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A Data-driven Smart District Toward Net Zero Using Generative Design and Urban Digital Twins: A Use Case of Nihonbashi, Tokyo

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Abstract

This study presents a data-driven framework for transforming high-density urban districts toward carbon neutrality through the integration of Generative Design (GD), Multi-Objective Optimization (MOO), and interactive Urban Digital Twins. Using Tokyo's Nihonbashi District as a case study, the research addresses the challenge of retrofitting 154 existing buildings under spatial and regulatory constraints. Buildings are categorized into three retrofit strategies—Reconstruction, Renovation, and Maintenance—based on structural condition, building age, and energy performance. The proposed methodology consists of a three-stage process: (1) baseline performance assessment using Urban Building Energy Modeling (UBEM), (2) design generation and evaluation of alternative design scenarios via parametric modeling and optimization across four key criteria (Resilience, Energy Performance, Financial Feasibility, and Social Impact), and (3) real-time scenario exploration through an interactive digital twin's interface. Additional modeling layers include occupancy analytics and renewable energy simulations. Results indicate that coordinated redevelopment and hybrid energy strategies could achieve significant reductions in energy use intensity (up to 99 kWh/m²/year) and support on-site generation (up to 42.5 kWh/m²/year). The framework provides a scalable approach for carbon-neutral urban regeneration that balances technical, environmental, and human-centered goals.

1. Introduction

As cities worldwide commit to ambitious decarbonization targets, high-density urban districts face unique challenges in achieving carbon neutrality due to complex land ownership, aging infrastructure, and intense spatial constraints. Japan's pledge to reach net-zero greenhouse-gas emissions by 2050, reinforced by the Tokyo Metropolitan Government's "Zero Emission Tokyo" roadmap, places unprecedented decarbonization pressure on the capital's high-density inner districts. Nihonbashi as Tokyo's historical mercantile nucleus and a contemporary hub for finance, retail, and tourism epitomizes this challenge (Ramnarine et al., 2025). This area faces compounded challenges from aging buildings, outdated energy infrastructures, and inefficient urban layouts, which exacerbate energy consumption and vulnerability during extreme climate events (Shen et al., 2024). Nihonbashi's urban form is a palimpsest of Edo-period street grids containing post-war mid-rise concrete stock and fragmented land ownership, in which critical energy, water and highway infrastructure date largely back to the 1960s–1980s urban renewal wave (Ramnarine et al., 2025). These conditions, coupled with rising heat-island intensities, pluvial flood hazards along the Sumida watershed, and seismic exposure, create a complex context in which carbon-neutral retrofits must simultaneously deliver climate-adaptation and heritage-conservation benefits.

In Tokyo, where bottom-up stakeholder-driven redevelopment dominates, there is a need to explore design decisions of diverse urban form scenarios while accounting for multiple, often competing, performance goals to facilitate comprehensive, data-

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driven assessments and proactive urban decision-making for enhancing energy resilience and sustainability. This research introduces a framework of integrating Generative Design (GD) and Multi-Objective Optimization (MOO) that aims for transforming Nihonbashi toward a net-zero smart urban district. This framework will build upon systems architecting principles and an urban digital twin platform previously demonstrated by this research team (Ramnarine et al., 2025).

1.1 Literature Review

1.1.1 Data-driven Smart Urban Districts

Smart cities are becoming a new global movement that uses technologies to drive urban development. Test beds are sprouting up in cities and their strategic areas like Sidewalk Toronto, smart city-nation initiative in Singapore, and Kashiwanoha in Tokyo. There are increasing literatures on smart urban districts to explore impacts of emerging technologies including artificial intelligence (AI), urban automation, Internet of Things (IoT), pervasive computing, and data science to cities, urban infra-structures, public spaces, and our daily life spaces for live, work, and play (Yang and Yamagata., 2020; Yang et al., 2020). The concept of urban digital twins is also emerging as a new field of study in urban planning, systems engineering and geospatial information science, with a focus on high-fidelity computational models of cities or 'replicas' of urban systems over 4D space and time (Bettencourt, 2024, Batty, 2018).

1.1.2 Generative Design (GD)

Generative design methods offer an algorithmic approach to exploring a wide array of spatial configurations and building typologies. Within urban design, generative systems define and manipulate parameters such as building density (FAR), height, orientation, land-use distribution, and façade characteristics like window-to-wall ratio. Rather than relying on singular masterplans or fixed interventions, generative design methods allow for rapid production of hundreds of spatial variants, enabling comparative assessment of form-based performance outcomes (Saha et al., 2020; Zhang et al., 2024). These techniques are essential for revealing unexpected synergies between urban form and performance goals, especially under high uncertainty (Mao et al., 2020; Franch-Pardo et al., 2023).

1.1.3 Multi-Objective Optimization (MOO) Framework for Performance Evaluation

The Urban Building Energy Modeling (UBEM) approach is a key component of this study. UBEM is a method for evaluating the energy and environmental performance of urban districts. This bottom-up, physics-based methodology simulates energy use intensity (EUI), carbon emissions, and operational dynamics across multiple buildings and scenarios (El Kontar et al., 2020). Integrated with the broader framework, UBEM supports performance modeling and impact assessments linked to generative design options (Zhang et al., 2024).

The framework employs simulation-driven performance evaluation and multi-objective optimization to guide retrofit decision-making across four key criteria: Resilience, Energy Performance, Financial Feasibility, and Social Impact (Figure 1). Optimization objectives include minimizing energy consumption, carbon emissions, and peak energy load, while maximizing on-site renewable energy generation (e.g., solar PV, kinetic floor systems), energy storage, occupant thermal comfort, and daylight and view quality (Mao et al., 2020; Franch-Pardo et al., 2023). The framework also considers structural and aging conditions (resilience), retrofit costs and potential savings (financial feasibility), and incentive structures (Shen et al., 2024). These interdependent and sometimes conflicting goals require a robust optimization engine capable of handling multidimensional trade-offs and visualizing scenario outcomes across performance domains.

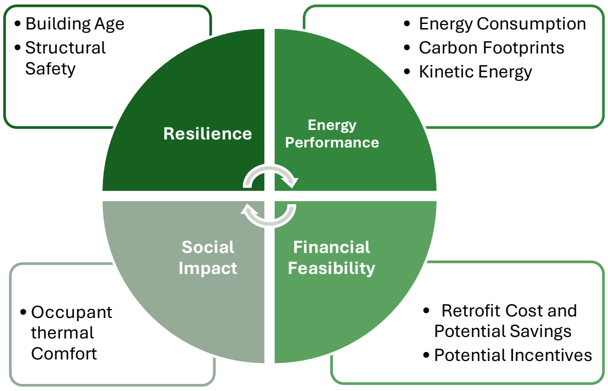

Figure 1. Four evaluation criteria in the multi-objective optimization framework.

1.1.4 From Planning Support Systems (PSS), Geodesign to Urban Digital Twins

The proposed methodology builds on decades of planning support tools and geodesign practices that emphasize scenario-based decision making. However, it advances conversation by embedding these capabilities into a live and interactive urban digital twin. Urban digital twins are dynamic representations of the built environment that synchronize real-time data with predictive modeling (Yang et al., 2020a). These platforms extend beyond visualization to support creation, negotiation, and iterative refinement with stakeholders transforming design from a static outcome into a collaborative and informed process (Bettencourt, 2024).

1.2 Problem Formulation

Tokyo's commitment to becoming a carbon-neutral metropolis by 2050 includes sustainable urban regeneration policies and an emphasis on bottom-up participation. Yet, the fine-grained urban form of districts like Nihonbashi poses major challenges to large-scale retrofitting or conventional urban redevelopment (Ramnarine et al., 2025). The current revitalization efforts often follow fixed retrofit pathways such as reconstruction, façade renovation, or operational upgrades, but do not explore the broader design space nor adequately support complex multi-criteria optimization.

Moreover, the current energy simulation methods such as UBEM provides a strong technical foundation for energy performance of the built environment (El Kontar et al., 2020), it remains disconnected from generative design and lacks tools to meaningfully engage stakeholders in evaluating and selecting among alternatives.

To address these gaps, we propose a data-driven smart district systems design framework that fuses GD with MOO on a high-resolution urban digital twins of Nihonbashi. Building upon the systems-architecting principles, the framework will algorithmically generate data-driven redevelopment scenarios, evaluate their performance across carbon-neutrality and resilience metrics, and visualize solutions for stakeholder deliberation (Figure 2). By embedding rigorous analytics within an exploratory design environment, the framework seeks to operationalize Tokyo's carbon-neutral agenda at the district scale while safeguarding Nihonbashi's cultural identity and economic vitality.

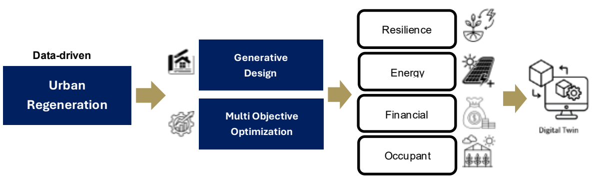

Figure 2. Data-driven urban regeneration workflow integrating GD, MOO, and Digital Twins.

1.3 Research Questions

This study investigates how computational design and decision-support tools can inform the carbon-neutral transformation of existing urban districts. Specifically, it addresses the overarching question: What are urban regeneration pathways toward carbon neutrality by 2050 in Nihonbashi through retrofitting existing buildings? To answer this, the research explores the following sub-questions:

1. How can generative design methods systematically broaden the urban design space by altering form variables such as building density, orientation, height, mixed uses, and façade characteristics to enhance resilience and energy performance?
2. What trade-offs and synergies emerge when optimizing redevelopment scenarios across the four evaluation domains—resilience, energy performance, financial feasibility, and social impact?
3. How can interactive urban digital twins be utilized as decision-support tools to guide stakeholders in evaluating retrofit strategies and selecting optimal pathways toward carbon neutrality?

2. A Methodology on Urban Digital Twins for a Net Zero Smart District

This study adopts a three-stage methodology to support carbon-neutral retrofitting of Nihonbashi. The Descriptive Stage establishes baseline energy and emissions through UBEM analysis of 154 existing buildings. The Predictive Stage generates and simulates hundreds of design scenarios using generative design and multi-objective optimization (MOO) across key criteria: resilience, energy performance, financial feasibility, and social impact. The Prescriptive Stage leverages an interactive urban digital twin to visualize optimal scenarios, enable real-time adjustments, and support stakeholder-informed decision-making (Figure 3).

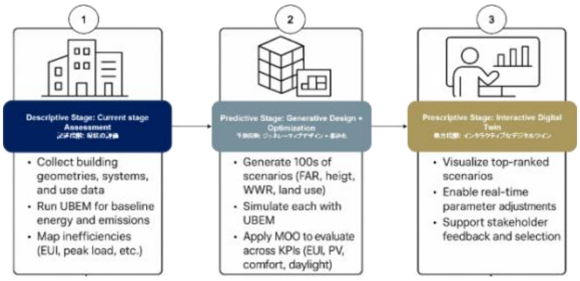

Figure 3. Three-stage methodological framework for carbon-neutral retrofitting: Descriptive, Predictive, and Prescriptive.

3. Case Study and Findings

3.1. Stage One – Descriptive and Evaluative Model: Analysis of Existing Conditions

The first stage of the methodology involves a comprehensive descriptive and evaluative analysis of the existing conditions in the Nihonbashi district. This analysis focuses on three primary aspects: urban form, building characteristics (including building use, geometry, height, and age), and pedestrian flows throughout the district and hourly occupancy rates within each building in a neighborhood of Nihonbashi of Tokyo (Figure 4).

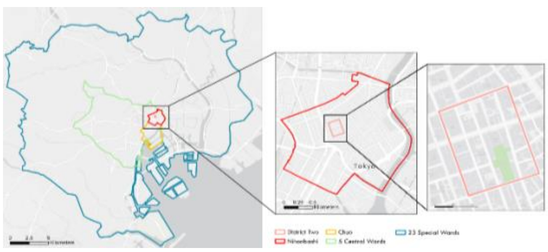

Figure 4. Location of the study area within Tokyo highlighting Chuo Ward, Nihonbashi, and District Two.

A detailed Urban Building Energy Modeling (UBEM) assessment was conducted for 154 buildings within Nihonbashi District, providing simulation-based insights into energy use intensity (EUI) and carbon emissions. These performance metrics reveal spatial patterns of inefficiency and identify high-emission hotspots, establishing a baseline for future interventions (Figure 5).

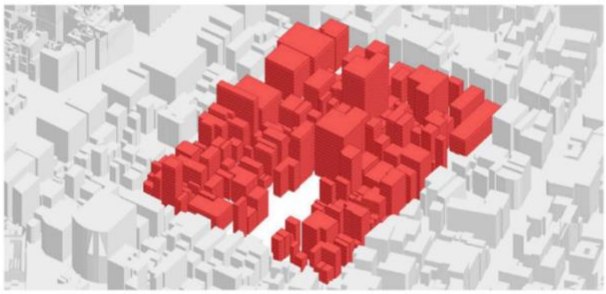

Figure 5. 3D model of 154 buildings in Nihonbashi District used for UBEM baseline analysis.

By understanding the current energy and carbon performance at the building scale, this analysis informs district-wide retrofit strategies aimed at achieving carbon neutrality by 2050. The evaluation leverages data provided by the University of Tokyo, ensuring contextual accuracy aligned with the city's unique urban and climatic conditions. To structure these retrofit strategies, buildings in Nihonbashi are classified into three categories as Reconstruct, Renovate, and Maintenance (Table 1, Figures 6). The classification strategy is based on Tokyo's 2020s redevelopment standards and seismic codes. This classification considers structural safety, age, and retrofit potential. Buildings constructed before 1980 fall under the Reconstruct category due to non-compliance with post-1981 seismic codes, requiring demolition and rebuild, often incentivized by FAR bonuses. Buildings from 1981 to 2000 are categorized as Renovate, being structurally sound but aging, and thus eligible for system upgrades. Buildings constructed after 2000 are classified under Maintenance, requiring only operational improvements, as they already comply with modern building standards. This typology enables targeted, performance-driven interventions to support carbon-neutral urban transformation.

Category	Built Year	Action	Typical Age
Reconstruct	≤ 1980	Demolish & Rebuild	40+ years
Renovate	1981 – 2000	Structural/System Upgrades	20–40 years
Maintenance	≥ 2001	Maintain; Energy Upgrades	< 20 years

Table 1. Building classification criteria for retrofit strategy based on construction years, required action, and typical age

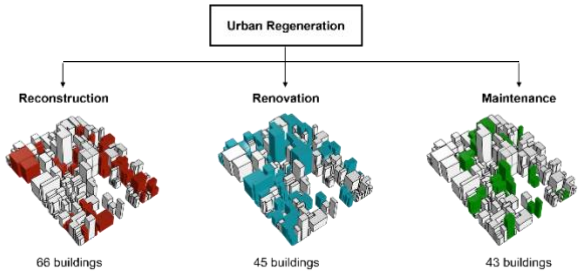

Figure 6. 3D visualization of building classification in Nihonbashi District showing the distribution of 68 buildings for reconstruction, 45 for renovation, and 43 for maintenance under the urban regeneration strategy.

3.2. Stage Two – Predictive Model: Generative Design (GD), Design of Experiment (DOE) and Multi-Objective Optimization (MOO)

3.2.1 Generative Design

Following the classification of buildings into Reconstruction, Renovation, and Maintenance categories, we first focus on the Reconstruction group. Two key redevelopment assumptions were tested. The first assumption takes each building as to be reconstructed individually by its owner, without coordination with adjacent properties. However, this approach has limitations, particularly for narrow plots where individual redevelopment may be inefficient or infeasible. The second assumption explores a more integrated strategy, where neighboring building owners collaborate on a joint redevelopment vision or where a single developer acquires multiple adjacent parcels, merging them into larger blocks for holistic redevelopment.

Based on this integrated assumption, three potential redevelopment blocks were identified to illustrate complex decisions for are construction project that could be supported by generative design. These blocks serve as the basis for generative design exploration. The generative design process begins by defining the boundary of each redevelopment block, which is then subdivided into parcels and structured by a circulation network. Building masses are procedurally generated and refined with floor-level definitions, resulting in 3D volumetric typologies that reflect parametric variations in urban form (Figure 7). Developed using Rhino/Grasshopper (with DOTS), this process enables the rapid generation of hundreds of design alternatives by systematically adjusting parameters such as floor-area ratio (FAR), building height, orientation, land-use distribution, and window-to-wall ratio (WWR) (Saha et al., 2020). Each scenario represents a spatial configuration that can be computationally evaluated for performance.

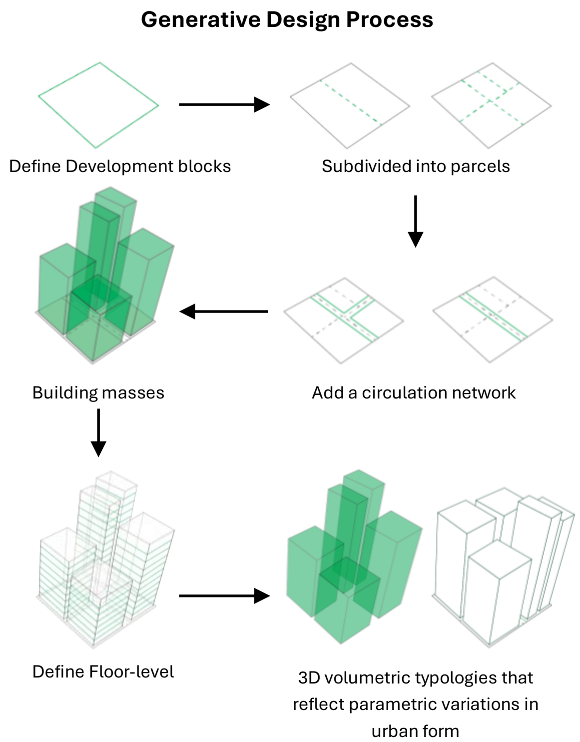

Figure 7. Generative design workflow for creating parametric redevelopment scenarios in Nihonbashi.

The next step focuses on the Renovation category. All buildings within this group were analyzed to develop tailored renovation strategies aimed at improving operational performance and reducing carbon emissions. The strategies include enhancing the thermal performance of the building envelope, specifically by increasing the R-values of walls and roofs, and improving the U-values of windows. In addition, proposed interventions address HVAC system upgrades, programmatic changes in building use, and parametric variations in window-to-wall ratio (WWR) and floor-area ratio (FAR). These modifications aim to optimize energy efficiency while preserving the structural integrity of the existing buildings.

Finally, the Maintenance category includes relatively newer buildings that already meet modern standards and require no major structural interventions. For these buildings, the strategy focuses on operational improvements to further enhance energy performance. This includes minor envelope upgrades, lighting retrofits, and HVAC system tuning to reduce energy use intensity (EUI). Where feasible, on-site renewable energy systems such as rooftop photovoltaics (PV) are also considered. These low-impact interventions are cost-effective and aimed at maximizing performance within the constraints of already-efficient, long-life buildings.

3.2.2 Design of Experiment and MOO

A Python-based multi-objective optimization engine is then applied to identify optimal design configurations that minimize energy use, peak load, and emissions, while maximizing solar generation, energy storage, comfort, daylight access, connectivity, and walkability. This integrated workflow transforms traditional urban planning into a high-resolution, data-driven design exploration that balances sustainability, resilience, and livability objectives.

The MOO process includes a surrogate model to enable optimization analysis and to identify interactions between four retrofit key criteria. In the case study, 10 input variables are identified among key criteria (Table 2). Out of the ten variables, 4 are considered in the UBEM step to generate energy consumption, carbon emissions, and peak energy load, while the other 6 are considered in the renewable energy generation (e.g., solar PV, kinetic floor systems), energy storage and optimization step to find the most optimal design combination. To build the surrogate model, 100 cases configurated from 10 variables were run in a space filling Design of Experiment (DOE). The use of surrogate model and decision-making methods enables rapid assessment of unsimulated design alternatives, streamlining the decision-making process by quickly identifying optimal solutions based on various criteria and stakeholder preferences. This surrogate model served as a simplified representation of the complex relationships within the dataset, allowing for more efficient analysis and visualization.

The four input variables in the UBEM and six variables related to renewable energy are displayed in **Error! Reference source not found.**. The optimization process yielded four key outputs for further analysis including annual CO2 emission in tons, energy use intensity, total renewable energy generation, and total retrofit cost.

Input Variables in DOE
floor area ratio (FAR)
window-to-wall ratio
occupancy schedule
building type distribution (office/residential percentage)
PV efficiency
PV surface percentage
PV install cost per kW
PV Operation & Maintenance Cost per kW
Kinetic energy floor percentage
Kinetic energy tiles efficiency

Table 2 Input Variables in DOE

3.3. Urban Building Energy Modeling (UBEM)

To evaluate the performance of these generated scenarios, Urban Building Energy Modeling (UBEM) is conducted using URBANopt (El Kontar et al., 2020). URBANopt is an open-source simulation platform developed by the National Renewable Energy Laboratory (NREL) for modeling and analyzing energy performance at the building, block, and district scales. It builds upon OpenStudio and EnergyPlus engines to perform detailed energy simulations across multiple buildings within an urban context.

URBANopt operates by defining building archetypes and aggregating inputs such as geometry, climate data, construction systems (R-values), typologies, window-to-wall ratios (WWR), HVAC configurations, and renewable energy systems such as solar panels. The tool then runs energy simulations to calculate energy use intensity (EUI), carbon emissions, and related performance indicators. Outputs include annual EUI broken down by end-use categories such as heating, cooling, lighting, equipment, and water systems, as well as hourly and seasonal load profiles. These results enable comparison across generative design scenarios to identify optimal configurations for carbon-neutral urban redevelopment.

3.3.1. Occupancy analytics and agent-based modeling

To support design decisions in real human–space interactions, an integrated occupancy-analytics and agent-based modeling workflow are developed. This framework delivers three essential capabilities:

- Real-time density visualization facilitates decision-making for block selection and classification.
- Occupants' activity pattern reveals how different zones are used over time. It reflects actual building uses based on high-frequency data that would inform retrofitting planning through building use transition. It provides policy implications for the land use regulation adjustments.
- Scenario-driven occupancy simulation is for testing any future urban design, in which occupancy is a key criterion of urban building performance.

The workflow imports 3D building data from OpenStreetMap into Rhino/Grasshopper, links it to hourly device count logs, and uses a Python script to compute and normalize occupancy densities. A real-time heatmap visualizes these densities from low (blue) to high (red), adjustable by day and hour sliders.

An agent-based simulation layer assigns virtual occupants to buildings with hourly schedules based on real data. It tracks entries and dwell times, visualized alongside the occupancy heatmap, ensuring design scenarios align with actual human behavior (Figure 8).

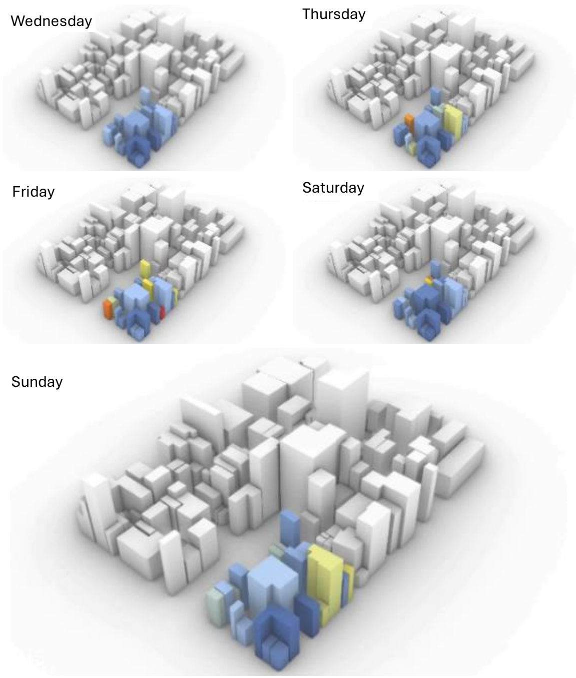

Figure 8. Occupancy mapping for the selected block, based on GPS data, Seven-day period 10:00 - 11:00 PM

An integrated occupancy-analytics and agent-based modeling (ABM) module serves as a diagnostic tool to assess space utilization and as a predictive tool to simulate human movement in design scenarios, guiding generative design toward improved spatial efficiency and comfort.

3.2.3 Renewable Energy: Solar PV and Kinetic Flooring

A hybrid renewable energy system combining piezoelectric floor tiles (Bairagi et al., 2023) and rooftop solar PV panels were proposed to optimize clean energy in urban environments. This approach addresses the temporal mismatch between energy generation and demand by leveraging different peak periods for sunlight and foot traffic. Solar panels are placed on rooftops, while kinetic tiles are installed on ground floor interiors (Figure 9).

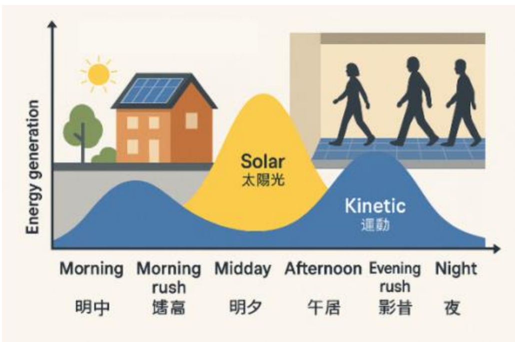

Figure 9. Temporal spread of the solar and kinetic energy potential across 24 hours. Solar peaks midday and kinetic peaks during rush hour.

Spatial analysis of the kinetic energy generation potential within the Nihonbashi District boundary was performed using GPS data and ArcGIS Pro, revealing significant variation of kilo-watt hours potential across the different building types. A custom Python-based tool was created in ArcGIS, so the analysis logic can be re-applied to different urban areas based on different input data.

Considering 90% floor area coverage of the tiles, office buildings demonstrate the highest kinetic energy generation potential across the study area, representing 79.1% total harvesting capacity. Commercial buildings represent the lowest energy potential of the designated building types 0.2457% of the total energy production (in kWh) in the scenario. The hospital footprint accounts for 11.83% of the total energy production, residential 8.37%, hotel 0.447%, and all other building types 0.02404% (Table 3).

		Kinetic Floor Coverage (% of GFA)				
		10%	**25%**	**50%**	**75%**	**90%**
Total kWh per building type (yearly)	**Office**	41.59	103.97	207.94	311.90	374.29
	Hospital	6.22	15.55	31.10	46.65	55.98
	Residential	4.40	10.99	21.99	32.99	39.59
	Hotel	0.24	0.59	1.18	1.76	2.12
	Commercial	0.13	0.32	0.65	0.97	1.16
	Others	0.01	0.03	0.06	0.095	0.11

Table 3. The yearly kinetic kWh potential per building type in Nihonbashi District; based on the percentage of the ground floor area covered with kinetic tile.

The distribution closely aligns with commuter density from GPS visitor data, indicating potential to boost ROI by increasing foot traffic in the commercial area. The kinetic energy payback analysis applies realistic market parameters to evaluate the economic viability of piezoelectric floor tile installations across 154 buildings. The calculation uses pricing (¥56,700 per 0.25 m² tile) with ¥30,000/m² installation costs and 2% annual maintenance rates, while modeling energy generation at 5 joules per footstep converted to kWh and valued at building-specific electricity rates for Tokyo metropolitan area (¥30.18/kWh commercial, ¥36.70/kWh residential). The methodology calculates total installation costs, projects annual energy output based on daily footstep counts, determines revenue potential, and computes payback periods by dividing installation costs by net annual benefits (revenue minus maintenance). Due to the absence of major transit hubs, foot traffic is too low to justify installation costs. Even with high-density traffic simulations, no buildings achieve a break-even point within the tiles' lifespan.

Despite cost reductions by manufacturers like Pavegen—offering tiles at ¥4,275.15 per 0.25 m² (Stein & Oputa, n.d.)—kinetic energy systems remain economically unviable on their own. However, their integration into hybrid renewable setups (e.g., with solar PV or UBEM-based strategies) may offset costs. Future research should focus on reducing hardware and installation expenses through technological advances and batch manufacturing to enhance ROI and feasibility in smart urban environments.

3.4. Stage Three – Prescriptive and Interactive Model: A Web-based Digital Twin as an Interactive Platform

Finally, the optimized scenarios are integrated into an interactive dashboard inspired by the CANVAS urban digital twins (Ramnarine et al., 2025). This interface allows users, planners, architects, and community members to manipulate variables (e.g., WWR, FAR, PV efficiency) and immediately view the impacts on performance. The enabled interactivity and dynamic performance modeling provides each user benefits (Figure 10).

The dashboard enables urban designers to visualize future impacts and align design preferences with environmental targets, real estate developers to easily identify opportunities for redevelopment, and for community members to engage with and see the resource impacts of their community.

This web-based digital twin requires a rearchitecting of the traditional energy performance analysis pipeline used by Rhino/Grasshopper which performs interactive visualization and energy analysis on the same system. The web-based platform instead separates the interactive elements requiring high responsiveness from the computational complexity of the detailed energy analysis. It achieves this by running two independent servers – one for each task.

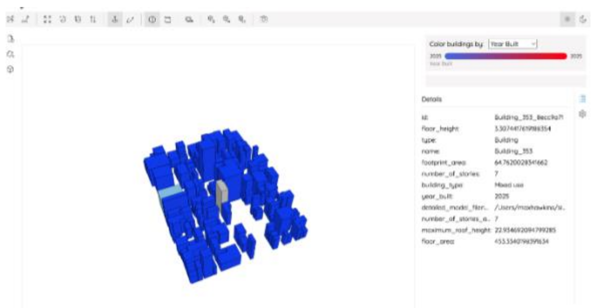

Figure 10 Web-based digital twin showing building-level data and performance metrics

4. Concluding Remarks

This study presents a comprehensive, data-driven framework that integrates generative design, multi-objective optimization (MOO), and urban digital twins to support carbon-neutral urban regeneration at the district scale. Applied to Tokyo's Nihonbashi District, the framework offers a novel methodology for evaluating and prioritizing retrofit strategies across a diverse building stock, classified into Reconstruction, Renovation, and Maintenance categories. By embedding high-resolution energy modeling, real-time occupancy analytics, and hybrid renewable energy simulations within a generative workflow, the study enables stakeholders to explore design trade-offs across four key domains: resilience, energy performance, financial feasibility, and social impact.

Quantitative findings from the case study demonstrate the framework's potential impact. Prior research estimates suggest that combining reconstruction with operational upgrades could reduce energy use intensity (EUI) by 99 kWh/m²/year, while rooftop solar PV systems alone could generate up to 42.5 kWh/m²/year. These results highlight the benefits of coordinated redevelopment and integrated clean energy systems. Moreover, the proposed interactive digital twins platform facilitates informed, real-time decision-making by allowing users to manipulate variables and visualize performance outcomes dynamically.

Overall, this research contributes to a scalable and transferable methodology for achieving carbon neutrality in dense urban districts while preserving cultural identity and promoting stakeholder collaboration. Future work will focus on expanding the surrogate modeling capability, refining economic modeling of renewable energy systems, and testing broader applications of the framework in other urban contexts.

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