exPEDite
Enabling Positive Energy Districts through Digital Twins

ExPEDite

WP4: T4.2 – Building Stock Modelling

Advancements and Methodological Frameworks in Building Stock Modelling for Positive Energy Districts

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Abbreviations

BIM	Building Information Modelling
BIPV	Building Integrated Photovoltaics
BSM	Building Stock Modelling
CAD	Computer Aided Design
CMS	Content Management System
DEC	Display Energy Certificates
EPC	Energy Performance Certificates
ESRI	Environmental Systems Research Institute
ESS	Energy Storage Systems
EUI	Energy Use Intensity
GIS	Geographic Information System
HVAC	Heating, Ventilation, and Air Conditioning
IEQ	Indoor Environmental Quality
LCA	Life Cycle Cost
LCC	Life Cycle Cost assessment
MAPED	Model for Energy Analysis of Positive Energy District
MICS	Material Intensity Coefficient
OSM	Open Street Map
PED	Positive Energy District
PV	Photovoltaic
QGIS	Quantum Geographic Information System
RES	Renewable Energy Sources
TSC	Thermal Systems Cadastre
UBEM	Urban Building Energy Model
UMI	Urban Modelling Interface

1 Abstract

This literature review explores the critical role of building stock modelling in understanding and predicting energy consumption, carbon emissions, and overall building performance across various scales, from individual structures to entire cities. The review highlights the significance of building stock modelling in addressing climate change and investigates the existing methodological frameworks for building stock modelling and their role in facilitating the design of Positive Energy Districts (PEDs), particularly in the context of the ExPEDite project, which aims to develop a digital twin for real-time energy management at the district level. The review employs a systematic approach, utilising the Scopus database to screen and select relevant studies, ultimately including 121 documents. The review categorises building stock modelling methodologies into top-down and bottom-up approaches, discussing their respective strengths and limitations. Top-down models provide macro-level insights but may lack detail for specific energy efficiency opportunities, while bottom-up models offer high accuracy through detailed data but can be resource-intensive. Findings reveal that the integration of advancements in modelling techniques, such as digital twin and urban building energy modelling (UBEM), significantly improves energy consumption predictions and supports real-time energy management. Additionally, integrated energy demand-supply modelling is discussed as a critical approach for optimising energy consumption and production within urban areas, supporting the development of Positive Energy Districts (PEDs). The study highlights the necessity for improved data collection methods and the exploration of hybrid modelling approaches to address the complexities of urban energy dynamics. Furthermore, it emphasises the importance of stakeholder engagement in translating insights from building stock modelling into actionable strategies for achieving energy-positive outcomes. The findings underscore the potential of advanced modelling frameworks to facilitate evidence-based decision-making and effective energy management, ultimately contributing to the goals of the ExPEDite project and the broader transition to energy-positive urban environments.

Keywords: Building Stock Modelling, Positive Energy Districts, Energy Performance, Carbon Emissions, Urban Planning

2 Introduction

Building stock modelling as an area of research, aims to understand and predict the energy consumption, carbon emissions, and overall performance of buildings at various scales, from individual buildings to entire cities (Yang et al., 2023; Perwez et al., 2023 ;Shen & Wang, 2024).This field has gained significant attention due to the pressing need to address climate change and improve energy efficiency in the built environment.

Building stock modelling plays a crucial role in addressing climate change and formulating effective energy policies, as it enables policymakers to evaluate the impact of various design and retrofit strategies at the building stock level. Given that the building sector is responsible for approximately 40% of energy consumption and 36% of greenhouse gas emissions across European countries (European Commission, 2020), understanding the present and future performance of the building stock is essential for achieving national energy efficiency and environmental targets.

This literature review provides an overview of the key approaches, advancements, and challenges in building stock modelling research, with a focus on supporting the objectives of the ExPEDite project. ExPEDite focuses on developing and implementing an innovative digital twin that facilitates real-time monitoring, visualisation, and management of energy flows at the district level (exPEDite, 2024). By leveraging the insights from this review, ExPEDite will utilise replicable modelling tools to empower stakeholders in analysing planning initiatives aimed at achieving positive energy outcomes. This supports evidence-based decision-making in a cost-efficient manner, which is a key objective of the ExPEDite project.

The building stock modelling approaches, particularly bottom-up engineering methods such as archetype-based and building-by-building models, provide insights into energy efficiency measures, their implications on indoor environmental quality (IEQ) and occupant health, as well as the environmental impact of the building materials throughout their life cycle. To align with ExPEDite's vision, this review addresses building stock energy efficiency, one of the four components that contribute to Positive Energy Districts (PEDs) (1. Building stock energy efficiency; 2. Renewable energy sources (RES); 3. Energy flexibility; 4. E-mobility & sustainable transport) (exPEDite, 2024).

The integration of advanced modelling techniques, such as those discussed in this review, with the digital twin framework proposed by ExPEDite, can enhance the understanding of energy dynamics at the district level, ultimately contributing to more effective energy management and policy implementation.

3 Methodology

A scoping review approach was adopted, which is frequently used to assess the scope and nature of research within a particular area, summarise the findings, and identify gaps in existing literature (Pham et al., 2014). While it shares similarities with systematic reviews in its use of rigorous and transparent methods that enable replicability, scoping reviews generally do not include assessments of the quality of the literature (Grant & Booth, 2009).

3.1 Research question and search criteria

This review was guided by the following research question:

- What are the existing methodological frameworks for building stock modelling (BSM) and how do they support the design of Positive Energy Districts (PED)?

The aim is to identify and analyse the various frameworks employed in current literature and their potential to facilitate energy-positive urban environments. To achieve this, the review seeks to explore:

- What key frameworks or methodologies are commonly utilized in BSM?
- How do these frameworks facilitate the design and implementation of Positive Energy Districts?

The emphasis of this review is on BSM methodologies, leading to the exclusion of papers that do not directly contribute to this focus or that address broader urban systems without specific reference to building stock modelling. Given the focus on BSM and its application to Positive Energy Districts, the review excludes literature that primarily addresses buildings in isolation without pertinent context to energy performance and urban planning. The exclusion criteria are detailed further below. The review encompasses articles published from 2010 onwards to ensure a comprehensive understanding of the most recent developments in the field.

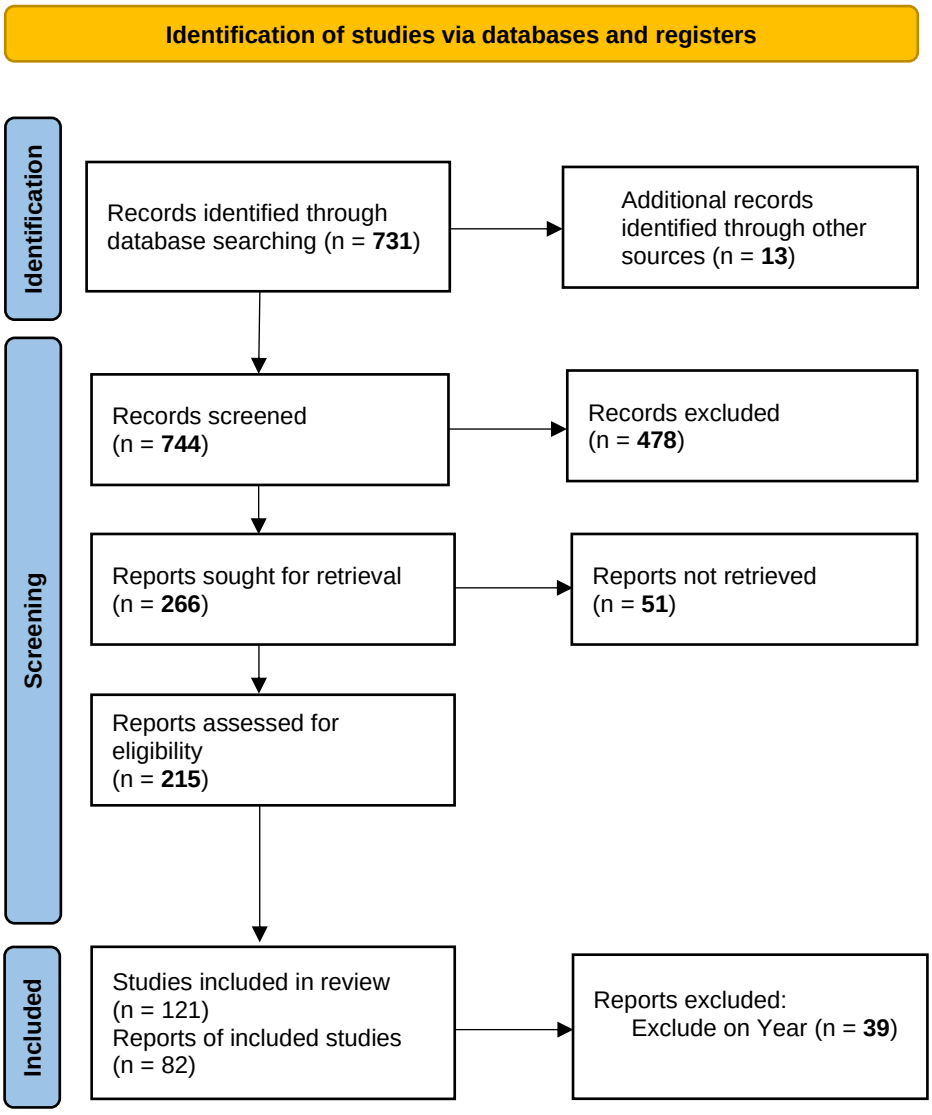
3.2 Database search and screening process

The Scopus database was used to conduct searches employing AND/OR Boolean operators. The terms “Building Stock Modelling” or “Building Stock Modeling” or “Building Stock Model” were identified as the primary keywords. These were then paired with a second keyword to create keyword strings that helped refine the search parameters. The terms “Positive Energy Districts” and

"Digital Twin" as second keywords resulted to little to no results, hence the broader terms "Energy", "Urban" and "City" were used, as shown below.

((Building Stock Modelling) OR (Building Stock Modeling) OR (Building Stock Model)) AND (Energy) AND ((Urban) OR (City))

The flow of documents through the review is shown in the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) diagram in Figure 1. There were 731 records identified in the database search. Of these, 215 were included in a full-text review. Finally, 121 documents were included in the review, of which 39 were excluded on the year of publication (before 2010).



3.3 Inclusion and exclusion criteria

Since the aim of this review is to cover the state-of-the-art knowledge in building stock modelling and its potential to facilitate the transition to energy-positive urban environments, the following eligibility criteria were established for inclusion and exclusion:

(1) Studies published in peer-reviewed journals

(2) Studies published from 2010 onwards

(3) Studies discussing city scale approaches

(4) Studies discussing more than one input parameter (e.g. window to wall ratio)

4 Results

4.1 Approaches to Building Stock Modelling

Historically, building stock modelling has evolved from simple statistical methods to more sophisticated approaches that leverage advanced technologies and data analytics. Building stock modelling methodologies can be broadly categorised into top-down and bottom-up approaches.

Top-down approaches use aggregated data at a macro level, such as national or regional energy consumption statistics, to estimate the performance of the building stock. These methods are useful for large-scale analysis but may lack the granularity needed for detailed insights at the building level (Prina et al., 2024). Bottom-up approaches, on the other hand, use detailed data from individual buildings to model energy performance. These methods provide high accuracy and granularity but can be data-intensive and time-consuming (ibid.).

4.1.1 Top-Down Models

Top-down models are often used for policy analysis and long-term energy planning. One of the main strengths of top-down models is their ability to provide a broad overview of energy consumption trends and identify macro-level drivers of energy demand. For example, econometric models can be used to analyse the relationship between energy consumption and factors such as economic growth, population, and energy prices (Bhattacharyya Govinda & Timilsina, 2009). These models can help inform policy decisions and support the development of energy efficiency programs.

However, top-down models also have limitations. The lack of detail can make it difficult to identify specific opportunities for energy efficiency improvements at the building or district level. Additionally, top-down models may not fully capture the impact of building characteristics and usage patterns on energy consumption, leading to potential inaccuracies in the results (Kavgic et al., 2010).

4.1.2 Bottom up Models

The current state and future evolution of building stocks are commonly studied by means of bottom-up models. Bottom-up models estimate the performance of the entire building stock based on data from individual buildings. These models typically rely on detailed building characteristics, such as geometry, building materials, and usage patterns, to simulate energy use and emissions (Swan & Ugursal, 2009). Bottom up models typically characterise the building stock using archetype buildings, which represent typical building types and usage patterns. This can help simplify the modelling process while maintaining accuracy (Kavgic et al., 2010).

4.1.2.1 Archetype-Based Models

Archetype-based models involve grouping buildings into categories to form a building typology matrix. Representative "virtual" buildings are then generated to

model the common features of a group of buildings. This approach allows for increased detail and geospatial distribution of findings (Mata et al., 2014).

One of the key advantages of archetype-based models is their ability to simplify the modelling process while maintaining accuracy. By representing typical building types and usage patterns, these models can provide detailed insights into energy consumption patterns and identify opportunities for energy efficiency improvements. Additionally, archetype-based models can be integrated with GIS data to capture the spatial distribution of buildings and their characteristics. (Langevin et al., 2020). This integration enhances the modelling capabilities and supports energy and emissions-related policy making and planning.

However, archetype-based models also face challenges. The accuracy of these models depends on the representativeness of the building archetypes, and obtaining accurate and up-to-date information on building characteristics can be difficult. Additionally, archetype-based models may not fully capture the diversity of building stocks, leading to potential inaccuracies in the results (Langevin et al., 2020; Swan & Ugursal, 2009)

4.1.2.2 Building-by-Building Models

The second approach used by bottom-up models is the building-by-building approach. Building-by-building models involve detailed modelling of individual buildings. This approach relies on collecting comprehensive information on each building's characteristics, such as geometry, construction materials, insulation levels, heating and cooling systems, and occupancy patterns (Saad & Eicker, 2023).

One of the key advantages of building-by-building models is their ability to capture the heterogeneity of building stocks. By considering the unique characteristics of each building, these models can provide detailed insights into energy consumption patterns and identify opportunities for energy efficiency improvements. This approach is particularly useful for detailed energy audits and targeted energy efficiency programs.

It’s important to consider that although the building-by-building approach can provide detailed insights into the performance of individual buildings, it may not necessarily reflect the overall performance of the entire building stock accurately (Perwez et al., 2023). While this approach can yield significant insights, it often lacks the ability to capture the spatiotemporal dynamics and broader interactions at larger scales (ibid.) Therefore, while it offers granularity, it may not always provide a comprehensive view of the entire stock's performance.

This is where the efforts of the ExPEDite project come into play, aiming to enable a Positive Energy District by leveraging digital twin technology. By integrating data from multiple buildings and simulating their interactions within a digital twin framework, the ExDEDite project can provide a more comprehensive view of energy performance across the entire district, aiming to address the gaps left by traditional approaches and facilitating better decision-making for energy efficiency and sustainability initiatives. This leads us to another advantage of the building-by-building models; the fact that they could be integrated with IoT sensors and meters, and provide real-time monitoring and management of energy consumption.

However, building-by-building models also face challenges. The extensive data collection and computational requirements can make this approach impractical

for large-scale building stocks. Data availability and quality are persistent issues, as accurate and up-to-date information on building characteristics and energy usage is often scarce. Additionally, the complexity and heterogeneity of building stocks pose significant modelling challenges, requiring sophisticated techniques to capture the diversity of building types and usage patterns (Saad & Eicker, 2023). Despite these challenges, the detailed nature of this approach makes it a valuable tool for policymakers, researchers, and practitioners aiming to develop precise and effective strategies for improving energy efficiency in the built environment.

The advantages and disadvantages of the approaches to building stock modelling are summarised in Table 1 below.

Table 1: Summary of Advantages and Disadvantages of Top Down and Bottom Up Models

Approach	Advantages	Disadvantages
Top Down Models	They provide a broad overview of energy consumption trends and can identify macro-level drivers of energy demand. Useful for policy analysis, decision making and long-term energy planning.	Lack of detail can hinder identification of opportunities at the building or district level. Can lead to potential inaccuracies in the results (Kavgic et al., 2010).
Archetype-Based Bottom Up Models	Can provide detailed insights into energy consumption patterns and identify opportunities for energy efficiency improvements. This method simplifies the modelling process while maintaining a level of accuracy (Kavgic et al., 2010; Mata et al., 2014).	Obtaining accurate and up-to-date information on building characteristics can be challenging (Langevin et al., 2020; Swan & Ugursal, 2009). Input assumptions cause uncertainties.
Building-by-Buildig Bottom Up Models	Can provide high accuracy and granularity by using detailed data from individual buildings. Can capture the heterogeneity of building stocks, allowing for detailed insights into energy consumption patterns and identification of opportunities for energy efficiency improvements.	Data-intensive and time-consuming, requiring comprehensive information on each building's characteristics. Extensive data collection and computational requirements can make this approach impractical for large-scale building stocks.

As can be observed in Figure 1 below, archetype-based approaches are prevailing in building stock modelling research. Their ability to efficiently represent the energy performance of large building stocks with reduced data and computational requirements makes the archetype models the most widely used approach.

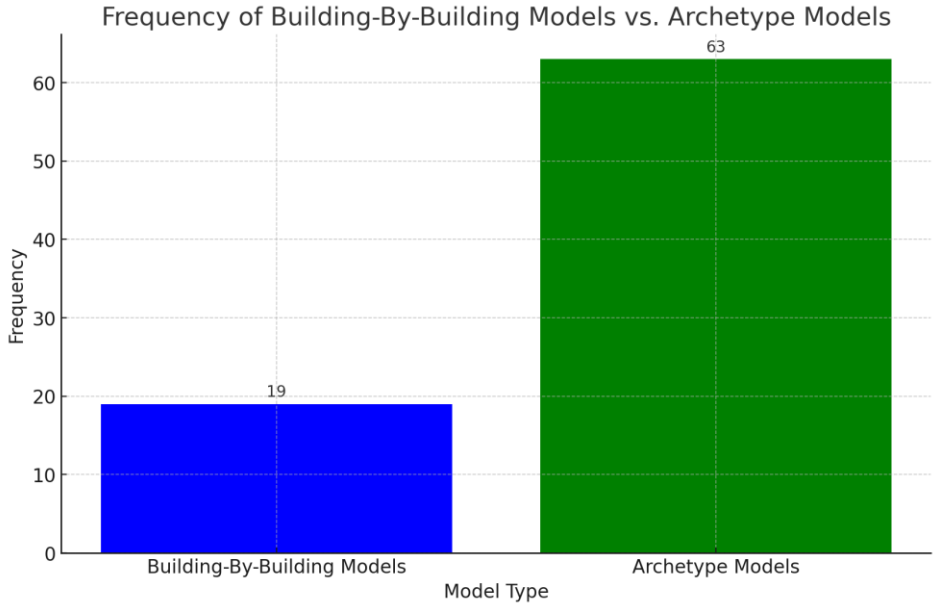


Figure 1: Frequency of papers following the different approaches (Building-By-Building vs Archetype)

4.2 Advancements in Building Stock Modelling

Recent advancements in building stock modelling have focused on incorporating high-resolution data and advanced computational techniques (Shen & Wang, 2024). These advancements have the potential to significantly improve the accuracy of building stock models and enhance our ability to analyse and optimise the energy performance of urban areas (ibid.), paving the way for the development of Positive Energy Districts (PEDs).

Recent studies highlight significant advancements in building stock modelling, particularly through the integration of machine learning, GIS, and data-driven approaches. A Spanish study introduces a hybrid method for developing building archetypes that enhances energy performance assessments using machine learning (Borges et al., 2022). A Belgian study enriches its building stock model with energy performance data and employs machine learning algorithms to analyse large datasets, leading to improved accuracy (Verellen & Allacker, 2022). Other notable methodologies include integrated energy demand-supply modelling, which optimises energy consumption and production in urban areas (Vahid-Ghavidel et al., 2024), and multi-scale urban building energy modelling (UBEM) that assesses energy performance across various spatial scales (Mutani et al., 2024). These approaches collectively support the development of Positive Energy Districts (PEDs) by providing detailed insights into urban energy dynamics and enhancing the effectiveness of energy efficiency measures. However, challenges such as data quality and model complexity remain critical considerations for future research and implementation.

4.2.1 Geographic Information Systems (GIS) and Remote Sensing

Geographic Information Systems (GIS) and remote sensing technologies have become key components in building stock modelling, as they can provide spatially explicit data and insights into the characteristics and performance of buildings.

For instance, a Japanese study presents a multi-scale urban building energy model (UBEM) that couples with Building-Integrated Photovoltaics (BIPV) using a hybrid approach that combines GIS and bottom-up archetype models (Perwez et al., 2023). The dataset used consists of geo-referenced building data, which enables detailed analysis of energy consumption and the potential for integrating renewable energy sources at both urban and district levels (ibid.).

Another study employs a bottom-up statistical model that leverages GIS data to evaluate energy performance on a building-by-building basis in Milan, Italy (Mutani et al., 2023). The integration of GIS allows for the precise mapping of energy consumption patterns and the identification of energy efficiency measures at the urban scale. This approach allows for a detailed analysis of energy-related variables and supports the development of effective energy policies for sustainable urban development (ibid.). In another study, Mutani et al. (2024) focus on Urban Building Energy Modelling (UBEM) to support climate change mitigation in Santiago, Chile, particularly in the commune of Renca. They combine archetype-based UBEM with GIS-based data to model energy consumption and emissions, which provides valuable insights for urban planners and policymakers (Mutani et al., 2024). The findings indicate that the period of construction and the surface-to-volume ratio significantly influence energy consumption (ibid.).

Similarly to Riga (from Task 2.4. *Review of development pathways*), the pilot city of the ExPEDite project, most residential buildings in Renca were constructed before 2001 (Mutani et al., 2024), when energy-saving regulations came into force (from Task 2.4). Both cities have a significant portion of thermally inefficient buildings, and hence, energy efficiency could be considerably improved by retrofitting interventions. In their study, Mutani et al. (2024), identify four (4) main retrofitting measures: window replacement with PVC casements and double-glazed windows, wall insulation with an additional 20 cm of thermal insulation, roof insulation with 15 cm of thermal insulation, and floor insulation with 1 cm of thermal insulation. A simulation of the Energy Use Intensity (EUI) following these retrofitting measures, revealed that improving the thermal performance of roofs, walls and windows, yield substantial energy savings compared to adding slab insulation (ibid). In addition to retrofitting, the study emphasises the importance of integrating renewable energy sources, particularly solar technologies (ibid.). As a means to enhance energy efficiency and reduce reliance on fossil fuels, the installation of solar collectors and heat pumps is proposed.

Muñoz et al. (2020) highlight the need for an integrated evaluation framework that encompasses various aspects of city energy systems, including buildings, transportation, and energy generation. They present a methodology for integrated modelling and impact assessment using a GIS-based tool (ENERKAD) (Muñoz et al., 2020). This approach allows for a comprehensive analysis of energy performance and the evaluation of different energy efficiency scenarios in the city of Valencia. Furthermore, a Belgian study aims to develop a building stock model enriched by energy performance data and GIS-enhanced archetype

models (Verellen & Allacker, 2022). The use of open-source GIS data enables the detailed mapping of urban energy performance, supporting climate change mitigation efforts (ibid).

These studies highlight the critical role of GIS and remote sensing technologies in building stock modelling. GIS and remote sensing data can also provide comprehensive information about building characteristics for applications like urban digital twins, which are virtual replicas of physical systems that can be used for real-time monitoring and management (Lei et al., 2024). This data integration facilitates multiple applications, such as simulating energy usage and examining the impacts of urban heat islands (ibid.). By leveraging these technological advancements, researchers can develop more accurate and detailed building stock models, supporting the design and implementation of Positive Energy Districts (PEDs) and promoting sustainable urban development. Table 2 below provides an overview of the reviewed studies utilising GIS tools, which includes their origin, spatial and time scale, their modelling approach and application, as well as the dataset and GIS tools used.

Table 2: Studies utilising GIS tools.

Study	Origin	Spatial Scale	Time Scale	Approach	Application	Dataset	GIS Tool
(Perwez et al., 2023)	Tokyo, Japan	Multi-scale (including building, district, city, and regional levels)	Transient (hourly)	Hybrid (GIS-synthetic) Combination of GIS and bottom-up archetype simulation method	Energy modelling (specifically for assessing carbon neutrality of commercial building stock)	The dataset used consists of a geo-referenced dataset that includes physical elements, which is integrated with synthetic stock models.	The GIS tool used is a geo-referenced dataset that consists of physical elements for modelling the energy demand and supply of commercial building stock.
(Berzolla et al., 2023)	Oshkosh, USA	Urban	Snapshot	Archetype-based bottom up	Urban building energy modelling (UBEM)	2019 electricity and natural gas consumption data for residential buildings in Oshkosh GIS data	The urban modeling interface (UMI) in the Rhinoceros3D CAD environment
(Mutani et al., 2023)	Milan, Italy	Urban	Snapshot	Bottom-up statistical Combination with GIS	Energy modelling	Energy Performance Certificates (EPCs) database	The GIS tool used is Quantum Geographic Information System (QGIS)
(Cinquepalmi et al., 2023)	Rome, Italy	Urban	Snapshot	Hybrid	Energy modelling	Building Information Modelling (BIM) data and Geographic Information System (GIS) data	The GIS tool used is Autodesk InfraWorks
(Congiu et al., 2023)	Carbonia, Italy	Urban	Transient	Hybrid	Energy modelling	Urban building energy model (UBEM) data	The GIS tool used is the GeoNode service, which is an open-source content management system (CMS) for geographic data.
(J. Yang et al., 2023)	Changsha, China	Urban	Transient	Archetype-based bottom up	Energy modelling and carbon emissions estimation	Integrated GIS datasets (building footprint, point of interest, community boundary) and satellite imageries	-

Study	Origin	Spatial Scale	Time Scale	Approach	Application	Dataset	GIS Tool
(Sasso et al., 2023)	Geneva, Switzerland	National	Snapshot	Archetype-based bottom up	Energy modelling	CECB-PLUS dataset, HDI database, RegBL dataset	-
(Mutani et al., 2024)	Renca, Santiago de Chile, Chile	Urban	Snapshot	Archetype-based bottom up	Energy modelling	Archetype data and energy-related variables.	The GIS tool used is QGIS.
(Yamaguchi et al., 2023)	Tokyo, Japan	Urban	Transient	Hybrid	Energy modelling	Population census and housing data	-
(Shen & Wang, 2024)	Shenzhen, China	Multi-scale (urban, regional, and national)	Varies	The approaches discussed include bottom-up, top-down, and hybrid methods.	The primary application is energy modelling.	The studies utilise large-scale building datasets, including those from the TABULA project and other national-level building stock models.	-
(Ang et al., 2023)	Illinois, USA	Urban	Transient	Hybrid	Urban building energy modelling (UBEM)	Smart meter data and census data.	The urban modelling interface (UMI) in the Rhinoceros3D CAD environment
(Khamenei et al., 2024)	Padova, Italy	Urban	Snapshot	Bottom up	Energy modelling	Various Italian datasets, OpenStreetMap (OSM), National Geoportal, and census data	QGIS
(Deng et al., 2023)	Geneva, Switzerland	Urban	Transient	Building by building bottom up	Energy modelling	GIS datasets and Swiss building norms	AutoBPS
(Kourgiozou et al., 2023)	London, United Kingdom	Urban	Transient	Building by building bottom up	Energy modelling	University's registry with names, addresses, floor areas, and DEC certificates	-
(Slavkovic et al., 2022)	Melbourne, Australia	Urban	Snapshot	Hybrid	LCA modelling	Geospatial data, year of asset construction, asset typology, local-specific database of embodied flows, database for simulating operational flows, and evolving parameters.	-

Study	Origin	Spatial Scale	Time Scale	Approach	Application	Dataset	GIS Tool
(Muñoz et al., 2020)	Valencia, Spain	Urban	Snapshot	Hybrid	Energy modelling	Top-down real consumption data supplied by the city, combined with bottom-up approaches for energy demand estimation	ENERKAD
(Ranjbar et al., 2023)	Bilbao, Spain	Urban	Transient	Bottom up	Energy modelling	Basic public information such as cadaster and building energy certificates, calibrated with real data from a gas distribution company.	GIS-based building stock energy model developed by TECNALIA.
(Colleto & Gomes, 2022)	Sao Paulo, Brazil	Urban	Snapshot	Hybrid	LCA modelling	The study includes data from 226 buildings on the campus of the State University of Campinas (UNICAMP)	-
(HosseiniHaghighi et al., 2022)	Kelowna, Canada	Urban	Snapshot	Archetype-based bottom up	Energy modelling	CityGML, GIS datasets, national and local data sources	Insel4Cities
(X. Yang et al., 2020)	Leiden, Netherlands	Urban	Snapshot	Archetype-based bottom up	Energy modelling	GIS data of buildings, archetype buildings, weather data, refurbishment records, occupant behaviour data	-
(Ferrari et al., 2021)	Milan, Italy	Urban	Transient	Bottom up	Energy modelling	Data from the GCPH (Census of the built environment) and Thermal Systems Cadaster (TSC)	-
(Mutani & Todeschi, 2021)	Turin, Italy	Urban	Transient	Top down	Energy modelling	Energy performance certificate database of the Piedmont Region	ArcGIS, ESRI
(Chang et al., 2022)	Taipei, Taiwan	Urban	Transient	Bottom up	Urban Building Energy Modelling (UBEM) and Urban	Information obtained via Building Information Modelling (BIM) and Geographic Information System (GIS)	-

Study	Origin	Spatial Scale	Time Scale	Approach	Application	Dataset	GIS Tool
					Building Material Modelling (UBMM)		
(Neumann et al., 2021)	Vienna, Austria	Urban	Snapshot	Bottom up	Energy modelling	Official buildings and dwellings register, mapped to statistical grid cells of 250 m× 250 m	-
(Ledesma et al., 2021)	Barcelona, Spain and Quito, Ecuador	Urban	Transient	Bottom up	Energy modelling	Real-reference buildings from educational building stocks.	-
(Ali et al., 2020)	Dublin, Ireland	Multi-scale (urban, district, city, national)	Snapshot	Bottom-up	Energy modelling	Historical building stock data, energy performance data, census data	ArcGIS
(Pittam et al., 2014)	Cork City, Ireland	Urban	Snapshot	Hybrid	Energy modelling	Housing data from stock asset rating surveys	Web-based GIS mapping application
(Marston et al., n.d.)	Copenhagen, Denmark	Urban	Transient	Hybrid	Energy modelling	GIS data for large communities	-

4.2.2 Machine Learning and Data-Driven Approaches

Machine learning and data-driven approaches offer new ways to enhance the accuracy and efficiency of energy performance assessments. It allows for enhanced automation and decision-making based on existing conditions, and facilitates the prediction of future demand without the need for extensive simulations (Vahed Ghoshchi et al., 2022). Mutani et al. (2023) present a bottom-up statistical model that leverages machine learning techniques to evaluate energy performance on a building-by-building basis. By integrating machine learning paradigms (Table 3), it is possible to analyse large datasets effectively, identify trends, and make informed predictions about energy consumption (ibid.). In Table 3, applicable machine learning approaches for typical tasks in the energy sector are shown. It is important to mention that the machine learning field is constantly evolving, and new techniques may arise that offer improved solutions for particular challenges (ibid.)

Table 3: Applicable Machine Learning Paradigms for each Typical Task in the Energy Sector, Source: (Mutani et al., 2023).

Typical tasks	Machine Learning Paradigms			
	Supervised	Reinforcement Learning	Online Learning	Unsupervised
Energy Demand Prediction	✓	✓	✓	✓
Energy Efficiency Measures	✓	✓	✓	✓
Energy Saving Prediction	✓	✓	✓	✓
Maximisation of Renewable Energy Generation	✓	✓	✓	
Reduction of Fossil Fuel Impacts	✓			
Omptimisation of Supply/Demand Distribution	✓	✓		✓
Decentralised Generation Systems	✓		✓	✓
Optimisation of the Distribution Network	✓		✓	✓
Optimisation of Energy Self-consumption	✓	✓		✓
Energy Data Management	✓			✓
Development of Next-generation Clear Energy Technologies	✓			
Planning of Sustainable Energy Systems	✓			✓

Typical tasks	Machine Learning Paradigms			
	Supervised	Reinforcement Learning	Online Learning	Unsupervised
Energy Policies and Incentives for a Sustainable Development	✓			✓

Jradi et al. (2023) introduce a digital twin solution, called DanRETwin, which aims at enhancing energy retrofit decision-making and promoting decarbonization within the Danish building sector. This innovative approach addresses the challenges associated with traditional retrofitting methods, which often rely on static building-by-building strategies that can lead to significant discrepancies between expected and actual energy savings (Jradi et al., 2023). The integration of digital twins allows for real-time data processing, enhancing the ability to manage and optimise energy systems dynamically.

A Spanish study presents a hybrid approach to representative building archetypes development, combining deterministic and data-driven methods to address inaccuracies in traditional archetype models (Borges et al., 2022). This approach leverages machine learning to refine archetype definitions and improve the accuracy of energy performance assessments. Furthermore, the building stock model of the Belgian study mentioned in the previous chapter, not only is enriched by energy performance data and GIS-enhanced archetype models, but also employs machine learning algorithms for the analysis of large datasets (Verellen & Allacker, 2022). This enables detailed insights into the urban energy performance. According to Verellen & Allacker (2022), the use of machine learning algorithms helps to fill data gaps and improve the accuracy of the model.

Another study proposes an automated stochastic modelling approach, referred to as "Fifty shades of grey," which combines grey-box modelling with machine learning techniques (Leprince et al., 2022). This approach allows for the efficient simulation of energy performance across a large number of buildings. Grey-box modelling is a hybrid method that integrates elements of both physics-based (white-box) models and purely data-driven (black-box) models (ibid.). Grey-box models generally need fewer experimental data for training compared to black-box models, which enhances their efficiency in data utilisation. The goal of grey-box modelling is to achieve a balance between accurately representing the physical reality of the system and effectively leveraging the information contained in the data (ibid.).

Lastly, as the title suggests, Ali et al. (2020) propose “a data-driven approach for multi-scale GIS-based building energy modelling..”, which employs machine learning techniques to analyse Energy Performance Certificates (EPCs) and other relevant datasets. This enables a comprehensive assessment of energy performance across different scales, from individual buildings to entire urban areas (Ali et al., 2020). The study highlights the potential of machine learning to uncover hidden patterns and insights that traditional modelling techniques might overlook (ibi).

These studies emphasise the potential of machine learning and data-driven approaches to revolutionise building stock modelling and support the development of Positive Energy Districts (PEDs) by providing detailed and

actionable insights into urban energy performance. These methods can handle large datasets and identify complex patterns that traditional models may miss (Ali et al., 2020). One of the key advantages of machine learning approaches is their ability to improve model accuracy by learning from data (Verellen & Allacker, 2022). For example, machine learning algorithms can be used to calibrate building stock models based on observed energy consumption data, reducing the need for manual parameter tuning (Amasyali & El-Gohary, 2018).

However, machine learning approaches also face challenges. The quality and representativeness of the training data are critical for model performance, and obtaining high-quality data can be difficult (Shen & Wang, 2024). Additionally, machine learning models can be complex and may require significant computational resources, particularly for large-scale building stock modelling (Amasyali & El-Gohary, 2018).

4.2.3 Integrated Energy Demand-Supply Modelling

Another critical approach in building stock modelling is integrated energy demand-supply modelling, which aims to optimise the balance between energy consumption and energy production within urban areas, thereby supporting the development of Positive Energy Districts (PEDs).

A notable study proposes an optimisation framework for urban energy systems that incorporates both demand and supply aspects (Vahid-Ghavidel et al., 2024). The study emphasises the importance of considering local renewable energy sources, such as photovoltaic (PV) panels and small-scale wind turbines, alongside energy storage systems (ESS) (ibid). This is crucial for PEDs, which seek to generate more energy than they consume, thereby contributing to decarbonisation and sustainability. Additionally, the case study conducted in a neighbourhood in Chicago illustrates how the integration of building energy demands with renewable energy supply can lead to significant reductions in CO2 emissions (up to 75%) with only a moderate increase in energy costs (15%) (ibid.). This demonstrates the feasibility of achieving the energy goals set for PEDs while maintaining economic viability.

Another study focuses on the feasibility of Positive Energy Districts in specific urban typologies by employing a bottom-up energy modelling tool, referred to as MAPED (Neumann et al., 2021). This tool assesses the potential of different energy technologies and strategies to achieve positive energy balances at the district level, focusing on urban neighbourhoods (ibid.). The datasets used include data from official building records and energy consumption statistics, which enable a comprehensive evaluation of energy demand and supply scenarios (ibid). Neumann et al. (2021) highlight the potential of integrated energy demand-supply modelling to identify optimal combinations of energy efficiency measures, renewable energy sources, and demand response strategies to achieve PEDs.

By simultaneously addressing energy consumption by buildings and energy production from various sources, integrated models can assess the potential for renewable energy integration, such as solar photovoltaics (PV) and wind energy, to meet the energy demands of buildings (Vahid-Ghavidel et al., 2024). Additionally, these models can evaluate the impact of energy efficiency measures and demand response strategies on the overall energy system (ibid.). As cities strive to achieve sustainability goals and develop Positive Energy Districts (PEDs), integrated energy demand-supply modelling will be essential for optimising energy systems, reducing emissions, and enhancing the resilience of urban areas.

4.2.4 Multi-Scale Urban Building Energy Modelling

Multi-scale urban building energy modelling (UBEM) has emerged as a powerful approach to assess and optimise energy performance across different spatial scales, from individual buildings to entire urban areas. This approach is particularly useful in contexts where detailed consumption data is limited, as it enables urban planners and policymakers to understand the energy performance of building stocks without needing extensive data on each individual building. (Mutani et al., 2024). According to Mutani et al. (2023), UBEM can consist of four

phases, as illustrated in the flowchart in Figure 2 below: 1. Pre-modelling, 2. Modelling, 3. Calibration, 4. Results Representation.

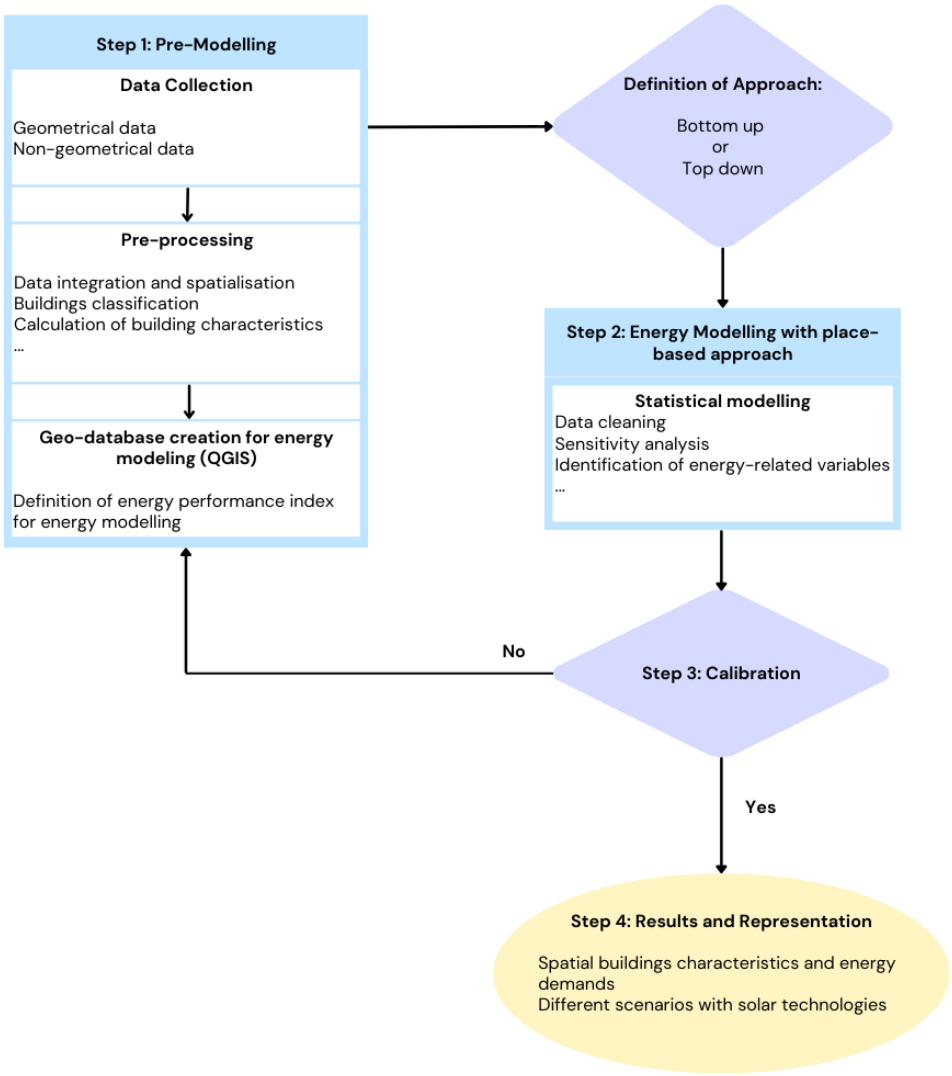


Figure 2: The phases of the statistical UBEM with a place-based methodology, as presented in the paper "*Statistical Building Energy Model from Data Collection, Place-Based Assessment to Sustainable Scenarios for the City of Milan*", Source: (Mutani et al., 2023). Recreated in Canva.com

A notable study presents a multi-scale UBEM that couples with Building-Integrated Photovoltaics (BIPV) using a hybrid approach that combines Geographic Information Systems (GIS) and bottom-up archetype models (Perwez et al., 2023). This approach enables detailed analysis of energy consumption and the potential for integrating renewable energy sources at both urban and district levels (ibid.). Mutani et al. (2024) focus on urban building energy modelling to support climate change mitigation in Santiago, Chile. This archetype-based UBEM is combined with GIS-based data to model energy consumption and emissions, offering a comprehensive assessment of urban energy performance and identifying opportunities for energy efficiency improvements (ibid.).

Berzolla et al. (2023) introduce “an eight-step simulation-based framework designed to help cities achieve their energy and emissions reduction targets”. This archetype-based UBEM utilises baseline energy and emissions data to simulate various energy optimisation scenarios, providing valuable insights for urban planners and policymakers (ibid.). According to Berzolla et al. (2023), calibration efforts would limit the scalability of the model and an uncalibrated model offers enough information to address questions from policymakers at the stock level. Previous research indicates that uncalibrated UBEMs typically produce results that are within 15% error in energy use intensity when compared to actual energy consumption at the building stock level, which Berzolla et al. (2023) consider a sufficient degree of accuracy for city-scale policy analyses.

To conclude, these studies highlight the versatility and effectiveness of multi-scale UBEM in providing detailed and actionable insights into urban energy performance. As can be seen in Figure 3 below, this is a widely preferred approach, as a substantial number of the reviewed papers utilize UBEM-related methods. By enabling the analysis of energy consumption and optimisation at various spatial scales, multi-scale UBEM can support the development of Positive Energy Districts (PEDs).

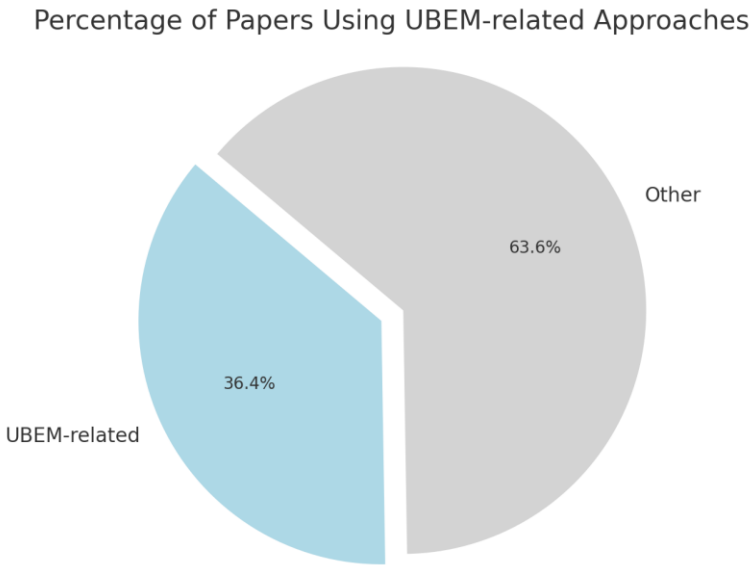


Figure 3: Percentage of reviewed papers using UBEM-related Approaches

4.2.5 Statistical Building Energy Models

Statistical building energy models are analytical tools used to assess and predict energy consumption and performance in buildings based on collected data (Mutani et al., 2023). These models leverage statistical techniques to analyse large datasets, allowing for the identification of trends, patterns, and relationships among various factors that influence energy use (ibid.).

Mutani et al. (2023) use statistical building energy models to assess energy consumption and production, by analysing large databases of energy-related data, such as Energy Performance Certificates (EPCs). The identification of trends and patterns in energy use allow for the classification of buildings based on their characteristics, such as geometry and period of construction (ibid.). As

exemplified in the city of Milan, by employing a place-based approach, these models can evaluate the availability of renewable energy resources and optimise energy supply and demand in urban areas, which aids in the formulation of effective energy policies for sustainable development (ibid.).

In a Chinese study, statistical building energy models are used to analyse and predict the carbon emissions and energy consumption of buildings (Yang et al., 2023). These energy models often rely on existing datasets, such as energy use intensities obtained from official statistics, to estimate the overall carbon emissions of a city's building stock. They can help in understanding the dynamics of building stock changes over time, including factors like population growth, urbanisation rates, and energy efficiency standards (ibid.). According to Yang et al. (2023), the limitations of these models include a lack of detailed building datasets and the challenge of accurately representing the energy performance of individual buildings, which can lead to deviations from actual energy consumption and emissions.

A Swedish study addresses the handling of data uncertainties when using Swedish statistical data to describe energy usage in the building stock (Mangold et al., 2015). It highlights the importance of assessing and remediating data quality issues to improve the accuracy and reliability of energy performance assessments. The paper details ways of handling uncertainty in Energy Performance Certificates (EPCs) with measured energy usage on a city scale, emphasising the need for data quality analysis before using the data for modelling or describing the building stock (ibid.).

Lastly, Verellen & Allacker (2022) emphasise that the use of statistical methods allows for the detailed mapping of urban energy performance, which supports climate change mitigation efforts. This approach is highlighted as necessary due to the limitations of available data and the need for accurate estimations of renovation needs in the building stock (ibid.).

These studies underpin the critical role of statistical building energy models in providing detailed and actionable insights into energy performance. By leveraging large datasets and advanced statistical methods, these models enable the identification of energy efficiency measures, support climate change mitigation efforts, and contribute to the development of Positive Energy Districts (PEDs).

4.2.6 Life Cycle Assessment of Building Energy Systems

Life Cycle Assessments (LCA) assess the energy demands, emissions, and costs associated with the production, use, and end-of-life phases of building materials and components (Harter et al., 2023). Although LCA is widely used at the individual building level, studies focusing on LCA at the building stock level are less frequent (Dong et al., 2023). One of the key components considered in LCA are the Heating, Ventilation, and Air Conditioning (HVAC) systems, which, despite their low mass share in the total mass of a building (1%-4%), can account for a significant portion of the primary energy demand and emissions (Harter et al., 2023). According to Harter et al. (2023), HVAC systems can take up a share of between 2% to 26% of the primary energy and emission output along a building's life cycle. The inclusion of heating system components, such as heat generators, domestic hot water tanks, and heat transfer systems, in LCA can cover a large proportion of the embodied energy demand and emissions (ibid.). Recent studies have developed methods to conduct LCA and Life Cycle Cost Assessment (LCC) of large residential building stocks, focusing on selected

heating system components (ibid.). They use semantic 3D city models, such as CityGML, to provide building-specific information for the assessments (ibid.). The results of these assessments show that the consideration of the entire life cycle of buildings and their energy systems is essential to achieve climate neutrality and optimise resource use in urban environments (ibid.). Lastly, the authors highlight the importance of focusing on existing building stock through renovations to achieve climate neutrality goals (ibid.).

4.2.7 Methodological Frameworks for Evaluating Positive Energy Districts

The development of Positive Energy Districts (PEDs) requires advanced methodological frameworks and tools that can accurately assess and optimise energy performance at the district level. Several studies have focused on creating and refining such frameworks.

Neumann et al. uses a bottom-up energy modelling tool called MAPED (Model for Energy Analysis of Positive Energy District) to assess the feasibility of PEDs (2021). Feasibility assessment tools are essential for evaluating the potential of different energy technologies and strategies in PEDs, as they help stakeholders determine whether they are worth pursuing. The MAPED tool evaluates the potential of various energy technologies and strategies to achieve positive energy balances at the district level, focusing on urban neighbourhoods (Neumann et al., 2021). This tool allows users to test different scenarios and implementation measures to explore transformation pathways towards PEDs (ibid.)

A study uses archetypes and Material Intensity Coefficients (MICs) to provide a detailed assessment of material stocks and flows, which can aid in decision-making regarding the availability of secondary resources from buildings (Mohammadiziazi & Bilec, 2023). Mohammadiziazi & Bilec (2023) highlight the importance of quantifying and spatialising building material stock and renovation flow, which can support the development of positive energy districts. By understanding the material intensity coefficients (MICs) and physical attributes of buildings, urban planners and developers can design buildings that are more energy-efficient and utilise materials in a way that aligns with circular economy principles.

Another crucial tool for understanding the impact of various parameters on energy performance in Positive Energy Districts is sensitivity analysis. In one of the studies, a global sensitivity analysis is conducted for Building Stock Energy Models, which broadens the knowledge of how key parameters influence energy performance (Van Hove et al., 2022). The analysis indicates that a substantial proportion of the variation in the average total primary energy consumption of a building stock is primarily influenced by a limited number of key input parameters, notably the heating set point temperature, average U-value, and the airtightness of the building envelope (ibid.).

Dynamic performance modelling is another key methodological framework for evaluating Positive Energy Districts. One of the reviewed studies develops a bottom-up model based on dynamic material flow principles and urban building energy models to estimate dynamic carbon emissions for city-scale buildings (Yang et al., 2023). This approach allows for a more accurate representation of energy consumption and potential savings by analysing the dynamic

development of building stock, energy consumption, and carbon emissions at the city level (ibid.), supporting the development of PEDs.

Hybrid approaches that combine multiple modelling techniques have shown great promise in evaluating Positive Energy Districts. For example, one study formulates a community-based hybrid bottom-up modelling approach using urban building energy modelling (UBEM) techniques to analyse the effectiveness of community-wide implementation of energy conservation guidelines (Ramalingam Rethnam & Thomas, 2024). The model is described as hybrid in this study for combining bottom-up modelling strategies with legitimate occupant behaviour characteristics (ibid.). In this context, a hybrid model leverages the strengths of both statistical and physics-based models to estimate building energy demand (ibid.). It incorporates detailed building characteristics and occupant behaviour data, which enhances the accuracy of energy analysis results (ibid.). Ramalingam Rethnam & Thomas (2024) argue that the hybrid nature of the framework allows for a more comprehensive analysis of energy consumption patterns. This approach aims to overcome the limitations of traditional models that either rely solely on aggregated data (top-down models) or detailed physical characteristics without considering occupant behaviour (bottom-up models).

According to Theodoridou et al. (2023), there are significant discrepancies between modelled and actual energy consumption due to uncertainties in building specifics and occupancy. They discuss how the Re-Polis platform addresses this by linking building footprints to statistical data through advanced procedures, utilising European databases and archetype buildings to create a more reliable dataset (ibid.). Additionally, they argue that many existing tools require high expertise, which limits their use among various stakeholders (ibid.). Hence, the Re-Polis platform aims to automate processes, ensure data accuracy, and enhance transparency, making it more accessible for users with low expertise. In general, the Re-Polis platform aims to support policymakers and enhance the implementation of efficient urban retrofitting actions (ibid.), ultimately contributing to the development of positive energy districts.

4.2.8 Integration with Other Urban Systems

The integration of building stock models with other urban systems, such as transportation and infrastructure, is a significant advancement in urban energy modelling. This holistic approach offers a comprehensive understanding of urban energy dynamics by reflecting potential synergies between the systems.

By linking building stock models with urban energy systems, a more comprehensive analysis is possible on how changes in building design and technology can influence urban energy dynamics, including the interactions between energy demand, land use, and transportation systems (Keirstead et al., 2012). This interconnectedness is crucial for addressing the complexities of urban energy systems and ensuring that interventions are effective and aligned with broader urban policy goals (ibid.).

However, integrating building stock models with other urban systems also presents challenges. The complexity and heterogeneity of urban systems can make it difficult to develop accurate and reliable models. Furthermore, issues related to data availability and quality can increase when integrating data from multiple sources and sectors (Li et al., 2017).

The advantages and disadvantages of the above advancements in building stock modelling are summarised in Table 4 below.

Table 4: Summary of Advantages and Disadvantages of Advancements in Building Stock Modelling

Advancement	Advantages	Disadvantages
GIS and Remote Sensing	- GIS tools enable the interconnection of maps, buildings, legislation, and specific variables. (Theodoridou et al., 2023) - Facilitates spatial analysis. - Enhances spatial-temporal analysis and improves understanding of building energy flows. (Shen & Wang, 2024)	- Reliance on the availability and accuracy of urban data. (Mutani et al., 2023) - Limited diffusion of digital technology in the construction sector. (Cinquepalmi et al., 2023) - Complexity and expertise required for effective use. (Congiu et al., 2023)
Machine Learning and Data-Driven Approaches	- Facilitates the prediction of future demand without the need for extensive simulations. (Vahed Ghoshchi et al., 2022) - Ability to analyse large datasets and identify trends. (Mutani et al., 2023) - Improved model accuracy by learning from data. (Verellen & Allacker, 2022a)	- Quality and representativeness of training data are critical for model performance. (Shen & Wang, 2024) - Complexity and significant computational resources required. (Amasyali & El-Gohary, 2018) - Difficulty in obtaining high-quality data. (Shen & Wang, 2024)
Integrated Energy Demand-Supply Modelling	- Optimises the balance between energy consumption and production. - Can identify optimal combinations of energy efficiency measures, renewable energy sources, and demand response strategies to achieve PEDs. (Neumann et al., 2021)	- May require extensive data and complex modelling techniques. - Integration challenges with existing urban energy systems.
Multi-Scale Urban Building Energy Modelling	- Provides insights across different scales (individual buildings to urban areas). - Facilitates understanding of the energy performance of building stocks without needing extensive data on each individual building. (Mutani et al., 2024)	- Can be resource-intensive and complex to implement.
Statistical Building Energy Models	- Allows for building-by-building energy performance evaluation.	- May not capture all local building characteristics.

Advancement	Advantages	Disadvantages
	- Can leverage existing datasets for analysis. - Provides insights into energy efficiency measures.	- Potential for inaccuracies if data is not representative. (Yang et al., 2023)
Life Cycle Assessment of Building Energy Systems	- Evaluates environmental impacts throughout the building's life cycle. - Supports sustainable decision-making in building design and retrofitting.	- Can be complex and time-consuming to conduct. - Requires comprehensive data on materials and processes.
Integration with Other Urban Systems	- Offers a comprehensive understanding of urban energy dynamics by reflecting potential synergies between the systems.	- Challenges in developing accurate and reliable models due to the complexity and heterogeneity of urban systems.
Methodological Frameworks for Evaluating Positive Energy Districts		
Framework	Advantages	Disadvantages
MAPED	- Allows users to test various scenarios and implementation measures to explore transformation pathways towards PEDs. (Neumann et al., 2021)	- Feasibility assessment tools may have limitations in terms of data availability and accuracy.
Archetypes and Material Intensity Coefficients (MICs)	- Supports decision-making regarding the availability of secondary resources from buildings. (Mohammadiziazi & Bilec, 2023)	- The complexity of quantifying and spatialising building material stock and renovation flow may pose challenges.
Sensitivity Analysis	- Can identify critical input parameters that significantly affect energy consumption.	- May not capture all variables influencing energy performance, leading to potential oversights.
Dynamic Performance Modelling	- Allows for a more accurate representation of energy consumption and potential savings. (Yang et al., 2023)	- The complexity of dynamic models may require significant expertise and data management.

4.3 Identification of Potential Areas for Replication of Strategies Related to PED

The identification of potential areas in the urban environment for the replication of strategies related to Positive Energy Districts (PEDs) is crucial for scaling up sustainable energy solutions. Several studies have focused on developing methodological frameworks and tools to identify and evaluate these potential areas. These analyses typically encompass various aspects, including spatial

analysis, resource assessment, socioeconomic factors, urban design and land use, infrastructure readiness, policy and regulatory framework, case studies, and stakeholder involvement.

Spatial analyses are often included in papers to map energy consumption patterns, renewable energy sources, and existing infrastructure. This helps identify areas with high energy demand and potential for integrating renewable energy systems. The specific GIS tools, datasets and approaches used in the reviewed studies are included in Table 2 in chapter 4.2.1 above.

An evaluation of available resources such as solar radiation, wind patterns, and biomass availability is crucial for determining which areas can effectively harness these resources for energy production. For instance, an Italian study employs a GIS-based urban energy modelling approach to identify potential areas for energy efficiency and renewable technology deployment (Mutani & Todeschi, 2021). The study evaluates the potential for deploying renewable technologies such as solar photovoltaics (PV), wind turbines, and biomass systems, considering factors like solar radiation, wind patterns, and biomass availability (ibid.).

Another study presents the CESAR tool, a bottom-up building stock modelling tool for energy performance assessment. This tool provides detailed energy performance assessments at the urban scale and enables the identification of areas with high potential for energy optimisation and the replication of energy transformation strategies (Wang et al., 2018).

Prina et al. demonstrate the application of clustering techniques to the building stock to identify groups of buildings with similar characteristics (2024). This approach aids in identifying areas with high potential for energy efficiency improvements and supports the replication of Positive Energy District (PED) strategies. The clustering analysis categorises the building stock based on inherent similarities, which is essential for evaluating energy-driven planning and forecasting (Prina et al., 2024).

When considering the potential areas for the replication of strategies related to PED, it is also important to understand the potential social acceptance and participation of the relevant stakeholders in those PED initiatives. An analysis considering demographics, economic activity, and community engagement levels may be required. One of the reviewed studies develops a participatory modelling approach that matches energy targets, stakeholders' needs, and urban planning, integrating bottom-up Urban Building Energy Models (UBEMs) with GIS data to identify areas with high potential for energy optimisation (Maiullari et al., 2022).

Research typically examines current land use patterns, zoning regulations, and building designs to identify how these factors can be optimised for energy efficiency and the integration of renewable technologies (Stermieri et al., 2020). By analysing the spatial distribution of reference buildings and their energy requirements, municipalities can pinpoint areas that would benefit from specific strategies.

Furthermore, the integration of demand and supply analyses can help in understanding the synergies between energy-saving measures and the deployment of clean energy sources, which is essential for achieving the goals of PEDs. Stermieri et al., emphasise the importance of collaboration with utilities as well as the use of data-driven approaches to enhance the representation of the supply side (Stermieri et al., 2020), which is vital for scaling up PED strategies in

different municipalities. It's important to note here that an analysis of local policies and regulations is a crucial step, as it can help identify any barriers or incentives that could impact the implementation of PED strategies.

4.4 Time Aspect and Prospective Analysis in Building Stock Modelling

4.4.1 Hourly Analyses

Hourly analyses can support a more accurate simulation of energy consumption, as energy usage can vary significantly between different times of the day and across different days of the week (Ang et al., 2023). They involve the use of high-resolution data, such as smart meter readings, to monitor energy use patterns on an hourly basis (ibid.). In the context of urban building energy modelling (UBEM), hourly electricity schedules serve as a digital fingerprint of the habits of building occupants (ibid.). The granularity of the hourly analyses helps bridge the performance gap between simulated and actual energy use in buildings, as behaviours in buildings are contextualised and can change based on socioeconomic factors and occupancy dynamics (ibid.).

Ang et al. (2023) present a novel methodology for developing hourly usage schedules in UBEM through smart meter data and socioeconomic indicators. This approach addresses the limitation of traditional models that primarily focus on physical building properties without considering demographic factors. By employing both supervised and unsupervised learning techniques, the authors generated hourly usage profiles for different socioeconomic personas in two cities, Evanston and Des Plaines, which have similar building stocks but differing socioeconomic compositions (ibid.). The resulting schedules enhance the accuracy of building archetypes, allowing for more reliable predictions of energy use and savings from retrofits. The analysis revealed that incorporating these indicators could alter predicted city-wide energy use for residential buildings by up to 10% (ibid.).

4.4.2 Prospective Scenarios

The use of prospective scenarios allows for a better understanding of potential future developments and their impacts, which is crucial for effective energy management and planning. Prospective scenarios are important for the ExPEDite project because they enable stakeholders to analyse planning initiatives aimed at achieving positive energy outcomes.

Scenario analysis involves the creation of multiple future scenarios, each representing a different set of assumptions about key variables such as population growth, building energy efficiency standards, and the adoption of renewable energy technologies. A study on the carbon emissions of Changsha's building sector by 2060, considered five scenarios (J. Yang et al., 2023). A baseline scenario, which assumes a business-as-usual approach, three additional scenarios that account for improvements in building energy efficiency, reductions in power carbon emission factors, and control of building stock size (ibid.). Lastly, a synergistic emission reduction scenario to combine all three measures (ibid.). The authors underline the need for realistic assumptions regarding input parameters and the impact of climate zones on energy use intensities in the modelling process (ibid.).

In the context of the ExPEDite project, a detailed analysis of prospective scenarios is essential for understanding the transition towards a positive energy district. The project aims to establish a design and configuration for the selected district that meets this objective. While it is possible to develop a current design that satisfies these criteria, such immediate results are not always feasible. Instead, a more pragmatic approach involves short- to medium-term planning, where the transformation of the district is outlined, the deployment of various technologies is detailed, and the associated investments and their expected returns are considered. It is important to acknowledge that the energy demands of buildings will evolve over time, influenced by factors such as climate change. Therefore, a key consideration in the modelling efforts will be the projected changes in temperatures, as well as the rate of building retrofit measures and the construction of new buildings.

4.4.3 Dynamic Stock Modelling

Dynamic stock modelling, as described by J. Yang et al. (2023), involves estimating the changes in building stock over time by considering various factors such as construction, renovation, and demolition. The model is developed based on the mass-balance principle and integrates dynamic material flow analysis with urban building energy models (ibid.). In the context of the dynamic building stock module described in the study, the mass-balance principle is applied to calculate the annual constructed, demolished, renovated, and existing buildings. According to this principle, the total mass (or quantity) of a substance in a system must remain constant over time unless there is an input or output of that substance (ibid.). In the case of building stock, this means that the existing building stock can be calculated by considering the population, urbanisation rate, and floor area per capita (ibid.). New buildings are added to the stock to meet demand, while buildings are also demolished or renovated, which affects the overall quantity of buildings in the system (ibid.).

Dynamic building stock models have been widely used to evaluate pathways to energy supply transitions and carbon emission reductions in various regions (ibid.). For instance, a bottom-up dynamic building energy model was applied to assess the energy transition of residential building stock in the Netherlands, linking dynamic material flow analysis with building energy modelling (ibid.). To conclude, this approach allows for a detailed evaluation of the impact of prospective technology upgrades on building carbon emissions and can provide specific guidance for formulating future emission reduction policies.

4.4.4 Integration of Temporal and Spatial Data

The methodology proposed by Khajedehi et al. (2024) highlights the need to combine various datasets, including geometric attributes of buildings and temporal usage patterns, to create a comprehensive input data frame for simulations. The study uses OpenStreetMap (OSM) data for building footprints and amenities, alongside census data for demographic insights, and illustrates how spatial data can be enriched with temporal information, such as operating schedules for different building types (ibid.). This integration allows for a more accurate representation of energy consumption patterns, as it accounts for the variability in building usage over time, thereby improving the reliability of energy performance simulations in urban environments (ibid.). The proposed workflow aims to ensure that the data will remain adaptable to changes in availability, and

ultimately facilitate better decision-making for energy efficiency improvements in cities (ibid.).

Mohammadiziazi & Bilec (2023) improved the accuracy of a bottom-up model that analyses accumulated materials in commercial buildings by employing photogrammetry and image processing techniques. This approach allowed for a detailed examination of how materials are distributed across different components of buildings over time, particularly focusing on renovation flows from 2020 to 2030 (ibid.). The authors found that the spatial distribution of materials is closely correlated with urban form and neighbourhood compactness, and emphasised the importance of considering both temporal and spatial dimensions in material stock analysis (ibid.). Such integration not only aids in identifying secondary resources available for reuse but also supports the implementation of circular economy strategies within the building sector (ibid.).

The integrated approach to monitoring, visualising, and managing energy flows at the district level is crucial for the successful development of Positive Energy Districts. Advanced modelling techniques and data analysis can give stakeholders a comprehensive understanding of energy consumption patterns and material flows within the built environment. This enables the identification of opportunities for energy efficiency improvements, renewable energy integration, and resource optimisation.

5 Discussion

5.1 Implications for the ExPEDite Project

The findings from the literature review on building stock modelling provide significant insights that are directly relevant to the objectives of the ExPEDite project, which aims to develop Positive Energy Districts (PEDs) through innovative digital twin technology.

The review indicates that both top-down and bottom-up modelling approaches have their respective strengths and limitations. Top-down models provide macro-level insights but may lack the detail necessary for identifying specific energy efficiency opportunities (Prina et al., 2024). In contrast, bottom-up models, particularly building-by-building approaches, offer high accuracy and granularity but can be resource-intensive and face challenges related to data availability and quality (Saad & Eicker, 2023). It was found that the bottom-up archetype-based approach is the most commonly used because it efficiently represents the energy performance of large building stocks while requiring reduced data and computational complexity, allowing for detailed insights into energy consumption patterns without the extensive resource demands of building-by-building models. However, this approach entails the risk of unrealistic assumptions regarding input parameters in the modelling process.

We covered the latest advancements in building stock modelling, such as the integration of machine learning and data-driven approaches, which enhance the accuracy and granularity of energy performance assessment (Ang et al., 2023), and the integrated energy demand-supply modelling; a critical approach for optimising energy consumption and production within urban areas, supporting the development of Positive Energy Districts (PEDs). Drawing on the importance of considering local renewable energy sources, the review confirms that the integration of building energy demands with renewable energy supply can lead to significant reductions in CO2 emissions while maintaining economic viability (Vahid-Ghavidel et al., 2024). Overall, the advanced modelling frameworks can facilitate evidence-based decision-making and can empower stakeholders in urban planning and energy management to achieve effective energy management, ultimately contributing to the goals of the ExPEDite project and the broader transition to energy-positive urban environments.

The review also acknowledges several limitations inherent in the methodologies discussed. One of the primary limitations is the reliance on the availability and quality of datasets, which may not always be up-to-date or comprehensive. This poses significant challenges, particularly for bottom-up models that require detailed information on individual buildings. Furthermore, the complexity and heterogeneity of building stocks can complicate modelling efforts and can potentially lead to inaccuracies in the results. These limitations would need to be addressed to minimise their impact on the effectiveness of the ExPEDite project.

While the review provides valuable insights, it is essential to acknowledge its limitations as well. The exclusion of literature that does not directly contribute to building stock modelling (BSM) or that addresses broader urban systems without specific reference to BSM may have limited the comprehensiveness of the review. Additionally, due to time and resource constraints, only one database (Scopus) has been searched, which also has limited the reach of the review. The exploration of integrating BSM with other urban planning frameworks is a subject for future research.

With regards to future work, there is a need for improved data collection methods to ensure the availability of accurate and up-to-date information on building characteristics and energy usage. This could involve the integration of IoT sensors and real-time monitoring systems to facilitate data-driven decision-making. Moreover, further research should explore the development of hybrid modelling approaches that combine the strengths of both top-down and bottom-up models. This could provide a more comprehensive view of energy performance across entire districts while maintaining the granularity needed for targeted interventions.

Lastly, the ExPEDite project should consider engaging with a broader range of stakeholders, including policymakers, urban planners, and community members, to ensure that the insights gained from building stock modelling are effectively translated into actionable strategies for achieving positive energy outcomes.

6 Conclusion

This study aimed to identify and analyse the various frameworks employed in current literature and their potential to facilitate Positive Energy Districts (PEDs). The review of existing frameworks and approaches in building stock modelling identified key methodologies that facilitate the analysis of energy consumption, carbon emissions, and overall building performance, thereby acting as a guide for stakeholders involved in the development of PEDs.

By examining both top-down and bottom-up approaches, the study reveals that while top-down models provide valuable macro-level insights, they often lack the granularity needed for targeted energy efficiency interventions. In contrast, bottom-up models offer detailed insights into energy consumption patterns and opportunities for improvement, albeit with challenges related to data availability and resource intensity. Additionally, the present findings confirm that the integration of advancements in building stock modelling, particularly digital twin technologies and urban building energy modelling (UBEM), can significantly enhance the accuracy of energy consumption predictions and carbon emission assessments. This integration allows for real-time monitoring and management of energy flows, which ultimately enables stakeholders to implement targeted energy-saving measures and retrofit strategies.

We have shown that archetype building energy models play crucial roles in informing engineering design, influencing regulations, optimising energy systems, guiding policy decisions, and contributing to finance, environmental, social, and governance strategies, and ongoing improvements in data availability and computational resources can improve the accuracy and representativeness of these models. Moreover, the review indicated an expansion of archetype building energy models to incorporate renewable energy systems and grid interaction, which shows the evolving role of buildings from mere energy consumers to active energy participants. This shift suggests the necessity of models that can handle the complexities of onsite energy production, storage, and demand response.

With regards to future research, the study highlighted the need for more comprehensive studies on the socio-economic factors that influence energy consumption patterns. There is also a need for better integration of community engagement in the planning process. Furthermore, the findings suggest the need for collaborative approaches, including partnerships with utilities, which can enhance the effectiveness of energy-saving measures and the deployment of renewable energy sources.

Overall, the findings from this study offer valuable insights that can guide both policy formulation and practical implementation. By leveraging these advanced technologies, stakeholders can make significant strides towards achieving sustainable urban development and mitigating climate change impacts.

References

Ali, U., Shamsi, M. H., Bohacek, M., Purcell, K., Hoare, C., Mangina, E., & O'Donnell, J. (2020). A data-driven approach for multi-scale GIS-based building energy modeling for analysis, planning and support decision making. *Applied Energy*, *279*. https://doi.org/10.1016/j.apenergy.2020.115834

Amasyali, K., & El-Gohary, N. M. (2018). A review of data-driven building energy consumption prediction studies. In *Renewable and Sustainable Energy Reviews* (Vol. 81, pp. 1192–1205). Elsevier Ltd. https://doi.org/10.1016/j.rser.2017.04.095

Ang, Y. Q., Berzolla, Z., & Reinhart, C. (2023). Smart meter-based archetypes for socioeconomically sensitive urban building energy modeling. *Building and Environment*, *246*. https://doi.org/10.1016/j.buildenv.2023.110991

Berzolla, Z., Ang, Y. Q., Letellier-Duchesne, S., & Reinhart, C. (2023). An eight-step simulation-based framework to help cities reach building-related emissions reduction goals. *Environmental Research: Infrastructure and Sustainability*, *3*(4). https://doi.org/10.1088/2634-4505/ad025d

Bhattacharyya Govinda, S. C., & Timilsina, R. (2009). *Energy Demand Models for Policy Formulation A Comparative Study of Energy Demand Models*. http://econ.worldbank.org.

Borges, P., Travesset-Baro, O., & Pages-Ramon, A. (2022). Hybrid approach to representative building archetypes development for urban models – A case study in Andorra. *Building and Environment*, *215*. https://doi.org/10.1016/j.buildenv.2022.108958

Chang, Y. T., Sierra, E. M., & Hsieh, S. H. (2022). Combining BIM & GIS Information to Simulate Circularity of Building Stocks in a City - A Case Study of Taipei City. *IOP Conference Series: Earth and Environmental Science*, *1122*(1). https://doi.org/10.1088/1755-1315/1122/1/012025

Cinquepalmi, F., Paris, S., Pennacchia, E., & Tiburcio, V. A. (2023). Efficiency and Sustainability: The Role of Digitization in Re-Inhabiting the Existing Building Stock. *Energies*, *16*(9). https://doi.org/10.3390/en16093613

Colleto, G. M., & Gomes, V. (2022). EXPLORING MACHINE LEARNING-BASED ARCHETYPES FOR URBAN LIFE CYCLE MODELING (UBIM). *Acta Polytechnica CTU Proceedings*, *38*, 169–175. https://doi.org/10.14311/APP.2022.38.0169

Congiu, E., Desogus, G., Frau, C., Gatto, G., & Pili, S. (2023). Web-Based Management of Public Buildings: A Workflow Based on Integration of BIM

and IoT Sensors with a Web–GIS Portal. *Buildings*, *13*(5). https://doi.org/10.3390/buildings13051327

Deng, Z., Javanroodi, K., Nik, V. M., & Chen, Y. (2023). Using urban building energy modeling to quantify the energy performance of residential buildings under climate change. *Building Simulation*, *16*(9), 1629–1643. https://doi.org/10.1007/s12273-023-1032-2

Dong, J., Schwartz, Y., Mavrogianni, A., Korolija, I., & Mumovic, D. (2023). A review of approaches and applications in building stock energy and indoor environment modelling. In *Building Services Engineering Research and Technology* (Vol. 44, Issue 3, pp. 333–354). SAGE Publications Ltd. https://doi.org/10.1177/01436244231163084

European Commission. (2020). *Energy efficiency in buildings*. https://commission.europa.eu/news/focus-energy-efficiency-buildings-2020-02-17_en

exPEDite. (2024). *exPEDite*. https://expedite-project.eu/

Ferrari, S., Zagarella, F., Caputo, P., & Dall'o', G. (2021). A gis-based procedure for estimating the energy demand profiles of buildings towards urban energy policies. *Energies*, *14*(17). https://doi.org/10.3390/en14175445

Grant, M. J., & Booth, A. (2009). A typology of reviews: An analysis of 14 review types and associated methodologies. In *Health Information and Libraries Journal* (Vol. 26, Issue 2, pp. 91–108). https://doi.org/10.1111/j.1471-1842.2009.00848.x

Harter, H., Willenborg, B., Lang, W., & Kolbe, T. H. (2023). Life Cycle Assessment of building energy systems on neighbourhood level based on semantic 3D city models. *Journal of Cleaner Production*, *407*. https://doi.org/10.1016/j.jclepro.2023.137164

HosseiniHaghighi, S. R., de Uribarri, P. M. Á., Padsala, R., & Eicker, U. (2022). Characterizing and structuring urban GIS data for housing stock energy modelling and retrofitting. *Energy and Buildings*, *256*. https://doi.org/10.1016/j.enbuild.2021.111706

Jradi, M., Madsen, B. E., & Kaiser, J. H. (2023). DanRETwin: A Digital Twin Solution for Optimal Energy Retrofit Decision-Making and Decarbonization of the Danish Building Stock. *Applied Sciences (Switzerland)*, *13*(17). https://doi.org/10.3390/app13179778

Kavgic, M., Mavrogianni, A., Mumovic, D., Summerfield, A., Stevanovic, Z., & Djurovic-Petrovic, M. (2010). A review of bottom-up building stock models for energy consumption in the residential sector. *Building and Environment*, *45*(7), 1683–1697. https://doi.org/10.1016/j.buildenv.2010.01.021

Keirstead, J., Jennings, M., & Sivakumar, A. (2012). A review of urban energy system models: Approaches, challenges and opportunities. In *Renewable and Sustainable Energy Reviews* (Vol. 16, Issue 6, pp. 3847–3866). https://doi.org/10.1016/j.rser.2012.02.047

Khajedehi, M. H., Prataviera, E., Bordignon, S., & De Carli, M. (2024). Exploiting geographic open data to improve urban building energy simulations: the Padova city center case study. *E3S Web of Conferences*, *523*. https://doi.org/10.1051/e3sconf/202452305007

Kourgiozou, V., Al-Saegh, S., Korolija, I., Dowson, M., Commin, A., Tang, R., Rovas, D., & Mumovic, D. (2023). Development of a dynamic building

stock model for smart energy transition decision support: university campus stock case study. *Building Simulation Conference Proceedings*, *18*, 3617–3624. https://doi.org/10.26868/25222708.2023.1686

Langevin, J., Reyna, J. L., Ebrahimigharehbaghi, S., Sandberg, N., Fennell, P., Nägeli, C., Laverge, J., Delghust, M., Mata, Van Hove, M., Webster, J., Federico, F., Jakob, M., & Camarasa, C. (2020). Developing a common approach for classifying building stock energy models. *Renewable and Sustainable Energy Reviews*, *133*. https://doi.org/10.1016/j.rser.2020.110276

Ledesma, G., Pons-Valladares, O., & Nikolic, J. (2021). Real-reference buildings for urban energy modelling: A multistage validation and diversification approach. *Building and Environment*, *203*. https://doi.org/10.1016/j.buildenv.2021.108058

Lei, B., Liu, P., Milojevic-Dupont, N., & Biljecki, F. (2024). Predicting building characteristics at urban scale using graph neural networks and street-level context. *Computers, Environment and Urban Systems*, *111*. https://doi.org/10.1016/j.compenvurbsys.2024.102129

Leprince, J., Madsen, H., Miller, C., Real, J. P., van der Vlist, R., Basu, K., & Zeiler, W. (2022). Fifty shades of grey: Automated stochastic model identification of building heat dynamics. *Energy and Buildings*, *266*. https://doi.org/10.1016/j.enbuild.2022.112095

Li, W., Zhou, Y., Cetin, K., Eom, J., Wang, Y., Chen, G., & Zhang, X. (2017). Modeling urban building energy use: A review of modeling approaches and procedures. In *Energy* (Vol. 141, pp. 2445–2457). Elsevier Ltd. https://doi.org/10.1016/j.energy.2017.11.071

Maiullari, D., Palm, A., Wallbaum, H., & Thuvander, L. (2022). Matching energy targets, stakeholders' needs and modelling choices in developing urban energy scenarios. *IOP Conference Series: Earth and Environmental Science*, *1078*(1). https://doi.org/10.1088/1755-1315/1078/1/012087

Mangold, M., Österbring, M., & Wallbaum, H. (2015). Handling data uncertainties when using Swedish energy performance certificate data to describe energy usage in the building stock. *Energy and Buildings*, *102*, 328–336. https://doi.org/10.1016/j.enbuild.2015.05.045

Marston, A., Garforth, P., Fleichammer, G., & Baumann, O. (n.d.). *URBAN SCALE MODELLING-HOW GENERALISED MODELS CAN HELP COMMUNITIES HALVE THEIR ENERGY USE IN 30 YEARS*. www.ashrae.org

Mata, É., Sasic Kalagasidis, A., & Johnsson, F. (2014). Building-stock aggregation through archetype buildings: France, Germany, Spain and the UK. *Building and Environment*, *81*, 270–282. https://doi.org/10.1016/j.buildenv.2014.06.013

Mohammadiziazi, R., & Bilec, M. M. (2023). Quantifying and spatializing building material stock and renovation flow for circular economy. *Journal of Cleaner Production*, *389*. https://doi.org/10.1016/j.jclepro.2022.135765

Muñoz, I., Hernández, P., Pérez-Iribarren, E., Pedrero, J., Arrizabalaga, E., & Hermoso, N. (2020). Methodology for integrated modelling and impact assessment of city energy system scenarios. *Energy Strategy Reviews*, *32*. https://doi.org/10.1016/j.esr.2020.100553

Mutani, G., Alehasin, M., Usta, Y., Fiermonte, F., & Mariano, A. (2023). Statistical Building Energy Model from Data Collection, Place-Based

Assessment to Sustainable Scenarios for the City of Milan. *Sustainability (Switzerland)*, *15*(20). https://doi.org/10.3390/su152014921

Mutani, G., Alehasin, M., Yang, H., Zhang, X., & Felmer, G. (2024). Urban Building Energy Modeling to Support Climate-Sensitive Planning in the Suburban Areas of Santiago de Chile. *Buildings*, *14*(1). https://doi.org/10.3390/buildings14010185

Mutani, G., & Todeschi, V. (2021). GIS-based urban energy modelling and energy efficiency scenarios using the energy performance certificate database. *Energy Efficiency*, *14*(5). https://doi.org/10.1007/s12053-021-09962-z

Neumann, H. M., Hainoun, A., Stollnberger, R., Etminan, G., & Schaffler, V. (2021). Analysis and evaluation of the feasibility of positive energy districts in selected urban typologies in Vienna using a bottom-up district energy modelling approach. *Energies*, *14*(15). https://doi.org/10.3390/en14154449

Perwez, U., Shono, K., Yamaguchi, Y., & Shimoda, Y. (2023). Multi-scale UBEM-BIPV coupled approach for the assessment of carbon neutrality of commercial building stock. *Energy and Buildings*, *291*. https://doi.org/10.1016/j.enbuild.2023.113086

Pham, M. T., Rajić, A., Greig, J. D., Sargeant, J. M., Papadopoulos, A., & Mcewen, S. A. (2014). A scoping review of scoping reviews: Advancing the approach and enhancing the consistency. *Research Synthesis Methods*, *5*(4), 371–385. https://doi.org/10.1002/jrsm.1123

Pittam, J., O'Sullivan, P. D., & O'Sullivan, G. (2014). Stock aggregation model and virtual archetype for large scale retrofit modelling of local authority housing in Ireland. *Energy Procedia*, *62*, 704–713. https://doi.org/10.1016/j.egypro.2014.12.434

Prina, M. G., Oberegger, U. F., Antonucci, D., Ma, Y., Shamsi, M. H., & Sharifi, M. (2024). Clustering of Building Stock. In *Learning and Analytics in Intelligent Systems* (Vol. 35, pp. 131–151). Springer Nature. https://doi.org/10.1007/978-3-031-47909-0_5

Ramalingam Rethnam, O., & Thomas, A. (2024). Urban building energy modelling-based framework to analyze the effectiveness of the community-wide implementation of national energy conservation codes. *Smart and Sustainable Built Environment*, *13*(5), 1213–1239. https://doi.org/10.1108/SASBE-09-2022-0210

Ranjbar, S., Hernandez, P., Rezaei, A., & Eicker, U. (2023). On the role of urban modelling tools to support of the urban energy transition. *Building Simulation Conference Proceedings*, *18*, 3148–3154. https://doi.org/10.26868/25222708.2023.1605

Saad, M. M., & Eicker, U. (2023). Investigating the reliability of building energy models: Comparative analysis of the impact of data pipelines and model complexities. *Journal of Building Engineering*, *71*. https://doi.org/10.1016/j.jobe.2023.106511

Sasso, F., Chambers, J., & Patel, M. K. (2023). Space heating demand in the office building stock: Element-based bottom-up archetype model. *Energy and Buildings*, *295*. https://doi.org/10.1016/j.enbuild.2023.113264

Shen, P., & Wang, H. (2024). Archetype building energy modeling approaches and applications: A review. In *Renewable and Sustainable Energy Reviews* (Vol. 199). Elsevier Ltd. https://doi.org/10.1016/j.rser.2024.114478

Slavkovic, K., Stephan, A., & Mulders, G. (2022). *A parametric approach to defining archetypes for an integrated material stocks and flows analysis and life cycle assessment of built stocks*.

Stermieri, L., Delmastro, C., Becchio, C., & Corgnati, S. P. (2020). Linking dynamic building simulation with long-term energy system planning to improve buildings urban energy planning strategies. *Smart Cities*, *3*(4), 1242–1265. https://doi.org/10.3390/smartcities3040061

Swan, L. G., & Ugursal, V. I. (2009). Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. In *Renewable and Sustainable Energy Reviews* (Vol. 13, Issue 8, pp. 1819–1835). https://doi.org/10.1016/j.rser.2008.09.033

Theodoridou, I., Mallinis, G., Pippis, I., Mermigas, A., & Christodoulou, K. (2023). Barriers of large-scale energy efficiency modelling of urban building stocks. Methods to overcome them - The case of the Re-Polis platform. *IOP Conference Series: Earth and Environmental Science*, *1196*(1). https://doi.org/10.1088/1755-1315/1196/1/012025

Vahed Ghoshchi, A., Zahedi, R., Moradi Pour, Z., & Ahmadi, A. (2022). Machine Learning Theory in Building Energy Modeling and Optimization: A Bibliometric Analysis. *Journal of Modern Green Energy*. https://doi.org/10.53964/jmge.2022004

Vahid-Ghavidel, M., Jafari, M., Letellier-Duchesne, S., Berzolla, Z., Reinhart, C., & Botterud, A. (2024). Integrated energy demand-supply modeling for low-carbon neighborhood planning. *Applied Energy*, *358*. https://doi.org/10.1016/j.apenergy.2023.122560

Van Hove, M. Y. C., Delghust, M., & Laverge, J. (2022). Global sensitivity analysis for Building-Stock Energy Models: Application of three global approaches. *E3S Web of Conferences*, *362*. https://doi.org/10.1051/e3sconf/202236210006

Verellen, E., & Allacker, K. (2022). Developing a Building Stock Model to Enable Clustered Renovation—The City of Leuven as Case Study. *Sustainability (Switzerland)*, *14*(10). https://doi.org/10.3390/su14105769

Wang, D., Landolt, J., Mavromatidis, G., Orehounig, K., & Carmeliet, J. (2018). CESAR: A bottom-up building stock modelling tool for Switzerland to address sustainable energy transformation strategies. *Energy and Buildings*, *169*, 9–26. https://doi.org/10.1016/j.enbuild.2018.03.020

Yamaguchi, Y., Shoda, Y., Yoshizawa, S., Imai, T., Perwez, U., Shimoda, Y., & Hayashi, Y. (2023). Feasibility assessment of net zero-energy transformation of building stock using integrated synthetic population, building stock, and power distribution network framework. *Applied Energy*, *333*. https://doi.org/10.1016/j.apenergy.2022.120568

Yang, J., Deng, Z., Guo, S., & Chen, Y. (2023). Development of bottom-up model to estimate dynamic carbon emission for city-scale buildings. *Applied Energy*, *331*. https://doi.org/10.1016/j.apenergy.2022.120410

Yang, X., Hu, M., Heeren, N., Zhang, C., Verhagen, T., Tukker, A., & Steubing, B. (2020). A combined GIS-archetype approach to model residential space heating energy: A case study for the Netherlands including validation. *Applied Energy*, *280*. https://doi.org/10.1016/j.apenergy.2020.115953

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