestamp.now(tz=LOCAL_TZ).date() +
pd.Timedelta(days=3),
                        freq="15T", tz=LOCAL_TZ)
    sp = pd.DataFrame(index=idx, columns=labels, data=19.0)
    sp.loc[(sp.index.hour >= 5) & (sp.index.hour < 8), :] = 21.0
    sp.loc[(sp.index.hour >= 17) & (sp.index.hour < 22), :] = 21.0
    return sp

def create_heating_bounds() -> pd.DataFrame:
    """Lower/upper bounds [W] for each zone except Garage."""
    labels = [
        "Bathroom_NW_2F", "Bedroom_NE_2F", "Bedroom_SE_2F",
"Bedroom_SW_2F",
        "Dining_Room_1F", "Kitchen_1F", "Living_Room_1F",
"Underground_Tech_N", "Underground_Tech_S",
    ]
    hb = pd.DataFrame(columns=labels, index=["minim", "maxim"],
dtype=float)
    hb.loc["minim", :] = 0.0
    hb.loc["maxim", :] = [1000, 1250, 1250, 1250, 1250, 1500, 1500, 2000,
2000]
    return hb

def create_price(morning: bool = False, evening: bool = False) ->
pd.Series:

```

```

"""Price series [cents/kWh]."""
idx = pd.date_range(pd.Timestamp.now(tz=LOCAL_TZ).date(),
                    pd.Timestamp.now(tz=LOCAL_TZ).date() +
pd.Timedelta(days=3),
                    freq="15T", tz=LOCAL_TZ)
price = pd.Series(index=idx, data=4.449) # base tariff
if morning:
    price[(price.index.hour >= 6) & (price.index.hour < 9)] = 51.967
if evening:
    price[(price.index.hour >= 16) & (price.index.hour < 20)] = 51.967
return price

def read_ABC(model: str) -> tuple[np.ndarray, np.ndarray, np.ndarray]:
    """Load state-space matrices A, B, C from Matrices/{model}_.npz."""
    mats = np.load(pathlib.Path(f"Matrices/{model}_.npz"))
    return mats["A"], mats["B"], mats["C"]

# ----- Aggregation helpers -----
def aggregate_data(data: pd.DataFrame, model: str, variable: str) ->
pd.DataFrame:
    """Aggregate to floor or orientation groups."""
    volume = pd.Series(index=data.columns, dtype=float)
    volume.loc[
        [
            "Bathroom_NW_2F", "Bedroom_NE_2F", "Bedroom_SE_2F",
"Bedroom_SW_2F",
            "Dining_Room_1F", "Kitchen_1F", "Living_Room_1F",
"Underground_Tech_N", "Underground_Tech_S",
        ]
    ] = [22.2, 29.7, 23.1, 26.2, 23.6, 27.9, 37.8, 54.8, 94.5]

    if model == "floor":
        zones = {
            "First": ["Living_Room_1F", "Dining_Room_1F", "Kitchen_1F"],
            "Second": ["Bathroom_NW_2F", "Bedroom_NE_2F", "Bedroom_SE_2F",
"Bedroom_SW_2F"],
            "Basement": ["Underground_Tech_N", "Underground_Tech_S"],
        }

```

```

elif model == "orientation":
    # FIX: make 'North' consistent with disaggregate_setpoints()
    zones = {
        "South": ["Living_Room_1F", "Bedroom_SW_2F", "Bedroom_SE_2F"],
        "North": ["Dining_Room_1F", "Kitchen_1F", "Bathroom_NW_2F",
"Bedroom_NE_2F"],
        "Basement": ["Underground_Tech_N", "Underground_Tech_S"],
    }
else:
    raise ValueError("model must be 'floor' or 'orientation'.")

out = pd.DataFrame(index=data.index, columns=zones.keys(), dtype=float)
if variable == "temperature":
    for k, z in zones.items():
        out[k] = (data[z] * volume.loc[z]).sum(axis=1) /
volume.loc[z].sum()
elif variable == "power":
    for k, z in zones.items():
        out[k] = data[z].sum(axis=1)
else:
    raise ValueError("variable must be 'temperature' or 'power'.")
return out

def disaggregate_setpoints(data: pd.DataFrame, model: str) -> pd.DataFrame:
    """Disaggregate 3-group setpoints back to 9 zones."""
    if model == "floor":
        zones = {
            "First": ["Living_Room_1F", "Dining_Room_1F", "Kitchen_1F"],
            "Second": ["Bathroom_NW_2F", "Bedroom_NE_2F", "Bedroom_SE_2F",
"Bedroom_SW_2F"],
            "Basement": ["Underground_Tech_N", "Underground_Tech_S"],
        }
    elif model == "orientation":
        zones = {
            "South": ["Living_Room_1F", "Bedroom_SW_2F", "Bedroom_SE_2F"],
            "North": ["Dining_Room_1F", "Kitchen_1F", "Bathroom_NW_2F",
"Bedroom_NE_2F"],
            "Basement": ["Underground_Tech_N", "Underground_Tech_S"],

```

```

    }
else:
    raise ValueError("model must be 'floor' or 'orientation'.")

cols = [
    "Living_Room_1F", "Dining_Room_1F", "Kitchen_1F",
    "Bathroom_NW_2F", "Bedroom_NE_2F", "Bedroom_SE_2F",
    "Bedroom_SW_2F",
    "Underground_Tech_N", "Underground_Tech_S",
]
out = pd.DataFrame(index=data.index, columns=cols, dtype=float)
for k, z in zones.items():
    out.loc[:, z] = data[[k]].values
return out

# ----- Optimization core -----
def run_optimization(weather_forecast: np.ndarray, X_init: np.ndarray,
setpoints: np.ndarray, timestep_s: float,
                    heating_bounds: np.ndarray, price: np.ndarray, A:
np.ndarray, B: np.ndarray, C: np.ndarray) -> tuple[np.ndarray, np.ndarray]:
    """Solve MPC: minimize energy cost + soft comfort penalties."""
    N = len(weather_forecast) - 1
    nx, nu = A.shape[1], B.shape[1]

    X_hat = cp.Variable((N + 1, nx))
    U_hat = cp.Variable((N, nu))

    # Handle models where nu > 9 by padding bounds
    if heating_bounds.shape[1] < nu:
        pad = np.zeros((2, nu - heating_bounds.shape[1]))
        heating_bounds = np.hstack([heating_bounds, pad])

    constraints = [
        X_hat[0, :] == X_init,
        U_hat >= heating_bounds[[0], :],
        U_hat <= heating_bounds[[1], :],
    ]
    for k in range(N):

```

```

        constraints += [
            X_hat[k + 1, :] == A @ X_hat[k, :] + B @ U_hat[k, :] + C @
weather_forecast[k, :]
        ]

    # Objective
    energy_kW = cp.sum(U_hat, axis=1) # sum of zone powers; if U is W or
kW align units below
    cost_energy = cp.sum(energy_kW * price[:-1] * (timestep_s / 3600.0)) #
price in c/kWh

    # Comfort: quadratic penalties, deadband and hard-violation penalty
    # First 9 states correspond to zone air temperatures
    comfort_low = cp.sum_squares(cp.neg(X_hat[:, :9] - setpoints) * 100.0)
    comfort_high = cp.sum_squares(cp.pos(X_hat[:, :9] - (setpoints + 3.0))
* 1000.0)
    obj = cp.Minimize(cost_energy + comfort_low + comfort_high)

    prob = cp.Problem(obj, constraints)
    try:
        prob.solve(solver=cp.GUROBI) # if available
    except Exception:
        prob.solve(solver=cp.OSQP, eps_abs=1e-4, eps_rel=1e-4,
max_iter=100000)

    return X_hat.value[:, :9], U_hat.value[:, :9]

# ----- Initialization and end-to-end run -----
-----

def get_initial_conditions_multi(A: np.ndarray, B: np.ndarray, C:
np.ndarray) -> np.ndarray:
    """Back-calculate envelope states for the multi-zone model using a 7-
day window."""
    end_date = pd.Timestamp.now(tz=LOCAL_TZ)
    start_date = end_date - pd.Timedelta(days=7)
    data = get_historical_data(start_date, end_date, savefile=None)
    temperature, heating = resample_data(data)
    n_air = len(temperature.columns)

```

```

n_total = A.shape[0]

# Weather history (Solcast + OWM)
if not (SOLCAST_URL and SOLCAST_KEY and OWM_KEY):
    raise RuntimeError("Weather API keys/URLs are not configured.")

resp1 = requests.get(SOLCAST_URL, params={"format": "csv", "api_key":
SOLCAST_KEY}, timeout=30)
resp2 = requests.get(
    OWM_HISTORY_URL,
    params={
        "lat": 46.561856,      # EHBE coords; consider externalizing if
sensitive
        "lon": -72.743525,
        "type": "hour",
        "start": int(start_date.tz_convert("UTC").timestamp()),
        "end": int(end_date.tz_convert("UTC").timestamp()),
        "appid": OWM_KEY,
    },
    timeout=30,
)
if not (resp1.status_code == 200 and resp2.status_code == 200):
    raise RuntimeError("Historical weather fetch failed.")

# Solcast to 15-min solar
weath1 = pd.read_csv(io.StringIO(resp1.text))
idx = pd.date_range(weath1.loc[weath1.index[-1], "period_end"],
weath1.loc[weath1.index[0], "period_end"], freq="30T")
idx = (idx.tz_localize("UTC").tz_convert(LOCAL_TZ) -
pd.Timedelta(minutes=30))[:-1]
weath1.index = idx
solar = weath1[["ghi"]].resample("15T").interpolate("pad") / 1000.0

# OWM to 15-min air temperature
weath2 = pd.read_json(io.StringIO(resp2.text))
lst = pd.DataFrame.from_records(weath2["list"].values)
temp = pd.DataFrame.from_records(lst["main"])
air = pd.DataFrame(

```

```

        index=pd.to_datetime(1st["dt"], unit="s", origin="unix"),
        data=temp["temp"].values - 273.15,
        columns=["air_temp"],
    ).resample("15T").interpolate("linear")
    air.index = (air.index.tz_localize("UTC").tz_convert(LOCAL_TZ))

# Align inputs to model structure
names = {
    "Bathroom_NW_2F": "T06",
    "Bedroom_NE_2F": "T07",
    "Bedroom_SE_2F": "T09",
    "Bedroom_SW_2F": "T08",
    "Dining_Room_1F": "T04",
    "Kitchen_1F": "T05",
    "Living_Room_1F": "T03",
    "Underground_Tech_N": "T02",
    "Underground_Tech_S": "T01",
}

temp_z = temperature.rename(columns=names).sort_index(axis=1)
temp_z.columns = temp_z.columns + "_TEMP"
temp_z = pd.concat([temp_z, pd.DataFrame(0.0, index=temp_z.index,
columns=[f"T{i+1:02d}_TEMP" for i in range(n_air, n_total)]]), axis=1)

heat_z = heating.rename(columns=names).sort_index(axis=1)
heat_z.columns = heat_z.columns + "_Wh"
heat_z = pd.concat([heat_z, pd.DataFrame(0.0, index=heat_z.index,
columns=[f"T{i+1:02d}_Wh" for i in range(n_air, n_total)]]), axis=1)

final = pd.concat([temp_z, heat_z, air, solar], axis=1).dropna()
final.iloc[0, n_air:n_total] = 20.0 # initialize unobserved envelope
states

X = np.zeros((len(final), n_total))
X[0, :] = final.iloc[0, :n_total].values
for i in range(len(final) - 1):
    X[i + 1, :] = A @ final.iloc[i, :n_total].values + B @
final.iloc[i, n_total:n_total * 2].values + C @ final.iloc[i, n_total *
2:].values

```

```

        final.iloc[i + 1, n_air:n_total] = X[i + 1, n_air:]
    return final.iloc[-1, :n_total].values

def write_file_to_pi(setpoints: pd.DataFrame) -> None:
    """Send setpoints CSV to the configured SFTP destination."""
    SETPOINTS_DIR.mkdir(parents=True, exist_ok=True)

    sp = setpoints.copy()
    sp.index.name = "idx"
    sp.loc[:, "Garage"] = 19.0
    sp.loc[:, "Bathroom_1F"] = sp.loc[:, "Living_Room_1F"]
    sp.index = sp.index.tz_convert(LOCAL_TZ).tz_localize(None)
    sp.index = sp.index.strftime("%Y-%m-%d %H:%M")
    sp = sp.loc[:, [
        "Living_Room_1F", "Dining_Room_1F", "Kitchen_1F", "Bedroom_SE_2F",
        "Bedroom_SW_2F",
        "Bedroom_NE_2F", "Bathroom_NW_2F", "Bathroom_1F",
        "Underground_Tech_N", "Underground_Tech_S", "Garage"
    ]]

    fpath = SETPOINTS_DIR / f"{pd.Timestamp.now(tz=LOCAL_TZ).strftime('%Y-%m-%dT%H-%M')}.csv"
    sp.to_csv(fpath)

    # SFTP (host key checking disabled here; consider enabling in
    production)
    cnopts = pysftp.CnOpts(); cnopts.hostkeys = None
    with pysftp.Connection(SFTP_HOST, username=SFTP_USER,
        password=SFTP_PASS, port=SFTP_PORT, cnopts=cnopts) as sftp:
        sftp.put(fpath, SFTP_DEST)

def run_mpc(model: str) -> None:
    """End-to-end MPC run: fetch data, solve, write new setpoints."""
    now = pd.Timestamp.now(tz=LOCAL_TZ)
    start_date, end_date = now - pd.Timedelta(hours=3), now

    weather = get_weather_forecast()
    setpoints = create_setpoints()

```

```

bounds_W = create_heating_bounds()          # W
price = create_price(True, True)            # c/kWh

if model != "multi":
    data = get_historical_data(start_date, end_date, savefile=None)
    temperature, heating = resample_data(data)
    temperature = aggregate_data(temperature, model, "temperature")
    heating = aggregate_data(heating, model, "power") / 1000.0 # kW
    setpoints = aggregate_data(setpoints, model, "temperature")
    bounds_W = aggregate_data(bounds_W, model, "power")

# Align horizon: from last observed time to +1 day
start_idx = weather.index[weather.index.get_indexer([end_date],
method="pad")][0]
end_idx = start_idx + pd.Timedelta(days=1)

A, B, C = read_ABC(model)

if model != "multi":
    X0 = temperature.loc[start_idx, :].values
else:
    X0 = get_initial_conditions_multi(A, B, C)

wMPC = weather.loc[start_idx:end_idx, ["air_temp", "ghi"]].values
spMPC = setpoints.loc[start_idx:end_idx, :].values
hbMPC = bounds_W.values
pMPC = price.loc[start_idx:end_idx].values

T_opt, Q_opt = run_optimization(wMPC, X0, spMPC, 900.0, hbMPC, pMPC, A,
B, C)

if model != "multi":
    idx_T = pd.date_range(start_idx, end_idx, freq="15T", tz=LOCAL_TZ)
    idx_Q = pd.date_range(start_idx, end_idx -
pd.Timedelta(minutes=15), freq="15T", tz=LOCAL_TZ)
    T_df = pd.DataFrame(index=idx_T, columns=setpoints.columns,
data=T_opt)

```

```

        Q_df = pd.DataFrame(index=idx_Q, columns=setpoints.columns,
data=Q_opt)
    else:
        cols = [
            "Underground_Tech_S", "Underground_Tech_N", "Living_Room_1F",
            "Dining_Room_1F", "Kitchen_1F", "Bathroom_NW_2F",
"Bedroom_NE_2F",
            "Bedroom_SW_2F", "Bedroom_SE_2F",
        ]
        idx_T = pd.date_range(start_idx, end_idx, freq="15T", tz=LOCAL_TZ)
        idx_Q = pd.date_range(start_idx, end_idx -
pd.Timedelta(minutes=15), freq="15T", tz=LOCAL_TZ)
        T_df = pd.DataFrame(index=idx_T, columns=cols, data=T_opt)
        Q_df = pd.DataFrame(index=idx_Q, columns=cols, data=Q_opt)

RESULTS_DIR.mkdir(parents=True, exist_ok=True)
out_csv = RESULTS_DIR / f"{idx_T[1].strftime('%Y-%m-%dT%H-%M')}.csv"
pd.merge(T_df, Q_df, left_index=True, right_index=True,
suffixes=["_temp", "_kW"]).to_csv(out_csv)

# Round to 0.5°C for device setpoints and enforce tariff-event
passthrough
new_sp = (T_df.shift(-1).iloc[:,-1, :] / 0.5 + 0.5).astype(int) * 0.5
for (h0, h1) in [(6, 9), (16, 20)]:
    ev_idx = new_sp.index[(new_sp.index.hour >= h0) &
(new_sp.index.hour < h1)]
    new_sp.loc[ev_idx, :] = setpoints.loc[ev_idx, :]

if model != "multi":
    new_sp = disaggregate_setpoints(new_sp, model)

write_file_to_pi(new_sp)

def run_resiliency() -> None:
    """If there is ongoing heating, fall back to BaU setpoints."""
    now = pd.Timestamp.now(tz=LOCAL_TZ)
    data = get_historical_data(now - pd.Timedelta(hours=3), now,
savefile=None)

```

```
_, heating = resample_data(data)
if heating.iloc[-1, :].sum() > 0.3: # kWh over last 15-min across
zones
    write_file_to_pi(create_setpoints())

if __name__ == "__main__":
    run_mpc("multi")
```