Towards an Energy Twin: Simulating Global Warming Potential in Hamburg's Building Stock

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Abstract

Urban areas are central to achieving global climate goals, yet cities face a core dilemma: demolishing and rebuilding creates high embodied carbon, while older buildings often perform poorly in operation. Urban Digital Twins (UDTs) can help navigate these trade-offs, but their use in municipal governance is limited. This paper introduces the Energy Twin, an Agent-Based Model (ABM) developed with Hamburg city stakeholders to assess long-term Global Warming Potential (GWP) in district-scale demolition-versus-retrofit scenarios. The model integrates embodied and operational emissions, enabling comparison of policy pathways towards the city's 2040s carbon-neutrality targets. A demonstration for the Hammerbrook district highlights the carbon payback period required for new construction to offset its embodied emissions. In particular, the results also show that rapid intervention—either through retrofits or demolition–reconstruction—is essential for meeting near-term climate goals. The Energy Twin provides a focused, problem-driven UDT that links energy modeling to real planning needs. Implemented on the GAMA Platform, it is interactive and decision-maker friendly. The paper also outlines the consultative methodology used to co-develop the model with municipal authorities, showing how collaborative, transdisciplinary processes can support more sustainable urban transformation.

Keywords

Digital-Twin-based Decision; Buildings Carbon Footprint; ABM Simulation

1 Introduction

The global effort to mitigate climate change hinges on the sustainable transformation of urban areas, which are primary centers of population, economic activity, and greenhouse gas (GHG) emissions [6]. This imperative is incorporated into international frameworks such as the Sustainable Development Goals (SDGs), particularly SDG 13 (Climate Action) and SDG 11, which calls for sustainable cities and communities [2]. A significant portion of urban emissions originates from the building sector. In Hamburg, for instance, heat consumption in residential and non-residential buildings accounts for approximately 4.7 million tonnes of CO2 emissions annually, cf. Figure 1. Addressing these emissions is critical for the city to achieve its goal of carbon neutrality by the 2040s [24].

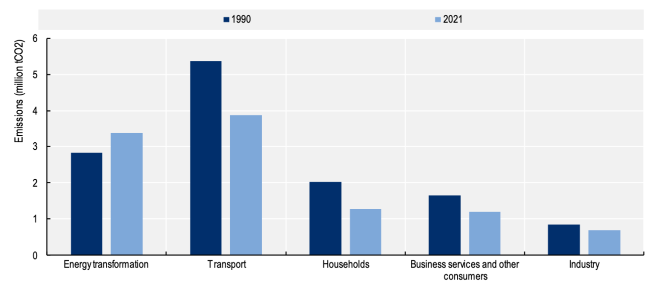

Figure 1: CO_2 emissions in Hamburg, per category. (OECD / Hamburg Statistics Office, 2022)

Urban planners and policymakers face a fundamental dilemma rooted in the life cycle of buildings [33]. A building's total carbon footprint is composed of both Operational Energy (OE)—consumed for heating, cooling, and electricity during its use—and Embodied Energy (EE), which includes emissions from material extraction, manufacturing, construction, and demolition [18]. While OE has traditionally accounted for the majority of a building's life-cycle emissions [11], the relative importance of EE has grown significantly, making the upfront carbon cost of new construction substantial [26]. One of the most urgent open questions is how to decarbonize concrete production. Specifically cement, the binding material required for concrete, currently releases significant amounts of CO_2 which are difficult to replace without scaling up carbon capture and storage technologies [4]. This creates a complex trade-off: demolishing an old, inefficient building to construct a new, highly efficient one (e.g., to the Passivhaus standard) generates a massive short-term spike in embodied emissions, which may only be offset by operational savings over several decades.

This challenge prompted a deliberately provocative research question, developed in collaboration with Hamburg's Authority for Environment, Climate, Energy and Agriculture (BUKEA)[1]: *Should buildings in Hamburg be demolished and reconstructed or retrofitted to help the city in reaching carbon neutrality by 2040s?* This question is not intended to have a simple answer, but to stimulate a nuanced, evidence-based exploration of long-term policy pathways.

Hamburg presents a particularly compelling case study for several reasons. First, the city has a wealth of available data, which is essential for grounding a digital twin in reality. Second, there is

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Generative AI tools (ChatGPT, Gemini) were used solely for language editing and text reformulation. No content, data analysis, interpretation, or conclusions were generated by AI. The authors take full responsibility for all parts of the manuscript.

[1] Official website of the Authority of BUKEA of the city of Hamburg.

a history of successful collaboration between the city's administration and research institutions, including the City Science Lab at HafenCity University, fostering a transdisciplinary and co-creative environment. Finally, Hamburg's ambitious climate goals, recently increased after a successful public referendum, necessitate the exploration of innovative decision-support tools like the one we propose. The specific policy problem we address pertains to the strategic management of the non-residential public building stock, where authorities must decide on the optimal balance between deep retrofitting and demolition-reconstruction to meet climate targets.

To navigate this complexity, we leverage Urban Digital Twins (UDTs)— use-case-specific virtual replicas of urban environments that enable exploratory modeling and impact assessment of various interventions. Specifically, we employ Agent-Based Modeling (ABM) [5], a bottom-up simulation paradigm well-suited for capturing the heterogeneity of urban actors and the emergent, system-level outcomes of their decisions. Our model, the Energy Twin, is developed on the GAMA platform[2] [30]. GAMA's interactive and visual nature transforms the model from a *black box* into a transparent *sandbox*, fostering easier collaboration between modelers and non-expert stakeholders. This approach promotes transparency and inclusion, which are critical for building trust and ensuring that the simulation has a real-world impact on policy. Within this framework, our case study focuses on the city of Hamburg, which aims for carbon neutrality by 2040s [24], a significant challenge given that the building sector accounts for a substantial portion of its CO2 emissions.

This paper makes a dual contribution. Firstly, we present the Energy Twin a novel ABM designed to analyze the demolition-versus-retrofit dilemma by simulating long-term global warming potential (GWP) impacts. Secondly, we formalize the iterative and consultation process with BUKEA (Authority for Environment, Climate, Energy and Agriculture of Hamburg) as a replicable methodology for developing policy-relevant UDTs. This work bridges the gap between urban simulation and the practical needs of municipal governance, offering both a decision-support tool and a collaborative framework for sustainable urban transformation.

This paper presents a State of the Art in Section 2, before introducing our methodology in Section 3 towards a model based on consultation presented in Section 4. The model policies, different scenarios, and calibrations are shown in Section 5.3, and experiments results in Section 6. At last we discuss limitations of our approach and conclude in Sections 7 and 8.

2 State of the Art

2.1 The Urban Decarbonization Dilemma

Global mitigation efforts hinge on transforming cities, where buildings account for a major share of energy use and greenhouse gas emissions. At the urban scale, the key dilemma is how to manage a building stock whose total carbon footprint combines operational emissions from heating, cooling, and electricity with embodied emissions from materials, construction, and end-of-life processes [18]. Historically, modelling and regulation have prioritized operational energy efficiency, but as grids decarbonize and standards tighten, embodied carbon—especially from concrete and cement production—now represents a growing share of life-cycle impact and is far harder to tackle [4, 26]. This reframes the classic policy question: whether demolishing an inefficient building to construct a more efficient one reduces or increases cumulative emissions over the relevant climate horizon, given the substantial upfront carbon spike of new construction [29]. While Life Cycle Assessment (LCA) provides a robust framework for this analysis [20], a significant gap remains in scaling this analysis to the district or city level and integrating it into dynamic, policy-oriented decision-support tools.

2.2 Modeling Paradigms for Urban Sustainability

To navigate this complexity, researchers are increasingly turning to Urban Digital Twins (UDTs) – use-case-specific virtual models of urban environments that enable exploratory modeling and impact assessment of various interventions [21, 23]. UDTs provide a platform to test *"what-if"* scenarios, allowing planners to assess potential impacts before they are implemented [36]. However, many UDT initiatives are critiqued for being technology-centered, creating black box models that are opaque to stakeholders and overlook crucial social and political dimensions [31]. This has led to a growing call for more problem-driven, participatory approaches.

Within the UDT paradigm, Agent-Based Modeling (ABM) offers a particularly suitable bottom-up perspective for studying complex adaptive systems like cities [9]. Unlike top-down models, ABM can represent heterogeneous actors (e.g., building owners, residents) with diverse decision-making rules, making it ideal for exploring the interplay between policy and urban decarbonization pathways [1, 7, 22].

2.3 The Research Gap and Our Contribution

While the aforementioned fields provide the foundation for our research, a critical gap exists at their intersection. As summarized in Table 1, existing models and platforms typically miss at least one of three capabilities needed to address the demolition–retrofit dilemma in real-world policy settings.

First, large-scale tools such as *Hotmaps* [16] offer valuable, macro-level heat-demand and supply mapping, but do not explicitly model building-level demolition–retrofit trade-offs. Second, detailed simulation environments like the *City Energy Analyst* (CEA) [13] focus on retrofit scenarios yet often treat demolition and its embodied carbon only implicitly. Third, many ABMs explore technology adoption, but are seldom co-designed with municipal stakeholders, which limits their practical uptake [35]. Our Energy Twin is therefore intended as a complementary, district-scale tool rather than a head-to-head replacement: it links building-level life-cycle emissions and interactive policies to the broader planning insights provided by such platforms.

The Hamburg Energy Twin combines (1) a focused ABM approach to the demolition-versus-retrofit dilemma, (2) an interactive visualization environment through the GAMA Platform [30], and (3) a development methodology centered on consultation with the Hamburg Authority for Environment, Climate, Energy and Agriculture (BUKEA). We thus respond to the call for problem-driven,

[2]Code available on GitHub here.

Model / Approach	Paradigm	Scale	Decision Focus (Demolition vs. Retrofit)	Stakeholder Integration
Hotmaps [16]	Geospatial Analysis (static)	EU/City	Top-Down, GIS-based decision-support tool for heat planning	Generic data provision
City Energy Analyst [13]	Building Physics Simulation	District/City	Focus on retrofit scenarios; no explicit demolition trade-off	User-defined scenarios
Generic ABM for Tech Adoption [1, 7]	Agent-Based Model	District/City	Not explicit; focuses on technology diffusion	Typically model-driven (N/A)
Hamburg Energy Twin (This work)	**Agent-Based Model (dynamic)**	**District/City**	**Bottom-Up, interactive decision-support tool on demolition-retrofit trade-off with custom policies**	**Consultative process with city authority (BUKEA)**

Table 1: Comparative Analysis of Some Complementary Urban Energy Modeling Approaches

policy-relevant UDTs that are not only technically robust but also salient and legitimate for their intended users.

3 Methodology

3.1 An Iterative and Consultative Methodology

Our methodology to develop the Energy Twin is not a rigid framework but an iterative and consultative process developed to meet the specific needs of both researchers and city officials. It is structured around a series of feedback loops between model development and stakeholders' expertise from BUKEA, ensuring the model's relevance and applicability. This process can be visualized as follows (see Figure 2).

This approach ensures that the model is salient to policy needs, credible through expert grounding, and methodologically legitimate in the eyes of its intended users. Along the exchanges, the Energy Twin model was developed and tailored progressively on the GAMA Platform [30] (detailed in Section 4), a capture of the model can be seen in Figure 3. The process was structured in four distinct phases:

3.1.1 Phase 1: ***Data Integration & Problem Definition.*** The process was initiated by defining the core policy problem with BUKEA. This involved identifying the specific challenges of managing Hamburg's non-residential public building stock. In parallel, we collected, cleaned, and integrated the essential datasets, primarily the Inspire ALKIS 3D geodata and the "Wärmekataster" (Heat Cadaster). Other data sources were integrated after feedback.

3.1.2 Phase 2: ***Model Development.*** Based on the model specification and data, a first prototype of the Energy Twin was developed on the GAMA platform, simulating the Hammerbrook district of Hamburg. This involved creating the agent population (buildings) and implementing the core mechanics of energy consumption, renovation, and demolition. Hammerbrook is chosen as it is primarily composed of industrial and commercial buildings, with less residential stock. This district accounts for a large share of urban energy use and emissions, making it highly relevant for climate-oriented building policies. Because many properties are publicly owned or under city management, Hammerbrook offers Hamburg direct leverage for impactful renovation and decarbonization strategies. Its profile thus makes it an ideal testbed for agent-based modeling and urban transformation experiments in GAMA.

3.1.3 Phase 3: ***Stakeholder Consultation.*** The model prototype and its initial outputs were presented to experts at BUKEA in a series of meetings. These sessions were not simple presentations, but interactive demonstrations where stakeholders could see the model in action, question its logic, and critique its assumptions. This prototype facilitated dialogue for an iterative model progression and enabled the elicitation of specific data needs (e.g., building materials, construction standards) and functional requirements (e.g., the city-wide generalizability need) that were not apparent in the initial phase.

3.1.4 Phase 4: ***Model Refinement & Scenario Design.*** The crucial feedback and expert insights gathered during the consultations were fed back into the development loop. This led to a significant refinement of the model's logic. More than just a technical validation, this phase was a process of co-design, where qualitative expert knowledge from BUKEA officials was systematically translated into quantitative model parameters and decision rules. This ensures that the model's assumptions reflect the institutional and practical realities of urban planning in Hamburg. The key parameters derived from this process are detailed in Table 2. Ultimately, this iterative refinement led to the collaborative design of relevant policy scenarios, completing the cycle and ensuring the model was sufficiently robust to be implemented as a decision-support tool.

3.2 Data Collection and Processing

When modeling digital urban twins, literature often distinguishes between models that rely on large-scale (open) datasets and those that suffer from limited data availability [19]. As these models depend heavily on a city's or country's data resources—whether open, commercial, or private—they vary significantly in performance. A digital urban twin becomes truly powerful when it is fueled by sufficient and meaningful data, enabling it to simulate complex urban environments with realistic fidelity.

3.2.1 Data Sources in the Hamburg Case Study. In the case of Hamburg, the majority of building and geospatial data was sourced

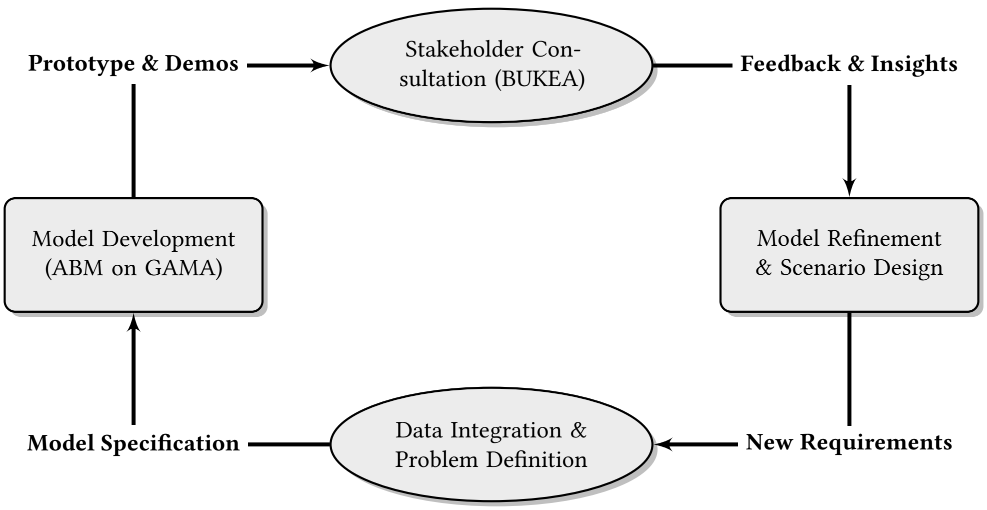

Figure 2: Overview of the Iterative and Consultative Modeling Process with Stakeholders from the city of Hamburg (BUKEA). The cycle represents a continuous feedback loop between model development, stakeholder input, and data refinement.

Parameter Category	Specific Parameter	Value / Rule	Source / Rationale
Timelines	Demolition Duration	0.5 years	BUKEA expert opinion: Average time for physical demolition, excluding administrative processes.
	New Building Planning	2.5 years	BUKEA expert opinion: Standard planning phase for a typical public building.
	New Building Construction	2.5 years	BUKEA expert opinion: Standard construction phase. Can be reduced to 1 year for "system building".
Building Standards	New Building Energy Standard	EH 40 (Effizienzhaus 40)	Mandated standard for new public constructions, requiring 60% less primary energy than a reference building.
	Renewable Energy Mandate (New Build)	≥ 65% of energy from renewable sources	A key component of the EH 40 standard and Hamburg's climate protection laws.
Decision Triggers	Rationale for Demolition/Retrofit	High energy costs; structural defects; need for spatial expansion	Qualitative triggers from BUKEA, modeled as different scenarios, or average monthly quota from statistics.

Table 2: Key Model Parameters Derived from Stakeholder Consultative Process

from the Urban Data Platform, relying on Metaver and Inspire resources[8]. Additional public data is accessible through OpenStreetMap and other open repositories. Nevertheless, critical datasets –especially those providing detail on building-level energy consumption—are typically restricted to commercial or private sources. Consequently, a significant portion of this study was devoted to identifying, retrieving, and evaluating the relevance and quality of all available data.

Building footprints in 2D were collected, and building heights were extracted from the city's official LoD3 3D dataset[32]–however, other datasets could have been used considering proper metadata requirements. These were further processed to correct shapes and enrich them with essential metadata such as energy consumption (heat and electricity), also downloaded from the geoportal.

3.2.2 Data Preparation and Gaps. Beyond collection, targeted processing and completion were essential for reliable analysis. Data gaps at the district or building scale were addressed using approximations: for missing values such as heating system energy demand, we selected buildings with similar attributes (e.g., building size, year of construction) within a defined range and averaged their values for substitution. Where floor numbers were unavailable, we

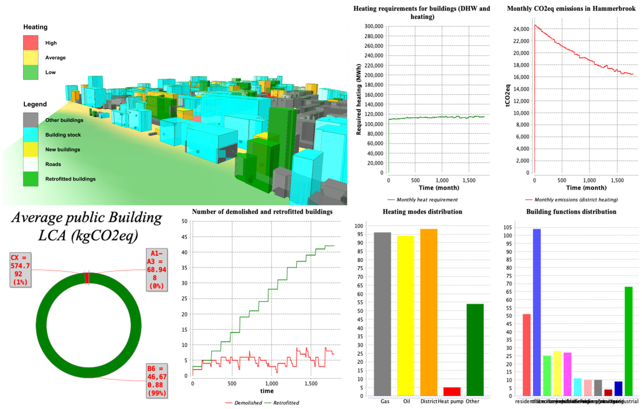

Figure 3: The Energy Twin Model Interface in GAMA, showing the district of Hammerbrook in Hamburg.

estimated them by dividing building height by an average floor height. These rules ensured that key energy and emissions-related parameters were consistently populated for all buildings.

All datasets were systematically preprocessed and merged into geodata files, focusing on those attributes most relevant for energy simulation and emission benchmarking.

3.2.3 Building Footprints and Metadata. Building-level data were compiled from Metaver, Zensus, and official city climate documentation. To obtain reliable height and volume estimates essential for energy and emissions modeling, we used the 2023 Inspire ALKIS LOD2 dataset, which offers city-wide 2D footprints. Manual data enrichment included building heights (meters), and floor counts; additional properties like roof type were available but not used.

The Inspire ALKIS dataset encodes buildings' *function* as a code, but no public key for interpretation was found. To augment this, the 2D ALKIS variant provides `currentuse_xlink_href` (building function) and `conditionofconstruction_xlink_href` (structural condition), which are web-link values referencing external Inspire code lists[3]. Furthermore, the `dateofconstruction` field supplies construction dates with high precision for a subset of buildings. Combining both sources allowed to construct a unified and complete geodata set.

For analysis, three key attributes—*function, construction condition, and construction date*—were integrated at the per-building level to enable categorization of buildings (e.g., identification of non-residential stock) and ages. While ownership is not accessible from public data, this information could be refined in future work through internal city records to isolate public non-residential buildings.

3.2.4 Data Enrichment Pipeline. Due to inconsistencies and gaps in default geodata and visual portal exports, we automated retrieval of 2D building attributes using a Python script that scrapes the Geodienste Hamburg HTML API[4] for each building's bounding box coordinates.

The ALKIS 3D XML data was parsed to extract the relevant building envelopes, with attribute names normalized and ground polygons merged to obtain full building geometries and bounding boxes. Outputs were exported as ESRI shapefiles for direct use in GAMA simulations.

Building bounding boxes were used to request further metadata with BeautifulSoup, which was merged with the main shapefile records. Lastly, polygon simplification was applied for efficient simulation.

4 The Energy Twin Model

4.1 Purpose

The Energy Twin consists in an agent-based model (ABM) developed on the GAMA platform. GAMA was selected for its capacity to integrate Geographic Information System (GIS) data, support multi-agent simulations, and provide 3D visualizations, making it an ideal environment for building a decision-support tool intended for stakeholder engagement and ease of communication. The model integrates most of the Key Model Parameters from Table 2 and additional model calibrations are detailed in Section 5.3. The model's architecture and dynamics are described below, following a structure adapted from the ODD (Overview, Design concepts, Details) protocol for describing agent-based models [15]. Other than the ABM itself, several modules to help track changes and assess the simulation (e.g., KPIs, energy distribution) were added. In this article, we present only some of them due to space constraints.

4.2 Entities, State Variables, and Scales

The model consists of three primary agent types operating within a spatially explicit environment. The simulation progresses in discrete time steps, with key events and calculations occurring on a monthly basis (*every(30#cycles)*), with *1 simulation step = 1#cycle*.

4.2.1 Environment. The environment is a GIS-based representation of a district in Hamburg (e.g., Hammerbrook), populated with Building agents loaded from a shapefile (named *buildings_shapefile*) enriched with metadata such as building heights, or heating consumptions. In addition, the model incorporates demographic dynamics through Building agents, whose population evolves monthly based on a configurable growth rate parameter (*population_growth_rate*). As population increases ($\approx$ 1000 people/month in the model), the model allows for vertical densification of buildings—such as through the addition of new floors—to accommodate growing occupancy demand. This expansion directly increases heated floor area in proportionality and consequently operational energy consumption and emissions. The model architecture is modular, enabling straightforward adaptation so that other districts—or eventually the entire city[5]—can be simulated in the same framework by swapping or expanding the input shapefiles and associated metadata.

4.2.2 Agents.

Building

These are static agents representing individual buildings. Each Building agent holds state variables for the simulation, including:

- **geometry**: The building's 2D footprint and buildings' heights

[3] http://inspire.ec.europa.eu/codelist/
[4] https://geodienste.hamburg.de/HH_WMS_INSPIRE_Gebaeude_2D_ALKIS
[5] Sufficient memory and computational power are required.

- **constructionDate**: The construction year of the building.
- **function**: The primary use of the building (e.g., *office, industrial, residential*).
- **reqHeatOld** and **reqHeatRetro**: The annual heat requirements (kWh/y) for the building in its fully-non retrofitted and retrofitted states, respectively.
- **heatMode**: The primary energy source for heating (e.g., *district_heating, gas_heating*).
- **status flags**: A series of boolean variables (*demolish, demolished, retrofit, retrofitted, rebuilt*) that track the building's current state in the renewal lifecycle.

Each building in the model is assigned a function type—industrial, public, or non-public/commercial—according to empirical distributions from E.ON data for Hamburg [28]. This setup allows users to flexibly focus scenario interventions on specific building stocks (e.g., only public non-residential), tailoring the analysis to different decision contexts and policy targets.

Owner

In the current implementation, a one-to-one relationship exists where each *Building* agent in the selected stock has its own dedicated *Owner* agent. This agent is the primary decision-maker, responsible for its single building (stock). Its key behavior is the *decideOnStock()* action, which evaluates the GWP impacts of *"demolition"* versus *"renovation"* to make a choice when the *decision_making mode* is set to *"auto"* – for deep-custom policies. The mode *"stats"* make owners follow the monthly trends defined by custom scenarios and policies based on real data. We refer interchangeably to the decision of the *Owner* of its *Building* stock.

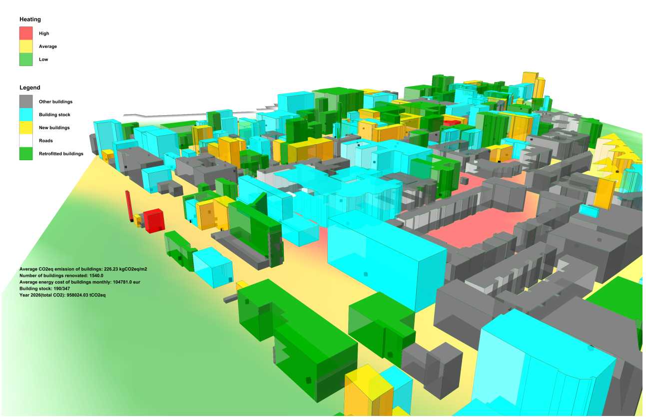

Figure 4: Interactive 3D Energy Twin Interface with Building-level Heatmap.

4.2.3 Interactive 3D Visualization. A module of the Energy Twin is the interactive 3D environment, illustrated in Figure 4, where each building is rendered and updated over time. The color of a building matches its state (e.g., rebuilt is yellow) and if it is part of the building stock (cyan color). It features a dynamic heat-demand heatmap, allowing users to visually follow how renovation, demolition, and decarbonization pathways affect spatial energy patterns across the simulation horizon.

During simulation, stakeholders can click individual buildings to inspect attributes such as CO_2 emissions, energy demand, or intervention flags, and can also trigger manual retrofit or demolition/reconstruction actions. This interactive view links visuals to scenario-policy exploration, and supports both expert analysis and discussion with non-technical audiences.

4.3 Process Overview and Scheduling

The simulation unfolds over a user-defined period in monthly time steps. Each step follows a clear sequence:

1. Initialization (Step 0): The user selects a policy and scenario from the available options. The model loads the GIS data, creating a *Building* agent for each feature in the shapefile. For buildings designated as part of the active stock (e.g., *public_non_residential*), a corresponding *Owner* agent is created and assigned.

2. Trigger Urban Need (Month Step): A building is flagged for potential renewal when its expansion variable is set to true. This can be triggered in two ways: either probabilistically based on a global parameter (*BUILD_CHANGE_PROB*), or systematically as part of a scenario-driven process (the GAMA reflex (i.e., a function) *expandBuildings*).

3. Decision-Making (Month Step): Once a building is flagged, a decision is made based on the global *decision_making* parameter. The primary mode used for scenario analysis is *"stats"*, where the reflex *expandBuildings* directly determines whether a building is demolished (result = 0) or retrofitted (result = 1) according to the scenario's logic.

4. State Update (Month Step): The *updateBuilding(result)* action is called, which manages the building's transition over time.

A retrofit decision (result = 1) sets the *retrofit* flag to true. After a *retrofit_period* (quasi-instantaneous), the building's *baseHeat* is updated to *reqHeatRetro*, the *retrofitted* flag is set, and its *heatMode* is changed based on the active policy, then, a one-time embodied emission for renovation is recorded.

A demolish decision (result = 0) sets the *demolish* flag to true. The model simulates a *destruction_period* (approx. 6 months), during which the building's height is animated to zero. After demolition, the *demolished* flag is set, and a one-time embodied emission for demolition is recorded. The model then simulates a *reconstruction_period* (approx. 2.5 years), during which the building is rebuilt. Upon completion, a one-time embodied emission for construction is recorded, the *rebuilt* flag is set, the *baseHeat* is updated to *reqHeatRetro*, the *constructionDate* is reset to the current simulation time, and the *heatMode* is updated according to the active policy.

5. Data Logging (Month Step): Key Performance Indicators (KPIs), such as *CO2_eq_per_building_m2*, are calculated and recorded monthly (reflexes *computeKPIS* and *computeDataMonthly*).

4.4 Climate Assessment Submodel

4.4.1 Building-Level Emission Accounting. To evaluate the climate impact of different scenarios, the model calculates the Global Warming Potential (GWP), measured in CO_2 equivalents (CO_2eq), for both operational and embodied emissions.

The operational GWP (GWP_{OE}) is calculated annually for each building based on its energy standard and heating source. When retrofitted, operational GWP results in a partial cumulative emission when retrofitted. For a given building, the used formula is:

$$GWP_{OE} = Area \times HeatingDemand_{\text{standard}} \times \text{EmissionFactor}_{\text{source}}$$

where *Area* is the building's floor area in m², $HeatingDemand_{standard}$ is the energy demand per m² associated with its standard (e.g., EH 40), and $EmissionFactor_{source}$ is the GWP per kWh for its energy source (e.g., district heating, natural gas).

The embodied GWP (GWP_{EE}) is calculated as a one-time emission event when a building is demolished and rebuilt. For a building, the used formula is:

$$GWP_{EE} = GWP_{demolition} + GWP_{reconstruction}$$

where the GWP values for demolition and reconstruction are derived from LCA literature and urban studies—in particular from DNGB (German Sustainable Building Council), a sustainable construction network [12, 20]. In the current model version, we apply averaged emission factors across the building stock for computational simplicity and due to data availability constraints. While in reality, embodied emissions vary by building type (e.g., industrial vs. office), construction year (affecting material types and structural systems), and specific construction materials, our averaged approach provides a reasonable first-order approximation for district-level policy comparison. These values account for material manufacturing, transport, and on-site construction processes.

Future model iterations could incorporate differentiated emission factors by building typology to enhance accuracy, particularly for buildings with extreme characteristics (e.g., heritage structures requiring specialized materials, or heavy industrial facilities).

4.4.2 Progressive Decarbonization of Energy Sources. To capture progressive decarbonization, the model applies annually declining emission factors to all building heating energy sources, parameterized from municipal and national guidance (Hamburg Wärmekataster, ENEV, KfW, dena). For instance, the district heating emission factor is initialized at 0.25 kgCO_2eq/kWh and reduced by around 1% annually in the simulation, a trajectory which matches both recent measurement data and Hamburg's official 2045 climate neutrality goals (targeting values below 0.18 kgCO_2eq/kWh) [10, 12, 14]. The 1% annual reduction, while not directly mandated in the climate plan, provides a linear pathway from the current baseline to the city's long-term emission targets and is consistent with the aggregate reduction required by Hamburg's climate strategy. This aligns operational emission modeling in the Energy Twin with the city's decarbonization trajectory and provides a transparent policy-relevant basis for scenario analysis.

4.4.3 Indicators and Model Outputs. Key Performance Indicators (KPIs) tracked and output by the model include, among others, the per-building greenhouse gas emissions (CO_2eq/m²), the number of buildings renovated (*nb_buildings_renovated*), the number of buildings demolished (*nb_buildings_demolished*), and the buildings monthly heat demand averaged (*heat_demand_monthly*). These KPIs provide a transparent and quantitative basis for evaluating intervention impacts, comparing scenario results, and benchmarking progress towards climate neutrality goals, as implemented directly in the simulation code.

4.5 Buildings' Life Cycle Assessment (LCA)

The Energy Twin model tracks average Buildings' emissions across two principal lifecycle phases: embodied and operational emissions, inspiring from ISO 14040/44 and EN 15978 standards for building LCA [20]. The Figure 5 illustration of the LCA module in an early stage simulation of mostly demolished-rebuilt buildings.

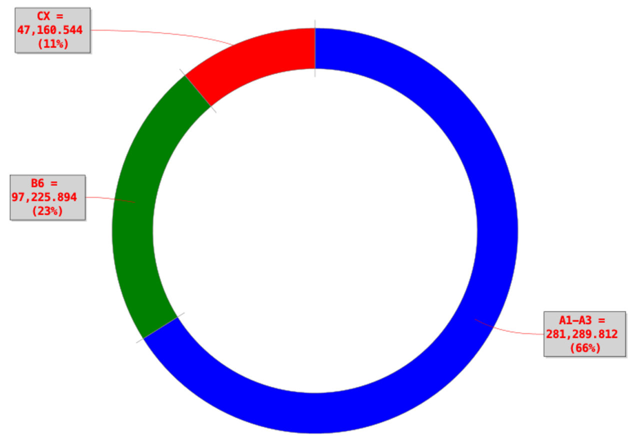

Figure 5: Early-stage LCA Module with all shares simulated for the Hammerbrook district. Values are in kgCO2eq.

4.5.1 Embodied Emissions (Construction and Renovation). Embodied emissions represent the carbon footprint of materials, transportation, and construction processes associated with building interventions. The model distinguishes between two interventions' embodied emission:

Renovation (Retrofit): When a building undergoes energy renovation to a higher standard (e.g., EH 40 and energy source change), the model incurs a one-time embodied emission cost:

$$GWP_{renovation} = Area \times refurbishment_{kgCO2eq}/m^2$$

where $refurbishment_{kgCO2eq}/m^2$ is the annualized embodied carbon intensity per square meter (3.1 kgCO2eq/m^2/year), over a period of an average building lifespan of 50 years. We convert the annualized value to a total one-time embodied cost per operation. This approach reflects the reality that material production, transport, and construction labor all occur in the year of renovation, not spread across the building's remaining life.

Demolition and Reconstruction: When a building is demolished and rebuilt, the model incurs embodied emissions from both activities:

$$GWP_{dem./ren.} = Area \times (demolition_{kgCO2eq} + reconstruction_{kgCO2eq})$$

where $demolition_{kgCO2eq}$ accounts for material removal and waste processing (*CX*), and $reconstruction_{kgCO2eq}$ (*A1-A3*) represents the embodied carbon of new construction materials and assembly. The two values are averages parameterized per square meter based on LCA literature and occur as one-time emissions in the simulation year when the intervention takes place.

The average embodied emissions from construction and renovation share a part of the model's LCA, while demolition-related emissions have their own share in the Building's accounting system.

The operational emissions (*B6*) are calculated monthly with the above formula GWP_{OE} and averaged through all buildings, this constitutes the last share in the LCA's module. The heating demand decreases when a building is renovated to a higher energy standard (by changing the energy source or renovating part of the building), resulting in progressively lower monthly operational emissions post-intervention. Operational emissions are calculated and accumulated every month, to reflect the recurring nature of energy consumption.

4.5.2 Total Lifecycle Carbon Accounting. The model's total global warming impact is the sum of embodied and operational emissions over the simulation period–at each simulation step it is:

$$GWP_{\text{total}} = \sum_{\text{buildings}} GWP_{EE} + \sum_{\text{buildings}} GWP_{OE}$$

This allows direct comparison of policy scenarios and the identification of carbon payback periods—the time required for operational savings from renovation to offset the upfront embodied carbon cost of the intervention. By tracking both components separately and temporally, the model reveals the critical tradeoff between short-term embodied carbon spikes (from construction/renovation) and long-term operational savings, a distinction essential for evidence-based climate policy in the building sector [12, 20].

5 Policies, Scenarios, and Calibration

To explore the central research question on *should Hamburg's buildings be demolished and rebuilt or go through a retrofitting process for ecological impacts*, the model implements a set of policies that act as constraints on agent behavior, which are then tested across several experimental scenarios.

5.1 Implemented Policies

Policies represent the fixed rules that Building agents must adhere to upon renewal, reflecting legal mandates or standards discussed with BUKEA. These are implemented as options within a list in the model, and the selected policy dictates the outcome of a renewal action within the *updateBuilding* logic. The current key policies modeled are:

- **New buildings: 65% R.E. (Renewable Energy) and renovated: 100% R.E.**: When a building is rebuilt, it has a 65% chance of switching to a renewable heating source (*heat_pump_heating* or *other_heating*). When a building is retrofitted, it is guaranteed to switch to a renewable source.
- **New buildings and renovated - 50% renewable energy**: Both rebuilt and retrofitted buildings have a 50% chance of switching to a renewable heating source.
- **New buildings - all renewable energy**: All newly constructed buildings are assigned a renewable heating source.

5.2 Experimental Scenarios

To explore the trade-offs between retrofitting and demolition, we designed five distinct strategic scenarios to be simulated over a 25-year horizon, each reflecting different policy priorities and decision logics. Scenarios define the strategic approach the simulation uses to prioritize buildings for renewal, with each scenario representing a separate policy experiment. The experimental scenarios are presented in Table 3.

5.3 Intervention Rates and Scenario Calibration

To ensure empirical realism, our model scenarios are calibrated to observed renovation and demolition rates for German non-residential buildings. Current data indicates that Germany's overall building renovation rate is approximately *0.7% per year* [34], with non-residential buildings renovating at a lower rate of approximately *0.5% annually* [17, 27]. However, climate policy targets require this rate to increase to *1.7-1.9% per year by 2030* to meet decarbonization goals [10]. By contrast, demolition of non-residential buildings is significantly less common, with comprehensive statistics specific to this building category lacking in current German databases. Based on aggregate demolition data from BBSR[6] (approximately 12,000 buildings demolished annually across all building types) and accounting for the higher demolition likelihood of commercial and industrial buildings compared to residential stock, we conservatively estimate non-residential demolition rates at *0.1-0.2% annually* [25]. This lower rate reflects in part policy preferences for adaptive and ecological reuse, and heritage preservation over demolition.

For the Hammerbrook district case study, which contains approximately more than 300 buildings, including around 180 non-residential buildings as of 2023, these rates scale down to the following intervention frequencies–associated with scenarios:

- **Baseline scenario (Pessimistic):** 0.5-0.7% annually ($\approx$ *1-2 buildings renovated per year*) + 0.1% demolition annually ($\approx$ *1 building demolished and rebuilt every two years*)
- **Realistic scenario:** 1.0% annually ($\approx$ *3 buildings renovated per year*) + 0.1% demolition annually (idem as in baseline)
- **Optimistic scenario (climate target):** 1.7-1.9% annually ($\approx$ *5-6 buildings renovated per year*) + 0.1% demolition annually (idem as in baseline)

Note that these data remain empirical estimation rates. These parameter values ensure our scenarios reflect both current practice and policy-relevant futures, allowing meaningful comparison of intervention strategies. A scenario example on three pathways (pessimistic, realistic, optimistic) with very high intervention rates (3-4 buildings renovated/demolished per month) is shown with the KPI buildings $kgCO_2eq/m^2$ in Figure 6. This example highlights a settled carbon debt (red curve: demolition-heavy) after decades with much lower cumulative emissions than the retrofit/balanced-centered scenarios (green and orange curves, respectively). In order to consider feasible and relevant scenarios and policies, we adopt estimation rates given above.

[6] Germany's Federal Office for Building and Regional Planning.

Scenario	Decision Logic	Energy Policy (chance percentages of energy source change)	Decarbonization Rate (%/year)
All refit (Optimistic)	All buildings flagged for renewal are exclusively retrofitted, no demolition takes place.	New buildings and renovated: 100% renewable energy.	District heating: 1.5 Electricity: 1.2
All demolition (Pessimistic)	Every building flagged for renewal is demolished and rebuilt; processed in random order.	New buildings and renovated: 50% renewable energy.	District heating: 0.5 Electricity: 0.5
Worst-first (Realistic)	Buildings selected for renewal are sorted in descending order of energy inefficiency (highest heat demand first).	New buildings: 65% renewable; renovated: 100% renewable.	District heating: 1.0 Electricity: 1.0
Old-first (Realistic)	Renewal prioritizes buildings by age (oldest first), processing them sequentially.	New buildings: 65% renewable; renovated: 100% renewable.	District heating: 1.0 Electricity: 1.0
Random (Realistic)	Buildings flagged for renewal are randomly chosen to be either retrofitted or demolished.	New buildings: 65% renewable; renovated: 100% renewable.	District heating: 1.0 Electricity: 1.0

Table 3: Definition of Experimental Scenarios with Policies and Decarbonization Rates

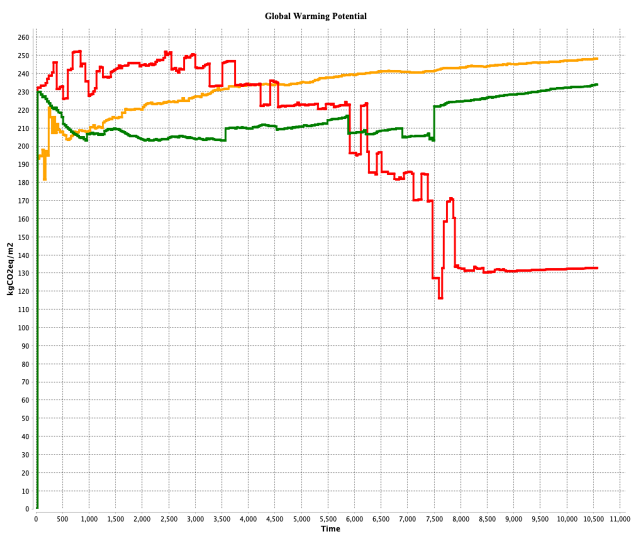

Figure 6: Three scenarios with monthly intervention rates – OE compensates the carbon spike of 'All demolition'.

5.4 Reference Energy Standard: ENEV 2014 vs. EH 40

The initial heating energy demand for buildings in our model is sourced from the Hamburg Urban Data Platform (geoportal Wärmekataster) and calibrated using the German ENEV 2014 standard, which sets regulatory requirements for building primary energy use and thermal insulation. ENEV 2014 stipulates that buildings must achieve at least 25% lower primary energy demand than the historic reference building, serving as the ordinary standard benchmark in our simulations. While the EH 40 standard (Effizienzhaus 40) [3], commonly used in policy discussions, would further restrict energy demand to 40% of the ENEV 2014 reference, detailed EH 40 energy demand data are not available for the Hamburg building stock. Accordingly, EH 40 is not implemented in our quantitative simulations, but is included for reference as a theoretical upper-bound for potential energy savings. This offers useful context when interpreting operational emission reduction potentials in ambitious retrofit scenarios.

6 Simulation Results and Policy Implications

6.1 Comparative Analysis of Scenarios

Simulations reveal distinct carbon trajectories for each intervention strategy (see Figure 7). The *All Refit* scenario consistently minimizes cumulative GWP, avoiding the substantial embodied carbon spikes associated with demolition. Over the whole simulation period, the "short-term" operational efficiency gains are higher than most of the other scenarios (*All demolition*, *Old-first*, *Worst-first*). Furthermore, the *All Refit* scenario benefits from higher annual decarbonization rates for district heating and electricity (1.5% vs. 1% and 0.5% in realistic and pessimistic scenarios, respectively), which accelerates the decline of operational emissions and amplifies the cumulative carbon savings of renovation-focused pathways. The absence of upfront reconstruction emissions makes it the most climate-effective pathway over the 2025–2050 horizon.

In contrast, demolition-oriented scenarios (*All Demolition*, *Old-first*) incur immediate, large-scale embodied carbon debts. Although new buildings eventually operate at higher efficiency, our results show that this operational advantage fails to offset the initial construction emissions within the critical timeframe for 2040s climate neutrality.

Interestingly, the targeted demolition/renovation of the worst-performing stock (*Worst-first*) results in better emission gains over the whole period of 2020-2040 than comprehensive retrofitting (see

Table 4 for quantitative results), before the set-up operational efficiency gains of the *All retrofit* scenario catches up– with a *Buildings* $kgCO_2eq$'s value of 2,5% lower than *Worst-first*'s.

6.2 Implications for Urban Climate Neutrality Pathways

The simulation results identify a central constraint for achieving climate neutrality by 2040–2045: both the type and the timing of building stock interventions determine whether targets remain feasible. The renovation-oriented pathway consistently yield lower cumulative GWP than demolition/balanced-oriented ones, even though new buildings can achieve superior operational performance. This is because demolition and reconstruction front-load substantial embodied emissions, creating a carbon debt that operational savings cannot repay within the available timeframe to reach climate goals.

Across scenarios, the *All Refit* trajectory remains below *All Demolition* over 25 years (9.2 vs. 10.3 ktCO_2eq by 2050), and even selective demolition (*Worst-first*: 9.9 ktCO_2eq) cannot match continuous retrofit. Thus, even with improved operational efficiency, the embodied emissions from demolition and rebuilding remain too large to be repaid within the decarbonization timeline.

Intervention timing is equally decisive: slow, random, or gradual pacing fails to meet 2040s targets. The model shows that *renovation rates above 2% annually, combined with prioritization of the worst-performing buildings*, are required to stay within the cumulative carbon budget. Demolition should be reserved for exceptional cases where retrofit is technically or economically impossible. Overall, rapid, renovation-centered transformation emerges as the only viable pathway to get closer to climate neutrality.

6.3 Implications for Decision Support

Coming back to our central research question, these findings translate into a clear policy direction: urban climate strategies must prioritize deep renovation as the primary instrument for minimizing whole-life carbon, while limiting demolition to exceptional circumstances. As summarized in Table 4, meeting neutrality hinges not only on selecting renovation over demolition but also on ***scaling renovation rates beyond 2% per year*** *(national climate goals [10])*, ***sequencing interventions strategically*** (e.g., *worst energy-efficient buildings first*), and ***aligning actions with grid decarbonization***, which improves renovation's carbon payback.

For decision-makers, this shifts emphasis from operational metrics to whole-life carbon accounting. The Energy Twin supports this transition by quantifying cumulative impacts and identifying feasible intervention pathways. A key question for policy, however, is whether governance, financing, and institutional capacity can accelerate interventions fast enough to reach genuine climate neutrality and not only stabilizing emissions.

7 Limitations

The Energy Twin is intentionally designed as a specialized urban digital twin, built by and for Hamburg to address a specific policy question in collaboration with municipal stakeholders. The model's core focus is the trade-off between demolition and renovation for Hamburg's public, non-residential building stock, as guided by the interests of BUKEA. Consequently, several complex urban dynamics are simplified through current mechanisms.

Regarding socio-economic effects, the model does not yet simulate second-order effects like resident displacement, market-driven rent changes, new land development or other economic factors such as accurate retrofitting/reconstruction costs. Extending to residential buildings or towards a socio-economic modeling, complex household behaviors are yet to be included. While this depends on stakeholders' collaboration and decision power to make a relevant co-created model, including refined socio-economic factors could greatly change simulation's predictions.

About the modeling of energy and emissions, the model's current GWP calculations are mostly about heating-related emissions. Currently, the model does not simulate a dynamic energy grid. Buildings are assigned a primary *heatMode* at initialization, and the decarbonization of the energy supply is modeled using a fixed reduction factor (*decarb_factor_district_heating*). A key future work could use a full energy system model, and implement energy-related geographical constraints (e.g, for pump heating).

Embodied GWP values for construction and demolition are applied as uniform constants per m^2 (*construct_buildings_gCO2eq, demolish_buildings_gCO2eq*). Future iterations could use variable values based on different construction materials and techniques.

The most interesting perspectives lie in scalability and decision logic. The model is currently optimized for district-level simulation. While it is generic enough to be applied to different areas of Hamburg and has been applied to other districts, a full city-scale simulation would present significant computational challenges, potentially requiring model optimization or high-performance computing resources. This reflects a deliberate choice to maintain the model as a tangible, user-friendly tool.

The primary experimental mode (*"stats"*) focuses on prioritizing buildings' ordering to ensure scenario comparability. Here, the approach is equivalent whether top-down or bottom-down: owners could decide on their building stock based on their current energy-efficiency state or a central system (the government) can decide. Future work could further develop the *"auto"* decision mode, which incorporates a more detailed, agent-based logic for Owner agents by taking into account refined economic and environmental assessments–supposing the building stock is not owned by other parties.

These defined boundaries allow the model to provide clear insights into its core question while establishing a robust framework for future expansion. Subsequent research can build upon this foundation by developing more nuanced agent behaviors, urban-related second-order effects, integrating energy mix and a wider range of energy uses, and exploring computational strategies for city-scale analysis.

8 Conclusion

This study presents the Energy Twin, an agent-based simulation model to compare the climate impacts of alternative building stock transformation pathways in an urban district context. Our results confirm that retrofit-driven scenarios deliver lower cumulative

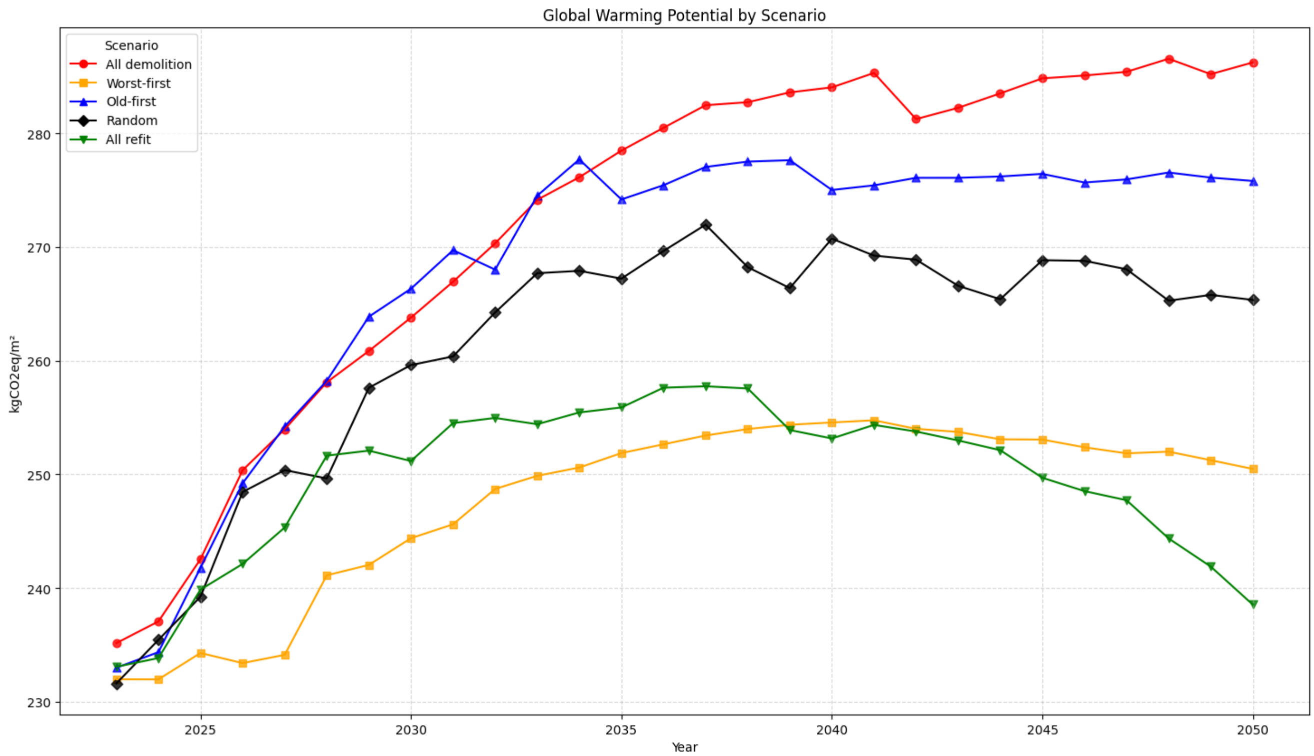

Figure 7: Comparison of Buildings kgCO$_2$eq/m^2 on scenarios defined in Table 3, over a period of 25 years in simulation. The results are averaged through 10 simulations.

Scenario	Total Cumul. CO$_2$ (ktCO$_2$eq)	Buildings kgCO$_2$eq/m^2	Renovated	Demolished	A1-13 (Emb.) (kgCO$_2$eq)	B6 (Op.) (kgCO$_2$eq)	CX (Demo.) (kgCO$_2$eq)
All demolition	10294.8	286.1	0	78	19746.6 (13%)	119780.3 (78%)	13954.6 (9%)
All refit	9246.8	242.8	133	0	146591.6 (60%)	95056.8 (40%)	0
Old-first	9885.4	278.2	73	78	113435.9 (46%)	108677.0 (44%)	26610.1 (10%)
Random	9702.8	260.2	46	147	105586.1 (41%)	106331.4 (42%)	42284.2 (17%)
Worst-first	9864.5	248.2	73	75	52293.4 (31%)	106834.8 (63%)	10990.4 (6%)

Table 4: Key Performance Indicators (KPIs) at the end of the 25-year simulation for each scenario

global warming potential, highlighting the climate benefits of prioritizing renovation over demolition and rebuild. The analysis confirms critical insights: achieving climate neutrality by 2040–2045 requires renovation to be the dominant intervention mode, as importantly as strategic prioritization of worst-performing buildings. Demolition-heavy approaches create a substantial upfront carbon debt that operational efficiency gains cannot repay within the timeframe required for climate targets, making them incompatible with urban decarbonization goals unless reserved for exceptional cases.

However, the scenarios explored here represent theoretical boundaries; real stakeholders—including city planners, residents, and private developers—face major demographic, social, and financial barriers such as housing displacement, heritage constraints, and capital requirements. In practice, transformation strategies involve nuanced trade-offs shaped by stakeholder priorities and local context. The sequence and prioritization of building interventions further shape emissions, reinforcing that whole-life carbon minimization—not operational efficiency alone—must guide urban planning, especially as faster grid decarbonization enhances the payback of deep renovation to reach climate goals in time.

Our Energy Twin platform offers policymakers a transparent, interactive sandbox for creating and visualizing intervention pathways, testing scenarios against practical constraints, and supporting evidence-based decision-making for sustainable urban transformation. Future work should deepen integration with stakeholder engagement, refined energy and carbon modeling, and evolving demographic–or other socio-economic factors–trends to improve decision-making aid for climate neutrality objectives.

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