Multi-Objective Evolutionary Sunshade Design

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ABSTRACT

Sunshades integrated into building facade design critically influence the building's thermal conditions, natural lighting, energy usage, and occupant comfort. However, heuristic designs often neglect the multi-faceted trade-offs among these objectives. This study compares two multi-objective evolutionary algorithms, NSGA-II and MO-CMA-ES, in optimizing five performance metrics: thermal comfort, *Useful Daylight Illuminance* (UDI), energy consumption, outside view obstruction, and cost. We integrate annual energy and daylight simulations, incorporating real-world weather data from Cape Town, South Africa, and Nairobi, Kenya. Results indicate that both MO-EAs generate Pareto-optimal sunshades exceeding the performance of five traditional designs for all metrics. In cooler climates, the best solutions featured upward-angled fins to admit beneficial solar gain, while warmer climates favored configurations blocking high-angle sunlight. These findings underscore the importance of climate-specific optimization for identifying cost-effective, occupant-friendly building designs to balance daylight management and energy efficiency.

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1 INTRODUCTION

Sunshades are essential in regulating solar gains, glare, and daylight in buildings, yielding lower energy consumption and aligning with ASHRAE[1] 90.1 guidelines [1]. However, traditional shading designs rely on heuristic methods that overlook vital trade-offs across occupant comfort, cost, and exterior views [2]. Evolutionary methods have been applied to numerous architectural applications in what is popularly known as evolutionary design [3]. Such applications include energy consumption optimization for building climate control [4], structural design [5], and floor-plan layout design [6]. With notable exceptions [7, 8], the evolutionary design of optimally shaped building facades is less explored in evolutionary architectural design applications [9]. This is especially the case for multi-objective evolutionary design applied to optimize facade (sunshade) design given competing objectives. For example, multi-objective optimization systematically explores such competing objectives, yet existing methods frequently omit cost or view preservation [10], and advanced methods like NSGA-II [11] and MO-CMA-ES [12] remain unused in automated sunshade design [13].

Traditional sunshade (Figure 1, left) design relies on heuristic methods, where designers iteratively modify overhangs or louvers to reduce solar gain and glare [2]. While suitable for a few objectives, such design approaches lack systematic frameworks for balancing multiple competing objectives associated with modern commercial (office) building design, including energy use, occupant comfort, and outside-view aesthetics. This has resulted in limited design variability and reduced design effectiveness given varying climates [13]. Since effective building design must satisfy competing objectives, such as minimizing material cost and maximizing structural integrity [8], *multi-objective optimization* (MOO) is a suitable approach.

NSGA-II [11] and MO-CMA-ES [12] are well-established evolutionary MOO methods. In building applications, NSGA-II has been applied to effectively balance glare, cooling load, and natural lighting [14]. MO-CMA-ES extends the CMA-ES method to multi-objective problems, adapting covariance matrices to navigate complex, high-dimensional solution landscapes [12]. However, MO-CMA-ES has not been applied to architectural design applications [13], even though the intricate geometry-climate relationships of building facade design (for example, mandating maximal and minimal sunlight in winter versus summer months [15]), makes MO-CMA-ES an ideal evolutionary design method. In terms of sunshade design, MOO uses task-performance objectives such as thermal comfort, daylight, for example, *Useful Daylight Illuminance* (UDI), energy consumption, cost, and view obstruction [16, 17]. This enables architects to suitably weigh priorities and select designs best suited to project constraints [10, 18].

Although some *heating, ventilation, and air conditioning* studies have integrated multiple objectives, few simultaneously address cost, outside views, and occupant comfort in sunshade design [10]. This study applies NSGA-II and MO-CMA-ES to optimize five objectives: thermal comfort, UDI, annual energy use, cost, and outside view, for evolutionary sunshade design across various climate types. Climate data from Cape Town (Mediterranean) and Nairobi (tropical highland) capture seasonal dynamics for a simulated year, integrating ASHRAE considerations [19]. This study's key contribution is an initial demonstration that MOO evolutionary design is a suitable and currently under-used method for generating novel designs that out-perform heuristic designs across multiple objectives [20]. Despite the demonstrated benefits of MOO optimization [10, 13] in architectural design, this is the first application of MOO evolutionary methods to building facade (sunshade) design.

[1]American Society of Heating, Refrigerating, Air-Conditioning Engineers

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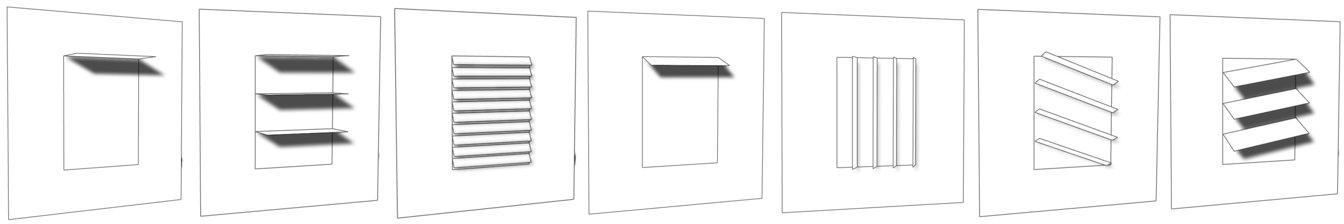

Figure 1: From *far-left:* Traditional heuristically designed window sunshades: Horizontal overhang, overhang with three louvers, sloped 10 fins, steeper sloped overhang, vertical louver with four fins. *Inner-right:* Example evolved sunshade (Cape Town) from final NSGA-II Pareto front, with upward-angled fins to admit winter sun. *Far-right:* Example sunshade (Nairobi) from final MO-CMA-ES Pareto front, featuring downward-angled fins to reduce solar heat gain.

2 METHODS AND EXPERIMENTS

We simulated[2] annual sunlight on a single windowed building facade using parametric simulation packages to model internal building temperatures given varying sunlight [21, 22]. Evolutionary MOO methods (NSGA-II [11], MO-CMA-ES [12]) were applied to adapt sunshade design to satisfy objectives for energy use, comfort, daylight, cost, and view preservation, given varying sunlight for two geographic locations. We simulated office spaces in Cape Town, South Africa, and Nairobi, Kenya, to capture different climates (Mediterranean and tropical highland conditions, respectively). Each office measured 3m x 4m x 3m (width x height x length), with one window (1.3m x 1.7m x 0.2m). Each simulation evolved a fin geometry for [1, 10] fins on the building facade. The computational package *Radiance* [22] computed annual UDI, factoring in solar angles, cloud cover, and shading geometry, given climate data for 2023 Cape Town and Nairobi[2]. The degree of sunlight that permeated through the window was calculated as a percentage of the maximum. The *EnergyPlus* package [21] was applied to compute annual heating and cooling loads based on hourly temperature and humidity, and cost was calculated as total sunshade volume.

An experiment comprised applying NSGA-II or MO-CMA-ES for multi-objective sunshade design. Evolutionary design varied the number of fins, angle, depth, offset, and contour angle of sunshade manifolds, enabling both conservative and aggressive shading strategies. Each experiment initialized a population of randomly generated sunshades within given design constraints: fin numbers, angles, depths, and offsets (Table 1). Each experiment executed 10 runs, where Pareto optimal solutions were selected from all runs. To demonstrate the efficacy of evolved sunshades, we compared NSGA-II and MO-CMA-ES evolved sunshade designs with five traditional sunshade designs [23], presented in Figure 1). Since these designs were fixed, one experiment with a pre-designed sunshade entailed simulating the impact of sunshade on the five metrics: energy use, comfort, daylight, cost, and view preservation, given annual sunlight simulation for a given location.

One run of NSGA-II or MO-CMA-ES comprised 100 generations, with a population of 100 individuals, a 0.1 mutation rate and *elitism and crowding* [11] parent selection (Table 1). Random offspring injection [24] helped sustain population diversity. NSGA-II sorted candidate solutions via non-dominated fronts with crowding to preserve diversity [12]. Offspring were generated via crossover and mutation and combined with parents for elitist selection, ensuring improvement toward the Pareto front. MO-CMA-ES adapted a covariance matrix to capture variable interactions, refining directed search over time. Such elitist and non-dominated sorting methods retain top-performing solutions while promoting exploration [11]. Table 1 presents an overview of simulation and evolutionary design method parameters. NSGA-II and MO-CMA-ES were applied with the following five optimization objectives:

(1) *Minimize energy consumption:* Total heating and cooling loads, reflecting demands for maintaining indoor temperatures under real-world weather data.
(2) *Maximize thermal comfort:* Derived from occupant comfort metrics [19], where under- or over-shading directly affects heating and cooling demands.
(3) *Maximize UDI:* The proportion of occupied hours within a comfortable daylight range [22].
(4) *Maximize outside view preservation:* Unobstructed total area of the window.
(5) *Minimize cost:* Total sunshade volume and thus equivalent material (construction) cost.

3 RESULTS AND DISCUSSION

Figure 2 presents results for NSGA-II and MO-CMA-ES with respect to the task-performance metrics: First: UDI, where higher values are desired in building design, second: thermal discomfort, given as the percentage of office hours outside comfort thresholds where lower is more desirable for building occupants, third: view obstruction, defined as the percentage of the window area covered by designed sunshades, where lower coverages are desirable, fourth: cost, indicating sunshade manufacturing cost, and fifth: energy consumption, indicating heating and cooling energy loads given varying degrees of sunlight blocked by evolved sunshades.

For ease of comparison, all metrics have been normalized, and the Kruskal–Wallis test with Bonferroni correction [25] ($p<.05$), applied to comparative result sets. Specifically, comparisons between NSGA-II and MO-CMA-ES, and between each MOO method and pre-designed sunshades (Figure 1), with respect to the five task-performance objectives. In Figure 2, the task performance of the best performing (of the five) heuristically designed sunshades is presented as a red diamond per geographic location. Figure 1 (right) presents examples of Pareto optimal sunshades evolved by NSGA-II and MO-CMA-ES for simulated office building spaces in Cape Town

[2] https://anonymous.4open.science/r/SunShadeOptimization/

Table 1: Simulation and Experiment Parameters

	Simulation Environment
Locations	Cape Town (South Africa), Nairobi (Kenya)
Office dimensions	Width: 3m, Height: 4m, Length: 3m
Window dimensions	Width: 1.3m, Height: 1.7m, Depth: 0.2m
Simulated timeline	1 year
Number of runs	10
Fins on facade	[1, 10], increments of 1
Fin Angle	[0, 90] Degrees, increments of 5
Fin Depth	[0.05, 0.5] Meters, increments of 0.05
Fin Offset	[0.01, 0.1] Meters, increments of 0.01
Fin contour angle	[0, 360] Degrees, increments of 5
	Evolutionary Design Settings
MOO Methods	NSGA-II, MO-CMA-ES
Generations	100
Population size	100
Offspring Generation	Random injection [24]
Mutation rate	0.1
Parent selection	Elitism, Crowding [11]
	Task Performance Objectives (Metrics)
Energy consumption	Annual heating, cooling (EnergyPlus [21])
Thermal comfort	Occupant discomfort (EnergyPlus [21])
UDI	Aggregated UDI metrics [17]
Preserved view	Window area (%) unobstructed by sunshade
Cost	Sunshade volume (As portion of: $0.4m^3$)

and Nairobi. One may observe these Pareto optimal evolved designs are variations on the established, traditional, sunshade designs, with similar configurations of fin numbers and angles.

Statistical tests ($p<0.05$) indicate NSGA-II and MO-CMA-ES achieved significantly improved values for all objectives (except view obstruction) compared to traditional designs. Superior UDI results support the efficacy of evolutionary design for determining suitable fin angles and dimensions for balanced daylight provision, compared to the best of the heuristic designs, which tended to over-shade or under-shade. Similarly, thermal discomfort results (Figure 2, second from top), measured as a percentage of hours outside comfort thresholds (Table 1), indicated both MOO method designs significantly out-performed the effectiveness of traditional sunshades. Specifically, in Cape Town, cooler ambient conditions made shading less important but favored upward-angled fins that captured winter sun, whereas in Nairobi, evolved designs blocked high-angle solar rays to reduce cooling loads.

This supports the benefits of an evolved design that is adapted to the climate (sunlight) conditions across various locations. However, outside view obstruction results (Figure 2, middle), indicate that the best heuristic design used significantly less window coverage compared to NSGA-II and MO-CMA-ES evolved designs. Though this supports the importance of multi-objective evolutionary design since the traditional sunshades (Figure 1) were designed to be minimally obstructive [23], and the best heuristic designs performed relatively poorly on the UDI, thermal discomfort, view obstruction, and energy consumption objectives. That is, evolved designs balanced moderate obstruction with high daylight and comfort benefits, whereas heuristic designs favored open views at the expense of thermal or lighting efficiency (Figure 2). Similarly, since traditional sunshades are designed to be minimally obstructive they also have a low material volume (cost, Table 1), whereas evolved designs concurrently satisfied all objectives and as such a higher sunshade volume (cost) of ≈30% across Pareto optimal designs was an acceptable trade-off (Figure 2).

In terms of energy consumption results, NSGA-II and MO-CMA-ES evolved designs yielded a significantly lower energy consumption (for heating and cooling the office space in winter and summer months) in the tropical highland climate of Nairobi. Whereas, in a cooler Mediterranean climate (Cape Town), evolved designs yielded comparable (MO-CMA-ES) or less energy efficiency (NSGA-II) compared to traditional sunshade designs. This is a result of evolved trade-offs given competing multi-objective optimization, but is also likely due to the relatively higher levels of annual sunshine in Cape Town versus Nairobi (Figure 2, bottom).

However, for all objectives, per geographic location, there was no significant difference between NSGA-II and MO-CMA-ES evolved designs, indicating that both MOO methods were suitable for this evolutionary design task, given the five design objectives (Table 1) and the varying environments (geographic climate simulations). Though importantly, per location for all objectives, except for sunshade volume (cost), MOO evolutionary design significantly out-performed the task-performance of the heuristically designed traditional sunshades, supporting further work using evolutionary design and MOO optimization to satisfactorily address the many competing design objectives and constraints associated with building design [10, 13].

4 CONCLUSION

This study demonstrated the efficacy of evolutionary multi-objective optimization (MOO) methods (NSGA-II and MO-CMA-ES) applied to building facade (sunshade) design and optimization, compared to various manually designed sunshades. This efficacy was demonstrated for simulated building office spaces (and facades) in two geographic locations (climates) and for five task performance objectives: thermal comfort, UDI, energy consumption, cost, and view obstruction. Results indicated that the evolutionary MOO methods produced Pareto optimal designs that significantly out-performed the pre-designed sunshades, per location, for four objectives. This suggests that MOO evolutionary design is an excellent yet under-utilized automated design method for generating and optimizing future architectural designs that must conform to many design objectives and constraints in green building construction across changing and diverse climates.

Ongoing work is evaluating NSGA-II, MO-CMA-ES and other MOO evolutionary design methods on a broad range of locations (climate conditions) to ascertain core sets of design features that could be applied as the basis of evolutionary MOO design and optimization of green buildings for diverse climates [26]. Future work also aims to apply multi-objective evolutionary design methods to examine the robustness of automated building design and construction [27] given regional climate data [28].

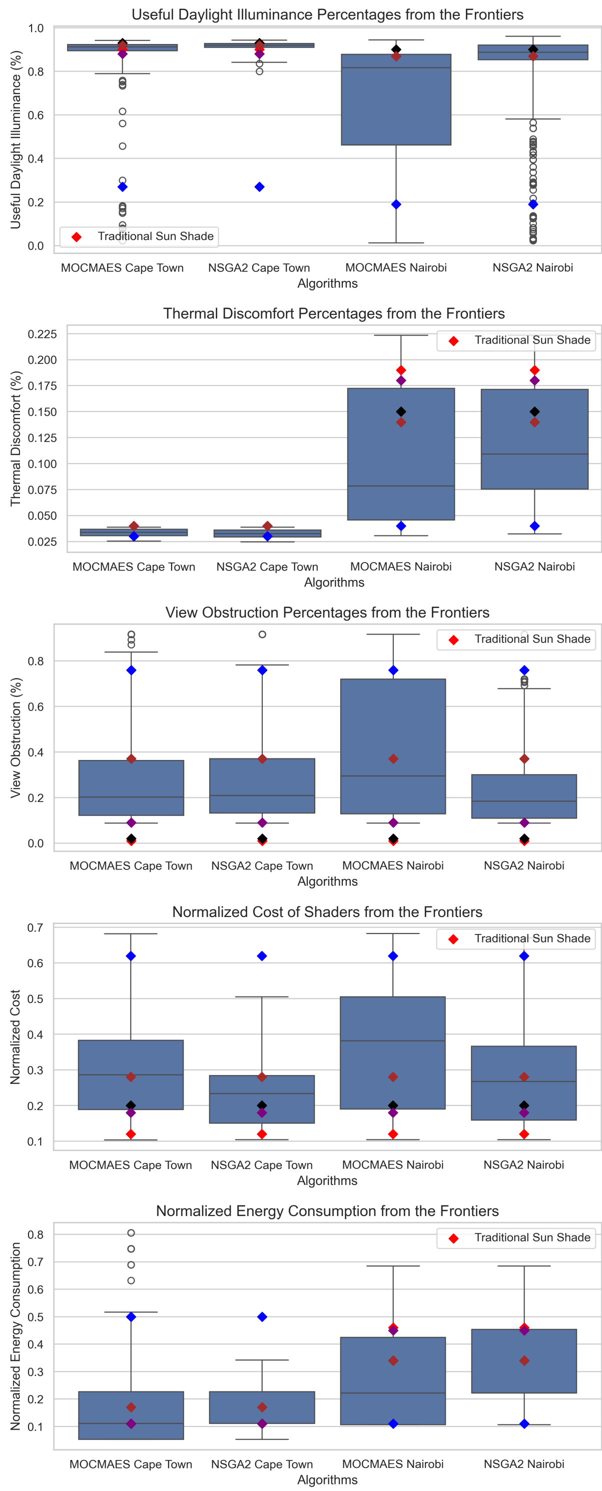

Figure 2: Box-plots showing the five performance metrics from the evolutionary and traditional sunshade designs (best selected from simulation of all five). Top: UDI, where higher values are better. Thermal Discomfort: Percentage of office hours outside comfort thresholds (lower is desired). View Obstruction: Percentage of window area covered (lower is better). Cost: Total volume of the sunshade, normalized given maximum feasible sunshade volume (low volume, thus cost is desired). Bottom: Energy Consumption, defined as office space heating and cooling loads (low energy is desired).

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