

Unveiling the Potential of Urban Building Energy with 5R3C Thermal Modeling in Energy Communities

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Abstract: This paper reviews the role of grey-box Resistance–Capacitance (RC) thermal models within Urban Building Energy Modeling (UBEM) to support Energy Communities (ECs) and building stock decarbonization. Given the growing need for scalable and computationally efficient forecasting tools, RC models are examined as reduced-order approaches that balance physical interpretability and simulation performance. The study analyzes how architectural and operational parameters, including compactness ratio, building age, typology, window-to-wall ratio, and occupancy behavior, influence thermal resistances, capacitances, and dynamic heat demand. The findings highlight the suitability of 5R3C models for district-scale applications, renovation scenario analysis, and renewable integration, while identifying challenges related to parameter calibration, behavioral uncertainty, and large-scale validation.

1 INTRODUCTION


Building designs and their codes play a pivotal role in safety, comfort, and occupants' well-being, ensuring livable standards during their operation (Yin Siu *et al.*, 2023). In Europe, the ageing, energy-intensive, and substantial building stock imposes major challenges, accounting for more than 40% of total energy consumption and approximately one-third of global greenhouse gas emissions (Hernandez *et al.*, 2024). From this perspective, energy forecasts for buildings are critical tools for demand reduction, while shifting in the urban levels remains challenging.


Belgian regional policies have become increasingly ambitious to achieve a near-zero-carbon building stock through deep renovation and strict reinforcement of the Energy Performance Certificate (EPC) framework, requiring robust modeling tools to support renewable integration, and community-scale coordination.


Consequently, building energy forecasting becomes a critical instrument for anticipating climatic and usage-related variations and coordinating intermittent contributions. A detailed understanding of building energy consumption is therefore essential to guide transformative design and management decisions, and pursue just and people-oriented energy transitions (Pulselli *et al.*, 2021). This shift is driving growing demand for dynamic, coupled modeling frameworks that go beyond isolated computational calculations to accurately capture occupants' needs and behavioral patterns (Froufe *et al.*, 2020). From this perspective, a growing research interest has emerged in the fields of building energy design, e.g. (Shen *et al.*, 2021), forecasting and estimations on energy use, e.g. (Lauster *et al.*, 2014), and optimization strategies, e.g. (Hong *et al.*, 2020).

Firstly introduced by Reinhart and Davila as a computational framework for energy simulation in building and urban scales, Urban Building Energy Modeling (UBEM) is in line with bottom-up and

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physics-based approaches (Reinhart and Davila, 2016), aiming to enable dynamic simulations and synthesis of data streams (Zhou *et al.*, 2025) and provide high accuracy, with relevant limitations on interpretability and generalizability. Given current trends toward top-down approaches and limitations in predictive performance, UBEM is expected to integrate energy supply-demand scenarios based on physical descriptions of communities, scaling up from individual building scales (Hong and Chen, 2020). Considering the growing interest in UBEM, this study maps advancements and trends to identify opportunities for coupling modeling research frameworks, sets targets for quantitative evidence in Energy Communities (ECs), and addresses architectural and urban challenges.

In this study, simplified Building Energy Modeling (BEM) Resistance-Capacitance (RC) thermal networks are systematically explored, revealing their potential for EC design, particularly given the evident lack of review in the field (Yang *et al.*, 2024). Hence, this study focuses on a systematic review of key indicators of building design, a core element of energy demand optimization, to sketch the significance of their integration in community-level approaches. The paper is structured as follows: Section 2 reviews families of building energy models and positions grey-box RC models within UBEM frameworks. Section 3 provides a systematic understanding of 5R3C models and their potential through architectural parametrization for conceptualizing Energy Communities. Section 4 concludes with the main reviewing findings and 5 with further recommendations for validation and future work.

2 GREY RC THERMAL MODELS COMPREHENSIVE REVIEW

To contextualize grey RC models within urban-scale energy simulation, this section first reviews the main building energy modeling families and their evolution toward district-level applications.

2.1 Urban Building Energy Performance From Building to Urban Districts

Building energy modeling approaches are commonly classified into three main families: white (detailed physical descriptions within the principles of heat and mass transfer), black (purely data-driven and based on statistical and machine learning techniques), and grey-box models (Harish and Kumar, 2016; Ahmad *et al.*, 2018), which combine simplified physical representations with data-driven calibration in hybrid processes (Chen, Guo, *et al.*, 2022; Somu *et al.*, 2020), offering a compromise between physical interpretability and computational efficiency.

The typology of buildings, the diversity of building envelopes, and the heterogeneity of occupancy patterns increase the complexity of modeling at the urban level. This context reinforces the need for reduced-order approaches that allow benchmarking, scenario exploration, and parametric analysis while maintaining manageable computational costs, e.g. (Swan and Ugursal, 2009). In UBEM-based approaches, two principal modeling logics are distinguished (e.g. (Ali *et al.*, 2021)) with detailed data-driven models characterized by high spatiotemporal details in multi-zone dynamic thermal simulation models, RC methods (Happle, Fonseca and Schlueter, 2018), or top-down approaches (e.g. (Bouyer, Inard and Musy, 2011) and specific data related to each single building, but with few interconnections to the Renewable Energy Community (REC) trends, as indicated in the literature search (only 91 documents are available on the Scopus dataset on REC and UBEM, Figure 1).

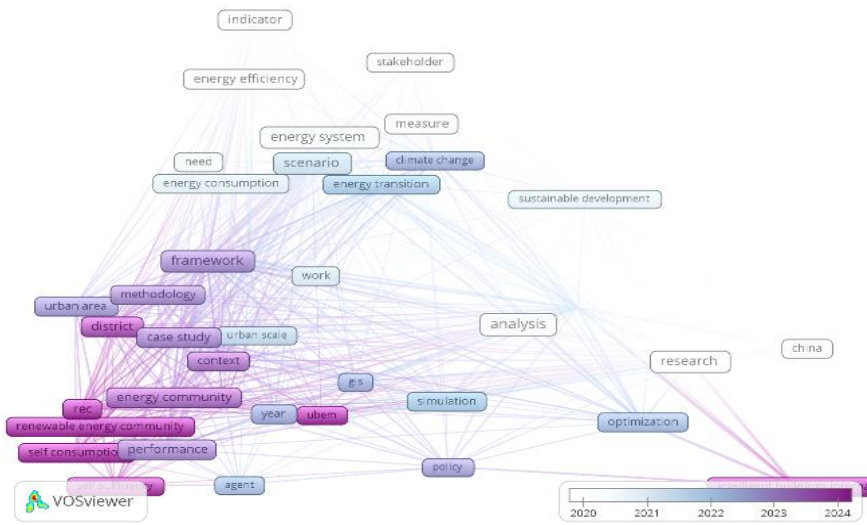


Figure 1. Bibliometrics on UBEM and REC (Scopus analysis).

Although currently UBEM has been extensively applied at the level of individual buildings being employed in the design principles (Harish and Kumar, 2016), it seeks simulations of standalone buildings in larger ecosystems (e.g. ECs) to facilitate the generation of complex scenarios of energy demand and generation. Current methodologies have been extended from single buildings to multiple blocks, there is a need for information coupling for larger simulation environments (Reinhart and Cerezo Davila, 2016). Scholars discussed the limitations of UBEM, among them the amount of simulation data for the heat model generation (Reinhart and Cerezo Davila, 2016), the complexities in the occupant behavioral model (Happle, Fonseca and Schlueter, 2018), the microclimate models (Brogger and Wittchen, 2018), or the technological assessment (Ferrari *et al.*, 2019). Other scholars, e.g. Kamel (Kamel, 2022) analyzed physics-based modeling techniques, and tools on various building systems, occupancy levels, weather conditions, and land-use, while others, as Fathi (Fathi, Srinivasan and Fenner, 2020) investigated the machine learning implications for energy forecasting in UBEM models, addressing the challenges of efficiency. Yet, scalability and parameter identification remain critical bottlenecks in urban ecosystems, and naturally direct attention toward reduced-order modeling strategies.

2.2 Significance of Grey Thermal Models

Resistance-Capacitance thermal networks constitute one of the most widely adopted grey-box approaches.

By exploiting the analogy between heat transfer and electrical circuits, where temperature differences correspond to voltages and heat fluxes to currents, RC networks offer compact representations capable of capturing both steady-state and transient thermal behavior with limited computational effort (Yang, Wang, Cheng, Gao, et al., 2024). These models are widely used to represent the thermal performance of building envelopes. Numerous studies have applied them to representative case studies. For example, Mohammad et al. developed a second-order RC grey-box model within an uncertain environment (Shamsi *et al.*, 2020). Similarly, Murphy et al. proposed a 2R2C grey-box model for dynamic predictions (Murphy *et al.*, 2021).

At the spatial scale, RC models can be formulated as single-zone or multi-zone representations. Single-zone models are typically used for global energy indicators, rapid assessments, or control prototyping, particularly when data availability is limited (Hassid, 1985). In contrast, multi-zone RC models explicitly represent thermal interactions between rooms through shared resistances, enabling the analysis of localized comfort and zoning strategies, albeit at the cost of increased parameterization effort and reduced identifiability (Yang et al., 2024).

A central advantage of RC models lies in their flexibility regarding parameter estimation and the acceleration of computational efforts for dynamic simulations of complex structures and for investigating thermal behavior. In practical terms, RC models are tailored to key architectural attributes related to the assessment of envelope structure thermal performance (Yang et al., 2024), which may

be derived from physical properties, inferred from measurement data, or estimated using hybrid approaches. In practice, inverse modeling through system identification is particularly valuable when construction data is incomplete. State-space formulations are commonly adopted to facilitate efficient simulation and parameter estimation using optimization or filtering techniques. However, reliable identification requires sufficiently rich excitation of building dynamics and adequate measurement quality, which often constrains the achievable model complexity. While RC models offer a promising compromise between accuracy and scalability, their deployment in decentralized and cooperative energy systems remains underexplored (Schweidtmann, Zhang and von Stosch, 2024).

3 RESISTANCE-CAPACITANCE THERMAL MODELS AND THE 5R3C IMPORTANCE

In the existing literature, common models represent two (2) thermal resistances and one (1) heat capacity (2R1C) for building envelope, employed by Hassid (Hassid, 1985), whereas current trends widely used are the 3R2C models, e.g. (Bueno *et al.*, 2012; Fabre *et al.*, 2018). Recent studies have explored the potential of RC models for complex building structures, e.g. (Li, Sun and Xu, 2017), insulation, e.g. (Ding and Yu, 2022), among others.

The 5R3C model is a reduced-order RC-network representation (as shown in Figure 2 (Dumont, Feldheim and Lybaert, 2025)) that simplifies a building's thermal behavior into a limited number of thermal nodes connected by heat transfer paths. In this framework, thermal resistances (R), expressed in K/W, represent conductive, convective, and ventilation heat transfer mechanisms through the envelope and between internal nodes, while thermal capacitances (C), expressed in J/K, account for the building's thermal mass and its ability to store and release heat over time. This modeling approach originates from the simplified hourly calculation method described in (ISO, 2017), where the building is represented using a reduced RC-network to compute space heating and cooling demand. By reducing the complex heat transfer processes into a small number (5) of interconnected nodes, the model achieves high computational efficiency while retaining sufficient physical accuracy, making it particularly suitable for hourly dynamic simulations, building stock modeling, and district-scale energy performance assessments (Fraisse *et al.*, 2002) (Boodi *et al.*, 2018).

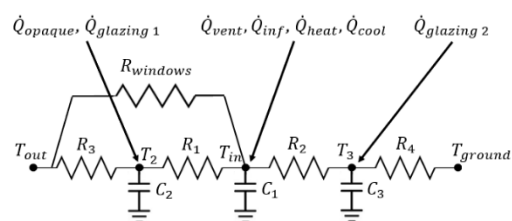


Figure 2 Thermal network representation of a building using a 5R3C model (Dumont *et al.*, 2025).

In a 5R3C network model, opaque (R1 and R3) and glazing (Rwindows) resistances explicitly represent heat transfer through non-transparent envelope elements and transparent elements, respectively, with each resistance defined as the inverse of the product of U-value and surface area, thereby preserving a clear physical link between envelope quality and heat losses. Opaque resistances capture the effect of insulation level and thermal mass interaction, while glazing resistances account for the typically higher transmittance of windows, with solar gains treated as separate heat inputs. This distinction is particularly relevant for residential buildings, where envelope characteristics strongly determine heating demand, peak loads, and thermal time constants. At the scale of REC, 5R3C is a suitable modeling network as it is separating opaque and glazing resistance, which enables fast yet physically meaningful simulation of varying building archetypes and renovation scenarios, supporting hourly load profiling, heat demand aggregation, and optimization of shared resources such as heat pumps, photovoltaics, and storage.

In a macroscopic regard, R and C values are determined by direct calculations of a common 'set' of physical parameters, simulating the energy dynamics, as a foundational element of communities' performance. This physically grounded parameterization can be naturally reformulated into a state-space representation, where the thermal behavior of a building is expressed as a system of first-order differential equations. In this framework, node temperatures define the state vector, while external climatic conditions and internal heat gains act as inputs. Such a formulation enables efficient numerical simulation and provides a structured basis for parameter identification. In particular, RC parameters can be estimated from measured data using system identification techniques, thereby improving model calibration and predictive accuracy. This approach has been further explored in (Dumont, Feldheim and Lybaert, 2025), where a dedicated methodology for RC parameter estimation is proposed. However, when scaling up to the urban level, physics-based engines, such as CityBES and

Urban Modeling Interface (UMI) (Reinhart et al., 2020), the integration of datasets exceeds their capacity, neglecting significant interactions. In this lens, responsive design based on reduced RC model has been developed, as CitySim, capable of energy consumption simulations in multiblock buildings, and behavioral analogy, or SimStadt for 3D applications based on reduced RC models (Nouvel *et al.*, 2015), or the Energy Urban Resistance Capacitance Approach (EURECA), utilized for thermal behavioral simulations at hourly time scale based on the ISO 52016 and RC models.

Given the scope and objectives of this research, the following section examines the architecture-specific and occupant-related parameters expected to significantly influence the thermal behavior represented by the 5R3C model, and namely: compactness ratio, building age, building typology, window-to-wall ratio (WWR), and occupancy patterns.

Each of these factors plays an impactful role in shaping the dynamic thermal response of the building and, consequently, the accuracy and reliability of the 5R3C model representation, capturing complexities of interactions occurring in buildings. Creating reliable datasets for simulation and calibration of EC levels requires detailed input and careful consideration of computational approaches and still remains challenging. Different tools, with single or specific aspects, integrate thermo-physical characterization in detailed analysis, driven by quantitative data, such as the envelope and geometry; building fabric, devices, but also geographical contextual factors are the elementary attributes assigned to powerful simulations (Table 1).

Table 1. Examples of UBEM simulations tools and parameters (adapted from (Guo *et al.*, 2024).

Tool	Parameter(s)
SimStadt	Occupancy Building Physical Parameters
City Energy Analyst	Meteorological data Thermal characteristics Energy consumption U-Values
TEASER	Architectural form and function Type of construction materials

3.1 Compactness Ratio

The compactness ratio, defined as the ratio of the building's envelope surface to its internal volume, determines its thermal performance critically, by influencing directly the heat transfer coefficients (Jankovic *et al.*, 2025). A lower compactness ratio reduces overall heat exchange with the outdoors,

reducing the global transmission conductance and increasing effective thermal resistance, and thus lowering heating and cooling loads, a key dynamic behavior captured by the lumped RC network used for annual demand and peak load calculation (Ourghi, Al-Anzi and Krarti, 2007) (Yan *et al.*, 2025).

Typically, in REC context, adjacent buildings with higher compactness exhibit lower heat losses and more stable thermal performance, compared with buildings that are less compact. This potentially facilitates shared renewable supply capacity planning and reduces buffer storage requirements at community scale, hence a smoother energy balance. (Bekkouche *et al.*, 2013)

3.2 Building Age

Building age serves as a proxy for envelope quality, infiltration rates, and material conditions, all of which could change resistances and capacitances in the lumped model. Older buildings typically have higher U-values, more uncontrolled ventilation, increasing cooling needs, and possibly greater exposed volume of mass. In dynamic thermal models like 5R3C, these characteristics increase thermal conductance and alter effective capacitance, resulting in higher energy demand and less stable indoor temperatures, especially through infiltration losses. (Dascalaki *et al.*, 2011; Waddicor *et al.*, 2016).

Within RECs, older building stocks often have higher and more variable thermal losses, necessitating more robust energy solutions such as enhanced energy efficiency measures, retrofits, and demand response schemes.

3.3 Building Typology

From an RC modeling perspective, typology affects the magnitudes of global resistances, due to differing exposure and insulation, capacitances, due to variations in thermal mass, and internal gain profiles. Building typology frameworks have shown that classifying buildings by type allows systematic assessment of energy performance. Empirical study by Dascalaki et al. demonstrates significant energy use variability across typologies, even when there are built in similar climates, indicating strong links to geometry, thermal mass, and functional characteristics that impacts dynamic heat flows. (Dascalaki *et al.*, 2011)

Typology can drive aggregated demand within RECs. An REC of high-density residential typologies, for instance with moderate thermal mass, will typically have lower peak heating loads relative to scattered detached buildings with larger exposures.

Understanding morpho-typological mixes in an REC helps to optimize shared renewable generation, storage needs, and demand-side flexibility.

3.4 Window-To-Wall Ratio (WWR)

WWR directly affects dynamic heat transfer by altering the balance between transparent and opaque surface areas. A higher WWR increases transmission conductance, lowers overall resistance, and simultaneously introduces solar heat gains, which feed directly into the RC network's gain nodes. Research demonstrates that increasing WWR tends to raise indoor temperatures, consequently changing annual and seasonal energy demand, especially in office buildings and residential typologies subject to solar exposure (Hao and Sohn, 2024).

In a community setting, WWR affects aggregate demand variability and solar potential: higher WWR may increase passive gains during low-generation periods (e.g., mornings/evenings), reducing active heating needs, but also can amplify cooling needs that align poorly with PV generation.

3.5 Occupancy

Occupancy behavior affects building energy performance by modifying internal heat gains, ventilation rates, and heating schedules and controls, which directly influence the dynamic heat balance in the 5R3C model. Unlike compactness, age, or typology, behavior does not alter physical resistances or capacitances, but it changes the time-dependent inputs to the model, namely internal gains and ventilation heat transfer, it is one of the significant contributors to building's energy consumption and a challenging uncertainty factor for load forecast and simulation (Hong *et al.*, 2016). A study by Guerra-Satin *et al.* on the effect of occupancy characteristics on the Dutch building stock suggests that behavioral factors can explain 4.2% of variation in residential heating demand, even among physically similar dwellings (Guerra-Santin, Itard and Visscher, 2009)

4 CONCLUSIONS

The challenges related to energy in cities and buildings are inherently linked. This review summarizes the theoretical foundations and specific parametric representations of dynamic urban modeling incorporating the assets of resistance-capacitance networks. Unveiling the potential of this robust strategy for building thermal dynamics and

interactive parametrization based on physical characteristics of the building (see section 3). Key challenges and uncertainties still remain, including ambiguities on data acquisition and accuracy, behavioral aspects of users, coupled with knowledge transfer. Addressing these limitations is essential for advancing reliable and scalable modeling frameworks for RECs.

5 FURTHER RESEARCH

The early research entails integrated modeling with physical interpretation based on architectural parametrization; such developments strengthen the links between modeling researches. Going beyond calculation processes and including prototypes of structural building attributes of its envelope to demand forecasting, is the key element that will pilot the validation of the proposed methodology and insights for common datasets for EC responsive and optimized decision-making designs.

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