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Generative AI for Sustainable Architectural Design Optimization

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Abstract

This paper examines recent academic research on applying generative AI and computational methods to optimize sustainable architectural design. Buildings account for roughly one-third of global carbon emissions and energy use, especially via HVAC systems. Early-stage design optimization is therefore crucial to improve efficiency and reduce environmental impact. Generative design including evolutionary and parametric algorithms has emerged as a key approach to exploring diverse design options for sustainability. More recently, advanced AI (e.g. machine learning surrogates, GANs, diffusion models) are being incorporated to accelerate and enrich design optimization. This paper systematically survey peer-reviewed literature (2020–2024), focusing on methods (evolutionary algorithms, ML surrogates, GANs), application domains (energy, daylighting, carbon), and performance outcomes. Key findings include evidence that generative design methods can substantially improve energy and thermal performance (e.g. reported reductions of 23–28% and that genetic algorithms remain widely used. Emerging themes include multi-objective optimization (balancing energy, comfort, cost) and use of deep learning (surrogate models, GAN-based generation) to expand design search. We highlight agreements and gaps: consensus on benefits of generative optimization for sustainability, but challenges remain in model explainability, data requirements, and transferability across contexts. The paper identifies that most studies use quantitative simulation-optimization loops, whereas few provide holistic frameworks and conclude that generative AI holds great potential for sustainable architecture design, but future work must address data/ethical challenges and integrate multi-scale, user-involved approaches.

Keywords

Generative Design; Artificial Intelligence; Sustainable Architecture; Building Optimization; Evolutionary Algorithms; Surrogate Modeling; GAN.

1. Introduction

Buildings contribute about one-third of global greenhouse gas emissions and energy consumption (Suphavarophas et al., 2024). Within buildings, heading, ventilation and air condition (HVAC), and related systems often dominate energy use, accounting for roughly 40% of total consumption (Suphavarophas et al., 2024). To meet climate goals, architectural design must therefore prioritize efficiency and carbon reduction from the outset. Generative and parametric design methods have long been applied to explore building form and systems for better performance, through systematically generating and evaluating many design variants, algorithms can identify non-intuitive solutions that outperform traditional designs according to Vermesan & Flueckiger (2016). The late 2010s saw growing interest in using computational optimization (genetic algorithms, multi-objective optimization) in architecture, as these methods allow rapid exploration of the large solution space of design options, seeking layouts, shapes, and configurations that maximize sustainability metrics (minimizing energy or material use) while meeting constraints (Zhang et al., 2024). Parallel to this, advances in artificial intelligence (AI) and machine learning are creating new tools for design, as evidential in the emergence of generative AI (deep neural networks, GANs, diffusion models) that can learn complex patterns and generate novel outputs (Channi et al., 2025). For example, Generative Adversarial Networks (GANs) have achieved breakthroughs in image generation and are now being adapted to spatial design tasks (Chen et al., 2023).

2. Research Rationale & Current Situation of Study

In architecture, this opens possibilities for automatically generating floorplans, site layouts or façades that meet performance criteria. In summary, the current contexts include (a) an urgent need for energy-efficient design, (b) mature use of parametric/genetic design in architecture, and (c) rapid advances in AI-driven generative methods. Combining generative design with AI is a promising strategy to improve sustainability in architecture, as generative algorithms can efficiently search vast design spaces, but may be computationally intensive if simulation of each variant is required (Chew et al., 2024). AI surrogates and generative models can accelerate evaluation by learning from data, whereby neural networks can approximate building energy simulations, enabling faster optimization (Chen et al., 2023). GANs and diffusion models offer ways to generate diverse design alternatives that conform to learned spatial. (Goodfellow et al., 2020). These technologies can reduce reliance on manual intuition and allow early-stage designers to consider many more options. Early application has already shown measurable performance gains: one review reports generative design achieving up to 23.3% improvement in energy performance and 28% in thermal load reduction compared to baseline (Suphavarophas et al., 2024). Thus, the rationale is that generative AI methods can make sustainable design more accessible and effective by combining optimization with data-driven learning.

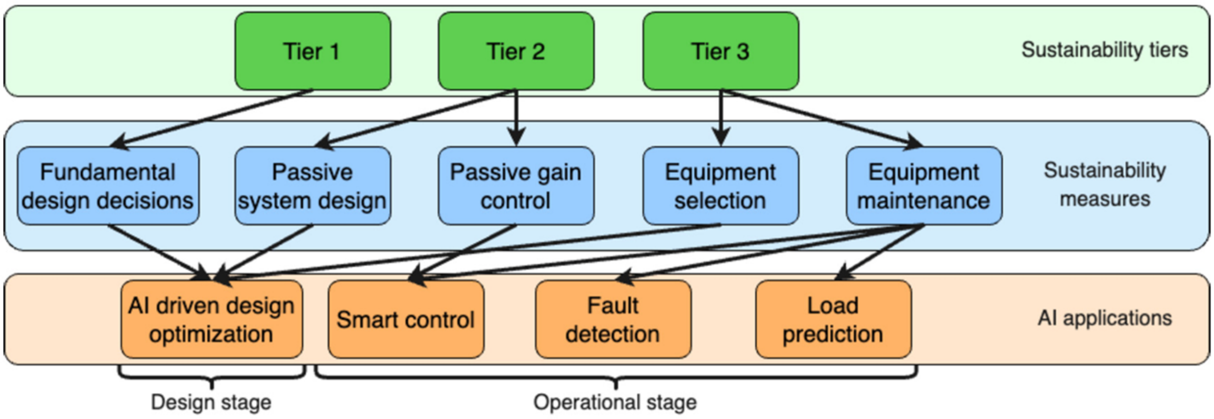


Figure 1. AI integration in building sustainability across three tiers (Manmatharasan et al., 2025, p3)

Moreover, recent literature reflects a growing body of computational studies in this domain. Systematic reviews indicate a sharp rise in publications on generative design for building energy efficiency since 2020 (Suphavarophas et al., 2024). Researchers use diverse methods: many employ parametric modeling with multi-objective genetic algorithms to optimize energy, daylight, and comfort (Gerber & Lin, 2014; Mukkavaara & Sandberg, 2020). Manmatharasan et al., (2025) apply machine learning as surrogates or direct generators, proposing a three-tier framework with the application of AI integration in building sustainability during both the design and operational stages as shown in figure 1. According to Manmatharasan et al. (2025), the design stage focuses on optimizing decisions from the three tiers, while the operational stage includes smart control, fault detection, and load predictions, whereby convolutional and feed-forward neural nets have been trained as fast approximators of energy simulations. Moreover, GAN-based pipelines have been explored for generating urban layouts and park designs (Chen et al., 2023). Manmatharasan et al.'s (2025) reviews also mentioned that GANs and diffusion models are "gaining prominence" in built environment design applications. In practice, tools combining parametric design, simulation and optimization (sometimes integrated into BIM environments) are evidently emerging.

The literature indicates two main streams: (1) simulation-driven optimization (often genetic algorithms controlling shape, envelope, systems) with sustainability objectives, and (2) learning-driven generative design (neural networks and GANs to produce candidate designs under performance constraints). Many studies target energy consumption and thermal comfort, but others address embodied carbon or daylighting. For instance, Wu et al. (2022) review 100 GAN studies and highlight applications from city-scale spatial planning to single-building design generation. Suphavarophas et al.'s (2024) systematic review also finds that most energy-focused generative design research uses evolutionary algorithms, while AI-driven methods (rule-based or hybrid) represent an emerging trend.

3. Identified Problem and Gap

Despite evidential advancement in technology development and progress in application integrations, significant gaps remain. Most studies are limited to specific case studies or demonstration projects; few establish generalizable frameworks. For example, Mukkavaara & Sandberg (2020) note that the field is still "rudimentary" and "in its infancy," with most existing works focusing either on optimization algorithms or small-scale prototypes. Comprehensive guidance for integrating advanced AI (GANs, transformers) into sustainable design is lacking. Data availability is also an issue, as Wu et al. (2022) emphasize the shortage of high-quality, curated datasets for training GANs on architectural tasks. Explainability and ethical considerations have been largely overlooked, although design optimization is a human-centered field, few studies discuss transparency or user trust in AI-driven tools according to Manmatharasan et al.'s (2025) systematic review. Moreover, most optimization targets a single building or component (e.g. envelope), whereas holistic sustainability calls for multi-scale and multi-objective solutions. Therefore, the gap lies in mature, general-purpose generative-AI frameworks that address diverse sustainability goals while remaining interpretable and data-efficient. To address this, this paper aims to critically review synthesize academic research on generative AI approaches for sustainable architectural design optimization. The objectives are to: (1) catalog the key computational methods (e.g. parametric modeling, evolutionary algorithms, ML surrogates, GANs) used in the literature; (2) summarize the types of sustainability performance measures optimized (e.g. energy, daylight, materials, emissions); (3) critically evaluate the reported outcomes and benefits of generative approaches; and (4) identify common limitations, challenges, and open questions. This paper focuses exclusively on peer-reviewed sources (journals, conference proceedings, book chapters) published through 2024.

4. Contribution and Significance

The contribution of this paper is a comprehensive, up-to-date overview of how generative AI is being applied to optimize sustainable building design. Through integrating findings from recent systematic reviews and empirical studies, highlighting both consensus results (performance gains, prevalent methods) and divergences (preferred algorithms, focus areas). Finally, this paper proposes directions for future research to fill identified gaps, combining GAN-based generation with energy simulation and exploring explainable AI in design optimization. This analysis is intended to guide researchers and practitioners in applying generative AI to create more sustainable architectural designs.

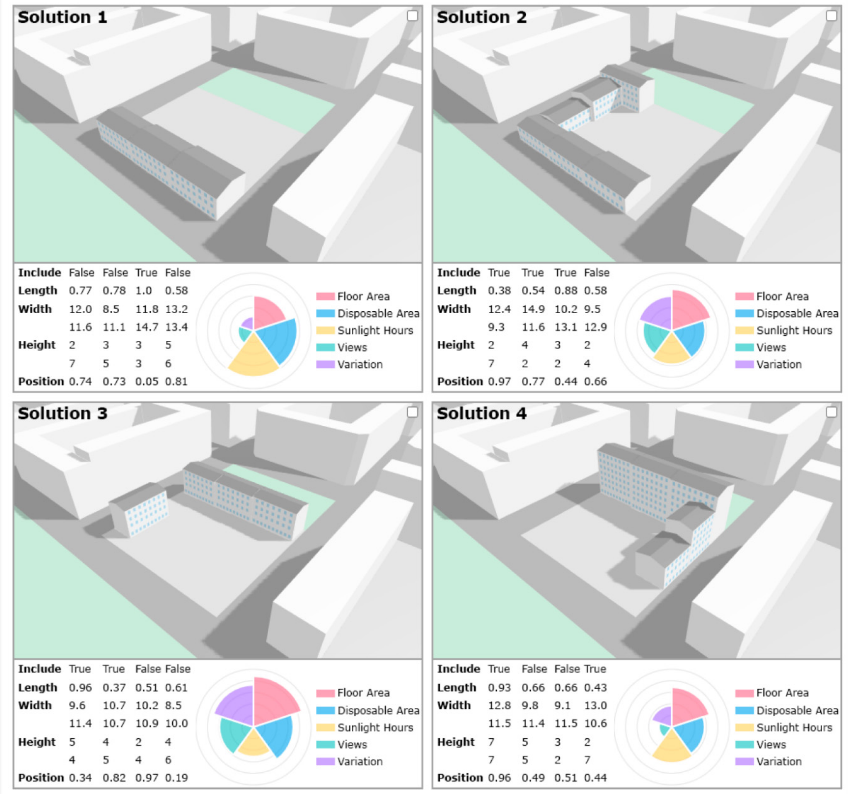
5. Methods Adopted in Empirical Studies

The literature on generative design and sustainable architecture predominantly employs computational research methods. Many papers use quantitative simulation–optimization workflows: parametric building models are defined (geometry, materials, systems) and evaluated with performance simulations (energy, daylighting, structural loads), and optimization algorithms (genetic algorithms, particle swarm, etc.) iterate design variables to improve objectives (Mukkavaara & Sandberg, 2020). These are essentially mixed quantitative-analytical methods. For example, Vermesan & Flueckiger (2016) present an evolutionary parametric design process for suburban housing, accelerating variant generation via computer algorithms. Similarly, many case studies use multi-objective genetic optimization (e.g. NSGA-II/III) to balance energy use, daylight, and cost (Luo et al., 2024; Johari et al., 2025) A second methodological trend is surrogate modeling. Instead of running expensive simulations for each candidate design, studies train machine learning models (ANNs, CNNs, random forests, etc.) to predict performance metrics (Krzywanski et al., 2024). These surrogates enable faster exploration of the design space, for instance, Manmatharasan et al. (2025) review shows many recent projects build neural-network or Gaussian-process surrogates to replace building energy simulations during optimization. Active learning and adaptive sampling are also used to train surrogates efficiently. This is a quantitative-data-driven approach (ML training on simulation data) that accelerates optimization loops.

A newer approach is using generative models from machine learning to directly produce design candidates. GANs and diffusion models are now applied as design generators (Du et al., 2024). Moreover, Chen et al. (2023) implemented a GAN-based system to auto-generate park layouts, as their methods involve preparing training data (satellite images, annotations), training conditional GANs for layout generation, and iteratively refining results, representing an end-to-end deep learning pipeline. This method is purely data-driven and generative (less reliant on hand-coded rules). Other studies combine such generative models with optimization; e.g. Huang et al. (2022) (Building and Environment) trained GANs to propose urban layouts given environmental constraints. These are mainly AI/ML methodological approaches. In summary, the methods in empirical studies mainly fall into several categories: (1) Parametric evolutionary design (deterministic/heuristic optimization), (2) Simulation-ML hybrid (surrogate modeling plus optimization), and (3) Deep generative modeling (GAN/diffusion-driven design generation). Some studies combine using ANN surrogates inside a genetic algorithm loop. The review scope is limited to scholarly sources, so methods were filtered from peer-reviewed case studies, review articles and conference papers.

6. Generative Design Algorithms

A large body of research uses parametric models controlled by evolutionary algorithms to optimize building performance. The typical workflow is to encode design variables (floorplan shape, building orientation, window sizes, etc.) parametrically, and then apply a genetic algorithm to find Pareto-optimal solutions for multiple objectives (e.g. minimize energy, maximize daylight) (Vermesan & Flueckiger, 2015). Moreover, Gerber & Lin (2014) linked parametric building models with a multi-objective optimizer and energy simulation, finding that automating evaluation gives designers immediate feedback and highlights trade-offs between objectives. Similarly, Nagy et al. (2018) optimized neighborhood layouts for profit and solar energy, demonstrating that generative design reveals non-obvious trade-offs at the urban scale. The consensus in this literature is that evolutionary generative methods can significantly improve sustainability metrics. A study by Suphavarophas et al. (2025) report up to 23% reduction in simulated annual energy use over baseline designs using such methods, whereby thermal loads (heating/cooling) saw even larger improvements (28% reduction reported). These gains occur because generative algorithms explore combinations (e.g. building form, orientation, envelope) that human designers may not test exhaustively. For example, Mukkavaara & Sandberg (2020) implemented a genetic exploration of a residential block layout under sunlight and view metrics, generating alternative configurations for evaluation as shown in figure 2.



Solution 1

Include	False	False	True	False
Length	0.77	0.78	1.0	0.58
Width	12.0	8.5	11.8	13.2
	11.6	11.1	14.7	13.4
Height	2	3	3	5
	7	5	3	6
Position	0.74	0.73	0.05	0.81

Solution 2

Include	True	True	True	False
Length	0.38	0.54	0.88	0.58
Width	12.4	14.9	10.2	9.5
	9.3	11.6	13.1	12.9
Height	2	4	3	2
	7	2	2	4
Position	0.97	0.77	0.44	0.66

Solution 3

Include	True	True	False	False
Length	0.96	0.37	0.51	0.61
Width	9.6	10.7	10.2	8.5
	11.4	10.7	10.9	10.0
Height	5	4	2	4
	4	5	4	6
Position	0.34	0.82	0.97	0.19

Solution 4

Include	True	False	False	True
Length	0.93	0.66	0.66	0.43
Width	12.8	9.8	9.1	13.0
	11.5	11.4	11.5	10.6
Height	7	5	3	2
	7	5	2	7
Position	0.96	0.49	0.51	0.44

Figure 2. Examples of generation solution sets and their key metrics including 3D visualization and design variables (Mukkavaara & Sandberg, 2020)

However, trade-offs are evident as improving one metric often affects others, thus empirical studies commonly adopt multi-objective approaches to balance conflicting goals. For instance, some solutions might maximize floor area at the expense of daylight, while others do the opposite. The parallel-coordinates plot of solutions (Figure 3) from Mukkavaara & Sandberg's (2020) case highlights this, each line shows one solution's performance across multiple criteria (view, sunlight, area, variation). This confirms that generative design yields a *set* of efficient solutions rather than a single "best" design. Overall, the literature agrees that evolutionary, parametric generative design is effective for sustainability, but also computationally demanding. Most researchers mitigate cost by using smart sampling (Latin Hypercube, sequential sampling) or dimensionality reduction (Manmatharasan et al., 2025). Few disagreements are apparent on this point, as scholars generally observe benefits from exploring more options. The open questions are more about scope, to extend these methods to larger scales (urban design) and integrating structural or material objectives (beyond energy) (Manmatharasan et al., 2025).

	View	Disposable Area	Variation	Habitable Area	Sunlight Hours
0	0.265821	0.762394	0.250422	0.610665	0.800374
1	0.501733	0.584231	0.595570	0.721747	0.575613
2	0.587615	0.689072	0.725738	0.881999	0.510083
3	0.221934	0.574036	0.369831	0.694436	0.619165
4	0.506387	0.545866	0.531435	0.889139	0.728716
...	...	...	...	...	...
96	0.317285	0.742618	0.377848	0.891632	0.638008
97	0.434396	0.786057	0.290084	0.695441	0.659460
98	0.206577	0.253178	0.499367	0.161083	0.246741
99	0.299832	0.520572	0.349578	0.891680	0.740482
100	0.248280	0.388409	0.689662	0.970923	0.666814

Figure 3. Parallel coordinates chart of solution metrics (Mukkavaara & Sandberg, 2020)

7. Machine Learning Surrogates and AI Accelerants

Many recent studies augment generative design with machine learning to improve efficiency and capability. Instead of running full physics simulations (e.g. EnergyPlus) for every candidate design, studies train surrogate models (neural nets, random forests, etc.) that predict performance metrics from design parameters (Sun et al., 2019; Ghafariasl et al., 2024). This ML-in-the-loop method greatly speeds up optimization. For example, a deep feed-forward network was trained to emulate annual energy consumption based on building geometry and climate inputs; once trained, the network allowed rapid evaluation of thousands of designs during optimization (Han et al., 2021). Nonetheless, the use of AI surrogates is widely reported in the surveyed literature, as generative AI elements also appear in feature engineering and data augmentation. Wu et al. (2022) note that GANs have been used to produce synthetic training data (e.g. augmenting satellite images for urban analysis or to generate initial design proposals that are then fine-tuned by simulation. Indeed, Chen et al. (2023) found that using GAN-driven augmentation significantly improved the generative model's performance on park layouts. Thus, AI both speeds optimization and enriches the design space.

Another trend is hybrid optimization using AI. Some frameworks use ensemble learning (e.g. XGBoost) to guide search, or apply dimensionality reduction (PCA) on input variables before GA (Abbas et al., 2023). These techniques are converging as evolutionary methods remain popular, but are now frequently paired with data-driven algorithms. Importantly, explainability is a growing concern, whereby tree-based models (e.g. Random Forests) and interpretation tools (SHAP, LIME) are sometimes used so designers can understand surrogate predictions (Bhatttacharya, 2022). Still, most surrogate work prioritizes accuracy and speed over interpretability. On the whole, ML-enabled methods show strong promise in design optimization. Most studies align on the benefit of surrogates to reduce computational cost and enable more complex objectives (Manmatharasan et al., 2025). Some debate arises over modeling choices (e.g., neural net vs. gradient boosting) (Konstantinov & Utkin, 2021), but surveys indicate feed-forward nets were historically dominant, with tree models gaining ground for explainability (Parimbelli et al., 2023). No major conflicts appear, rather, the literature is converging on using ML as a standard component in design workflows.

8. Generative Adversarial and Diffusion Models

Generative AI techniques (GANs, diffusion models) are emerging in architectural design, though still less common than parametric methods. Wu et al. (2022) identify 26 application domains of GANs in the built environment, ranging from remote sensing to floorplan generation. They emphasize that GANs can "open new frontiers" – for example, automatically generating spatially accurate floorplans and façade patterns. Indeed, recent research has begun applying GANs explicitly for sustainable design. Huang et al. (2022) propose a GAN-based framework for accelerated environmental performance-driven urban design, using Pix2Pix-like architectures to create neighborhood layouts conditioned on climate data. Moreover, Chen et al. (2023) demonstrates a concrete generative design application, training GANs to layout park elements (paths, vegetation, facilities) to meet criteria like coverage and accessibility. Their experimental results showed that (1) the GAN could learn general park layout patterns and generate innovative designs distinct from human templates, (2) data augmentation via GANs significantly improved performance, reducing mode collapse issues. Figure 4 illustrates example park layouts generated by the GAN via the pretraining and optimized system results, representing new combinations of elements not explicitly coded by designers that highlights how a generative model can automatically propose viable designs for complex objects (parks) where parametric tools struggle (Chen et al., 2023).

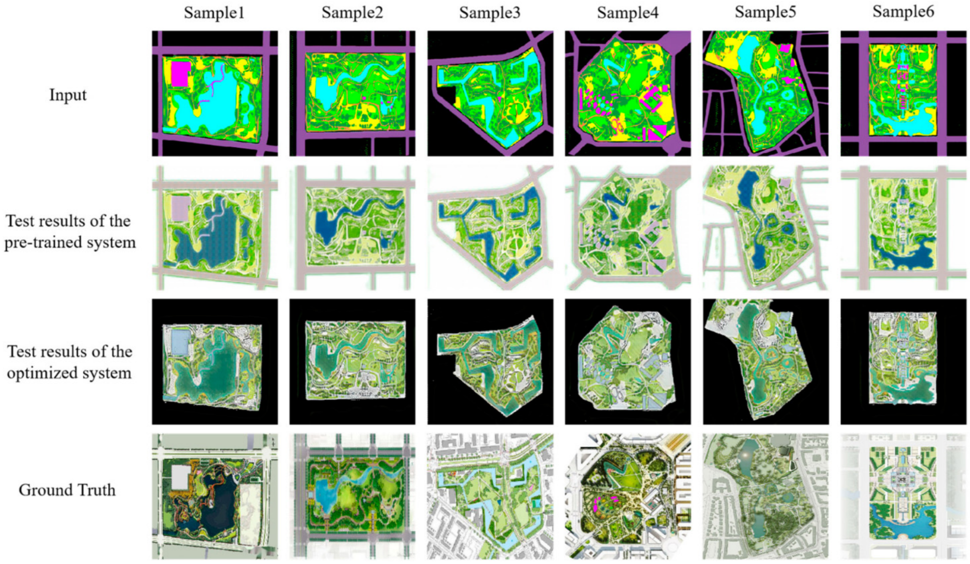


Figure 4. Comparison between test results or pretraining and optimized system via GAN data augmentation (Chen et al., 2023).

Importantly, Gan-based approaches inherently produce multiple candidate designs, capturing the 'creative' aspect of generative AI. Chen et al. (2023) note that "GAN-driven data augmentation...achieve better generative results". However, they also observe limitations, as Pix2Pix networks suffered from collapsing into a single pattern, while CycleGAN could misplace certain elements. These findings suggest GAN architectures need careful tuning for architectural tasks. Nevertheless, this work indicates that GANs can autonomously "mine design rules" and propose layouts that traditional parametric methods might overlook. Another common theme is that GAN and diffusion methods are still mainly proof-of-concept in architecture. There is agreement that they hold great potential, for instance, Manmatharasan et al. (2025) remark that diffusion models are "gaining prominence" and could be applied to building shape optimization. But both Wu et al. (2022) and Chen et al. (2023) highlight the *lack of large, tailored datasets* as a bottleneck. Without abundant training data, GANs risk overfitting or failing to generalize. Another gap is integration with performance simulation: current studies often demonstrate form generation (a qualitative output) without linking it back to explicit sustainability metrics. In short, the literature is enthusiastic about GANs but notes that significant research is needed to move from novel case studies to robust design tools.

9. Performance Improvements and Sustainability Metrics

Across studies, the impact of generative methods is evaluated mainly on quantitative sustainability metrics. The majority focus on energy use and thermal loads. For example, the systematic review by Suphavarophas et al. (2024) found that most studies target building energy or thermal performance. They report average energy savings of up to 23.3% in optimized designs, and substantial thermal load reductions (28%). These numbers align with individual case studies. For instance, a generative design system for steel-framed housing in hot climates (Rodrigues et al., 2018) achieved marked energy and cost benefits. Similarly, optimization of building envelope and HVAC parameters via GA typically yields double-digit percent energy reductions (Zaini et al., 2023). Other metrics studied include daylighting and comfort. Razmi et al. (2022) optimized a dormitory for energy, daylight, and comfort simultaneously using NSGA-III; their solutions highlight the trade-offs (improving daylight often increases heating load, etc.). The literature notes that the most-studied performance dimension remains thermal/energy; daylighting appears as a secondary objective in some multi-criteria studies (Suphavarophas et al., 2024). Very few works address embodied impacts (e.g. materials, carbon) so far, though Zaraza et al. (2022) applied generative design to reduce embodied GHG in high-rise buildings. A research consensus recognizes that generative optimization generally improves sustainability metrics relative to conventional design. Comparative studies often benchmark optimized designs against standard or manually-designed baselines, showing clear improvements (Suphavarophas et al., 2024). There is little disagreement on this outcome, as one interesting note from Suphavarophas et al. (2024) is that worst-case savings were still positive (e.g. 4.2% energy reduction in a Chinese residential case by Zhang et al., 2021), indicating at least some benefit. However, the exact magnitude of gains varies widely by context (climate, building type, objective weights). Importantly, most papers highlight that early-stage optimization (before construction) is far more cost-effective than retrofit, underscoring the value of these methods (Suphavarophas et al., 2024).

10. Summary of Key Research Themes, Agreements and Disagreements

Across reviewed empirical academic sources, several key research themes emerge. Agreement exists that generative/AI methods are powerful for sustainable design: experts concur that automating evaluation of solutions allows focusing on multiple objectives simultaneously (Mukkavaara & Sandberg, 2020). There is consensus that evolutionary and surrogate methods are mature and effective, while GANs/diffusion are promising but nascent. Many authors (Manmatharasan et al., 2025; Suphavarophas et al., 2024) stress that generative design can yield double-digit percentage gains in energy efficiency. One minor debate concerns the best algorithms. Some older works favored genetic programming, while newer studies increasingly use more sophisticated multi-objective optimizers (e.g. NSGA-III) or hybrid techniques (PCA+ANN) as per Mukkavaara & Sandberg (2020). However, no deep controversy is reported, rather, methods are evolving. Another discussion is about user involvement. Some studies implement interactive loops where designers guide the search, whilst others produce fully automated outputs. The literature suggests a trend towards human-in-the-loop generative design, since purely algorithmic solutions still need expert judgment (Mukkavaara & Sandberg, 2020). However, a significant concern noted by several reviews is explainability and ethics. Manmatharasan et al. (2025) highlight that tree-based surrogates and tools like SHAP/LIME are being used to open the “black box” of ML models. Additionally, ethical impacts (e.g. bias, privacy, employment) are largely unaddressed and flagged for future work as this is a point of caution rather than conflict, urging careful adoption of AI as posited by Manmatharasan et al. (2025). Overall, the literature is fairly unified recognizing generative AI methods as beneficial for sustainability (energy, material, comfort) and the main issues are technical (data, transferability, explainability), not fundamental disagreement about viability.

11. Conclusion & Implications for Future Studies

This review has shown that generative AI and computational design methods are increasingly applied to optimize sustainable architectural outcomes. Generative design – using parametric models and evolutionary algorithms – enables exploration of many design alternatives, and studies consistently report substantial improvements in energy efficiency and other metrics (often 10–30% gains). Machine learning is enhancing this process: surrogate models reduce computational cost, and GANs/diffusion models open up new avenues for automated design generation. The most significant findings are that (1) Evolutionary and parametric design methods remain dominant and effective, especially for early-stage energy optimization, (2) AI-based surrogates are widely used to speed optimization, with increasing attention to interpretability, and (3) Generative models like GANs show promise in creating innovative spatial layouts (e.g. parks, floorplans) with improved performance. The findings indicate a maturing field where traditional computational design and modern AI increasingly converge. However, limitations are clear. Most studies rely on limited datasets or single-case scenarios, making generalization difficult. Many approaches lack user interface and still treat AI as a black box. Few works address the full lifecycle (e.g. from concept to construction).

Additionally, very little work considers embodied carbon or long-term resilience. Ethical and social factors (e.g. how automated design impacts practitioners, biases in data) are rarely examined. Thus, future research should fill these gaps. Promising directions include creating large, diverse datasets of building designs for training generative models; integrating multi-scale optimization (linking building and urban scales); and exploring explainable AI so designers trust AI suggestions. Combining GAN/diffusion generation with physics-based optimization loops could yield very rapid sustainability-driven design. Interdisciplinary studies including human factors will be needed to ensure adoption. In conclusion, generative AI for sustainable architecture is a dynamic, rapidly evolving field. The literature evidences substantial potential to achieve greener buildings, but realizing this potential will require addressing data, explainability, and practical integration challenges. As methods like deep generative models mature, they will likely become standard tools in architects' sustainability toolkits.

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