Comparison Between Popular Genetic Algorithm (GA)-Based Tool and Covariance Matrix Adaptation - Evolutionary Strategy (CMA-ES) for Optimizing Indoor Daylight

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Abstract

To maximize indoor daylight, design projects commonly use commercial optimization tools to determine optimum window configurations. However, experiments show that such tools either grossly suboptimal or are very slow to compute in certain conditions.

This paper presents an empirical comparison between a gradient-free optimization technique, Covariance Matrix Adaptation Evolution Strategy (CMA-ES), and the widely used Genetic Algorithm (GA)-based tool, Galapagos, for optimizing window parameters to improve indoor daylight. Results are reported for six locations across different latitudes. A novel combination of daylight metrics, sDA, and ASE, is proposed for single-objective optimization comparison. Results indicate that GA in Galapagos takes progressively more time to converge, from 11 minutes in southernmost to 11 hours in northernmost latitudes, while runtime for CMA-ES is consistently around 2 hours. On average, CMA-ES is 1.5 times faster than Galapagos, while consistently finding optimal solutions. The conclusions from this paper can help researchers in selecting appropriate optimization algorithms for daylight simulation based on latitudes, desired runtime, and desired solution quality.

Key innovations

- This paper demostrates the benefits from using CMA-ES over the commonly used GA-based tool, Galapagos, for daylight optimization.
- The paper proposes a novel combination of the daylight metrics, sDA and ASE, into a single objective such that the optimum value corresponds to sDA=100%; ASE = 0%.
- Results suggest that CMA-ES consistently converges to optimal solutions, unlike Galapagos.
- Experimental results for six states in the USA suggest that, for southern latitudes, Galapagos provides faster runtime, however, as latitudes rise toward the north, CMA-ES is relatively faster.
- CMA-ES runtime is consistent in finding the optimal solution on all six locations, unlike Galapagos.

Practical implications

Use CMA-ES optimization for more reliable results regarding shading design and consistent optimization time.

Use Galapagos optimization for faster results in lower latitudes where shading significantly influences daylight control.

Introduction

Daylight is a critical parameter to address in building envelope design. Daylight consideration in architecture is known to improve comfort, health, and productivity. In the works of Hwang and Kim (2011), and Baker and Steemers (2014), daylight has been shown to improve occupant health, comfort, and satisfaction. However, with increased daylight availability through glazing surfaces comes an increased risk of visual discomfort through glare. There is an extensive body of literature that investigated the relationship between daylight and glare (Nabil and Mardaljevic, 2006; Araji and Boubekri, 2008) using a wide array of daylight and glare metrics. In addition to daylight access, glare control for windows in the form of horizontal and vertical shading devices, therefore, are crucial design elements that need to be incorporated to obstruct disturbing levels of glare (Chan and Tzempelikos, 2013; Yun, Yoon, and Kim, 2014). This balance between daylight and glare is further encouraged in building design through the Daylight credit category under the LEED v4 rating system (USGBC, 2014). Daylight and proxy glare calculations for LEED v4 credit require the use of daylight metrics such as Spatial Daylight Autonomy (sDA) and Annual Sunlight Exposure (ASE), which are essentially a time series of illuminances over a year. Dynamic metrics such as these allow performance measurements based on daily and seasonal variations for a specific location. However, the total time required to try out all possible design variable options scales exponentially with additional design variables.

With the recent advancements in the fields of artificial intelligence researchers in the building industry have begun to incorporate artificial intelligence in various settings. One such application is to reduce the time required for simulation for exploring different room configurations during the design phase by using optimization techniques (Nguyen, Reiter, and Rigo, 2014).

Several algorithms exist to solve a wide variety of optimization problems in building design, each with its strengths and limitations, the most robust of which is considered to be evolutionary or stochastic algorithms, and in particular, Genetic Algorithms (GA) (Goldberg, 1989). In architecture, GAs are being widely used in

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recent years by architects and designers with the creation of Galapagos (Rutten, 2013), a user-friendly evolutionary solver plugin in Grasshopper. Despite its extensive application, Galapagos suffers from some limitations, in particular regarding inconsistent runtime and the nature of the optimal solution it generates, as will be shown in the following section.

This paper investigates a gradient-free optimization technique called "Covariance Matrix Adaptation Evolution Strategy" (CMA-ES) for daylight optimization. Specifically, the goal of the paper is to present a comparative analysis between CMA-ES and the GA-based tool Galapagos, henceforth referred to as simply Galapagos, with respect to three parameters namely, average run time, solution quality, and consistency in runtimes. The paper also investigates if a correlation exists between optimizer runtime and solution quality with the test location for each optimizer. For comparison, the paper selects six locations spanning different latitudes. The locations include a variety of solar incident angles creating different annual daylight conditions in order to optimize a test geometry to improve daylight and minimize glare in compliance with LEED v4. Additionally, the study proposes a novel way to combine multiple objective functions, in this case, sDA (Spatial Daylight Autonomy) and ASE (Annual Sunlight Exposure), into a single objective since both the algorithms being compared require a single objective. This study will help architects and researchers in choosing a better optimization technique based on the location being considered.

Background

In the last decade, several studies in the field of architecture have applied various optimization methods to optimize building systems and envelopes in order to maximize indoor daylight and minimize energy consumption and glare, thereby improving indoor comfort conditions for occupants. Optimization problems essentially are formulated to discover 'the best result under the circumstances' (Venkataraman, 2009). This is done by minimizing or maximizing a function, called the 'objective function' subject to a set of constraints. The search for an optimal design also requires a set of 'input variables', the values of which can change over a specified range. Input variables, thus, characterize a specific design.

Among the commonly used optimization methods (Goldberg, 1989), Genetic Algorithms (GA) are based on biological processes, inspired by natural evolution, and are frequently used in architecture to optimize building performance (Nguyen, Reiter, and Rigo, 2014; Machairas, Tsangrassoulis, and Axarli, 2014; Wortmann et al., 2017). As a ' "classic" metaheuristic algorithm,' GA initially begins the search with a number of random individuals as the 'first generation' of solutions, the performance of which is evaluated based on the objective function. If this objective value is not met in a generation, GA utilizes crossover, mutation, and selection to create successive generations (Murray-Smith, 2012, Wortmann et al., 2017, Kheiri, 2021). Once the objective function is met, the optimization stops.

GA has been extensively used in building optimization since the late 1990s, with more than 80% of these studies focused on optimizing building systems and envelopes (Li, Shao, Zuo, and Huang, 2017). Gagne and Andersen (2012) proposed a GA-based tool to find the optimum façade configurations for illuminance and glare objectives. Yi (2019) proposed a method to integrate the quality and quantity performance of the envelope into one measurable goal for optimization. In the works of Kim (2020), Charpentier (2020), and Torres and Sakamoto (2007) shading devices are optimized to improve indoor daylight levels according to LEED and minimize the cooling load. Most of these works use commercial optimization tools. Some optimization tools developed for the field of architecture include Galapagos (Rutten, n.d.) and Octopus (Vierlinger, n.d.). In Galapagos, the user can choose between GA (Genetic Algorithm) or SA (Simulated Annealing) as an optimizer. It is a single-objective optimization tool, whereas Octopus is a multi-objective evolutionary algorithm, based on SPEA-2. The user can choose a solution between Pareto optimal surfaces. Single-objective optimization problems have one objective to optimize, whereas multi-objective optimizations involve optimizing multiple objective functions. Despite the extensive application of GA in architecture optimization studies, for hourly daylight simulations, GA has its limitations in that it requires a large number of simulation samples, which becomes computationally expensive (Kheiri, 2018) and slow to compute (Elbeltagi, 2005). Although studies have attempted to address this limitation by either simplifying the objective function or reducing the number of individuals, the former tends to disregard detailed information while the latter results in non-optimal solutions (Kheiri, 2018).

Covariance Matrix Adaptation - Evolutionary Strategy (CMA-ES) (Hansen 2006) is another genetic algorithm. Unlike other genetic algorithms, CMA-ES models pairwise correlations between every pair of input variables. Further, CMA-ES was shown to be empirically effective for optimizing "difficult functions," especially in cases when the number of input variables is relatively large (Hansen 2010). In the daylight optimization setting, considering pairwise correlations of the input variables, such as the correlation between window dimension and building orientation, is hypothesized to be beneficial. As a result, the paper investigates using CMA-ES for optimizing window shading devices to maximize indoor daylight. Additionally, since CMA-ES is an evolutionary algorithm for single objective optimization, the paper utilizes Galapagos for comparison, which, as stated before, is also a single objective evolutionary solver.

Methods

The methodology consists of three major steps (Figure 1). The first step consists of geometry modeling with specific parameters. In the second step, a daylight model is generated using climatic conditions of selected locations

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to run daylight simulations. The third step involves running optimization using two different optimizers: Galapagos and CMA-ES to compare their performance in terms of the quality of the solution returned and runtime. A solution with sDA 100% and ASE 0% is referred to as the optimal solution. Solution quality refers to how close the solution is to the optimal solution.

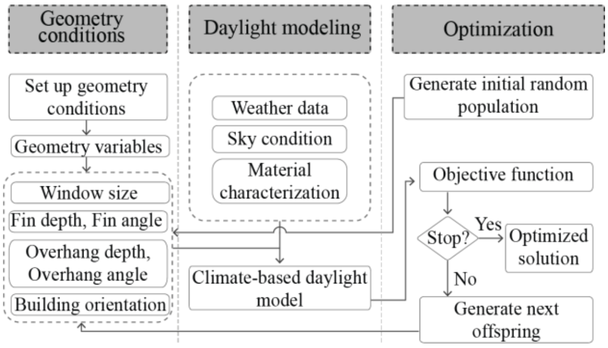

Figure 1: Overall methodology flowchart.

Test Case and Parameters

A simple shoebox geometry measuring 6 m wide, 9 m deep, and 3 m high was modeled to run daylight simulations (Figure 2). The geometry contained one rectangular window on the south façade with horizontal overhangs and vertical fins as shading devices. The window sill height was fixed at 0.9 m from the floor. The illuminance grid spacing was fixed at a 0.6 m distance, located at a height of 0.8 m from the floor.

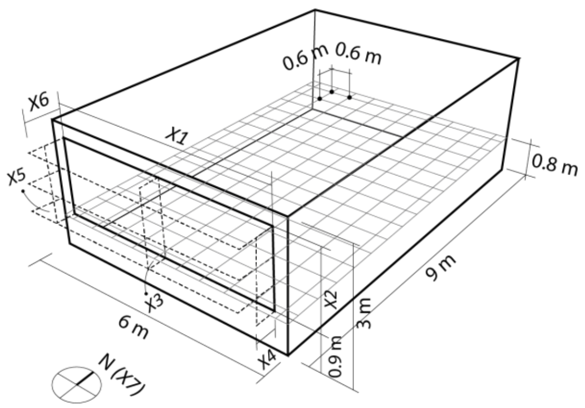

Figure 2: Geometry modelling parameters with daylight grid.

The input variables for the study include window width (X1) and height (X2), number and depth of vertical fins (X3 and X4), number and depth of horizontal overhangs (X5 and X6), and the orientation (X7). Table 1 shows the input variables with their value ranges.

Table 1: Variable parameters used in the study.

Variable label	Variable name	Value range
X1	Window width	1.5 – 6.0 m
X2	Window height	1.2 – 3.0 m
X3	Fin number	1 – 6
X4	Fin depth	0.0 – 1.2 m
X5	Overhang number	1 – 6
X6	Overhang depth	0.0 – 1.2 m
X7	North offset	0.0 – 360.0°

Six locations in the U.S.A. at different latitudes from north to south were considered for the study including, Bozeman, MT; New York City, NY; Dulles, VA; Los Angeles, CA; Houston, TX; and Miami, FL (Table 2). This is done to find out how the different sky conditions and amounts of solar radiation reaching the earth will influence the performance of the optimization.

Table 2: Test locations and corresponding latitudes.

Location	Latitude (°)
Bozeman, MT	45.7
New York City, NY	40.7
Dulles, VA	38.9
Los Angeles, CA	34.1
Houston, TX	29.8
Miami, FL	25.8

The materials used for the daylight model are listed in Table 3. The glazing assembly was a Double-Glazed Unit (DGU) with a U-value of 1.36 W/(m2.K), a Solar Heat Gain Coefficient (SHGC) of 0.38, and a Visible Transmittance (TVis) of 50.6%. Reflectance (R) for the other surfaces was set as shown in Table 3.

The Radiance parameters used were -ab 6 –lw 0.01. According to existing literature (Mardaljevic, 1995), higher accuracy in results is achieved with -ab values higher than 4.

Table 3: Material properties of the exterior objects used in the daylight model.

Object	R (%)	TVis (%)	SHGC
Ceiling	70	-	-
Floor	20	-	-
Wall	70	-	-
Window	-	50.6	0.38

Performance indices

Several indicators exist to measure and predict daylight performance in architecture, based on Climate-Based Daylight Modelling (CBDM). CBDM uses the meteorological dataset to extract sun and sky information to run daylight models using various climate-based daylight metrics including, Daylight Autonomy (DA), sDA (Spatial Daylight Autonomy), ASE (Annual Sunlight Exposure), and Useful Daylight Illuminance (UDI) (Mardaljevic, Heschong, and Lee, 2009; Mohsenin and Hu, 2015). Among them, sDA and ASE are two well-established performance indicators used to assess indoor daylight, that have been adopted by the LEED rating system (USGBC, 2014).

The Illuminating Engineering Society (IES) (2012) defines sDA as ‘a percentage of floor area that exceeds a specified illuminance level for a specified number of annual hours.’ In other words, sDA measures the ‘sufficiency’ of indoor illuminance over a year during standard operating hours (8 am to 6 pm). Daylight in an area is said to be ‘sufficient’ if the sDA value is 55% i.e., at least 55% of the space receives at least 300 lux for at least 50% ($sDA_{300/50\%}$) of the occupied hours. sDA value of 75% indicates ‘preferred’ lighting conditions by the occupants.

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ASE, on the other hand, is defined as a metric to assess the 'potential risk of excessive sunlight penetration' (Illuminating Engineering Society, 2012) for a specified number of annual hours, as a percentage of the floor area. Therefore, ASE indicates visual discomfort by measuring the amount of direct sunlight entering a space annually. The acceptable threshold for ASE is a maximum of 1000 lux of direct sunlight for a maximum of 250 hours (ASE $_{1000/250}$) of the occupied hours. An ASE value higher than 10% indicates potential glare and increased cooling load.

The objective of the optimizers is to maximize sDA and minimize ASE. However, Galapagos, as well as CMA-ES, are single objective optimization algorithms. To overcome this, the following objective function is considered that combines sDA and ASE into a single objective considered for maximization.

$$x_{sDA} = \begin{cases} 0.0177 \times sDA^2 & if\ sDA < 75\% \\ 100 & otherwise \end{cases}$$

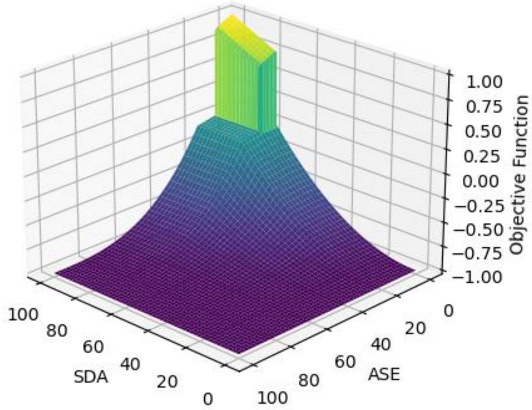
$$x_{ASE} = \begin{cases} 100 & if\ ASE < 10\% \\ 103 - 0.4 \times ASE & if\ ASE < 20\% \\ 0.000186 \times (100 - ASE)^3 & otherwise \end{cases}$$

$$Objective = \begin{cases} -\left(1 - \frac{(x_{sDA} \times x_{ASE})}{10000}\right) + \frac{sDA - ASE}{100} & if\ LEED \\ -\left(1 - \frac{(x_{sDA} \times x_{ASE})}{10000}\right) & otherwise \end{cases} \quad (1)$$

The functions were designed with the following speculations:

1. The powers were set to be higher when the solution quality is very poor, so that the optimizer gets a good signal (to improve) when there's a slight improvement,
2. The weights and additive constants (for e.g., 0.0177) were set with the reported specific values to make the function monotonic,
3. The product between x_{sDA} and x_{ASE} ensures both need to be of high quality to have a maximum product, and
4. An additional bonus for cases achieving LEED threshold = (sDA-ASE) / 100. This results in an objective function with a maximum value with sDA = 100%; ASE = 0%.

The final evaluation of the function with values of sDA and ASE values can be seen in Figure 3.



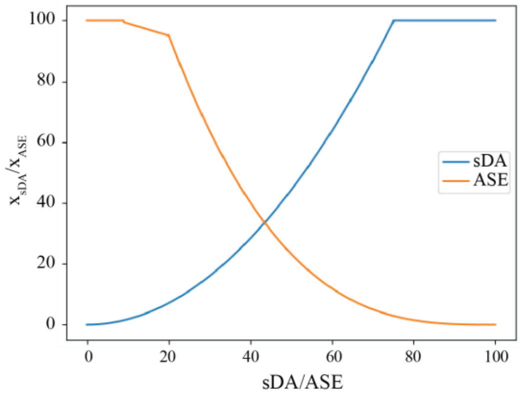


Figure 3: Visualization of the objective function for various sDA and ASE values.

Testing

Galapagos

Galapagos evolutionary solver was used in Grasshopper as a baseline for comparison. As stated previously, seven variables were defined as input. The combined sDA and ASE metric was defined as the objective function, which was set to be maximized in Galapagos (Eq. 1). The optimization was run with 10 individuals per generation, with an initial boost set to 2. Initial boost multiplies the number of individuals in the first generation to reduce the risk of getting stuck in local optima right in the beginning due to insufficient individuals. The fittest individuals (i.e., parents) are selected from the initial population, which goes on to create the next generation of offspring. Thus, each new generation is better than the previous generation. Reasonable variance among generations was ensured by allowing 5% of individuals to be carried over to the next generation and a maximum inbreeding factor of 75%. The maximum number of stagnant generations before the solver stops, if no improvement of the fitness function was reached, was set at 50.

CMA-ES

CMA-ES is not supported by any of the standard Grasshopper libraries. Moreover, Python blocks available in Grasshopper are instances of IronPython (Ironpython, n.d.) and are not capable of running native Python libraries. We address this issue by using the following software pipeline:

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- Run a Python server in the form of Remote Procedure Calls (RPC) (Nelson, 1981).
- Set up gh Python remote (Gh-python-remote, 2022) in Grasshopper
- Perform RPC calls to the server from the IronPython as suggested by gh-python-remote documentation.

Such a setup enables access to native Python and all the computational libraries available for Python Grasshopper. CMA-ES (CMA-ES, 2023) along with Numpy (Millman, 2020) were used for the experiments. The population size was set to 9, following the recommendation (Hansen 2016). All the other hyperparameters (like stopping criteria) were set following (Hansen 2016). The initial mean vector was randomly selected within the input variables range. The initial standard deviation for each variable was chosen following (Hansen 2016), set as approximately half of the range of variables used as shown in Table 4.

Table 4: Initial Standard deviation for CMA-ES per variable.

Variable label	Variable name	Standard deviation
X1	Window width	2
X2	Window height	2
X3	Fin number	2
X4	Fin depth	2
X5	Overhang number	2
X6	Overhang depth	2
X7	North offset	240

Results and Discussion

To analyse the performance consistency of both methods, each of the locations was run five times with the same initial setup. Therefore, a total of thirty runs were analysed for each optimizer to identify a trend in runtime and the solution quality.

Runtime

Results indicate a marked difference between the two optimizers with respect to the time taken by the simulations to converge for different test case latitudes.

Judging by the negative slope (Figure 4), Galapagos shows a sharp negative incline between latitudes and total runtime, with a slope of -0.0484. This means, higher latitudes on the north, on average, take the most time to converge while lower southern latitudes take the least time. The runtime for all six latitudes ranged from nearly 11 hours in MT (latitude = 45.7°) to 11 minutes in FL (latitude = 25.8°).

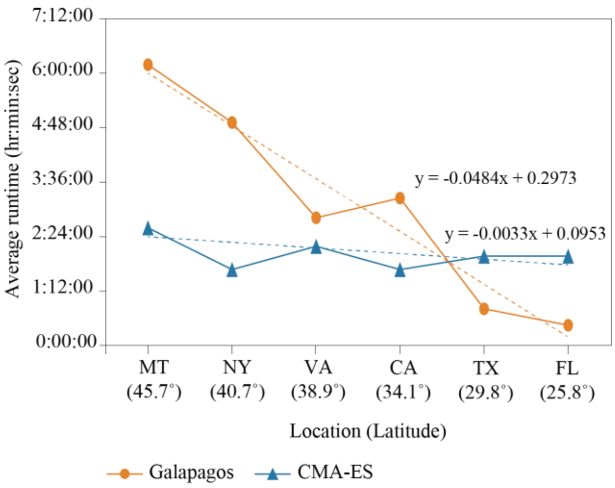

Figure 4: Average of five optimization runtimes for all six locations.

On the other hand, CMA-ES shows a relatively flat slope of -0.0033. Galapagos shows more than 15 times higher slope ratio than CMA-ES. On average, all latitudes displayed a similar runtime of around 2 hours. However, out of all five simulation runs for the six locations, the maximum and minimum values were still observed in the northernmost (4.5 hours in MT) and southernmost (35 minutes in FL) latitudes respectively.

On average, CMA-ES performs 1.5 times faster than Galapagos. Figure 5 compares the range and distribution of runtimes. The presence of large outliers in data from all locations for Galapagos, except CA and TX, indicates that there is a greater variance in the runtimes. CA has the largest range of data and hence the largest spread, while FL has the smallest spread. CMA-ES, on the other hand, shows lesser variance for the runtime for any particular latitude due to the absence of any major outliers, which indicates that CMA-ES runtime is consistent across multiple latitudes, unlike Galapagos.

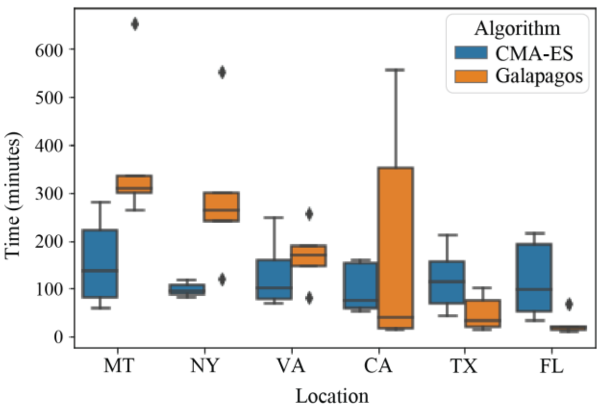

Figure 5: Optimization runtime and variance comparison between Galapagos and CMA-ES.

We believe the reason for this runtime difference among locations in Galapagos is based on the sensitivity of shading devices to control indoor daylight conditions. In lower latitudes, the impact of shading devices on indoor daylighting is significant, which is why finding an optimum solution is relatively easy than in higher latitudes.

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Solution Quality

As mentioned before, the objective function with sDA = 100% and ASE = 0% results in a value of 1. Solution quality is defined as how close the objective function in each optimization run is to the desired objective value of 1.

Similar to runtime, Galapagos also showed a correlation between solution quality and latitude. Figure 6 shows that northern latitudes achieved a lower solution quality, such as 0.95 in MT, while southern latitudes achieved the desired solution quality of 1. However, with CMA-ES, all optimization runs with all six latitudes achieved the optimum solution of 1.

This shows that CMA-ES is not only more consistent in simulation run time across latitudes than Galapagos, but also returns optimal solutions. to our objective, unlike Galapagos.

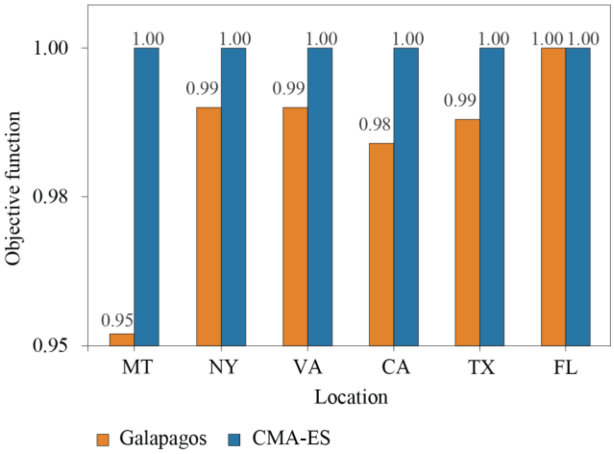

Figure 6: Solution quality comparison between Galapagos and CMA-ES for all locations.

Conclusion

In this paper, a comparative analysis between two widely used genetic algorithms which are Galapagos and CMA-ES was presented. The analysis was conducted using a simple test case geometry located in six different latitudes within the USA. In terms of both optimization runtime and solution quality, CMA-ES was found to outperform Galapagos. Using the CMA-ES algorithm, lighting conditions in different locations can be optimized in around 2 hours, whereas using Galapagos, runtime for locations in northern latitudes will be significantly higher than in southern latitudes.

Therefore, for relatively quick tests for comparative studies between different scenarios, Galapagos can offer faster results in lower latitudes. However, CMA-ES was found to be more robust as it shows lesser variance for runtime and solution quality with respect to latitudes.

The CMA-ES algorithm can potentially be used to optimize other building performance areas such as indoor thermal energy, ventilation, solar radiation, etc. Additionally, since CMA-ES takes less time for higher latitude locations, it makes it favorable for use in complicated cases such as those that require running time-specific optimization problems or that require optimizing multiple performance criteria simultaneously, etc. Findings from the paper can help practitioners make informed decisions with regard to which optimization method to adopt based on the location of their project and the desired optimum solution quality for indoor daylight. Future studies can explore the use of CMA-ES as a plugin embedded in Rhino Grasshopper for ease of use.

The paper evaluates optimization methods on daylight metrics at different locations with a fixed set of design variables. It would be worthwhile to explore how these methods perform when the number of design variables increases. This paper is also limited to a simplified geometry. A more complex geometry with multiple openings, complex shading devices, and detailed material properties might make the optimization problem more challenging, and highlight the effectiveness of CMA-ES.

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