

A Framework for Automatic Optimal Sizing and Modelling of Energy Systems in Urban Areas

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Abstract

A Framework for Automatic Optimal Sizing and Modelling of Energy Systems in Urban Areas

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Urban areas account for the majority of global energy consumption and greenhouse gas (GHG) emissions, with buildings alone responsible for nearly 40% of worldwide energy use and 30% of emissions. Achieving carbon neutrality in cities requires large-scale electrification, integration of renewable energy systems, and systematic retrofitting of existing building stocks. However, current energy system modelling tools remain limited in their ability to support these transitions. They often rely on fragmented data structures, lack interoperability with urban building energy models, depend on benchmark or static demand values rather than validated hourly simulations, and provide no automated or scalable pathways for scenario exploration, comparative assessment, or retrofit prioritization at the portfolio level.

This thesis addresses these gaps through the development of an automated, open-source Energy System Modelling Framework and a scalable Retrofit Prioritization Workflow, both integrated within the TOOLS4CITIES urban simulation platform at Concordia University's Next-Generation Cities Institute. The Energy System Modelling Framework is built on a generic, object-oriented data model that organizes generation, storage, distribution, and emission components in a unified and extensible structure. Semi-empirical performance models for key low-carbon technologies—including heat pumps, boilers, photovoltaic systems, and thermal storage—are coupled with a life cycle cost assessment module and a multi-objective non-dominated sorting genetic algorithm II (NSGA-II) optimization engine to identify cost-effective and energy-efficient system configurations.

Complementing component-level design optimization, the Retrofit Prioritization Workflow combines measured monthly utility data with archetype-based urban building energy modelling using the PRinceton Scorekeeping Method (PRISM) and Kernel Density Estimation (KDE). This enables the detection of underperforming buildings and employs multi-criteria decision-making to generate transparent, scalable retrofit rankings across large building portfolios.

The methods are demonstrated through three sets of case studies: (1) cross-climate analysis of air-source heat pump and rooftop photovoltaic systems in Montreal and Palma de Mallorca; (2) feasibility-driven, multi-objective system design optimization for representative high-rise and mid-rise buildings; and (3) portfolio-scale retrofit prioritization and scenario assessment for 201

residential buildings from the Office municipal d'habitation de Montréal. These applications illustrate the framework's ability to evaluate renewable integration, identify optimal electrification pathways, and support data-driven decisions on retrofit investment.

Collectively, the developed framework and workflow offer a unified, automation-ready methodology for building- and portfolio-scale energy system analysis. They provide researchers, planners, and practitioners with a flexible platform for evaluating urban decarbonization strategies, enabling more consistent, transparent, and scalable assessments of future low-carbon urban energy futures.

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List of Abbreviations

AMY Actual Meteorological Year.

ASHP Air-Source Heat Pump.

COP Coefficient of Performance.

DHI Diffuse Horizontal Irradiance.

DHW Domestic Hot Water.

DNI Direct Normal Irradiance.

DP Dynamic Programming.

DSS Decision Support Systems.

EIR Energy Input Ratio.

ER Entity-Relationship.

ESM Energy System Model.

ESMF Energy System Modelling Framework.

EUI Energy Use Intensity.

FFR Flow Fraction Ratio.

GA Genetic Algorithm.

GDP Gross Domestic Product.

GHEX Ground Heat Exchanger.

GHG Greenhouse Gases.

GHI Global Horizontal Irradiance.

GIS Geographic Information System.

GSHP Ground-Source Heat Pump.

HVAC Heating, Ventilation and Air Conditioning.

LCA Life Cycle Assessment.

LCC Life Cycle Cost.

LEAP Long-Range Energy Alternatives Planning System.

LP Linear Programming.

MCA Multi-Criteria Analysis.

MCDA Multi-Criteria Decision Analysis.

MCDM Multi-Criteria Decision-Making.

MILP Mixed-Integer Linear Programming.

NSGA-II Non-Dominated Sorting Genetic Algorithm.

OEMOF Open Energy Modelling Framework.

OEO Open Energy Ontology.

OEP Open Energy Platform.

OSEMOSYS Open-Source Energy Modelling System.

PLR partial load ratio.

POA plane-of-array.

PSO Particle Swarm Optimization.

PV Photovoltaic.

ROI Return on Investment.

SA Simulated Annealing.

SAREF Smart Applications REference ontology.

SBX Simulated Binary Crossover.

SC Self-Consumption.

SOC State-of-Charge.

SRA Simplified Radiosity Algorithm.

SS Self-Sufficiency.

STC Standard Test Condition.

TEMOA Tools for Energy Model Optimization and Analysis.

TES Thermal Energy Storage.

TLCC Total Life Cycle Cost.

TMY Typical Meteorological Year.

TOPSIS Techniques for Order of Preference by Similarity to Ideal Solution.

UBEM Urban Building Energy Modelling.

UML Unified Modeling Language.

WWHP Wastewater Heat Pump.

WWR Window-to-Wall Ratio.

1 Introduction

1.1 Background and Motivation

The rapid growth in urban population around the world places a substantial demand on energy resources. As urbanization accelerates, forecasts suggest that by 2050, approximately 68% of the global population will reside in urban areas, which is expected to increase infrastructure and energy consumption in these regions [2]. On the other hand, according to various reports, the building sector accounts for approximately 40% of worldwide energy consumption and is also responsible for roughly 30% of Greenhouse Gases (GHG) emissions [3, 4, 5]. Understanding the link between urbanization and building energy use is crucial, especially in reaching long-term clean energy supply goals in urban areas. Within buildings, Heating, Ventilation and Air Conditioning (HVAC) systems or, in general terms, building energy systems, account for 40 to 60% of building energy consumption [3], highlighting their role as primary energy consumers in urban environments. Jaccard [6] defines an energy system as a "combined process of acquiring and using energy in a given society or economy." Also, the Intergovernmental Panel on Climate Change (IPCC) defined an energy system as a "system that comprises all components related to the production, conversion, delivery, and use of energy" [7]. Another definition of energy systems is given by the International Energy Agency (IEA): an energy system is a "set of technologies, policies, and practices that work together to convert, deliver, and consume energy" [8]. All these definitions take the role of source, supply and sink into account. An energy system is designed to supply any energy demand, such as electricity or heating, by converting the primary energy stored in natural resources, including renewable or fossil fuels. Then, the produced energy will be transported or stored for immediate or future use by the final user.

To achieve sustainable development and carbon neutrality, replacing the current fossil fuel energy systems with renewable ones and improving the infrastructure to increase the renewable capacity in urban areas is necessary. To ensure that renewable and decentralized energy systems function efficiently, it is crucial to develop models that cater to the user's specific needs. However, developing physical pilots for all energy system types can be expensive and complicated, making computer models increasingly valuable and essential. In general, energy system modelling involves predicting and simulating different components of the energy system or the overall system to understand the performance of these components or the system under various circumstances, using mathematical relations. When going through different models and modelling tools, one may encounter two terms that are used often: Energy System Model (ESM) and ESMF. These terms are different and it is important to understand their difference. To differentiate between models and frameworks, we consider frameworks as a generic modelling environment that provides the mathematical structure to analyze systems. Frameworks may have pre-designed structures that offer reusable functions for building models, such as tasks in a programming language to read, process, and analyze data. On the other hand, models

are a specific application of a framework to a particular case study. Models consist of data, assumptions, and equations and are generally tailored to a particular scenario [9].

As the need to address climate change events and their impact has become more severe and crucial worldwide, numerous ESM and ESMF have been developed in recent years, primarily focusing on integrating more renewables into urban areas. However, there are still numerous challenges in the field of energy modelling, and the present work is an effort to address some of these challenges by introducing a new ESMF that can be used for various building energy system assessments.

1.2 Background, Problem Statement and Research Questions

With the ever-increasing number of ESMFs, which have various scopes and purposes, review papers are valuable assets for users with different levels of expertise to acquire an overview of existing models and find a suitable tool for their specific purpose. Review papers on ESMs date back to the 1990s [10, 11], and since then, numerous reviews have been published dealing with different aspects of ESMFs.

A group of the available review papers is concerned with *energy system modelling in general*. These papers review the classification of ESMs, challenges and gaps in modelling energy systems, and trends in energy system modelling. Van Beeck [12] was among the first authors to review different ESM characteristics. Subramanian et al. [13] presented two different types of categorizations based on modelling methodology and field of application. Klemm et al. [14], Hall and Buckley [15], and Prina et al. [16] all reviewed features of ESMs and classified existing models based on their proposed categorization methodology. While Lopion et al. [17] focused on trends in modelling methodology, programming language, region of development, and other characteristics of ESMs, Pfenninger et al. [18] concentrated on the existing challenges in energy system modelling in the 21st century. After reviewing the characteristics of ESMs, Ringkjøb et al. [19] also presented a study of the existing challenges in modelling energy systems with a large share of renewables. Fodstad et al. [20] also reviewed existing challenges and proposed solutions in energy system modelling to create a foundation for those who intend to develop a new model or framework. They divided the challenges into four groups: challenges arising from the emergence of multi-energy systems, spatiotemporal resolution, uncertainty associated with renewable sources, and how to model the energy transition and policies dynamically. Another topic assessed in this group of review papers is the existing gaps in the field of energy system modelling. Yazdanie and Orehounig [21] reviewed technical, institutional, and methodological gaps and solutions in urban energy system modelling tools. Süsser et al. [22] adopted an alternative approach by conducting interviews with various users of energy system modelling tools to examine whether the path taken by modellers aligns with the needs of users.

The second group of review papers focuses on one or more specific characteristics of an energy

system model. For example, Pfenninger et al. [23] concentrated on developing open-access energy system models. While Lund et al. [24] focused on comparing simulation models with optimization models, several studies have solely focused on optimization energy system models. The credibility of open-source optimization models [25], how to formulate optimization models [26], categorization of optimization methods [27], applications of computational methods in optimization models [28, 29], and available methods for complexity reduction in optimization methods [30] have been reviewed over the past years. Martinez-Gordon et al. [31] assessed the significance of spatial resolution in energy system modelling by examining different methods for including spatial resolution in 34 energy system models. Applying their comprehensive literature review findings to the North Sea region, they found that spatial resolution is crucial in analyzing a region's renewable potential and improving the layout design of energy transmission networks.

The third group of reviews focuses on the specific scopes of application for energy system models and modelling frameworks. For instance, some researchers have only reviewed papers and modelling tools used in district-level modelling. Allegrini et al. [32] reviewed the general methodologies used for modelling energy systems on a district scale. In contrast, Klemm et al. [14] presented an overview of optimization models used in mixed-use districts. Scheller and Bruckner [33] also assessed the existing optimization models at the municipal level. Another topic of interest in this group is the integration of renewable energy sources in urban energy systems and the transition toward smart energy systems. Majidi et al. [34], Yoro et al. [35], Prina et al. [36], and Kakodkar et al. [37] all focused on this matter from different viewpoints. Samarasinghe et al. [38] and Liu et al. [39] focused on tools and frameworks that could be used for modelling net-zero emissions energy systems. There are review papers that focus on various specific sectors in cities. Buildings are the highest contributors to GHG emissions and account for the largest share of energy consumption in urban areas. Thus, several researchers have extensively reviewed the state of the art in building energy system models, energy efficiency improvement in buildings, and energy system retrofit analysis [40, 41, 42, 43]. Ahmadi et al. [44] also focused on the resiliency of energy systems, which could be an assessment criterion in an ESMF from technical, analytical, and mathematical viewpoints.

The last group of review papers on ESMFs conducts Multi-Criteria Analysis (MCA)s of existing modelling frameworks and tools. Prina et al. [45] presented an overview of existing methods for comparing energy system modelling frameworks. A branch of these MCA analyses only reviews the properties and structural features of ESMFs [16, 14, 46, 32, 47]. Lyden et al. [48] reviewed 13 tools capable of modelling renewable energy systems, demand-side management, and storage and proposed a tool selection process for choosing the appropriate tool for different applications. Tozzi Jr. and Jo [49] also compared 14 other tools for simulating or optimizing renewable energy systems. Hall and Buckley [15] analyzed the 22 most common energy system models in the UK, while Ringkjøb et al. [19] reviewed 75 modelling frameworks and tools used in

electricity systems. Another branch of MCA papers includes those that, in addition to comparing properties and features, use the models on a mutual case study to compare performance, outputs, and results [50, 51]. Gardian et al. reviewed the significance, challenges, and methods for data harmonization in inter-model comparison studies [52]. Luderer et al. [53] compared the AIM/CGE, MESSAGE, IMAGE, POLES, REMIND, and WITCH models, focusing on global low-carbon scenarios through the integration of solar and wind power. Bistline et al. [54] studied different pathways to increase the share of renewables in North American electricity markets through utilization of eight different energy-economy models. Their work demonstrates that the net trade between the US and Canada varies significantly across different models. Germany's future power supply system with high penetration of renewables was also modelled by Gils et al. [55] using 11 different tools, all with regional and hourly resolutions.

Despite the variety of ESMs and ESMFs, numerous challenges and gaps remain in the energy modelling field. The following is a list of existing challenges in this field:

- **Data-related gaps:** Urban energy system modelling faces several persistent data-related challenges. First, the absence of centralized regulatory standards has led to disjointed data sources and ineffective sharing mechanisms, complicating the development of comprehensive and integrated models. Restrictive licensing and privacy concerns further limit data availability, making it difficult to obtain essential information. Furthermore, the absence of standardized quality controls leads to inconsistent datasets across domains, thereby reducing the reliability of simulations and assessments. A further and often overlooked challenge is the *absence of general ontologies or common data models for defining energy systems*. Current datasets rarely follow a shared representation of system components, their attributes, and the interactions between them. As a result, modelling frameworks must repeatedly construct bespoke, incompatible definitions of technologies and system boundaries, which severely limit interoperability and hampers model exchange or reuse. This issue is becoming more pronounced as data collection becomes more decentralized and heterogeneous. Ultimately, the inflexibility of existing data frameworks hinders the incorporation of emerging technologies and new data types, thereby limiting the adaptability and long-term relevance of urban energy models.
- **Demand calculation:** Demand calculation is crucial in any energy system sizing and modelling practice, where an error could lead to economic and energy losses. In existing tools, especially urban-scale modelling tools, the validation and calibration of hourly and sub-hourly modelling for different building archetypes are often overlooked. In most cases, benchmark values are used.
- **Automated scenario assessment:** The selection of the best energy system configuration that could serve the energy, economic, and environmental objectives of the user is complex

and requires a high level of input. Therefore, assessing various options can be time-consuming and complex, especially for non-expert users such as urban developers. A centralized data model can help structure and standardize the required data in energy system modelling, leading to pre-parameterized models that are ready for easy and automatic scenario assessments.

- ***Large-scale system retrofit management:*** To reach sustainable development goals, it is essential to replace current inefficient fossil fuel-based systems with efficient clean alternatives. The careful evaluation of retrofitting scenarios is essential for determining the best option in each building. However, in a portfolio of buildings or district and urban retrofit planning, it is crucial to identify the priority buildings quickly and rank them accordingly. Currently, there is no retrofitting tool capable of prioritizing buildings in a portfolio.

The current study was designed to address the above-mentioned problems by answering the following questions:

- How should energy systems-related data be structured and organized to enable the automation of energy system modelling and scenario assessment in various climate zones? What is the role of system configuration, and how could it be included in this standard structure? In what ways does the data model contribute to the practical implementation of optimized designs in urban areas and their alignment with efficiency and sustainability goals? How can this standard data structure be interactively integrated with an Urban Building Energy Modelling (UBEM) workflow for optimal sizing of urban energy systems?
- What are the best energy system configurations in existing and new developments? What are the energy and economic impacts of energy system centralization in urban buildings? What is the role of thermal storage systems at the energy system centralization level?
- How could a building portfolio be managed optimally for retrofit scenario assessment? What are the most important factors in ranking buildings for retrofitting? What is the best energy system configuration in priority buildings to achieve minimum energy consumption and minimum Life Cycle Cost (LCC)?
- What is the impact of climate zone on the feasibility and performance of heat pump-based heating systems in urban buildings, and how can Photovoltaic (PV) integration assist in meeting electrification goals?

1.3 Research Objectives

This research project is part of the ongoing development of an Urban Simulation Platform at the Next-Generation Cities Institute of Concordia University. The main objectives of this work are summarized as follows:

- (1) To develop a generic data model for organizing input data involved in the energy system sizing and modelling process, which can be easily integrated with any simulation engine and applied to different climate zones.
- (2) To design and implement an ESMF that utilizes the proposed data model to enable a rapid assessment of the feasibility of implementing various types of energy generation units, the life cycle cost analysis of energy system configurations, and the optimal sizing of system components.
- (3) To develop an automated workflow for identifying and ranking the buildings in need of retrofit in a building portfolio, and evaluating different retrofitting scenarios.

To achieve these objectives, the following steps were undertaken:

- An extensive review of existing research on energy system modelling frameworks, tools, and energy system retrofit methodologies.
- Identification of prevalent energy system configurations in selected cities used as case studies.
- Development of a generic data model to establish a central, standardized structure for data required in modelling urban energy systems across different climate zones.
- Preparation of detailed simulation models for both existing and proposed efficient energy system templates.
- Implementation of the Non-Dominated Sorting Genetic Algorithm (NSGA-II) for the optimal sizing of energy system components.
- Development of a methodology for automated life cycle costing of energy systems.
- Development of a novel approach for identifying and ranking buildings within a portfolio, neighbourhood, district, or city that require retrofitting measures.

1.4 Thesis Structure

The remainder of this thesis is organized as follows:

- **Chapter 2: Literature Review:** Provides a comprehensive review of previous studies on energy system modelling frameworks and tools, as well as building energy system retrofit workflows.
- **Chapter 3: Methodology:** Describes the methodology developed for the proposed energy system modelling framework and the building retrofitting prioritization workflow.
- **Chapter 4: Use Case Results and Analysis:** Presents multiple use cases of the framework, including the assessment of PV-integrated heat pump systems in the residential sector across two different climates, optimal retrofit planning for a portfolio of social housing

buildings in Montreal, and automatic feasibility evaluation of various heat pump types in different building archetypes, along with the optimal sizing of a HVAC system using feasible components.

- **Chapter 5: Conclusions and Recommendations:** Summarizes the main findings, presents the contributions of the study and provides recommendations for future research.

2 Literature Review

The transition to decarbonized and integrated energy systems requires advanced tools to evaluate design options, simulate performance, and support investment decisions. As shown in Chapter 1, with advances in computational capabilities, increased data availability, and more pressing sustainability goals, the modelling of energy systems has evolved significantly. However, this evolution has not occurred uniformly; variations persist in how input data are structured, how models are categorized and compared, and how building-scale retrofit assessments are integrated into broader planning efforts. This chapter comprehensively reviews the literature across three key dimensions: (i) the development of input data structures and data modelling techniques in energy system tools, (ii) the classification and characterization of modelling frameworks, and (iii) the methodologies and tools used to evaluate building energy system retrofits.

2.1 From Data Structures to Semantic Data Models in Energy System Modelling

Structuring input data is a very important part of modelling energy systems. The way the input data is set up has a big effect on how flexible, scalable, and easy to use the model or framework is. A well-structured and standardized input format makes the model more generalizable, meaning it can be applied to a wider range of situations, scenarios, and scales.

In this context, ‘data structures’ refers broadly to the concrete representations used to encode model inputs, while ‘data models’ define the underlying conceptual organization of entities, attributes, and relationships that those structures implement.

The first models and frameworks used static input data structures. The input data were typically stored in fixed-format text files, which were often created for use with punch cards and lacked structure or standardization. The most significant issue with these methods was the lack of a standard format for different models. These tabular text files stayed the most popular, and each modelling tool used its own format. The next step was to utilize relational database architectures to ensure consistent data entry and manage the increasing volume of data. Tools like TIMES (which is an update of MARKAL) used structured Excel templates that were brought into back-end databases (like PostgreSQL in VEDA). These templates mapped user-defined tables into normalized parameter schemas. This modular approach made it possible to change scenarios and reuse basic data, but schemas were still specific to the framework and could not be used with other frameworks.

In the early 2000s, XML-based schematics were introduced as the first steps toward a standardized energy model input structure that would work on all platforms. After identifying problems with existing structures and examining how XML-based data structures have been applied in other fields, Gowri [56] developed EnerXML, an XML Document Type Definition standard

designed to meet the needs of energy simulation programs. The next generation of input file structures utilized text formats, such as YAML and JSON files, to drive configuration. These structured text files made it easier to set up models, keep track of versions, and automate tasks. For instance, Calliope [57] uses nested YAML configurations for technologies, scenarios, and constraints. OSeMOSYS, on the other hand, added the "otoole" utility to change between CSV, Excel, and JSON formats. This generation of tools emphasized openness, clarity, and flexibility in scripting, enabling analysts to set and modify model parameters through code. It is important to note that XML, JSON, and YAML are meta-formats: they define syntax and structure, but not semantics. Meaning is introduced through schemas, conventions, or application-specific data models layered on top of these formats.

Semantic data models and ontologies are the latest methods for organizing input data for energy system models. Ontology and data models play distinct yet important roles in information systems, particularly in areas such as energy management. An ontology provides a formal and clear description of how to think about a domain, including the relationships and properties of entities within that domain. Unlike XML- or JSON-based configurations, ontologies such as SAREF, BRICK, and OEO explicitly encode domain semantics, enabling machine-interpretable meaning rather than merely structured syntax. A data model, on the other hand, is a systematic way to organize, store, and manage data by defining structures like tables, fields, and relationships between data items. It usually refers to relational or object-relational schemas [58].

Pritoni et al. [59] conducted a review of 40 metadata schemas and ontologies used in building modelling. Smart Applications REFerence ontology (SAREF) and its extensions for energy systems are two well-known projects. SAREF gives IoT and energy domain data an ontology that aims to "enable interoperability between solutions from different providers and among various activity sectors" [60]. In real life, SAREF and similar ontologies establish classes (such as devices, energy carriers, and units) and relationships that many tools can easily comprehend. Bjornskov and Jradi made an ontology-based building energy modelling framework using the SAREF ontology as a base [61]. The Open Energy Ontology (OEO) is a formal ontology designed to standardize the terms and data structures used in energy system analysis within the field of energy modelling [62]. OEO provides a clear and precise definition for model concepts, such as technologies, scenarios, and costs, among others. This creates a "common language for energy system modelling" that all fields can use. Researchers make models and datasets easier to combine and more transparent (the meaning of each data point is clear) by adding ontology terms to the inputs and outputs of the models. In this context, 'meaning' refers to the explicit, machine-interpretable definition of what a data element represents in the real world, including its physical interpretation, units, valid relationships, and constraints, rather than just its name or position in a file. For instance, OEO has a controlled vocabulary that clears up any confusion about terms and makes it easier to search for and combine data. Semantic frameworks also enhance reusability by facilitating the combination or comparison of data across different

models that have been annotated with an ontology. Semantic data models also support explicit representation of data provenance, enabling models to distinguish between measured, simulated, estimated, or assumed inputs. They also facilitate automation through advanced tools such as knowledge graphs and reasoners.

Strong data modelling is still a key part of frameworks for modelling energy systems. In real life, input data structures are often based on well-defined data models, such as Entity-Relationship (ER) database schemas or object-oriented class structures in code. These data models ensure that information is organized in a way that makes sense and remains consistent. They do this by enforcing integrity constraints (like valid value ranges and required relationships) that are based on real-world rules.

Compared to ontologies, traditional data models are typically application-specific and optimized for the needs of a specific modelling tool. According to Spyns et al. [63], a data model illustrates how data is organized and protected for a single application. Its vocabulary is not intended for use by other applications. Because the scope is smaller, data models can be designed to work more effectively and be easier to use in a specific situation. In energy modelling, this means that the model only processes the parameters and relationships it needs, which speeds up calculations and makes data handling easier.

Keep in mind that data models and ontologies are not mutually exclusive; they can work together. Ontologies are great at giving you a conceptual overlay: a formal vocabulary that works with any application and makes it clear what terms mean in different models. Data models, on the other hand, provide a solid and efficient way to utilize the data of a specific application. Recent efforts often combine the two approaches because each has its own strengths. The Open Energy Ontology, for example, is being used to semantically annotate entries in traditional energy databases (like datasets on the Open Energy Platform) so that each field in a relational table is connected to a clearly defined ontology class or property.

In summary, the evolution of input data structures in energy system modelling has come full circle, embracing both rigorous data modelling practices and rich semantic descriptions. Ontologies provide a high-level common language that fosters collaboration and sharing of knowledge, whereas data models supply the dependable backbone that ensures models run efficiently and correctly. Going forward, energy modelling frameworks are likely to continue leveraging robust data models (both ER-style databases and object-oriented structures) for their core computations, while utilizing ontological standards to enhance adaptability and generalizability, which enables models to exchange data and insights more effectively in an increasingly interconnected energy research community.

2.2 Categorization of energy system models

With the emergence of high-computing power machines, work on developing computer-aided energy system models began in the 1970s and 1980s [17]. Since then, numerous ESMFs and ESMs that differ in various characteristics have been developed. The increasing number of available modelling tools and frameworks has raised the question, “Which model is better for users in different applications?” Therefore, several studies have been devoted to categorizing energy system models to facilitate the choice between different user options. Prina et al. [16] and Lopion et al. [17] provided a brief history of the classification of energy system models and proposed their classification scheme. Hall and Buckley [15] focused on the challenges arising from the variety of models, proposed a new schema for the classification of ESMFs, and urged researchers developing a new ESMF to follow their scheme to provide an accurate representation of the model and a better understanding of the results.

After carefully evaluating existing papers on categorizing energy system models, the criteria for classifying ESMFs can be divided into two groups: ESMF properties and structural and technical features. Klemm and Vennemann [14] first adopted this approach, which is modified and expanded upon here. The properties show how the problem is approached analytically and mathematically, while the structural details refer to the technical abilities of each framework. The different properties and structural features of ESMFs are explained in detail in the following sections.

2.2.1 Properties of ESMFs

Figure 2.1 shows the various properties of ESMFs that can be used as criteria for categorizing them. As mentioned above, these properties show what the purpose of the framework is, what the behaviour toward the problem is, and how much the framework is accessible to others.

2.2.1.1 Analytical approach refers to the method by which the system is broken into smaller parts and how these parts interact with each other [46]. The ESMFs can be divided into the following three categories based on their analytical approach:

- Top-down
- Bottom-up
- Hybrid

Economists and public administrations mainly use the **top-down** or macroeconomic approach. In this approach, the energy system is considered part of the entire economy, and its interactions with other macroeconomic sectors are studied [16]. This method is based on more aggregated data and economic relations [17], and the technical details and complexity of energy system components are neglected in this approach, leading to inaccurate results in some cases [14].

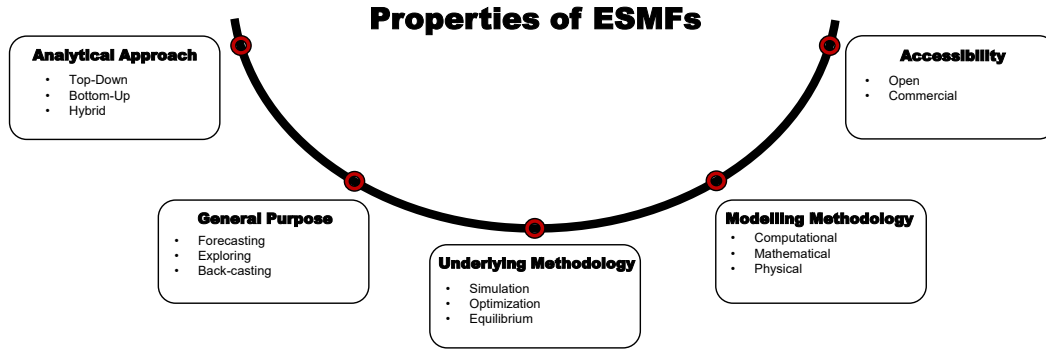


Figure 2.1: Properties of Energy System Modelling Frameworks

The objective of top-down models is to study the impacts of the energy sector on macroeconomic, socio-economic, and environmental indicators like economic growth, public welfare, employment, Gross Domestic Product (GDP), global warming, and GHG emissions [16, 46].

On the other hand, in the *bottom-up* approach, the system is built component by component from the bottom to the top, which enables modellers to create a model with a high level of technological detail [14]. This method is also known as the techno-economic approach [13] and is primarily used by engineers to conduct feasibility studies and identify the most efficient or cost-effective system [17]. The bottom-up models themselves have also been divided into two groups of short-term and long-term models based on the chosen modelling time horizon by Prina et al. [16].

A comparison between these two approaches reveals that while bottom-up models contain higher levels of technical and technological detail, they are less capable of accounting for macroeconomic impacts [33]. Bottom-up models' ignorance of consumer preferences and hidden costs has led them to be called the *optimistic engineering paradigm*, since they are overly optimistic about energy policies [15].

Finally, *hybrid* models were developed to compensate for the shortcomings of both top-down and bottom-up approaches and bridge the gap between them. This work can be accomplished by transferring data and parameters from one model to another, thereby accounting for the macroeconomic impacts of the top-down approach and the technical details of the bottom-up approach [16, 15]. This manual approach of linking two models is referred to as soft-linking. The linking process can be automated, allowing a reduced order of one model to exchange data with the master model, which runs simultaneously. This linking method is called hard-linking [46]. Greening et al. [64] have published a review of hybrid models that integrate top-down and bottom-up approaches. A review of studies in energy system modelling shows that with the start of the 21st century, most models are either bottom-up or hybrid [17].

2.2.1.2 General purpose shows why the energy system model is developed in the first place and what questions the modeller is trying to answer. According to Van Beeck [12], the general purpose of an ESMF could be forecasting, exploring, or back-casting. **Forecasting** is used to assess the impacts of a set of actions in the short term by extrapolating trends based on historical data. On the other hand, **exploring** models or scenario analysis is implemented for comparing a specific scenario with a so-called business-as-usual scenario based on different socio-economic assumptions. Finally, **back-casting** models define a long-term future target for the properties of the system and then develop various realistic paths to achieve those goals. This type of model is helpful for policymakers [14].

2.2.1.3 Underlying methodology expresses the method taken to reach the general purpose of the model. Generally, the underlying methodology of an ESMF can be categorized into simulation (forecasting), optimization, and hybrid. However, there are more detailed classifications in this regard; Scheller and Bruckner [33] declared the following as the available underlying methodologies in ESMFs: (a) econometric, (b) macroeconomic, (c) economic equilibrium, (d) optimization, (e) simulation, (f) spreadsheet, (g) back-casting, and (h) multi-criteria. However, to avoid complexity, after carefully reviewing different classifications, all economic classes in Scheller and Bruckner's categorization (a–c) have been grouped as equilibrium methodologies. Therefore, the underlying methodology of an ESMF can be simulation, optimization, and equilibrium, similar to what Ringkjøb et al. [19] have suggested.

Due to the high cost of creating a physical replica of a system or doing experiments on the system, **simulation** models are developed to assess the outputs of a specific system configuration based on given input values. Using specified equations, indicators such as total annual costs, annual CO₂ emissions, primary energy savings, or renewable share can be found using a simulation model to make decisions mainly over a short-term period.

Numerous **optimization** models, including linear, nonlinear, dynamic, and heuristic methods, have been developed to find the optimal value of the desired objective function(s) over the defined time horizon. The result of an optimization model can be used to determine the optimal investment strategies for municipalities or the optimal operational strategy for a system, based on the given constraints. Optimization models are less complex than simulation models but can be used for long-term strategy-making [24]. While simulation and optimization models, especially simulation models, use the bottom-up approach, **equilibrium** models adopt a top-down approach. These models consider the whole or a part of the economy and assess the impacts of adopting certain energy-related strategies on the selected part of the economy [19].

2.2.1.4 Modelling methodology is the programming approach adopted in the modelling process. The modelling methodology of an ESMF can be categorized into physical, mathematical, and computational approaches.

- **Physical models** are real systems built on smaller scales to experiment with them in different situations. Due to high costs, the use of physical models is uncommon in energy system modelling.
- **Mathematical models** represent the energy system with the help of equations showing the association between meaningful variables and parameters. Mathematical models existed even before computers, but solving these mathematical equations was hard. However, with the advent of computers, numerical techniques for approximating mathematical models can be easily implemented. Linear Programming (LP), Mixed-Integer Linear Programming (MILP), and Dynamic Programming (DP) are the most common approaches used in the literature, listed in order of complexity from lowest to highest [33]. LP is an optimization method that seeks to find arrangements of activities that minimize or maximize a defined objective function under operational constraints. All the activities, relationships, and criteria are expressed in linearized terms. LP is a simple method leading to quick results, but all coefficients must be constant, and it is prone to error when input parameters vary [12]. MILP is an enhanced form of LP with more detailed information. Some or all variables can only be integers, enabling modellers to include binary variables (0/1 or Yes/No) decisions [16]. MILP can be used to find the number of storage units or CHP plants in the system or to decide whether a particular converter should be included [19]. DP is the process of breaking the original problem into several sub-problems to find the optimal solution of the original problem [12]. Stochastic programming approaches are another group of mathematical models. These approaches utilize linear and dynamic programming methods, in which fixed parameters are replaced with probabilistic elements. Using probabilistic elements allows uncertainty in outputs to be taken into account [14].
- **Computational models** are sequences of instructions executed by a computer [13]. These models are in the form of an algorithm produced to imitate intelligent behaviour. Agent-based models, knowledge-based models, neural networks, and meta-heuristic methods are different computational methods. Agent-based models divide the system into separate, autonomous decision-making entities called agents, which assess their situation individually and make decisions based on a set of rules [65, 66]. Knowledge-based models contain the knowledge of a domain expert encoded as rules, cases with solutions for training the algorithm, and an inference engine to derive new decisions based on the attained knowledge [13, 67]. Neural network models are representations of how the human brain processes information. These models do not contain certain rules, consisting of nodes that process the input and output information. A neural network model is trained by adjusting the connection weights between these nodes [13]. Neural network models have

garnered the attention of numerous energy modellers, particularly in forecasting renewable energy production and controlling energy systems [68, 69]. Unlike other optimization methods, meta-heuristic methods do not necessarily find the optimal solution but require less computational effort [16, 19]. Instead, these methods find an optimal solution from a discrete search space [28]. Various meta-heuristic methods, including Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Simulated Annealing (SA), have been used in the modelling, sizing, and control of energy systems [29].

2.2.1.5 Accessibility of an ESMF is the availability and reusability of its source code, underlying assumptions, and the data it uses. The source code of **open** models is publicly available, enabling other modellers to modify or extend it and helping to create a more sophisticated model [17]. In contrast, there are some models and frameworks for which a license is required to access the model, and the user cannot access the source code.

2.2.2 Structural and technical features of ESMFs

This section reviews the characteristics of an ESMF that show its level of detail and generality. Figure 2.2 shows the most common technical features of ESMFs that have been used to distinguish them.

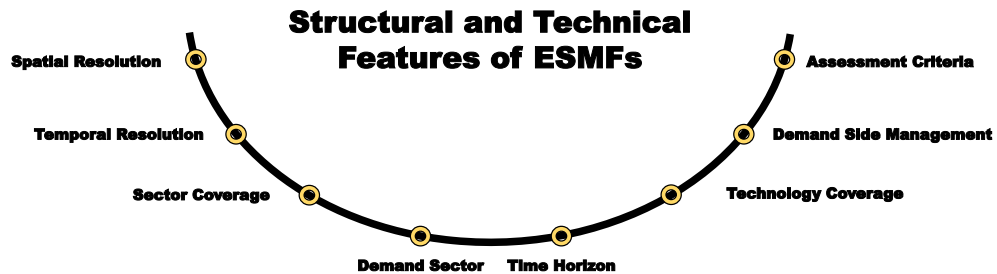


Figure 2.2: Structural and Technical Features of Energy System Modelling Frameworks

2.2.2.1 Spatial resolution of a model is the geographical boundary of a model, which could be limited to a single node (building) or multiple nodes (districts, cities, countries, continents, or even the whole world).

2.2.2.2 Temporal resolution denotes the time-step size in the energy system analysis. Higher temporal resolution means a smaller time-step size. The time-step size could vary from milliseconds to years and be either fixed or variable [70]. Generally, higher computational power is needed when the time-step size is as small as 15 minutes or less. Moreover, the time-step size indicates the type of research question that can be answered in the analysis [17]. For example, a

higher temporal resolution could effectively capture the variations in renewable sources. It is worth noting that there is a trade-off between temporal and spatial resolution. Similar to temporal resolution, a higher spatial resolution results in increased computational time. Therefore, as the geographic boundary of the analysis increases, the temporal resolution needs to be decreased, meaning that a larger time step is required.

2.2.2.3 Sector coverage refers to the commodities included in the ESMF. These energy sectors include electricity, heating, cooling, domestic hot water, hydrogen, and fossil resources [17, 14].

2.2.2.4 Demand sector could include residential and commercial buildings, industry, agriculture, and transport. However, in most cases, residential and commercial buildings are combined, while the agricultural sector is also considered part of the industry [19].

2.2.2.5 Time horizon is the length of the considered time frame in future scenario analysis. The time horizon could be short (5 years or less), medium (between 5 and 15 years), or long (greater than 15 years) [15].

2.2.2.6 Technology coverage is related to the type of components included in the model. This feature is important due to advances in renewable energy systems and the new policies different countries are adopting to implement these systems. Therefore, any new ESMF should be able to model these systems and consider their intermittent nature. The included technologies could be categorized into the following groups:

- **Conventional generation** includes fossil fuel-based systems like boilers, gas furnaces, and CHP plants.
- **Renewable generation** modelling differs from conventional systems due to their intermittent nature and dependency on meteorological conditions. Solar photovoltaic systems, solar thermal collectors, wind turbines, hydropower systems, heat pumps, and geothermal heat exchangers are among the renewable generation systems integrated into various ESMFs.
- **Energy storage** components must compensate for periods when renewable generation is low or zero. Additionally, incorporating energy storage into an energy system enhances operational flexibility and facilitates demand response. Batteries, thermal energy storage, pumped hydro storage, hydrogen, and compressed air energy storage systems are among the storage systems that have been modelled in different ESMFs.

2.2.2.7 Demand-side management as a feature of an ESMF is its capability to model different scenarios that focus on the consumer's side of the energy system. These scenarios

represent the actions consumers take to improve the system's energy efficiency. These measures could include demand reduction through building refurbishment or adopting demand response strategies, such as load shifting or peak shaving. The increasing share of renewable electricity production in urban areas and the growing energy demand in these areas further stress the grid, especially during peak periods.

2.2.2.8 Assessment criteria are the adopted perspectives in energy system modelling. In other words, in optimization models, the assessment criteria (single criterion or multi-criteria) are the objective function of the problem. In most studies, cost is the single criterion for decision-making in energy system design and policies. Apart from costs, environmental, socio-economic, energy efficiency, and technical criteria are also used to evaluate the performance of the energy system [14]. A full list of target criteria apart from costs in energy system analysis is presented by Weinand et al. [71].

2.3 Existing energy system models and modelling frameworks

After reviewing review papers focused on existing energy system models and modelling frameworks and browsing the OpenMod [72] and the Open Energy Platform (OEP) [73], over 100 models and modelling frameworks were identified. This section presents the properties and technical features of 9 selected different energy system models and modelling frameworks, and some of the research articles using these tools are reviewed. The main selection criterion in this process was the accessibility of the tool. All tools with commercial licenses were removed from the assessment. Therefore, some popular tools like MARKAL [74], TIMES [75], HOMER [76], and TRNSYS [77] were dropped from further investigations. Another criterion used in the selection procedure was sector coverage, where only those tools where the heating sector is included, either solely or alongside other sectors, were considered for the analysis. Tables 1 and 2 show the properties and technical features of the selected models and modelling frameworks. A review of papers using the selected models is presented in the subsequent parts of this section.

2.3.1 Calliope

Calliope [57] is a Python-based open-source energy system modelling framework developed at ETH Zurich in 2013, focusing on assessing different energy system scenarios with high shares of renewables. This framework can evaluate systems with high spatial and temporal resolutions ranging from single urban districts to countries and continents [78]. Calliope is an investment and operational dispatch optimization model that employs a bottom-up approach, and one of its key features is the interactive visualization of results [79]. A possible challenge in Calliope might be the computation time that arises due to the high spatial and temporal resolutions [16]. Common applications include regional studies on low-carbon energy transitions, capacity expansion planning, and operational simulations under policy constraints.

A set of configurational YAML files is used for data input in Calliope. These YAML files contain technical component data, locations of components, links between locations, and model-wide settings like objective functions and CO₂ emission factors. These YAML files are supplemented by CSV files for representing time-series data, such as energy demands. The typical outputs are the optimal capacity portfolio of technologies and the detailed operation of each technology to meet demands over the modelled time horizon.

Calliope has been utilized in various studies, including the analysis of decarbonization in the national power systems of the UK [80] and South Africa [81], which involve a combination of renewables, natural gas, and nuclear power. Also, Trondle et al. modelled the fully renewable supply in Europe using the Calliope framework [82]. In another study, Lombardi et al. [83] implemented Calliope as a part of a multi-layer modelling methodology to assess the economic and environmental impacts of replacing traditional residential gas stoves with electric stoves.

2.3.1.1 Strengths and Limitations The transparency, flexibility, and accessibility are the main strengths of Calliope. The interactive dashboard, which showcases the results, is another strength of this tool. However, high computational time is among the limitations. Moreover, the inability to calculate or estimate energy demands or be connected to a demand modelling tool is another limitation of Calliope.

2.3.2 DER-CAM

The Distributed Energy Resources Customer Adoption Model (DER-CAM) [84] is a MILP optimization energy system modelling framework developed in the Grid Integration Group of the Berkeley Lab in the early 2000s. DER-CAM is an investment optimization tool using a bottom-up analytical approach to find the optimal combinations of onsite generation, storage, and demand-side measures.

The key inputs of DER-CAM include typical loads (electric, cooling, refrigeration, space heating, hot water, and natural gas) in a year, the electricity and natural gas tariffs, investment costs and interest rates, and the site's topology. The optimal DER Portfolio, dispatch strategy, energy flows, a balance, emission profile, reliability metrics, and cost breakdown form the list of DER-CAM outputs.

The optimization is divided into two parts: the first is the Investment and Planning DER-CAM, based on which the best building retrofit scenario and the optimal combination of technologies are identified. Then, in the second part, the Operations DER-CAM, the capability of the tool to model the demand response comes into play as the optimal technology dispatch scenario is presented using load-shifting and peak-shaving schemes [33]. It should be noted that DER-CAM is not regarded as an open-source framework; however, users do not need to purchase a commercial license, as it is free to use. The DER-CAM models are predominantly used for

optimal investment, sizing, scheduling, technology dispatch, policy and regulatory analysis, and placement of multi-energy microgrids [85, 86, 87].

2.3.2.1 Strengths and Limitations The detailed technical and economic modelling of distributed energy systems is the key strength of DER-CAM. Its capability in considering complex tariff structures makes the outputs financially robust. Moreover, using MILP, the global optimal portfolio is found. However, there are still certain areas that can be improved in the tool. DER-CAM requires detailed inputs, especially energy demands, which makes it challenging to use in urban-scale simulations. Moreover, despite its strength, MILP relies on linear approximations for parameters such as the energy generation component efficiency curve.

2.3.3 EnergyPlan

Developed by the Sustainable Energy Planning Research Group at Aalborg University, EnergyPlan [88] is one of the most common tools for national energy analysis globally. EnergyPlan is a deterministic simulation model for strategic system analysis. The primary application of EnergyPlan is to simulate how a given configuration of energy technologies operates under specific strategies, rather than to optimize capacity expansion decisions. Lund et al. [89] outlined all the steps to follow in the analysis using EnergyPlan and described the entire tool structure.

The key features of EnergyPlan are: 1) detailed hourly analysis of energy supply and demand balance for one representative year, 2) integrated coverage of major sectors including electricity, heat, transport, and industry in national energy systems, 3) dispatch optimization, and 4) aggregated representation of components of the same type.

The annual and hourly energy demands, renewable profiles, capacities of supply technologies, operational parameters, including system efficiencies, and economic data are the inputs required by EnergyPlan. The outputs of the tool include a detailed annual energy balance presenting how each demand was supplied, the operational statistics, emissions, total annual system cost, broken into components: fuel costs, variable O&M, fixed O&M, annualized investment costs, and revenues from exported electricity. Ostergaard et al. [90] reviewed 315 articles from peer-reviewed journals that utilized EnergyPlan in various applications, demonstrating how the case studies became increasingly complex and how EnergyPlan has evolved to address this complexity. Moreover, in another study, Ostergaard [91] reviewed the general and optimization criteria used in EnergyPlan-based energy system analysis. EnergyPlan is a free simulation tool that provides hourly analysis using a bottom-up approach and an analytical programming methodology [71]. This tool can do a one-year simulation at the country, regional, town or municipality level [36]. Still, as mentioned before, it has been most used for nationwide energy analysis. Bamisile et al. [92] used EnergyPlan to simulate the pathway toward deep decarbonization of energy systems in China's Sichuan province. Several other studies used EnergyPlan to assess the decarbonization scenarios through the integration of district-scale energy systems and renewable energies in

Europe [93], China [94], and Finland [95, 96]. As mentioned before, the EnergyPlan tool is a simulation tool, and to do an optimization analysis, it should be linked with an optimization tool or framework. EPlanOpt, developed by EURAC Research [97], is a Python script developed to optimize the simulations of EnergyPlan through a Multi-Objective Evolutionary Algorithm. Prina et al. [98] coupled EnergyPlan and EPlanOpt to determine the optimal configuration of energy resources for a case study in South Tyrol, optimizing costs, CO₂ emissions, and the renewable share. Herc et al. [99] also integrated these two tools to find the cost-optimal flexibility options for increasing the share of renewables in Europe. In their recent study, Herc et al. [100] used EnergyPlan and EPlanOpt to minimize curtailments of renewables and costs, aiming to achieve a specified level of emissions and renewable share in Europe. Other studies have utilized a multi-objective evolutionary algorithm [101, 102, 103] or GenOpt [104, 105] in conjunction with EnergyPlan to optimize the transition pathways toward a sustainable future.

2.3.3.1 Strengths and Limitations High spatio-temporal resolution to evaluate different scenarios in a user-transparent and quick way, flexibility in assessing various scenarios, and free-of-charge accessibility (closed-source though) are among the strengths of EnergyPlan. On the other hand, similar to DER-CAM there is no demand calculation or estimation module in EnergyPlan and detailed annual and hourly demands must be provided by the user. Moreover, the tool does not find the optimum configuration and requires the user to input the component sizes. Another limitation is EnergyPLAN's aggregated representation. While this makes it fast, it abstracts away local bottlenecks and individual unit constraints. For example, it assumes all plants of a type act as one large plant. Therefore, EnergyPlan is not capable of modelling one specific plant reaching minimum load while another is off; it simply sees the total required generation from that category.

2.3.4 ficus

Ficus is a Python-based MILP optimization model for finding the minimum cost through optimal sizing of components and storage and the optimal energy flow in a local energy system to supply various commodities [106]. It is an optimization framework to find the optimal component sizes and energy dispatch. Ficus was initially developed to optimize factory energy systems – for example, determining the optimal set of on-site generation units, boilers, and storage for a factory with both electricity and heat requirements, given time-varying loads and energy tariffs. It is an open-source optimization model in Python, utilizing the Pyomo optimization library, which makes it accessible and modifiable by users familiar with Python. This tool is quite similar to DER-CAM but in an open, academic context. The ability to perform multi-commodity optimization (e.g. heat and electricity) with a high temporal resolution with an extensive range of technologies is among the capabilities of ficus. Another key feature of ficus is the ability to switch between MILP and pure LP.

To use *ficus*, the user needs to provide the energy demands, a list of components alongside their capital costs, fixed and variable O&M, energy prices with their tariff structure, operational constraints, and solver settings. The framework provides the optimal sizes of components and the system's operation, alongside a breakdown of costs and emissions.

Dennis Atabay, the developer of the model, showed the application of this model in optimal sizing and operation of an industrial energy system [107]. The implemented case study comprises four factories: a steel mill, an iron and aluminum foundry, an automobile manufacturer, and a carbon products manufacturer. The study evaluated the economic viability of using CHP and batteries to supply these factories' electricity and heating demands, considering various pricing schemes and tariffs for electricity purchases.

2.3.4.1 Strengths and Limitations Open-source accessibility, high temporal resolution analysis, ability to handle complex tariffs, and flexibility in selecting the optimization algorithm are the main strengths of *ficus*. On the other hand, once again, the inability to estimate energy demands, which requires the user to provide detailed hourly or sub-hourly data, is a limitation of *Ficus*. Additionally, *ficus* is designed to be used in small-scale plantations and cannot be used for large regions. However, this limitation is mainly due to the high temporal resolution, which makes it difficult to solve a MILP problem for 15-minute intervals. Another limitation is that the optimization problem is designed only for cost optimization; if the user seeks other objectives, the code must be reconfigured.

2.3.5 oemof

The Open Energy Modelling Framework (OEMOF) is one of the most exciting energy system modelling frameworks [108]. This framework uses a bottom-up approach to simulate and optimize LP and MILP methodologies. This framework utilizes a graph-based representation of energy systems, where nodes represent sources, sinks, and storage processes, while edges show the energy flows. The framework is comprised of several libraries that together form a modular ESMF. Examples of these libraries include *oemof.solph* [109] is used for linearly optimizing energy systems based on graph theory, *oemof.tabular* [110] is developed for facilitating access to the data model through a spreadsheet interface, and the *demandlib* is developed for creating the load profiles. This framework approach allows significant flexibility. For instance, users have modelled national power systems, local multi-energy grids, sector coupling scenarios (power-to-heat, power-to-gas) and so on using *oemof*. Essentially, OEMOF provides the building blocks for an energy model rather than a single model of a specific system.

There is an optimization mode in OEMOF that allows setting up a linear optimization problem to minimize costs, emissions, and other objectives (single or multi-objective) for capacity expansion or operational optimization purposes. The framework could also be used solely for simulation, where the user should provide the operational rules and component sizes so that

OEMOF can assess the system's performance. To use OEMOF, the user must define the system under study, specify the constraints, configure the solver, and provide time-series data, including energy demands, renewable generation, and price signals. The component capacities, costs, and storage state are among the outputs of OEMOF. In OEMOF, demand is an external input time series that the optimization must satisfy using available resources. The model is very capable of finding the least-cost way to satisfy that demand (with whichever generation, storage, or imports installed). Examples of applications of OEMOF include finding the optimal energy mix of Italy in 2050 [111], a feasibility study of a 100% renewable energy system in Germany by 2050 [112], and an assessment of different electrification scenarios in rural areas of Nigeria [113].

2.3.5.1 Strengths and Limitations The main advantages of this tool are its openness and structural flexibility. Users are not limited to a specific predefined model. They can represent novel technologies, new system configurations, or unusual constraints by essentially “plugging” them into the energy system graph as needed. Regarding its limitations, building a full system model with oemof requires collecting all necessary data and carefully structuring the model, and it demands more modelling effort and expertise. Additionally, using linear programming for optimization may affect accuracy due to the linearization of parameters.

2.3.6 OSeMOSYS

The Open-Source Energy Modelling System (OSEMOSYS), developed at the KTH, is an open-source LP optimization tool for long-term planning with a flexible spatial resolution [114] used to find the optimal energy mix that minimizes the system's total discounted cost in OSEMOSYS [115]. The applications of OSEMOSYS include energy security, short-term dispatch, long-term energy planning, and the expansion into analysis of the Climate, Land, Energy, and Water systems (CLEWS) modelling [116]. OSEMOSYS has been widely used in nationwide energy analysis. Since OSEMOSYS is fully open-source, the code is accessible, allowing modellers to customize features according to their specific needs.

The user must provide energy demands, technology characteristics, policy and emission data, and economic data to calculate the energy balance, investment decisions, emissions, and total costs in a simple CSV format.

Pinto de Moura et al. [117] assessed 4 scenarios for exporting the electricity of Bolivia by modelling the cross-border trades between Bolivia and their neighbours using OSeMOSYS. Olsson and Gardumi [118] utilized OSEMOSYS to determine the most cost-effective technology mix in Bangladesh. Regarding capacity expansion studies using OSEMOSYS, English et al. [119] focused on increasing the share of wind energy in British Columbia and Alberta, considering interregional transmission and flexibility requirements, and Quevedo et al. [120] assessed the expansion of renewable capacity in the Dominican Republic. The ability of OSEMOSYS to conduct optimization analysis, combined with its open-source nature, can be

linked with other tools, such as the Long-Range Energy Alternatives Planning System (LEAP), to facilitate long-term planning or capacity increase studies. Emodi et al. [121] used the LEAP-OSEMOSYS combination to optimize Australia's electricity generation transition pathway under different climate change scenarios. Shah [122] also utilized LEAP-OSEMOSYS integration to examine various scenarios for decarbonizing the US Virgin Islands' energy sector, taking into account extreme weather events and the impact of electric vehicles on the grid.

2.3.6.1 Strengths and Limitations Similar to OEMOF, the accessibility of OSeMOSYS is its main strength. Moreover, the ability to handle large spatial resolution problems and conduct long-term planning assessments is another strong point of OSEMOSYS. On the other hand, while the simplicity of OSeMOSYS makes it fast in analysis, it is considered one of its limitations, as some advanced features of larger models are not considered, which can reduce realism or analytical depth in certain studies.

2.3.7 TEMOA

The Tools for Energy Model Optimization and Analysis (TEMOA) [123] is an open-source, bottom-up energy economy optimization model using the LP method to minimize the total cost (summation of loan, capital, operation and maintenance costs) of an energy system [124]. The main features of TEMOA are its flexible temporal structure and advanced analytical options.

Using either a structured text file or a relational database, the user must provide the demands and technologies. The optimal configuration of the system is the final output of TEMOA. The output includes the capacities of each technology to install (per period), activity levels (energy produced/consumed by each tech in each time slice), commodity flows through the network, and system-wide metrics such as total cost and emissions. Cotterman et al. [125] assessed the impact of considering socio-technical constraints in determining the optimal decarbonization pathway for the US energy systems using TEMOA. Patankar et al. [126] attempted to modify the structure of TEMOA to incorporate consumer behaviour into the optimization process.

2.3.7.1 Strengths and Limitations The accessibility to the source code and modularity are the key strengths of TEMOA. Moreover, the model's capability in flexible time slicing makes it useful for better evaluation of seasonal impacts. The lack of a demand calculation module is one of the limitations of this relatively new framework. Moreover, a full TEMOA model requires assembling a complete dataset, which can be both data and labour-intensive. Another limitation is that TEMOA inherits the typical simplifications of linear programming and might lose accuracy due to linearization.

Table 2.1: Comparison of Modelling Tools

Modelling Tool	AA	GP	UM	MM	SR	TR	DS	TC
Calliope	BU	-	O	M	UD	UD	A	Renewables, Conventional Generation, CHP
DER-CAM	BU	-	O	M	Loc	years	A	Renewables, Conventional Storage
Energy Plan	BU	E, F	S, M	C	Loc. to Cont.	1 hour	B, T, I	Any
Ficus	BU	-	O	M	Loc. to Nat.	15 min.	A	Any
oemof	all	-	O	M	UD	UD	B, T, I	Any
OSeMOSYS	BU	E	O	M	UD	UD	A	Any
TEMOA	BU	-	O	M	UD	years	B, T, I	Any

Acronyms: AA Analytical Approach: BU Bottom-Up TD Top-Down H Hybrid, GP General Purpose: E Exploring F Forecasting, UM Underlying Methodology: S Simulation O Optimization E Equilibrium, MM Modelling Methodology: P Physical C Computational M Mathematical, SR Spatial Resolution: Loc. Local Cont. Continental Nat. National Int. International Reg. Regional UD User-Defined, TR Temporal Resolution, DS Demand Sector: B Buildings T Transport I Industry A Aggregated, TC Technology Coverage

2.4 Building Energy System Retrofit Tools

As stated in the previous chapter, the building sector accounts for almost 40% of global energy consumption and 30% of CO₂ emissions. Since the majority of current buildings are expected to still exist in 2050, proper energy retrofit assessment and planning of high-consuming buildings at both the individual building and building stock levels are crucial to pursuing net-zero emission development pathways. It should be noted that this perspective is particularly relevant for regions in the Global North, where building stocks are mature and long-lived. In contrast, in many regions of the Global South and East, new construction plays a more dominant role in shaping future energy demand and emissions, making new-build design and standards equally critical. Nevertheless, retrofit assessment remains essential even in rapidly developing contexts, as existing buildings often represent a significant share of near- to mid-term energy consumption and provide immediate opportunities for emission reductions.

HVAC and Domestic Hot Water (DHW) systems are the primary end-use energy consumers in buildings, and their impact must be carefully evaluated in any retrofitting study. Therefore, an ESMF capable of evaluating different system retrofit scenarios from technical, economic, and environmental perspectives is highly beneficial for all stakeholders involved in the retrofitting process. This section presents a review of existing tools and methodologies for assessing building energy retrofits, with a specific focus on studies at the building stock level.

The building energy retrofitting tools and frameworks fall into the following categories:

- (1) **Building energy simulation tools:** Detailed physics-based modelling tools provide the basis for retrofit analysis. EnergyPlus, TRNSYS, eQUEST, and IDA Indoor Climate and Energy (IDA-ICE) are among the most frequently used tools for estimating how a building's energy performance will change with different retrofit approaches. To determine heating, cooling, and other end-use needs, these white-box tools require extensive information about geometry, the envelope, systems, and processes. One of the biggest challenges in using these tools for retrofit studies is the significant modelling effort required to represent and compare multiple scenarios.

Several studies rely on advanced graphical interfaces built on top of these simulation engines to streamline scenario generation. For example, Umar and Afsour [127] utilized *DesignBuilder*, a graphical user interface based on the EnergyPlus simulation engine, to evaluate 24 distinct retrofit scenarios. These scenarios included various combinations of internal and exterior wall insulation, roof insulation, window glazing improvements, and HVAC enhancements in Saudi Arabia. In a separate study, *DesignBuilder* was used in conjunction with computational fluid dynamics (CFD) to evaluate four different roof retrofitting scenarios in Athens [128]. Shen [129] developed a multi-objective optimization algorithm to determine appropriate retrofit paths under future climatic scenarios.

- (2) **Optimization frameworks:** Due to the high computational cost of manually evaluating

all retrofit scenarios, many researchers have adopted simulation-integrated optimization algorithms to identify optimal solutions. In such frameworks, the simulation tool evaluates performance for a set of retrofit parameters, and an optimization algorithm iterates to improve outcomes. A multi-objective technique is often utilized, which creates a Pareto front that indicates how several objectives might be balanced against each other. Decision-makers can then use this front for more analysis. Simulation-based optimization has become a key component of retrofit assessment studies. These studies look for the most effective or cost-efficient strategies across multiple performance goals. Cai et al. [130] developed an automated multi-objective GA to identify the optimal envelope retrofit scenario, maximizing both energy savings and Return on Investment (ROI).

- (3) **DSS:** This group of studies combines simulation and optimization with Decision Support Systems (DSS) that help decision-makers choose the best retrofit alternatives from a group of Pareto-optimal solutions. Techniques for Order of Preference by Similarity to Ideal Solution (TOPSIS) and other Multi-Criteria Decision Analysis (MCDA) methodologies are often used to make modelling results easier to understand and more transparent. Giresini et al. [131] developed a DSS architecture that utilizes histograms, radar charts, proficiency ratios, and iso-class plots to identify the most effective retrofit solutions, considering energy, economic, environmental, and seismic factors. Their framework was applied to a two-story structure in Italy that an earthquake had damaged; however, the scenarios did not involve retrofits for the energy system. In a separate DSS study, D'Agostino et al. [132] developed a Multi-Criteria Decision-Making (MCDM) framework to assess and prioritize viable retrofit interventions for a shopping mall in Italy. Their approach graded ideas based on how well they worked for the economy and the environment, considering the views of diverse groups.
- (4) **Data-Driven and AI-Based Tools:** The utilization of data-driven and AI-based methodologies in retrofit assessment has increased in recent years [133]. These black-box or gray-box models learn from historical building performance or simulation-generated datasets to predict the outcomes of retrofit measures. Applications include regression or ensemble learning for energy savings prediction, clustering to identify retrofit typologies, and reinforcement learning for control-oriented retrofits. Piscitelli et al. [134] developed a methodology combining data-driven modelling and AI techniques to benchmark energy performance in residential buildings. Seraj et al. [135] created a web-based, data-driven tool to predict residential energy use, CO₂ emissions, and EPC ratings, assess retrofit measures, and estimate costs using real-time market data. Their hybrid framework, tested on a UK case study, identified Air-Source Heat Pump (ASHP) systems as the most favourable retrofit scenario.

Regarding spatial resolution, there is growing interest in methodologies to assess and prioritize retrofitting measures across building portfolios or entire urban stocks. A bottom-up approach is

typically required to calculate the energy demand of a building portfolio. Two main modelling strategies exist: archetype-based and building-by-building. Dong et al. [136] reviewed these approaches and their applications in urban policy making. Due to lower data requirements, archetype-based models are generally preferred for urban-scale building energy modelling. Large-scale retrofit assessments frequently fall under the DSS and data-driven categories.

By combining a spreadsheet model with Geographic Information System (GIS) data, Aruta et al. [137] developed a tool for quick identification of areas needing retrofits within urban districts. Yu et al. [138] combined a geographic archetype dataset with an UBE tool to pinpoint high-consumption building types. In their Düsseldorf case study, they found that targeted retrofits for buildings constructed before 1957 could reduce annual CO₂ emissions by 42–46% and heating demand by roughly 70% by 2050. Wang et al. [139] examined large-scale retrofit options in areas with hot summers and cold winters, considering how people use energy and their behavioural patterns.

In another study, Aruta et al. [140] developed a framework that optimizes retrofit incentive policies based on the building function and its climate condition. SHAPE, a DSS developed by Martin et al. [141], enables community-level retrofit planning with building-level resolution. Simulations conducted for 4,000 buildings in a French region revealed that approximately 50% require major retrofits. CityEL [142] is another web-based, city-scale retrofit assessment tool that integrates EnergyPlus models with GIS. Tested in Shanghai, CityEL identified 245 out of 304 neighbourhoods as economically viable for retrofitting.

In summary, the growing diversity of retrofit assessment tools demonstrates the complexity and multifaceted nature of decision-making in building energy upgrades. From detailed simulation engines to AI-powered benchmarking and large-scale decision-support systems, researchers now have a wide range of methodologies to evaluate retrofit strategies at both the individual building and building stock levels. Despite these advances, there are still challenges to overcome in this area. These challenges include prioritizing buildings within a portfolio, integrating occupant behaviour, and harmonizing outputs across tools. Prioritizing buildings for retrofit remains a complex task due to numerous methodological and practical limitations. One of the main issues is the limited ranking criteria, which leads to a failure in capturing the true impact of retrofitting. Many academic models fail to address the comprehensive decision-making landscape, which encompasses selecting buildings, choosing interventions, and scheduling investments under various constraints.

Furthermore, there is a widespread lack of integration of LCC, Life Cycle Assessment (LCA), and social equity considerations; most tools continue to focus narrowly on technical and economic metrics. Furthermore, data-related issues, including restricted availability, low resolution, and inconsistent formats, all affect the strength and scalability of prioritizing frameworks. Additionally, performance forecast uncertainty, which arises from factors such as how people

utilize the space, the quality of installation, and changes in weather conditions, is not always considered. Existing tools are frequently designed for single-building analyses, lack budget constraint functionality, or require expertise that limits their broader adoption. These limitations underscore the urgent need for a more adaptable and comprehensive ESMF that can support data-driven, multi-criteria, and uncertainty-aware retrofit planning at scale—ultimately serving as a powerful decision-support resource for policymakers, building owners, and urban planners.

2.5 Summary

This chapter has provided a comprehensive review of the evolution and classification of ESMFs, focusing on three key dimensions: input data structuring and modelling techniques, the categorization of modelling frameworks based on analytical and technical features, and methodologies for assessing energy system retrofits, particularly at the building and urban stock levels. The review highlights the increasing complexity and diversity of energy system models in response to decarbonization goals, multi-vector integration, and policy-driven planning requirements.

A clear timeline emerges in the evolution of input data structures—from rigid, static formats and spreadsheet-based templates to relational databases, configuration-driven inputs, and the integration of semantic ontologies. Despite these advancements, a critical gap remains in the standardization and interoperability of input structures across frameworks. Many ESMFs continue to rely on proprietary or highly customized formats, which restrict model reuse, hinder automation, and complicate cross-model comparisons.

The classification of ESMFs based on their analytical approach, purpose, methodology, and resolution reveals a trade-off between technical detail and system scope. While bottom-up, optimization-based models provide granular insights into technology configurations and operational behaviour, they often overlook macroeconomic dynamics and behavioural factors. Conversely, top-down and equilibrium models offer broader economic insights but lack technological specificity. Hybrid frameworks attempt to bridge this divide, but are often hindered by the complexity of integration. Furthermore, while many ESMFs offer high spatial or temporal resolutions, few effectively balance both due to computational limitations.

In the domain of energy retrofit assessment, the landscape is equally fragmented. Detailed simulation tools, such as EnergyPlus, provide high-fidelity results but are cumbersome for large-scale applications. Optimization frameworks and DSS platforms introduce automation and multi-criteria evaluation but frequently rely on oversimplified assumptions or demand expert calibration. Data-driven tools and AI-based methods promise scalability and adaptability, yet often lack transparency or generalizability beyond the training dataset. Notably, most retrofit tools do not integrate fully with broader ESMFs or support iterative decision-making processes across building portfolios.

Several persistent limitations and research gaps remain across the reviewed domains. First,

there is a lack of a unified, flexible data structure that can support diverse modelling needs while enabling automation, validation, and semantic clarity. Second, model interoperability and comparability are still in their infancy, with few efforts to harmonize input/output definitions or metadata standards across tools. Third, many existing retrofit assessment tools fail to adequately account for occupant behaviour, investment constraints, life-cycle impacts, or socio-spatial equity. Lastly, prioritization frameworks are often linear and deterministic, failing to account for the uncertainty and complexity inherent in real-world retrofitting decisions.

Addressing these gaps, this thesis proposes the development of a modular, object-oriented ESMF that integrates semantic data layers and supports building-to-district-scale simulations. This framework aims to improve model adaptability and enhance decision support.

3 Methodology

In the previous chapter, it was explained that a generic, unified, and flexible structure for organizing the input and output data for simulating urban energy systems is missing. Moreover, most of the existing tools are not interconnected with building modelling tools and require a high level of detailed input data, especially energy demands from the user. The linearization in the majority of optimization tools, combined with the lack of integration with detailed simulation models of components and systems, also impacts the accuracy of outputs.

On the other hand, existing building retrofit tools either focus on individual buildings or aggregate buildings based on their location or type. Therefore, a workflow to assess buildings of any type and location in the same portfolio and rank them for energy retrofit could be useful for urban planners, facility managers, and building owners.

To address these issues, an automated urban energy system modelling framework and a building portfolio retrofit management workflow have been developed to be integrated into the TOOLS4CITIES urban simulation platform in the Next-Generation Cities Institute of Concordia University. TOOLS4CITIES is an urban simulation platform designed to simulate urban areas holistically. This platform includes several tools and services, including a UBEM workflow whose outputs are directly used in the energy system modelling framework.

In this chapter, the technical details of the UBEM and energy system modelling frameworks, as well as the retrofit management workflow, are explained in detail.

3.1 Urban Building Energy Modelling Workflow

The initial step in sizing and simulation of any energy system is acquiring the energy demands of the buildings under study. In this study, the TOOLS4Cities UBEM workflow is used to calculate the lighting, appliances, heating, cooling, and DHW energy demands. The development of this workflow is not a part of this research thesis but the researcher has collaborated in improvement of different parts of it. While here a brief explanation of the UBEM workflow is presented, a detailed explanation of the workflow structure is given in [143, 144]. Figure 3.1 represents a schematic of the UBEM workflow.

Object-oriented programming was the key to the development of the whole TOOLS4Cities. The codebase is developed around classes that represent physical and logical entities, such as buildings in an urban area. In the backend, a set of data models, data catalogues, data files, importers and exporters are created, leading to the formation of what is called the Hub. The primary data model in the Hub is the central or city data model, which enables users to replicate an urban area with various urban objects of different types. The steps in running the developed UBEM workflow are similar to those of most existing building simulation tools, such as eQUEST, where the user must provide the building geometry and then create thermal zones

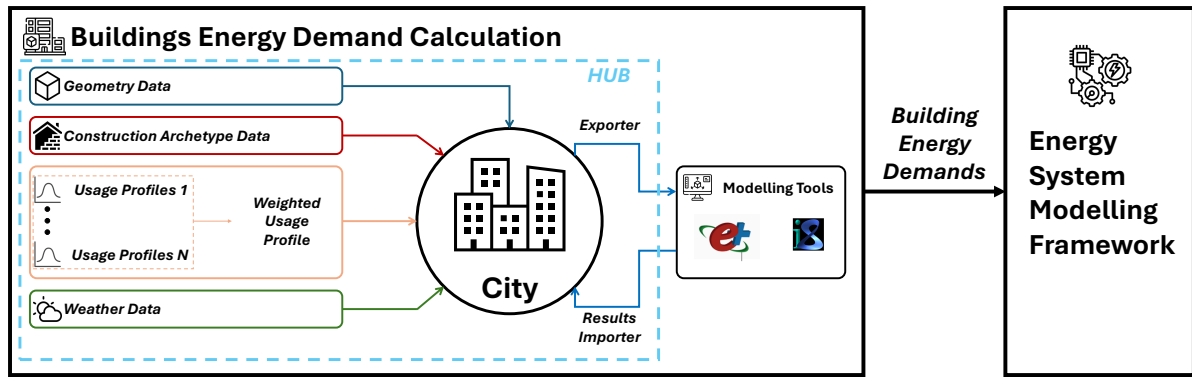


Figure 3.1: The structure of the UBE M workflow of TOOLS4Cities

with full physical and thermal characteristics, specify zone usages and thermal controls, and provide weather data. The developed workflow uses archetypal data for thermophysical and usage parameters. Therefore, for any urban area, the first step is to either create the archetypes or select a set of existing archetypes in the platform.

To use the UBE M workflow, a 'City' must be created first from a geometry data file. This file should be in GeoJSON format and can include 1 or many building features. In addition to footprint vertex coordinates, each building feature in the file must have data on building height, construction year, and building function. The buildings can have single or multiple usage types making a mixed-use building. In the geometry file of a mixed-use building, each usage type with the percentage of the total floor area that each usage occupy should be mentioned. These data are necessary for retrieving the proper construction archetype. An importer is designed to read the geometry file and, using the building height in the file, extrude the building footprint to form all the building surfaces, including the ground, walls, and roof. While footprint extrusion provides an efficient and robust approach for large-scale urban modelling, it is most accurate for buildings with relatively regular geometries. Irregular features such as setbacks, overhangs, articulated façades, and complex roof forms (e.g., pitched, stepped, or multi-level roofs) are not explicitly captured by simple extrusion methods and may introduce geometric simplifications. In the context of urban-scale energy modelling, these approximations are generally acceptable, as envelope-level thermal properties and usage patterns tend to dominate energy demand estimates. Another part of this step involves creating internal zones within each building. Currently, each building has one internal zone, and multi-zoning of buildings is underway.

Once the building geometries are created, the City buildings must be enriched with construction data and form the thermal zones and thermal boundaries inside the internal zones. To identify the proper construction archetype for each building in the city, another importer is created that assigns an archetype based on that building's construction period, function and climate zone. Once the archetype is identified, each building is enriched with the following parameters:

- Average storey height
- Infiltration rate per area for when ventilation system is ON or OFF
- Construction materials and their thicknesses alongside thermophysical characteristics of these material for ground, wall, ceiling, and roof surfaces of the building.
- Window-to-Wall Ratio (WWR) for outdoor walls of the building facing every geographic direction. For every direction, the WWR is defined as percentage of the surface.
- Solar heat gain coefficient and U value of windows.

The calculation of building internal gains is an important part of each building energy model. The usage archetypes are created to provide the data on how each building is operating. A thermal zone can be assigned a single usage or a mixture of usages. The imported data from the usage archetypes can be divided into 2 groups: usage intensity values and usage schedules. The usage intensity values include the following:

- Lighting per area (W/m^2)
- Electrical appliances per area (W/m^2)
- Ventilation per area ($m^3/(m^2.s)$)
- Domestic hot water peak flow per area (m^3/s)
- Occupancy per area ($number\ of\ people/m^2$)

The schedules define the building's occupancy and operation, which directly impact the building's internal gains. Deterministic and stochastic schedules can be used for modelling. The used schedules are heating and cooling setpoints, domestic hot water consumption, lighting, appliance, and occupancy. Apart from heating and cooling setpoint schedules that contain real setpoint values, the rest of the schedules contain fractions of the corresponding intensity value. In the current study, only deterministic schedules were used. In these deterministic schedules, there are 3 separate sets of values representing weekdays, Saturdays, and Sundays or Holidays. Regarding mixed-use buildings, the assignation of usage archetypes is done by calculating the weighted average values of intensities and schedules based on the percentages of each usage type.

The climate data, including ambient temperature and solar irradiance data, are also imported to the City from weather data in various formats, such as '.epw'. In this study, the default weather inputs are Typical Meteorological Year (TMY) files in EPW format, which provide representative long-term climate conditions for building energy simulations. This default choice ensures consistency across all simulated buildings and aligns with common practice in UBEM studies. However, the workflow is fully flexible: the TMY data can be replaced by Actual Meteorological Year (AMY) files or any other weather dataset provided in the supported formats, allowing users to analyse specific years, extreme events, or future climate scenarios when

needed.

A key design principle of the UBEM workflow is the use of a single, tool-agnostic internal data model to represent buildings, zones, constructions, usages, and climate inputs. Rather than tailoring the core data structures to the requirements of a specific simulation engine, all information is first mapped into the City data model within the Hub. Tool-specific input requirements are then satisfied through dedicated exporters, which transform the canonical internal representation into the schema, syntax, and conventions required by each simulation tool (e.g., EnergyPlus IDF files, INSEL or TRNSYS input formats). This approach ensures that the same underlying building model can be consistently evaluated using different simulation engines without duplicating or modifying the core data, while preserving reproducibility and comparability across tools.

One of the strengths of the Hub is a set of various exporters designed to export the input file for running different simulation tools, including EnergyPlus, INSEL, and TRNSYS. In the UBEM workflow, the idf exporter is used to generate an idf with thermal and physical characteristics of every thermal zone and different schedules associated with each zone. After exporting the idf file, a CSV file of the results is generated, and then the values are imported back to the City to be used in further analysis. From the UBEM workflow, the hourly energy demands for heating, cooling, lighting, appliances, and domestic hot water are calculated. Alongside these values, monthly and yearly demands are stored in the Hub.

3.2 Energy System Modelling Framework

The UBEM workflow assumes an ideal load system for supplying heating and cooling demands. An ideal load system is a conceptual representation with an efficiency of 1, meaning that the system requires exactly the same amount of final (end-use) energy as the thermal energy it delivers to the building. While this assumption is appropriate for isolating building-level energy demands, it does not represent the behaviour, efficiency, or constraints of real energy conversion systems.

The energy system modelling framework is therefore introduced as a methodological extension of the UBEM workflow to explicitly model real energy systems, including their efficiencies, operational constraints, and interactions with energy carriers. At the individual building level, the framework replaces the ideal load system with a physically realistic energy system, sizes its components, and calculates the resulting final energy consumption. The same modelling logic is then applied consistently across multiple buildings by instantiating identical or archetypal system templates and aggregating them at the neighbourhood or district scale. In this way, the transition from single-building to urban-scale energy system modelling is achieved through systematic replication and aggregation rather than a change in modelling assumptions.

Various modules for selecting, simulating, optimizing, and costing urban energy systems have

been developed, all of which directly benefit from the underlying data model. The system-selection module enables a rapid feasibility pre-assessment of different technologies based on technical, environmental, and spatial constraints. This step efficiently eliminates infeasible options, ensuring that subsequent simulation and optimization efforts focus only on viable configurations. The simulation, optimization, and costing modules operate in an integrated manner to evaluate a wide range of system designs and performance outcomes. The current applications of the framework, as illustrated in this figure, span from building retrofit assessment to the analysis of renewable energy integration strategies.

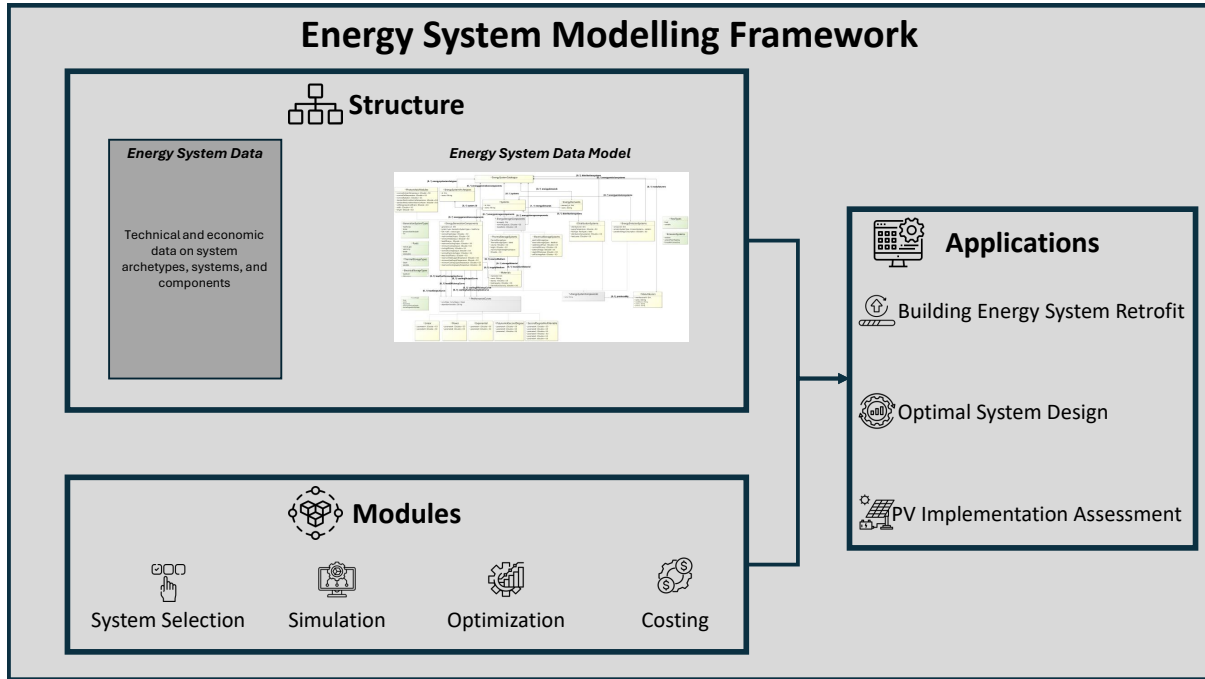


Figure 3.2: Developed Energy System Modelling Framework Structure and Applications

3.2.1 Energy System Data Model

In the previous chapter, it was discussed how the input data structure of energy system models evolved from static punch-card-like structures to current efforts in developing ontologies and semantic data models. Due to their superior efficiency, structure, and alignment with implementation needs, data modelling was selected as the technique for structuring and organizing energy system data. Data models provide the framework with a solid foundation for computation, validation, and automation. This makes them more suitable for application-specific energy simulations and managing large-scale scenarios. Their ability to encode complicated hierarchical relationships makes it easier to combine them with performance curves, system limitations, and evolving use cases.

In simple terms, a data model is a conceptual representation of what data is stored in a database, how the stored data are associated and how this data is organized [58]. A data model is more

concerned with the necessary data and its organization than with the operations performed on the data. The importance of data modelling lies in its ability to provide a clear picture of the original data, helping database developers create a physical database. Overall, data models improve the quality of the information in decision-making [145].

Over the years, different techniques have been developed for data modelling. The following is a comprehensive list of different methods for data modelling [146]:

- Hierarchical data modelling
- Relational data modelling
- Entity-relationship data modelling
- Dimensional data modelling
- Object-oriented data modelling

Among the methods mentioned above, a review of studies on this topic shows that **Entity Relationship** and **Object-Oriented** approaches have been used more often, not only because they are common in the literature, but because they offer clear advantages for modelling complex energy systems. Both approaches allow the representation of system components as structured entities with well-defined attributes and relationships, making them particularly suitable for capturing the hierarchical, modular, and data-rich nature of urban energy systems.

It is important to distinguish the scope of the proposed data model from that of established Building Information Modelling (BIM) standards such as IFC, gbXML, and CityGML. BIM standards primarily focus on the detailed representation of building geometry, construction elements, and asset information to support design coordination, documentation, and information exchange across the building lifecycle. While these standards provide rich descriptive detail, they are not inherently designed for executable energy system simulation, optimization, or large-scale scenario analysis.

In this work, BIM-based representations are therefore considered complementary rather than competing approaches. The developed energy system data model operates at a higher abstraction level, emphasizing system topology, performance characteristics, techno-economic attributes, and inter-component relationships required for automated simulation and optimization workflows. When available, relevant information from BIM models such as geometry, construction properties, or system inventories can be mapped into the proposed data model through preprocessing or import mechanisms. This deliberate separation allows the framework to remain lightweight, scalable, and computation-oriented, while preserving compatibility with BIM-driven workflows when detailed building information is required.

Chen introduced the ER model [147] in 1977. An ER diagram is a structural diagram that presents the major entities within the system scope and how these entities are related. A basic

ER diagram is comprised of the following 3 main components [148]:

- **Entities** are any concept, object or anything in the system or business you want to store information about. It is called an entity. In the ER diagram, an entity is shown with a box. For example, heat pumps and storage tanks could be entities of an energy system.
- **Relationships** are how entities are associated with each other. For instance, an energy system might have a district heating network. Here, the energy system and district heating network are the two entities, while the fact that the energy system includes a district heating network forms a relationship between these two.
- **Attributes** are characteristics of entities that provide information about the respective entity. Attributes have names and types and are divided into two groups: primary key and foreign key attributes. A primary key uniquely defines an instance of an entity, like the ID number of a student. On the other hand, a foreign key denotes a non-unique characteristic of a particular entity instance.

In contrast to the entity-relationship model, the object-oriented data model employs objects as the foundation for conceptualizing and defining information. These objects, representing real-world entities like customers with various attributes, offer a more holistic approach. While object-oriented programming spurred the popularity of this model in the mid-1990s, its essence lies in abstracting entities into objects, forming class hierarchies with associated features. In this paradigm, objects encapsulate data attributes and behaviours. At the same time, classes act as templates for their creation, enabling the inheritance of attributes and behaviours, fostering code reusability, and promoting system flexibility. At its core, it revolves around four key components:

- **Objects:** Objects are the fundamental building blocks of object-oriented data modelling. They encapsulate data attributes and behaviours, making them self-contained entities in the system.
- **Classes:** Classes serve as blueprints for creating objects. They define the common structure and behaviour shared by a group of objects. By specifying attributes and methods within a class, you establish a template that can be instantiated to create individual objects.
- **Inheritance:** is a mechanism that allows classes to inherit attributes and methods from other classes. This promotes code reusability and establishes a hierarchy of classes where subclasses inherit characteristics from superclasses. For example, a "HeatPump" class can inherit attributes and methods from the "ThermalEnergyDevice" class, adding specific attributes like "nominalHeatOutput."

In summary, object-oriented data modelling leverages objects, classes, and inheritance to create a modular and organized representation of data and its associated behaviour, facilitating the

development of flexible and maintainable software systems.

Unified Modeling Language (UML) class diagrams serve as a fundamental tool in object-oriented data modelling, offering a structured representation of classes, their attributes, methods, and relationships within a system. These diagrams are instrumental in visualizing the static structure of a software application or database schema. UML and ER diagrams are vital software engineering and database design tools yet possess distinct focuses and applications. As a richer and more versatile language, UML caters to a broad spectrum of analysis and design requirements, encompassing structural, behavioural, and architectural aspects of software systems [58]. Due to its versatility and object-oriented nature, the UML class diagram is used to create the energy system data model for this study. The UML diagram, on the one hand, provides an easy and understandable representation of the model. On the other hand, it is compatible with object-oriented programming languages such as Python.

There are 14 different types of structural and behavioural UML diagrams. In the current work, the UML class diagram is chosen to represent the ESMF data model as it suits the application better. Figure 3.3 shows an example UML diagram, and the developed energy system data model, with a detailed explanation of the logic, is presented in the first section of the next chapter 4. A UML class diagram depicts classes as rectangles with compartments for attributes and methods. Relationships, represented as lines connecting classes, highlight associations between objects and convey various connections, such as associations, generalizations (inheritance), dependencies, and aggregations [148, 149]. Relationships in UML class diagrams are crucial in modelling how objects interact and collaborate in a system. They allow for the depiction of hierarchies, dependencies, and collaborations among classes, providing a comprehensive view of the data structure and behaviour of the system. In UML class diagrams, classes are rectangles that encapsulate attributes of that class, and any instance of a class is called an object. Attributes are used to store information that is relevant and known for all objects in a class, but can differ for each object. Additionally, the type of the attribute must be defined. Types can be, for example, integers, strings or doubles (floating-point numbers).

As explained earlier, one objective of a UML class diagram is to show the relationship among classes. There are several types of relationships, and some of them have been used here. One of the most common relations used in object-oriented data modelling is inheritance, where common properties of several classes can be combined or generalized into superclasses. Subclasses inherit the attributes and operations outlined in their respective superclasses, thus making each instance of a subclass simultaneously an instance of the superclass with access to its attributes and operations. Additionally, subclasses have the flexibility to introduce new attributes and operations that are not originally defined in the superclass. This linkage is visually depicted in diagrams through arrows from the subclass pointing to the superclass.

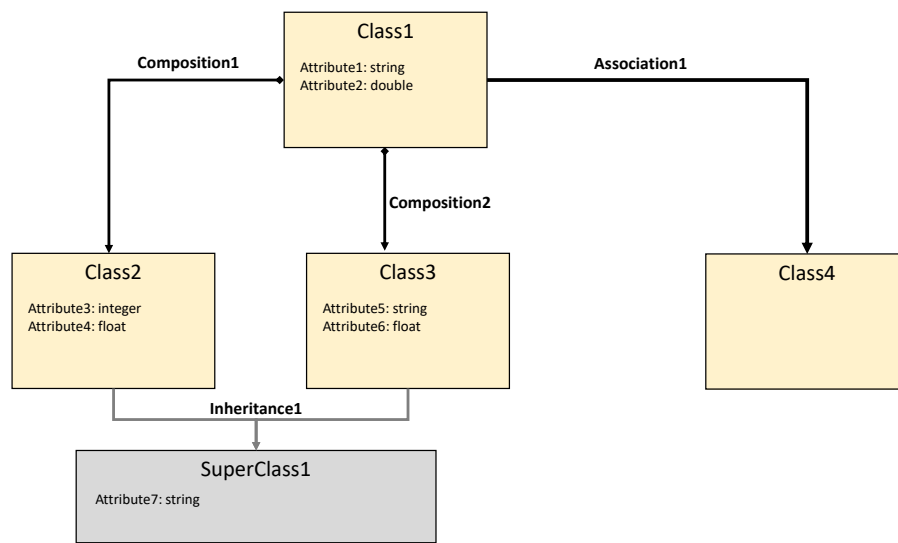


Figure 3.3: An example UML diagram

Superclasses can be designated as abstract, indicating that no instances of this class exist independently but only within its subclasses. This abstraction facilitates the construction of hierarchies and the development of a well-structured model. This approach prevents redundancies and errors while maintaining a coherent model structure by transitioning from broad, high-level properties to specific attributes tailored to individual subclasses.

The other type of relation between classes in a UML class diagram is called composition, which represents a strong "whole-part" or "container-contained" association between two classes, where the part (or component) is a fundamental part of the whole and has no meaningful existence outside of the whole. It implies that the whole's existence determines the existence of its parts, and when the whole is deleted, its parts are also destroyed. The composition relation is shown using a solid arrow with a diamond on the head connected to the whole or container class. Multiplicity is used to specify the number of instances of one class associated with the number of instances of another class in a particular relationship. This is indicated by the numbers on the arrow connecting the classes.

The third type of relationship used in the developed data model is called association. It is shown using lines connecting the involved classes, often annotated with multiplicity, roles, and other properties to describe the nature of the relationship and the characteristics of its instances. An association in UML is a structural relationship that denotes a connection or linkage between two or more classes or objects, specifying that instances of those classes can interact, collaborate, or be related within a system or model.

3.3 Energy System Simulation

The framework contains simulation models for different generation, distribution, and storage components. Additionally, simulations of models for some prevalent systems with rule-based control strategies have also been included. Advanced concepts of energy systems are out of the scope of this study. A combination of physics-based and empirical curve-based models is developed to simulate various energy system components. The reason that physics-based models are not used in all cases is to avoid complexity in simulations and save computational time. In this section, a series of simulation models that have been created so far are presented. Given the open-source nature of the TOOLS4Cities platform and its various frameworks and workflows, these models can be modified by users. Before explaining the model, Table 3.1 presents the different types of curves used in empirical modelling.

At the current stage of development, the framework prioritizes generation and storage components, and includes one representative distribution model (central air distribution with explicit fan power). The framework does not yet implement the full range of non-residential HVAC components (e.g., multi-fan air handling configurations, economizers, dedicated outdoor air systems, terminal units with reheat, detailed duct-network pressure models, or advanced supervisory controls). Similarly, energy emitters (e.g., radiators, fan coils, VAV terminals, baseboards) are represented implicitly through their impact on required loads and supply conditions rather than through detailed component-level dynamics. This scope choice is deliberate: the primary methodological objective of this thesis is to develop a modular, extensible, and computationally tractable framework for city-scale scenario analysis, where the dominant contributors to annual energy use and retrofit comparison must be captured without the computational burden and input-data requirements of full HVAC system emulation.

Importantly, these simplifications do not constrain the data model itself. The proposed energy system data model explicitly separates generation, distribution, storage, and emission subsystems, and defines uniform interfaces for adding new component classes. As a result, additional distribution and emitter models can be incorporated incrementally without modifying the overall workflow. In other words, the present implementation reflects a practical “minimum viable” set of component models for large-scale studies, while the metamodel remains general enough to support future integration of richer non-residential HVAC configurations.

3.3.1 Heat Pump

In recent years, various types of heat pump models have been developed to simulate and analyze the performance of heat pumps in different applications. In general, heat pump models can be categorized into three types: thermodynamic or physics-based models, data-driven or black-box models, and semi-empirical models. While the first two categories work purely on thermodynamic principles or measured data, the latter utilize empirical data to create correlations

Table 3.1: Common curve formulations used in the framework

Curve Type	Equation
Linear	$c_0 + c_1x$
Quadratic	$c_0 + c_1x + c_2x^2$
Cubic	$c_0 + c_1x + c_2x^2 + c_3x^3$
Quartic	$c_0 + c_1x + c_2x^2 + c_3x^3 + c_4x^4$
Biquadratic	$c_0 + c_1x + c_2x^2 + c_3y + c_4y^2 + c_5xy$
Bicubic	$c_0 + c_1x + c_2x^2 + c_3y + c_4y^2 + c_5xy + c_6x^3 + c_7y^3 + c_8x^2y + c_9xy^2$
Quadlinear	$c_0 + c_1w + c_2x + c_3y + c_4z$
Power	$c_0 + c_1x^{c_2}$
Exponential	$c_0 + c_1e^{c_3}$

that predict the performance of heat pumps under varying conditions. They range from simple curve fittings that approximate the heat pump performance based on manufacturer data to more complex deterministic models grounded in physical principles and thermodynamics. In this work, the semi-empirical curve-fitting approach is adopted due to its balance between computational efficiency and the ability to capture performance variations under different operating conditions, while remaining compatible with modular component-based modelling in the proposed framework.

To model heat pumps using empirical curves, two separate sets of equations are applied: one for determining the thermal output capacity and another for calculating the Energy Input Ratio (EIR). The EIR of a heat pump is defined as the ratio of its electrical power input to its delivered heating or cooling output, and is the inverse of Coefficient of Performance (COP). Therefore, it is a key parameter for assessing system efficiency in performance modelling. These curves are normalized to a value of 1.0 at the nominal reference conditions, with outputs typically ranging between 0 and 1. The curve outputs must be multiplied by the nominal values obtained from manufacturer catalogues or determined through a sizing procedure.

To calculate the thermal output capacity of a heat pump, a temperature-based curve and a Flow Fraction Ratio (FFR) curve are employed (Eq. 1). These curves may take any of the mathematical forms listed in Table 3.1. For the temperature-based curve, the input variables depend on the type of heat pump; however, biquadratic curves are commonly used to represent performance as a function of source and supply temperatures. The FFR curve accounts for deviations from the nominal supply-side flow rate, reflecting the effect of reduced or increased fluid flow on capacity. The impact of partial load ratio (PLR) is also incorporated by comparing the computed capacity with the actual load requirement. In the final step, the heat pump's thermal output is set to any value less than the calculated capacity, as determined by the system control.

$$C_{HP} = f(T) \cdot f(\text{FFR}) \cdot C_{\text{nom}} \quad (1)$$

$$\text{PLR} = \frac{P_{\text{load}}}{C_{\text{nom}}} \quad (2)$$

$$C_{\text{HP}} = f(\text{PLR}) \cdot C_{\text{nom}} \quad (3)$$

In equations above, C_{HP} refers to the heat pump capacity at any time step and C_{nom} is the nominal capacity of the heat pump.

The same set of equations are used to calculate the heat pump EIR (Eq. 4). After calculating the capacity and EIR, the values of COP and heat pump power input can be found.

$$\text{EIR}_{\text{HP}} = f(T) \cdot f(\text{FFR}) \cdot f(\text{PLR}) \cdot \text{EIR}_{\text{nom}} \quad (4)$$

$$\text{COP} = \frac{1}{\text{EIR}} \quad (5)$$

This formulation closely parallels the performance-curve approach used in tools such as *Energy-Plus*, while offering greater flexibility in curve functional forms, and differs from *TRNSYS* in that it relies solely on analytical curve fits rather than tabulated performance maps.

Accurate representation of the *heat pump source temperature* is essential, as it directly influences both the instantaneous capacity and the overall efficiency of the unit. While air-source heat pumps (ASHP) obtain their source temperature directly from ambient conditions provided in the building simulation weather file, other source types like wastewater and the ground require dedicated modelling approaches. These media exhibit more complex thermal behaviour than air, influenced by hydrological, climatic, and infrastructural factors, and therefore cannot be approximated using simple static temperature assumptions.

For wastewater-source heat pumps (Wastewater Heat Pump (WWHP)), no widely accepted universal method was found for predicting wastewater temperature, due to local variability in sewer network configuration, water-use patterns, and climatic conditions. However, for the specific case of some Canadian cities, the wastewater temperature is modelled using correlations adapted from [150], which provide empirically derived seasonal and diurnal wastewater temperature estimates. Importantly, due to the open-source and modular design of the framework, this empirical model may be replaced or customized using alternative datasets, sewer thermal models, or site-specific measurements, allowing users to adapt the workflow to any region or study area.

Modelling the source temperature for ground-source heat pumps requires a more detailed representation of subsurface thermal behaviour. The proposed workflow integrates a generic sizing methodology for vertical ground heat exchangers (Ground Heat Exchangers (GHEXs)) using the open-source *GHEDesigner* library [151]. The sizing algorithm determines the borehole depth required to maintain the entering fluid temperature (EFT) within prescribed operational limits over the entire simulation horizon.

The *GHEDesigner* framework is based on the transient thermal response of the ground represented by non-dimensional *g*-functions. For a borefield with spacing B , borehole radius r_b ,

soil thermal conductivity k_s , and thermal diffusivity α_s , the characteristic time scale is defined as

$$t_s = \frac{H^2}{9\alpha_s} \quad (6)$$

The dimensionless temperature response is captured by a g -function of the form

$$g(\ln(t/t_s); B/H, r_b/H),$$

which characterizes the ground temperature rise at the borehole wall due to a uniform line heat source. For a sequence of piecewise-constant loads Q_j applied over time intervals Δt_j , the resulting temperature rise at the borehole wall (T_b) relative to the undisturbed ground temperature T_g is obtained using superposition as

$$\Delta T_b(t_i) = \frac{1}{2\pi k_s} \sum_{j=1}^i \frac{Q_j}{H} \left[g\left(\ln \frac{t_i - t_{j-1}}{t_s}\right) - g\left(\ln \frac{t_i - t_j}{t_s}\right) \right], \quad (7)$$

This method is consistent with the finite line-source solution of Hellström [152]. In Eq. 7, T_g denotes the *undisturbed* ground temperature that serves as a reference baseline for the borefield thermal response. In practice, ground temperature can vary with depth and exhibits seasonal fluctuations near the surface; however, below a characteristic depth (typically several meters to tens of meters, depending on climate and soil properties) the annual temperature swing becomes small and the temperature approaches an approximately constant value close to the mean annual air temperature. Consistent with common vertical borehole modelling practice, T_g is therefore taken as the representative far-field ground temperature at borehole depth (i.e., a deep-ground baseline) rather than a near-surface seasonal temperature.

Seasonal and multi-year temperature evolution *at the borehole wall* is not neglected: it is captured by the load superposition term in Eq. 7, where the sequence of piecewise-constant heat extraction/rejection rates $\{Q_j\}$ produces a time-dependent borehole-wall temperature rise $\Delta T_b(t)$ through the g -function response. This formulation inherently accounts for (i) short-term and seasonal load variations, (ii) cumulative thermal build-up over long simulation horizons, and (iii) thermal interference effects across the borefield, all of which contribute to the gradual departure of borehole temperatures from the undisturbed baseline. Accordingly, the time-varying impact of the borefield is represented by $\Delta T_b(t)$, while T_g provides the initial reference state.

It is acknowledged that additional site-specific effects are not represented explicitly in this simplified formulation. When such effects are important (e.g., very shallow boreholes, strong groundwater flow, or large surface temperature gradients), the framework can be extended by adopting a depth-dependent ground temperature profile or by coupling to a site-calibrated ground model. In the present work, the chosen approach provides a computationally efficient representation suitable for urban-scale scenario analysis while retaining the dominant physics

governing borefield temperature evolution over seasonal to multi-year time scales.

The borehole wall temperature is linked to the circulating fluid temperature through the *effective borehole thermal resistance* R_b^* , which comprises convective, conductive, and interference components:

$$R_b^* = R_{\text{conv}} + R_{\text{cond,pipe}} + R_{\text{cond,grout}} + R_{\text{int}}. \quad (8)$$

This resistance accounts for heat transfer between the fluid and the pipe walls (R_{conv}), through the pipe and grout ($R_{\text{cond,grout}}$), and between adjacent U-tubes ($R_{\text{cond,pipe}}$). In GHEDesigner, R_b^* is evaluated using a detailed radial numerical model that resolves near-borehole thermal behaviour over short time scales.

Given the borehole wall temperature T_b and the linear heat extraction rate per borehole $q' = Q/(n_{bh}H)$ for a borefield with n_{bh} boreholes, the mean fluid temperature satisfies

$$T_{f,m} - T_b = q' R_b^*, \quad (9)$$

and the entering fluid temperature, including effects of hydraulic mixing, is approximated as

$$T_{\text{in}} = T_b + q' R_b^* + \frac{Q}{2\dot{m}c_{p,f}}, \quad (10)$$

where $\dot{m}$ is the mass flow rate and C_p is the specific heat capacity of the circulating fluid.

By incorporating the GHEDesigner methodology within the modelling framework, consistency is ensured between building energy simulation, heat pump performance estimation, and GHEx sizing. Unlike simplified or steady-state approaches, the use of g -functions allows the model to capture long-term thermal interactions and the cumulative heating and cooling history of the borefield. This capability is particularly important for optimization workflows, where multiple borefield configurations and load profiles must be compared rigorously.

3.3.2 Boiler

In the current status of the work, boilers are not modeled in detail. A bi-quadratic equation (11) is used to calculate the boiler efficiency based on boiler PLR and supply water temperature.

$$\eta_{\text{boiler}} = \eta_{\text{nom}} \cdot (a_0 + a_1 \cdot \text{PLR} + a_2 \cdot T_{w,\text{boiler}} + a_3 \cdot \text{PLR}^2 + a_4 \cdot T_w^2 + a_5 \cdot \text{PLR} \cdot T_{w,\text{boiler}}) \quad (11)$$

In this equation $T_{w,\text{boiler}}$ is the supply water temperature. Once the efficiency of the efficiency of the boiler is calculated, the thermal power input of the boiler and fuel consumed can be

calculated from (Eq. 12). In this equation, LHV refers to the lower heating value of the fuel.

$$F_{\text{fuel}} = \frac{P}{\eta \cdot \text{LHV}} \quad (12)$$

3.3.3 PV System

The first step in any PV modelling workflow is the calculation of solar irradiance on roofs, façades, and PV module surfaces. As described in the previous section, building geometries are enriched with meteorological irradiance data obtained from the weather file; however, these data alone do not capture the effects of mutual shading, urban obstruction, or surface orientation within dense city environments. Therefore, the exact irradiance incident on each building surface is computed using radiosity analysis. In this work, the Simplified Radiosity Algorithm (SRA) [153] is employed to calculate the irradiance on all external surfaces of every building in the city.

The SRA is a computationally efficient method for estimating the transfer of direct sunlight, diffuse skylight, and reflected radiation between buildings, the ground, and other urban surfaces. Rather than tracing individual light rays, the algorithm discretizes the sky and surrounding environment into finite “patches” and evaluates the visibility of each patch from a given surface, accounting for geometric obstructions. Using simplified assumptions such as uniform (Lambertian) surface reflection and matrix-based solution techniques, the SRA captures urban-scale radiative exchanges with significantly lower computational cost than conventional ray-tracing approaches, while maintaining sufficient accuracy for applications in urban building energy modelling, daylight analysis, and planning studies.

In the current implementation, building geometries are generated through vertical extrusion of footprint polygons, resulting in planar façades and flat roof surfaces. As a consequence, explicit roof slopes, overhangs, and complex roof forms are not reconstructed unless such information is provided in the input dataset. For flat roofs—which are common in many urban building stocks and particularly relevant for large-scale PV deployment—the irradiance computed by the SRA directly represents the plane-of-array irradiance on a horizontal surface. When PV systems are assumed to be installed on tilted mounting structures atop flat roofs, the irradiance on the inclined module surface is derived in a subsequent step using standard irradiance transposition models. This approach separates urban-scale shading effects, which are explicitly captured by the radiosity analysis, from local PV orientation, which is handled parametrically.

It is acknowledged that for buildings with pitched roofs, setbacks, or complex architectural features, footprint-based extrusion introduces geometric simplifications that may affect surface-level irradiance estimates. Nevertheless, at the urban scale targeted in this study, the adopted methodology provides a robust balance between physical realism and computational efficiency, preserving the dominant effects of urban morphology and mutual shading. When detailed roof

geometry or building information models are available, the framework can be readily extended to incorporate explicit roof facets and orientations without altering the underlying simulation workflow.

Using the SRA, the plane-of-array (POA) irradiance is calculated for every surface of the building. For example, if the building roof is flat, the SRA output corresponds to the POA on a horizontal surface. To size and model PV systems, the POA on a tilted surface must be calculated. In this work, the methodology proposed by Erbs, Klein, and Duffie [154] is used to calculate the diffuse fraction of the Global Horizontal Irradiance (GHI). First, the clearness index (k_t) is calculated using the GHI and the extraterrestrial solar radiation on a horizontal surface (I_{oh}) (Eq. 13):

$$k_t = \frac{GHI}{I_{oh}} \quad (13)$$

Once the clearness index is obtained, the diffuse fraction of GHI ($f_{diffuse}$) is determined using Eq. 14:

$$f_{diffuse} = \begin{cases} 1 - 0.09 \cdot k_t, & \text{if } k_t \leq 0.22 \\ 0.9511 - 0.1604 \cdot k_t + 4.388 \cdot k_t^2 - 16.638 \cdot k_t^3 + 12.336 \cdot k_t^4, & \text{if } 0.22 < k_t \leq 0.8 \\ 0.165, & \text{if } k_t > 0.8 \end{cases} \quad (14)$$

The Diffuse Horizontal Irradiance (DHI) and Direct Normal Irradiance (DNI) are then calculated as:

$$DHI = f_{diffuse} \times GHI \quad (15)$$

$$DNI = \frac{GHI - DHI}{\cos(Z)} \quad (16)$$

In Eq. 16, Z is the solar zenith angle which is defined as the angle between the vertical (directly overhead) and the line to the sun:

- $Z = 0^\circ$ when the sun is directly overhead.
- $Z = 90^\circ$ when the sun is at the horizon (e.g., sunrise or sunset).

Using the calculated solar angles for the city, the module's incident angle (θ) and tilt angle (γ) are applied to compute the total irradiance on a tilted surface. In the following equations, G_{bt} , G_{dt} , and G_t represent tilted beam irradiance, tilted diffuse irradiance, and total tilted irradiance, respectively:

$$G_{bt} = DNI \cdot \cos(\theta) \quad (17)$$

$$G_{dt} = DHI \cdot \left(\frac{1 + \cos(\theta)}{2} \right) \quad (18)$$

$$G_t = G_{bt} + G_{dt} \quad (19)$$

The next step in the sizing methodology is to determine the minimum distance between PV

module rows. In the Northern Hemisphere, the longest shadow at solar noon occurs on the winter solstice; therefore, the solar altitude angle (α) and solar azimuth angle (ψ) at that time are used to compute the minimum inter-row spacing:

$$d = \frac{h \cdot \sin(\beta) \cdot |\cos(\psi)|}{\tan(\alpha)} \quad (20)$$

Here, h is the height of the module (the side not in contact with the ground). This allows flexibility in vertical or horizontal mounting configurations.

Once d is known, the number of panels per row (n_p) and the number of rows (n_s) can be calculated.

For hourly PV performance modelling, the explicit model from [155] is implemented. This model uses weather data and module specifications. The PV cell temperature (T_{cell} at time step k) is calculated as:

$$T_{\text{cell}}^k = T_{\text{out}}^k + \frac{G_{\text{tot}}^k}{G_{\text{tot,nom}}} (T_{\text{cell,nom}} - T_{\text{out,nom}}) \quad (21)$$

In this equation, $T_{\text{cell,nom}}$ and $T_{\text{out,nom}}$ the module cell temperature and outdoor temperature in nominal test condition, respectively. The AC power output of the PV system (P_{pv} at time step k) is then calculated as:

$$P_{\text{pv}}^k = \eta_{\text{inv}} \cdot n_s \cdot n_p \cdot \frac{G_{\text{tot}}^k}{G_{\text{tot,stc}}} [1 - \lambda (T_{\text{cell}}^k - T_{\text{cell,stc}})] \quad (22)$$

where η_{inv} is the inverter efficiency, $G_{\text{tot,stc}}$ is the POA at Standard Test Condition (STC), $T_{\text{cell,stc}}$ is the cell temperature at STC, and λ is the temperature coefficient of power.

3.3.4 Thermal Storage Tank

The framework supports two types of hot water storage tank models. In the first approach, the tank is treated as an ideally mixed volume, where the temperature is uniform throughout. In contrast, stratified tank models are implemented to capture the vertical temperature gradient caused by buoyancy effects—warmer, less dense water naturally rises to the top, while cooler water remains at the bottom. As a result, the top layers of a Thermal Energy Storage (TES) tank are typically hotter than the lower layers. In the stratified approach, the tank is divided into multiple vertical segments, with an energy balance applied to each layer independently.

In the fully mixed model, the tank is represented as a single control volume. The energy balance for this control volume is used to update the tank temperature at each time step:

$$T_{\text{tank}}^{k+1} - T_{\text{tank}}^k = \left[\dot{m}_{\text{ch}}^k (T_{\text{sup}}^k - T_{\text{tank}}^k) - \dot{m}_{\text{dis}}^k (T_{\text{tank}}^k - T_{\text{return}}^k) - \frac{U A_{\text{side}} (T_{\text{tank}}^k - T_a^k)}{C_p} \right] \cdot \frac{1}{\rho V \Delta t} \quad (23)$$

Here, T_{tank} , T_{sup} , T_{return} , and T_a are the tank temperature, supply temperature from the heat

source, return temperature from the load, and ambient temperature, respectively. The mass flow rates $\dot{m}_{\text{ch}}$ and $\dot{m}_{\text{dis}}$ represent charging (heat source to tank) and discharging (tank to load) flows. The parameters U , A_{side} , and V denote the tank's heat loss coefficient, peripheral surface area, and volume, respectively. The superscript k refers to the current time step.

In the stratified model, the TES tank is divided into smaller control volumes (layers), and the energy balance is applied to each separately. *Top layer:*

$$T_1^{k+1} - T_1^k = \left[\dot{m}_{\text{ch}}^k (T_{\text{sup}}^k - T_1^k) + v_1 (\dot{m}_{\text{dis}}^k - \dot{m}_{\text{ch}}^k) (T_2^k - T_1^k) + \frac{U A_{1,\text{side}} (T_a^k - T_1^k)}{C_p} + \frac{\lambda A_1 (T_2^k - T_1^k)}{C_p \Delta x_1} \right] \cdot \frac{1}{\rho V_1 \Delta t} \quad (24)$$

Middle layers: Middle layers have no direct heat exchange with the source or load. Their energy balance accounts for convective and conductive heat transfer between adjacent layers:

$$T_i^{k+1} - T_i^k = \left[v_1 (\dot{m}_{\text{dis}}^k - \dot{m}_{\text{ch}}^k) (T_{i+1}^k - T_i^k) + v_2 (\dot{m}_{\text{ch}}^k - \dot{m}_{\text{dis}}^k) (T_{i-1}^k - T_i^k) + \frac{U A_{i,\text{side}} (T_a^k - T_i^k)}{C_p} + \frac{\lambda A_i (T_{i+1}^k - T_i^k)}{C_p \Delta x_i} + \frac{\lambda A_i (T_{i-1}^k - T_i^k)}{C_p \Delta x_i} \right] \cdot \frac{1}{\rho V_i \Delta t} \quad (25)$$

Bottom layer: The bottom layer does not receive heat directly from the source, but can gain heat from the return line. Its energy balance includes conductive and convective exchanges with the layer above and the return flow:

$$T_N^{k+1} - T_N^k = \left[v_2 (\dot{m}_{\text{ch}}^k - \dot{m}_{\text{dis}}^k) (T_{N-1}^k - T_N^k) + \dot{m}_{\text{dis}}^k (T_{\text{return}}^k - T_N^k) + \frac{U A_{N,\text{side}} (T_a^k - T_N^k)}{C_p} + \frac{\lambda A_N (T_{N-1}^k - T_N^k)}{C_p \Delta x_N} \right] \cdot \frac{1}{\rho V_N \Delta t} \quad (26)$$

In these equations, the superscripts k and $k+1$ denote the current and next time step, respectively. The binary variables v_1 and v_2 are determined based on the relationship between charging and discharging flow rates:

$$v_1 = \begin{cases} 1 & \text{if } \dot{m}_{\text{dis}}^k - \dot{m}_{\text{ch}}^k > 0 \\ 0 & \text{otherwise} \end{cases} \quad (27)$$

$$v_2 = \begin{cases} 1 & \text{if } \dot{m}_{\text{ch}}^k - \dot{m}_{\text{dis}}^k > 0 \\ 0 & \text{otherwise} \end{cases} \quad (28)$$

Table 3.2 lists the parameters used in the stratified TES tank model.

Table 3.2: Description of parameters used in stratified TES tank model

Parameter	Description
T_1, T_i, T_N	Temperatures at the top, middle, and bottom layers
T_{sup}	Supply temperature from heat source to TES
T_{ret}	Return temperature from load to TES
T_{amb}	Ambient temperature
$\dot{m}_{\text{ch}}$	Charging flow rate
$\dot{m}_{\text{dis}}$	Discharging flow rate
$A_{1,\text{side}}, A_{i,\text{side}}, A_{N,\text{side}}$	Peripheral surface area of top, middle, and bottom layers
A_1, A_i, A_N	Cross-sectional area of top, middle, and bottom layers
V_1, V_i, V_N	Volume of top, middle, and bottom layers
$\Delta x_1, \Delta x_i, \Delta x_N$	Height of top, middle, and bottom layers
ρ	Water density
C_p	Specific heat capacity of water
λ	Effective thermal conductivity

3.3.5 Battery Storage System

The framework includes a detailed time-step battery storage model capable of simulating charging, discharging, self-limiting behavior, and long-term degradation. The model operates using power and energy balances at each simulation step and supports asymmetric efficiencies, $\text{SOC}_{\text{min,batt}}\text{--}\text{SOC}_{\text{max,batt}}$ limits, power limits, and capacity fade. All variables are updated dynamically, making the model suitable for long-term simulations involving thousands of time steps.

The battery is parametrized by its nominal energy capacity ($C_{\text{nom,batt}}$), charging and discharging rated powers ($P_{\text{ch,max,batt}}, P_{\text{dis,max,batt}}$), SOC bounds ($\text{SOC}_{\text{min,batt}}, \text{SOC}_{\text{max,batt}}$), charging and discharging efficiencies ($\eta_{\text{ch,batt}}, \eta_{\text{dis,batt}}$), and an annual capacity fade rate (γ_{batt}). At each time step Δt , the usable capacity is updated to reflect gradual degradation:

$$C_{\text{batt}}^{k+1} = C_{\text{batt}}^k \left(1 - \gamma_{\text{batt}} \frac{\Delta t}{8760} \right), \quad (29)$$

where C_{batt}^k and C_{batt}^{k+1} represent the available battery capacities (kWh) before and after degradation at time step k .

At the start of each step, available PV power is first allocated to the load:

$$P_{\text{pv} \rightarrow \text{load}}^k = \min(P_{\text{pv}}^k, P_{\text{load}}^k), \quad (30)$$

and the remaining PV power becomes available for charging:

$$P_{\text{pv, left}}^k = P_{\text{pv}}^k - P_{\text{pv} \rightarrow \text{load}}^k. \quad (31)$$

Battery charging is constrained by the PV surplus, the charging power limit, and the remaining free storage capacity. The charging power is therefore given by:

$$P_{\text{ch,batt}}^k \leq \min \left(P_{\text{pv,left}}^k, P_{\text{ch,max,batt}}, \frac{C_{\text{max,batt}}^k - E_{\text{batt,start}}^k}{\eta_{\text{ch,batt}} \Delta t} \right), \quad (32)$$

where $E_{\text{batt,start}}^k$ is the stored energy at the beginning of the time step and

$$C_{\text{max,batt}}^k = \text{SOC}_{\text{max,batt}} \cdot C_{\text{batt}}^k. \quad (33)$$

The stored energy after charging is:

$$E_{\text{batt,after ch}}^k = E_{\text{batt,start}}^k + \eta_{\text{ch,batt}} P_{\text{ch,batt}}^k \Delta t. \quad (34)$$

After charging, any remaining net load may be supplied by the battery. Discharging is limited by net load, the rated discharging power, and the minimum SOC:

$$P_{\text{dis,batt}}^k \leq \min \left(P_{\text{load}}^k - P_{\text{pv} \rightarrow \text{load}}^k, P_{\text{dis,max,batt}}, \frac{E_{\text{batt,after ch}}^k - C_{\text{min,batt}}^k}{\Delta t / \eta_{\text{dis,batt}}} \right), \quad (35)$$

where

$$C_{\text{min,batt}}^k = \text{SOC}_{\text{min,batt}} \cdot C_{\text{batt}}^k. \quad (36)$$

The stored energy after discharging is calculated as:

$$E_{\text{batt,end}}^k = E_{\text{batt,after ch}}^k - \frac{P_{\text{dis,batt}}^k \Delta t}{\eta_{\text{dis,batt}}}. \quad (37)$$

The state of charge at the end of the step is then:

$$\text{SOC}_{\text{batt},k+1} = \frac{E_{\text{batt,end}}^k}{C_{\text{batt}}^{k+1}}. \quad (38)$$

Grid exchange is calculated explicitly. Any remaining unmet load after discharging is imported from the grid:

$$P_{\text{grid,import}}^k = \max \left(0, P_{\text{load}}^k - P_{\text{pv} \rightarrow \text{load}}^k - P_{\text{dis,batt}}^k \right), \quad (39)$$

while excess PV power not used by the load or battery is exported:

$$P_{\text{grid,export}}^k = \max \left(0, P_{\text{pv,left}}^k - P_{\text{ch,batt}}^k \right). \quad (40)$$

This formulation ensures that State-of-Charge (SOC) limits are respected, charging and discharging account for efficiency losses, degradation reduces usable capacity over time, and PV energy

is prioritized for serving the load and charging the battery before interacting with the grid. The model offers a computationally efficient and physically meaningful representation of battery storage, making it suitable for integration with the broader modular simulation framework.

3.3.6 Central Air Distribution System (Fan and Airflow Model)

In addition to generation and storage components, the framework includes a simplified but physics-informed model for central air distribution systems, intended to represent the dominant electrical consumption associated with air-side HVAC in many commercial and institutional buildings. The objective of this model is to capture the coupling between delivered thermal load, required supply airflow rate, and fan electricity use, while remaining computationally tractable for large-scale urban simulations.

The *CentralAirDistributionSystem* component is parameterized by (i) design heating and cooling peak loads ($Q_{\text{heat,peak}}$, $Q_{\text{cool,peak}}$), (ii) supply air temperatures during heating and cooling operation ($T_{\text{sup,heat}}$, $T_{\text{sup,cool}}$) or, alternatively, prescribed temperature differences between supply and zone air (ΔT_{heat} , ΔT_{cool}), (iii) fan total pressure rise Δp and overall fan efficiency η_{fan} , and (iv) an optional empirical fan power modifier curve expressed as a function of flow ratio. These parameters can be assigned from archetypal assumptions (e.g., based on building function) or overridden using measured or design data when available.

Design airflow sizing. The design supply airflow rate is derived from an air-side sensible heat balance. Assuming that the central air system must satisfy the peak sensible heating and/or cooling demand through a supply air stream, the required volumetric flow rate $\dot{V}$ is computed as

$$\dot{V}_{\text{heat}} = \frac{Q_{\text{heat,peak}}}{\rho_{\text{air}} c_{p,\text{air}} \Delta T_{\text{heat}}}, \quad \dot{V}_{\text{cool}} = \frac{Q_{\text{cool,peak}}}{\rho_{\text{air}} c_{p,\text{air}} \Delta T_{\text{cool}}}, \quad (41)$$

where ρ_{air} and $c_{p,\text{air}}$ are the air density and specific heat capacity, respectively. The design airflow rate is then taken as

$$\dot{V}_{\text{des}} = \max(\dot{V}_{\text{heat}}, \dot{V}_{\text{cool}}). \quad (42)$$

If ΔT_{heat} or ΔT_{cool} is not provided explicitly, it is inferred from the difference between the relevant supply air temperature and the mean zone setpoint temperature.

Design fan power. Given $\dot{V}_{\text{des}}$, the design fan electrical power is computed from the standard fan power relationship

$$P_{\text{fan,des}} = \frac{\Delta p \dot{V}_{\text{des}}}{\eta_{\text{fan}}}. \quad (43)$$

This formulation captures the first-order dependence of fan power on airflow rate and pressure rise. In the current implementation, Δp and η_{fan} represent lumped system-level values (fan, motor, and distribution losses), consistent with an archetype-based modelling approach.

Part-load fan power. During simulation, the fan power at any time step is evaluated as a function of the instantaneous airflow rate $\dot{V}$ relative to the design value. The flow ratio is defined as

$$r_{\dot{V}} = \frac{\dot{V}}{\dot{V}_{\text{des}}}. \quad (44)$$

A linear baseline approximation is first applied,

$$P_{\text{fan,base}} = P_{\text{fan,des}} r_{\dot{V}}, \quad (45)$$

and an optional empirical modifier $f(r_{\dot{V}})$ can then be included to better represent non-linear fan behaviour and control effects (e.g., variable speed drives):

$$P_{\text{fan}} = P_{\text{fan,base}} f(r_{\dot{V}}). \quad (46)$$

The modifier $f(\cdot)$ is represented using the fitted curve formulations listed in Table 3.1 (e.g., quadratic, cubic, quartic). This approach enables the framework to reproduce typical part-load fan power relationships without requiring a full duct-network or detailed fan component model.

Overall, this distribution subsystem model provides an explicit estimate of central fan electricity consumption and design airflow requirements, enabling the framework to represent a key class of non-residential HVAC energy use that is not captured when only thermal generation efficiency is modelled. At the same time, the formulation remains compatible with large-scale simulations and can be extended to include additional air-side processes (e.g., economizers, heat recovery, duct heat gains/losses) when higher model fidelity is required.

3.4 Life Cycle Cost Assessment

The economic indicator selected for inclusion in the framework analysis is the TLCC of the energy system. Life cycle cost analysis is a comprehensive methodology that evaluates the total financial cost of a project over its entire lifespan, discounted to its present value, accounting for all costs and revenues associated with the project. Unlike simple payback or upfront cost comparisons, LCC integrates capital expenditures, financing structures, operation and maintenance costs, replacement and end-of-life costs, as well as potential incomes such as subsidies and energy sales. In the context of energy system analysis, TLCC provides the foundation for comparing different scenarios and technologies.

The TLCC in the developed framework is calculated from Eq. 47. The output of the costing workflow provides insight into total capital, operational, maintenance, and end-of-life expenditures, as well as revenues from subsidies and energy sales. In addition to the total values, the cash flows in different financial assessment sectors can also be provided to the framework user.

$$\text{TLCC} = \text{CAPEX}_{\text{disc}} + \text{OPEX}_{\text{disc}} + \text{Maint}_{\text{disc}} + \text{EOL}_{\text{disc}} - \text{OpInc}_{\text{disc}} \quad (47)$$

In all cost categories, the subscript “disc” denotes the *discounted* value of future cash flows. Discounting converts costs or incomes occurring in year t into their present-value equivalent by dividing them by $(1 + r)^t$, where r is the discount rate. This reflects the time value of money, acknowledging that a monetary amount in the future is worth less than the same amount today.

The CAPEX are divided into two groups: (i) lump-sum payments and incomes that occur at specific points in time, and (ii) recurring yearly payments incurred during the lifespan of each system component. The discounted CAPEX is calculated using Eq. 48. In Eq. 48, the first summation represents the CAPEX cash flows over the analysis horizon N , while the second summation aggregates the total CAPEX associated with each of the components in the system. For each component, the investment cost (IC_i) at the starting year of the analysis is subtracted by any subsidies (S_i) received for purchasing that component. The term $LP_{i,t}$ refers to yearly loan repayments if any loan has been received upon the purchase of the component. The equation to calculate the yearly loan installments is shown in Eq. 49. In this equation, L_i is the financed portion of the investment, r_{int} is the interest rate, and n_{cr} denotes the number of years in the credit repayment period. The final term in Eq. 48, $RC_{i,t}$, refers to the reposition cost of the component. As shown in Eq. 50, the reposition cost is taken into account only when the lifetime of the component (LT_i) is over. In calculating the reposition cost, the impact of inflation on the re-purchase of the component is considered. The CPI is an economic indicator that measures the average change in prices paid by consumers for a basket of goods and services over time. It is commonly used to represent the rate of inflation, allowing cost projections to account for the loss of purchasing power in future years. Finally, the r in the denominator of Eq. 48 is the discount rate.

$$\text{CAPEX}_{\text{disc}} = \sum_{t=0}^N \frac{[\sum_{i \in \mathcal{C}} (IC_i \cdot \delta_{t,0} - S_i \cdot \delta_{t,0} + LP_{i,t} + RC_{i,t})]}{(1 + r)^t} \quad (48)$$

$$LP_i = \frac{r_{\text{int}} \cdot L_i}{1 - (1 + r_{\text{int}})^{-n_{\text{cr}}}} \quad (49)$$

$$RC_{i,t} = \begin{cases} IC_i \cdot (1 + \text{CPI})^t, & \text{if } t \bmod LT_i = 0 \text{ and } t \neq 0 \\ 0, & \text{otherwise} \end{cases} \quad (50)$$

It should be mentioned that the investment and reposition costs can be single values fetched from manufacturers and distributors, or it can be a mathematical function based on component capacity.

The discounted OPEX depends on the fuel type and its yearly consumption. In the calculation of the yearly OPEX, the fuel consumption at the starting year of the analysis is calculated (EC_f), and then using the fuel price ($P_{f,0}$) and a fuel price index (π_f), the fuel cost in every year is projected. One of the limitations of the current methodology is that the component performance degradation is not taken into account.

$$\text{OPEX}_{\text{disc}} = \sum_{t=0}^N \frac{\left[\sum_{f \in \mathcal{F}} EC_f \cdot P_{f,0} \cdot (1 + \pi_f)^t \right]}{(1 + r)^t} \quad (51)$$

The other component in TLCC assessment is the yearly maintenance cost of the system. The default assumption in the costing workflow is that the yearly maintenance cost for each component is a fraction of the initial investment cost of that component. However, these default fractions can be replaced by any custom maintenance cost function or fraction.

The discounted yearly maintenance costs of the system throughout its lifespan are found using Eq. 52. The effect of inflation is incorporated by compounding the initial maintenance cost $M_{k,0}$ annually, multiplying it by $(1 + \text{CPI})^t$, where t is the year number, to account for cumulative price increases over time. The base maintenance cost is defined in Eq. 53, where m_k is the maintenance cost fraction.

$$\text{Maint}_{\text{disc}} = \sum_{t=0}^N \frac{\left[\sum_{k \in \mathcal{K}} M_{k,0} (1 + \text{CPI})^t \right]}{(1 + r)^t} \quad (52)$$

$$M_{k,0} = m_k IC_k, \quad k \in \mathcal{K} \quad (53)$$

The next term in the calculation of TLCC is the EOL costs. The EOL covers decommissioning (labour, dismantling), waste disposal, and environmental compliance. Similar to maintenance costs, the EOL costs are assumed to be a fraction of the initial investment costs by default and can be customized using cost functions. The fractional coefficient is denoted by α_{EOL} .

$$\text{EOL}_{\text{disc}} = \sum_{t=0}^N \frac{\left[\sum_{i \in \mathcal{C}} \text{EOL}_{i,t} \right]}{(1 + r)^t} \quad (54)$$

$$\text{EOL}_{i,t} = \begin{cases} \alpha_{\text{EOL}} \cdot IC_i \cdot (1 + \text{CPI})^t, & \text{if } t \bmod LT_i = 0, t \neq 0 \\ 0, & \text{otherwise} \end{cases} \quad (55)$$

Finally, in case of installing on-site generation components like PV or wind turbines, the possible operational incomes should be taken into account as well. Therefore, similar to the calculation of the yearly operational costs, the operational income at the initial year is calculated and using the

compounded electricity price index π_{el} , the operational income of the future years is projected. The discounted operational income is found from Eq. 56. In this equation, $E_{gen,0}$ shows the yearly energy generated on-site, and $P_{el,0}$ is the price of the generated energy.

$$OpInc_{disc} = \sum_{t=0}^N \frac{[E_{gen,0} \cdot P_{el,0} \cdot (1 + \pi_{el})^t]}{(1 + r)^t} \quad (56)$$

In summary, the life cycle cost assessment approach employed in the framework provides a clear and comprehensive picture of all costs and income streams relevant to the project's analytical horizon. The TLCC is a comprehensive measure of the long-term economic performance of energy systems, as it accounts for capital, operational, maintenance, and end-of-life costs, as well as potential profits from subsidies and on-site energy generation.

3.5 Energy System Sizing Optimization

As explained in Chapter 2, numerous studies have been conducted in recent years to optimize the investment or energy dispatch in energy systems. However, due to the complexity of the problem, achieving the global optimum point in a reasonable amount of time is computationally difficult. Therefore, heuristic and meta-heuristic approaches are introduced to alleviate computational difficulties and/or to obtain near-optimal results [156]. While heuristic algorithms are problem-specific and do not conduct a global search in the problem domain, meta-heuristic approaches are generalizations of heuristic algorithms that can be applied to many applications. Additionally, meta-heuristic optimization algorithms can handle non-convex problems in shorter computation time [157]. Since the proposed energy system design framework is intended to be integrated with other frameworks to form an urban simulation platform, computation time is crucial. Therefore, a meta-heuristic optimization algorithm is chosen to optimize the sizes of the components in the selected configurations from the component selection module.

Among various heuristic and meta-heuristic optimization algorithms, GA and PSO are the most commonly used algorithms in the optimization of energy systems, especially hybrid renewable energy systems [158]. A GA is a computational optimization method inspired by the concept of heredity in nature. Heredity involves the transmission of genetic information, carried by genes, from one generation to the next, influencing a species' physical and behavioural traits. Genetics is the scientific field that studies the relationship between genes and traits, crucial for understanding how species evolve. In the context of GAs, the idea of adaptation is central. Adaptation is viewed as an optimization process in which individuals or solutions strive to improve their characteristics to enhance their chances of survival. GAs draw inspiration from the principles of heredity and adaptation in natural ecosystems. They aim to find optimal or near-optimal solutions to complex problems by mimicking the evolutionary forces that shape biodiversity. In summary, Genetic Algorithms are computational tools that model optimization

problems based on principles of heredity and adaptation from the natural world. They employ processes such as crossover and mutation to evolve potential solutions and find optimal outcomes iteratively [159]. With years of incremental development since its introduction, the adaptability and versatility of the algorithm make it suitable for various applications, and its capability to solve multi-objective optimization problems render it the ideal optimization algorithm for this research study.

The Non-Dominated Sorting Genetic Algorithm II (NSGA-II) is a prominent multi-objective optimization technique that combines fast non-dominated sorting with an elitist strategy, facilitating the effective exploration of solution spaces characterized by competing objectives. Introduced by Deb et al. [160], NSGA-II addresses several limitations of its predecessor, NSGA, including computational complexity and non-elitism, making it suitable for various applications across different domains, including energy systems.

In the domain of energy system sizing, NSGA-II has proven particularly effective due to its ability to balance conflicting objectives such as cost efficiency, energy output, and sustainability. For instance, Vitorino et al. [161] applied NSGA-II to the reconfiguration of power distribution systems, demonstrating its potential to optimize multiple objectives, such as reducing power losses, enhancing reliability, and minimizing investment costs. This multi-faceted approach is essential in modern energy systems where operational efficiency and sustainability are paramount. Moreover, the versatility of NSGA-II is reflected in its application to renewable energy resource allocation. The algorithm's robust search capabilities enable the exploration of optimal configurations that meet energy demands while considering environmental impacts. NSGA-II has also been utilized in sizing hybrid energy systems, which often involve multiple generation sources and storage technologies. Combining solar, wind, and traditional energy sources requires sophisticated optimization techniques to balance the reliability of generation and its economics. Vargas-Hákim et al. [162] highlighted that NSGA-II is particularly effective in optimizing energy production across multiple sources, focusing on reducing operational costs while minimizing emissions. The algorithm has been effectively employed to find the optimal mix of renewable technologies, balancing trade-offs between initial investment, operational expenditure, and environmental sustainability [163].

Furthermore, the algorithm's ability to provide a well-distributed set of optimal solutions (Pareto front) makes it ideal for decision-makers who must weigh trade-offs between often conflicting objectives, such as cost and performance. Despite the challenges inherent in multi-objective optimization, NSGA-II remains a leader due to adaptations and refinements that enhance its convergence and diversity capabilities. Therefore, this study selected NSGA-II as the optimization algorithm to determine the optimal size of energy system archetype components based on the selected objectives.

Figure 3.4 shows the process of the NSGA-II optimization algorithm. The algorithm begins

with the initialization of an initial population P_0 , which is typically generated randomly within the decision space. Each individual in the population is evaluated across all objective functions to obtain a set of fitness values. NSGA-II then applies genetic operators to create an offspring population Q_t from the current parent population P_t . This process ensures exploration of the search space and introduces new solution candidates. The parent and offspring populations are then combined into a single set R_t , which contains twice as many individuals as the original population size.

Non-dominated sorting is what makes NSGA-II unique. In a multi-objective framework, Pareto dominance is the most important rule for comparing solutions. A solution A is better than another solution B if and only if A is equal to or better than B in all objectives and better in at least one objective. If neither option is better than the other, they are considered non-dominated in relation to each other. In the implementation used in this work, this concept is extended with a constraint-handling mechanism where feasible solutions always dominate infeasible ones; if two solutions are both infeasible, the solution with the smaller aggregated constraint violation is preferred, and only when feasibility status and violation are identical is Pareto dominance in the objective space applied. The total population R_t is divided into several levels of non-domination, called “fronts.” The first front, F_1 , is made up of all solutions in R_t that are not dominated by any other solution. The second front, F_2 , contains solutions dominated only by those in F_1 . This process continues until all solutions are assigned to a front.

To fill the next population P_{t+1} , solutions are added starting with the best-ranked front F_1 and moving down the hierarchy of fronts until the population size limit is reached. If adding all solutions from a particular front would exceed the limit, NSGA-II selects only a subset from that front. The crowding distance metric, which quantifies how densely solutions are packed around each individual in the objective space, is used to make this selection. An Individual with a higher crowding distance is located in a less populated regions in the solution space and they are preferred to maintain diversity among solutions. Crowding distance is applied only to the partially included front.

The algorithm repeats the cycle of evaluation, offspring generation, combination, non-dominated sorting, and crowding-based selection until a termination criterion is met. This criterion may be a maximum number of generations, a convergence threshold, or computational budget constraints. The final result is an approximation of the Pareto-optimal front, providing decision-makers with a diverse set of trade-off solutions rather than a single point.

In this study, up to four objective functions can be considered simultaneously, reflecting different performance criteria relevant for archetype energy systems. The optimization problem can be expressed compactly as in Eq. 57, where the decision vector is denoted by $\mathbf{x}$ and the vector of objective functions is $\mathbf{f}(\mathbf{x})$. The number of active objectives is given by n_{obj} . Inequality constraints are represented by $g_j(\mathbf{x})$, and equality constraints where applicable by $h_k(\mathbf{x})$. In this

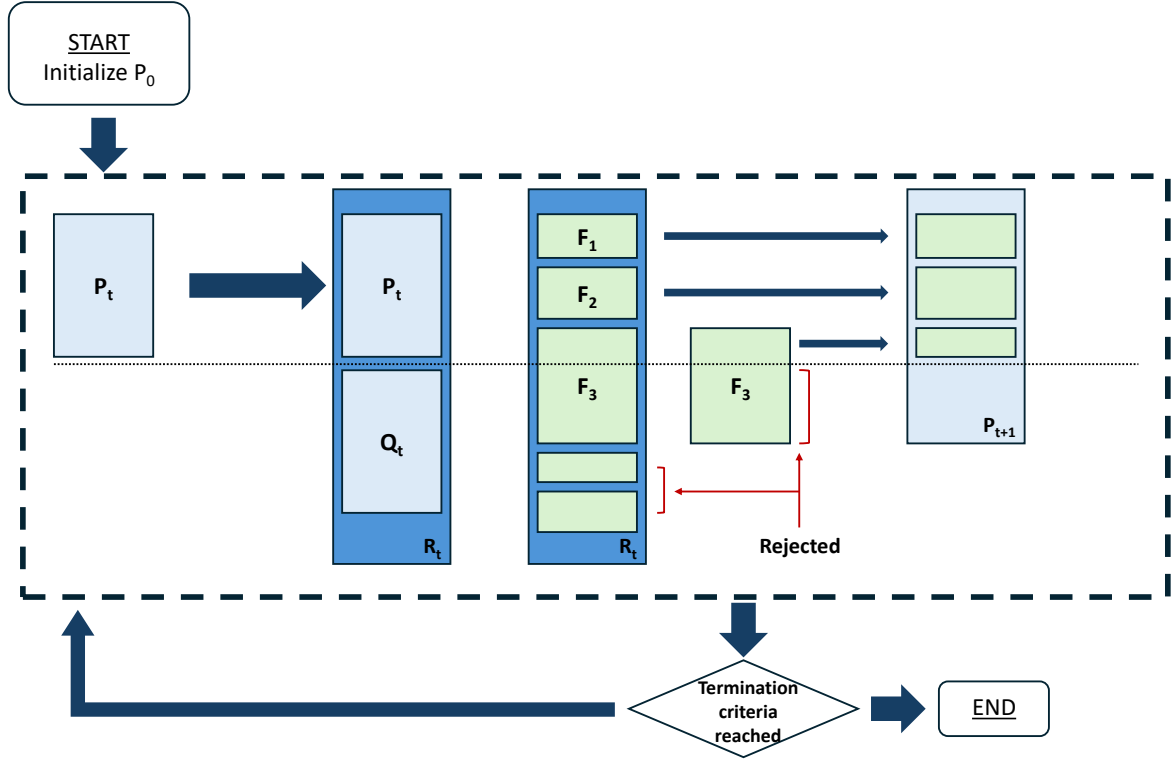


Figure 3.4: NSGA-II optimization algorithm

implementation, available objective functions include (i) peak electricity intensity in W/m^2 , (ii) life cycle cost intensity (LCCI) in $Currency/m^2$, (iii) annual energy use intensity (EUI) in kWh/m^2 , and (iv) operational yearly $CO_{2,eq}$ emission intensity in $\left[\frac{g\ CO_{2,eq}}{m^2}\right]$. Depending on the case study and decision-maker preferences, different subsets of these objectives may be activated while the NSGA-II machinery remains unchanged.

$$\begin{aligned}
 \min_{\mathbf{x}} \quad & \mathbf{f}(\mathbf{x}) = (f_1(\mathbf{x}), \dots, f_{n_{obj}}(\mathbf{x})) \\
 \text{subject to} \quad & g_j(\mathbf{x}) \leq 0, \quad j = 1, \dots, m, \\
 & h_k(\mathbf{x}) = 0, \quad k = 1, \dots, p,
 \end{aligned} \tag{57}$$

The next stage in the optimization workflow is the definition of decision variables and their corresponding bounds. In the proposed framework, the bounds are derived based on the feasibility of system components identified in the earlier component-selection module (See 3.6). Component feasibility like whether a ground-source heat pump can operate given the available ground area or whether a wastewater heat pump is viable based on wastewater flow conditions, determines which technologies can be included in the design vector and the admissible range of their capacities.

Once the feasible technologies and their allowable size ranges are established, the decision variables are defined. In the suggested structure, an energy system can include up to four types of

components: generation, storage, distribution, and emitters. The selection and parametrization of decision variables depend on which of these components are present and feasible in the specific building configuration. In the concrete implementation of the framework, these variables include, among others, the nominal capacities of generation units (air-source heat pumps, water-source heat pumps, ground-source heat pumps, gas boilers, electric boilers), the nominal energy capacity of the thermal energy storage, and the geometric parameters of the ground borefield (number of boreholes in each direction and borehole depth). During crossover and mutation, these variables are handled as continuous quantities; however, to maintain compatibility with realistic equipment sizes and catalogue constraints, each variable is ultimately quantized to discrete step sizes after modification. This ensures that all candidate solutions explored by the NSGA-II algorithm correspond to technically meaningful system designs.

The NSGA-II optimization's search space is made up of these decision variables. Each candidate solution is a specific set of component capacities and operational parameters that will be tested against the given objective functions.

Another crucial part of making the optimization problem is figuring out what the restrictions are. In the suggested framework, the main requirement for any possible solution is that it follows the first law of thermodynamics, which says that energy cannot be created or destroyed. The total instantaneous energy produced and used by a system at each time step must equal the change in the energy content of its storage parts. This makes sure that the system is thermodynamically achievable and that no operating conditions that aren't possible in real life are taken into account when optimizing.

The instantaneous energy balance is given in Eq. 58, where $P_{i,t}^{\text{gen}}$ denotes the generation output from unit i , $P_{j,t}^{\text{load}}$ denotes the load consumption, and $P_{s,t}^{\text{ch}}$ and $P_{s,t}^{\text{dis}}$ represent storage charging and discharging. Sets $\mathcal{G}$, $\mathcal{L}$, and $\mathcal{S}$ denote generation, load, and storage components. Additional constraints enforce capacity limits as shown in Eqs. 59–62, involving symbols such as P_i^{nom} , $\dot{V}_{d,t}$, $\dot{V}_{\text{nom},d}$, E_s^{min} , $E_{s,t}$, E_s^{max} , $P_s^{\text{ch,max}}$, and $P_s^{\text{dis,max}}$. These ensure thermodynamic feasibility and component-level operational compliance. Constraint violations are quantified and play a role in dominance comparison, ensuring feasible solutions always dominate infeasible ones.

$$\sum_{i \in \mathcal{G}} P_{i,t}^{\text{gen}} = \sum_{j \in \mathcal{L}} P_{j,t}^{\text{load}} + \sum_{s \in \mathcal{S}} P_{s,t}^{\text{ch}} - \sum_{s \in \mathcal{S}} P_{s,t}^{\text{dis}}, \quad \forall t \quad (58)$$

$$0 \leq P_{i,t}^{\text{gen}} \leq P_i^{\text{nom}}, \quad \forall i \in \mathcal{G}, \quad \forall t \quad (59)$$

$$0 \leq \dot{V}_{d,t} \leq \dot{V}_{\text{nom},d}, \quad \forall d \in \mathcal{D}, \quad \forall t \quad (60)$$

$$E_s^{\text{min}} \leq E_{s,t} \leq E_s^{\text{max}}, \quad \forall s \in \mathcal{S}, \quad \forall t \quad (61)$$

$$0 \leq P_{s,t}^{\text{ch}} \leq P_s^{\text{ch,max}}, \quad 0 \leq P_{s,t}^{\text{dis}} \leq P_s^{\text{dis,max}}, \quad \forall s \in \mathcal{S}, \quad \forall t \quad (62)$$

The initial parent population P_0 is generated by sampling the decision variables uniformly within bounds. For a decision vector $\mathbf{x}$ with n variables and bounds $\mathcal{B}$, each component x_k is drawn from $[L_k, U_k]$, and infeasible candidates are rejected. After sampling, continuous values are projected to discrete sizes as needed.

At each generation, offspring Q_t are produced from P_t using Simulated Binary Crossover (SBX). In this formulation, two parent vectors $\mathbf{x}^{(1)}$ and $\mathbf{x}^{(2)}$ produce two offspring $\mathbf{c}^{(1)}$ and $\mathbf{c}^{(2)}$ through a spread factor β_k , controlled by the crossover index η_c . SBX preserves continuity and supports both exploration and refinement.

$$\beta_k = \begin{cases} (2u_k)^{\frac{1}{\eta_c+1}}, & u_k \leq \frac{1}{2}, \\ \left[\frac{1}{2(1-u_k)} \right]^{\frac{1}{\eta_c+1}}, & u_k > \frac{1}{2}, \end{cases} \quad (63)$$

where $u_k \sim \mathcal{U}(0, 1)$ is a random number and η_c that controls the extent to which offspring deviate from their parents: a lower η_c value produces offspring farther away from the parent values, expanding the search space, whereas a higher η_c value generates offspring closer to the parents, promoting a more localized search and fine-tuning around existing good solutions. The offspring values are computed as:

$$\begin{aligned} c_k^{(1)} &= 0.5[(1 + \beta_k)x_k^{(1)} + (1 - \beta_k)x_k^{(2)}], \\ c_k^{(2)} &= 0.5[(1 - \beta_k)x_k^{(1)} + (1 + \beta_k)x_k^{(2)}]. \end{aligned} \quad (64)$$

This study applies SBX to all continuous decision variables associated with generation components, such as nominal heating and cooling capacities, as well as storage components, including nominal energy capacity, and borefield-related design variables such as borehole depth and layout. Physical realism is maintained by correcting any negative or out-of-bound values through projection onto the feasible range and by snapping capacities to predefined step sizes that represent realistic equipment sizing. This enables the crossover process to produce diverse but valid system configurations in each generation of the NSGA-II optimization.

To maintain diversity in the population and explore new regions of the search space, the mutation operator is applied to offspring solutions at each generation after crossover. In this work, *polynomial mutation* is used, which is a widely adopted mutation operator for real-coded genetic algorithms. It perturbs a decision variable by a small or large amount depending on a mutation distribution index, thereby enabling both fine-tuning and exploration. The distribution index η_m controls the extent of variation: a high η_m produces mutated values close to the original, favouring local search, whereas a low η_m allows larger deviations, enhancing global exploration.

For a decision variable x_k with lower and upper bounds $[L_k, U_k]$, a random number $u \sim \mathcal{U}(0, 1)$ is drawn and the mutation step δ_q is computed as:

$$\delta_q = \begin{cases} (2u)^{\frac{1}{\eta_m+1}} - 1, & u < 0.5, \\ 1 - [2(1-u)]^{\frac{1}{\eta_m+1}}, & u \geq 0.5. \end{cases} \quad (65)$$

The mutated variable is then given by:

$$x'_k = x_k + \delta_q \cdot (U_k - L_k), \quad (66)$$

followed by projection onto $[L_k, U_k]$ to ensure feasibility. In practice, the mutated continuous values of component capacities are again mapped to discrete increments, and integer design variables such as the number of boreholes in each direction are modified through small ± 1 perturbations within their admissible ranges. The mutation bounds are dynamically determined based on the design period energy demands and physical constraints such as available space in the building which is deduced from various available geometrical information like the lot area or the archetypal average storey height, ensuring that mutated values remain technically feasible while introducing sufficient variability to prevent premature convergence of the NSGA-II search process.

As previously described, in each generation, the aggregated population is organized into non-dominated fronts. The initial front comprises solutions that are not dominated by any others, while the subsequent front includes those dominated solely by members of the first, and this pattern continues accordingly. The subsequent generation is formed by selecting individuals from the highest-ranked fronts, utilizing the crowding distance metric when a front cannot be entirely included to maintain diversity.

Once the termination criterion is met, in the final generation, the first front represents the *Pareto-optimal front*, containing the set of best trade-off solutions between the active objectives. The Pareto front provides decision-makers with multiple equally optimal solutions, each representing a different balance between the competing objectives. Depending on technical, economic, or environmental priorities, a final configuration can be selected from this set without sacrificing optimality in one objective more than necessary in the other. In this way, the Pareto front serves as a comprehensive decision-support tool rather than yielding a single fixed solution.

In the implementation developed for this study, the raw Pareto front obtained from NSGA-II is further refined in two steps. First, duplicate or nearly identical designs are removed to prevent over-representing very similar configurations. Second, all remaining Pareto-optimal candidates are re-simulated using higher-fidelity component models like a stratified thermal storage tank model to verify their thermodynamic and operational feasibility under more detailed physics. Only the solutions that remain feasible under these refined simulations are retained, and a final

non-dominated sorting is performed on this filtered set to obtain the “true” Pareto front. This post-processing step ensures that the recommended system designs are robust with respect to a more realistic representation of component behavior and system interactions.

However, if one is interested in finding the best solution among all on the Pareto front, decision-making algorithms can be used. In this study, the TOPSIS), which is a multi-criteria decision-making algorithm, is used to rank the solutions and find the best solution among the ones on the Pareto front. Before applying TOPSIS, the objective values of the Pareto-optimal solutions are normalized using Euclidean normalization, so that differences in units and scales between cost-, energy-, and emission-related indicators do not bias the ranking. For each objective, an ideal “best” and “worst” value is identified across the Pareto set, and TOPSIS evaluates each solution based on its relative closeness to the ideal best and distance from the ideal worst. In addition to a global best solution, the method is also used to identify, for each individual objective, the Pareto-optimal solution that attains the most favourable value for that indicator. The TOPSIS method has also been used in the building retrofit prioritization workflow. Therefore, a separate section (Section 3.8) at the end of this chapter is dedicated to explaining the working principles of this method.

3.6 Energy System Component Selection

Finding possible energy system components and eliminating unsuitable ones is an important first step in automating the design of building energy systems. This step narrows the solution space, improves computational efficiency, and ensures that subsequent simulation and optimization focus only on feasible technological options. In this work, we adopt and extend the hybrid qualitative decision-tree approach proposed by Weiler [164, 165], which reduces the range of supply variants based on spatial, geological, environmental, strategic, and legal restrictions. In Weiler’s framework, these context-specific constraints are evaluated through a structured checklist that screens technologies such as district heating, heat pumps, CHP systems, and gas networks for suitability at both district and building scales.

In addition to these qualitative feasibility gates, the present framework introduces a complementary quantitative pre-sizing step for specific components. This step evaluates whether a candidate technology can provide a meaningful maximum feasible capacity given local physical conditions (e.g., available ground area, wastewater flow, or air temperature distribution). In the current study, this procedure is applied primarily to heat pumps, which play a central role in sustainability assessments and decarbonization pathways. However, the underlying logic can be straightforwardly extended to other energy system components wherever a capacity-based feasibility threshold is required.

Among the available technologies, heat pumps play a key role in the transition toward low-carbon building energy systems. Their performance, however, strongly depends on the characteristics

of the thermal source from which they extract or reject heat. In this work, three main categories of heat pump sources are considered: *air*, *ground*, and *wastewater*. Each source has its own thermodynamic, geographical, and regulatory limits that must be carefully examined to see if it will work in a certain city or building. The following section presents the framework developed to identify and evaluate these potential sources prior to detailed system design.

In this framework, all candidate sources are first screened through a series of binary go/no-go gates, including site and regulatory constraints, climatic or quality thresholds, and a preliminary capacity check to ensure that each option can provide a meaningful contribution to the building load which is by default set to 10% of the design load. Depending on the availability, the workflow automatically considers the sources individually and their combination in a hybrid configuration. In such cases, air-, ground-, and wastewater-based systems may be coupled to share the load according to their seasonal performance and availability, ensuring overall technical feasibility and improved resilience of the energy system design.

Figure 3.5 illustrates the pre-assessment workflow implemented in the framework for the three considered heat pump source types. Each source follows a sequence of qualitative exclusion criteria, followed by a quantitative estimation of its maximum feasible capacity. The qualitative checks filter out infeasible options based on local constraints, while the quantitative step determines whether the remaining option can cover at least a fraction of the building's peak heating or cooling load. This combined procedure ensures that only technically viable sources are passed to the subsequent detailed design stage. The workflows for wastewater-source, ground-source, and air-source heat pumps are described below.

Air-source heat pumps

Air-source heat pumps are evaluated first based on climatic and regulatory suitability. Because ASHP performance degrades in very cold climates, the share of hours in which the outdoor temperature falls below a lower threshold T_{crit} is examined. In this work, ASHPs are considered feasible if

$$\frac{1}{8760} |\{ t : T_{\text{out}}(t) < T_{\text{crit}} \}| < x_{\text{ashp}},$$

where T_{crit} is set to -20.00°C and x_{ashp} is a user-defined fraction (here 0.1). Both of these values represent default assumptions that may be adjusted by the user.

The parameter x_{ashp} denotes the *maximum allowable fraction of annual hours* during which the outdoor temperature is permitted to fall below the critical threshold T_{crit} while still considering an ASHP to be climatically feasible. For example, the default value $x_{\text{ashp}} = 0.1$ allows up to 10% of the year to be colder than -20°C .

In addition to climatic suitability, the installation must satisfy local acoustic restrictions (e.g., maximum permitted sound pressure levels at property boundaries). If these constraints are met, the ASHP is considered feasible, subject to the need for supplemental heating during the coldest

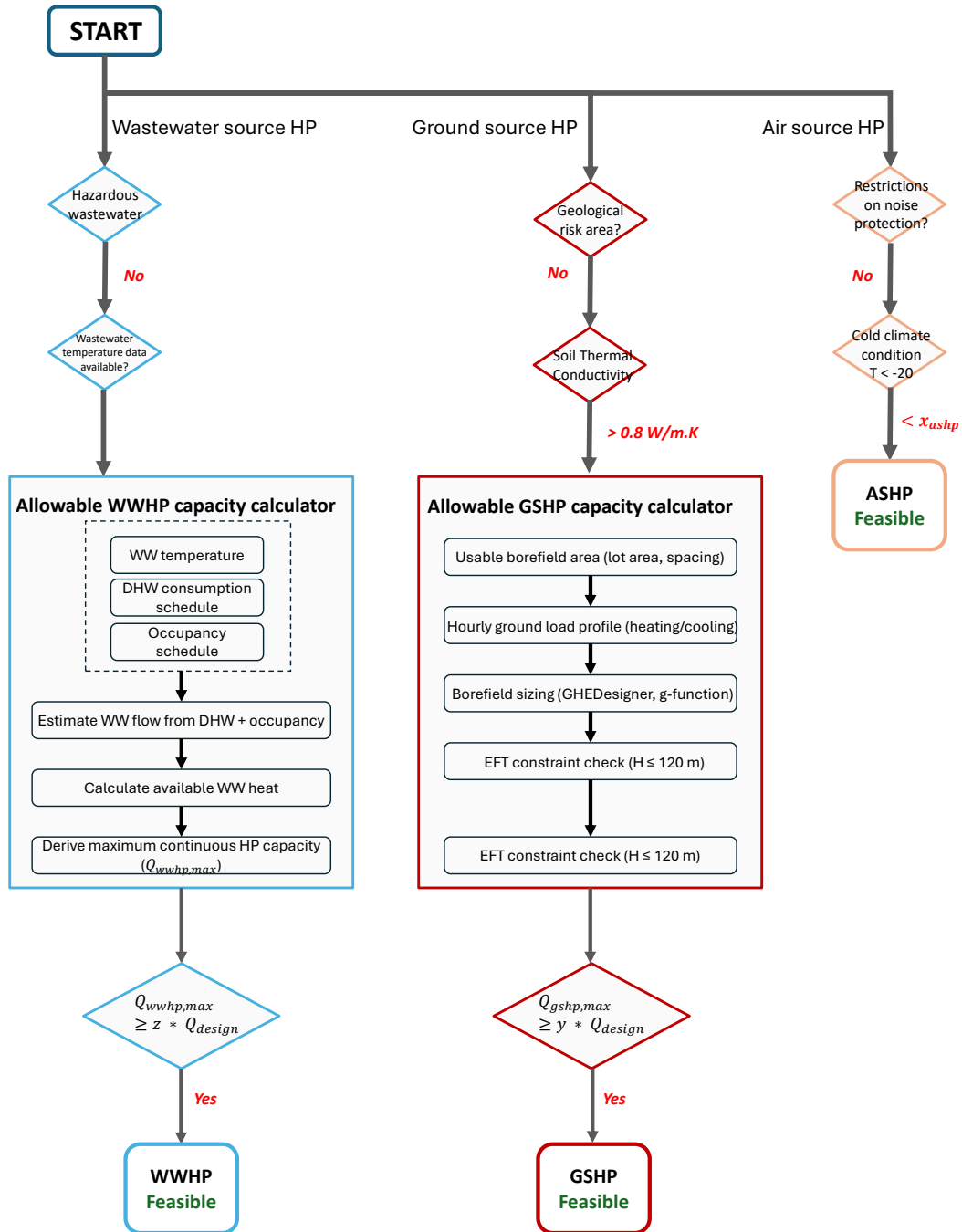


Figure 3.5: Heat pump pre-assessment workflow

periods. No quantitative sizing is required at this stage because ASHPs do not face intrinsic physical source limitations such as available flow or soil capacity.

Ground-source heat pumps

Ground-source heat pumps require both geological and spatial suitability. First, sites located within groundwater protection zones, contamination areas, or geological risk regions are excluded. Second, the soil must exhibit sufficient thermal conductivity λ_{soil} to sustain long-term extraction without excessive temperature decline. As a conservative threshold, GSHPs are only considered if

$$\lambda_{\text{soil}} \geq 0.8 \text{ W m}^{-1} \text{ K}^{-1}.$$

If these qualitative conditions are satisfied, a quantitative capacity estimation is performed. The maximum usable borefield area is determined from the lot area minus building footprint, applying minimum borehole spacing (typically 6.00 m) and edge clearances. From this, the maximum number of boreholes (n_x, n_y) is obtained.

A synthetic ground load profile $q_g(t)$ is constructed from the building's hourly heating and cooling loads:

$$q_g(t) = Q_h(t) \left(1 - \frac{1}{\text{COP}_h} \right) - Q_c(t) \left(1 + \frac{1}{\text{COP}_c} \right),$$

representing net heat extraction from or rejection to the ground.

For each candidate borehole depth H , the hybrid g -function approach recommended by ASHRAE is used to compute the entering fluid temperature (EFT) trajectory $T_{\text{in}}(t; H)$. The depth H^* is accepted only if

$$T_{\text{min}}^{\text{EFT}} \leq T_{\text{in}}(t; H^*) \leq T_{\text{max}}^{\text{EFT}} \quad \forall t,$$

and if H^* does not exceed the practical drilling limit of 120.00 m.

The allowable GSHP capacity is then calculated as the highest continuous load that satisfies the EFT constraint and optional geometric extraction limits:

$$Q_{\text{gshp,max}} = \min(Q_{\text{EFT}}, Q_{\text{geom}}),$$

where Q_{geom} is the geometric cap defined by $w_{\text{geom}} n_{\text{bh}} H^*$.

Finally, GSHPs are considered feasible if

$$Q_{\text{gshp,max}} \geq y Q_{\text{design}},$$

with y set to 0.1 as default.

Wastewater-source heat pumps

Wastewater-source heat pumps require acceptable wastewater quality (absence of hazardous or industrial discharges) and sufficient temperature data for the source. If either criterion fails, the WWHP option is discarded.

For feasible locations, the allowable WWHP capacity is estimated by computing the recoverable heat from wastewater flows. Using the DHW consumption schedule, occupancy profile, and wastewater temperature $T_{\text{ww}}(t)$, the available hourly mass flow $\dot{m}$ is reconstructed. The recoverable heat is then

$$Q_{\text{ww}}(t) = \rho c_p \dot{V}(t) \Delta T_{\text{hx}},$$

where ΔT_{hx} is the temperature drop across the heat exchanger.

To ensure stable operation, a rolling averaging window and safety factors are applied to determine the conservative continuous capacity:

$$Q_{\text{wwhp,max}} = \min_t Q_{\text{ww}}(t) \quad \text{or a chosen low percentile (e.g., 5th).}$$

The wastewater heat pump is deemed feasible when

$$Q_{\text{wwhp,max}} \geq z Q_{\text{design}},$$

with z set to 0.1 by default.

Hybrid configurations

If multiple sources pass the screening individually, they may also be combined in a hybrid configuration. The framework allocates seasonal load fractions among sources based on their availability and temperature-dependent efficiency. For example, wastewater or ground sources may be prioritized for base load coverage due to higher temperature stability, while ASHPs cover intermediate loads and backup systems ensure peak coverage. This combined strategy enhances system resilience and reduces dependence on a single resource.

3.7 Urban Building Retrofit Prioritization Workflow

The workflow for prioritizing buildings in retrofitting projects is applicable to large-scale projects where buildings in a portfolio, neighbourhood, district or city need to be prioritized for any retrofitting action. This workflow is designed to help urban planners and managers for better streamlining of their retrofitting plans and making optimal decisions to achieve energy conservation and sustainability goals faster. The PRInceton Scorekeeping Method (PRISM) is at the heart of this workflow and it is used to identify each building's vulnerability to climate

change. Therefore, before explaining the principles of the prioritization workflow, the PRISM method is explained in detail.

3.7.1 PRInceton Scorekeeping Method (PRISM)

The PRISM method, which was created at Princeton University in the mid-1980s, is a regression-based method that aims to standardize how energy savings in buildings are measured. The main use of this tool is to monitor changes in energy use while taking into account changes in the weather. This makes it possible to accurately measure the effects of energy saving measures and retrofitting [166]. PRISM can be implemented using either monthly or daily energy consumption data, depending on data availability.

PRISM uses statistical approaches to standardize energy use data based on environmental conditions, especially heating degree-days (HDD), which usually distort building energy performance indicators [167]. This normalization makes it possible to make accurate comparisons of energy use across different time periods and environmental conditions. This is why PRISM is so beneficial for figuring out how well residential and commercial buildings are doing.

This method is effective for long-term monitoring, as it captures variations in energy consumption due to physical modifications, operational changes, and occupant behaviours. PRISM has been widely employed to estimate potential energy savings from retrofitting projects, especially in regions with significant seasonal variability. PRISM utilizes segmented linear regression to model the relationship between outdoor temperature and energy consumption, identifying three key parameters:

- **Base load** refers to the energy consumption that remains constant regardless of temperature fluctuations, primarily arising from lighting, appliances, and plug loads.
- **Heating (or cooling) slope** refers to the variation in energy consumption corresponding to a unit change in outdoor temperature, reflecting the thermal sensitivity of the building. A steeper slope indicates increased heating or cooling requirements and may reflect inadequate envelope performance.
- **Change-point temperature** refers to the outdoor temperature threshold that triggers the activation of heating or cooling systems.

For a building with both heating and cooling demands, PRISM can be expressed as:

$$E(T) = \begin{cases} B + S_H \cdot (T_{\text{bal,H}} - T), & \text{if } T < T_{\text{bal,H}} \quad (\text{heating regime}) \\ B, & \text{if } T_{\text{bal,H}} \leq T \leq T_{\text{bal,C}} \quad (\text{base load zone}) \\ B + S_C \cdot (T - T_{\text{bal,C}}), & \text{if } T > T_{\text{bal,C}} \quad (\text{cooling regime}) \end{cases} \quad (67)$$

where:

- $E(T)$ = average energy use at mean outdoor temperature T ,
- B = base load ($\text{kW h}/\text{m}^2$),
- S_H = heating slope ($\text{kW h}/(\text{m}^2 \text{ } ^\circ\text{C})$),
- S_C = cooling slope ($\text{kW h}/(\text{m}^2 \text{ } ^\circ\text{C})$),
- $T_{\text{bal,H}}, T_{\text{bal,C}}$ = heating and cooling change-point temperatures ($^\circ\text{C}$).

If cooling is negligible, the model simplifies to a single change-point formulation:

$$E(T) = \begin{cases} B + S_H \cdot (T_{\text{bal}} - T), & \text{if } T < T_{\text{bal}} \\ B, & \text{if } T \geq T_{\text{bal}} \end{cases} \quad (68)$$

Figure 3.6 shows the basic idea of PRISM. First, the monthly energy consumption and outside temperature data are looked at in the time domain. Then, they are turned into a scatter plot of energy use versus mean outdoor temperature. This update makes it possible to find the base load, the heating and cooling sensitivities, and the change-point temperature that divides energy usage to two groups of dependent on temperature and independent of it.

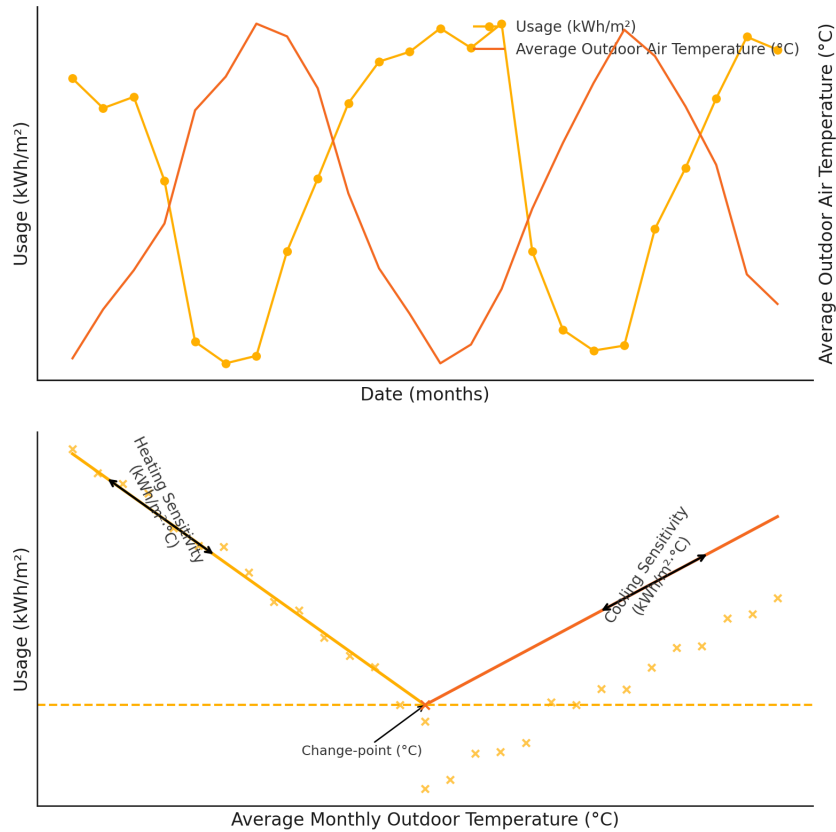


Figure 3.6: Basic principles of the PRISM method

In practice, PRISM fits separate linear regressions to each temperature regime—one for heating, one for cooling (if applicable), and a flat segment for the base load. This segmentation improves

clarity in distinguishing between temperature-dependent and temperature-independent loads. Figure 3.7 presents an application of PRISM to measured building data from this study. The plot shows the fitted regression lines for the heating and cooling regimes, the base load region, and the 95% confidence intervals. The highlighted areas indicate the operational zones: the heating regime (left), the base load zone (center), and the cooling regime (right).

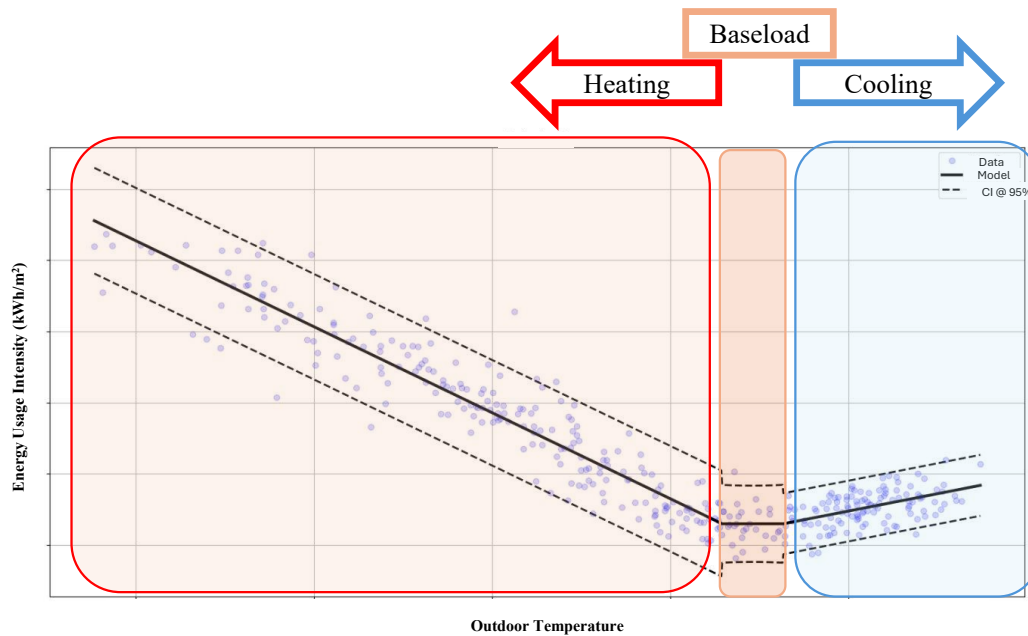


Figure 3.7: Application of PRISM and regions in the resulting plot

Its continued use in both research and practice is attributed to its robustness, interpretability, and adaptability to various building types and climates. PRISM's legacy extends to contemporary energy management frameworks, reinforcing the importance of weather-normalized regression analysis in advancing sustainable building operation

3.7.2 Retrofit Prioritization Workflow

An overview of the workflow is shown in Figure 3.8. To apply the proposed retrofit prioritization workflow, access to measured building energy consumption data is required. In its minimal configuration, aggregated monthly billing data is sufficient, avoiding the need for high-resolution or sub-metered data. While access to such data can be constrained by privacy regulations and data-sharing policies in many jurisdictions, the workflow is designed to operate with the type of energy consumption information that is most commonly available to building owners, municipalities, and public asset managers.

In practice, aggregated monthly energy consumption data are often accessible in Canada for publicly owned buildings and large institutional portfolios through utility data-sharing agreements, benchmarking programs, or building energy disclosure initiatives. Similar mechanisms exist in other regions, although availability varies by country and governance context. Where direct

access to individual building data is restricted, the workflow may be applied at the portfolio or anonymized building level, provided that consistent billing records are available.

In parallel, a GeoJSON file containing the building geometries and basic attributes is required to run the UBEM workflow within the TOOLS4Cities platform. Following the UBEM simulation, the PRISM methodology is applied to both the metered consumption data and the simulated results. For each building, PRISM yields two key parameters: the heating sensitivity slope and the non-weather-dependent base load. These indicators are subsequently used to identify buildings with high retrofit potential and to support informed retrofit prioritization decisions.

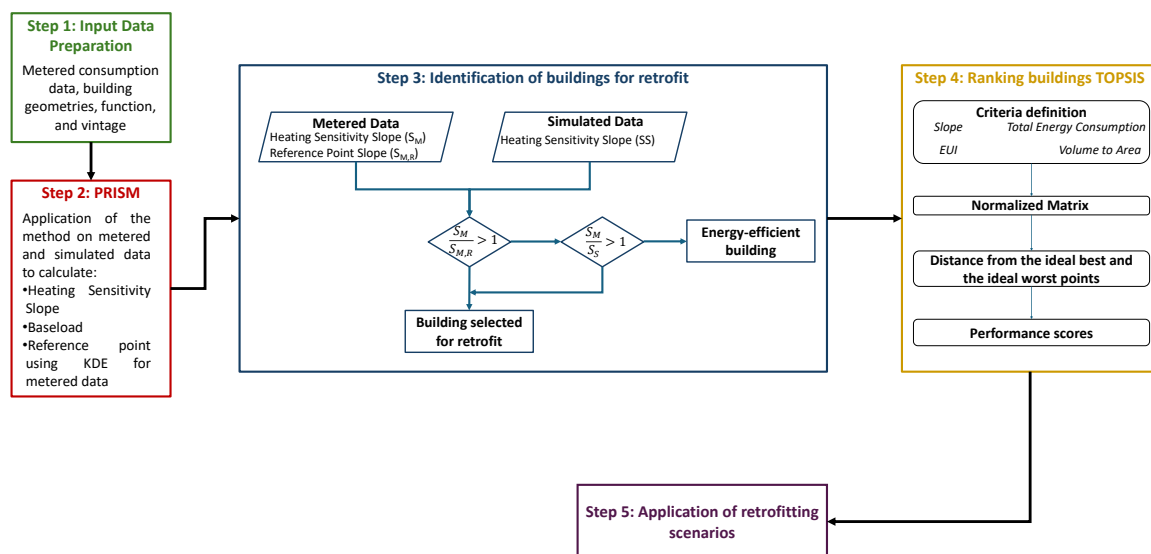


Figure 3.8: Urban building retrofit prioritization workflow

The first step in identifying buildings for retrofit actions is the definition of a reference point within the assessed building portfolio. This reference point serves as a benchmark against which individual buildings are evaluated in order to identify underperforming candidates for retrofit. In the proposed workflow, the reference point is derived using Kernel Density Estimation (KDE) applied to the two-dimensional distribution of heating sensitivity slope and base load values obtained from metered data.

Unlike conventional retrofit prioritization approaches that rely on fixed external benchmarks—such as absolute energy-use intensity thresholds, code-based performance targets, or predefined retrofit standards—the KDE-based reference point is intentionally defined relative to the existing building stock. This choice is motivated by the high heterogeneity typically observed in real-world building portfolios, where construction period, usage patterns, system types, and operational conditions vary significantly. In such contexts, externally defined performance thresholds may not accurately reflect locally achievable performance levels or operational realities.

The KDE technique provides a smooth, non-parametric approximation of the underlying probability density function, allowing the identification of the most statistically representative operating condition without assuming any predefined distribution. The peak of the KDE surface corresponds to the most frequently observed combination of heating sensitivity and base load within the portfolio, representing the dominant or typical operational behaviour of the existing buildings. As such, this point characterizes the prevailing performance of the stock rather than an aspirational or idealized target.

Using this internally derived reference point as a benchmark enables a relative performance assessment, where buildings that significantly deviate from the portfolio norm—particularly those exhibiting higher heating sensitivity or elevated base loads—are identified as priority candidates for retrofit. This relative benchmarking approach is particularly well suited for early-stage screening and prioritization, as it allows decision-makers to focus on buildings that are demonstrably underperforming compared to their peers, even in the absence of explicit energy targets or detailed retrofit standards.

It should be noted that the KDE-based reference point is not intended to replace absolute performance targets or regulatory benchmarks. Instead, it provides a data-driven and context-sensitive baseline that supports portfolio-level decision-making, especially when the objective is to rank buildings and allocate limited retrofit resources efficiently. Figure 3.9 illustrates an example of the slope–base load scatter plot and the identified KDE reference point.

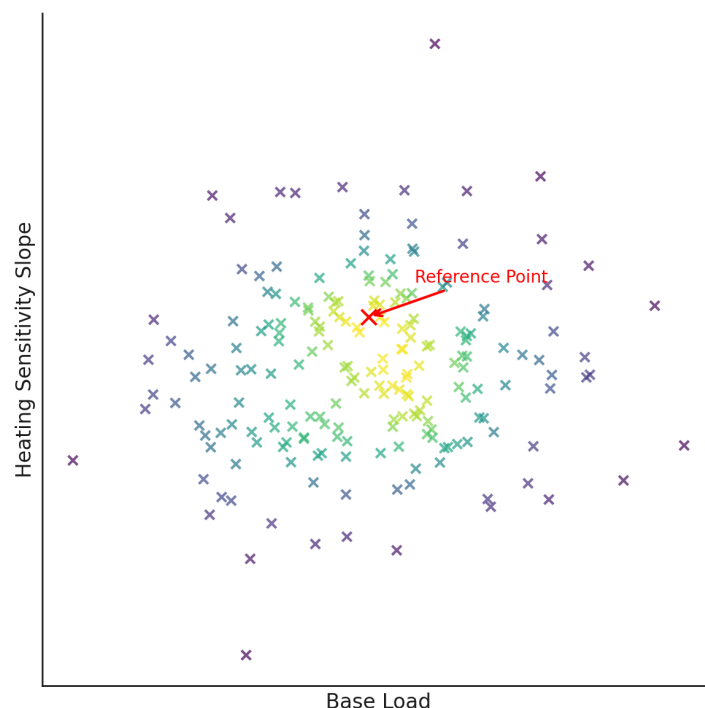


Figure 3.9: Identification of a reference point using KDE based on PRISM application results

For each building, its measured heating slope S_M , simulated heating slope S_S , and reference slope $S_{M,R}$ are used to determine retrofit need. First, buildings with S_M exceeding $S_{M,R}$ are

directly flagged for retrofit. For remaining buildings, S_M and S_S are compared: if S_M exceeds S_S , the building is also marked for retrofit. This comparison identifies buildings whose actual heating sensitivity is worse than expected based on simulation, suggesting underperformance due to degradation, poor operation, or hidden inefficiencies. The two-step logic ensures robust and context-aware identification of retrofit candidates.

After identifying the buildings that need retrofitting, they should be ranked and prioritized to find the ones that need it the most. To do so, the TOPSIS decision-making algorithm is used to rank the buildings. This method of making decisions based on more than one criterion entails choosing indicators that show both how well the facility uses energy and how much money it may make from retrofitting. This framework uses four criteria:

- (1) **Heating Sensitivity Slope** calculated using PRISM based on the metered data shows how much more energy a structure needs to heat when the temperature outside drops. A steeper slope means more heat is lost because to things like poor insulation, too much air coming in, or heating systems that don't work well. This criterion directly addresses a building's thermal inefficiency, making sure that retrofit operations are focused on those that can most reduce heating demand.
- (2) **Energy Use Intensity (EUI)** which is defined in kWh/m².year, tells you how much energy a building uses in a year compared to its floor space. The heating slope only looks at losses that rely on temperature, while the EUI looks at all end uses to give a full picture of total operating efficiency. This makes it easier to put buildings that typically have high energy intensity for their size at the top of the list. This shows that there are common inefficiencies that retrofitting could fix.
- (3) **Total Energy Consumption** shows how much energy a structure uses overall, without taking its size into account. EUI gives a measure of how efficient something is compared to other things, whereas total consumption shows which facilities are responsible for a large part of the portfolio's energy use and greenhouse gas emissions. Retrofitting buildings that consume a lot of energy can save a lot of money and have a big overall effect, even if the EUI is only moderate.
- (4) **Volume-to-Envelope-Area Ratio** is a geometric indicator that shows how compact a building is, and it has cost effects on retrofit efforts. Structures with lower volume-to-area ratios usually have more complicated envelopes, more surface area exposed, and maybe even bigger façade portions that need work like adding insulation, replacing windows, or sealing air leaks. This could raise the cost of retrofitting each unit of enclosed space. The priority approach uses the volume-to-area ratio to order things, taking into account both possible energy savings and cost-effectiveness. This method works best for structures where retrofitting is expected to give a better return on investment than the amount of work that needs to be done on the building envelope.

Together, these four criteria combine operational performance metrics (heating slope and EUI), an impact metric (total energy consumption), and a cost-related geometric metric (volume-to-area ratio), ensuring that retrofit prioritization balances potential savings, total impact, and financial feasibility.

After ranking the buildings, different retrofitting scenarios including improving or changing the energy system, building envelope, and building glazing can be assessed and compared to select the best scenario based on the user preferences for each building separately.

3.8 TOPSIS Decision-Making Algorithm

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is a well-established multi-criteria decision-making (MCDM) method that ranks alternatives based on their geometric distance from an ideal best and an ideal worst solution [168]. Unlike other MCDM methods such as Analytic Hierarchy Process (AHP) or Multi-Attribute Utility Theory (MAUT), TOPSIS does not require pairwise comparisons or subjective weighting of criteria. Instead, it operates on normalized objective or performance data and identifies the alternative that is simultaneously closest to the ideal best solution and farthest from the ideal worst solution. This geometric perspective provides a balance between competing objectives and enables a transparent and reproducible ranking process.

TOPSIS is particularly effective in applications involving trade-offs among conflicting objectives, such as balancing cost and energy performance in building system design, or prioritizing retrofit interventions based on multiple indicators. Compared to methods like ELECTRE or PROMETHEE, which are based on outranking relations and can be computationally intensive, TOPSIS offers simplicity, scalability, and clear interpretability, making it suitable for large-scale building portfolios and multi-objective optimization studies. This multi-criteria decision-making algorithm is used in the current study in two different workflows: the NSGA optimization workflow to find the best solutions in the Pareto front, and in the building portfolio retrofit prioritization workflow to rank the buildings for application of different retrofitting measures.

In the optimization workflow developed in this research, TOPSIS is applied to identify the best solution among the non-dominated alternatives obtained from the Pareto front. Each solution in the Pareto front is characterized by a set of normalized objective function values, such as life-cycle cost, total energy consumption, or emissions. The ideal best and ideal worst points are defined by selecting the minimum and maximum normalized values for each objective, respectively.

For each solution, the Euclidean distances to the ideal best D_i^+ and ideal worst D_i^- points are computed using:

$$D_i^+ = \sqrt{\sum_{j=1}^n (x_{ij} - x_j^+)^2}, \quad D_i^- = \sqrt{\sum_{j=1}^n (x_{ij} - x_j^-)^2} \quad (69)$$

where x_{ij} is the normalized value of objective j for solution i . The relative closeness of each solution to the ideal best, referred to as the performance score C_i , is then calculated as:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad (70)$$

The solution with the highest C_i is selected as the optimal one. This approach allows for a balanced decision that considers all objectives simultaneously, providing a rational criterion for selecting a single solution from the Pareto front without introducing external weighting factors.

In the building retrofit prioritization workflow (Figure 3.8), TOPSIS is employed to rank buildings based on multiple energy and geometric indicators that influence retrofit potential. Each criterion is normalized using Euclidean normalization to ensure comparability across different scales. For beneficial criteria (e.g., volume-to-area ratio), higher values are preferred, while for non-beneficial criteria (e.g., energy use intensity or heating slope), lower values are preferred. Similar to the optimization case, distances to the ideal best and worst points are calculated, and a TOPSIS performance score is obtained for each building. The resulting score provides a quantitative measure of retrofit priority, with higher scores corresponding to higher retrofit urgency. This data-driven ranking method enables an objective comparison of buildings across the entire portfolio and ensures that retrofit decisions are guided by both energy performance and geometric efficiency, rather than relying on subjective expert judgment.

4 Use Case Application and Analysis

In the previous section, the fundamentals of the developed framework and workflows were outlined. This chapter demonstrates their application through three distinct use cases. First, the role of the generic data model in streamlining input data and automating the energy system modelling process is illustrated through the implementation of PV-integrated air-source heat pumps in two different climates. Second, the building portfolio retrofit prioritization workflow is applied to rank several gas-based buildings managed by the social housing office of the City of Montreal, followed by a detailed retrofit analysis of the highest-priority building. Finally, the framework is used to evaluate the optimal integration of heat pumps in future multi-unit residential buildings, with a particular focus on the degree of system centralization.

4.1 A generic data model for automating building energy system analysis in different climates

Building energy system retrofitting plays a critical role in advancing global sustainable development goals by reducing greenhouse gas emissions, improving energy efficiency, and enhancing resilience. However, as the spatial resolution of analysis increases from regional to building-level scales, the task of modelling individual buildings becomes increasingly time-consuming, data-intensive, and computationally complex. To address this challenge, systematic workflows are required for detecting existing energy systems, evaluating retrofit options, and consistently assessing their impacts across diverse building stocks. A key enabler of such workflows is a standardized data structure that can harmonize input data for both baseline and retrofit scenarios. By ensuring consistency and transferability across different climatic contexts, this standardized model not only accelerates large-scale simulations but also supports automation, comparability, and scalability in building energy system analysis.

The primary objective of this section is to demonstrate how the proposed generic data model accelerates large-scale energy system retrofit assessments and facilitates cross-climate comparisons. The process begins with the systematic definition of both existing energy system archetypes and prospective, future-proof archetypes for a given context. Pre-defined simulation models of these archetypes are then generated, forming a reusable library of standardized system representations that can be directly applied in retrofit assessment studies across different regions and climatic conditions.

It is acknowledged that archetype-based representations inherently abstract away certain building-specific nuances, including detailed operational practices, occupant behaviour, and localized system configurations. However, this abstraction is a deliberate and necessary trade-off when addressing large-scale retrofit planning problems, where the objective is not to predict the exact performance of individual buildings, but rather to enable consistent, scalable, and computationally tractable comparisons across a heterogeneous building stock. At the urban or portfolio scale,

the availability and quality of detailed system-level data are often limited, making fully bespoke modelling impractical.

Within the proposed framework, archetypes serve as flexible templates rather than rigid classifications. They define a structured baseline that can be systematically adapted through parameterization, calibration, and scenario-based modification. Context-specific information—such as climate, technology availability, fuel mixes, regulatory constraints, and retrofit strategies—is incorporated through the data model and associated simulation inputs, allowing archetypes to evolve beyond static representations. In this sense, the archetype approach does not eliminate contextual detail, but organizes it in a way that supports transparent comparison, reproducibility, and cross-climate transferability.

As a result, the use of archetypes within the proposed data model enables a balance between realism and scalability: sufficient detail is retained to capture dominant system behaviour and retrofit impacts, while the modular structure allows additional complexity to be introduced where data availability and study objectives justify it.

4.1.1 Energy System Data Model

Figure 4.1 presents a summarized UML class diagram of the developed energy system data model. In any building, several energy systems coexist, each responsible for meeting specific energy demands. Over time, characteristic combinations of these systems have emerged, which can be formalized as energy system templates or archetypes. The *Archetype* class, shown at the top of the UML diagram, represents these templates. As indicated, each archetype is composed of one or more (1..*) energy systems, illustrated by the composition relationship (a solid line with a diamond symbol).

Each *System* instance is itself composed of several subsystems: a *GenerationSystem*, a *DistributionSystem*, an *EnergyStorageSystem*, and an *EnergyEmitterSystem*. Accordingly, separate composition relationships are defined between the *System* class and each of these subsystem classes. Beyond these relationships, the *System* class is also linked to an enumeration defining the possible demand types (e.g., heating, cooling, electricity, domestic hot water) that a system can supply. An important modelling rule established in the development phase was that an energy system can supply multiple demand types, but each demand type within a building must be supplied by exactly one system to avoid redundancy and conflicts.

The *GenerationSystem* class represents all components capable of producing either thermal or electrical energy. It provides a set of shared attributes applicable across all generation technologies. This base class is further specialized into *RenewableGenerationSystem* and *NonRenewableGenerationSystem*, a separation introduced primarily to manage attribute complexity. For example, the *NonRenewableGenerationSystem* class includes attributes such as nominal heating and cooling output capacities, as well as performance-characterizing curve-based attributes

(e.g., *heat_energy_input_ratio_curve*). These curves, defined as instances of the *FittedCurves* class, capture technical performance relationships and are linked through associations annotated as *technical_performance_curves* with multiplicity (0..1). The functional forms of these fitted curves are provided in Table 3.1.

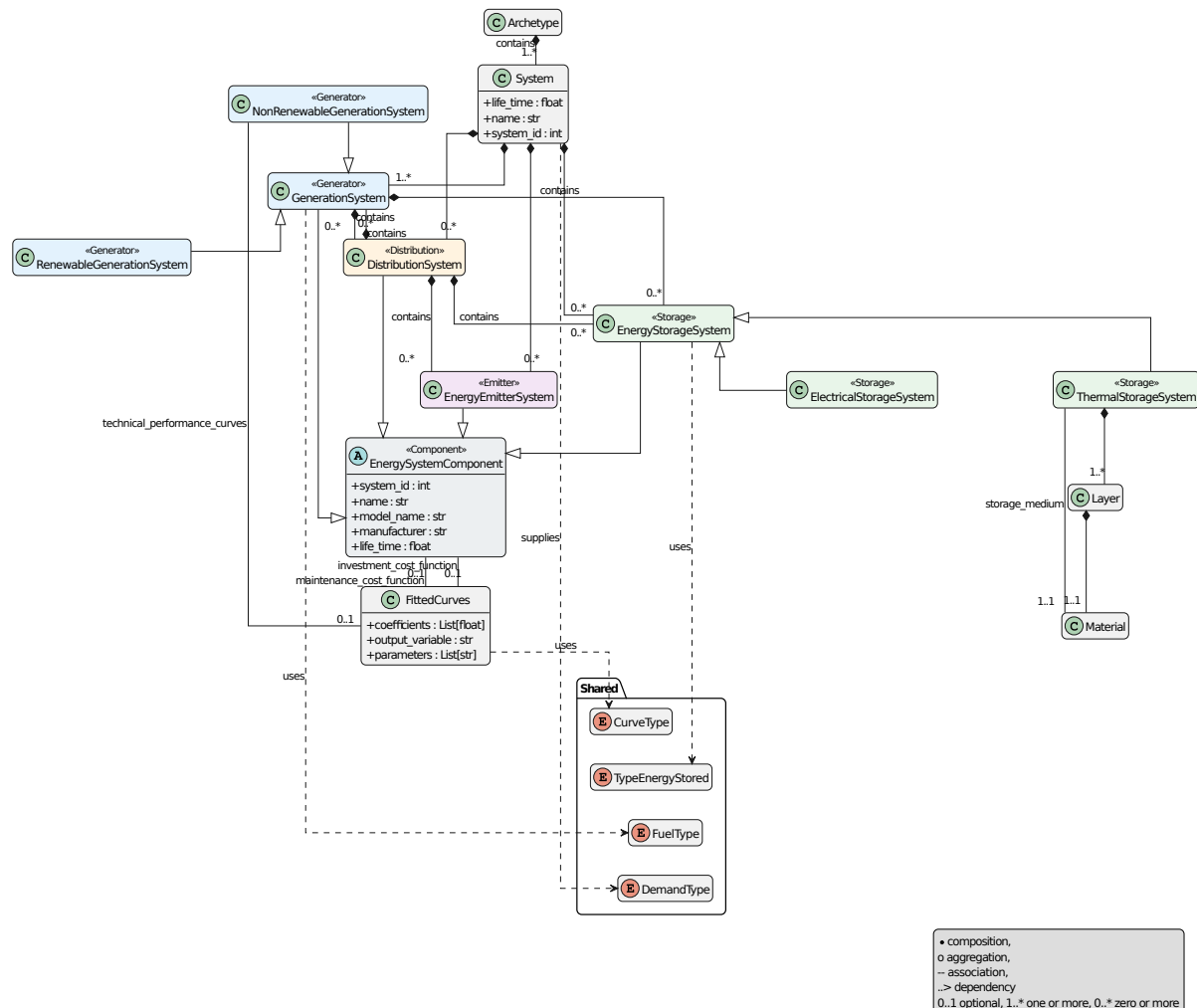


Figure 4.1: Summarized UML class diagram of the energy system data model.

The *DistributionSystem* class refers to components that distribute energy within the building, such as air handling units (AHUs). These may include integrated generation or storage subcomponents (e.g., heating coils within AHUs). This capability is reflected by composition relationships between *DistributionSystem* and both the *GenerationSystem* and *EnergyStorageSystem* classes, each with multiplicity (0..*).

The *EnergyStorageSystem* class represents generic storage technologies and is further specialized into *ElectricalStorageSystem* and *ThermalStorageSystem*, enabling the model to capture batteries, thermal tanks, and other storage devices. The *ThermalStorageSystem* is further linked to the *Layer* and *Material* classes, which specify its construction and storage medium properties.

The *EnergyEmitterSystem* class describes components responsible for delivering energy to

building zones, such as fan coils, radiators, or baseboards. While the distribution subsystem manages central energy delivery, emitters operate at the end-use level.

At the core of the diagram, the abstract *EnergySystemComponent* class consolidates attributes shared across all subsystems. These include identifiers (e.g., *system_id*), descriptive fields (e.g., *name*, *model_name*, *manufacturer*), lifetime, and links to cost functions for investment and maintenance. The ability to associate system components with cost functions and performance curves provides flexibility for techno-economic and performance assessments. Importantly, this design supports the inclusion of commercially available components directly into the model, thereby facilitating the integration of real-world product data into simulations.

Finally, the diagram includes several shared enumerations and data types. These include *CurveType*, *TypeEnergyStored*, *FuelType*, and *DemandType*, which standardize system attributes and ensure consistency across the data model.

Overall, the proposed energy system data model provides a flexible and extensible structure for representing a wide range of building energy systems. By separating generation, distribution, storage, and emission components while linking them through consistent archetypes and shared attributes, the model ensures both modularity and interoperability. The inclusion of performance curves and cost functions enables detailed techno-economic and operational analysis, while the abstraction of shared attributes across all components facilitates the direct integration of manufacturer data into simulations. This combination of modular design, extensibility, and real-world compatibility makes the data model a powerful foundation for automating building energy system analysis across diverse climates, building types, and retrofit scenarios. The complete and detailed version of the uml class diagram is presented in Appendix 5.3.

4.1.2 Case Study

This section demonstrates the functionality of the energy system data model and the retrofit workflow through a case study that evaluates the replacement of existing systems with PV-integrated unitary heat pumps. The assessment is conducted for the same neighbourhood but with two distinct climatic conditions, enabling a comparative analysis of system performance and highlighting the model's capability to support cross-climate retrofit evaluations.

The selected area for this study was the La Soledat Sud district in Palma de Mallorca, Spain. As part of the EU-funded ARV Horizon 2020 project [169], the neighbourhood serves as a priority zone for deep energy retrofits aimed at reducing non-renewable primary energy consumption by at least 30% while addressing energy poverty and housing affordability. Historically shaped by waves of industrial activity, worker housing, and later large-scale social housing developments, La Soledat Sud today faces a combination of aging, energy-inefficient multifamily buildings and persistent social vulnerability. The retrofitting programme, supported by Spain's Neighbourhood



Retrofit Assistance Programme, targets these building typologies through envelope improvements, the integration of renewable energy systems, and the deployment of energy-efficient heating technologies.

Figure 4.2 shows the residential building footprints in the selected area. The non-residential buildings have been left out of this study. The area contains 228 residential buildings where their construction year ranges from as early as 1850 to as recent as 2011. The majority of the stock was built between the 1930s and 1970s, corresponding to the main waves of industrial expansion and social housing development in Palma. Only a small fraction of the buildings were constructed after 1990, indicating that most of the neighborhood predates modern energy efficiency standards. This age profile underscores both the technical challenges and the opportunities for deep energy retrofits, particularly in improving hvac and domestic hot water (dhw) systems.

To analyze the neighbourhood under climate conditions of Montreal, using the UBE_M workflow capacities, the only change required was to change the weather file input. Table 4.1 shows a comparison between the climates of Palma in Spain, and Montreal in Canada.

Table 4.1: Climatic indicators for Palma de Mallorca and Montreal.

Location	HDD	CDD	Mean Dry Bulb Temp. (°C)	Yearly GHI (kWh/m ²)
Palma	951	855	17.7	1647
Montreal	4562	303	6.3	1316

4.1.3 Base Case Analysis

4.1.3.1 Palma For any urban areas, to use the UBEM workflow the set of construction and usage archetypes must be defined. These construction archetypes are distinguished by building function, construction period, and climate zone the building is located in. Based on the construction area and height of the buildings, residential buildings in the La Soledad Sud are divided into single family houses, multifamily house, and mid-rise apartment. It should be noted that the thresholds and criteria for defining archetypes are different from place to place. Figure 4.3 shows the distribution of building archetypes in the climate of Palma. The thermophysical characteristics of walls, roof, and ground for different archetypes are shown in Table 4.2. The values in this table are the results of the research done by the IREC research institute as one of the involved teams in the ARV project. The details of their analysis could be found in [169].

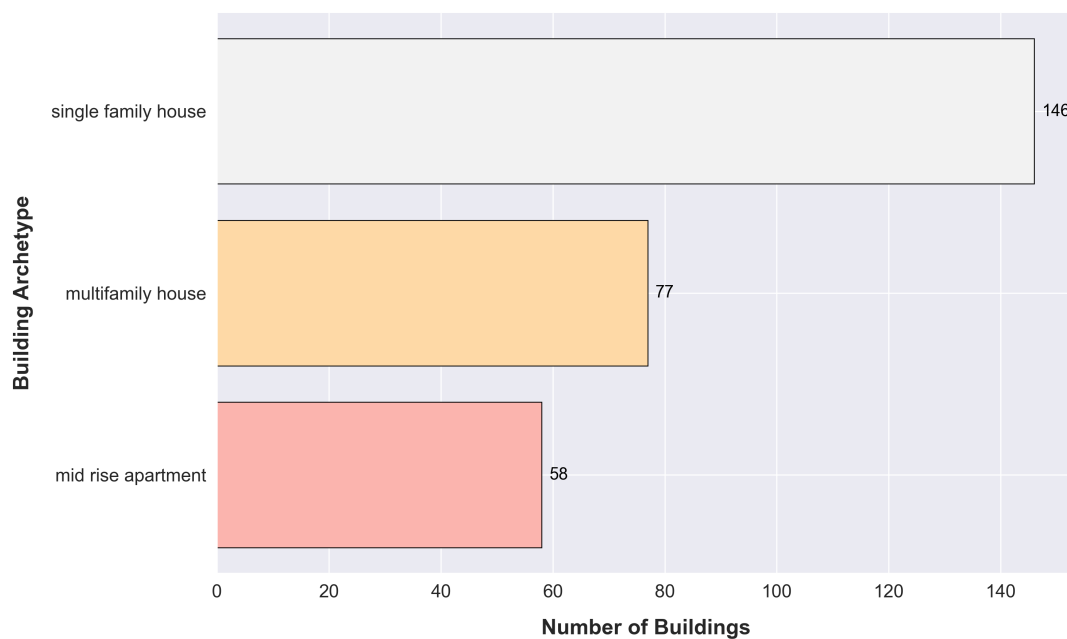


Figure 4.3: Palma de Mallorca building archetype distribution

Table 4.2: Envelope characteristics of Palma building archetypes by construction period.

Archetype	Construction Period	Wall U	Roof U	Window U	SHGC
		(W/m ² K)			(–)
Mid-Rise Apartment	1800–1900	1.65	1.39	4.02	0.76
	1901–1940	1.80	1.28	3.44	0.76
	1941–1960	1.82	1.47	3.44	0.76
	1961–1980	2.21	1.93	5.69	0.82
	1981–2007	0.73	1.69	3.44	0.76
	2008–2014	0.60	1.59	3.44	0.76

Continued on next page

Table 4.2 (continued)

Archetype	Construction Period	Wall U	Roof U	Window U	SHGC
			(W/m ² K)		(–)
Multi-Family House	1800–1980	2.70	1.23	3.44	0.76
	1981–2007	0.73	1.69	3.44	0.76
	2008–2014	0.60	1.59	3.44	0.76
	2015–2019	0.60	0.57	3.44	0.71
Single-Family House	1800–1980	2.70	1.23	3.44	0.76
	1981–2007	0.73	1.69	3.44	0.76
	2008–2014	0.60	1.59	3.44	0.76
	2015–2019	0.60	0.57	3.44	0.71

The usage archetypes that help in calculating the building internal gains only depend on the building function. Each archetype contains usage intensity values for lighting, electrical appliances, occupancy, ventilation rate, and domestic hot water usage accompanied by deterministic usage schedules. Table 4.3 shows the different usage intensity values for residential buildings in Palma de Mallorca. The values in this table are retrieved from the Spanish code for buildings [170].

Table 4.3: Internal load and service water parameters in Palma de Mallorca

Parameter	Value	Unit
Lighting density	4.40	W m ⁻²
Electric equipment density	4.40	W m ⁻²
Occupancy density	0.01	people m ⁻²

To calculate the base case primary energy consumption in buildings, the type of systems in use at each building needs to be assigned. Table 4.4 presents the probability distribution of using different types of components for supplying heating, cooling, and DHW demands. Based on these statistics, energy systems and system archetypes for the city of Palma are created.

Figure 4.4 shows the heating and cooling energy consumption intensity (EUI) for all the buildings in Palma de Mallorca. The data show that, unlike in colder regions, cooling EUI makes up a large part of total demand. This is because the Mediterranean environment has hot, extended summers. Heating EUI values are still greater generally, which shows that space conditioning is needed in the cooler months. However, the presence of considerable cooling loads shows that both end uses are equally important in retrofit design. On the one hand, improving heating efficiency and reinforcing the thermal envelope are the most critical measures, as heating EUI remains consistently higher across all archetypes despite the region's mild winters. On the other hand, reducing summer cooling demand through passive design strategies and the adoption of

Table 4.4: Distribution of base case systems in Palma de Mallorca

Demand Type	Technology	Penetration index (%)	Coefficient of Performance
Heating	Electrical resistance heater	35	1
	Heat pump	28	2
	Natural gas boiler	22	0.7
	Butane	15	0.7
Cooling	Heat pump	26.5	2
	Split	71	2
	Multi-split	2.5	2
DHW	Natural gas boiler	64	0.7
	Butane	10	0.7
	Electrical resistance heater	26	1

efficient cooling technologies is still necessary to mitigate peak electricity consumption during hot periods. These findings collectively emphasize that in Mediterranean climates like Palma, energy retrofitting must employ a comprehensive strategy that harmonizes both heating and cooling technologies, rather than favouring one exclusively.

The distribution of heating systems and heating energy use intensity of buildings per their heating system are shown in figure 4.5. Over half of the buildings use electricity as their heating fuel either using heat pumps or joule (electrical resistance heaters) and these buildings have lower heating EUI compared to those that use fossil fuels for their heating.

4.1.3.2 Montreal After completing the analysis for Palma using the capabilities of the UBEM workflow, the same district with identical building footprints can be re-evaluated as if it were located in Montreal. To enable such a climate-transfer analysis, two modifications are required:

- (1) As discussed in Section 3.1, the geometry file used to create the "City" must contain a field that specifies the building function. Because GeoJSON files do not follow a universal standard for defining building use, each location requires a custom dictionary that maps the functions present in the geometry file to the standardized functions expected by the UBEM workflow. Therefore, when repeating the analysis for a new climate, the first step is to update the building-function field so that it conforms to the mapping dictionary of the target location. For example, in the original GeoJSON, single-family houses are labeled as "Single-family building," whereas in Montreal the same category is represented by a numeric code, specifically "1100".

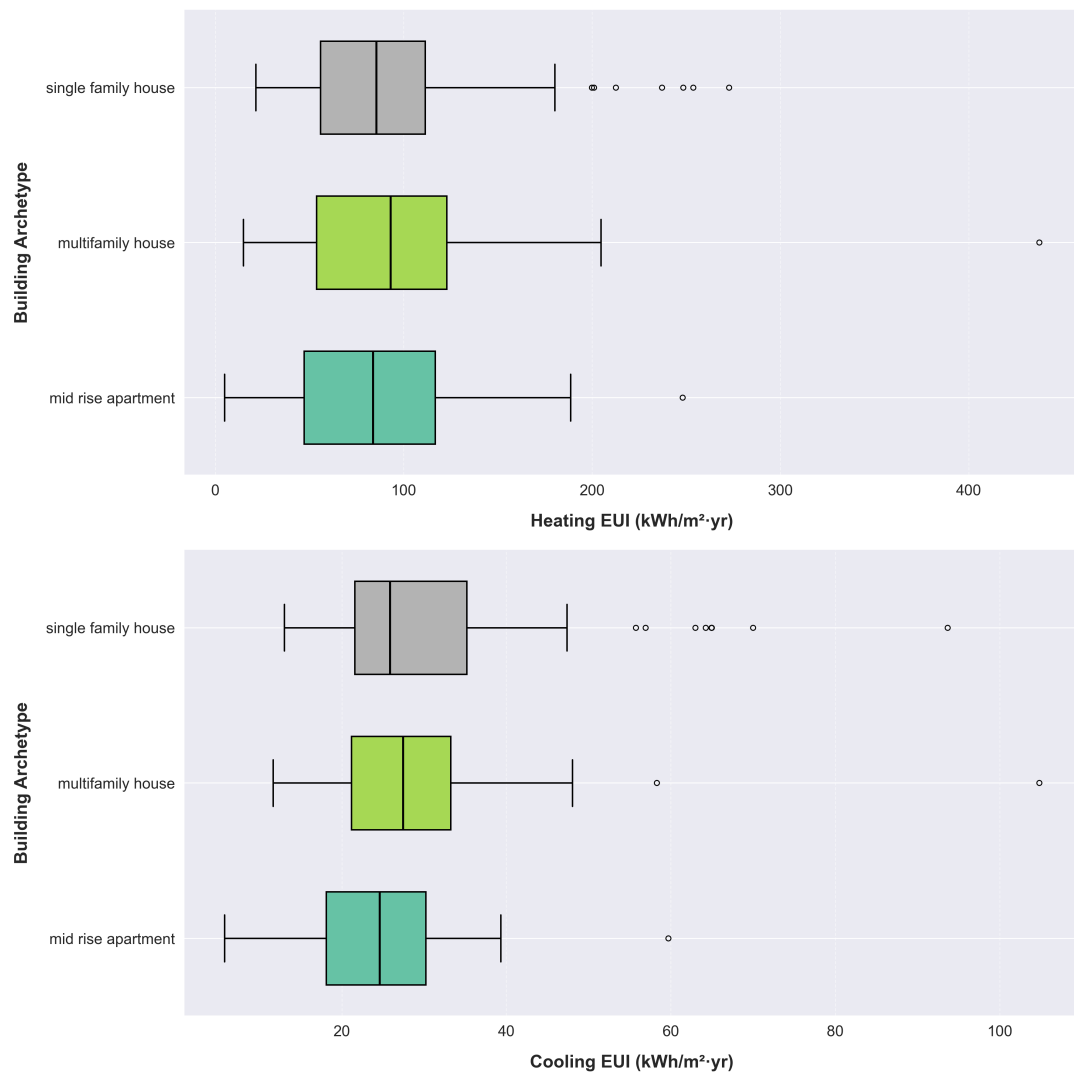


Figure 4.4: Base case energy use intensity for heating and cooling in Palma de Mallorca from the UBEM workflow

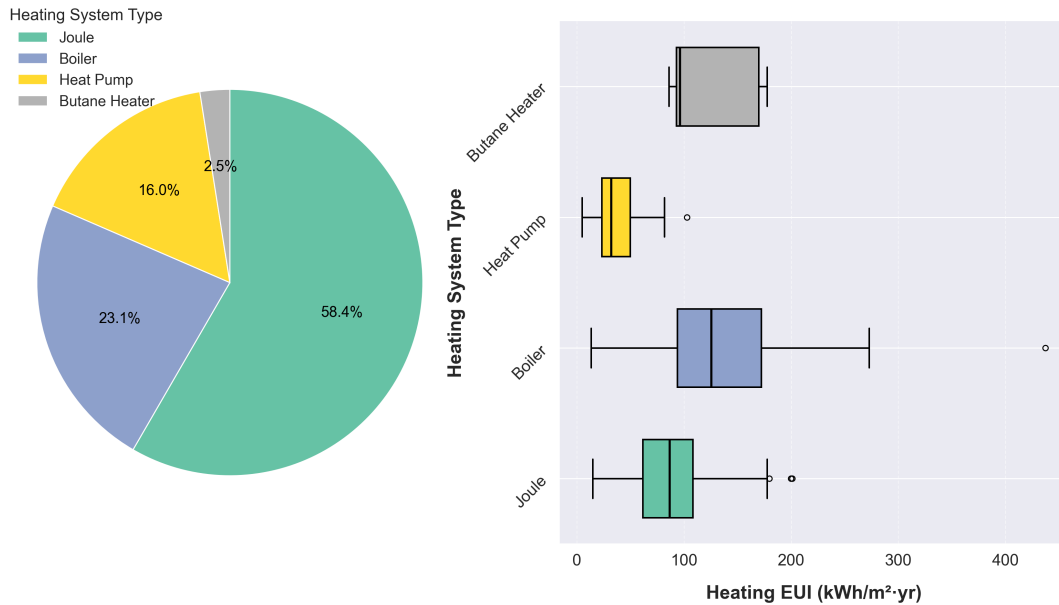


Figure 4.5: Heating system fuel mix and corresponding EUI values in Palma de Mallorca

- (2) Weather data are assigned either by the user to buildings manually if they have AMY data, or through a link to the TMY data stored in a parser dictionary. As a result, the second step in changing the city's climate is to replace the original weather-file link with the appropriate Montreal dataset.

An additional consideration is that building typology identification does not follow the same rule set across locations. In Palma, typologies were defined based on building floor area, while in Montreal the classification relies solely on adjacency and building height. Consequently, the typology distribution shown in Figure 4.6 differs from the one derived for Palma (Figure 4.3).

The construction archetypes for Canadian cities, including Montreal, were created primarily based on work by Natural Resources Canada (NRCan) and are implemented in the BTAP tool [171]. However, the BTAP archetypes include only a limited number of vintage categories. For instance, all buildings constructed before 1980 which represent more than 65% of Montréal's floor area, are grouped under a single construction type.

To improve resolution, additional data sources were incorporated into the archetype development process. For example, throughout various projects the construction archetypes that correspond to the climate of Montreal are updated through Quebec construction code [172]. The final archetype set for Canadian cities distinguishes buildings by function, construction period, and climate zone. The thermophysical characteristics of the archetypes assigned to the selected Montreal area are shown in Table 4.5.

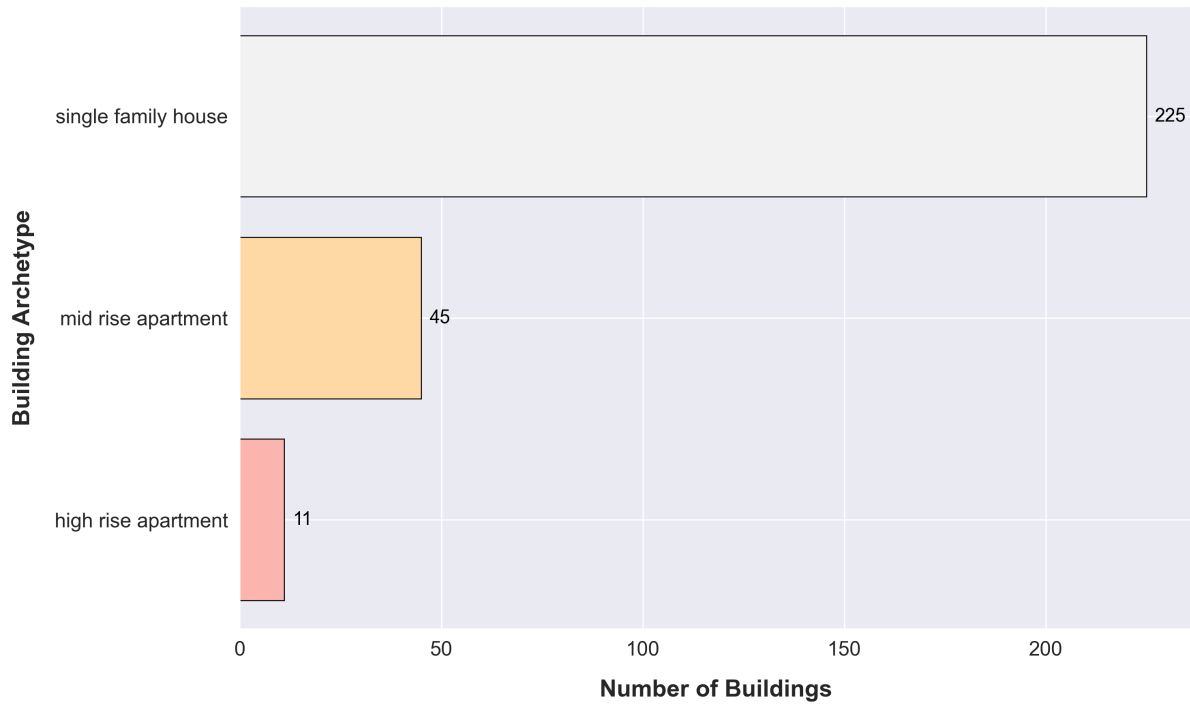


Figure 4.6: Montreal archetype distribution

Table 4.5: Envelope characteristics of Montreal building archetypes by construction period.

Archetype	Construction Period	Wall U	Roof U (W/m ² K)	Window U	SHGC (-)
Single-Family House	1800–1950	0.68	0.68	3.10	0.66
	1951–1980	0.68	0.68	3.10	0.66
	1981–2010	0.46	0.46	2.80	0.66
	2011–2020	0.18	0.18	2.20	0.39
	Post-2021	0.16	0.16	1.90	0.39
Mid-Rise Apartment	1850–1950	0.68	0.68	3.10	0.66
	1951–1980	0.68	0.68	3.10	0.66
	1981–2010	0.46	0.46	2.80	0.66
	2011–2020	0.18	0.18	2.20	0.39
	Post-2021	0.16	0.16	1.90	0.39
High-Rise Apartment	1800–1950	0.68	0.68	3.10	0.66
	1951–1980	0.68	0.68	3.10	0.66
	1981–2010	0.46	0.46	2.80	0.66
	2011–2020	0.18	0.18	2.20	0.39
	Post-2021	0.76	0.76	1.73	0.39

For Montreal, the National Energy Code for Buildings of Canada dataset, which uses fixed profiles for each building, was used to populate the usage data for all types of buildings and spaces, based on the previously defined archetypes per building. Table 4.6 presents a selection

of key usage parameters that are important in the calculation of any building's internal gains. The usage archetypes are independent of building vintage or climate zone, and they are only distinguished by the building function.

Table 4.6: Internal load and service water parameters in Montreal

Parameter	Value	Unit
Lighting density	5.50	W m^{-2}
Electric equipment density	5.00	W m^{-2}
Occupancy density	0.04	people m^{-2}

The recommendations from the National Energy Code of Canada for Buildings (NECB) [173] for base case analysis is used to assign energy system archetypes to buildings. Table 4.7 shows the main systems included in the NECB.

Table 4.7: Description of the considered energy systems based on the NECB.

System	Configuration	Fan Control	Cooling	Heating
System 1	Unitary air conditioner with baseboard heaters	CV	Air-cooled DX with external condenser	Fuel-fired water boiler with baseboards
System 2	4-pipe fan-coil	CV	Water-cooled, water chiller	Fuel-fired or electric resistance water boiler
System 3	Single-zone packaged rooftop unit with baseboard heaters	CV	Air-cooled DX	Fuel-fired or electric resistance furnace; hot water or electric resistance for baseboards
System 4	Single-zone make-up air unit with baseboard heating	CV	Air-cooled DX	Fuel-fired or electric resistance furnace; hot water or electric resistance for baseboards
System 5	Two-pipe fan-coil	CV	Water-cooled, water chiller	None
System 6	Multi-zone built-up system with baseboard heaters	VAV	Water-cooled, water chiller	Baseboards: electric resistance or hydronic with fuel boiler

The main challenge in using the table above is that the energy source is not mentioned. Therefore, another data source was used to find the primary energy sources used in building consumption in Quebec. Figure 4.7 show the share of different fuels in the heating system from the Survey of

Household Energy Use (SHEU) conducted by Statistics Canada [1]. Therefore, by combining the information from Table 4.7 and Figure 4.7, the energy systems were assigned to Montreal buildings according to the probabilities shown in Table 4.8.

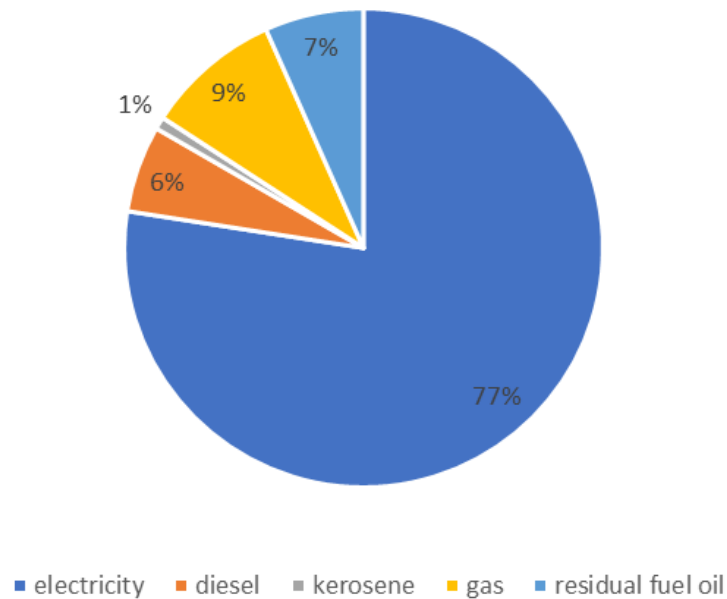


Figure 4.7: Split between different data sources for residential buildings [1]

Table 4.8: System configurations and assigned probabilities.

System	Heating and DHW	Cooling	Probability (%)
System 1 Gas	Natural gas boiler	Air cooled DX unit	15
System 1 Electricity	Electrical resistance heaters	Air cooled DX unit	35
System 2 Gas	Natural gas boiler	-	15
System 2 Electricity	Electrical resistance heaters	-	35

After creating the city and enriching buildings with construction, usage, weather, and energy system data, the UBEM workflow is used to calculate the base case energy consumption in different building archetypes in Montreal. Figure 4.8 presents the base case heating and cooling EUI distributions for different residential building archetypes in Montreal. The results clearly show that heating demand is the most important factor for all archetypes, which makes sense given the city's cold climate. Single-family homes have the greatest heating EUI, with median values over 200 kWh/m²·yr and a wide range that goes up to 600 kWh/m²·yr in extreme cases. This is because detached homes have more envelope exposure per unit floor area and less thermal compactness. In contrast, mid-rise and high-rise apartments have much lower heating EUIs, usually less than 200 kWh/m²·yr, because they share walls and lose less heat per unit. Cooling EUI values are not very high for any of the archetypes; the median is less than 15 kWh/m²·yr,

yet they remain non-negligible during summer periods. Apart from climate conditions of Montreal, another reason for low cooling EUI values is the absence of any cooling system in half of the buildings in the area. High-rise apartments show the lowest heating EUI but a relatively higher spread in cooling demand, indicating sensitivity to internal gains and solar exposure in denser building typologies. High-rise apartments have the lowest heating EUI but a higher range of cooling demand. This means that they are more sensitive to internal gains and sun exposure in denser building types. Overall, these data show that Montreal's retrofit plans need to focus on lowering heating demand while also adding ways to lower cooling demands in multifamily buildings. This is because climate change is likely to make summer cooling needs worse.

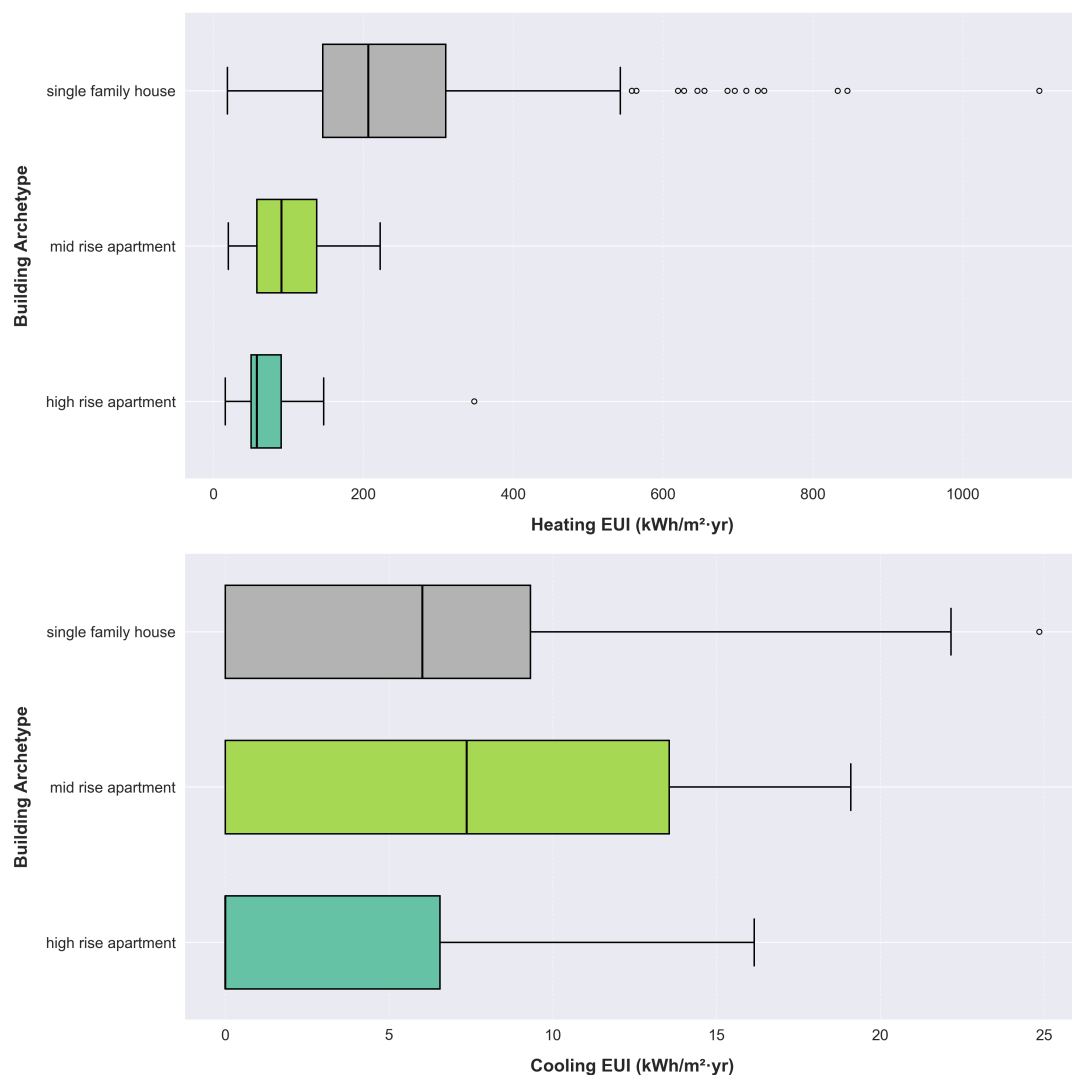


Figure 4.8: Base case energy use intensity for heating and cooling in Montreal.

Similar to Palma, the heating Energy Use Intensity (EUI) per heating system type is plotted and shown in Figure 4.9. Due to the low price of electricity in the province of Quebec, majority of buildings use electrical baseboard heaters to supply their heating and DHW needs. The plot shows that the buildings that use electricity for heating have a slightly lower heating EUI compared to gas-based buildings.

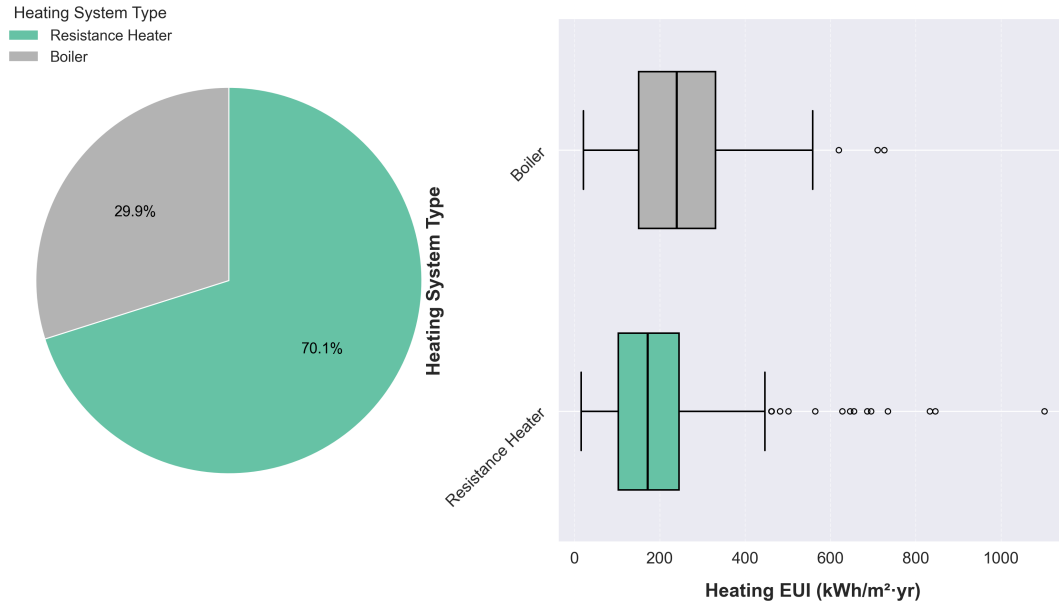


Figure 4.9: Heating system fuel mix and corresponding EUI values in Montreal

4.1.4 Retrofit Technical Analysis

The proposed retrofit for the selected area consists of installing unitary air-to-air heat pumps for space heating and cooling, an air-source domestic hot water heat pump with an integrated storage tank, and a rooftop PV system with and without a battery. The general modelling strategy for these technologies is described in Chapter 3; here the specific approach applied to the retrofit analysis is summarized.

Air-to-air heat pumps are represented using the standard performance-governing relationships between capacity, EIR, and the key operational variables: indoor return air temperature T_i , outdoor source-air temperature T_s , PLR, and FFR. For each operating condition, the model computes modifier values that scale the nominal heating or cooling capacity and the nominal EIR. These modifiers are defined by biquadratic and linear functions recommended in manufacturer data and ASHRAE performance representations. The required mass-flow rate at each time step is determined from the instantaneous heating or cooling load, and the resulting FFR informs the part-load performance. When outdoor temperatures fall below -20.00°C , an auxiliary electric-resistance heater is assumed to meet the remaining demand.

All mathematical expressions for the temperature-dependent and part-load modifier curves used in this analysis—including cooling and heating capacity modifiers, cooling and heating EIR modifiers, and flow-fraction effects—are provided in Appendix 5.3. These functions return dimensionless multiplier values that are applied directly to the nominal performance parameters of each heat pump to compute the actual capacity and efficiency at every simulation time step.

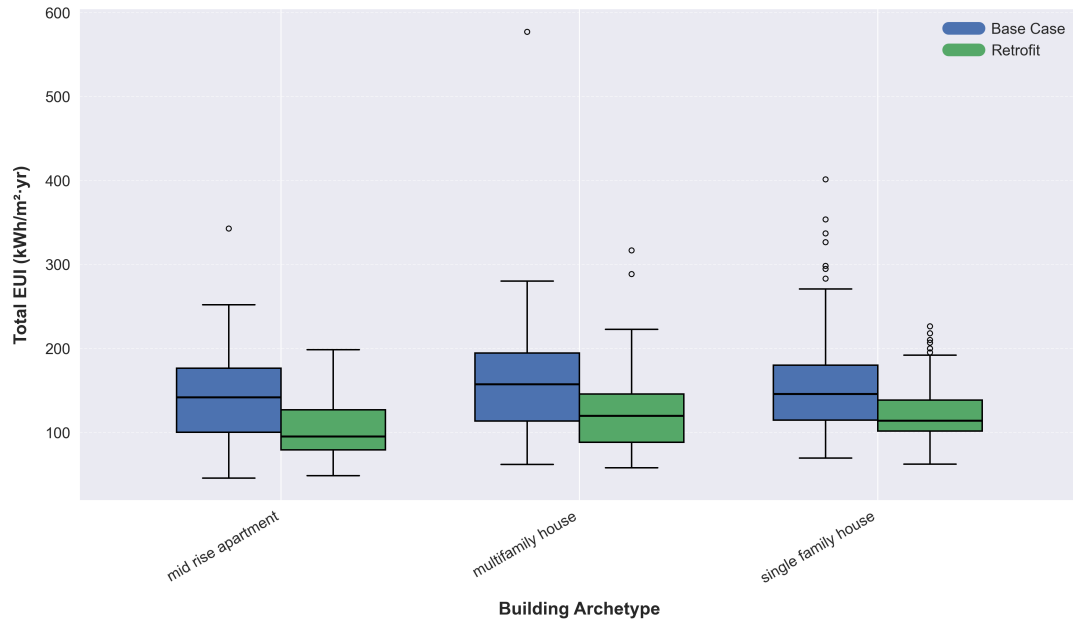
Figure 4.10 compares the total EUI for base case and retrofit scenarios across building archetypes in Palma de Mallorca and Montreal. The results demonstrate the significant impact of retrofit

measures on reducing overall energy consumption in both climates, albeit with differing magnitudes due to climatic context and baseline performance.

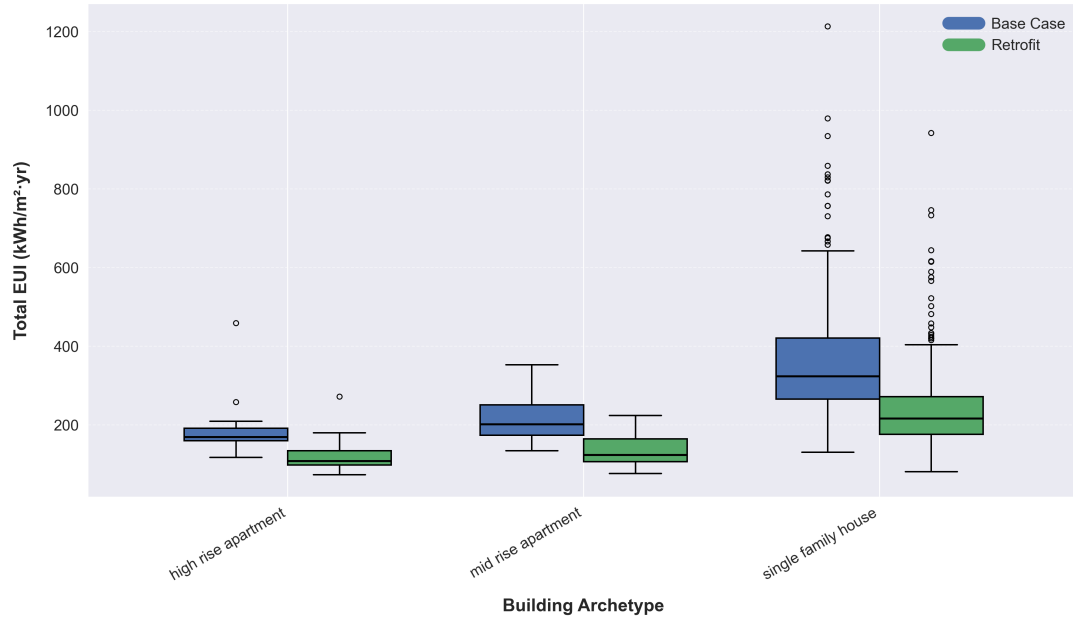
In Palma de Mallorca (Figure 4.10a), the base case EUIs range between 100 and 200 kWh/m²·yr for most archetypes, with single-family houses showing higher variability and some outliers above 300 kWh/m²·yr. The retrofit scenarios consistently reduce median EUIs by approximately 30–40%, with the strongest relative savings observed in multifamily houses. This reduction reflects the effectiveness of heat pump implementation in a Mediterranean climate where both heating and cooling contribute substantially to the annual energy balance.

In Montreal (Figure 4.10b), total EUIs are considerably higher due to the severe heating demand characteristic of cold climates. Single-family houses exhibit the highest baseline EUIs, with medians around 400 kWh/m²·yr and numerous outliers above 800 kWh/m²·yr. Mid- and high-rise apartments perform better on a per-unit-area basis, largely due to compactness and shared envelope surfaces. Retrofit measures yield substantial absolute reductions, with median values dropping by more than 100 kWh/m²·yr in single-family houses and around 50–80 kWh/m²·yr in multifamily archetypes. Despite these improvements, post-retrofit EUIs in Montreal remain higher than the base case EUIs in Palma, underscoring the dominant influence of climate on building energy performance.

Overall, the results confirm that while retrofitting delivers significant energy savings in both climates, the absolute benefits are more pronounced in Montreal due to its higher baseline heating loads. In contrast, in Palma the retrofits serve to balance heating and cooling demands, achieving proportionally large reductions even from lower baseline values. These findings emphasize the need to tailor retrofit strategies to local climatic conditions and building typologies in order to maximize energy performance improvements.



(a) Palma de Mallorca



(b) Montreal

Figure 4.10: Total EUI comparison between base case and retrofit scenarios with air source heat pumps

After evaluating the electrification of HVAC and DHW systems, the self-sufficiency of building electrical demand by using rooftop PV is assessed. The analysis is conducted once with battery and once without battery to understand technical and economic benefits and downsides of implementing battery with residential-scale PV system. In this framework, the performance of PV integration is assessed using two key indicators: Self-Sufficiency (SS) and Self-Consumption (SC). SS represents the fraction of the building's annual electricity demand that can be directly supplied by on-site PV generation, thereby quantifying the degree of autonomy from the grid.

SC, on the other hand, measures the fraction of the PV electricity produced that is consumed within the building, indicating how efficiently the system utilizes its renewable generation without exporting to the grid.

Starting with Palma, the results in Figure 4.11 show a marked improvement in both self-sufficiency (SS) and self-consumption (SC) when batteries are integrated with rooftop PV systems. Without storage, median SS values remain below 0.5 across all archetypes, indicating that less than half of the building’s annual electricity demand is directly covered by on-site PV production. The inclusion of a battery increases median SS to the range of 0.7–0.8, particularly for multifamily houses and single-family houses, highlighting the role of storage in shifting excess PV generation to periods of demand.

A similar pattern is observed for SC. In the base case without batteries, SC values are relatively low, especially for single-family houses where median values remain below 0.3, due to the temporal mismatch between daytime PV production and residential load profiles. With the addition of battery storage, median SC increases substantially to around 0.6–0.7 for mid-rise apartments and single-family houses, demonstrating improved alignment between generation and demand. This improvement is especially pronounced in the mid-rise apartment archetype, where the larger aggregated load profile leads to better utilization of stored PV energy.

Overall, the Palma results suggest that while rooftop PV alone can contribute to reducing grid dependency, its effectiveness is limited without complementary storage. The addition of batteries not only enhances energy autonomy (higher SS) but also improves the efficiency of PV utilization (higher SC). However, these technical benefits must be weighed against the additional investment costs, which are further addressed in the economic sections of this work.

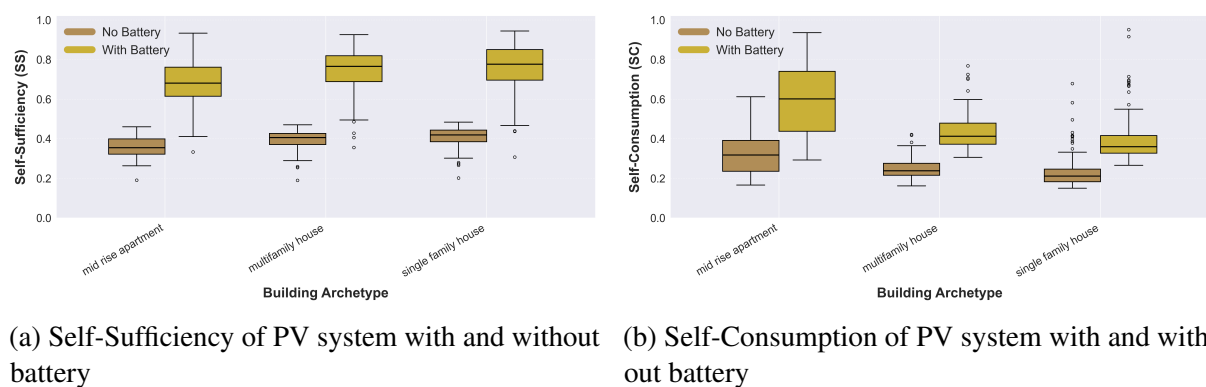


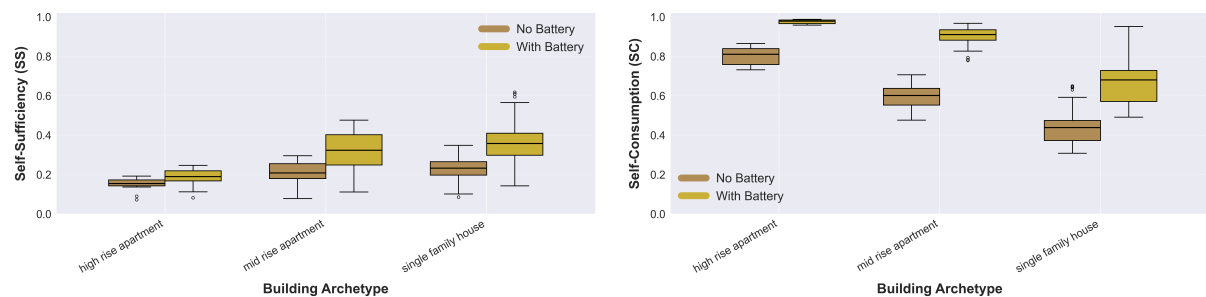
Figure 4.11: PV system KPIs in building archetypes of Palma de Mallorca

The impact of climate on PV system capability in supplying the building electricity demand is clear when comparing the results for Montreal (Figure 4.11). Due to the higher heating loads and lower solar resource compared to Palma, self-sufficiency (SS) values remain relatively modest across all archetypes. Without batteries, median SS values do not exceed 0.25, even in single-family houses where rooftop PV area is relatively large. The addition of battery storage

improves SS, particularly for single-family houses where median values rise above 0.4, but the overall levels remain well below those observed in Mediterranean conditions. This underscores the limitations of PV alone in offsetting demand in cold climates dominated by heating loads.

The trends in self-consumption (SC) highlight the strong influence of building load profiles on PV utilization. Without batteries, high-rise apartments already achieve very high SC values (above 0.8) because their aggregated demand aligns closely with PV generation, leaving little surplus energy for storage. In contrast, single-family houses show lower base-case SC (around 0.4), reflecting a larger mismatch between production and demand. Battery integration increases SC significantly in these cases, with median values approaching 0.7. Mid-rise apartments fall in between, showing clear benefits from batteries but still constrained by their higher winter demands.

Overall, the Montreal results indicate that while battery storage enhances both SS and SC, its role is more critical in low-density residential archetypes where mismatch between PV production and demand is greatest. However, even with batteries, PV systems are not capable of reaching high levels of self-sufficiency under cold-climate conditions, reaffirming the importance of complementary strategies such as deep envelope retrofits, demand-side management, and low-carbon centralized heating solutions.



(a) Self-Sufficiency of PV system with and without battery

(b) Self-Consumption of PV system with and without battery

Figure 4.12: PV system KPIs in building archetypes of Montreal

4.1.5 Retrofit Economic Analysis

The methodology explained in 3.4 is used to calculate the life cycle cost of system retrofit project in both climates. The costing workflow uses the cost functions defined in the energy system data model. Therefore, for any urban area, during preparation of the input data file for creating the catalogue of energy system archetypes, the cost functions using an optional currency must be provided. For example, the cost functions defined for Palma are in Euros (€), while the Montreal cost functions are in Canadian dollar CA\$. Therefore, the results presented in this section for each city are in their corresponding currencies and in the following section for cross-climate analysis, all costs are converted to CA\$.

4.1.5.1 Palma Table 4.9 presents the LCC analysis parameters, fuel costs, and component cost functions. All the costs have been found from peer-reviewed journal papers or engineering reports.

Table 4.9: Fuels, LCC analysis parameters, and component cost functions used for Palma de Mallorca

Fuels [174]		
Fuel name	Price (€/kWh)	
Purchased electricity (from grid)	0.23	
Sold electricity (to grid)	0.08	
Natural gas	0.10	
Butane	0.13	
LCC analysis parameters		
Parameter	Value	
LCC duration (years)	30	
Interest rate (%)	4	
Discount rate (%)	3	
Energy system components cost function		
Component (units)	Purchase cost	Maintenance cost
Air-to-Air heat pump (€/kW)	997 [175]	22 [176]
Battery (€/kWh)	400 [177]	-
DHW heat pump (€/unit)	780 [178]	24 [176]
Storage tank (€/m ³)	500 [177]	-

The PV cost is not included in the table as the following function is used for calculating the investment cost of PV modules alone [179]. Moreover, the maintenance cost of the PV system with and without battery is assumed to be 25 €/ kW / year and 52 €/ kW / year [180].

$$C(P) [e/kW_p] = \begin{cases} 1600, & P \leq 10, \\ 1800 - 20 P, & 10 < P \leq 20, \\ 1566 - 8.33 P, & 20 < P \leq 50, \\ 1178 - 0.556 P, & 50 < P \leq 500, \\ 900, & P > 500. \end{cases} \quad (71)$$

The costing workflow is capable of assessing the LCC of each system in the archetype, separately. However, here only the total LCC of all systems together with a focus on the impact of including battery in the system is presented. As shown in 4.10a, the total EUI of all archetypes drops after replacing current HVAC and DHW systems with air source heat pumps. This drop leads to reduction of yearly energy billing cost. Figure 4.13 shows a comparison between the median yearly operational cost of HVAC and DHW systems in base case and retrofitted scenarios for

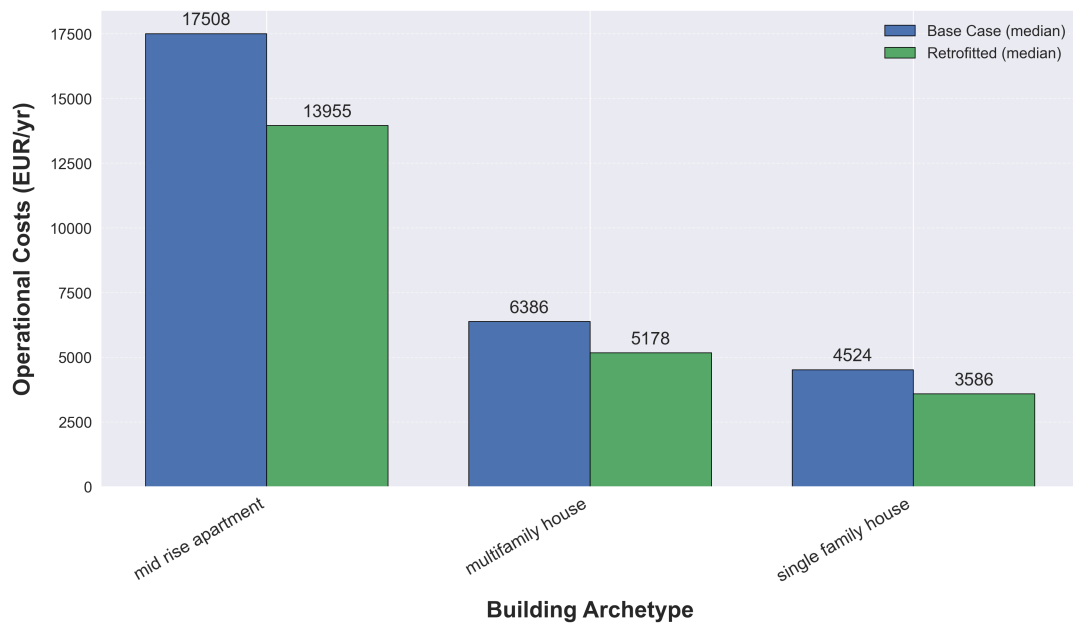


Figure 4.13: Yearly operational costs of HVAC and DHW systems before and after retrofit in Palma de Mallorca

each archetype. It should be noted that each archetype represents a complete building rather than an individual dwelling unit. In the case of apartment archetypes, the reported operational costs correspond to the entire residential block, comprising multiple housing units and a substantially larger conditioned floor area than single-family houses. The results illustrate the impact of electrification and retrofitting on the annual operational costs of HVAC and DHW systems in Palma. In all building archetypes, replacing conventional systems with air-source heat pumps leads to a noticeable reduction in yearly energy bills. Mid-rise apartments, which represent the largest and most energy-intensive archetype, show the highest absolute reduction, with median costs decreasing from approximately 17,500 €/yr in the base case to around 13,950 €/yr after retrofitting. Multifamily houses and single-family houses experience more moderate savings in absolute terms, but still achieve reductions of roughly 1,200 €/yr and 940 €/yr, respectively. In relative terms, the operational cost reductions correspond to approximately 20% for mid-rise apartments, 19% for multifamily houses, and 21% for single-family houses, indicating that the retrofit strategy delivers consistent proportional savings across archetypes despite differences in absolute energy use.

In the life cycle cost (LCC) analysis of the proposed energy system archetypes, four cost categories are considered: annualized capital costs, operational costs, maintenance costs, and operational incomes. No incentive scheme or subsidy is included in this study, and according to Spanish regulations, the annual revenues from selling electricity back to the grid cannot exceed the operational costs of the building. The costing workflow is applied to two scenarios: one including battery storage and one without, in order to evaluate the financial implications of PV–battery integration in Palma.

Figure 4.14a shows the median cost components for systems with battery storage. The most evident trend is the significant increase in capital costs, with values between 280 and 476 €/m², depending on the archetype. Operational costs are lower than in the no-battery case, reflecting improved self-consumption and reduced grid dependence, but this reduction is partially offset by higher maintenance costs, which reach up to 330 €/m². Operational incomes are relatively modest, in the range of 108–217 €/m², limited by the regulatory cap. As a result, total LCC values with batteries are the highest across both scenarios, exceeding 800 €/m² for multifamily and single-family houses.

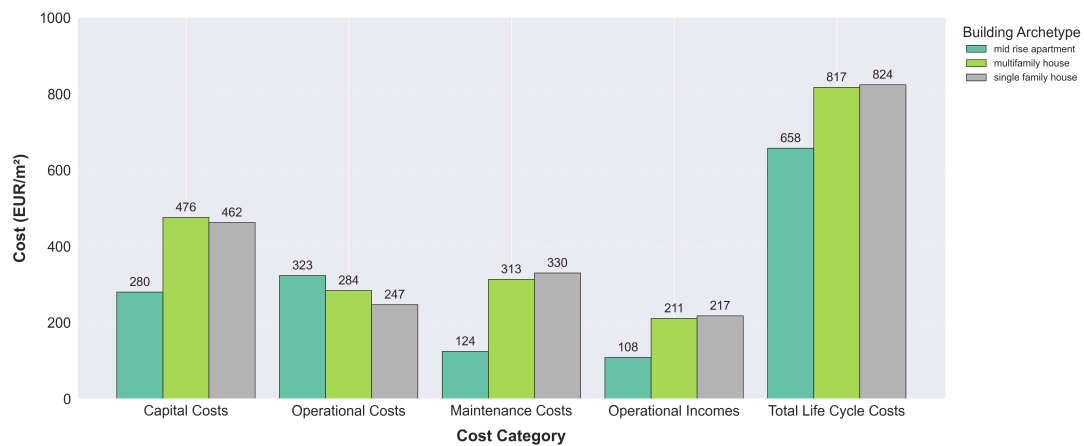
By contrast, Figure 4.14b illustrates the no-battery scenario. Here, capital costs are much lower, ranging from 203 to 230 €/m², while operational costs increase to 609–652 €/m² due to greater reliance on grid electricity. Maintenance costs are lower than in the battery case, and operational incomes are substantially higher, between 491 and 562 €/m², since a larger share of surplus PV generation is exported. Despite the higher operational costs, the combination of lower capital and maintenance expenditures together with higher incomes results in total LCC values that are consistently lower than the battery case, ranging between 466 and 627 €/m².

These results highlight a critical trade-off: while batteries improve technical performance indicators such as self-sufficiency and self-consumption, their higher capital and maintenance costs make them financially less attractive under current Spanish market and policy conditions. In the absence of stronger incentives for storage or higher compensation for grid exports, PV systems without batteries appear to provide more favorable long-term economics in Palma.

This type of insight illustrates the value of the proposed framework, which enables the systematic evaluation of trade-offs between technical performance and economic feasibility across competing retrofit options. At the same time, it is important to note that even the most cost-effective configurations still entail substantial life-cycle costs, underscoring that electrification and decarbonization pathways require significant upfront investment despite their long-term operational benefits.

4.1.5.2 Montreal The same procedure is repeated for the city of Montreal. Table 4.10 contains the cost data of the city of Montreal. The main source of data for Montreal is the RSMEANS [181] online data repository which is the leading source of construction cost information in North America. In Montreal, electricity is billed under a net-metering scheme, meaning that exported electricity is credited at the same rate as electricity purchased from the grid; therefore, the same price is used for both purchased and sold electricity in the table. Natural gas tariffs in Quebec include both a fixed monthly service charge and a variable volumetric charge. For the purpose of the LCC analysis, these components were combined into a single effective average price expressed in CA\$/kWh.

Figure 4.15 shows that, although the majority of buildings in Montreal already rely on electrical systems to supply their household heating needs, the retrofit scenario consistently reduces the



(a) System with battery



(b) System without battery

Figure 4.14: Median values of LCC components in Palma de Mallorca with and without battery

Table 4.10: Fuels, LCC analysis parameters, and component cost functions used for Montreal

Fuels		
Fuel name	Price (CA\$/kWh)	
Purchased electricity (from grid)	0.07	
Sold electricity (to grid)	0.07	
Natural gas	0.07	
LCC analysis parameters		
Parameter	Value	
LCC duration (years)	30	
Interest rate (%)	4	
Discount rate (%)	3	
Energy system components cost function		
Component (units)	Purchase cost	Maintenance cost
Air-to-Air heat pump	$750.93 \cdot (P)^{1.051}$ (CA\$/kW) [181]	30 (CA\$/unit/year) [176]
DHW heat pump	2200 ((CA\$/unit) [182]	24 [182]
PV module	$3086.6 \cdot (P)^{-0.061}$ (CA\$/kW _p)	40 (CA\$/kW _p /year) [180]
Battery (CA\$/kWh)	400 [177]	45 (CA\$/kW _h /year) [180]

yearly operational costs across all archetypes. Despite achieving comparable relative savings, apartment archetypes retain the highest absolute operational costs due to their larger conditioned floor area, higher aggregate domestic hot water demand, and the presence of centralized systems serving multiple dwelling units. The most significant absolute reduction is observed in high-rise apartments, where median annual costs decrease from approximately 37,100 CA\$/yr in the base case to about 21,850 CA\$/yr after retrofitting. Mid-rise apartments also benefit substantially, with costs falling from 17200 CA\$/yr to 10,656 CA\$/yr. Single-family houses exhibit the lowest absolute costs but still achieve meaningful savings, with operational expenditures reduced from slightly over 5,700 CA\$/yr to 3,528 CA\$/yr.

It should also be noted that in the base case scenario, approximately half of the buildings were assumed to have no active cooling systems, whereas the retrofitted systems provide both heating and cooling. Despite this added service, the retrofitted configurations still achieve lower operating costs, demonstrating the efficiency advantage of heat pump technology over conventional systems.

These results underscore the strong link between technical performance improvements and economic benefits at the household level. They highlight that even in an electricity-dominated heating context such as Montreal, where fossil-fuel substitution plays a limited role, significant cost reductions can be realized through electrification with high-performance heat pump systems. The results further confirm that the economic benefits of retrofitting are not limited to fuel-switching contexts, but extend to cases where efficiency improvements and the provision of integrated heating and cooling lead to direct household savings.

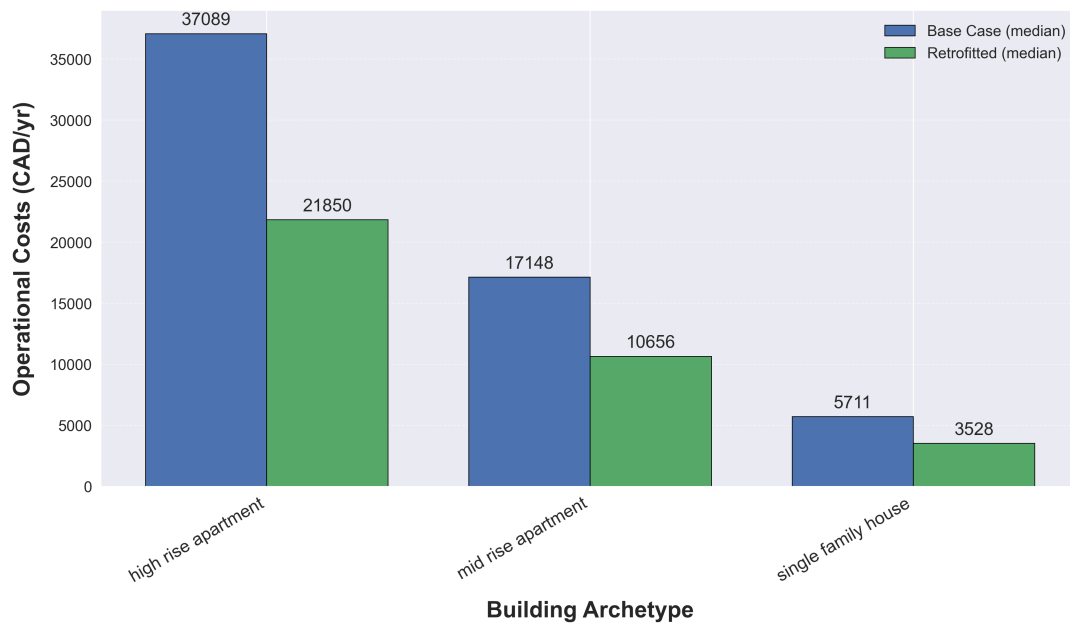


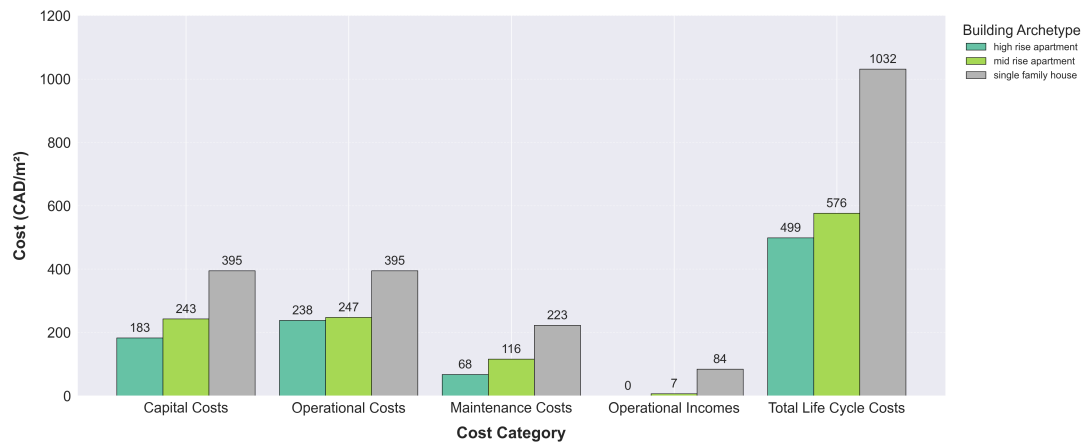
Figure 4.15: Yearly operational costs of HVAC and DHW systems before and after retrofit in Montreal

Figure 4.16 presents the life cycle cost (LCC) components of the retrofitted energy systems in Montreal for the two scenarios of PV deployment with and without battery storage. The results highlight the financial implications of battery integration in a cold-climate context, where both the demand profile and regulatory framework play a critical role in shaping cost-effectiveness.

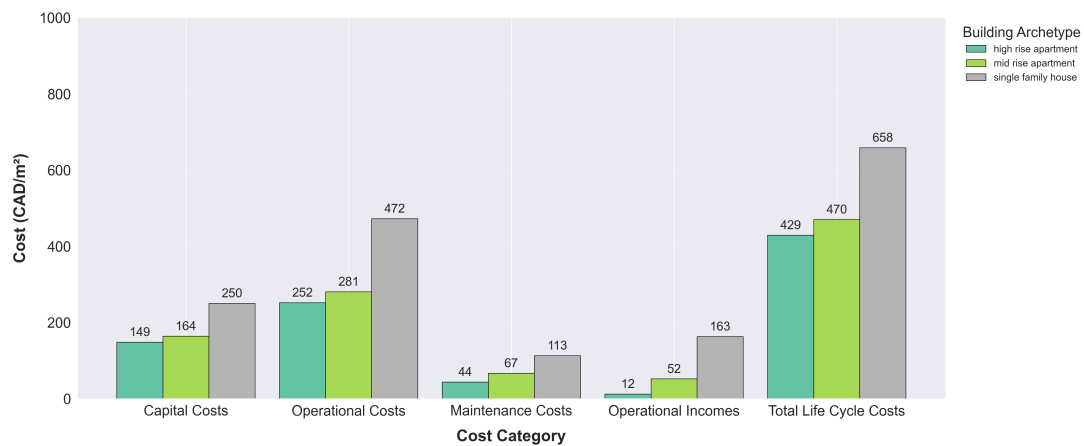
In the battery scenario (Figure 4.16a), capital costs are noticeably higher than in the no-battery case, ranging between 187 and 406 CAD/m², depending on the archetype. Operational costs are also significant, particularly for single-family houses where values reach 395 CAD/m². Maintenance costs increase across all archetypes, reflecting the additional service requirements of storage systems, while operational incomes remain relatively modest (below 100 CAD/m²) because of limited compensation for exported electricity. As a result, total LCC values are highest in this scenario, exceeding 1,000 CAD/m² for single-family houses and approaching 600 CAD/m² for multifamily buildings.

In contrast, the no-battery case (Figure 4.16b) demonstrates a more favorable cost distribution. Capital costs are lower, ranging from 153 to 281 CAD/m², and although operational costs remain substantial—particularly for single-family houses at 472 CAD/m²—the absence of storage reduces maintenance costs considerably. Operational incomes are slightly higher in this case, as more surplus PV generation is exported, though still capped by regulatory rules. The overall effect is that total LCC values remain below those of the battery case, ranging between 428 and 664 CAD/m², making the no-battery systems more financially viable in the Montreal context.

Taken together, these results suggest that while batteries can provide technical benefits in terms



(a) System with battery



(b) System without battery

Figure 4.16: Median values of LCC components in Montreal with and without battery

of self-sufficiency and self-consumption (as shown in Section ??), their economic justification is less compelling under current conditions in Montreal. The high capital and maintenance costs of storage systems outweigh the limited operational savings and modest revenues from electricity exports. This finding emphasizes the importance of local market design and policy support: unless incentives, higher feed-in tariffs, or carbon pricing mechanisms are introduced, PV systems without batteries remain the more cost-effective solution for residential archetypes in cold climates such as Montreal.

4.1.6 Cross-Climate Analysis

Across both Palma and Montreal, the retrofit packages anchored by unitary air-source heat pumps perform robustly: they reduce delivered energy for space conditioning relative to the baseline and lower operating costs across all archetypes. This consistency across two contrasting climates establishes heat pumps as a climate-agnostic and economically effective first step for building decarbonization.

When photovoltaic generation is introduced, battery storage remains economically challenging in

both contexts, although for different underlying reasons. In Palma, adding a battery substantially improves technical autonomy—raising median self-sufficiency and self-consumption into the 0.7–0.8 range for several archetypes—but this benefit comes at a clear economic premium. Median life-cycle costs exceed 800 €/m² in battery-equipped systems, whereas PV-only configurations remain significantly more cost-effective (approximately 466–627 €/m²), supported by strong solar resources and favorable export compensation. In Montreal, battery systems are likewise financially unattractive: winter-dominated heating loads and limited seasonal PV surplus constrain storage utilization, leading to higher LCC values (approaching 600 CAD/m² for multifamily buildings) without commensurate gains in self-sufficiency.

These trends are synthesized in Figure 4.17, which compares *no-battery* scenarios only and presents Palma results converted to CAD for parity. Montreal solutions (circles) cluster at lower self-sufficiency with comparatively lower life-cycle costs, reflecting heating-driven demand profiles and modest PV surplus, while Palma solutions (squares) extend toward higher self-sufficiency levels—often exceeding 60%—at increased cost intensity. Archetype effects persist in both climates: mid-rise apartments benefit from scale effects and occupy the lower-cost envelope, whereas single-family houses exhibit greater cost sensitivity as self-sufficiency increases. Overall, the cross-climate analysis indicates that (i) heat pumps represent the universal and most cost-effective retrofit lever, (ii) PV-only systems provide the best cost–benefit balance in both cities, and (iii) battery storage remains economically unattractive under current market and tariff conditions, becoming justifiable only where very high self-sufficiency targets outweigh the associated cost premium.

4.1.7 Summary

This section showcased the development and application of the developed ESMF supported by its generic energy system data model. The framework enables the representation of diverse energy systems through modular object classes, capturing generation, storage, conversion, and distribution technologies in a unified structure. By separating data from simulation logic, the approach ensures adaptability to different contexts, ranging from building-scale retrofits to community-scale microgrids.

The results demonstrate that the framework can capture a wide range of techno-economic and performance indicators, while remaining computationally efficient and transparent. Its generic structure allows for straightforward integration of new technologies, empirical performance curves, and optimization algorithms, without requiring changes to the underlying architecture. This provides significant advantages for analyzing complex energy transitions, where flexibility and interoperability across data sources are critical.

The framework was tested through case studies that compared energy system performance across different climates and archetypes. By applying the same generic data model in both



Figure 4.17: Variations of LCC per floor area against PV self-sufficiency in Palma and Montreal

Mediterranean (Palma) and cold-climate (Montreal) contexts, the framework successfully captured variations in heating and cooling demands, seasonal performance of heat pumps, and the economic implications of integrating PV and battery storage. The results confirmed the robustness of the approach: heat pumps consistently improved efficiency in both climates, PV reduced operational costs, and batteries provided additional flexibility, though with higher capital expenditures. These findings validate the framework’s capacity to reproduce realistic system behaviors and highlight its utility for cross-contextual analyses of renewable energy integration.

4.2 Building retrofit prioritization workflow: Case study of low-rent municipal housing in Montreal

Managing energy performance across a portfolio of buildings is complex, especially when financial and operational resources are constrained. The developed retrofit prioritization workflow offers a practical decision-support tool that helps managers identify which buildings should be upgraded first, based on objective performance and economic criteria. This approach enhances the strategic planning of retrofit investments and supports long-term energy management goals.

The principles and structure of the proposed workflow are described in Section ?? . In this section, the application of the workflow is demonstrated using a group of municipal buildings located in Montreal. First, the case study is introduced, followed by an overview of the current condition and energy performance of the buildings. The workflow is then applied to identify which

buildings are most in need of retrofitting and to establish their priority for intervention. Finally, the capabilities of the workflow are illustrated through an energy system retrofit scenario analysis performed across the selected buildings, along with a detailed assessment of the highest-priority building.

4.2.1 Case study

The Office municipal d'habitation de Montréal (OMHM) is a public organization responsible for managing social and affordable housing in Montreal. Their office oversees many residential buildings, most for low-income people, seniors, and families. The OMHM is also important for urban renewal and community development in many neighbourhoods, in addition to providing safe and affordable housing. It helps people who live there by working with other groups and running social programs to improve life, encourage energy efficiency, and ensure the long-term sustainability of the housing stock.

Among its many responsibilities, one of the most critical roles of OMHM is ensuring that its building portfolio remains in good physical and operational condition. Given the aging infrastructure and rising energy costs, it is essential to continuously monitor these buildings to identify those with poor energy performance. Targeted retrofits help reduce energy consumption and improve indoor thermal comfort for residents, many of whom belong to vulnerable populations. This study selected a subset of 201 buildings from the OMHM portfolio for detailed energy assessment. The common feature of all these buildings is that they use natural gas for heating. The reason behind this selection is that in their “2030 Energy Policy”, the government of Québec has reiterated its main objective of reducing Québec’s greenhouse gas emissions by 37.5% below 1990 levels by 2030. According to the statistics, residential, commercial, and institutional buildings accounted for 10.3% of GHG emissions in Québec in 2017, which is the third largest emitting sector in the province. Therefore, retrofitting these buildings reduces energy consumption while helping achieve the government’s objectives. Going forward, these selected buildings will be called the OMHM buildings.

The selected buildings are categorized into 3 groups of mid-rise apartments, high-rise apartments, and duplex-triplex buildings. This categorization is done solely based on building heights using the following constraints:

- **Duplex/Triplex:** $H \leq 10$ m
- **Mid-Rise Apartment:** $10 < H \leq 20$ m
- **High-Rise Apartment:** $H > 20$ m

Figure 4.18a and Figure 4.18b show the vintage and usage distribution of selected buildings. Over half of the buildings are mid-rise apartments, and most buildings were built between 1951 and 1980. Given the fact that 96% of buildings are over 25 years old, these buildings need to be

studied carefully to choose the best retrofitting option for them.

In order to assess the severity of the need to retrofit the OMHM buildings, their monthly gas and electricity consumptions are retrieved from their energy bills to calculate their measured total EUI. This data was compared against two other sets of data: the first data is received from the utility company of the Quebec province, HydroQuebec, and contains the energy consumption of multifamily buildings as well as duplex-trip buildings around Montreal that use electricity for all their energy needs, including heating and domestic hot water. The other dataset is the simulation results of the OMHM buildings using the UBEM workflow, using the construction, usage, and energy system archetypes in Montreal.

The comparison in Figure 4.19 reveals that OMHM buildings generally exhibit higher total Energy Use Intensity (EUI) than fully electrical buildings from the Hydro-Québec (HQ) dataset. For multifamily buildings (Figure 4.19a), the median of the EUI values calculated from the measured data is between 250 and 300 kWh/m²·yr, which is about twice as much as the median for HQ buildings (100–150 kWh/m²·yr). The simulated results (CERC) are very close to the measured OMHM data, which shows that the UBEM workflow accurately shows how well they work. For duplex/triplex buildings, the same pattern can be seen (Figure 4.19b), with both measured and simulated EUIs around 300–350 kWh/m²·yr, which is again higher than HQ benchmarks. The consistently higher consumption during construction periods shows that the OMHM stock hasn't gotten much more efficient, even for newer buildings.

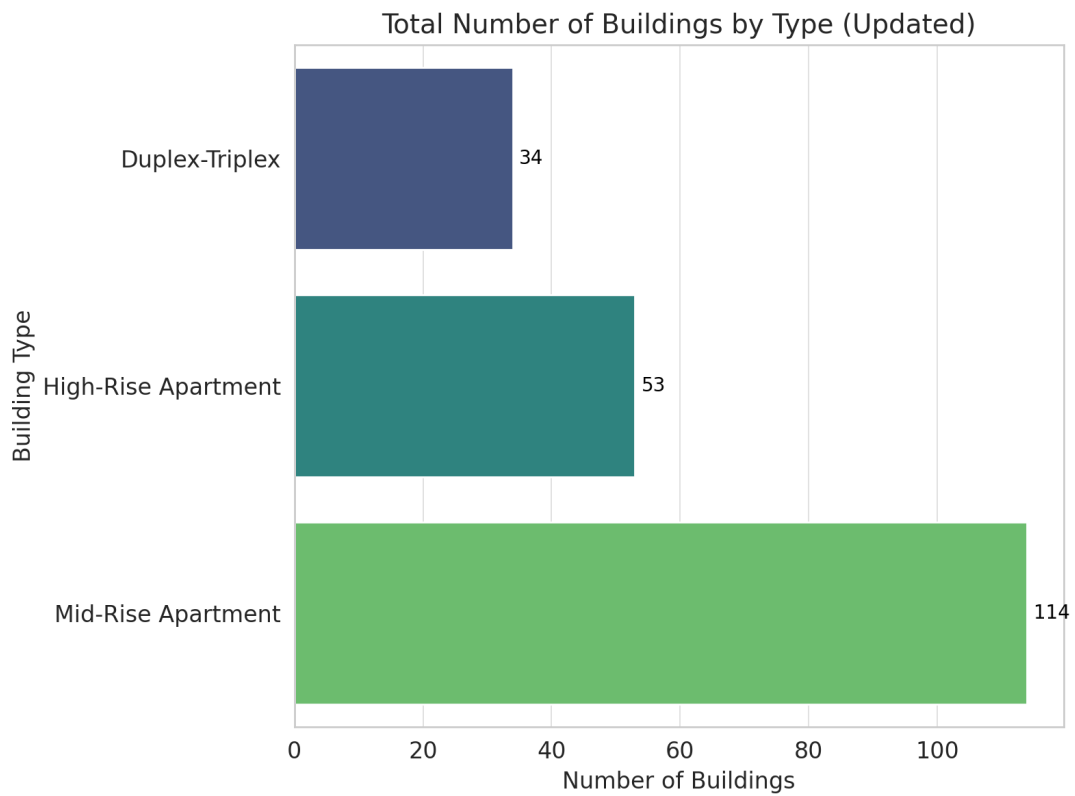
Overall, these comparisons highlight the severity of the retrofit need in the OMHM portfolio. Despite being located in the same climatic region and having similar functional uses, the OMHM buildings consume roughly two to three times more energy than comparable electrically heated buildings in Montreal. This reinforces the necessity for targeted retrofit strategies.

4.2.2 Building Retrofit Prioritization

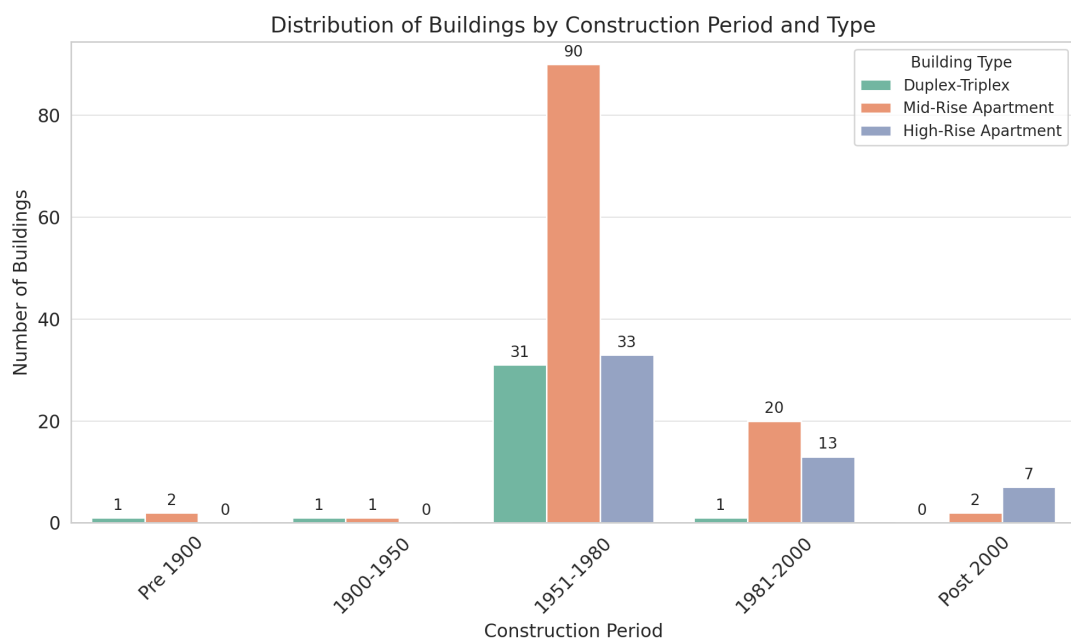
After preparing the input files, including the geometry file and the energy billing data of the buildings, the UBEM workflow was applied to simulate the energy needs of the OMHM stock. The PRISM methodology (Section 3.7.1) was then used on measured and simulated data to evaluate the actual and expected thermal performance of building envelopes and heating systems.

The output of the analysis for the measured data is shown in Figure 4.20. The colour of each point shows the change-point temperature of the building, which is the outdoor temperature at which the building goes from heating to cooling. The x-axis represents the base load (non-weather-dependent energy use) and the y-axis represents the absolute value of the heating slope, corresponding to the sensitivity of energy demand to outdoor temperature variations.

As mentioned in the Methodology (3), a reference point based on kernel density estimation (KDE) is identified, representing the most typical operational behaviour within the dataset. Buildings with higher slope values (i.e., above the horizontal reference line) exhibit greater

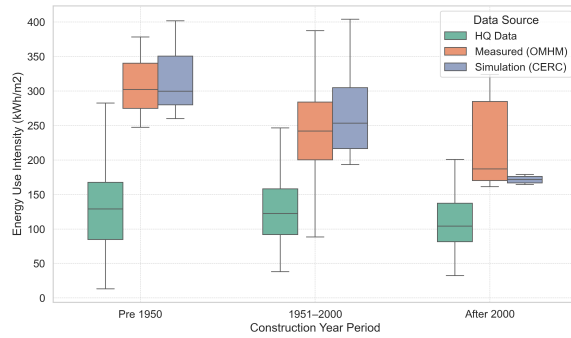


(a) Building types in the studied portfolio

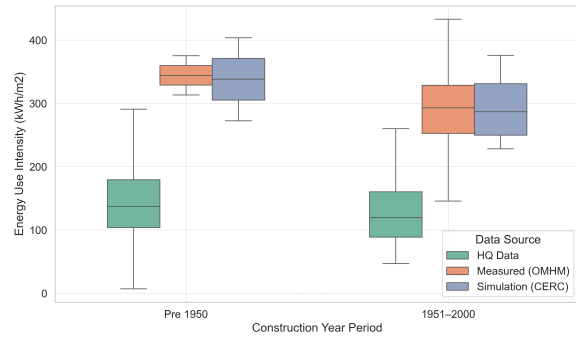


(b) Construction periods of building archetypes

Figure 4.18: Building portfolio types and vintages



(a) Multifamily buildings



(b) Duplex/Triplex buildings

Figure 4.19: Comparison of measured total EUI in OMHM buildings with fully electrical buildings and simulation results

sensitivity to outdoor temperature variations, which may indicate inadequate thermal envelope performance, inefficient heating systems, or both. Similarly, buildings located to the right of the vertical reference line exhibit higher base-load values, reflecting elevated non-weather-dependent energy consumption. This higher base load is primarily associated with increased electrical and process-related loads, such as appliances, lighting, and equipment, which in turn contribute to higher internal heat gains as a secondary effect.

Based on this classification, the upper half of the plot identifies buildings that should be prioritized for retrofit actions *relative to the rest of the portfolio*, as they exhibit a stronger dependence of energy use on outdoor temperature. Buildings located in the top-right quadrant are the most critical cases, combining high base-load values with steep heating sensitivity slopes, which indicates concurrent inefficiencies in non-weather-dependent energy use and temperature-driven heating performance.

Conversely, buildings located in the bottom-left quadrant perform comparatively better *within the analyzed dataset*, as they exhibit both lower base loads and reduced sensitivity to outdoor temperature variations. This suggests relatively more efficient envelope characteristics, system operation, or internal load management compared to the portfolio average. It is important to note, however, that this relative classification does not imply compliance with an absolute performance standard or best-practice benchmark. Rather, the KDE-based reference point provides a data-driven means of ranking buildings against their peers, enabling the robust identification of the worst-performing buildings that warrant immediate retrofit attention.

This plot provides a clear, data-driven foundation for identifying the buildings in most need for retrofit in the building stock. It highlights which buildings perform poorly and distinguishes between where improvements should target the envelope (slope reduction) versus the internal systems (base load reduction). At this stage, 79 buildings have a slope worse than the reference point and have been selected for retrofit.

To complement the PRISM-based shortlist, the absolute heating slopes derived from monthly

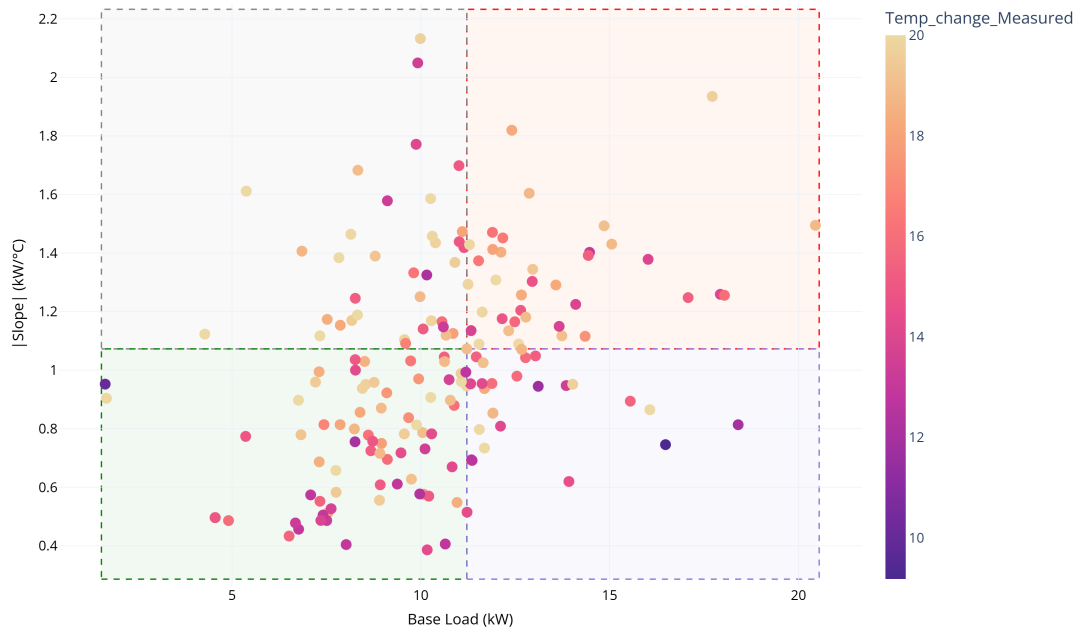


Figure 4.20: Heating slope against the base load values for all the buildings in the OMHM stock based on monthly energy bills. Each point represents a building and is color-coded according to its change-point temperature.

bills are compared with those predicted by the calibrated archetype simulation. Since archetypes encode the prevailing standards and systems of their construction era, a building whose measured sensitivity to outdoor temperature exceeds the simulated sensitivity is likely underperforming relative to its peer archetype. This second screen, therefore, helps recover buildings that the first phase may miss.

Figure 4.21 plots $|\text{Slope}|_{\text{Measured}}$ against $|\text{Slope}|_{\text{Simulated}}$, with dashed reference lines at (1, 1). The decision rule is deliberately simple and transparent:

$$r = \frac{|\text{Slope}|_{\text{Measured}}}{|\text{Slope}|_{\text{Simulated}}}.$$

Buildings with $r > 1$ underperform their archetype and are added to the retrofit list if not selected. In the figure, red points are the buildings selected in Phase 1; gold points are newly identified here because their measured slope exceeds the simulated slope; green points are not selected.

This consistency check provides diagnostic insight in both directions. First, gold points frequently appear when measured heating sensitivity is high while simulated sensitivity is low, suggesting performance degradation or operational issues that are not captured by the archetype assumptions. Second, when simulated performance appears worse than measured performance, it is often more appropriate to review modelling assumptions—such as schedules, setpoints, or system efficiencies—before initiating retrofit actions.

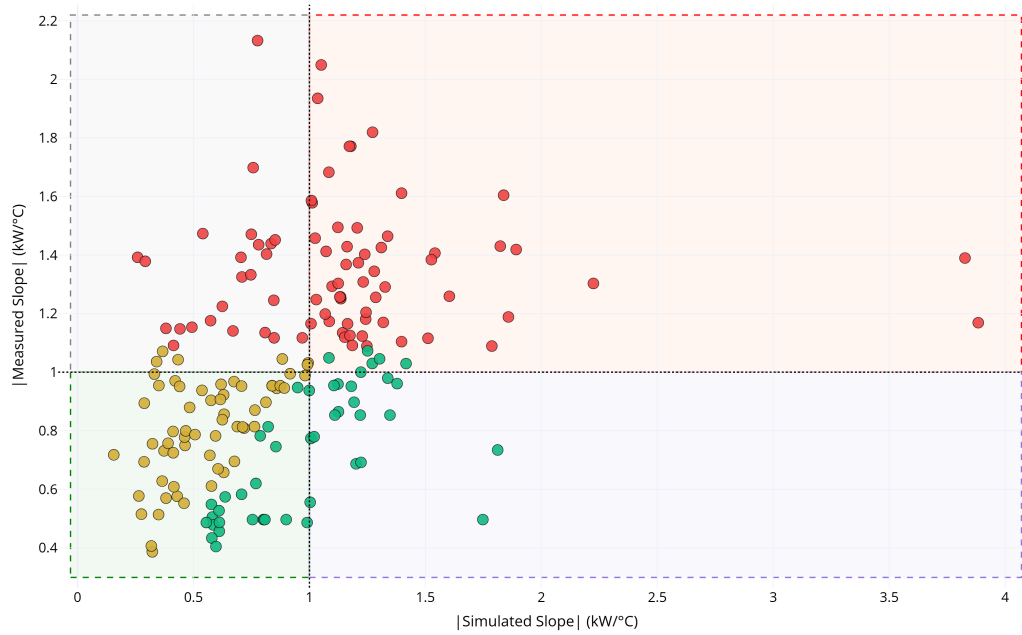


Figure 4.21: Heating slope against the base load values for all the buildings in the OMHM stock based on monthly energy bills. Each point represents a building and is color-coded according to its change-point temperature.

It should be noted that this diagnostic approach is based on observed energy consumption and therefore may not fully capture situations of suppressed demand, such as fuel poverty. In cases where occupants are unable to afford adequate heating, measured energy use and heating sensitivity may appear artificially low despite poor envelope or system performance. As a result, fuel-poor households could be misclassified as better-performing assets within the portfolio. While the proposed workflow cannot directly identify fuel poverty, the comparison between simulated demand (representing required energy for nominal comfort conditions) and measured consumption can help flag atypical discrepancies that warrant further socio-technical investigation. Consequently, the method should be interpreted as a technical screening tool that supports—rather than replaces—contextual assessments when prioritizing retrofit actions.

In the end, out of the initial 202 buildings in the stock, 140 buildings were identified as requiring retrofit interventions at different levels of priority. As explained in Sections 3.7.2 and 3.8, the selected buildings were ranked using the TOPSIS decision-making algorithm based on four criteria: the building volume-to-skin-surface-area ratio, total measured yearly energy consumption, total measured energy use intensity (EUI), and the heating slope derived from the PRISM analysis of the measured data.

Figure 4.22 illustrates the Euclidean-normalized values of the four retrofit prioritization criteria for the top 20 ranked buildings. Each row corresponds to a building, while each column represents one of the decision criteria. The colour gradient (from dark to bright) shows how big each criterion is after being normalized on a 0–1 scale. Higher intensities mean bigger

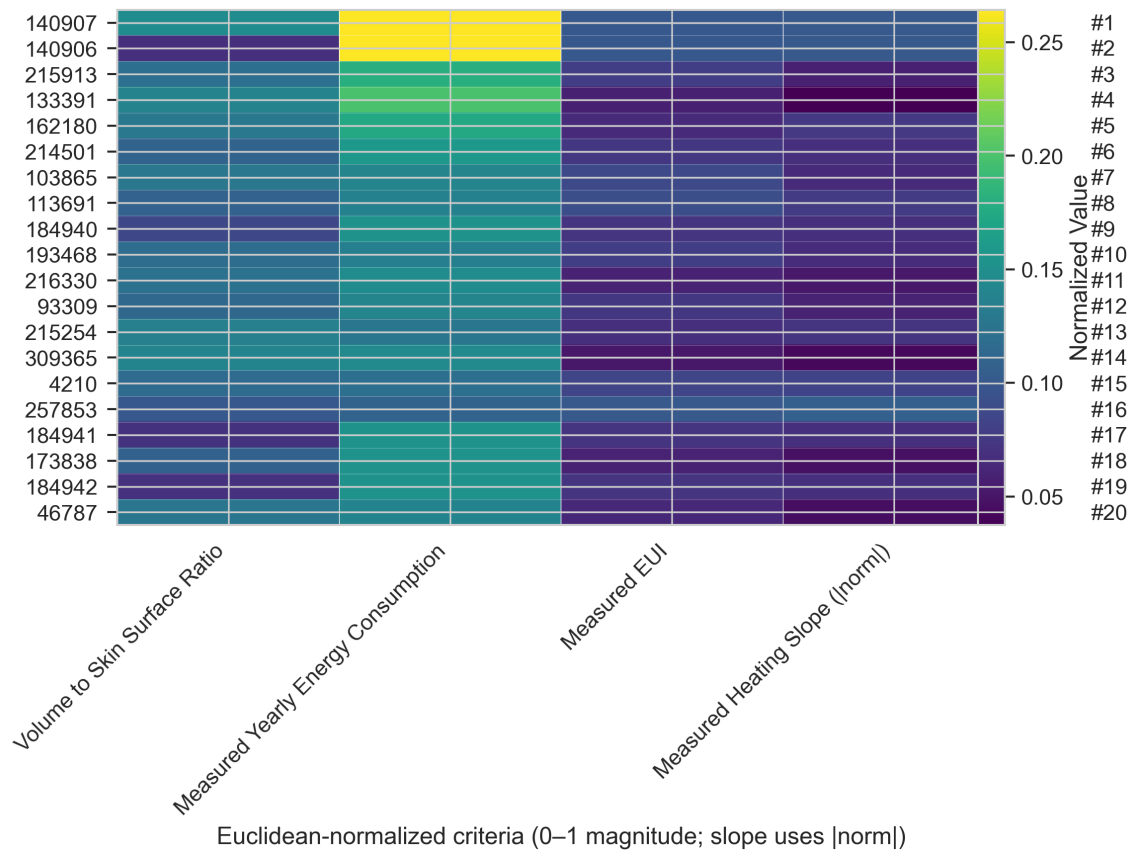


Figure 4.22: Euclidean-normalized values of retrofit prioritization criteria (absolute heating slope normalization) for the top 20 ranked buildings.

normalized values.

Buildings that rank high on the list usually have high normalized values for total energy consumption, EUI, and heating slope magnitude. These three things together mean that the building is not very thermally efficient and is more sensitive to changes in outdoor temperature. In contrast, buildings with darker colours tend to occupy lower positions in the ranking, indicating more favourable energy and envelope performance. The distinct colour variations across the top-ranked buildings demonstrate how the combined influence of geometry (volume-to-skin-surface ratio), energy consumption, and thermal behaviour drives the overall prioritization outcome.

4.2.3 Building stock retrofit analysis

The developed workflow automatically performs retrofit scenario analyses for all buildings identified as candidates for energy renovation. In this case study, a total of 140 buildings were subjected to a series of retrofit simulations representing different levels of intervention. Each scenario targets a specific aspect of the building, enabling the quantification of potential improvements individually and in combination. The four considered scenarios are described below:

- **Glazing:** Replacing old windows with high-performance triple-glazed units that have lower U-values and better solar heat gain coefficients, in line with current efficiency standards. Although glazing-only interventions are included as an isolated scenario for comparative purposes, it is acknowledged that replacing windows without improving the surrounding envelope can lead to hygrothermal issues such as increased risk of condensation at wall interfaces.
- **Skin:** Upgrading the building envelope, which includes the walls, roofs, and floors, to meet modern thermal transmittance standards.
- **System:** Replacing current HVAC and DHW systems with high-efficiency heat pump technologies, such as unitary air-to-air heat pumps for heating and cooling spaces and unitary air-to-water heat pumps for making DHW.
- **Full:** An integrated retrofit scenario that combines the glazing, envelope, and system improvements, representing a comprehensive deep retrofit case.

This systematic approach makes it possible to assess each retrofit action's individual and total benefits, which helps with making smart choices about planning for large-scale building stock renovation. Figure 4.23 shows how the total EUI is spread out over the three main types of buildings: Duplex–Triplex, Mid-Rise Apartment, and High-Rise Apartment. The boxplots show how the simulated annual EUI values ($\text{kWh}/\text{m}^2\cdot\text{yr}$) for all buildings of the same type change when retrofitting. Across all typologies, a consistent downward trend can be observed from the base case toward the full retrofit scenario, indicating that progressive combinations of envelope and system upgrades lead to substantial energy savings. The *System* retrofit has the biggest effect because it replaces old heating and DHW systems with efficient heat pumps. The "Full" scenario, which includes all retrofit measures, has the lowest median EUI and the narrowest distribution range. This means that buildings perform better and there is less variation between them. This overall pattern shows that the integrated retrofit approach improves energy performance across a wide range of building types.

The most common indicators to compare after applying various retrofit scenarios are operational costs, emissions, and peak electricity load. The developed workflow evaluates these performance indicators and automatically generates comparative boxplots for all retrofitted buildings. Figure 4.24 shows the impact of each retrofit scenario on the annual operational cost, CO₂-equivalent emissions, and electricity peak demand.

The first subplot shows that the operational cost per unit floor area (CAD/m^2) goes down with each level of intervention. The *Skin* and *System* scenarios demonstrate significant reductions, mostly due to better thermal performance and the use of high-efficiency heat pump systems. Glazing improvements alone don't have as big of an impact compared to the base case. The "Full" retrofit scenario, which includes both envelope and system upgrades, has the lowest median operational cost (about 6.5 CAD/m^2), which is a big drop from the base case.

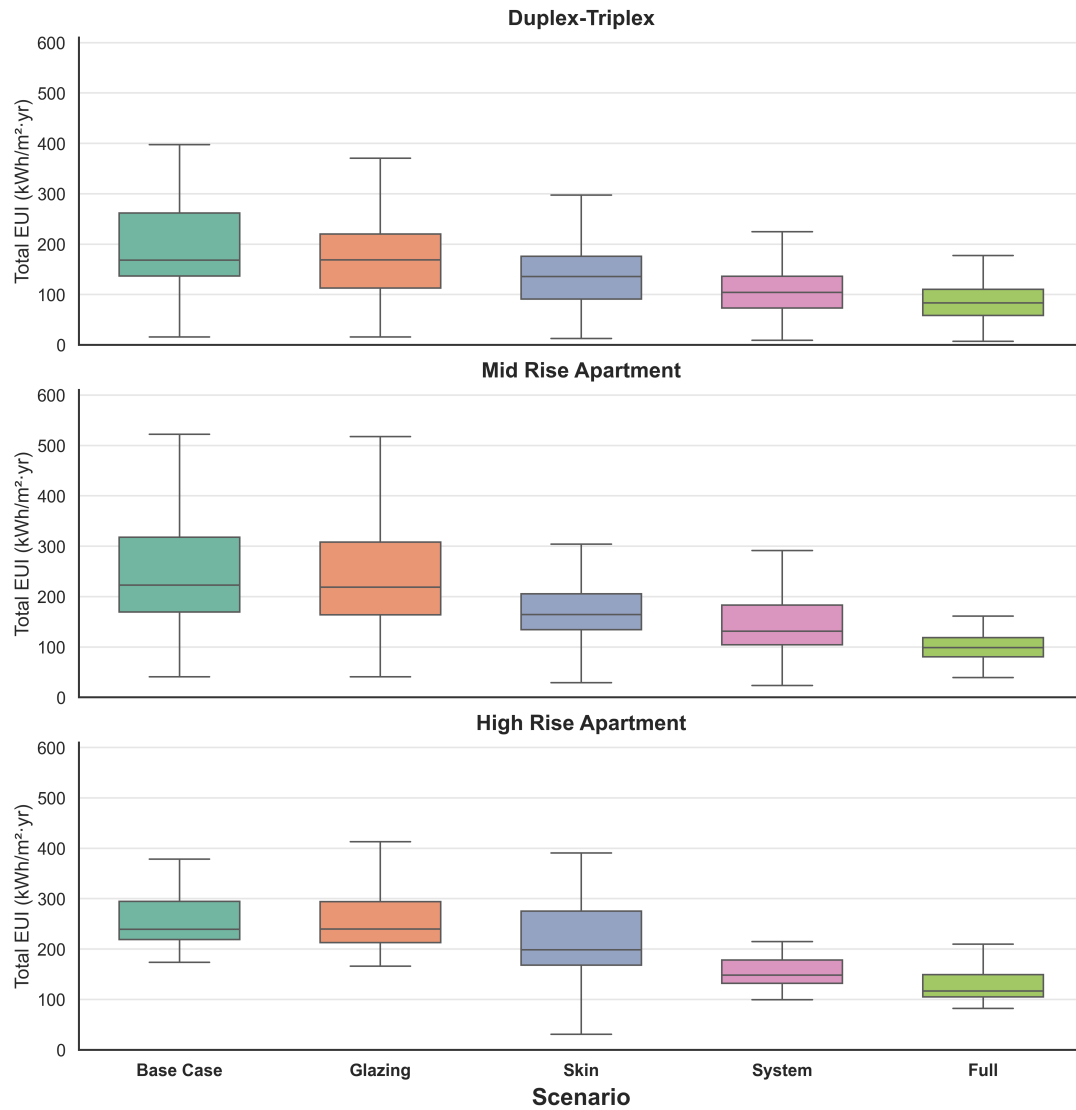


Figure 4.23: Distribution of total EUI across retrofit scenarios for the three main building types.

The second subplot illustrates the annual CO₂-equivalent emissions (kgCO₂e/yr) across the retrofit scenarios. Similar to operational costs, emissions decrease significantly with increasing retrofit depth. The *Skin* scenario achieves an average reduction of nearly 45% compared to the base case, while the *Full* scenario results in the lowest overall emissions. This improvement is primarily attributed to the low-carbon electricity mix in the province of Québec, Canada, where the emission factor for grid electricity is approximately 1.7 gCO₂/kWh, compared to 172.8 gCO₂/kWh for natural gas [183, 184]. Consequently, retrofitting measures that switch out fossil-fuel-based systems for electrically powered heat pumps cut down on total GHG emissions significantly, even though they consume more electricity.

The third subplot presents the simulated peak electricity demand (W/m²). In contrast to cost and emissions, the *System* and *Full* scenarios show an increase in peak demand relative to the base case, reflecting the higher electrical loads introduced by the electrification of heating and domestic hot water systems. Although this transformation increases the electricity peak load,

it is followed by a notable reduction in total energy use and emissions, which is in line with long-term decarbonization objectives. These results emphasize the importance of integrating demand-side management and load-shifting strategies when planning large-scale electrified retrofits to avoid stressing the electrical grid.

4.2.4 Summary

This section presented a use case of the building portfolio retrofit prioritization workflow by applying it on a subset of the OMHM building stock in Montréal. The analysis demonstrated how monthly energy billing data, archetype-based UBEM simulations, and PRISM-derived thermal performance indicators can be combined to identify underperforming assets and prioritize retrofit needs across a large portfolio. Using a two-phase screening process, 140 buildings were selected as candidates for intervention based on excessive heating slopes, elevated base loads, and underperformance relative to their simulated archetypes. These buildings were then ranked using the TOPSIS decision-making method, which incorporated geometric characteristics, measured energy consumption, EUI, and PRISM-derived heating sensitivity to establish an objective and transparent priority order.

The workflow also enabled a large-scale retrofit scenario analysis across the selected buildings, quantifying the impact of envelope improvements, glazing upgrades, and system electrification using heat pumps. Results showed consistent reductions in EUI, operating costs, and GHG emissions across all building typologies, with the combined *Full* retrofit scenario yielding the greatest improvements. At the same time, the transition to high-efficiency electric systems led to increased peak electrical demand, underscoring the need for coordinated planning with grid operators. Overall, the case study highlights the practicality, scalability, and diagnostic value of the proposed workflow for supporting data-driven, portfolio-wide retrofit decisions in urban housing stocks.

4.3 An energy system modelling framework for optimal sizing and life cycle cost assessment of energy systems in urban areas

In the previous sections, the applications of the proposed frameworks to district- and urban-scale assessments were presented. Another use case of the developed ESMF is the automatic optimal sizing of energy systems in individual buildings. Figure 4.25 summarizes the corresponding workflow. Once the building heating and cooling demands have been calculated using the UBEM workflow (Section 3), the framework performs a rapid feasibility screening of candidate generation components, with the current implementation focusing on heat pump technologies. In this step, the maximum achievable capacities of WWHP and Ground-Source Heat Pump (GSHP) systems are also determined based on site- and source-specific constraints.

Based on the feasibility results, an energy system archetype is selected from the system catalogue

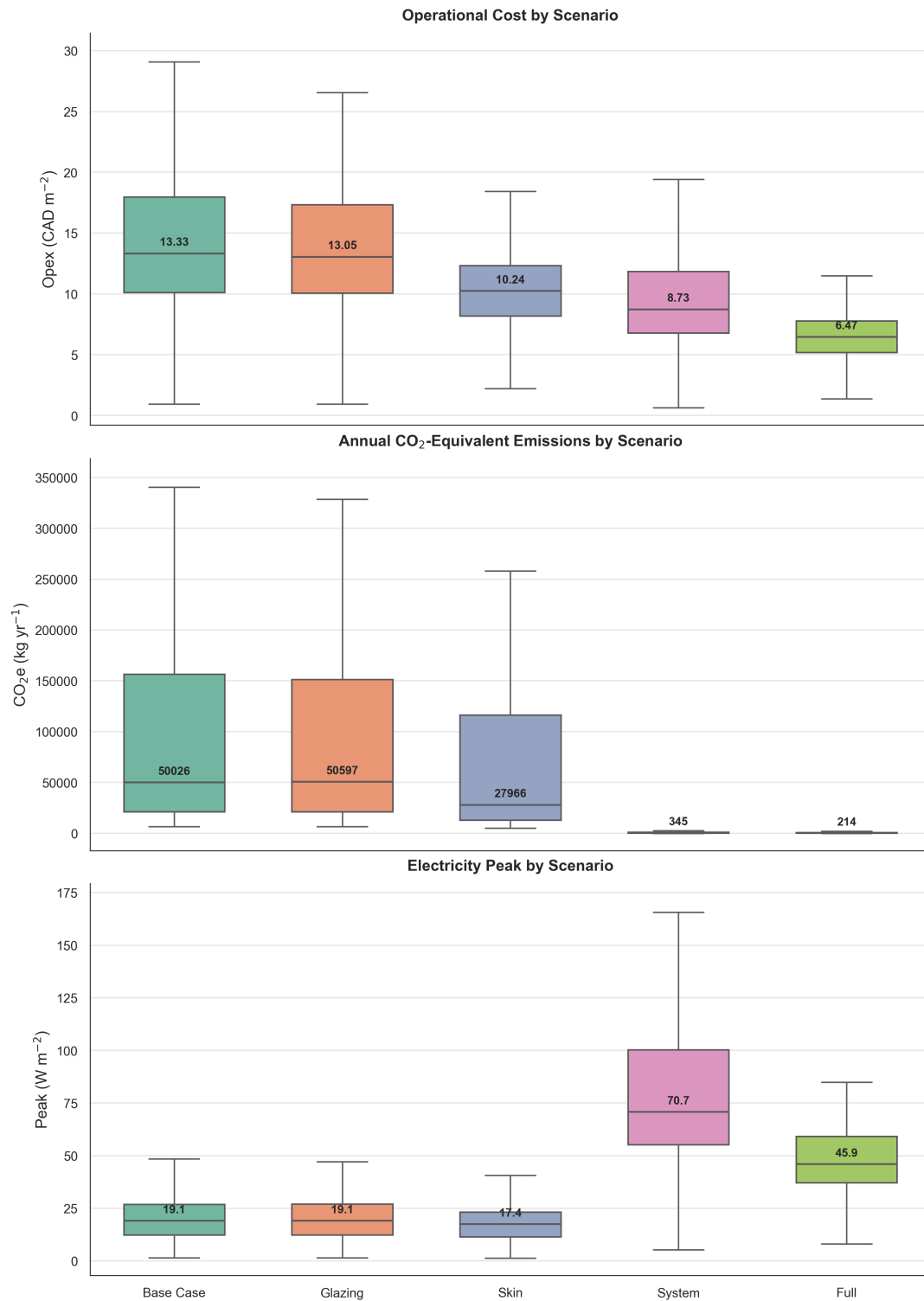


Figure 4.24: Distribution of operational costs, CO₂-equivalent emissions, and peak electricity demand across retrofit scenarios for the entire building stock

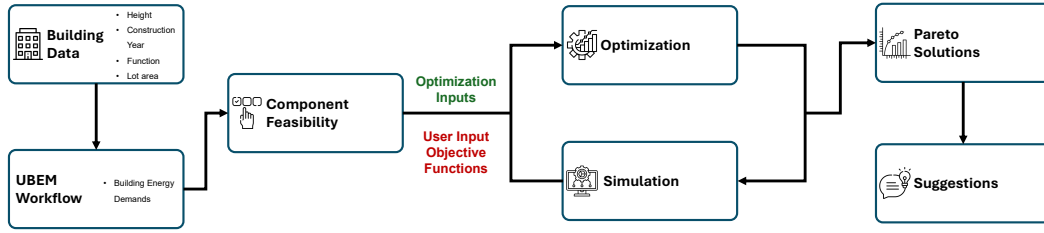


Figure 4.25: Application of the energy system optimization workflow at the building scale.

that contains exactly those components deemed viable. This archetype defines the set of decision variables and their bounds, as well as the boundary conditions passed to the NSGA-II algorithm. The multi-objective optimization then searches for optimal values of the selected decision variables (e.g., generation capacities, storage size, borehole depth) with respect to user-defined objectives such as peak heating capacity, life-cycle cost intensity, energy use intensity, or emissions. To evaluate the fitness of each individual and verify its feasibility, a pre-defined simulation model associated with the chosen archetype is executed as part of the optimization loop.

The optimization focuses exclusively on system design; operational optimization is not within the scope of this work. Each energy system archetype is therefore associated with a predefined rule-based control strategy, which remains fixed throughout the optimization.

The output of the optimization is a Pareto set of non-dominated solutions. Using the TOPSIS method, a preferred “balanced” solution is selected from the Pareto front, together with solutions that minimise each individual objective. These representative designs can then be reported back to the user and compared against the performance of the existing system where applicable.

In the following, the capabilities of the optimization workflow are illustrated and assessed using two buildings from the OMHM portfolio and three analysis cases:

- (1) A high-rise building constructed in the 1970s, identified for retrofitting by the retrofit prioritisation workflow.
- (2) A mid-rise building constructed in the 1960s. This case enables a preliminary assessment of how building archetype and lot geometry influence feasible technologies.
- (3) A hypothetical new development obtained by updating the construction year of the selected high-rise building to 2025, in order to reflect current construction standards while preserving the same geometry.

4.3.1 Feasibility Assessment and Component Pool

In the first step of the workflow, the hourly heating and cooling demands of the three study cases are computed using the UBEM methodology described in Chapter 3. Table 4.11 summarizes the key geometric and energy-related characteristics of the buildings, together with parameters that

directly influence the feasibility of ground-source and wastewater-source heat pump systems. The peak thermal loads reported in the table are used to bound the decision-variable capacities during optimization, while the lot and borefield geometry determine the maximum feasible size of a ground heat exchanger field. Wastewater access is available in all cases, enabling the inclusion of WWHP technology in the pre-assessment step.

Table 4.11: Geometric and energy characteristics of the three study cases.

	Case 1	Case 2	Case 3
Building type	High-rise	Mid-rise	High-rise
Construction year	1977	1968	2025
Footprint area (m ²)	1542	950	1542
Lot area (m ²)	5510	1300	5510
Total floor area (m ²)	18515	5890	18515
Building height (m)	37	17	37
Maximum number of boreholes (-)	100	4	100
Current heating system	Gas boiler	Gas boiler	–
Current cooling system	Air-cooled DX	Air-cooled DX	–
Heating peak load (kW)	829	230	474
Cooling peak load (kW)	758	226	521
Yearly heating EUI (kWh/m ²)	99	79	–
Yearly cooling EUI (kWh/m ²)	13	13	–
Total HVAC EUI (kWh/m ²)	112	92	–

The rows *Available borefield area* and *Maximum number of boreholes* in Table 4.11 are computed directly from the site geometry using a simple geometric pre-sizing approach. First, the effective borefield area A_{bf} is defined as

$$A_{bf} = 0.8 (A_{lot} - A_{fp}), \quad (72)$$

where A_{lot} is the lot area and A_{fp} is the building footprint area. The factor 0.8 accounts for setbacks, circulation space, underground utilities, and other practical constraints that typically prevent the full unbuilt portion of the lot from being used for borehole installation.

A square borefield is then inscribed within the available area, giving a side length $s = \sqrt{A_{bf}}$. A clearance of 1 m between the outermost boreholes and the field boundary is imposed. Boreholes are assumed to have default diameter $d_{bh} = 0.12$ m and horizontal pitch

$$p = s_{bh} + d_{bh}, \quad (73)$$

where s_{bh} denotes the centre-to-centre spacing between adjacent boreholes. The maximum

number of boreholes per side of the square field is then

$$n_{\text{side}} = \left\lfloor \frac{s - 2 \text{edge}_{\text{clear}} - d_{\text{bh}}}{p} \right\rfloor + 1, \quad (74)$$

with $\text{edge}_{\text{clear}} = 1$ m. The resulting maximum number of boreholes is

$$N_{\text{bh}} = n_{\text{side}}^2. \quad (75)$$

This computed value is included in Table 4.11 and also can be used as an upper bound for the number of boreholes if it is selected as a decision variable in the optimization process.

The next step is to assess the feasibility of implementing ASHP, GSHP, and WWHP. In the present implementation, the feasibility screening is performed at the level of the heat source rather than the emission side. Once a given source (air, ground, or wastewater) is classified as feasible, all catalogue components that rely on that source (e.g., water-to-water and water-to-air variants) are treated as available for system configuration. Conversely, if a source is deemed infeasible, none of its associated component variants are included in the component pool for that case. For GSHP, the borefield geometry derived above is used as input to the dynamic ground heat exchanger model (Section 3). Given the hourly ground load profile and an assumed ground thermal conductivity, the model determines the maximum extractable capacity that can be supported without violating thermal constraints. In particular, the total borehole depth is limited to 120 m per borehole as suggested by [185], and the entering fluid temperature must remain above a -1.00°C throughout the simulation. An additional geometric cap on the specific heat extraction rate (40 W/m) [185] is applied to avoid unrealistically high loading of the borefield. The resulting maximum achievable GSHP capacity is then compared against the building design peak load: if it is less than 10 % of the peak load, the GSHP option is classified as infeasible. This combined geometric and thermal screening ensures that only sites with sufficient geo-exchange potential are carried forward to the detailed optimization stage.

For WWHP, the measured or simulated hourly wastewater temperatures for the building under assessment are required. In this study, the methodology proposed by [150] is used to calculate the hourly wastewater temperature in Montreal. Following their approach, the wastewater temperature is expressed as a function of the outdoor dry-bulb temperature and a fifth-degree polynomial that captures the diurnal variation of sewer temperature. The intercept of the polynomial is adjusted using a linear correlation with the outdoor dry-bulb temperature and a constant bias term, ensuring that seasonal and hourly variations are represented consistently. The resulting hourly sewer temperature is then shifted by $\pm 6.83^\circ\text{C}$ to obtain the entering water temperature at the heat pump for heating and cooling modes, respectively, corresponding to the temperature drop (or rise) across the wastewater–ambient-loop heat exchange process identified in [150]. This procedure provides a complete year of hourly wastewater-source temperatures

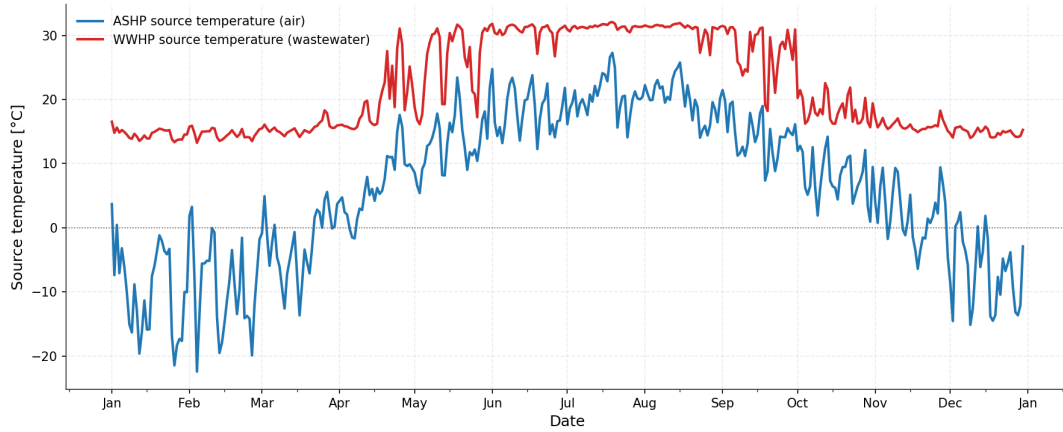


Figure 4.26: Comparison of source temperature for ASHP and WWHP in Montreal

required for evaluating WWHP feasibility and performance within the proposed framework.

Figure 4.26 presents the hourly averaged source temperatures for the ASHP and WWHP systems in Montreal. The ASHP source temperature follows the outdoor air temperature and therefore exhibits strong seasonal and diurnal variability, with winter values frequently dropping below -20°C and summer peaks exceeding 25°C . In contrast, the WWHP source temperature remains significantly more stable throughout the year, generally fluctuating within a narrower range around $15\text{--}32^{\circ}\text{C}$. This damped thermal behaviour reflects the large thermal inertia of the sewer network and highlights the advantage of wastewater as a reliable low-grade heat source.

Table 4.12 summarizes the outcome of this feasibility screening for the three cases, showing in particular that WWHP is feasible in all buildings, whereas GSHP is ruled out for the mid-rise case due to the limited borefield area and resulting low maximum capacity.

Table 4.12: Feasibility analysis results for the three cases.

Parameter	Case 1	Case 2	Case 3
ASHP feasibility	True	True	True
GSHP feasibility	True	False	True
WWHP feasibility	True	True	True
Maximum boreholes per row	10	2	10
Maximum boreholes per column	10	2	10
Maximum capacity of GSHP (kW)	389	10	389
Maximum capacity of WWHP (kW)	160	51	160
Design peak load (kW)	829	230	521

4.3.2 Optimization Setup and Objective Functions

Once the feasible components have been identified, the next step is to assemble the corresponding energy system archetype and specify the inputs required for life-cycle cost assessment and multi objective optimization. In the intended full implementation of the framework, the user will be

able to browse all archetypes in the system catalogue that are compatible with the feasibility results and then select:

- (1) the preferred archetype configuration, and
- (2) the set of objective functions to be optimized.

In the present study, a single archetype is automatically constructed for each case based on the feasible component pool identified in the previous section. Table 4.13 summarizes the resulting component availability for the three cases examined in this work. In all archetypes, the system is assumed to supply both space heating and space cooling: the same reversible heat pumps operate in heating and cooling modes, while the thermal storage tank is used only on the heating side.

Table 4.13: Component pool for each study case based on feasibility screening

Component Type	Case 1	Case 2	Case 3
Air-Source Heat Pumps			
Air-to-Water ASHP	✓	✓	✓
Air-to-Air ASHP	✓	✓	✓
Wastewater-Source Heat Pumps			
Water-to-Water WWHP	✓	✓	✓
Water-to-Air WWHP	✓	✓	✓
Ground-Source Heat Pumps			
Water-to-Water GSHP	✓	✗	✓
Water-to-Air GSHP	✓	✗	✓
Auxiliary Heating Systems			
Gas Boiler	✓	✓	✓
Electrical Boiler	✓	✓	✓

In this section, to provide a comprehensive demonstration and verification of the optimization algorithm, each case is implemented with an energy system archetype that includes all feasible generation components and a single stratified hot-water storage tank. The reversible heat pumps are sized to meet both heating and cooling demands, while the storage tank is used only for thermal buffering on the heating side.

Now that the system components have been selected for each configuration, the optimization decision variables, their bounds, and the governing constraints of the problem can be formally defined. The optimization problem relies on a set of design-oriented decision variables that determine the configuration and sizing of the hybrid system. These variables include the installed capacities of the wastewater-source heat pump (C_{wwhp}), ground-source heat pump (C_{gshp}), air-source heat pump (C_{ashp}), gas boiler ($C_{boiler,gas}$), electric boiler ($C_{boiler,electric}$), and the thermal

energy storage system (C_{tes}). In order to focus on the algorithm's ability to explore the space of generation and storage capacities, the geometric characteristics of the borefield (number of boreholes per row and column, and borehole depth) are kept fixed at their pre sized values and are not treated as decision variables.

Table 4.14: Optimization decision variables for the three cases.

Case	Decision Variables
Case 1	$C_{wwhp}, C_{gshp}, C_{ashp}, C_{boiler,gas}, C_{boiler,electric}, C_{tes}$
Case 2	$C_{wwhp}, C_{ashp}, C_{boiler,gas}, C_{boiler,electric}, C_{tes}$
Case 3	$C_{wwhp}, C_{gshp}, C_{ashp}, C_{boiler,gas}, C_{boiler,electric}, C_{tes}$

Regarding the system control, all generation units prioritize charging the TES, while the TES itself is solely responsible for meeting the building's instantaneous heating demand. The control logic in these systems is therefore centered on maintaining the SOC of the thermal storage between specified upper and lower thresholds. The operation of the generation components follows these rules:

- The TES is charged whenever its SOC is below the upper threshold. Once the upper threshold is reached, all generation units are turned off, allowing the tank to discharge naturally until it reaches a safe SOC.
- The operation of the WWHP and GSHP is governed entirely by the SOC of the storage tank. If the SOC falls below the lower threshold, both heat pumps operate at full capacity. If the SOC lies between the upper and lower limits and the tank is actively being charged, only the larger of the two heat pumps operates.
- The ASHP operates only when the other heat pumps are unable to raise the tank supply temperature sufficiently to increase the SOC, and only when outdoor air temperature is above -20.00°C .
- The auxiliary boilers operate exclusively as a last resort, activated only when all heat pumps are unable to raise the supply flow temperature to the required level.

The SOC of the TES is computed using the instantaneous tank temperature and the thermodynamic temperature limits that define the usable energy content of the storage. These limits are not the same as the operational charging and discharging thresholds used for control. If T_{tank} denotes the bulk temperature of the tank, and $T_{\text{min}}^{\text{SOC}}$ and $T_{\text{max}}^{\text{SOC}}$ represent the minimum and maximum temperatures corresponding to the usable storage capacity, the SOC is defined as:

$$\text{SOC}(t) = \frac{T_{\text{tank}}(t) - T_{\text{min}}^{\text{SOC}}}{T_{\text{max}}^{\text{SOC}} - T_{\text{min}}^{\text{SOC}}}.$$

Within the optimization, the thermal storage tank state of charge (SOC) is constrained to remain within physically allowable bounds at every time step. These bounds ensure sufficient thermal

buffering while preventing overheating or overcooling of the storage medium. Importantly, the SOC constraints are distinct from operational control thresholds that govern component on/off behavior, as they represent thermodynamic feasibility limits rather than control logic.

For configurations that include a ground-source heat pump (GSHP), an additional feasibility constraint is imposed on the entering source temperature of the borefield loop. This temperature must remain above a minimum extraction limit throughout the simulation horizon to prevent long-term thermal degradation of the ground and to ensure sustainable geo-exchange operation.

Together, the storage SOC bounds and borefield temperature constraints guarantee that all optimized system configurations remain technically feasible and operate safely under realistic physical conditions. The fitted performance curves used for the air-to-water and water-to-water heat pumps, as well as the associated fan power curve, are summarized in Appendix 5.3.

The following table presents the unit costs of generation and storage components. The costs of WWHP and GSHP include the costs of required heat exchangers, drilling and installation.

Table 4.15: Investment costs of different energy system components

Component	Cost	Reference
Air-to-water heat pump	1981 (C\$/kW)	[186]
Ground-source water-to-water heat pump	2500 (C\$/kW)	[187]
Wastewater-source water-to-water heat pump	2300 (C\$/kW)	[150]
Natural gas boiler	$4248.3 + 36.65 \cdot C_{\text{boiler,gas}}$	[181]
Electric boiler	$6877 + 26.092 \cdot C_{\text{boiler,electric}}$	[181]
TES	2500 (C\$/m ³)	[188]

4.3.3 Behaviour of the optimization algorithm and Pareto fronts

The verification of the optimization process focuses on assessing whether the NSGA-II explores the design space effectively, produces physically meaningful solutions, and converges toward a stable and coherent Pareto set. In the context of building decarbonization, the transition toward electrified heating systems introduces additional challenges related to the capacity of the electrical grid. Peak electricity consumption becomes a critical driver of upstream generation capacity, transformer sizing, and local distribution constraints. For this reason, peak electricity consumption intensity is included as one of the optimization objectives to ensure that the resulting system designs are not only cost- and carbon-efficient, but also compatible with long-term grid electrification targets.

To evaluate multi-objective trade-offs under these considerations, the Pareto fronts obtained for each building and each objective set are analyzed in detail. For the three study cases (high-rise 1970s, high-rise 2025, and mid-rise 1960s), two distinct optimization runs are performed:

- **Set A:** peak electricity consumption intensity, life-cycle cost intensity, and operational yearly $CO_{2,\text{eq}}$ emission intensity;

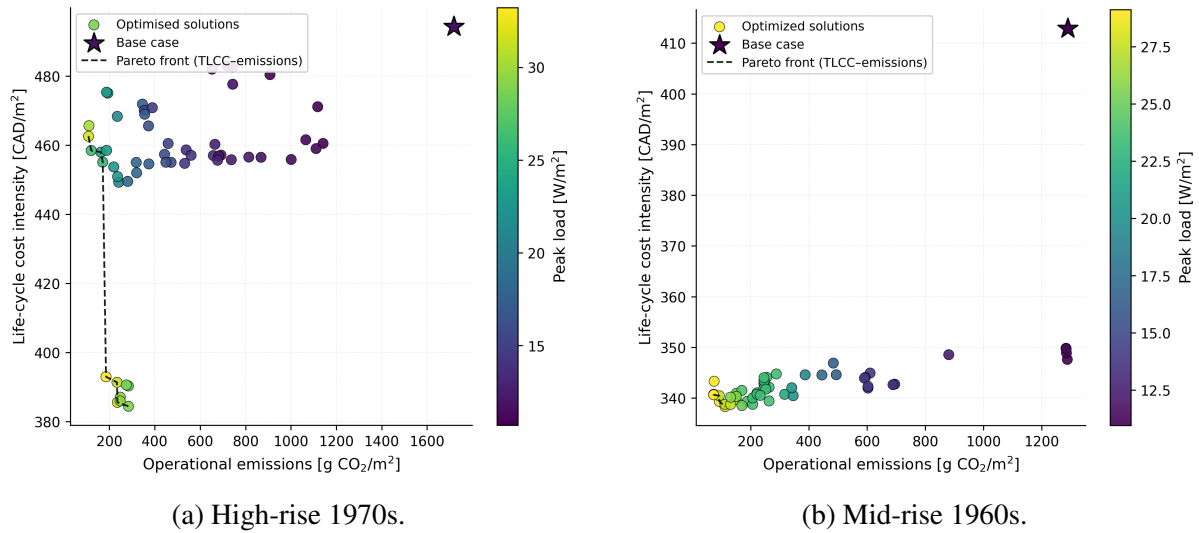


Figure 4.27: Pareto fronts in the TLCC–emissions objective space (Set A) for the two analyzed existing buildings

- **Set B:** peak electricity consumption intensity, life-cycle cost intensity, and EUI.

The resulting Pareto-optimal solutions are compared against the corresponding base-case system to determine the extent to which the optimization improves performance across the selected objectives. In addition, the evolution of key design variables along the fronts is examined to verify that the trade-off patterns identified by the algorithm are consistent with engineering intuition. Further verification is provided through constraint-checking of representative solutions.

4.3.3.1 Set A: Life-cycle cost vs emissions Figure 4.27 shows the Pareto fronts in the Total Life Cycle Cost (TLCC)–emissions objective space for the high-rise 1970s building (panel 4.27a) and the mid-rise 1960s building (panel 4.27b). In both cases, the base-case system lies well above and to the right of the Pareto front, indicating that it is *dominated* by the majority of optimized solutions. The optimization therefore identifies configurations that are simultaneously less expensive and less carbon intensive than the existing systems.

For the 1970s high-rise building (Figure 4.27a), the front exhibits a characteristic L-shaped structure: moving along the front first reduces TLCC with modest changes in emissions, followed by a region where emissions decrease sharply at relatively small cost increases. This indicates a distinct “knee” where the trade-off between cost and emissions becomes more pronounced. The spread of points is wide, showing that the algorithm explores both high-emission/low-cost and low-emission/higher-cost regions.

In contrast, the mid-rise building (Figure 4.27b) displays a flatter front: TLCC varies only slightly, while emissions span a broader range. This behaviour is consistent with physical expectations for a smaller building with lower loads, where emission reductions are driven mainly by the generation mix rather than strong storage or interaction effects.

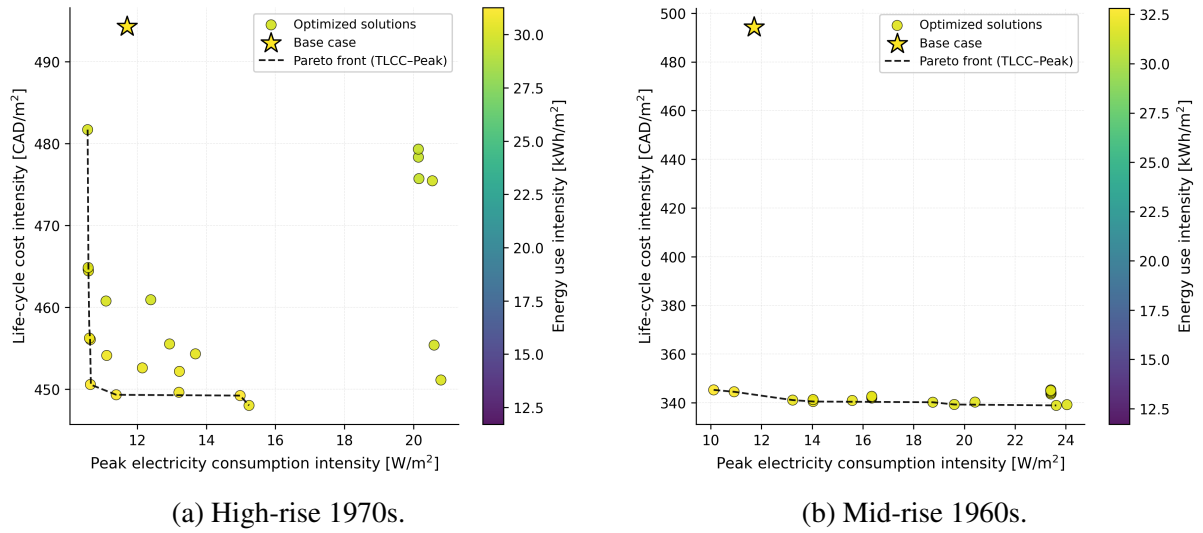


Figure 4.28: Pareto fronts in the TLCC–peak objective space (Set B)

4.3.3.2 Set B: Life-cycle cost vs peak electricity demand Figure 4.28 illustrates the Pareto fronts for Set B, where life-cycle cost intensity is plotted against peak electricity consumption intensity, while the third objective, EUI, is represented by the colour scale. In both buildings, the base-case configuration lies clearly above and to the right of the Pareto front, confirming that the optimized designs achieve simultaneous reductions in both peak demand and life-cycle cost.

For the high-rise building (Figure 4.28a), the Pareto front exhibits a characteristic L-shaped structure. Moving along the front from right to left, peak electricity intensity is progressively reduced from values comparable to the base case to less than half of that level, with only a moderate increase in TLCC. The colour distribution shows that the optimized solutions also feature consistently lower EUI than the base case, with only limited variation in energy use among the non-dominated designs. This indicates that the main trade-off in Set B lies between investment/operational cost and peak demand rather than between cost and overall energy consumption.

The mid-rise case (Figure 4.28b) displays a similar but more compact pattern: TLCC varies within a relatively narrow band, while peak electricity intensity spans a wider range. Again, the base-case point is dominated by the Pareto set in both objectives. The colour map confirms that nearly all optimized solutions achieve substantially lower EUI than the existing system, with only modest variation along the front. Overall, the Set B results demonstrate that NSGA-II systematically identifies low-peak, low-cost solutions that also deliver robust reductions in energy use intensity, consistent with engineering expectations for heat-pump-based systems.

4.3.3.3 Verification of design–variable trends To further verify that the optimization produces physically meaningful solutions, the variation of design variables along the Pareto fronts is examined. Figure 4.29 shows the peak–emissions and peak–EUI objective spaces, with marker colour indicating the gas boiler capacity fraction.

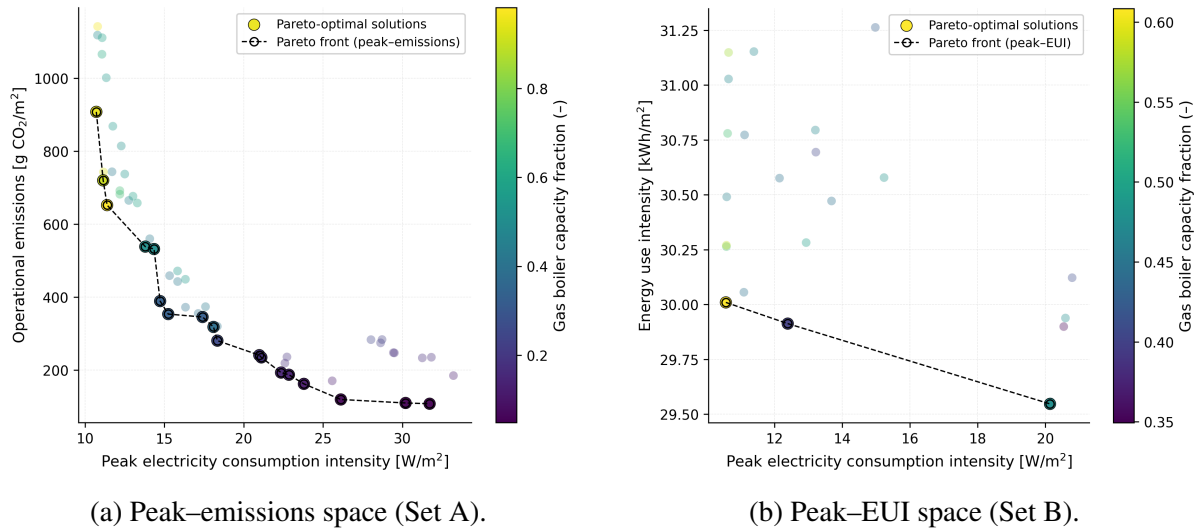


Figure 4.29: Variation of gas boiler capacity fraction along Pareto-optimal solutions in Set A and Set B for the 1970s high-rise.

In both spaces, the gas boiler fraction varies systematically along the Pareto front: solutions with higher emissions or slightly lower electric peaks retain a larger share of gas boiler capacity, whereas low-emission and low-EUI solutions reduce the boiler to nearly zero and rely primarily on heat pumps. This monotonic behaviour matches engineering intuition and confirms that the developed NSGA-II workflow explores meaningful trade-offs rather than producing arbitrary capacity combinations, thereby validating the internal consistency of the optimization.

4.3.4 High-rise building – existing vs. 2025 envelope

This section compares the optimal system configurations for the high-rise building under two envelope conditions: the existing 1970s construction (Case 1) and a 2025-standard high-performance envelope (Case 3). For each case, representative solutions from the Pareto fronts are reported for two objective sets. Objective Set A considers peak electricity demand, TLCC, and operational emissions, while Objective Set B replaces operational emissions with EUI. The following discussion highlights how the envelope influences total capacity requirements, technology selection, and the overall system architecture.

Table 4.16 shows the results for Objective Set A. With the 1970s envelope, the optimization must accommodate high heating loads, which leads to large generation capacities. The peak-minimizing solution relies heavily on gas (790 kW) and sizeable ASHP and GSHP capacities. In contrast, the TLCC-optimal solution significantly reduces gas boiler size (190 kW) and eliminates WWHPs, while the emissions-optimal configuration becomes strongly electrified, with a large electric boiler (575 kW) and substantial TES capacity. The TOPSIS solution provides a balanced compromise between these tendencies, combining moderate electrification with reduced reliance on fossil backup.

Under the 2025-standard envelope, all Objective Set A solutions shift toward smaller and more uniform capacities. Gas boilers are nearly eliminated, electric boilers assume only a supplementary role, and heat pump capacities decrease in line with the reduced heating load. GSHP and WWHP capacities remain relatively stable, supported by the improved thermal performance of the building. TES requirements decline for the TLCC-optimal case but remain valuable in the emissions-optimal solution, where storage helps minimise operational emissions.

Table 4.16: Decision-variable values for selected Pareto-optimal solutions of the high-rise building with existing (Case 1) and 2025-standard (Case 3) envelopes under Objective Set A (TLCC, peak demand, and operational emissions).

Case	Decision variable	Lowest peak	Lowest TLCC	Lowest emissions	TOPSIS
Case 1	Gas boiler (kW)	790	190	40	215
	Electric boiler (kW)	0	560	575	150
	ASHP (kW)	280	620	430	280
	WWHP (kW)	115	0	80	155
	GSHP (kW)	365	140	245	325
	TES (kWh)	2300	1160	1900	1800
Case 3	Gas boiler (kW)	210	5	0	10
	Electric boiler (kW)	365	190	225	15
	ASHP (kW)	15	145	55	60
	WWHP (kW)	160	90	130	130
	GSHP (kW)	345	285	335	330
	TES (kWh)	1350	475	1375	1130

Table 4.17 summarizes the solutions for Objective Set B, where EUI replaces emissions as an explicit objective. For the 1970s envelope, the peak-minimizing solution again requires large generation capacities, including a 505 kW gas boiler, while the EUI-optimal configuration shifts almost entirely to electrification via a full-size electric boiler (830 kW) and slightly larger GSHP capacity. The TLCC-optimal and TOPSIS solutions lie between these extremes, reducing gas capacity and increasing TES size. These patterns show how the optimization trades off lower EUI against higher capital cost and peak demand under a weak envelope.

With the 2025 envelope, heating demand reductions translate directly into smaller optimal capacities. Gas boiler use is either eliminated or kept at minimal levels, and moderate electric boiler and heat pump capacities become the dominant supply components. ASHP capacity drops sharply due to reduced peak loads, while WWHP and GSHP remain relatively stable in all solutions. TES requirements are lower overall but remain beneficial in the EUI-optimal configuration, where storage helps lower energy use and improve system efficiency.

Across both objective sets, the results reveal a consistent trend: upgrading the envelope fundamentally reshapes the design space. Lower loads enable smaller, more electrified, and lower-emission system configurations, reduce reliance on fossil backup, and enhance the

cost-effectiveness of the optimal systems. These findings emphasise the central role of high-performance envelopes in practical decarbonization strategies for high-rise buildings.

Table 4.17: Decision-variable values for selected Pareto-optimal solutions of the high-rise building with existing (Case 1) and 2024-standard (Case 3) envelopes under Objective Set B (TLCC, peak demand, and EUI).

Case	Decision variable	Lowest peak	Lowest TLCC	Lowest EUI	TOPSIS
Case 1	Gas boiler (kW)	505	400	395	440
	Electric boiler (kW)	0	90	830	0
	ASHP (kW)	230	270	214	235
	WWHP (kW)	160	160	160	155
	GSHP (kW)	370	340	385	370
	TES (kWh)	1250	1870	2100	1250
Case 3	Gas boiler (kW)	210	0	0	105
	Electric boiler (kW)	475	140	390	100
	ASHP (kW)	50	90	60	55
	WWHP (kW)	160	135	160	155
	GSHP (kW)	315	295	300	310
	TES (kWh)	1350	480	1045	650

Figure 4.30 presents the performance of the base case and the TOPSIS-selected solutions for Objective Sets A and B, expressed as *normalised values* where the base case is set to 1.0 for each metric. Values below one indicate improvements relative to the existing system. Both solutions yield substantial reductions in energy use: EUI drops to 0.29 for both objective sets (a reduction of roughly 71 %). Operational emissions also decrease, most significantly under Objective Set A (0.16, an 84 % reduction), while Set B achieves a 45 % reduction. Life-cycle cost intensity improves moderately, with reductions of about 9 % (Set A) and 5 % (Set B). The main difference between the two solutions lies in peak electricity demand: the Set B solution achieves a slight reduction (0.92), whereas the Set A solution leads to a substantial peak increase (1.57) due to a more aggressively electrified system configuration. Overall, the normalised comparison illustrates that while both optimised designs significantly reduce energy use, emissions, and long-term costs, deep decarbonization strategies (Set A) may shift more load to the electricity grid, resulting in higher peak demand.

4.3.5 Mid-rise building

Table 4.18 summarises the TOPSIS-selected solutions for the mid-rise building under Objective Sets A and B. The selected configurations reflect the much lower heating demand of the mid-rise building compared with the high-rise case, resulting in generally smaller system capacities and a more uniform technology mix across the two objective sets.

In both solutions, ASHP and WWHP capacities remain identical, indicating a consistent reliance

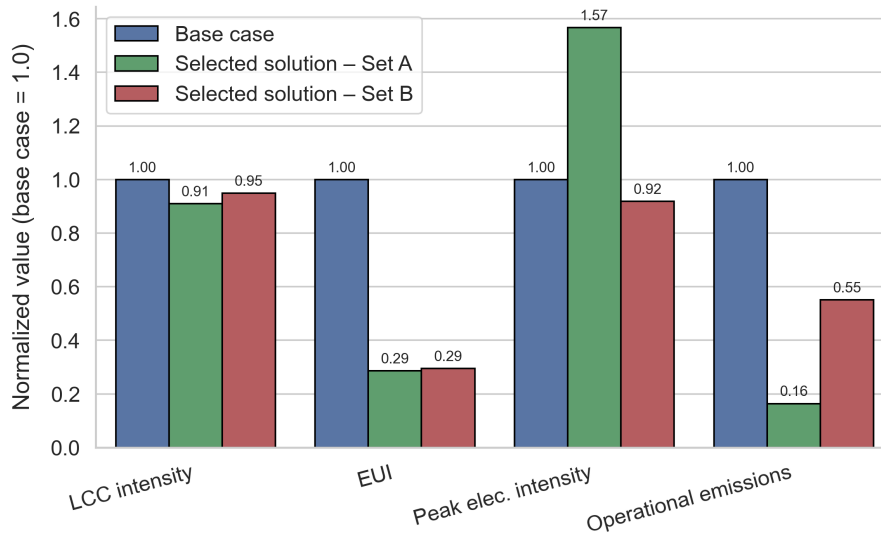


Figure 4.30: Normalized performance of the high-rise base case and the TOPSIS-selected solutions for Objective Sets A and B

on air-source and wastewater-source heat pumps regardless of objective weighting. The primary differences lie in the boiler and TES sizing. The Set A solution incorporates a modest gas boiler (30 kW) combined with a 130 kW electric boiler and a larger TES volume (572 kWh). This configuration supports peak reduction and emissions mitigation by enabling a higher share of heat-pump operation and effective load shifting. In contrast, the Set B solution allocates a substantially larger gas boiler (200 kW) and eliminates the electric boiler entirely, paired with a smaller TES volume (400 kWh). This reflects a greater emphasis on lowering EUI while maintaining peak constraint compliance, even if that requires retaining more combustion-based backup capacity.

Table 4.18: TOPSIS-selected solutions for the mid-rise building under Objective Sets A and B.

Parameter	Set A (TLCC–peak–emissions)	Set B (TLCC–peak–EUI)
Gas boiler (kW)	30	200
Electric boiler (kW)	130	0
ASHP (kW)	177	177
WWHP (kW)	50	50
TES (kWh)	572	400

Figure 4.31 presents the normalised performance of the mid-rise base case and the TOPSIS-selected solutions, with all metrics scaled to the base case (value = 1.0). Values below one therefore indicate improvements relative to the existing system. Both objective sets achieve large reductions in energy use, with EUI falling to 0.36–0.38 (a reduction of roughly 62–64 %). Operational emissions also decline substantially: the Set A solution achieves the largest reduction (0.13, an 87 % decrease), while Set B yields a 45 % decrease (0.55). Life-cycle cost intensity improves in both cases, with normalised values of 0.83 (Set A) and 0.84 (Set B), demonstrating

that improved performance can be achieved without increasing long-term costs.

The primary distinction between the two solutions appears in peak electricity demand. The Set A solution yields a moderate reduction in peak intensity (0.92), consistent with its larger TES and use of an electric boiler to support load-shifting. In contrast, the Set B solution significantly increases the peak (2.19), driven by a higher reliance on gas-fired backup and reduced storage capacity, which reduces flexibility and shifts more load into the peak period. Overall, the normalised comparison confirms that both TOPSIS-selected designs substantially outperform the mid-rise base case in terms of energy, emissions, and cost, while highlighting the trade-off between EUI minimisation and peak demand under different objective sets.

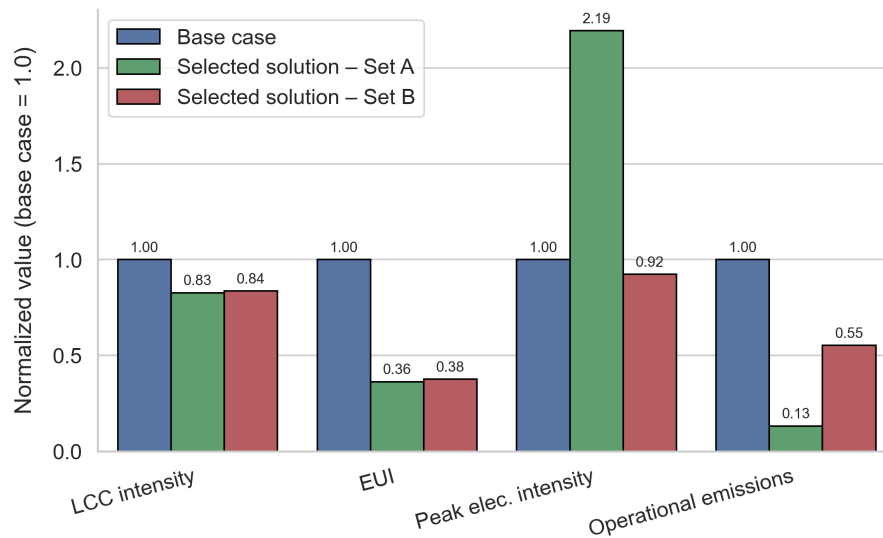


Figure 4.31: Normalised performance of the mid-rise base case and the TOPSIS-selected solutions for Objective Sets A and B (base case = 1.0).

4.3.6 Cross-case summary and key trends

Across all cases and objective sets, the Pareto fronts confirm that the NSGA-II-based workflow explores the design space effectively and produces consistent trade-offs. The base-case systems are dominated in every considered objective plane: there always exist solutions that simultaneously reduce life-cycle cost intensity, energy use intensity or emissions, and peak electricity demand. The fronts are well populated and typically exhibit recognisable L-shaped or gently convex structures, with identifiable “knees” where small sacrifices in one objective yield large gains in another. The design-variable trends along the fronts further indicate that the algorithm behaves in line with engineering intuition rather than generating arbitrary capacity combinations.

In terms of technology patterns, the results show that when the envelope is weak (1970s high-rise and existing mid-rise), deep decarbonization requires hybrid solutions combining GSHP and/or WWHP with ASHP, supported by sizeable TES and a residual gas boiler or electric boiler as backup. As the envelope improves (2025-standard high-rise), total installed capacities decrease

and the optimal systems become simpler and more electrified: gas boilers are almost entirely phased out, heat pump capacities can be reduced without compromising comfort, and storage volumes remain moderate. The mid-rise building, with its lower loads and limited borefield potential, consistently favours compact ASHP–WWHP configurations with smaller storage, illustrating how the framework adapts to both archetype and site constraints.

From a planning perspective, these findings demonstrate that the proposed framework can support both retrofit and new-build decision-making while accounting for local physical limitations such as lot geometry and sewer availability. By jointly optimising TLCC, emissions or EUI, and peak electricity demand, the method highlights the trade-offs between deep electrification, grid impact, and long-term costs. In practice, this enables stakeholders to identify building-specific decarbonization pathways that are compatible with wider network capacity constraints and to prioritize envelope upgrades where they unlock simpler, smaller, and more cost-effective low-carbon energy systems.

5 Conclusions and Outlook

5.1 Summary

This study examined the development and application of a unified, modular, and automation-ready ESMF capable of supporting detailed techno-economic assessment, optimal component sizing, and the systematic planning of retrofit interventions for individual buildings and building portfolios. Throughout the work, attention was given to issues identified in Chapter 2, such as the need for flexible and standardized data structures, the integration of high-resolution simulation with optimization workflows, and the evaluation of system feasibility across diverse building types and climates. The study also incorporated a portfolio-scale retrofit prioritization approach that enables consistent ranking of buildings based on energy performance, operational cost, and retrofit potential. Together, these elements allowed the framework to address building-level modelling and broader urban energy planning within a single methodological environment.

A central component of the methodological framework was the development of a generic, object-oriented energy system data model designed to represent a wide spectrum of building-scale and district-scale technologies in a coherent structure. The model is organized around the abstract `EnergySystemComponent` class, which encapsulates shared attributes such as component identifiers, lifetimes, cost relationships, and technical performance descriptions. Building on this foundation, four major subsystems—*generation*, *distribution*, *storage*, and *emitter*—are represented through modular classes that reflect the physical and operational characteristics of real-world energy systems. The data model links each component to empirical performance curves and investment or maintenance cost functions stored in a standardized format, enabling accurate representation of key behaviours such as heat pump performance variations, boiler efficiency changes, thermal storage dynamics, and inverter losses. Integrated with the TOOLS4CITIES UBEM workflow, the model forms a continuous pipeline from automated geometry processing and archetype assignment, to hourly demand modelling, to detailed system simulation and optimization. This organization ensures consistency across climates, building archetypes, and retrofit scenarios while maintaining transparency and extensibility.

The first application of the developed framework focused on assessing rooftop PV systems combined with air-source heat pumps in two contrasting climates: cold-temperate Montreal (Canada) and Mediterranean Palma de Mallorca (Spain). Using identical energy system templates and modelling assumptions across archetypal residential buildings, the analysis captured the influence of heating-dominated versus cooling-dominated load profiles on system sizing, annual energy flows, self-sufficiency, self-consumption, and life cycle cost outcomes. The results revealed consistent trends: heat pumps significantly reduced energy use intensity and operational emissions in both climates; PV integration lowered operational costs, with benefits expressed differently depending on solar availability; and battery storage was strongly climate-dependent, offering large gains in self-sufficiency in solar-abundant contexts but limited value in

cold climates. Overall, heat pumps proved to be robust low-carbon solutions, PV-only systems generally offered favourable cost–benefit performance, and batteries were justified primarily under high-autonomy or high-solar conditions.

The developed ESMF includes several modules including an energy system component feasibility assessment, life cycle costing workflow, and an NSGA-II optimization workflow to optimally size an energy system component based on the user input objective functions. Before optimization is performed, the framework incorporates a rapid pre-assessment module that evaluates the technical feasibility and allowable capacities of candidate energy system components. This module currently focuses on heat pumps—air-source, wastewater-source, and ground-source—reflecting their central role in low-carbon electrification strategies. Feasibility is determined based on site-specific characteristics such as available borefield area, wastewater temperature and flow, lot geometry, and the required peak thermal demand. Although the present implementation concentrates on heat pumps, the structure is intentionally extensible: additional technologies, sources, or hybrid configurations can be incorporated without modifying the underlying architecture. By identifying infeasible or capacity-limited technologies early, the pre-assessment module reduces the optimization dimensionality and ensures that only realistic system configurations are considered.

Following feasibility screening, the ESMF applies a multi-objective optimization and life-cycle costing workflow to determine cost-effective and energy-efficient system configurations. A suitable system archetype is selected from the catalogue based on feasible components, defining the decision variables, their bounds, and the associated rule-based control strategy. The NSGA-II algorithm is used to explore the design space, optimizing component sizes with respect to objectives such as life-cycle cost intensity, operational emissions, energy use intensity, and peak electrical demand. Each candidate design triggers a pre-defined simulation model, allowing the framework to evaluate techno-economic performance under realistic operating conditions. The resulting Pareto set offers a spectrum of non-dominated solutions, from which a balanced configuration is selected using TOPSIS. This integrated workflow ensures a transparent and consistent mapping between component-level feasibility, performance, and long-term cost outcomes.

Another key contribution of this work is the development of an automated and scalable building retrofit prioritization workflow designed to support portfolio-wide decision-making using only monthly billing data and archetype-based simulation. The workflow integrates measured energy consumption, UBEM outputs, and PRISM-derived thermal performance indicators. Using kernel density estimation, a representative reference point of heating-sensitivity slope and baseload is identified, and buildings exceeding this benchmark or underperforming relative to their simulated slopes are flagged for retrofit. Candidate buildings are subsequently ranked using TOPSIS based on four indicators—heating-sensitivity slope, energy use intensity, total energy consumption, and volume-to-envelope-area ratio—capturing thermal inefficiency, operational impact, and

retrofit cost considerations.

The workflow was applied to a stock of 201 natural-gas-heated OMHM buildings, of which 140 were identified as requiring intervention. Four retrofit scenarios—*Glazing*, *Skin*, *System*, and *Full*—were then simulated across all selected buildings. The results demonstrated substantial and consistent reductions in energy use intensity, operating costs, and greenhouse gas emissions across building typologies, with the Full scenario providing the most comprehensive improvements. Electrification via heat pumps increased peak electrical demand, underscoring the need for coordinated planning with grid operators. Overall, the workflow offered a practical and reproducible method for diagnosing underperforming assets, prioritizing investments, and quantifying retrofit impacts at the portfolio scale.

The final use case demonstrated the capabilities of this optimization framework using three buildings: a 1970s high-rise, a 1960s mid-rise, and a hypothetical new-construction high-rise created by updating the same geometry to 2025 standards. The results highlight the influence of building archetype, envelope thermal quality, and site geometry on feasible system configurations and the structure of the Pareto front. In the existing high-rise, limited borefield area restricted GSHP capacity, producing hybrid ASHP–GSHP solutions that reduced emissions and costs but still required auxiliary capacity to manage peak winter loads. The mid-rise building, characterized by weaker envelope performance and higher thermal demands, exhibited Pareto fronts dominated by ASHP-based systems, which offered substantial reductions in energy use intensity but at the cost of higher peak electrical demand. In contrast, the new-construction high-rise yielded simpler and lower-cost optimal configurations, often relying solely on ASHPs or modest WWHP systems without the need for hybridization or large storage volumes. Across all three cases, the optimization consistently identified system designs that substantially reduced life-cycle cost intensity, energy use, and operational emissions relative to existing systems, demonstrating the applicability of the workflow for early-stage design and retrofit planning.

Taken together, the three use cases demonstrate the breadth and coherence of the proposed ESMF. From cross-climate system evaluation, to rapid feasibility assessment and multi-objective optimal sizing, to portfolio-scale retrofit prioritization, the framework provides a unified methodological environment capable of supporting both detailed system design and strategic urban energy planning. Its modular structure, extensible data model, and tight integration with the TOOLS4CITIES UBEM platform enable consistent analyses across diverse building types, climates, and decision-making contexts. By combining detailed simulation, optimization, and data-driven screening within a single workflow, the framework helps bridge the gap between building-level engineering analysis and the broader planning needs of cities seeking to decarbonize their building stock. As such, it offers a robust foundation for future research and practical applications in low-carbon energy system design, retrofit decision-making, and long-term urban sustainability strategies.

5.2 Contributions

The main contribution of this work is the development of a new, open-source ESMF that addresses several long-standing limitations of existing modelling frameworks. Unlike many current ESMFs, which often rely on rigid data structures, require extensive manual configuration, or are tightly coupled to specific simulation engines, the proposed framework is designed around a generic, object-oriented data model that explicitly separates data representation from simulation logic. This design enables a high degree of automation, extensibility, and semantic clarity.

In the present implementation, the ESMF is integrated with the TOOLS4Cities UBEM workflow, which provides hourly building energy demands and spatial context. This integration allows demand modelling, system simulation, parameter extraction, and optimization to operate as a unified and automated pipeline. While the current use case is coupled to TOOLS4Cities at the data-exchange level, the framework itself is not intrinsically bound to this specific UBEM. Any UBEM workflow capable of supplying equivalent demand time series and metadata (e.g., building identifiers, demand types, temporal resolution) could be interfaced with the ESMF with limited adaptation.

The framework supports user-defined spatial and temporal resolution, enabling applications ranging from individual buildings to district-scale analyses, and it facilitates cross-climate and cross-archetype studies without requiring restructuring of the core modelling logic. By abstracting energy system components, performance curves, and cost functions within a generic data model, new technologies or alternative UBEM inputs can be incorporated with minimal implementation effort. Furthermore, its open-source design provides a transparent and reproducible foundation for future urban energy system research and tool development. Overall, the proposed ESMF combines the flexibility of research-grade modelling tools with the robustness required for large-scale, automation-driven urban energy analysis.

The primary target users of the proposed framework are energy analysts, urban planners, and researchers involved in the assessment, design, and optimization of building- and district-scale energy systems. These users typically operate at the interface of data processing, simulation, and decision support, and require modelling tools that can accommodate heterogeneous data sources, multiple technologies, and diverse climatic and regulatory contexts. In this sense, the framework is intended not as a replacement for existing UBEM tools, but as a modular energy-system layer that can be coupled to different urban energy modelling workflows as data availability and project scope permit.

Building on these overarching contributions, the specific technical innovations introduced in this work can be summarized as follows:

Generic unified energy system data model. A major contribution of this thesis is the development of a generic, object-oriented energy system data model that provides a unified structure

Table 5.1: Characteristics of the developed ESMF.

Analytical Approach	Bottom-Up
General Purpose	Exploring
Underlying Methodology	Hybrid
Modelling Methodology	Computational
Accessibility	Open-Source
Spatial Resolution	User Defined
Temporal Resolution	User Defined
Demand Sector	Building
Technology Coverage	Heat Pumps, PV, Thermal Storage, Electrical Storage, Boiler
Demand-Side Management	No

for representing a broad range of building-scale and district-scale energy technologies. The model formalizes components through the abstract `EnergySystemComponent` class, which encodes shared attributes such as identification, lifetime, cost relationships, performance curves, and operational constraints. This approach enables technology-agnostic extensibility: new components—such as advanced heat pumps, emerging storage technologies, or alternative generation systems—can be incorporated without modifying existing simulation or optimization logic. The separation of data representation from simulation ensures that component models remain reusable across climates, archetypes, and retrofit contexts. The model also embeds standardized interfaces for technical, operational, and economic parameters, facilitating seamless coupling to the TOOLS4CITIES UBEM workflow and enabling automated transitions between geometry-driven demand modelling, system simulation, and techno-economic optimization. This unified, semantically explicit structure distinguishes the proposed data model from many existing ESMFs, which typically rely on fragmented or technology-specific formulations.

Heat pump pre-assessment workflow. This work introduces a rapid and automated pre-assessment workflow for evaluating the feasibility and allowable capacity of key heat pump technologies, including ASHP, WWHP, and GSHP systems. The workflow integrates building-level heating loads with site-specific constraints such as available surface area for borefields, wastewater flow and temperature conditions, and lot geometry limitations. By quantifying the maximum feasible capacity of each technology prior to optimization, the workflow ensures that system designs always respect physical and operational constraints that may otherwise be overlooked in high-level modelling tools. Although the current implementation focuses on heat pumps, the architecture is intentionally extensible. Additional generation or storage technologies, hybrid system configurations, and source-specific feasibility criteria can be included with minimal structural modifications.

Automation-ready energy system optimal sizing workflow. The thesis develops a fully automation-ready workflow for multi-objective optimal sizing of building energy systems,

integrating component feasibility, detailed simulation, and life-cycle costing within a single pipeline. Once the feasible technologies are identified, the workflow selects an appropriate system archetype from the catalogue and automatically configures the decision space, boundary conditions, and control rules. A coupling between the NSGA-II algorithm and pre-defined system simulation models enables the evaluation of candidate designs under realistic hourly operation. Unlike many existing frameworks that rely on simplified linearized models or static performance assumptions, the proposed workflow incorporates component-level performance curves, storage dynamics, and rule-based operational strategies. The automation-oriented design allows the workflow to scale across buildings of different sizes, functions, envelopes, and climates—without requiring manual restructuring of the modelling process.

Building portfolio retrofit prioritization workflow. Another major contribution of this thesis is the development of a robust, data-driven workflow for prioritizing retrofit interventions across large building portfolios using only monthly billing data and archetype-based simulation. The approach integrates PRISM-derived heating-sensitivity slopes, simulated archetype performance, and kernel density-based reference identification to classify buildings according to their thermal inefficiency and deviation from expected behaviour. A two-step screening process distinguishes genuine operational under-performance from modelling discrepancies, thereby reducing false positives and directing attention toward buildings with the greatest upgrade potential. The workflow then employs the TOPSIS multi-criteria decision-making method to generate an objective ranking based on four indicators: heating-sensitivity slope, energy use intensity, total energy consumption, and volume-to-envelope-area ratio. This combination ensures that both thermal inefficiency and retrofit impact potential are accounted for, while also incorporating a geometric measure related to retrofit cost-effectiveness. By automating candidate identification, ranking, and scenario simulation, the workflow is able to evaluate retrofit strategies across large portfolios, enabling planners and housing managers to make informed, transparent, and scalable decisions.

Beyond these technical contributions, the outcomes of this work provide practical value to a wide community of stakeholders involved in building energy planning and decarbonization. Urban planners and municipal housing authorities can benefit from automated retrofit prioritization tools that enable transparent, data-driven allocation of limited renovation budgets. Engineering consultants and energy system designers can use the optimization and feasibility modules to develop consistent, cross-climate system-sizing studies without rebuilding models for each project. Software developers and research groups can extend the open-source ESMF to create new analytics services, including rapid techno-economic assessment platforms, interactive design assistants, and digital twins for building portfolios. Together, these opportunities illustrate how the proposed framework can serve as a foundational layer for future tools and services that accelerate the transition toward low-carbon, energy-efficient urban building stocks.

5.3 Limitations and Outlook

While the proposed workflows demonstrate broad applicability across building- and portfolio-scale analyses, several limitations should be acknowledged. These arise from modelling assumptions, data availability, and the scope defined for this research.

- (1) **Ideal-load demand modelling.** All building thermal loads were generated using ideal load systems in EnergyPlus. This approach facilitates automation and cross-climate consistency but prevents HVAC performance from influencing thermal zone conditions or comfort. Future work could integrate detailed HVAC models or co-simulation approaches to capture system–zone interactions more accurately.
- (2) **Imperfect, incomplete, and heterogeneous input data.** Urban-scale energy modelling relies on data from multiple sources with varying levels of completeness, accuracy, and consistency, including geometry files, billing records, archetype libraries, and secondary statistical datasets. In many cases, key attributes—such as energy carrier or system type—are not available directly at the building level and must be inferred through the combination of multiple external sources (e.g., census surveys, regional energy statistics, or technology penetration studies). This requires non-trivial data wrangling, reconciliation, and probabilistic assignment prior to the application of automated workflows. While the proposed data model is designed to be robust to such imperfections, uncertainties inevitably propagate through simulation, optimization, and prioritization results. Future work could integrate explicit data quality indicators, uncertainty quantification, automated data-cleaning pipelines, and Bayesian calibration techniques to better characterize and reduce the impact of imperfect inputs.
- (3) **Lack of system simulation validation.** The energy system simulations and optimization outputs were not validated against measured data from real buildings or monitored systems. Validation using measured heat pump performance, PV and storage operation profiles, or metered building demand would help quantify modelling accuracy and strengthen confidence in the framework’s predictions.
- (4) **Restricted technology implementation.** Although the framework is designed to be technology-agnostic, the present implementation focuses on heat pumps, boilers, PV, and storage systems. Expanding the technology catalogue to include CHP, district energy interfaces, demand-response technologies, and emerging thermal systems would broaden the applicability of the approach.
- (5) **Archetype-based UBEM representations.** The UBEM models rely on archetypal assumptions rather than detailed, building-specific physics or measurements. While archetypes enable scalability, they limit accuracy for individual buildings. Integrating BIM-derived geometries, measured schedules, or surrogate modelling techniques could better capture building-specific behaviour.

- (6) **Randomized base-case system assignment in retrofit analysis (data-driven limitation).** Due to limited information on existing HVAC systems within the OMHM portfolio, base-case system configurations were assigned probabilistically. Although this is statistically reasonable, it introduces uncertainty at the building level. Access to audited system data or Bayesian inference methods could improve baseline characterization.
- (7) **Monthly billing data and PRISM regression (data-driven limitation).** The retrofit prioritization workflow operates on monthly billing data and linear PRISM-based heating-sensitivity models because higher-resolution data were not available. This limits temporal resolution and may overlook nonlinear or control-driven phenomena. Future work could utilize smart-meter data or more flexible statistical fitting methods to enhance diagnostic fidelity.
- (8) **Simplified representation of occupant behaviour.** Occupant schedules and internal gains follow standardized archetype assumptions, limiting the ability to represent behavioural diversity or rebound effects. Incorporating stochastic occupancy models or agent-based representations could improve behavioural realism.
- (9) **Design-only optimization with fixed controls.** The optimization framework focuses solely on system sizing, using predefined rule-based control strategies for operation. Integrating operational optimization, demand flexibility models, or model-predictive control would enable assessment of dynamic, grid-interactive performance.
- (10) **No capability for demand-side management studies.** The current workflow cannot evaluate demand-side management strategies due to the absence of smart, adaptive, or price-responsive controls. Extending the control layer to model flexible loads, demand shifting, or real-time price signals would enable DSM-focused analysis.
- (11) **Fixed criteria and weights in TOPSIS.** The prioritization framework employs a fixed indicator set with implicitly uniform weighting. Different stakeholders may prioritize cost, emissions, or retrofittability differently. Sensitivity analysis, stakeholder-informed weights, or participatory multi-criteria methods could increase transparency and adaptability.

Addressing these limitations would enhance the realism, robustness, and decision relevance of the proposed workflows. Future research integrating calibrated models, validated system simulations, richer behavioural and climatic representations, broader technology sets, improved baseline data, and more advanced operational and decision-support layers would enable the framework to support an even wider range of urban energy planning and decarbonization applications.

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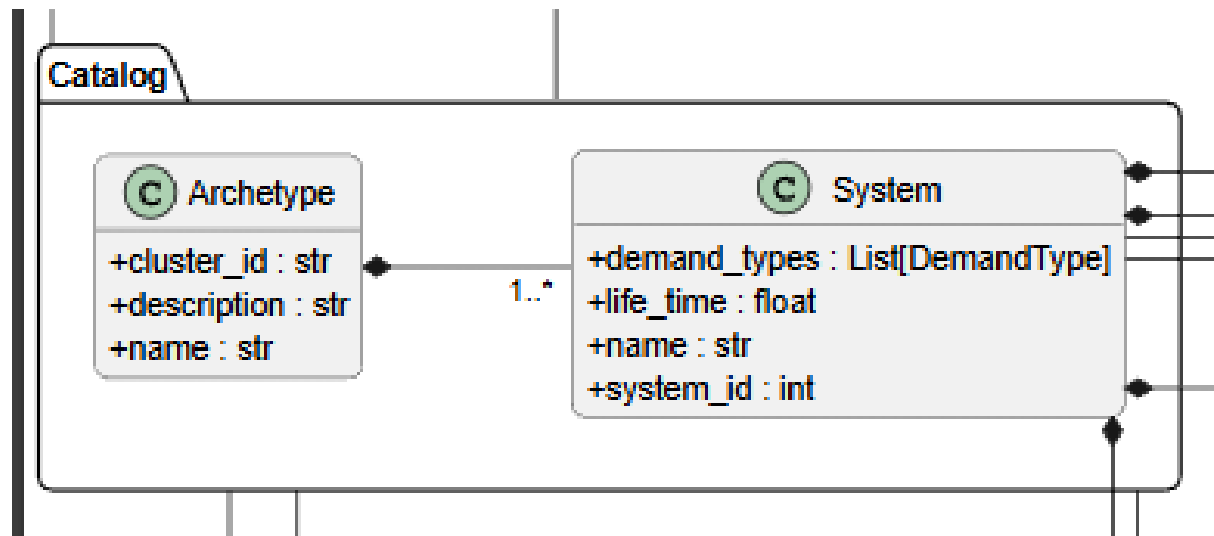
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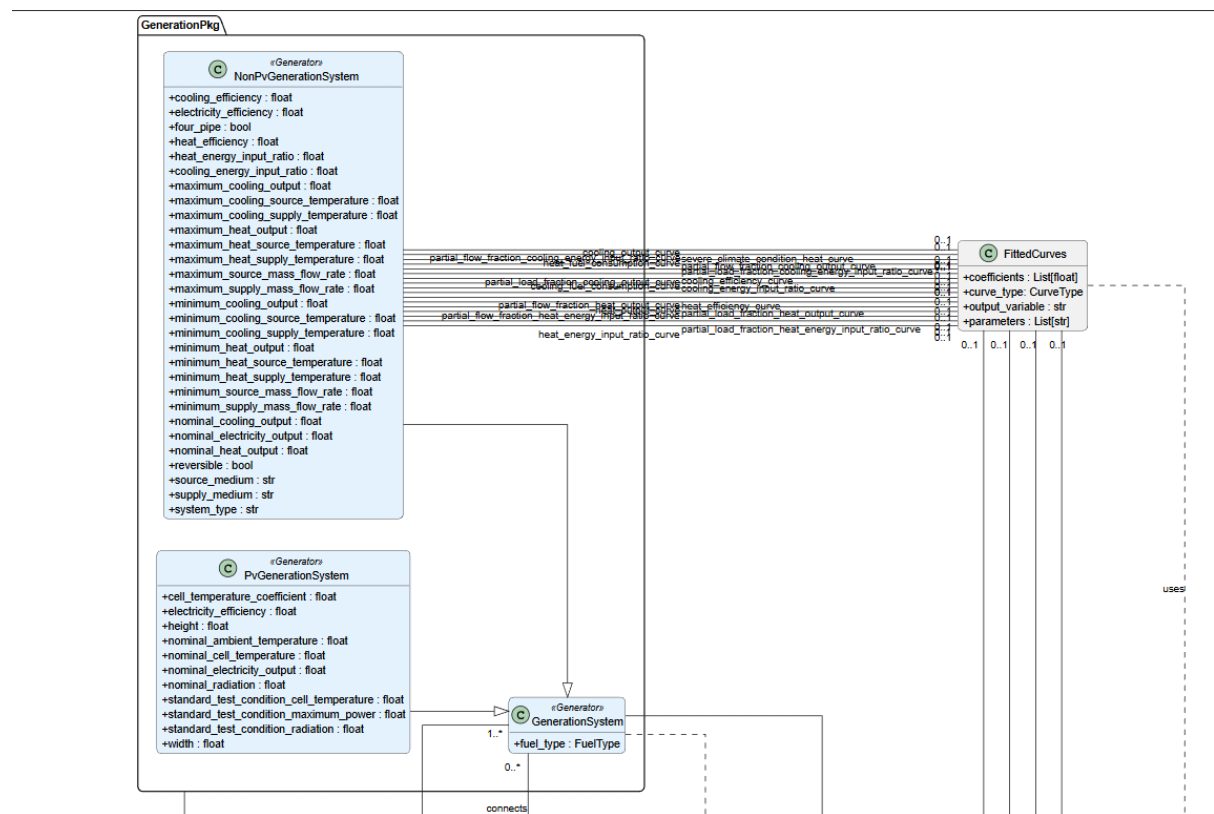
Energy System Data Model UML Diagram

Full UML Class Diagram

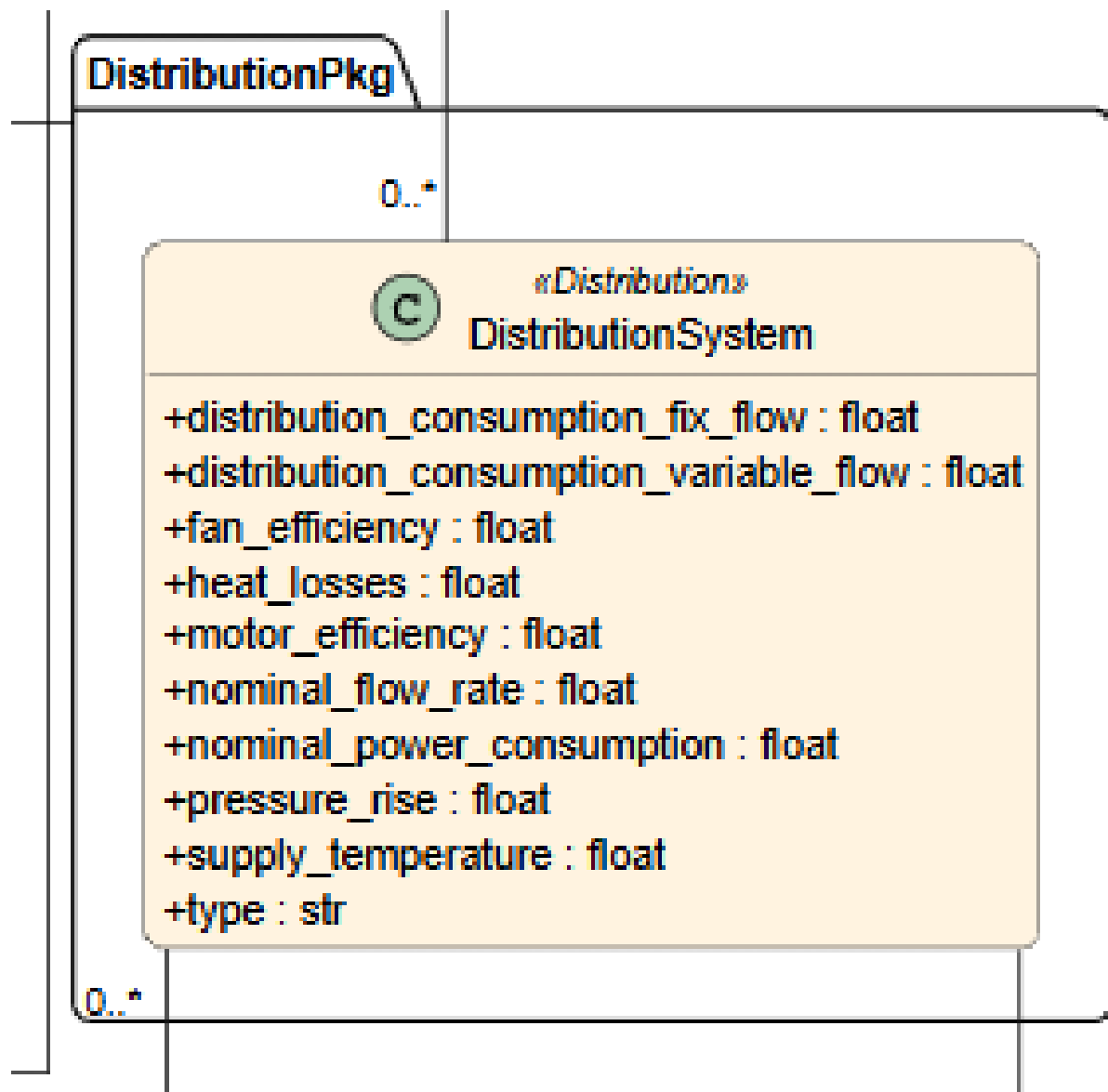
Package-Level Class Diagrams



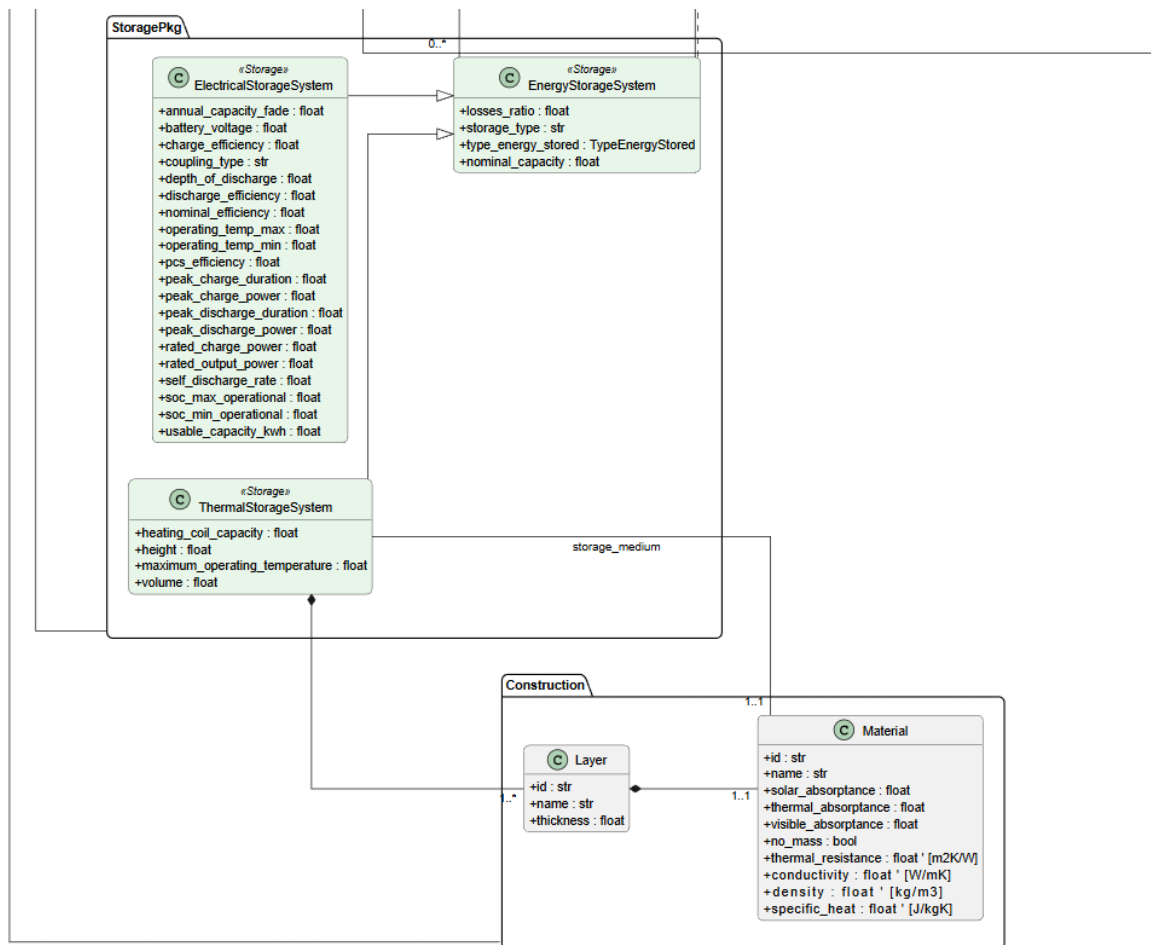
Catalog package (Archetype and System classes).



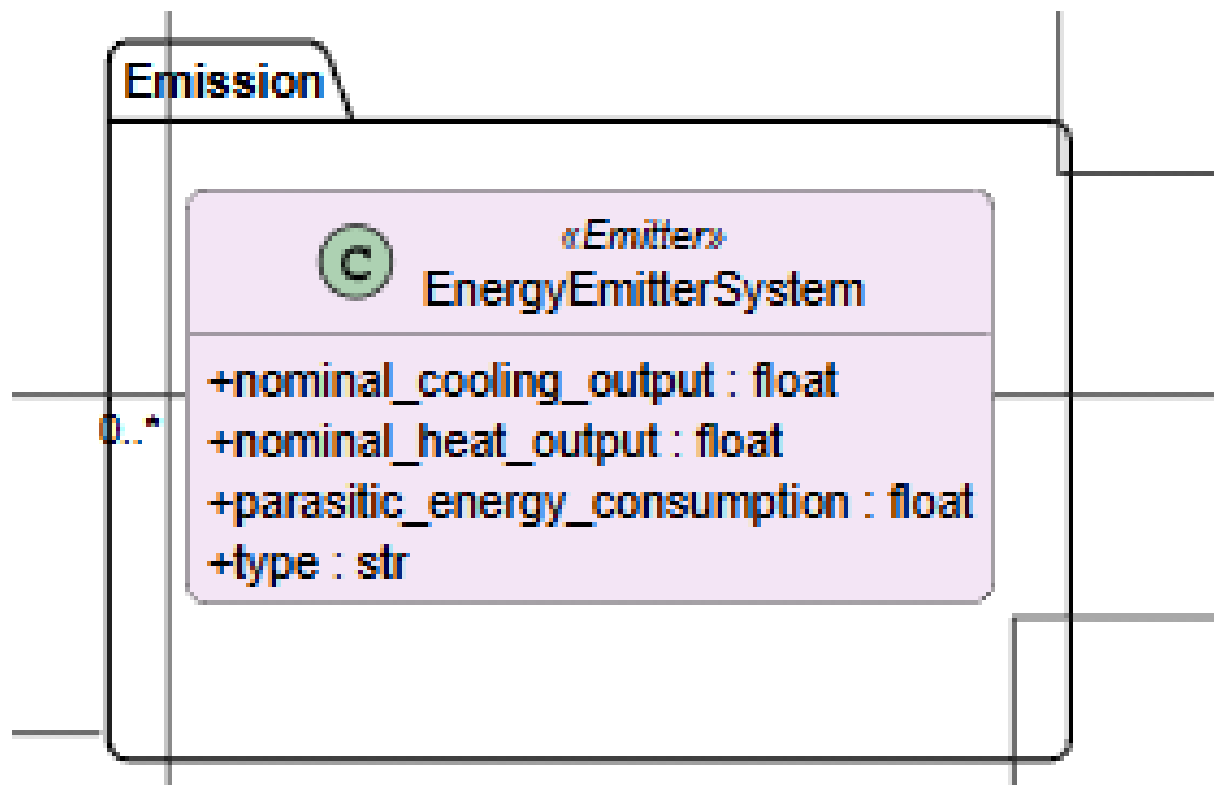
Generation package (GenerationSystem, Renewable and Non-Renewable classes).



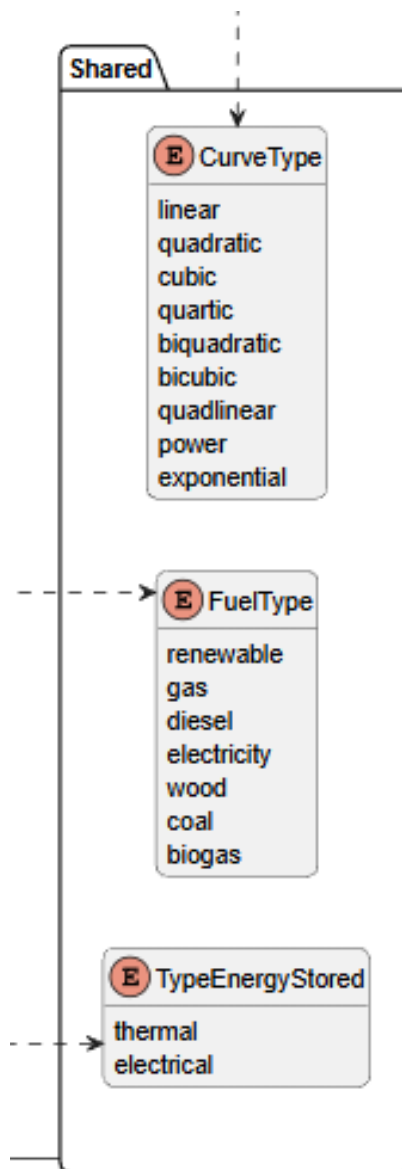
Distribution package.



Storage package (Electrical and Thermal storage systems).



Emitter package (EnergyEmitterSystem).



Class diagram for the `Shared` package (`CurveType`, `FuelType`, `TypeEnergyStored`).

Unitary Air-to-Air Heat Pump Performance Modifier Functions

This appendix compiles all performance modifier equations used in the modelling of the air-to-air heat pumps in the retrofit analysis. These functions follow standard manufacturer-based biquadratic, quadratic, and linear forms commonly used in heat pump performance maps. All functions return dimensionless modifier values, which are multiplied by nominal capacities or nominal energy-input ratios to determine the instantaneous performance at each simulation time step.

Let T_i denote the indoor return-air temperature, T_s the outdoor source-air temperature, PLR the partial-load ratio ($0 \leq \text{PLR} \leq 1$), and FFR the flow-fraction ratio ($\dot{m}/\dot{m}_{\text{ref}}$). The reference mass flow rate $\dot{m}_{\text{ref}}$ corresponds to the flow required to meet peak heating or cooling load with a prescribed maximum coil temperature difference.

Cooling Mode

Cooling capacity modifier vs. indoor and outdoor temperatures

$$f_{\text{cool}}^{\text{cap}}(T_i, T_s) = 0.767 + 0.011 T_i - 4.147 \times 10^{-5} T_i^2 + 0.001 T_s - 2.611 \times 10^{-4} T_s^2 + 4.575 \times 10^{-4} T_i T_s. \quad (76)$$

Cooling capacity modifier vs. partial-load ratio

$$f_{\text{cool}}^{\text{cap}}(\text{PLR}) = 0.85 + 0.15 \text{PLR} \quad (77)$$

Cooling EIR modifier vs. indoor and outdoor temperatures

$$f_{\text{cool}}^{\text{EIR}}(T_i, T_s) = 0.631 - 9.002 \times 10^{-4} T_i + 1.09 \times 10^{-4} T_i^2 + 4.651 \times 10^{-3} T_s + 5.8 \times 10^{-5} T_s^2 - 9.7 \times 10^{-5} T_i T_s. \quad (78)$$

Cooling capacity modifier vs. flow-fraction ratio

$$f_{\text{cool}}^{\text{cap}}(\text{FFR}) = 0.8 + 0.2 \text{FFR} \quad (79)$$

Cooling EIR modifier vs. flow-fraction ratio

$$f_{\text{cool}}^{\text{EIR}}(\text{FFR}) = 1.156 - 0.1816 \text{FFR} + 0.0256 \text{FFR}^2 \quad (80)$$

Heating Mode

Heating capacity modifier vs. outdoor temperature

$$f_{\text{heat}}^{\text{cap}}(T_s) = 0.759 + 0.028T_s + 1.488 \times 10^{-4}T_s^2 + 3.499 \times 10^{-6}T_s^3 \quad (81)$$

Heating EIR modifier vs. outdoor temperature

$$f_{\text{heat}}^{\text{EIR}}(T_s) = 1.192 - 0.03T_s + 1.037 \times 10^{-3}T_s^2 - 2.33 \times 10^{-5}T_s^3 \quad (82)$$

Heating capacity modifier vs. flow–fraction ratio

$$f_{\text{heat}}^{\text{cap}}(\text{FFR}) = 0.84 + 0.16 \text{ FFR} \quad (83)$$

Heating EIR modifier vs. flow–fraction ratio

$$f_{\text{heat}}^{\text{EIR}}(\text{FFR}) = 1.3824 - 0.4336 \text{ FFR} + 0.0512 \text{ FFR}^2 \quad (84)$$

Fitted Performance Curves for Hydronic Heat Pumps

This appendix documents the polynomial performance curves used to model the air-to-water and water-to-water heat pumps and the associated circulating fan in the hybrid heating systems. Each curve is implemented using the `FittedCurves` class and returns a dimensionless modifier that is applied to a nominal capacity, power, or energy-input ratio.

Unless stated otherwise, biquadratic curves are defined as

$$f(T_L, T_S) = a_0 + a_1 T_L + a_2 T_L^2 + a_3 T_S + a_4 T_S^2 + a_5 T_L T_S, \quad (85)$$

where T_L and T_S denote the load-side and source-side temperatures, respectively. Cubic and quartic curves in a single variable x (e.g. part-load ratio or normalised flow rate) are defined as

$$f(x) = a_0 + a_1 x + a_2 x^2 + a_3 x^3 \quad (\text{cubic}), \quad (86)$$

$$f(x) = a_0 + a_1 x + a_2 x^2 + a_3 x^3 + a_4 x^4 \quad (\text{quartic}). \quad (87)$$

The coefficients listed below correspond to these general forms.

Fan power consumption

A quartic curve is used to represent the normalised fan power consumption as a function of normalised air-flow rate x :

$$f_{\text{fan}}(x) = 0.00153028 + 0.00520806 x + 1.1086242 x^2 - 0.11635563 x^3 + 0.0 x^4. \quad (88)$$

Air-to-water heat pump (ASHP) curves

Heating capacity modifier vs. temperatures (biquadratic)

$$\begin{aligned} f_{\text{ASHP,heat,cap}}(T_L, T_S) = & 0.582512 - 0.001308 T_L - 1 \times 10^{-6} T_L^2 \\ & + 0.006413 T_S + 0.000189 T_S^2 \\ & - 0.000016 T_L T_S \end{aligned} \quad (89)$$

Heating EIR modifier vs. temperatures (biquadratic)

$$\begin{aligned} f_{\text{ASHP,heat,EIR}}(T_L, T_S) = & 1.039924 + 0.014600 T_L + 0.000060 T_L^2 \\ & - 0.05026 T_S + 0.000635 T_S^2 \\ & - 0.000154 T_L T_S. \end{aligned} \quad (90)$$

Heating EIR modifier below 39.00 °C (biquadratic)

$$\begin{aligned} f_{\text{ASHP,heat,EIR}}^{<39}(T_L, T_S) = & -0.394123 + 0.019639 T_L + 0.000004 T_L^2 \\ & + 0.012190 T_S - 0.000010 T_S^2 \\ & - 0.000277 T_L T_S. \end{aligned} \quad (91)$$

Heating EIR modifier vs. PLR (cubic)

$$f_{\text{ASHP,heat,EIR,PLR}}(\text{PLR}) = 0.088065 + 1.137742 \text{PLR} - 0.225806 \text{PLR}^2 + 0.0 \text{PLR}^3. \quad (92)$$

Cooling capacity modifier vs. temperatures (biquadratic)

$$\begin{aligned} f_{\text{ASHP,cool,cap}}(T_L, T_S) = & 0.813499 + 0.011955 T_L + 0.000115 T_L^2 \\ & - 0.004194 T_S + 0.000003 T_S^2 \\ & - 0.000046 T_L T_S. \end{aligned} \quad (93)$$

Cooling EIR modifier vs. temperatures (biquadratic)

$$\begin{aligned} f_{\text{ASHP,cool,EIR}}(T_L, T_S) = & 0.631347 - 0.009002 T_L + 0.000109 T_L^2 \\ & + 0.004651 T_S + 0.000058 T_S^2 \\ & - 0.000097 T_L T_S. \end{aligned} \quad (94)$$

Cooling EIR modifier vs. PLR (cubic)

$$f_{\text{ASHP,cool,EIR,PLR}}(\text{PLR}) = 0.088065 + 1.137742 \text{PLR} - 0.225806 \text{PLR}^2 + 0.0 \text{PLR}^3. \quad (95)$$

Water-to-water heat pump (WWHP) curves

Heating capacity modifier vs. temperatures (biquadratic)

$$\begin{aligned} f_{\text{WWHP,heat,cap}}(T_L, T_S) = & 0.421783 - 0.000674 T_L + 0.000007 T_L^2 \\ & + 0.013689 T_S + 0.000040 T_S^2 \\ & - 0.000039 T_L T_S. \end{aligned} \quad (96)$$

Heating EIR modifier vs. temperatures (biquadratic)

$$\begin{aligned} f_{\text{WWHP,heat,EIR}}(T_L, T_S) = & 0.132733 + 0.012322 T_L + 0.000032 T_L^2 \\ & - 0.011109 T_S + 0.000125 T_S^2 \\ & - 0.000123 T_L T_S. \end{aligned} \quad (97)$$

Heating EIR modifier vs. PLR (cubic)

$$f_{\text{WWHP,heat,EIR,PLR}}(\text{PLR}) = 0.088065 + 1.137742 \text{PLR} - 0.225806 \text{PLR}^2 + 0.0 \text{PLR}^3. \quad (98)$$

Cooling capacity modifier vs. temperatures (biquadratic)

$$\begin{aligned} f_{\text{WWHP,cool,cap}}(T_L, T_S) = & 0.453776 + 0.015342 T_L + 0.000182 T_L^2 \\ & - 0.001328 T_S + 0.000021 T_S^2 \\ & - 0.000140 T_L T_S. \end{aligned} \quad (99)$$

Cooling EIR modifier vs. temperatures (biquadratic)

$$\begin{aligned} f_{\text{WWHP,cool,EIR}}(T_L, T_S) = & 0.951894 - 0.010518 T_L + 0.000126 T_L^2 \\ & - 0.003399 T_S + 0.000183 T_S^2 \\ & - 0.000206 T_L T_S. \end{aligned} \quad (100)$$

Cooling EIR modifier vs. PLR (cubic)

$$f_{\text{WWHP,cool,EIR,PLR}}(\text{PLR}) = 0.088065 + 1.137742 \text{PLR} - 0.225806 \text{PLR}^2 + 0.0 \text{PLR}^3. \quad (101)$$