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Metaheuristic Optimization in Architecture: A Multi-Objective Framework for Building Form Generation, Energy Performance, and Daylighting Design

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Abstract

The escalating demand for high-performance buildings necessitates advanced computational methods capable of navigating the complex, multidimensional design spaces inherent in architectural optimization. This study proposes a multi-objective metaheuristic framework integrating four nature-inspired algorithms: Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Whale Optimization Algorithm (WOA) for three interrelated architectural optimization problems: building form generation for minimum energy consumption, façade design for optimal daylighting performance, and spatial layout optimization for maximum space efficiency. The framework is benchmarked on a 15-story office building in Tehran, Iran, using EnergyPlus 23.1 coupled with MATrix LABoratory (MATLAB) -based optimization routines and Typical Meteorological Year 3 (TMY3) meteorological data. Decision variables encompass building geometry, orientation, Window-to-Wall Ratio (WWR), shading device parameters, glazing properties, and spatial adjacency matrices. Performance is evaluated through Energy Use Intensity (EUI), Daylight Autonomy (DA), Useful Daylight Illuminance (UDI), construction cost indices, and spatial efficiency metrics across 30 independent runs per algorithm with 500 iterations each, totaling 60,000 function evaluations per algorithm. Results demonstrate that GWO achieves the most favorable trade-off between energy performance and daylighting quality, reducing EUI by 31.4% (from 118.5 to 81.2 kWh/m²/yr) and increasing DA by 22.7 percentage points (from 53.7% to 76.4%) compared to the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) 90.1 baseline design. Statistical analyses using Wilcoxon signed-rank tests and Friedman rankings confirm the superiority of GWO at the 0.001 significance level. The study provides actionable guidelines for integrating metaheuristic optimization into architectural practice, including recommendations for algorithm selection, parameter tuning, and Building Information Modeling (BIM) workflow integration. Implications for sustainable design practice and future research directions involving surrogate-assisted optimization and generative Artificial Intelligence (AI) coupling are discussed.

Keywords: Metaheuristic algorithms, Architectural optimization, Building energy performance, Daylighting design, Multi-objective optimization, Sustainable architecture, Generative design.

1 | Introduction

The built environment is responsible for approximately 36% of global final energy consumption and 39% of energy-related carbon dioxide emissions, establishing it as a critical sector for achieving international

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decarbonization targets set forth under the Paris agreement and subsequent Conference of the Parties (COP) frameworks [1]. Within this context, the architectural design phase represents a decisive juncture at which decisions regarding building form, envelope configuration, and spatial organization can influence up to 80% of a building's lifetime operational energy demand [2]. Despite this recognized significance, conventional architectural design processes remain predominantly driven by heuristic judgment, aesthetic intuition, and precedent-based reasoning, with quantitative performance feedback typically introduced only in later stages of design development through post-hoc simulation analyses.

Architectural design optimization is inherently characterized by multi-objective complexity, involving the simultaneous consideration of energy efficiency, thermal comfort, visual quality, structural feasibility, construction cost, and subjective aesthetic criteria. The design search space is typically non-convex, multi-modal, and high-dimensional, with intricate interdependencies among decision variables such as building orientation, aspect ratio, floor plate geometry, Window-to-Wall Ratio (WWR), glazing properties, and shading device configurations [3]. These characteristics render traditional gradient-based optimization methods largely impractical, as they require continuous and differentiable objective functions, conditions rarely satisfied in simulation-coupled architectural problems where discrete material selections, integer-valued floor counts, and non-linear thermal behavior prevail.

The advent of parametric design environments, notably Grasshopper for Rhinoceros 3D and Autodesk Dynamo for Revit, has democratized computational design exploration among practitioners. These platforms enable architects to construct parametric models in which geometric and material attributes are exposed as adjustable parameters, facilitating rapid generation of design variants. However, parametric variation alone does not constitute optimization. Without robust search algorithms, designers are confined to manual parameter sweeps, random sampling, or exhaustive grid search strategies that become computationally intractable as the number of decision variables exceeds single digits. Existing optimization plugins such as Galapagos, Octopus, and Opossum provide limited algorithmic diversity and offer restricted control over convergence behavior, population dynamics, and multi-objective trade-off management [4].

Metaheuristic optimization algorithms, inspired by natural phenomena ranging from biological evolution to swarm intelligence and predator-prey dynamics, have emerged as particularly well-suited tools for architectural design problems. Their population-based search strategies, gradient-free operation, and inherent capacity for global exploration across discontinuous and multi-modal landscapes align closely with the computational structure of simulation-based design optimization [5]. Since the pioneering application of Genetic Algorithms (GA) to building envelope optimization by Caldas and Norford [6] and the subsequent work of Tuhus-Dubrow and Krarti [7] on building shape optimization, the field has witnessed growing adoption of Particle Swarm Optimization (PSO), Simulated Annealing (SA), Ant Colony Optimization (ACO), and more recent nature-inspired algorithms including the Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), and Salp Swarm Algorithm (SSA).

Despite this growing body of literature, significant research gaps persist. First, the majority of existing studies employ a single metaheuristic algorithm without systematic benchmarking against alternative approaches, making it difficult to assess relative algorithmic performance for specific architectural problem classes. Second, most investigations address isolated optimization objectives, typically energy minimization without integrating daylighting quality, spatial efficiency, and cost as concurrent objectives. Third, few studies provide statistically rigorous comparisons with sufficient independent runs to establish significance, often reporting single best-run results that may not be reproducible. Fourth, the disconnect between computational optimization research and practical architectural workflows remains pronounced, with limited guidance on how optimization outputs translate into actionable design decisions within Building Information Modeling (BIM) environments.

This study addresses these gaps through three primary contributions: 1) a unified multi-objective optimization framework that simultaneously addresses building form generation, façade design, and spatial layout optimization within a single computational architecture; 2) a comprehensive four-algorithm benchmark comparing GA, PSO, GWO, and WOA across all three problem domains using identical population sizes, function evaluation budgets, and statistical testing protocols; and 3) a validated case study on a 15-story office building in Tehran, Iran, coupled with EnergyPlus 23.1 energy simulation, providing physically plausible results grounded in actual climatic conditions and code-compliant baseline designs conforming to American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Standard 90.1-2019.

The remainder of this paper is organized as follows. Section 2 presents a comprehensive literature review covering metaheuristic algorithms in building design, energy optimization, daylighting, and spatial layout. Section 3 details the methodology, including problem formulations, algorithm implementations, simulation setup, and statistical testing protocols. Section 4 presents and discusses the results across all three optimization problems. Section 5 provides a broader discussion of findings, practical implications, and limitations. Section 6 concludes the paper with recommendations and future research directions.

2 | Literature Review

2.1 | Metaheuristic Algorithms in Building Design

The application of metaheuristic algorithms to architectural and building engineering problems has evolved substantially over the past two decades. Early foundational work by Caldas [8] demonstrated the viability of GAs for generating energy-efficient building shapes, establishing a paradigm in which population-based search algorithms are coupled with whole-building energy simulation engines to navigate complex design spaces. This coupling of stochastic optimization with deterministic physics-based simulation has since become the standard methodology in the field [9].

PSO was introduced to building optimization by Tuhus-Dubrow and Krarti [7], who coupled PSO with DOE-2 to optimize building envelope parameters, including insulation levels, window areas, and wall constructions across five U.S. climate zones. Their work demonstrated that PSO could achieve solutions comparable to GA with significantly fewer function evaluations, an advantage attributed to the swarm's cooperative information-sharing mechanism. Subsequent extensions by Delgarm et al. [10] applied Multi-Objective PSO (MOPSO) to building energy optimization in four Iranian climatic regions using EnergyPlus, establishing Pareto-optimal trade-off curves between cooling, heating, and lighting energy demands.

More recently, novel metaheuristic algorithms have attracted research attention. The GWO, proposed by Mirjalili et al. [5], mimics the social hierarchy and hunting strategy of grey wolves and has demonstrated competitive performance on engineering benchmark problems. Ghalambaz et al. [11] applied GWO to building energy optimization coupled with EnergyPlus, reporting that GWO achieved marginally superior optima compared to PSO while exhibiting more consistent convergence behavior. The WOA Mirjalili et al. [12], inspired by the bubble-net hunting strategy of humpback whales, has been applied to structural optimization but remains underexplored in architectural energy optimization contexts.

2.2 | Building Energy Optimization

Building energy optimization has focused predominantly on envelope parameters, including WWR, insulation thickness, glazing type, wall construction, and building orientation. Magnier and Haghighat [13] employed multi-objective GA coupled with Transient System Simulation (TRNSYS) to optimize thermal comfort and energy consumption in residential buildings, identifying Pareto-optimal designs that reduced energy demand by 20–25% while maintaining acceptable Predicted Mean Vote (PMV) indices. Ascione et al. [14] applied GA to retrofit optimization of existing buildings in Mediterranean climates, demonstrating energy savings of 30–40% through envelope improvements and Heating Ventilation and Air Conditioning (HVAC) upgrades.

The integration of renewable energy systems into building optimization has expanded the decision variable space to include Photovoltaic (PV) panel sizing, orientation, and integration with building form. Chen et al. [15] developed a multi-objective framework optimizing building form, envelope, and rooftop PV simultaneously, demonstrating that form-integrated optimization yields 12–18% greater energy savings than sequential optimization approaches. The computational cost of simulation-coupled optimization has motivated research into surrogate-assisted methods, whereby machine learning models approximate simulation outputs to accelerate convergence. Westermann and Evins [16] demonstrated that Gaussian process-based surrogates could reduce required EnergyPlus evaluations by 70–85% while maintaining solution quality within 3% of direct simulation-optimization.

2.3 | Daylighting Optimization

Daylighting design optimization addresses the maximization of useful natural illumination while controlling solar heat gain and visual discomfort. Key performance metrics include Daylight Autonomy (DA), which quantifies the percentage of occupied hours during which task illuminance exceeds a threshold (typically 300 lux for office spaces) through daylight alone; Useful Daylight Illuminance (UDI), measuring hours within a comfortable illuminance range (100–2000 lux); and Daylight Glare Probability (DGP), assessing the likelihood of visual discomfort from excessive luminance contrasts [17].

Optimization of daylighting performance involves trade-offs with thermal performance, as increasing glazing area improves daylight availability but elevates cooling loads through solar heat gain. Torres and Sakamoto [18] applied GA to optimize window geometry and light shelf configurations, achieving DA improvements of 15–20% with negligible cooling penalty through integrated shading optimization. More recent work by Konis et al. [19] employed multi-objective optimization to simultaneously address DA, DGP, and thermal comfort in open-plan offices, demonstrating that Pareto-optimal solutions cluster around WWR values of 35–50% with moderate shading depths of 0.5–1.0 m for cooling-dominated climates.

2.4 | Spatial Layout Optimization

Spatial layout optimization represents a combinatorial challenge in which functional spaces must be arranged to satisfy adjacency requirements, circulation efficiency, natural ventilation potential, and programmatic constraints. The problem has traditionally been addressed through space syntax theory Hillier & Hanson [20], and has been formulated as a constraint satisfaction problem amenable to evolutionary computation. Rodrigues et al. [21] developed an evolutionary strategy for floor plan generation that optimizes topological and geometric properties simultaneously, demonstrating that GA-based approaches can produce architecturally viable layouts satisfying complex adjacency programs.

Recent advances have integrated performance simulation into layout optimization. Dino [22] coupled spatial layout generation with daylight and ventilation analysis, showing that performance-driven layouts achieve 15–25% improvements in daylight distribution compared to conventional arrangements. The integration of space syntax metrics with energy performance creates a multi-disciplinary optimization challenge that few studies have addressed comprehensively.

Table 1. Summary of key studies in metaheuristic-based architectural optimization.

Author(s)	Year	Algorithm	Architectural Problem	Objective(s)	Key Finding
Caldas and Norford [6]	2002	GA	Building shape and envelope	Energy minimization	GA is viable for generative design exploration with DOE-2 coupling
Caldas [8]	2008	GA	Building form generation	Energy+daylighting	Multi-objective GA produces diverse architectural solutions
Tuhus-Dubrow and Krarti [7]	2010	GA	Building envelope	Life-cycle cost	Rectangular shapes are optimal across five U.S. climates
Magnier and Haghighat [13]	2010	NSGA-II	Residential building	Energy+thermal comfort	20–25% energy reduction with acceptable PMV indices
Wright and Mourshed [23]	2009	GA + SA	HVAC system sizing	Energy+cost	Hybrid GA-SA outperforms individual algorithms by 8%

Table 1. Continued.

Author(s)	Year	Algorithm	Architectural Problem	Objective(s)	Key Finding
Rodrigues et al. [21]	2013	Evolutionary Strategy	Floor plan layout	Adjacency+geometry	Automated generation of architecturally viable layouts
Mirjalili et al. [5]	2014	GWO	Benchmark functions	Function minimization	GWO is competitive with PSO and GA on 29 benchmarks
Ascione et al. [14]	2016	GA	Building retrofit	Energy+cost	30–40% energy savings through envelope optimization
Delgarm et al. [10]	2016	MOPSO	Building envelope	Cooling+heating+lighting	Pareto fronts across four Iranian climate zones established
Dino [22]	2016	GA	Spatial layout	Daylight+ventilation	Performance-driven layouts improve DA by 15–25%
Wortmann and Nannicini [4]	2017	RBF + surrogate	Architectural design	Various	Surrogate models reduce evaluations by 60–80%
Westermann and Evins [16]	2019	Bayesian + GP	Building energy	Energy minimization	Surrogate reduces EnergyPlus calls by 70–85%
Chen et al. [15]	2020	NSGA-II	Form + PV integration	Energy+generation	Integrated optimization yields 12–18% greater savings
Ghalambaz et al. [11]	2021	GWO	Office building energy	Energy minimization	GWO achieves marginally better optima than PSO with EnergyPlus
Arabasy and Ghoneim [24]	2025	PSO, ACO, GA, SA	Sustainable urban design	Energy+carbon+comfort	PSO best convergence rate (24.1%); ACO best carbon reduction

3 | Methodology

3.1 | Problem Formulation

The proposed framework addresses three interconnected architectural optimization problems, each formulated as a multi-objective minimization (or maximization) problem with explicit decision variables, objective functions, and constraint sets. All problems are defined for a 15-story office building located in Tehran, Iran (35.69°N, 51.42°E), characterized by a hot semi-arid climate (Köppen classification BSk) with significant seasonal temperature variation, high cooling demand in summer months, and moderate heating requirements in winter.

3.1.1 | Problem 1: building form optimization

The first optimization problem seeks to determine the building massing configuration that minimizes operational energy while maximizing daylighting performance and minimizing construction cost. The decision variable vector x1 is defined as:

$$x1 = [\mathrm{L}, \mathrm{W}, \theta, \mathrm{AR}, \mathrm{SF}, \mathrm{Rc}], \tag{1}$$

where L is the building length (20–60 m), W is the building width (15–40 m), θ is the orientation angle from south (0–90°), AR is the floor-to-floor aspect ratio (0.6–1.8), SF is the self-shading factor controlling stepped massing (0–0.4), and Rc is the floor plate compactness ratio (0.7–1.0). The multi-objective function is formulated as:

$$\text{Minimize } \mathrm{F1}(x1) = [\mathrm{fEUI}(x1), -\mathrm{fDA}(x1), \mathrm{fcost}(x1)]. \tag{2}$$

subject to: total floor area ∈ [11,400, 12,600] m^2; floor-to-floor height = 3.6 m; structural grid ≥ 8 m span; floor plate area per floor ∈ [700, 900] m^2; EUI ≤ 150 kWh/m^2/yr (code compliance).

3.1.2 | Problem 2: façade design optimization

The second problem optimizes the building envelope to achieve the best trade-off between thermal performance and visual comfort. The decision variable vector x2 is defined as:

$$x2 = [\mathrm{WWRS}, \mathrm{WWRN}, \mathrm{WWRE}, \mathrm{WWRW}, \mathrm{Dsh}, \mathrm{Ugl}, \mathrm{SHGC}, \mathrm{VLT}]. \tag{3}$$

where WWRS, N, E, W represent WWRs for each cardinal orientation (10–80%), Dsh is the horizontal shading overhang depth (0–1.5 m), Ugl is the glazing thermal transmittance (0.8–3.0 W/m²K), SHGC is the solar heat gain coefficient (0.15–0.65), and VLT is the visible light transmittance (0.20–0.70). The objective function is:

$$\text{Minimize F2(x2)} = [\text{fEUI(x2)}, -\text{fDA(x2)}, \text{fDGP(x2)}]. \quad (4)$$

subject to: DA ≥ 40% (LEED v4 prerequisite); DGP ≤ 0.35 (imperceptible glare); U-value × WWR ≤ code maximum; VLT/SHGC ≥ 1.0 (selectivity index constraint).

3.1.3 | Problem 3: spatial layout optimization

The third problem addresses the arrangement of functional spaces within a typical floor plate to maximize adjacency satisfaction, minimize circulation area, and maximize natural ventilation potential. The decision variable vector x3 encodes the spatial positions and dimensions of n = 12 functional zones on a representative floor, including open offices, private offices, meeting rooms, break areas, service core, and reception. The objective function is:

$$\text{Minimize F3(x3)} = [-\text{fadj(x3)}, \text{fcirc(x3)}, -\text{fvent(x3)}], \quad (5)$$

where fadj quantifies the percentage of satisfied adjacency requirements from a 12 × 12 binary adjacency matrix, fcirc measures the ratio of circulation area to total floor area, and fvent scores natural ventilation potential based on the percentage of occupied spaces within 8 m of an operable exterior wall. Constraints include minimum area requirements per functional zone, fire egress code compliance, and structural column grid compatibility.

3.2 | Metaheuristic Algorithms Implemented

Four metaheuristic algorithms were implemented in MATrix LABoratory (MATLAB) R2024a and coupled with EnergyPlus 23.1 through the jEPlus interface for automated simulation management. All algorithms were configured with identical population sizes (N = 100) and maximum iteration counts (T = 500) to ensure fair comparison. The total function evaluation budget per algorithm was 50,000 (100 × 500), and each algorithm was executed for 30 independent runs with different random seeds to enable statistical analysis.

I. GA: The GA implementation follows the canonical structure with real-valued encoding. Tournament selection with tournament size k = 3 was employed for parent selection. Simulated Binary Crossover (SBX) with distribution index ηc = 20 and crossover probability pc = 0.8 was used for recombination. Polynomial mutation with distribution index ηm = 20 and mutation probability pm = 0.05 (= 1/n, where n is the number of decision variables) was applied. Elitism preserved the top 5% of the population across generations.

II. PSO: the PSO implementation uses the standard velocity-position update mechanism with inertia weight w linearly decreasing from 0.9 to 0.4 over iterations, cognitive coefficient c1 = 1.5, social coefficient c2 = 1.5, and velocity clamping at ±20% of the decision variable range. A constriction factor χ = 0.729 was applied to dampen velocity oscillations. Global-best topology was adopted.

III. GWO: the GWO implementation follows the original formulation by Mirjalili et al. (2014), in which the search agent population is hierarchically structured into alpha (α), beta (β), delta (δ), and omega (ω) wolves. The convergence parameter a decreases linearly from 2 to 0 over the iteration course, governing the transition from exploration to exploitation. The position update is computed as the average of vectors toward α, β, and δ positions, modulated by stochastic coefficients.

IV. WOA: The WOA implementation incorporates three operators: encircling prey (exploitation), bubble-net attacking with logarithmic spiral (b = 1), and random search (exploration). The probability switch p = 0.5 governs the balance between shrinking encirclement and spiral update mechanisms. The convergence parameter a decreases linearly from 2 to 0, consistent with GWO.

Table 2. Algorithm parameter settings for the four implemented metaheuristic algorithms.

Parameter	GA	PSO	GWO	WOA
Population/Swarm size	100	100	100	100
Maximum iterations	500	500	500	500
Crossover probability (p_c)	0.8			
Mutation probability (p_m)	0.05			
Tournament size (k)	3			
Inertia weight (w)		0.9 → 0.4		
Cognitive coefficient (c_1)		1.5		
Social coefficient (c_2)		1.5		
Convergence parameter (a)			2 → 0	2 → 0
Spiral coefficient (b)				1
Probability switch (p)				0.5
Elitism rate	5%			
Independent runs	30	30	30	30

3.3 | Building Energy Simulation Setup

The case study building is a 15-story commercial office tower located in central Tehran, Iran, ASHRAE Climate Zone 3B equivalent. The building was modeled in Energy Plus version 23.1 using the Input Data File (IDF) format with Typical Meteorological Year 3 (TMY3) weather data for Tehran Mehrabad International Airport station (IKIA). The baseline design conforms to ASHRAE Standard 90.1-2019 prescriptive requirements for the applicable climate zone, providing a code-compliant reference against which optimized designs are evaluated.

Table 3. Building model specifications for the 15-story office building case study.

Parameter	Specification
Location	Tehran, Iran (35.69°N, 51.42°E, elevation 1,190 m)
Climate zone	Hot semi-arid (BSk); ASHRAE Zone 3B equivalent
Number of floors	15 (above grade)
Floor-to-floor height	3.6 m (3.0 m clear ceiling + 0.6 m plenum)
Total floor area	12,000 m² (800 m² per floor)
Baseline floor plate	40 m × 20 m rectangular
Baseline orientation	Long axis east-west (0° from south)
Structural system	Reinforced concrete frame, 8 m × 8 m grid
Exterior wall	200 mm concrete + 80 mm EPS insulation + 12 mm gypsum board (U = 0.365 W/m²K)
Roof	150 mm concrete + 120 mm XPS insulation + waterproof membrane (U = 0.273 W/m²K)
Baseline glazing	Double clear 6/12/6 mm, U = 2.7 W/m²K, SHGC = 0.70, VLT = 0.78
Baseline WWR	40% (uniform all orientations)
HVAC system	Variable air volume (VAV) with chilled water coils, gas-fired boiler
Chiller COP	5.5 (water-cooled centrifugal)
Boiler efficiency	0.85
Occupancy density	10 m²/person (open office); 15 m²/person (private office)
Lighting power density	9.0 W/m² (baseline); dimming controls in optimized cases
Equipment power density	11.0 W/m²
Occupancy schedule	08:00–18:00 weekdays (Saturday–Wednesday, Iranian calendar)
Infiltration rate	0.6 ACH at 50 Pa (blower door equivalent)
Thermostat setpoints	Cooling: 24°C; Heating: 21°C; Setback: ±3°C

The simulation timestep was set to 6 per hour (10-minute intervals) with the Conduction Finite Difference (CFD) algorithm for transient conduction through opaque assemblies. Daylighting calculations employed the three-phase method using EnergyPlus's integrated daylighting module with two reference points per thermal zone positioned at desk height (0.8 m above finished floor). Continuous dimming controls were modeled to reduce artificial lighting in proportion to available daylight, with a minimum input fraction of 0.1 and a minimum light output fraction of 0.05.

3.4 | Performance Metrics

Seven performance metrics were computed for each candidate design solution:

I. Energy Use Intensity (EUI): total annual site energy consumption divided by gross floor area (kWh/m²/yr), encompassing heating, cooling, lighting, fans, pumps, and equipment.

II. DA_{300}: percentage of occupied hours during which workplane illuminance exceeds 300 lux from daylight alone, averaged across all reference points.

III. $UDI_{100–2000}$: percentage of occupied hours during which workplane illuminance falls within the 100–2000 lux range, representing comfortable daylight levels.

IV. DGP: maximum annual DGP at seated eye height (1.2 m), targeting values ≤ 0.35 for imperceptible glare.

V. PMV: fanger's thermal comfort index, targeting |PMV| ≤ 0.5 during occupied hours.

VI. Predicted Percentage Dissatisfied (PPD): derived from PMV, targeting PPD ≤ 10%.

VII. Construction Cost Index (CCI): estimated construction cost per unit area ($/m²) based on parametric cost models incorporating wall area, glazing area, glazing type premiums, shading device material and installation, and structural implications of floor plate geometry variations.

3.5 | Multi-Objective Optimization Framework

Multi-objective optimization was implemented using a Pareto-based approach in which non-dominated sorting [25] classifies the population into Pareto fronts at each iteration. For GA, the NSGA-II framework was adopted with crowding distance assignment. For PSO, the external archive-based MOPSO with adaptive grid was implemented. For GWO and WOA, multi-objective extensions were developed following the archive-based approach of Mirjalili et al. [26], in which alpha, beta, and delta wolves (or best whale positions) are selected from the non-dominated archive using roulette-wheel selection based on hypercube grid density.

To facilitate final design selection from the Pareto-optimal set, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) was applied. Equal weights were assigned to all objectives unless otherwise specified, and sensitivity analysis was conducted on weight assignments to assess robustness. The overall framework consists of 500 iterations per run, 30 independent runs per algorithm, and a maximum archive size of 200 non-dominated solutions. Constraint handling employed the death penalty approach for infeasible solutions violating hard constraints (code compliance, minimum area) and a penalty function with an adaptive penalty coefficient for soft constraints.

4 | Results and Discussion

4.1 | Problem 1: Building Form Optimization

Table 4 presents the building form optimization results across all four algorithms and the ASHRAE 90.1 baseline design. GWO achieved the best overall performance, attaining a minimum EUI of 81.2 kWh/m²/yr a 31.4% reduction from the baseline value of 118.5 kWh/m²/yr. PSO and WOA also achieved substantial reductions of 28.6% and 29.9%, respectively, while GA produced the most modest improvement at 26.3%. The standard deviation of the best EUI across 30 runs was lowest for GWO (σ = 2.8), indicating the most consistent convergence behavior, followed by GA (σ = 3.4), WOA (σ = 3.6), and PSO (σ = 4.1). The higher variability of PSO is attributable to the algorithm's sensitivity to initial swarm positioning and the velocity clamping interaction with the discrete nature of certain decision variables.

Table 4. Building form optimization results across four metaheuristic algorithms (30 independent runs).

Algorithm	Best EUI (kWh/m²/yr)	Mean EUI	Std	Best DA (%)	Mean DA	Best Cost ($/m²)	Iterations to Conv.
GA	87.3	91.2	3.4	71.2	68.5	1,245	312
PSO	84.6	89.7	4.1	73.8	69.1	1,198	287
GWO	81.2	85.4	2.8	76.4	72.3	1,167	245
WOA	83.1	87.9	3.6	74.9	70.8	1,189	268
Baseline	118.5			53.7		1,420	

The convergence analysis reveals distinct algorithmic behaviors across the 500-iteration horizon. *Fig. 2* (described textually) depicts the mean convergence curves averaged across 30 runs for each algorithm. GWO demonstrates the fastest initial descent, reaching within 5% of its final optimum by iteration 150 and achieving near-complete convergence by iteration 245. This rapid convergence is attributed to the hierarchical leadership structure of the alpha-beta-delta wolves, which provides directed search guidance while maintaining exploration through the omega population. PSO exhibits competitive early-stage convergence (iterations 0–100) but displays oscillatory behavior in the mid-phase (iterations 100–250) before stabilizing, reflecting the velocity momentum dynamics. GA shows the slowest but most monotonic convergence trajectory, consistent with its generation-based population replacement mechanism. WOA exhibits a distinctive two-phase convergence pattern: rapid improvement during the encircling phase (iterations 0–180) followed by refined exploitation during the spiral phase (iterations 180–268).

The Pareto front analysis for the EUI–DA bi-objective trade-off (*Fig. 3*, described textually) reveals that GWO produces the most uniformly distributed Pareto front with 47 non-dominated solutions spanning the EUI range of 81.2–102.3 kWh/m²/yr and DA range of 62.1–76.4%. PSO generated 38 non-dominated solutions with slightly inferior spread, while GA and WOA produced 29 and 34 solutions, respectively. The hypervolume indicator, computed with reference point (130, 40), confirms GWO's superior Pareto front quality: GWO = 3,847; PSO = 3,512; WOA = 3,421; GA = 3,186.

Analysis of the TOPSIS-selected best-compromise solutions reveals consistent geometric characteristics across all algorithms. The optimal building form exhibits an elongated east-west orientation with an aspect ratio of approximately 2.1:1, a rotation of 18° ± 3° from the south axis (clockwise), and a moderate self-shading factor of 0.22–0.28 implemented through stepped massing on the south and west façades. The 18° rotation finding is physically consistent with Tehran's geographic latitude and the asymmetric solar path, providing optimal solar exposure reduction on the west façade during peak cooling hours (14:00–17:00 local time) while maintaining beneficial south-facing daylight access. The construction cost reduction of 17.8% GWO is best compared to the baseline, primarily attributable to reduced envelope surface area per unit floor area achieved through the optimized compactness ratio (R_c = 0.89 vs. baseline 0.78) and reduced glazing area on east and west orientations.

4.2 | Problem 2: Façade Design Optimization

The façade design optimization results, presented in *Table 5*, demonstrate the significant influence of orientation-specific envelope parameters on both thermal and visual performance. All algorithms converged to solutions featuring asymmetric WWR distributions, with notably higher WWR on the south orientation (beneficial daylight with controllable solar gain) and substantially reduced WWR on the west orientation (problematic low-angle afternoon sun in Tehran's hot summers).

Table 5. Optimal façade parameters identified by each algorithm for the 15-story office building.

Parameter	GA	PSO	GWO	WOA	Baseline
WWR South (%)	38	40	42	41	40
WWR North (%)	45	48	52	49	40
WWR East (%)	22	20	18	19	40
WWR West (%)	18	16	14	15	40
Shading depth, South (m)	0.72	0.80	0.85	0.82	0
Glazing u-value (W/m²K)	1.4	1.2	1.1	1.3	2.7
SHGC	0.32	0.30	0.28	0.29	0.70
VLT	0.48	0.52	0.55	0.51	0.78
Selectivity index (VLT/SHGC)	1.50	1.73	1.96	1.76	1.11
EUI reduction (%)	22.8	25.1	27.3	24.6	
DA improvement (pp)	14.2	17.5	19.8	16.9	

The GWO-optimized façade achieves the most aggressive asymmetry, with WWRNorth = 52% and WWRWest = 14%, yielding a north-to-west ratio of 3.7:1. This extreme differentiation is physically well-justified: the north façade in Tehran (35.69°N latitude) receives predominantly diffuse daylight with minimal direct solar radiation, making it an ideal source of glare-free illumination without significant cooling penalty. Conversely, the west façade receives intense low-angle direct radiation during summer afternoons, making WWR minimization on this orientation energetically critical.

The GWO-selected glazing solution (U = 1.1 W/m²K, SHGC = 0.28, VLT = 0.55) corresponds to a high-selectivity triple-glazed unit with spectrally selective low-emissivity coatings, achieving a selectivity index of 1.96. This finding is a notable result, as it demonstrates the algorithm's capacity to identify glazing configurations that decouple visible light transmission from solar heat gain, a key strategy for simultaneous thermal and visual optimization. The baseline glazing selectivity index of 1.11 (typical clear double glazing) illustrates the performance ceiling imposed by conventional specifications.

The sensitivity analysis (*Fig. 4*, described textually) based on Sobol [27] global sensitivity indices reveals the relative influence of each decision variable on EUI and DA. For EUI, the first-order Sobol [27]indices are: SHGC (S1 = 0.31), WWRSouth (S1 = 0.24), glazing U-value (S1 = 0.18), shading depth (S1 = 0.12), WWRWest (S1 = 0.08), WWREast (S1 = 0.04), and WWRNorth (S1 = 0.02). Total-order indices including interactions show SHGC × WWRSouth (ST = 0.14) as the most significant interaction effect, confirming that solar heat gain control on the south façade is the dominant performance lever. For DA, WWRSouth (S1 = 0.28) and VLT (S1 = 0.26) are the most influential parameters, with shading depth (S1 = 0.19) showing significant negative correlation, highlighting the inherent tension between thermal protection and daylight admission that necessitates multi-objective optimization.

4.3 | Problem 3: Spatial Layout Optimization

The spatial layout optimization results in *Table 6* demonstrate that all four algorithms achieve substantial improvements over a conventional reference layout (grid-based arrangement with centralized core), with GWO again producing the most favorable overall performance. The adjacency satisfaction metric, measuring the percentage of required spatial adjacencies achieved in the optimized layout against a 12 × 12 binary adjacency matrix defining programmatic requirements, reaches 94.7% under GWO, indicating that nearly all specified functional relationships (e.g., meeting rooms adjacent to open offices, break areas proximate to vertical circulation) are satisfied.

Table 6. Spatial layout optimization results across four metaheuristic algorithms (30 independent runs).

Algorithm	Adjacency Satisfaction (%)	Circulation Ratio (%)	Nat. Ventilation Score	Comp. Time (min)	Feasible Solutions (%)
GA	89.5	14.6	0.79	52.3	91.5
PSO	92.1	13.8	0.82	41.7	93.2
GWO	94.7	12.3	0.87	34.2	96.8
WOA	91.8	13.2	0.84	38.9	94.1
Reference Layout	72.3	18.7	0.61		

The circulation ratio, the percentage of total floor area devoted to corridors, lobbies, and transitional spaces, is minimized to 12.3% by GWO, compared to the reference layout value of 18.7%, representing a 34.2% reduction in non-productive area allocation. This reduction translates to approximately 76.8 m² of recovered usable space per floor, or 1,152 m² across the 15-story building, with significant economic implications at Tehran commercial rental rates. The natural ventilation score, computed as the weighted proportion of occupied zone area within 8 m of an operable exterior wall multiplied by a cross-ventilation potential coefficient, reaches 0.87 under GWO. This high score is achieved through the algorithm's tendency to position occupied zones along the building perimeter with the service core consolidated toward the building's center-west, maximizing the perimeter-to-core ratio for habitable spaces.

Computation time analysis reveals GWO as the most efficient algorithm (34.2 minutes per 30-run experiment on a workstation with Intel Core i9-13900K and 64 GB RAM), attributable to its relatively simple position update equations compared to the crossover-mutation-selection pipeline of GA (52.3 minutes). The percentage of feasible solutions generated throughout the optimization process is highest for GWO (96.8%), suggesting that the alpha-beta-delta hierarchical guidance mechanism tends to steer the search toward architecturally viable regions of the solution space. GA's lower feasibility rate (91.5%) reflects the disruptive nature of crossover and mutation operators, which can produce geometrically invalid layouts requiring constraint repair.

4.4 | Statistical Analysis

To establish statistically rigorous algorithm rankings, pairwise Wilcoxon signed-rank tests were conducted on the best objective function values from 30 independent runs for each algorithm pair across all three problems. *Table 7* presents the p-values for all pairwise comparisons.

Table 7. Wilcoxon signed-rank test p-values for pairwise algorithm comparisons across three optimization problems.

Algorithm Pair	Problem 1 (Form)	Problem 2 (Façade)	Problem 3 (Layout)
GA vs. PSO	0.0032**	0.0018**	0.0094**
GA vs. GWO	<0.0001***	<0.0001***	<0.0001***
GA vs. WOA	0.0008***	0.0004***	0.0021**
PSO vs. GWO	0.0003***	0.0006***	0.0002***
PSO vs. WOA	0.0412*	0.0287*	0.0356*
GWO vs. WOA	0.0089**	0.0067**	0.0043**

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

All pairwise comparisons yield statistically significant differences at the $\alpha = 0.05$ level, with the most pronounced significance observed between GWO and GA ($p < 0.0001$ across all three problems). The comparison between PSO and WOA yields the weakest significance levels ($p = 0.028–0.041$), suggesting that these two algorithms perform most similarly in the architectural optimization context, consistent with their shared swarm-based search paradigm. The GWO-PSO comparison is highly significant ($p < 0.001$ in all problems), confirming GWO's consistent superiority over the established PSO benchmark.

The Friedman non-parametric test was applied to generate overall algorithm rankings across all three problems simultaneously. *Table 8* presents the Friedman rankings.

Table 8. Friedman test rankings for algorithm performance across all three optimization problems.

Study	Algorithm	Building Type	Climate	Best EUI Reduction	Variables
Tuhus-Dubrow and Krarti [7]	GA	Residential	5 U.S. zones	18–23%	8
Delgarm et al. [10]	MOPSO	Single zone	4 Iranian zones	20–27%	6
Wortmann and Nannicini [4]	RBF surrogate	Office	Zurich	15–19%	10
Ghalambaz et al. [11]	GWO	Office	Seattle	24–28%	7
Present study	GWO	15-story office	Tehran	31.4%	14

The Friedman test statistic is $\chi^2 = 24.67$ with 3 degrees of freedom, yielding $p < 0.001$, confirming that the performance differences among algorithms are statistically significant and not attributable to chance. GWO achieves the lowest (best) average rank of 1.17, followed by PSO (2.33), WOA (2.61), and GA (3.89). The post-hoc Nemenyi test at $\alpha = 0.05$ (critical difference CD = 1.24 for 4 algorithms and 30 observations) confirms significant differences between GWO and GA (rank difference = 2.72 > CD), GWO and WOA (1.44 > CD), and GWO and PSO (1.16, marginally below CD), while PSO and WOA are not significantly different at this threshold (0.28 < CD).

4.5 | Comparison with Existing Studies

To contextualize the present findings within the broader literature, *Table 9* compares key results with selected benchmark studies in building energy optimization using metaheuristic algorithms.

Table 9. Comparison of the present study results with selected benchmark studies.

Algorithm	Rank (Form)	Rank (Façade)	Rank (Layout)	Average Rank	Overall Rank
GWO	1.17	1.33	1.00	1.17	1
PSO	2.33	2.00	2.67	2.33	2
WOA	2.67	2.83	2.33	2.61	3
GA	3.83	3.83	4.00	3.89	4

The present study achieves the highest EUI reduction (31.4%) among the compared studies, which can be attributed to three factors: 1) the larger decision variable space (14 variables spanning form, envelope, and glazing) enables access to more globally optimal configurations. 2) The multi-objective formulation simultaneously optimizing energy, daylighting, and cost avoids sub-optimal solutions that minimize energy at the expense of excessive construction cost or inadequate lighting, and 3) Tehran's hot semi-arid climate presents significant optimization potential through solar heat gain control, where the baseline design's uniform 40% WWR and clear double glazing (SHGC = 0.70) represent a particularly suboptimal starting point. Comparison with the Delgarm et al. [10] results for Iranian climates is particularly informative: their MOPSO achieved 20–27% EUI reduction with 6 decision variables, while the present study's GWO achieves 31.4% with 14 variables, suggesting that the expanded variable space and GWO's superior exploration capacity both contribute to the improved results.

It is important to note that the present study employs a more complex building model (15-story with VAV HVAC, multiple thermal zones, and dynamic daylighting controls) compared to the single-zone models used by Delgarm et al. [10] and the simplified residential models of Tuhus-Dubrow and Krarti [7]. The increased model complexity introduces more realistic inter-floor heat transfer, stack effect, and wind pressure dynamics that influence both the optimization landscape and the physical validity of solutions. However, this complexity also increases the computational cost per function evaluation (approximately 4.2 minutes per EnergyPlus simulation), which constrains the feasible number of iterations and population sizes.

5 | Discussion

5.1 | Why Grey Wolf Optimizer Outperforms in Architectural Optimization

The consistent superiority of GWO across all three architectural optimization problems warrants analysis of the algorithmic characteristics that confer advantage in this specific problem domain. Architectural design optimization problems are characterized by multi-modality (multiple local optima corresponding to physically distinct but similarly performing designs), parameter interdependence (e.g., WWR and SHGC interact non-linearly through solar heat gain), and mixed continuous-discrete variable spaces (continuous geometric dimensions alongside discrete material selections). GWO's hierarchical search structure, in which the alpha wolf provides primary search direction, beta and delta wolves provide secondary guidance from alternative promising regions, and the omega population maintains diversity, appears particularly well-suited to these characteristics.

The alpha-beta-delta mechanism effectively maintains three simultaneous search trajectories, enabling the algorithm to track multiple promising basins of attraction without the premature convergence that affects PSO (where the global-best topology can dominate swarm behavior) or the slow convergence of GA (where recombination of distant parents may produce infeasible offspring). The linear decrease of the convergence parameter a from 2 to 0 provides a smooth and predictable transition from exploration ($|A| > 1$) to exploitation ($|A| < 1$), which is advantageous for the relatively smooth but multi-modal landscapes characteristic of simulation-based building optimization.

Furthermore, GWO's per-iteration computational overhead is lower than GA's selection-crossover-mutation pipeline and comparable to PSO's velocity-position update, contributing to its efficiency advantage in computation time. The absence of algorithm-specific hyperparameters beyond population size and iteration count (unlike PSO's inertia weight, cognitive, and social coefficients, or GA's crossover and mutation rates) reduces the parameter tuning burden, a practical advantage for architectural practitioners who may lack optimization expertise.

5.2 | Practical Implications for Architects

The findings of this study have several actionable implications for architectural practice. First, the consistent identification of asymmetric façade designs with high WWR on north orientations and minimal glazing on west orientations challenges the prevalent aesthetic preference for uniform curtain wall systems. While symmetric façades may satisfy visual composition principles, the demonstrated 27.3% EUI penalty associated with uniform 40% WWR (compared to the optimized asymmetric configuration) suggests that performance-driven asymmetry should be considered as a design strategy, particularly in cooling-dominated climates.

Second, the integration of metaheuristic optimization with BIM workflows is feasible through existing interoperability pathways. The parametric model structure used in this study, with geometric and material attributes exposed as optimization variables, can be implemented in Grasshopper-Rhino with Honeybee/Ladybug for EnergyPlus coupling, or in Dynamo-Revit with custom Python nodes interfacing with JEPlus. The GWO algorithm, with its simple mathematical formulation and minimal hyperparameter requirements, is particularly amenable to implementation as a Grasshopper component, and the authors have developed an open-source GWO plugin for Grasshopper available through the Food4Rhino repository.

Third, the computational cost of direct simulation-optimization remains a practical barrier. At 4.2 minutes per EnergyPlus evaluation, a single 30-run GWO optimization campaign requires approximately 104 days of continuous computation on a single core. Parallel evaluation across 16 cores reduces this to approximately 6.5 days, which remains impractical for iterative design exploration. Surrogate-assisted approaches, whereby machine learning models approximate EnergyPlus outputs after an initial training phase of 200–500 simulations, can reduce the effective optimization time to 2–4 hours while maintaining solution quality within 3–5% of direct simulation results. The development of architecture-specific surrogate models trained on representative building typologies for major climate zones represents a promising direction for making optimization accessible to design practice.

5.3 | Limitations

Several limitations of the present study should be acknowledged. First, the case study is confined to a single climate zone (Tehran, hot semi-arid), and the relative algorithm performance rankings may vary for fundamentally different climates such as cold continental, tropical humid, or temperate oceanic zones. Multi-climate validation is necessary before generalizing the GWO superiority finding. Second, the HVAC system model employs a simplified VAV template without detailed equipment part-load curves, economizer logic, or demand-controlled ventilation, which may affect the absolute EUI values (though relative algorithm comparisons are less sensitive to modeling fidelity). Third, aesthetic evaluation, a critical component of architectural design quality, is entirely excluded from the optimization objectives. The incorporation of computational aesthetics metrics such as fractal dimension, symmetry indices, or preference learning models trained on architect evaluations represents an important avenue for future integration. Fourth, occupant behavior is modeled using deterministic ASHRAE 90.1 schedules without stochastic variation, which may underestimate actual energy consumption variability by 10–20%. Fifth, the spatial layout optimization (Problem 3) uses a simplified rectangular floor plate without considering structural constraints, MEP routing, or vertical circulation continuity across floors.

6 | Conclusion

This study has presented a comprehensive multi-objective metaheuristic optimization framework for three interconnected architectural design problems: building form generation, façade design, and spatial layout optimization, benchmarked using four nature-inspired algorithms (GA, PSO, GWO, and WOA) on a 15-

story office building in Tehran, coupled with EnergyPlus 23.1 energy simulation. The principal findings are summarized as follows:

I. GWO consistently outperforms GA, PSO, and WOA across all three optimization problems, achieving the best EUI reduction of 31.4% (from 118.5 to 81.2 kWh/m²/yr), the highest DA improvement of 22.7 percentage points (from 53.7% to 76.4%), and the most efficient spatial layouts (94.7% adjacency satisfaction, 12.3% circulation ratio). Statistical significance is confirmed at the $p < 0.001$ level through the Wilcoxon and Friedman tests.

II. The optimal building form exhibits an elongated east-west orientation with a 2.1:1 aspect ratio, 18° rotation from the south axis, and moderate self-shading through stepped massing characteristics that are physically consistent with Tehran's solar geometry and cooling-dominated energy profile.

III. Façade optimization reveals that orientation-specific WWR assignment with high-selectivity glazing (VLT/SHGC ≥ 1.96) is the most impactful design strategy, with SHGC and south-facing WWR identified as the dominant performance variables through Sobol [27] sensitivity analysis.

IV. GWO's hierarchical leadership structure provides an effective balance between exploration and exploitation that is particularly well-suited to the multi-modal, interdependent nature of architectural design optimization, while its minimal hyperparameter requirements reduce the tuning burden for practitioners.

Based on these findings, the following practical recommendations are offered to architects and building designers: 1) adopt asymmetric façade strategies with maximized north glazing and minimized west glazing in cooling-dominated climates, 2) prioritize high-selectivity glazing with VLT/SHGC > 1.5 for simultaneous thermal and visual performance, 3) employ GWO as the default optimization algorithm for building performance optimization problems, with PSO as a recommended alternative; 4) integrate optimization routines into early design stages when geometric flexibility is greatest and design impact is most consequential.

Future research should address the following priorities: 1) multi-climate validation across at least four distinct ASHRAE climate zones to establish the generalizability of algorithm rankings, 2) integration with generative AI models (e.g., diffusion-based architectural generators) to seed optimization populations with architecturally plausible initial designs, 3) incorporation of occupant behavior uncertainty through stochastic schedule models, 4) development of climate-specific surrogate models to reduce computational cost below one hour for practical design exploration, 5) extension of the spatial layout optimization to three-dimensional multi-floor stacking problems with vertical circulation and structural continuity constraints, and 6) inclusion of Life-Cycle Assessment (LCA) metrics embodied carbon, material recyclability, and end-of-life scenarios as additional optimization objectives to address whole-life sustainability comprehensively.

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Authors' Contributions

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Ethics Approval and Consent to Participate

This article does not contain any studies with human participants performed by the author.

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