
Multi-Objective Optimization and Machine Learning Approaches for Low-Carbon Building Design

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Abstract

The building sector accounts for approximately 40% of global energy-related carbon dioxide emissions, making it a critical focus area for climate change mitigation. As the world advances toward carbon neutrality goals, low-carbon building design has emerged as an essential strategy combining environmental sustainability with economic viability. This review examines recent developments in multi-objective optimization approaches and machine learning techniques for low-carbon building design, covering the period from 2018 to 2025. We synthesize research on optimization algorithms including NSGA-II, SPEA2, and hybrid evolutionary approaches, alongside machine learning methods such as neural networks, random forests, and support vector machines. The review identifies three primary optimization objectives: carbon emissions reduction, cost minimization, and building performance enhancement including energy efficiency, daylighting, and thermal comfort. Key findings reveal that integrating Building Information Modeling with parametric design and surrogate modeling can reduce computational time by up to 50% while achieving 13 to 25% reductions in carbon emissions. However, significant challenges remain in data quality, model interpretability, and the integration of embodied and operational carbon across building lifecycles. This review provides a comprehensive framework for researchers and practitioners, identifying critical gaps and future research directions toward achieving net-zero buildings.

Keywords: Low-Carbon Buildings, Multi-Objective Optimization, Machine Learning, Carbon Emissions, Building Performance, Sustainability

1. Introduction

1.1 Background and Motivation

The global construction industry stands at a critical juncture in addressing climate change. According to the United Nations Environment Programme, the building and construction sector is responsible for 36% of global final energy consumption and nearly 40% of energy-related carbon dioxide emissions [17,24]. In China, the building sector contributed to 50.9% of national carbon emissions in 2020 [27], while industrialized nations face similar challenges in meeting Paris Agreement targets. These alarming statistics underscore the urgent need for innovative approaches to building design that prioritize carbon reduction without compromising functionality or economic feasibility.

The concept of low-carbon building design has evolved from simple energy efficiency measures to comprehensive, lifecycle-based approaches that consider both embodied carbon, which includes emissions from material production, transportation, and construction, and operational carbon, which represents emissions from building use [30,62]. Traditional design methods often optimize single objectives, leading to suboptimal solutions that may reduce energy consumption but

increase material use, or vice versa. This limitation has catalyzed the development of multi-objective optimization frameworks that simultaneously address multiple, often conflicting, design objectives.

1.2 The Rise of Computational Design Optimization

Recent advances in computational power, Building Information Modeling, and artificial intelligence have revolutionized building design processes [18,43]. Multi-objective optimization algorithms, particularly evolutionary algorithms such as the Non-dominated Sorting Genetic Algorithm II [7], Strength Pareto Evolutionary Algorithm 2 [20], and the Hypervolume-based Evolutionary Algorithm [3], have emerged as powerful tools for exploring vast design spaces and identifying Pareto-optimal solutions. These algorithms enable designers to balance trade-offs between carbon emissions, cost, energy consumption, daylighting, thermal comfort, and structural performance.

Concurrently, machine learning techniques have gained prominence in predicting building performance metrics and carbon emissions with unprecedented accuracy [52,53,55]. Neural networks, random forests, support vector machines, and ensemble methods can learn complex, non-linear relationships from building simulation data, significantly reducing computational time compared to traditional physics-based simulations. The integration of machine learning with optimization algorithms has created powerful frameworks for rapid, accurate building design exploration.

1.3 Scope

This review synthesizes research published between 2018 and 2025, focusing on multi-objective optimization and machine learning applications in low-carbon building design. We examine multi-objective optimization frameworks and algorithms for building design, machine learning techniques for carbon emission prediction and performance evaluation, integration of BIM with parametric modeling and surrogate models, case studies demonstrating real-world applications, and critical challenges with future research directions.

2. Multi-Objective Optimization Frameworks for Low-Carbon Building Design

2.1 Fundamental Concepts and Objectives

Multi-objective optimization in building design involves simultaneously optimizing multiple, often conflicting, objectives while satisfying various constraints [32,33]. The most common objectives in low-carbon building design include carbon emissions minimization covering both embodied carbon from materials and construction and operational carbon from energy use during building lifecycle [1,10,13], cost minimization including initial construction costs and lifecycle costs [2,40], and energy efficiency maximization focusing on reducing heating, cooling, and lighting energy demands [39,49].

Additional objectives frequently considered include thermal comfort optimization to maintain indoor temperature within acceptable ranges [41,50], daylighting performance to maximize useful daylight illuminance while minimizing glare [11,12,60], structural performance ensuring safety and material efficiency [5,9], and construction duration minimization [10]. The mathematical formulation typically involves minimizing or maximizing objective functions subject to inequality and equality constraints within specified design variable bounds, where design variables may include wall thickness, window-to-wall ratio, insulation type, and building orientation.

2.2 Evolutionary Algorithms for Building Optimization

The Non-dominated Sorting Genetic Algorithm II has emerged as the most widely adopted algorithm for building design optimization [7]. Its popularity stems from its elitist strategy, fast non-dominated sorting, and diversity preservation through crowding distance. Recent studies demonstrate NSGA-II's effectiveness across diverse applications. Zhong et al. [1] employed NSGA-II to optimize greenhouse designs, achieving 13.58 to 23.39% reductions in carbon emissions while improving material utilization by 108 to 132%. Wu et al. [50] integrated NSGA-II with Bayesian Optimization and XGBoost for residential building optimization, successfully balancing energy consumption, daylighting, and thermal comfort. Ge et al. [11] applied NSGA-II for railway station solar roof design, demonstrating effectiveness in large-scale public buildings.

The algorithm's success is attributed to its ability to maintain solution diversity throughout the optimization process, preventing premature convergence to local optima. However, computational expense remains a limitation, particularly for problems requiring thousands of building performance simulations. While NSGA-II dominates the literature, alternative algorithms offer specific advantages. SPEA2 utilizes fine-grained fitness assignment and archive truncation, showing superior performance in problems with many objectives [19,20]. Carvalho et al. [5] demonstrated SPEA2's effectiveness in truss structure optimization for buildings. The Hypervolume-based Evolutionary Algorithm is particularly effective for many-objective problems with more than three objectives common in building design [3]. The hypervolume indicator provides a single metric for solution quality, facilitating convergence.

Recent research explores hybrid approaches combining evolutionary algorithms with local search methods. Kaveh et al. [10] compared Enhanced Colliding Bodies Optimization, Enhanced Vibrating Particles System, and Particle Swarm Optimization for RC frame design considering carbon dioxide emissions, demonstrating that hybrid approaches can reduce computational time by 30 to 40% compared to pure evolutionary methods.

2.3 Design Variables and Parameter Selection

The selection of design variables significantly impacts optimization outcomes. Common envelope parameters include wall and roof insulation thickness and material type [2,40], window-to-wall ratio with glazing properties and shading devices [61,66], and external wall solar absorption rate [1,13]. System parameters encompass HVAC system type and coefficient of performance [39], lighting power density and control strategies [60], and heating and cooling setpoint temperatures [50]. Geometric parameters involve building orientation and form [32,49], floor height and structural dimensions [9,21], and solar roof geometry [4,11].

Recent studies emphasize the importance of considering interdependencies between variables. For instance, increasing window-to-wall ratio improves daylighting but may increase cooling loads, requiring optimization to find the ideal balance [12]. Evaluating optimization outcomes requires appropriate metrics including convergence metrics that measure how close the Pareto front is to the true optimal front, diversity metrics that assess solution spread across the Pareto front, and hypervolume that provides a unified metric combining convergence and diversity [3].

Studies comparing algorithm performance reveal that NSGA-II consistently achieves superior balance between convergence and diversity for building optimization problems with two to four objectives [50], while HypE performs better for problems with five or more objectives.

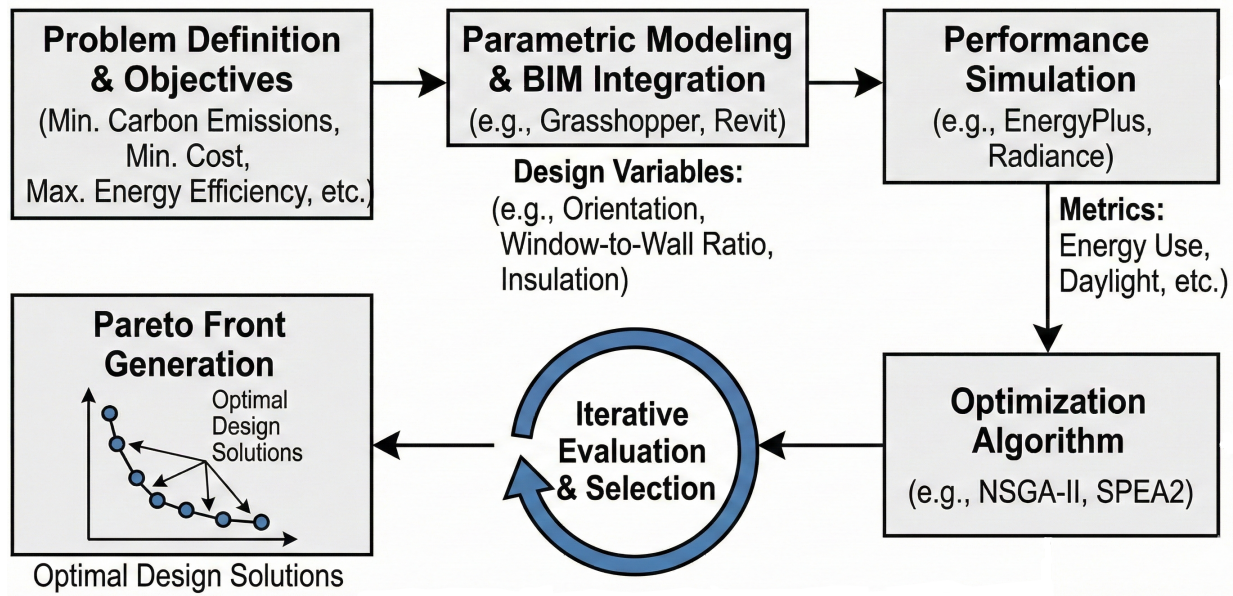


Figure 1: Multi-Objective Optimization Framework for Low-Carbon Building Design

3. Machine Learning for Carbon Emission Prediction and Building Performance

3.1 The Role of Machine Learning in Building Design

Machine learning has transformed building design by enabling rapid, accurate predictions of carbon emissions and performance metrics without time-consuming physics-based simulations [52,54,56]. ML models learn complex relationships from training data generated through building simulations or measured from existing buildings, then predict outcomes for new design configurations in milliseconds rather than minutes or hours required for detailed simulations.

3.2 Artificial Neural Networks

Artificial neural networks, particularly deep learning architectures, excel at capturing non-linear relationships in building performance data [53,58]. Yan et al. [53] developed a convolutional neural network for real-time operational carbon emission prediction in residential buildings, achieving prediction accuracy within 5% error. The CNN architecture effectively captures spatial patterns in building designs. Zhong et al. [13] proposed a novel neural network approach integrating parametric modeling, demonstrating 50.7% enhancement in computational precision compared to traditional methods. Their multi-layer architecture processes geometric parameters and window-to-wall ratios to simultaneously predict material utilization, daylighting, carbon emissions, and indoor temperature.

Kim et al. [58] compared ANNs with linear regression for campus building energy prediction, finding that ANNs achieved 20 to 30% higher prediction accuracy, particularly for buildings with complex occupancy patterns and variable environmental conditions. The superior performance of neural networks stems from their ability to model highly non-linear relationships and interactions between multiple input variables that linear models cannot capture effectively.

3.3 Random Forest and Ensemble Methods

Random forests have emerged as highly effective for building performance prediction due to their ability to handle high-dimensional data, capture complex interactions, and provide feature

importance rankings [56,60]. Wang et al. [56] demonstrated that random forest models achieve R-squared values exceeding 0.95 for hourly building energy prediction, outperforming support vector machines and artificial neural networks. The ensemble nature of random forests, which combines predictions from multiple decision trees, provides robust predictions that are less susceptible to overfitting compared to single decision trees.

Fenton et al. [52] applied machine learning, including random forest variants, for embodied greenhouse gas emission prediction in early-stage building design. Their models accurately predicted emissions based on limited design information available in preliminary phases, enabling informed decision-making before detailed design development. Ensemble methods combining multiple algorithms show particular promise. Wu et al. [50] integrated Bayesian Optimization with XGBoost in a multi-objective optimization framework, achieving superior prediction accuracy with R-squared greater than 0.96 while reducing training time by 40% compared to standard neural networks.

3.4 Support Vector Machines

Support vector machines effectively model complex, non-linear relationships between building parameters and performance outcomes [57,59]. Shao et al. [57] applied SVMs to hotel building energy prediction, achieving mean absolute percentage errors below 8%. SVMs particularly excel when training data is limited, as they maximize the margin between classes or regression boundaries, reducing overfitting risk. Li et al. [59] compared SVMs with ANNs for cooling load prediction, finding that SVMs demonstrated superior generalization performance when training data represented less than 70% of the total dataset, while ANNs performed better with larger training sets.

The kernel trick employed by SVMs allows them to operate in high-dimensional feature spaces without explicitly computing the coordinates in that space, making them computationally efficient for certain types of problems. However, the selection of appropriate kernel functions and hyperparameters requires careful tuning to achieve optimal performance.

3.5 Model Development and Validation

Effective ML application in building design follows a systematic process beginning with data generation through building energy simulations using tools such as EnergyPlus and DesignBuilder or from measured data in existing buildings [50,53,56]. Typical datasets include 500 to 10,000 building configurations with corresponding performance metrics. Feature engineering involves selecting relevant input features representing design variables and output targets representing performance metrics. Feature importance analysis identifies which parameters most significantly impact outcomes [52,54].

Data preprocessing includes normalizing or standardizing input features, handling missing values, and splitting data into training, validation, and test sets, typically using ratios of 70-15-15 or 80-10-10. Model training involves training multiple model architectures and tuning hyperparameters through grid search, random search, or Bayesian optimization [50,60]. Validation and testing evaluate model performance using metrics such as R-squared, mean absolute error, root mean square error, and mean absolute percentage error. Finally, trained models are integrated with optimization frameworks, deployed as surrogate objective functions replacing time-consuming simulations [18,60].

3.6 Comparative Performance Analysis

Recent comparative studies reveal the strengths of different ML approaches. Neural networks and ensemble methods including Random Forest and XGBoost generally achieve highest accuracy with R-squared greater than 0.95 for complex building systems [50,52,56]. SVMs perform well with limited data, while simpler linear models suffice for relationships dominated by linear trends [55,58]. Once trained, all ML models provide near-instantaneous predictions. Training time varies significantly, with random forests and SVMs training in minutes to hours, while deep neural networks may require hours to days depending on architecture complexity and dataset size [60].

Random forests provide clear feature importance rankings, aiding design insight [56]. Neural networks, particularly deep architectures, act as black boxes, making interpretation challenging despite high accuracy [54]. SVM interpretability falls between these extremes. Ensemble methods demonstrate robust generalization across building types and climates [52]. Neural networks require careful regularization to prevent overfitting, particularly with limited training data [53,58].

4. Integrated Frameworks Combining BIM, Parametric Modeling, and Optimization

4.1 BIM-Based Optimization Workflows

Building Information Modeling has revolutionized the integration of design, simulation, and optimization [43,45,47]. BIM provides a central repository of building geometry, materials, and systems information, enabling seamless data exchange between design tools and performance analysis software. Recent frameworks leverage BIM's parametric capabilities to automate design exploration and optimization. Huang et al. [45] conducted a systematic literature review of BIM-based embodied carbon evaluation, identifying that integration of BIM with lifecycle assessment databases enables real-time carbon footprint visualization during design. This immediate feedback empowers architects and engineers to make informed, low-carbon decisions from project inception.

Röck et al. [43] demonstrated a BIM-LCA workflow that visualizes environmental potentials at early design stages, reducing embodied carbon by 15 to 20% compared to conventional design approaches. The visualization capability proves crucial for stakeholder communication and decision-making, as it translates complex environmental data into intuitive visual representations that non-technical stakeholders can understand and use to inform their decisions.

4.2 Parametric Design Platforms

Parametric design environments such as Grasshopper for Rhino have become standard platforms for building optimization research [1,4,32]. These visual programming interfaces enable generative design through algorithmic generation of thousands of design alternatives through parameter variation, performance simulation integration through direct coupling with energy simulation tools such as Ladybug and Honeybee and structural analysis software, and optimization algorithm implementation through integration of evolutionary algorithms using plugins like Wallacei and Galapagos.

Pan et al. [32] demonstrated parametric modeling for multi-functional space and long-span structure optimization in indoor sports arenas, achieving 25% reduction in structural material use while improving spatial quality metrics. The parametric approach enabled exploration of over 5,000 design variants, identifying non-intuitive solutions superior to traditional design approaches. Bushra and Hartmann [4] developed a parametric optimization method for roof-integrated two-stage solar concentrators, showcasing how parametric platforms facilitate complex geometric optimization for renewable energy integration.

4.3 Surrogate Modeling Approaches

Surrogate models, also called metamodels or response surfaces, replace expensive building performance simulations with fast-running approximations [18,60]. This substitution dramatically reduces computational burden in optimization, enabling exploration of larger design spaces. Westermann and Evins [18] provided a comprehensive review of surrogate modeling for sustainable building design, identifying polynomial regression, Kriging, radial basis functions, and neural networks as the most common surrogate types. Their analysis reveals that neural networks and Gaussian process regression achieve highest accuracy for most building performance prediction tasks.

Dong et al. [60] proposed an intelligent optimization framework combining random forest surrogate models with NSGA-II for daylighting and energy optimization. The surrogate model achieved 98% accuracy while reducing optimization time from 72 hours to 2.5 hours, representing a 96% reduction. This efficiency enables designers to conduct multiple optimization studies exploring different scenarios and constraints. The surrogate modeling workflow typically involves generating initial design samples using Latin Hypercube Sampling or similar space-filling techniques, evaluating samples through detailed simulations, training surrogate model on simulation results, using surrogate in optimization algorithm, validating optimal solutions through detailed simulation, and iteratively improving surrogate with additional samples if needed.

4.4 Cloud-Based and Distributed Computing

The computational intensity of building optimization has driven adoption of cloud computing and parallel processing. Recent platforms distribute simulation workloads across multiple processors or cloud servers, achieving 10 to 50 times speedup compared to sequential processing on single workstations [22,50]. Ajide [22] discussed AI-driven optimization of sustainable infrastructure integrating cloud-based machine learning services with traditional building simulation tools. Cloud platforms enable scalable computational resources for large optimization problems, centralized data storage and team collaboration, access to pre-trained ML models and optimization services, and real-time optimization during design charrettes.

The shift toward cloud-based platforms represents a fundamental change in how building optimization is conducted, moving from isolated workstation-based analyses to collaborative, distributed computing environments. This transformation enables design teams distributed across different locations to work simultaneously on optimization studies, sharing computational resources and results in real-time.

5. Case Studies and Performance Comparisons

5.1 Educational Buildings

Educational buildings present unique challenges balancing energy efficiency, daylighting for learning environments, and carbon emissions. Shi et al. [12] conducted multi-objective optimization of educational buildings in China's schematic design stage, optimizing embodied carbon, energy consumption, and daylighting across 500 design variants. Results demonstrated 18.5% reduction in embodied carbon emissions, 12.3% decrease in operational energy consumption, and 35% improvement in useful daylight illuminance. Trade-offs revealed that excessive window area increases cooling loads despite daylighting benefits. These findings emphasize the importance of climate-specific optimization, as optimal designs varied significantly across China's diverse climate zones.

5.2 Railway Stations and Large-Space Public Buildings

Ge et al. [11] addressed solar roof design for railway stations, representative of large-space public buildings. Their two-stage optimization approach first optimized roof geometry for thermal efficiency, then refined photovoltaic panel arrangement for electricity generation. The methodology achieved 22% reduction in annual carbon emissions, 15% improvement in thermal comfort, and successful integration of daylighting considerations preventing excessive solar heat gain. This study demonstrates that large-scale public buildings require specialized optimization approaches due to their unique spatial configurations and high energy intensity. The two-stage approach proved more effective than simultaneous optimization of all parameters, as it allowed each stage to focus on a specific set of related objectives.

5.3 Residential Buildings

Residential buildings represent the largest portion of building stock in most regions, making them critical targets for carbon reduction efforts. Wu et al. [50] optimized a residential building in China using BO-XGBoost-NSGA-II, generating Pareto fronts revealing optimal window-to-wall ratios varying from 0.25 to 0.35 depending on orientation, high-performance HVAC systems providing 30 to 40% energy savings with 5 to 8 year payback periods, and strong correlation between daylighting and thermal comfort objectives suggesting joint optimization potential.

Abdeen et al. [39] conducted simulation-based multi-objective genetic optimization for existing residential buildings in hot climates, demonstrating potential for 35% energy savings and 25% carbon emission reductions through envelope retrofits and system upgrades. The study emphasizes that optimization can guide cost-effective retrofit strategies for existing building stock, which is particularly important given that the majority of buildings that will exist in 2050 have already been constructed.

5.4 Office Buildings and Commercial Structures

Office buildings feature different use patterns and performance priorities compared to residential structures. Qiao et al. [61] optimized building-integrated photovoltaic windows in office buildings, balancing electricity generation, daylighting, and energy consumption. Optimal solutions achieved 18% net energy consumption reduction, improved glare control compared to conventional glazing, and economic payback periods under 12 years. The integration of photovoltaic technology within the building envelope represents an emerging trend where building components serve multiple functions, generating energy while also providing essential envelope services.

Yu and Ho [36] explored tactics for carbon-neutral office buildings in Hong Kong, demonstrating that comprehensive optimization considering envelope, systems, and renewable energy can achieve net-zero operational carbon, though embodied carbon from construction remains a significant challenge requiring attention. Their work highlights the distinction between net-zero energy buildings and truly net-zero carbon buildings, emphasizing that achieving carbon neutrality requires addressing both operational and embodied emissions.

5.5 Prefabricated and Modular Buildings

Prefabricated construction offers potential carbon benefits through reduced construction waste and improved quality control. However, transportation and assembly considerations complicate optimization. Zhou et al. [21] developed an automated structural design approach for shear wall structures using modified genetic algorithms, demonstrating 12% reduction in construction duration, 8% decrease in material use through optimized component sizing, and highlighting the

importance of considering prefabrication rates as constraints in optimization. This research demonstrates that building industrialization and low-carbon design can achieve synergistic benefits through integrated optimization, though the optimization framework must account for manufacturing constraints and modular coordination requirements.

5.6 Algorithm Performance Comparison

Comparative studies across multiple case studies reveal consistent patterns in algorithm performance. NSGA-II demonstrates robust performance across diverse building types, typically requiring 1,000 to 5,000 evaluations for convergence in two to four objective problems [1,7,50]. Ant Colony Optimization shows competitive performance for discrete optimization problems such as selecting prefabrication strategies [10]. Hybrid approaches often achieve 20 to 40% faster convergence than single algorithms, at the cost of increased implementation complexity [10,60]. Machine learning-accelerated optimization reduces total computational time by 85 to 96% compared to direct coupling with building simulation tools, enabling real-time optimization during design meetings [50,60].

These performance comparisons indicate that while traditional evolutionary algorithms remain effective, the integration of machine learning surrogate models represents the most significant advancement in computational efficiency for building optimization. The dramatic reduction in computational time enables iterative design exploration that was previously impractical due to time constraints.

6. Challenges, Limitations, and Future Directions

6.1 Data Quality and Availability

Machine learning models require large, high-quality datasets for training, but building performance data often suffers from limited measured data from existing buildings due to sparse sensor deployment, simulation data quality depending on input parameter accuracy, and inconsistencies between simulated and actual building performance known as the performance gap. Future research should focus on developing standardized building performance databases across different climates and building types, implementing transfer learning approaches enabling models trained on one building type or climate to adapt to others with limited new data, leveraging growing IoT sensor deployments in smart buildings to create measured performance datasets, and establishing data sharing protocols and platforms within the building industry.

The performance gap between simulated and measured building energy consumption, which can reach 30 to 50% in some cases, represents a fundamental challenge for optimization approaches based on simulation data. Addressing this gap requires better understanding of occupant behavior, improved modeling of real-world operating conditions, and validation of optimization results against measured performance in completed buildings.

6.2 Embodied vs. Operational Carbon Integration

Most studies focus predominantly on operational carbon from energy use, with limited integration of embodied carbon from materials and construction [44,46]. Comprehensive lifecycle optimization remains challenging due to limited availability of embodied carbon data for building materials, regional variations in manufacturing processes and energy sources affecting embodied carbon, uncertainty in building lifetime and end-of-life scenarios, and complex trade-offs where reduced operational carbon may increase embodied carbon.

Future research should develop integrated lifecycle assessment tools seamlessly linking BIM with material carbon databases, create region-specific embodied carbon databases reflecting local manufacturing and transportation, research optimal balance points between embodied and operational carbon for different building types and locations, and investigate circular economy approaches and material reuse strategies in optimization frameworks. The increasing importance of embodied carbon as operational carbon decreases through improved building efficiency means that a comprehensive approach considering both emission sources becomes essential.

6.3 Multi-Scale Optimization

Current research predominantly addresses individual buildings, with limited consideration of district and neighborhood-level energy systems and shared resources, urban-scale interactions including heat islands and wind patterns, and infrastructure interdependencies between buildings. Future research should develop multi-scale optimization frameworks connecting building, district, and urban levels, integrate building optimization with grid-level renewable energy planning, consider shared resources like district heating and cooling systems in optimization, and account for urban microclimate effects in building performance predictions.

The transition from building-scale to district-scale optimization introduces additional complexity but also creates opportunities for achieving greater carbon reductions through shared infrastructure and coordinated operation of multiple buildings. District energy systems, shared renewable energy generation, and coordinated demand response can achieve efficiencies impossible at the individual building scale.

6.4 Uncertainty and Robustness

Building performance involves significant uncertainties including climate change projections affecting future operational performance [2,14], occupant behavior variability influencing actual energy use, material property variations from specified values, and economic uncertainties affecting cost projections and energy prices. Future research should incorporate robust optimization approaches explicitly considering uncertainty ranges, develop adaptive building designs performing well across multiple climate scenarios, integrate stochastic optimization methods for robust solution identification, and create sensitivity analysis tools quantifying design parameter influence under uncertainty.

Climate change introduces particular challenges for building optimization, as buildings designed for current climate conditions may perform poorly in future climate scenarios. Optimization frameworks must therefore consider not just current performance but also resilience and adaptability to future conditions that remain uncertain.

6.5 Model Interpretability and Trust

Advanced machine learning models, particularly deep neural networks, function as black boxes, making it difficult for designers and stakeholders to understand and trust predictions [54]. This opacity limits designer ability to develop intuition about design principles, stakeholder confidence in optimization outcomes, and regulatory acceptance of ML-driven design tools. Future research should develop explainable AI techniques for building performance prediction, create visualization tools illustrating relationships between design parameters and outcomes, combine interpretable ML models such as decision trees with high-accuracy models for validation, and establish industry standards for ML model validation in building design applications.

The tension between model accuracy and interpretability represents a fundamental challenge in applying advanced machine learning to building design. While complex models achieve higher accuracy, simpler interpretable models may be more valuable for developing design insight and building trust among practitioners.

6.6 Computational Efficiency vs. Accuracy Trade-offs

High-fidelity building simulations including CFD and dynamic thermal modeling provide accurate results but remain computationally expensive, limiting their use in optimization. Conversely, simplified models and surrogate models reduce computational time but sacrifice accuracy. Future research should develop multi-fidelity optimization approaches combining fast low-fidelity models for exploration with high-fidelity validation, research adaptive sampling strategies focusing computational resources on promising design regions, leverage emerging hardware including GPUs and specialized AI chips for faster simulation and optimization, and create problem-specific model simplifications capturing essential physics while reducing computational burden.

The choice between high-fidelity and low-fidelity models depends on the design stage and the specific performance metrics of interest. Early conceptual design may benefit from rapid exploration using simplified models, while detailed design and validation require high-fidelity simulation to ensure accuracy.

6.7 Integration with Design Practice

Despite extensive academic research, adoption of advanced optimization methods in practice remains limited due to complexity of tool setup and use, lack of integration with standard design software, insufficient training for design professionals, and perception that optimization constrains design creativity. Future research should develop user-friendly interfaces abstracting technical complexity, create plugins for popular design platforms including Revit, Rhino, and SketchUp, establish design guideline databases derived from optimization studies, frame optimization as design space exploration rather than constraint showing diversity of high-performing solutions, and develop educational programs training architects and engineers in computational design methods.

The gap between research and practice represents perhaps the most significant barrier to realizing the potential of optimization for low-carbon building design. Bridging this gap requires not just technical solutions but also cultural change within the design professions and recognition that optimization tools can enhance rather than constrain design creativity.

6.8 Dynamic Grid Carbon Intensity

Most studies assume static carbon emission factors for electricity, but grid carbon intensity varies temporally as renewable energy generation fluctuates [14]. Optimal building designs considering dynamic grid conditions may differ substantially from those assuming static factors. Future research should integrate dynamic carbon emission factors from grid forecasts into optimization, optimize building energy storage and load shifting capabilities alongside envelope and systems, consider building-grid interaction in optimization frameworks, and develop adaptive control strategies optimizing operations based on real-time grid conditions.

The increasing penetration of renewable energy in electricity grids creates both challenges and opportunities for building optimization. Buildings with thermal mass, battery storage, or flexible

loads can shift energy consumption to times when grid carbon intensity is low, achieving greater carbon reductions than possible through envelope and system efficiency improvements alone.

7. Conclusions and Recommendations

7.1 Key Findings

This comprehensive review of multi-objective optimization and machine learning for low-carbon building design reveals several critical insights. Multi-objective optimization algorithms, particularly NSGA-II, have achieved maturity for building design applications, consistently producing high-quality Pareto fronts across diverse building types and climates, though computational efficiency remains a challenge for problems requiring detailed building simulations. Machine learning models, especially ensemble methods and neural networks, accurately predict building performance metrics and carbon emissions, achieving R-squared values exceeding 0.95 in most applications. When integrated with optimization algorithms as surrogate models, ML reduces computational time by 85 to 96%, enabling real-time design exploration.

Case studies consistently demonstrate 10 to 25% carbon emission reductions through systematic optimization compared to conventional design approaches, with some achieving up to 35% reductions when considering both envelope and systems optimization. Building design involves complex trade-offs between multiple objectives, with optimal solutions varying significantly based on building type, climate, occupancy patterns, and stakeholder priorities, emphasizing the need for project-specific optimization rather than universal design rules. Despite strong academic progress, significant barriers prevent widespread adoption in practice, including tool usability challenges, lack of integration with standard design workflows, and insufficient professional training.

7.2 Recommendations

For algorithm development, researchers should prioritize development of hybrid algorithms combining evolutionary optimization with machine learning for enhanced efficiency, investigate many-objective optimization approaches handling five or more objectives simultaneously, develop robust optimization methods explicitly considering uncertainty in climate, occupancy, and material properties, and create adaptive optimization frameworks learning from design iterations to accelerate convergence.

For application research, the field needs more comprehensive lifecycle studies integrating embodied and operational carbon, expanded research to underrepresented building types including healthcare, industrial, and historical buildings and developing regions, investigation of retrofit optimization for existing building stock representing 70 to 80% of 2050 building inventory, and studies of long-term performance of optimized buildings through post-occupancy evaluation.

For interdisciplinary collaboration, researchers should engage building science, computer science, and architecture and engineering communities in collaborative research, conduct human-subjects research understanding how designers interact with and trust optimization tools, and collaborate with policymakers to align optimization objectives with building codes and incentives.

For design teams, practitioners should begin incorporating optimization early in design processes, ideally during conceptual design when decisions most significantly impact carbon performance, use optimization for design space exploration identifying ranges of high-performing solutions rather than single optimal designs, validate optimization results through detailed simulation and where possible measured data from similar existing buildings, and communicate optimization

results to clients and stakeholders through visualizations emphasizing co-benefits including reduced carbon, lower energy costs, and improved comfort.

For software developers, priorities include creating user-friendly interfaces abstracting technical complexity from design professionals, developing seamless integrations with industry-standard BIM and design platforms, providing extensive documentation with tutorials and example workflows demonstrating practical application, and implementing automated validation and error-checking to prevent common modeling mistakes.

For policymakers, key actions include establishing building carbon performance standards incorporating lifecycle emissions including both embodied and operational carbon, creating incentive structures rewarding low-carbon design beyond minimum code compliance, supporting development of regional embodied carbon databases and lifecycle assessment tools, and mandating carbon performance disclosure enabling data collection for machine learning model improvement.

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