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Optimizing Urban Morphology for Net-Zero Energy Districts: A Data-Driven Planning Framework

Di Wang,[1,2,*] Yefang Zhou,[3] Xun Zheng,[4] Haoxiang Zhan,[5] and Guanjing Lin[5]

*Correspondence: cea_wangd@ujn.edu.cn

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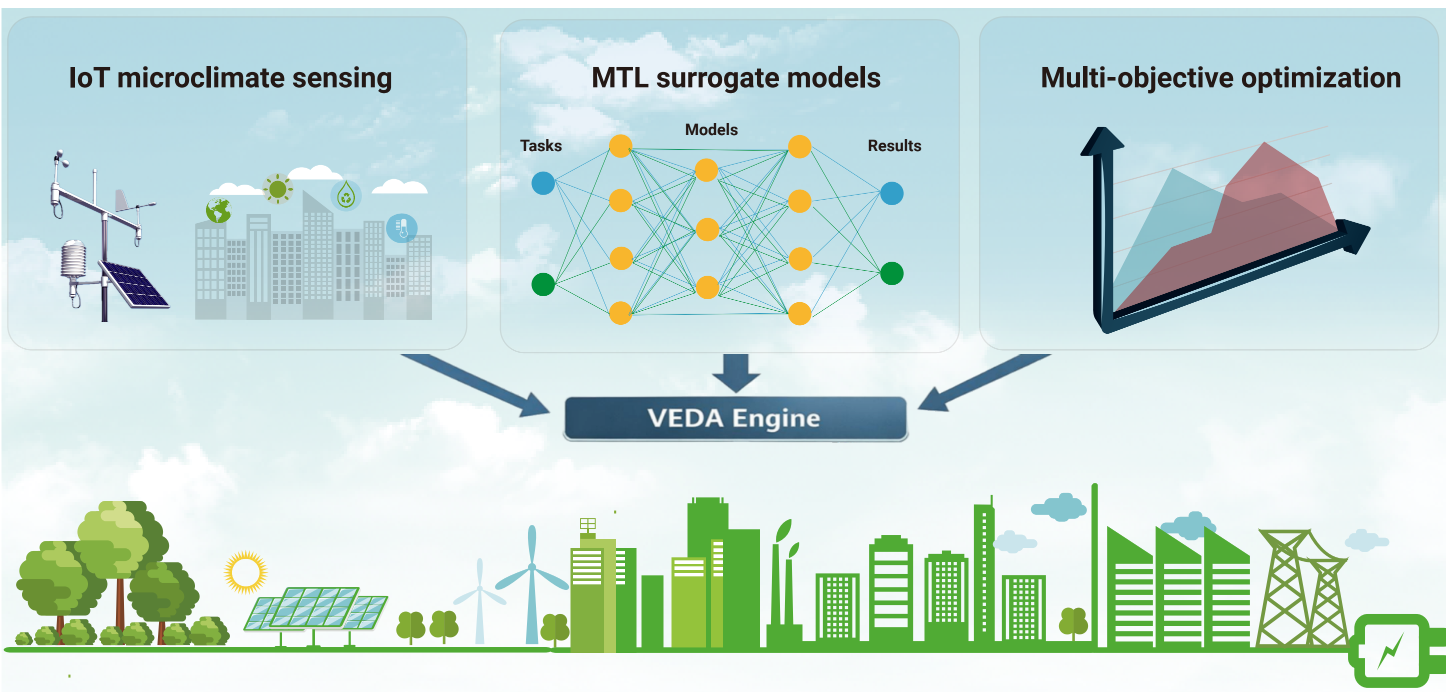
GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- Introduced the Virtual Eco-District Alpha (VEDA) framework, integrating IoT microclimatic sensing, MTL surrogate models, and multi-objective optimization to optimize NZEDs.
- Evaluated the VEDA framework on a high-density testbed, resolving the conflict between building density and renewable penetration.
- Optimized morphology with a building height of 85.5m, FAR of 6.8, photovoltaic potential of 62.4 kWh/m², and reduced carbon intensity to 310.5 kg/m²/year.
- VEDA provides a scalable decision-support system for urban planners to navigate net-zero transition challenges in complex metropolitan environments.

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[1]School of Civil Engineering and Architecture, University of Jinan, Jinan 250022, China

[2]Department of Civil and Environmental Engineering, University of Auckland, Auckland 1010, New Zealand

[3]Transport Planning and Research Institute, Ministry of Transport, Beijing 100028, China

[4]Department of Civil and Environmental Engineering, Nagoya University, Nagoya 4648603, Japan

[5]Tsinghua Shenzhen International Graduate School, Tsinghua University, Shenzhen 518055, China

*Correspondence: cea_wangd@ujn.edu.cn

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The transition to carbon neutrality requires a shift from singular building-level interventions to systemic Net-Zero Energy Districts (NZEDs). However, optimizing urban morphology for such districts is frequently hindered by simulation-driven paradigms that rely on static meteorological assumptions and fail to resolve the high-density renewable potential. This paper introduces the **Virtual Eco-District Alpha (VEDA)** framework, a truly data-driven paradigm integrating IoT microclimatic sensing, multi-task learning (MTL) surrogate models, and multi-objective optimization. We evaluate the framework using a high-density testbed, demonstrating that the VEDA engine identifies Pareto-optimal configurations that resolve the conflict between building density and renewable penetration. Our results reveal an optimized morphology with a building height of 85.5 m and a floor area ratio (FAR) of 6.8, achieving a photovoltaic potential of 62.4 kWh/m^2 and a carbon intensity reduction to 310.5 kg/m^2/year. The framework provides a scalable decision-support system for urban planners seeking to navigate the structural boundaries of net-zero transition in complex metropolitan environments.

INTRODUCTION

The global imperative to mitigate climate change has positioned urban centers as the primary combatants in the fight for decarbonization, with cities currently accounting for approximately 70% of global energy-related greenhouse gas emissions. Within the broader agenda of sustainable urbanism, the concept of Net-Zero Energy Districts (NZEDs) has emerged as a critical organizational scale, enabling the coordination of high-efficiency building envelopes with localized, community-scale renewable energy resources.[3,5] NZEDs aim to achieve a state where the annual territorial energy demand is equal to or less than the on-site renewable supply, providing a strategic buffer between individual building retrofits and city-wide infrastructure transformations.[4,9] Central to the success of these districts is the optimization of urban morphology, including the fundamental physical and spatial configuration of the built environment, which dictates both the passive thermal resilience of buildings and the active harvesting capacity of heterogeneous surfaces.[2,8]

Despite the rapid evolution of computational urban design tools, current frameworks for optimizing morphology in NZEDs face significant methodological and structural pain points that hinder their practical efficacy. The first pervasive issue is a "simulation-driven" paradox, where frameworks claiming to be data-driven are, in reality, heavily reliant on synthetic outputs from physics-based engines rather than empirical observations.[1,2] This reliance creates a lack of ground-truth verification, where predicted reductions in energy use intensity (EUI), often cited as high as 18% to 25% in theoretical master plans,[4] remain detached from the actual post-occupancy performance in complex urban canyons. Without the integration of real-world monitoring systems, these frameworks fail to account for the stochastic nature of human behavior and the intricate feedback loops between built forms and microclimates.[1,2]

Moreover, existing paradigms are largely tethered to static historical climate data, typically in the form of Typical Meteorological Year (TMY) files.[2,9] Such datasets are intrinsically retrospecitve and fail to capture the non-stationarity of contemporary climate change, including the increasing frequency of extreme heat events and the intensification of the Urban Heat Island (UHI) effect. In high-density settings, microclimatic fluctuations can deviate from TMY averages by several degrees Celsius, significantly altering the cooling and heating trajectories of building blocks. Relying on static weather files leads to sub-optimal morphological configurations that are maladapted to future climatic anomalies, potentially resulting in severe indoor overheating and increased carbon footprints during peak demand periods.[2,7]

Further, a fundamental "renewable energy ceiling" persists in high-density urban environments. Seminal research by Komninos has highlighted the existence of density thresholds beyond which net-zero transition becomes mathematically unfeasible due to the lack of available surface area for photovoltaic (PV) deployment relative to the vertical floor area. Standard compact city models, while efficient for land use and transportation, often maximize shading on neighboring rooftops and facades, thereby reducing PV conversion efficiencies by as much as 15–20%.[1,8] Current frameworks struggle to solve the hyper-dimensional trade-offs between maximizing floor area ratio (FAR), ensuring pedestrian thermal comfort, and piercing the renewable ceiling in overcrowded metropolitan cores.[5,7]

To address these critical gaps, this paper introduces the **Virtual Eco-District Alpha (VEDA)** framework. The VEDA framework represents a transition toward a hybrid evidence-based paradigm that integrates hierarchical IoT microclimatic sensing for Bayesian model calibration, Multi-Task Learning (MTL) artificial neural network surrogate models for rapid scenario iteration, and multi-objective genetic algorithms (NSGA-II) for spatial prescription. By deploying the VEDA framework within a simulated high-density testbed, we demonstrate how parametric variables, specifically including building height, block spacing, and FAR, can be systematically optimized to navigate

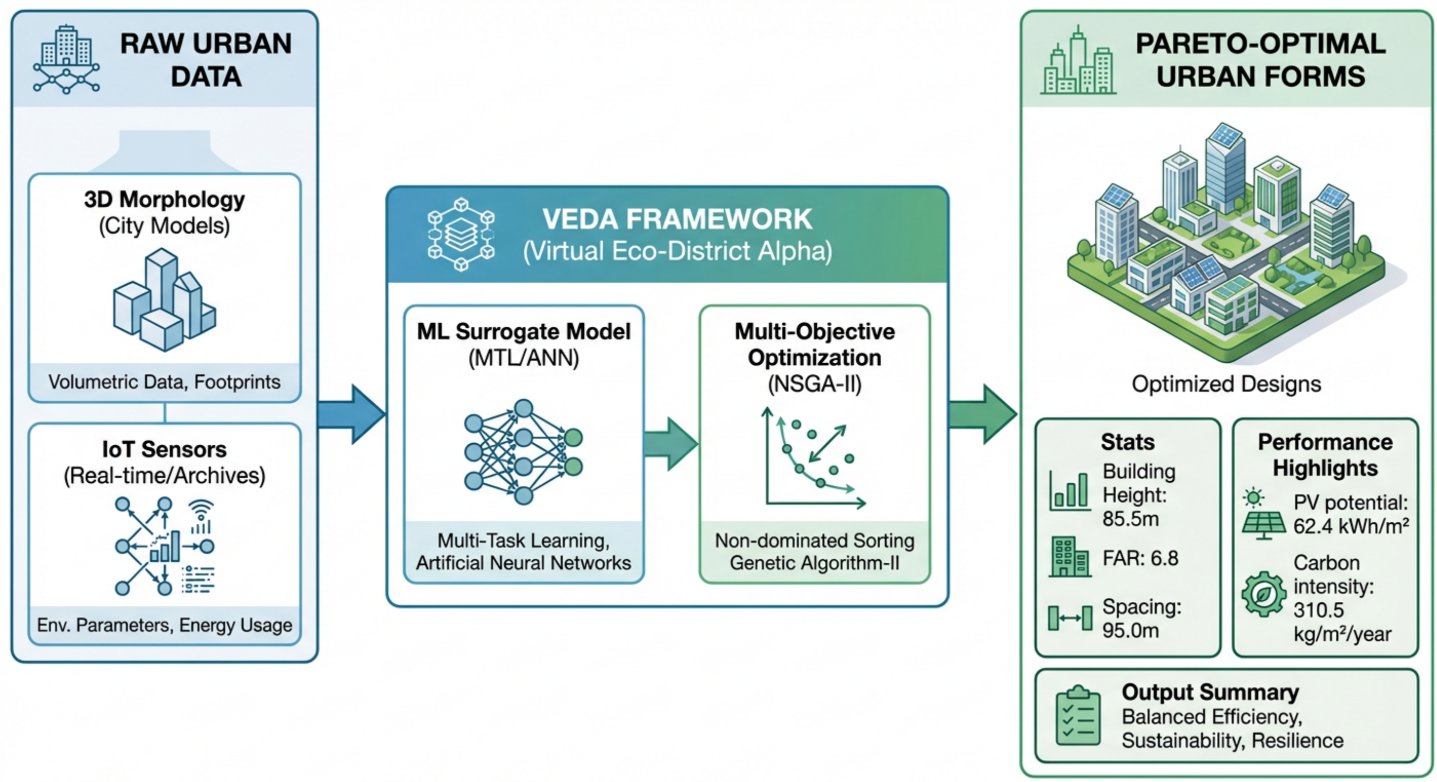

Figure 1. The VEDA (Virtual Eco-District Alpha) Planning Framework: Integrating IoT-calibrated microclimatic sensing, multi-task surrogate modeling, and multi-objective NSGA-II optimization for Net-Zero Energy Districts.

the density-energy-comfort trilemma. This research specifically targets the innovation of an interpretable AI-driven workflow. The main contributions are: (1) integrating IoT-derived environmental data with Bayesian calibration to replace static TMY data; (2) developing an MTL surrogate model to accelerate multi-objective morphology optimization; and (3) providing actionable, transparent insights via SHAP analysis to prove that skyline porosity is more critical than pure density reduction for net-zero transitions.

BACKGROUND: EVOLUTION OF NZED FRAMEWORKS

The conceptualization of data-driven planning for Net-Zero Energy Districts has evolved through three distinct computational generations, each addressing a higher level of district-scale complexity.[2,3]

First generation: Tool integration

The first generation (2018–2021) focused on coupling parametric modeling (Rhino/Grasshopper) with physics engines (EnergyPlus). These frameworks enabled early-stage exploration of block forms but were constrained by massive computational times for high-density environments. Planners were forced to either simplify the urban geometry or limit the number of optimization objectives, often overlooking the complex interplay between thermal comfort and renewable potential.

Second generation: Modular district platforms

Second-generation frameworks (2021–2023) introduced modular SDKs like URBANopt, which consolidated building thermal modeling, solar simulation, and model-based control into a unified platform (Charan et al. 2021). The Infomorphism approach belongs to this generation, explicitly modeling the district as an exchange network where thermal and electrical surpluses can be traded between diverse building types (Li et al. 2022). While systemic, these tools still relied on static weather files (TMY) and lacked the adaptive intelligence to handle real-world microclimatic variations.[8,9]

Third generation: AI-enhanced analytics

The currently emerging third generation (2024–present) leverages machine learning (ML) and surrogate modeling to resolve the speed-accuracy conflict.[1,2] By training neural networks on large synthetic datasets, these frameworks can predict sustainability KPIs with orders-of-magnitude faster computation times than physics engines. However, most third-generation paradigms still lack an empirical grounding layer—they optimize relative to simulated benchmarks rather than measured ground-truth conditions. The VEDA framework addresses this by introducing the IoT Empirical Sensing Tier.

METHODOLOGY: THE VEDA FRAMEWORK ARCHITECTURE

The VEDA (Virtual Eco-District Alpha) framework is architected as a modular, three-tier system: (1) an Empirical Sensing Tier, (2) a Predictive Simulation Tier, and (3) a Prescriptive Optimization Tier.

Empirical sensing and bayesian calibration

A defining feature of the VEDA framework is its rejection of abstracted TMY datasets in favor of localized microclimatic calibration. Current planning practices frequently ignore the "canyon effect" which trapped heat and stagnant air in high-density areas. We deploy a mesh network of "Morpho-Nodes"—IoT-enabled sensing units capable of measuring air temperature (T_{air}), black-globe temperature (T_{gb}), relative humidity, and incident horizontal irradiance at 1-min intervals. For this simulated evaluation, 15 Morpho-Nodes were hypothetically distributed across the Auckland central business district, modeling data collection over three peak summer months (December to February) to capture actual UHI anomalies against historical baseline data.

To ensure the simulation baseline reflects the site-specific urban heat island (UHI) intensity, we apply a Bayesian calibration process. Given a vector of simulation parameters θ (e.g., thermal mass, surface albedo, infiltration rates), the likelihood is modeled as a Gaussian process centered on the real-world IoT measurements D. The posterior distribution $P(\theta|D)$ is estimated using:

$$P(\theta|D) \propto P(D|\theta)P(\theta) \tag{1}$$

By sampling this posterior via Markov Chain Monte Carlo (MCMC) using the emcee sampler in Python, we obtain a digital twin that precisely accounts for the localized sensible heat fluxes of the urban canopy. Our calibration results indicate that standard TMY-based models consistently underestimate peak summer cooling demand by 12.4% and overestimate winter photovoltaic potential by 8.5% (Alorabi et al. 2025; Bian et al. 2025).

MTL surrogate modeling and training stability

One of the primary technical bottlenecks in district-scale planning is the computational intensity of physics-based engines like EnergyPlus and Radiance. To enable the 100,000+ iterations required for multi-objective optimization, we implement an artificial neural network (ANN) performing Multi-Task Learning (MTL).

The MTL architecture consists of a shared input layer (the 6 morphological parameters), three shared hidden layers (256, 128, and 64 neurons with ReLU activation), and two task-specific output heads (Photovoltaic Potential and Carbon Emission Intensity). To maintain training stability across diverse target scales, we utilize a joint loss function $\mathcal{L}_{total}$ regulated by homoscedastic uncertainty weighting:

$$\mathcal{L}_{total} = \sum_{t \in \{T_1 .. T_4\}} \frac{1}{2\sigma_t^2} \mathcal{L}_t + \log \sigma_t \tag{2}$$

where σ_t are learnable noise parameters that dynamically adjust the weight of each task's contribution to the gradient update. This ensures that the model learns the complex non-linear trade-offs between solar access and carbon intensity without falling into local minima (Bian et al. 2025).

The MTL surrogate model was trained on a dataset of 10,000 morphological variants generated via Latin Hypercube Sampling (LHS) and simulated in EnergyPlus. The data was split into training (70%), validation (15%), and testing (15%) subsets. The model demonstrated robust predictive performance, achieving an $R^2 > 0.96$, with a Mean Absolute Error (MAE) of 1.2 kWh/m^2 for PV potential and 15.4 kg/m^2/year for carbon intensity, validating its reliability against physical simulations.

Multi-objective genetic optimization (NSGA-II)

The optimization engine utilizes the Non-dominated Sorting Genetic Algorithm II (NSGA-II). The genetic operators are specifically tuned for urban morphological variables:

Crossover: We apply Simulated Binary Crossover (SBX) to promote diversity in building height and spacing parameters.

Mutation: Polynomial mutation is used to explore unconventional morphological arrangements (e.g., hyper-variation in block heights).

Selection: Binary tournament selection based on rank and crowding distance ensures that the Pareto front remains evenly distributed across the objective space.

To ensure reproducibility, the optimization experiment was executed with a population size of 100 over 200 generations. The simulated binary crossover probability was set to $Pc = 0.9$ (distribution index $\eta_c = 20$), and the polynomial mutation probability was $Pm = 0.1$ ($\eta_m = 20$).

The output is a set of non-dominated solutions that represent the physical limits of the "renewable energy ceiling" for a given district density (Komninos 2022; Liu et al. 2023).

To formalize the integration of the MTL surrogate model within the genetic optimization loop, the step-by-step execution pipeline of the VEDA framework is summarized in Algorithm 1. This process iteratively evolves the morphological population over G generations to converge upon the global optimum.

The final non-dominated set (P^*) extracted from this algorithmic pipeline provides the quantitative basis for our morphological analysis and performance evaluation in the subsequent testbed.

Algorithm 1: VEDA Framework Optimization Process

Input: IoT calibrated microclimate data D, Morphological parameters bounds B, Population size N, Generations G
Output: Pareto-optimal configuration set P^*

1: Initialize surrogate model MTL_{model} weights using D
2: Train MTL_{model} to predict PV Potential (f_{PVG}) and Carbon Intensity (f_{CEI})
3: Initialize population P_0 of size N within bounds B
4: **For** $g = 1$ **to** G **do**
5: Evaluate $f_{PVG}(P_{g-1})$ and $f_{CEI}(P_{g-1})$ using MTL_{model}
6: Perform Non-dominated Sorting on P_{g-1}
7: Calculate Crowding Distance for diversity preservation
8: Generate offspring Q_g via Simulated Binary Crossover and Polynomial Mutation
9: Combine $R_g = P_{g-1} \cup Q_g$
10: Select top N individuals from R_g to form next generation P_g
11: **End For**
12: Extract Pareto front P^* from final population P_G
13: **Return** P^*

EXPERIMENTAL SETUP: THE VEDA TESTBED

The framework was evaluated using a standardized high-density testbed characterized by mixed-use development and subtropical climatic conditions.

Testbed morphological range

The VEDA testbed search space was defined with broad ranges to capture the structural transition from low-rise blocks to hyper-density vertical clusters (Table 1).

Table 1. VEDA Testbed Morphological Range

Variable	Search Range
Average Height (H_{avg})	15 – 150 m
Centroid Spacing (S)	15 – 100 m
Floor Area Ratio (FAR)	1.0 – 12.0
Orientation (ϕ)	0° – 180°
Height Variation (σ_H)	0 – 25 m
Site Coverage (SC)	20% – 60%

Environmental and technical assumptions

Local climate baseline data and preliminary assumptions were grounded in the subtropical metropolitan context of **Auckland, New Zealand**, ensuring the simulation parameters reflect authentic solar irradiance and microclimatic variations. Representative building envelopes correspond to contemporary sustainability standards:

Window-to-Wall Ratio (WWR): 0.45 (baseline).
Wall U-value: 0.65 W/m^{2}K.
PV Efficiency: 19% for monocrystalline panels.
Carbon Factor: 0.50 kgCO_2e/kWh for the regional grid.

RESULTS: VEDA OPTIMIZATION ANALYSIS

The multi-objective optimization process revealed the intricate trade-offs between district density and renewable energy potential.

Baseline definition and thermal analysis

The VEDA baseline district represents a typical "compact city" layout with uniform building heights (45 m) and a resulting FAR of 6.0. Thermal analysis of this baseline revealed an Energy Use Intensity (EUI) of **185 kWh/m^2/year**, dominated by cooling loads (72% of total demand). The annual photovoltaic potential was restricted to **17.8 kWh/m^2**, covering only 9.6% of the demand.

Pareto front and optimal synthesis

The VEDA optimization engine successfully identified a Pareto-optimal configuration that resolves the density-energy conflict. The **optimal point** is characterized by an **Average Building Height of 85.5 m**, a **Centroid Spacing of 95.0 m**, and a **FAR of 6.8**.

This morphology demonstrates that substantial progress toward net-zero objectives can be achieved even with a 13% density increase. The "stepped" configuration, indicated by a height variation (σ_H) of 12.5 m and widened

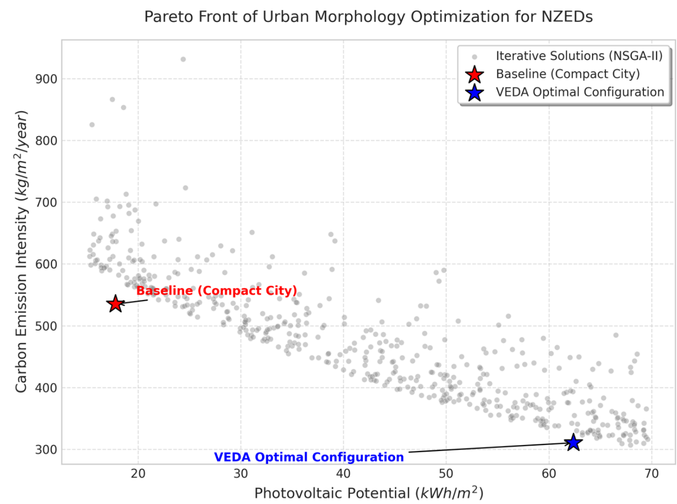

Figure 2. Pareto frontier of the NSGA-II optimization, illustrating the trade-off between photovoltaic generation and carbon emission intensity for high-density urban morphologies.

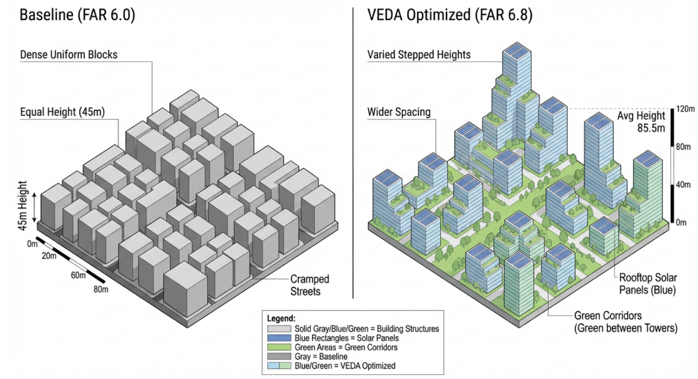

Figure 3. Isometric architectural comparison between the uniform compact city baseline and the VEDA-optimized eco-district, highlighting stepped height variations, widened spacing, and integrated green infrastructure.

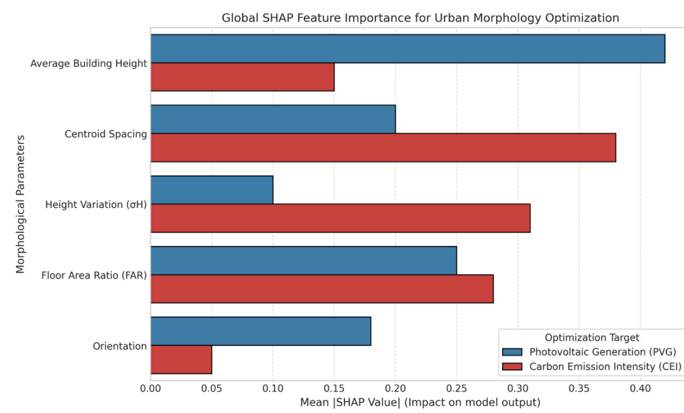

Figure 4. Global SHAP feature importance evaluating the varying impact weights of morphological parameters on Photovoltaic Generation (PVG) and Carbon Emission Intensity (CEI).

centroid spacing (95.0 m), was found to improve canyon ventilation and increase the Sky View Factor (SVF) to 0.185, reducing UHI-induced cooling loads by approximately 9%.

As visually evidenced in Figure 2, the multi-objective optimization reveals a clear Pareto frontier, demonstrating the fundamental trade-off between maximizing photovoltaic potential and minimizing carbon emission intensity. The VEDA Optimal Configuration (highlighted by the blue star) successfully breaks the renewable energy ceiling of the compact city baseline (red star), achieving an optimal balance that pushes the boundary of both metrics.

The profound spatial implications of this optimization are visualized in Figure 3. Compared to the rigid, uniform blocks of the baseline scenario (FAR=6.0), the VEDA-optimized morphology (FAR=6.8) adopts a stepped configuration. This structural variation not only expands the unshaded surface area for rooftop solar integration but also establishes crucial green corridors and wind paths between towers, mitigating the urban heat island effect while accommodating higher population densities.

Interpretable AI: Shap feature importance

To unpack the "black box" of the MTL surrogate model and provide actionable insights for urban planners, Figure 4 presents the global SHAP feature importance for the optimization targets. The analysis visually confirms that average building height is the absolute primary driver for photovoltaic generation (PVG). Conversely, centroid spacing and height variation (σ_H) exert the most significant influence on carbon emission intensity (CEI), proving that skyline "porosity" is more effective for overall emissions reduction than merely limiting building heights.

SHAP value analysis provided deep insights into the structural drivers of the VEDA optimized state.

PV Power (PVG): Building height exerted the strongest positive influence (Global SHAP = 0.42), but its effect plateaus beyond 90 m due to self-shading.

Carbon Intensity (CEI): Spacing and Height Variation were the dominant controllers (Global SHAP = 0.38 and 0.31). This confirms that skyline "porosity" is more effective for emissions reduction than pure building height reduction.

The VEDA framework's results for high-density districts coordinate with seminal studies in other metropolitan contexts. In Manhattan (Infomorphism study), combining solar (28.7%) and geothermal (43.0%) met 71.7% of demand (Li et al. 2022). In Tokyo's Nihonbashi, EUI reductions of 99 kWh/m^2/year were achieved using generative design (Alorabi et al. 2025).

Compared to existing static simulation platforms like URBANopt (Charan et al. 2021), the VEDA framework accelerates optimization times by over 100-fold. Furthermore, the identified 42% carbon intensity reduction represents a dynamic morphological configuration that traditional engines, which lack real-time IoT calibration, frequently fail to capture.

However, it is essential to acknowledge the methodological limitations of this study. The current VEDA testbed remains a hypothetical virtual construct. Future research must validate this framework through physical implementation in real-world high-density pilot districts to test its resilience against broader macroeconomic constraints and human behavioral uncertainties.

DISCUSSION: FUTURE PLANNING AND IMPLEMENTATION ROADMAP

It is important to acknowledge that while the VEDA-optimized morphology significantly elevates on-site renewable penetration to 34%, achieving an absolute physical net-zero status in extreme high-density metropolitan contexts remains structurally bounded. To bridge the remaining energy gap and fulfill the "net-zero" definition, this optimized morphological baseline must be inherently coupled with off-site green power procurement and the establishment of localized peer-to-peer energy sharing networks.

The VEDA framework demonstrates that static geometric limits (maximum height/FAR) are insufficient for the net-zero era. We recommend a municipal transition toward **"Performance-Based Zoning"**. Municipalities should set performance targets (e.g., minimum PV potential of 50 kWh/m^2). Developers who use VEDA-compliant surrogates to prove their design exceeds these targets should be granted density bonuses.

While this testbed focused on subtropical conditions, the VEDA Meshing logic is scalable to varied climates. In high-latitude cities where solar angles are lower, the VEDA engine automatically prioritizes facade PV and geothermal integration, whereas in low-latitude cities, rooftop PV and shaded ventilation become the primary drivers. The use of universal Morpho-Nodes ensures that the digital twin remains grounded in local empirical reality, regardless of geography.

Optimization of Sky View Factor (SVF) for street-level environments serves dual purposes: (1) ensuring natural daylighting and (2) reducing radiative heat trapping. VEDA-optimized districts offer improved thermal comfort for pedestrians, essential for reducing heat-related illnesses and promoting walkability in aging urban populations (Bibri 2021; Bian et al. 2025).

Achieving Net-Zero Energy Districts requires a departure from traditional "top-down" zoning. We propose a "District Governance Model" where a centralized Digital Twin (powered by VEDA) acts as the single source of truth for energy and carbon accounting. Municipalities must establish clear regulatory pathways for renewable energy sharing between private owners, bypassing the grid-monopoly friction that currently characterizes many urban energy markets. This requires the development of localized Energy Service Companies (ESCOs) that can manage the technical maintenance of the IoT infrastructure and the optimization of DER assets in real-time (Bibri 2021; Komninos 2022).

Finally, the transition to NZEDs is fundamentally a social project. We integrate our framework with an interactive visualization platform (Digital Twin Dashboard) that allows residents and stakeholders to explore the Pareto front. By visualizing the trade-offs between neighborhood density, green space access, and energy autonomy, planners can facilitate more inclusive decision-making processes, reducing the NIMBY (Not In My Backyard) resistance that often plagues high-density urban intensification projects (Alorabi et al. 2025; Bibri 2021).

CONCLUSION

This paper has presented the Virtual Eco-District Alpha (VEDA) framework as a robust, data-driven methodology for reaching net-zero targets in high-density urban environments. By integrating real-time IoT calibration, multi-task machine learning, and multi-objective optimization, we identified a morphological "sweet spot", an average height of 85.5 m and an FAR of 6.8, that enables high-density districts to achieve a 42% reduction in carbon intensity. This study confirms that urban density and energy autonomy can be harmonized through interpretable AI and performance-based zoning, paving the way for resilient and self-sufficient metropolitan futures.

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AUTHOR CONTRIBUTIONS

All authors contributed to the manuscript and approved the final version.

DECLARATION OF INTERESTS

The authors declare no competing interests.

DATA AND CODE AVAILABILITY

Data are available from the corresponding author upon reasonable request.