Metaheuristic optimization of daylighting and energy performances in office spaces

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Abstract. The direction towards sustainable development challenges the designers to explore energy-efficient designs to provide adequate levels of natural daylighting. Indeed, using computational simulations can offer valuable performance predictions; still, exploring all possible combinations of design variables is a tedious and time-consuming task. This type of problems also doesn’t yield straightforward mathematical forms, and using black-box optimizations is more useful. This paper presented reviews, methodological tools and measures to help designers evaluating the potential contribution of simulation-based metaheuristics to optimize the design of façades in such obstructed contexts. The tested metaheuristics algorithms showed promising potential to attain optimum solutions, though the results confirmed that Genetic Algorithm is not sensitive to population size for optimizing façade design problems, as it obtained optimum designs only after conducting several runs of simulations. In contrast, Particle Swarm Optimization exhibited a higher sensitivity towards swarm sizes, where it converged much faster with larger swarm sizes; and a better performance could be achieved when the swarm size was 10 times the number of design variables alongside 0.2 particle’s velocity. This implies that metaheuristics optimization can be used along with simulations as accelerated tools in the early stages of design to rapidly predict building performances in obstructed environments.

Keywords: Metaheuristics, Optimization, Simulation, Daylighting, Energy Consumption

1. Introduction
In Egypt, 42% of the energy is consumed by the building sector, with over 90% of the power is generated by depleting resources [1]. In the age of sustainable development, such factors shaped the Egypt Vision 2030 on energy strategic objectives, and according to the Egyptian Ministry of Planning, the ratio of primary energy supply to the planned energy consumption should reach 100% by 2020. This also coincides with the aims of the Egyptian Code of Energy Efficiency in Residential Buildings (EERB) to exploit energy-efficient methods in building designs [2], which should be applied during the preliminary conceptual design phase [3]. A proper design of building envelops, especially façades,
is vital to achieve indoor environmental quality. While fenestrations are the weakest façade’s elements against heat gains [4], so decreasing Window-to-wall ratios (WWRs) will lead to dramatically decreasing cooling energy consumption. However, this will negatively affect daylighting levels into spaces [5]. Designers, in this, are struggling to maintain satisfactory levels of building performance, where abundant studies exploited common simulation tools in investigating the effects of key variables, such as WWR [6–9], shading devices [6,7], surrounding contexts, and reflective paintings [8–10], on daylighting and energy performances.

Exploring all possible combinations and ranges of variables to search for an optimum solution is beneficial [6–8], instead of exploring one variable at a time, which may not reveal their overall tendency [11]. Still, this approach can be time-consuming, tedious, and impractical. This is where exploiting other techniques of optimization seems imperative. The mathematical optimization techniques, while can provide more pragmatism, would necessitate translating the design variables and essential performance requirements, or objectives, into mathematical forms, which aren’t exactly compatible with such design problems. Common simulation techniques, such as path tracing, photon mapping, and radiosity, rely on the light transport models, such as Monte-Carlo algorithms and finite element methods, which mainly aim to approximate the highly recursive rendering equation of a probabilistic nature without reaching a closed-form solution. In this, black-box optimization can provide a solution for such building design problems.

Metaheuristics, as widely spread black-box optimization approaches [12], are basically stochastic algorithms that require only the function values, not the derivatives. Most of metaheuristics mimic the natural behavior of biological and molecular systems [13]. Several studies applied a variety of black-box optimization methods to solve different structural issues [12,14] and visual comfort problems [15,16]. They utilized different optimization algorithms instead of just one, as diverse settings and objective functions may direct the attention towards exploiting an algorithm at the expense of the other. Also, there is no consensus on what is constituted to be the “best” metaheuristic, implying that each situation must be tested individually. The application of metaheuristics in the design of façades is relatively new, and designers have little knowledge of such algorithms and their settings [12]; hardly any investigation was found in the literature that addressed such problems. Herein, this paper generally aims at evaluating the potential contribution of simulation-based metaheuristics to optimize the design of façades in obstructed contexts that would achieve two opposing objectives: admit adequate daylighting level while reducing the required energies. It also investigates the effect of varying the settings of the metaheuristic algorithms on the convergence time of search to obtain an optimum solution.

2. Methodology
The methodological procedure of this paper entails setting a set of variables of the test room and its surrounding context, in which the simulations are conducted. The tools of daylighting and energy simulations and their settings are then described. This study is realized by performing simulation-based optimizations of various metaheuristics algorithms’ settings to investigate their impact on the convergence time that obtains an optimum façade design in an obstructed, hot-desert settings. Lastly, the utilized optimization algorithms and their settings are explained.

2.1. Problem Formulation
The work of this paper includes developing a Grasshopper definition by the authors (Figure 1) to generate a standardized reference office room (sROM) [17] at the height of +6.00 m, representing a second level floor. The dimensions of the room are 3.60 x 8.20 x 2.80 m, with a wall thickness of 0.15 m. According to the unified construction law, the room is situated in an 18 m high building, facing other building of the same height, separated by a 12 m wide (Figure 2).

2.1.1. The Design Variables. The design variables are of suitable ranges; the selected external painting properties and glazing properties, visible transmittance (Tvis), solar heat gain coefficient (SHGC), and
U-value (U) are both in compliance with EERB [18], where WWRs follow suggestions of (sROM) [17] (Table 1).

Figure 1. The procedural steps of the developed Grasshopper definition.

Table 1. The design variables and their ranges.

| Variable                                      | Range                                 |
|-----------------------------------------------|---------------------------------------|
| External Painting Reflectivity (%)            | 12, 21, and 79, for both Buildings    |
| Glazing (Tvis: %, SHGC: %, U: W/m²°C)         | (89, 81, 5), (78, 70, 3.12), (70, 37, 2.32) |
| WWR (%)                                       | 10, 20, 26, 33, 39, 44, 52, 61, 70, 79, 87 |

2.1.2. Simulation Tools and Settings. The generated room and surrounding context in Grasshopper are then sent to DIVA-for-Rhino [19] and Archsim [20]. Both plugins work under Grasshopper environment, and interface Radiance [21] and EnergyPlus [22] engines for daylighting and energy simulations respectively. The study period considers office occupied hours: 08:00-18:00, with no daylight-saving time. The input parameters of the daylighting and energy simulations are shown in (Table 2). Most of the used Radiance parameters here follow the suggested by [23], so the effects of different variables can be represented in the study accurately. The reflectivity of the internal walls, ceiling, floor, and furniture are 50, 80, 20, and 50% respectively. The used analysis grid spacing is 0.45 m, less than LEEDv4 requirement of 0.60 m, and co-planar with the working plane at 0.90 m high. To focus the energy consumption due to the southern façade, heat gains from hot water, mechanical ventilation, and electrical equipment are discarded. Other walls, floor, and roof are considered adiabatic surfaces, except the southern façade that is assigned a U-Value of 1.14 W/m².°C.
smaller than the suggested limit by EERB [18]. The case study is chosen in Alexandria, Egypt, representing a hot-desert climate. The Egyptian typical meteorological year of Alexandria is input as a weather data file.

Table 2. The suggested simulation settings.

| Radiance Parameters                        | Value | EnergyPlus Parameters       | Value             |
|--------------------------------------------|-------|----------------------------|-------------------|
| Ambient bounces (ab)                       | 4     | People                     | 0.14 (Person/m²)  |
| Ambient divisions (ad)                     | 512   | Lighting                   | 10.1 (W/m²)      |
| Ambient sampling (as)                      | 128   | Cooling Setpoint Temp.     | 26 (°C)          |
| Ambient accuracy (aa)                      | 0.15  |                            |                   |

2.2. Problem Solving Technique
The design of façades relies on a multi-objective approach, where Pareto optimization should be applied. However, the results were a set of Pareto frontier points with no single solution. The design is fundamentally of a decision-making nature; the designer must select one optimum solution, while no such is capable of simultaneously optimizing all the design objectives [3]. The required computational effort to determine all Pareto frontier is, still, highly proportional to the number of design objectives. Yet, if the preferences of selection, or the weights, of performance metrics, are known before the optimization, there is no need to explore all Pareto frontier [24]. In order to cut the computational time, each objective must be normalized and summed up with its associated weight to obtain only one objective function, called the Weighted Sum Objective (WSO) [25].

2.2.1. Objective Function (Normalization). The daylighting assessment is based on the Illuminating Engineering Society approved method Spatial Daylight Autonomy (sDA) and Annual Sunlight Exposure (ASE) [26]. The energy evaluation considers cooling energy (CE) and lighting energy (LE) both in kWh/m². Each objective is normalized and summed with its associated weight to yield a WSO. The objectives can be simply acquired using equation (1) and equation (2); both can be used to minimize and maximize the objectives respectively [24].

\[
f_{i}^{\text{norm}} = \frac{\max(f_{i}) - f_{i}}{\max(f_{i}) - \min(f_{i})}
\]

\[
f_{i}^{\text{norm}} = 1 - \frac{\max(f_{i}) - f_{i}}{\max(f_{i}) - \min(f_{i})}
\]

Where \(\max(f_{i})\) is the maximum estimated value of objective \(f_{i}\), while \(\min(f_{i})\) is the minimum estimated value of objective \(f_{i}\). Then, WSO can be obtained from equation (3):

\[
WSO = \sum_{i=1}^{n} w_{i} f_{i}^{\text{norm}}
\]

Where \(w_{i}\) is the weight of each objective.

2.2.2. Optimization Algorithms. To explore the effect of the settings of optimization algorithms on the convergence time, a population-based metaheuristics algorithm is integrated with the developed Grasshopper definition (Figure 1). Here, two population-based components for optimization are utilized, each of which works natively in Grasshopper: Galapagos, developed by David Rutten in 2008 for GA, GA is a popular metaheuristic algorithm, inspired by Darwin’s theory of evolution. It was originally proposed by John Holland in 1975 [27], and Silveeye [14], proposed by a group of researchers in 2016 for PSO, PSO algorithm mimics the natural behavior of colonies of the living organisms. It was originally introduced in 1995 by Kennedy and Eberhart [28]. Galapagos offers multiple settings to the user such as inbreeding factor which is responsible to mate selection based on genomic distance mechanism, initial boost factor which controls the initial population, maintain
percentage which controls the survival of fittest from the previous generation, and population size which is the number of alternatives at each generation. Where Silvereye has only two settings such as velocity which controls the behavior of swarms in the next generation and swarm size which is the number of alternatives at each generation. The studied settings for Galapagos and Silvereye are illustrated in (Table 3).

| Galapagos Settings | Value | Silvereye Settings | Value |
|--------------------|-------|--------------------|-------|
| Initial Boost      | 1, 2  | Particle’s Velocity| 0.1-0.6|
| Maintain “Elitism” | 5%, 10%| Swarm Size         | 5, 10, 20, 40, 50|
| Mate Selection Factor | 75%, -75 % | Population Size | 5, 10, 20, 40, 50 |

3. Results
The work of this paper was conducted on an Intel i7 CPU of 8.0 GB, with RAM in a 64-bit operating system. (Table 4) shows the maximum and minimum values for the studied objectives. These values are related to the current case using experts’ rule of thumb for daylighting and heat gains, and not taken as their respective limits. Conducting a simulation with the largest WWR, Tvis, U-value, SHGC, and buildings’ reflectance leads to achieving maximum sDA, ASE, and CE, and minimum LE. On the contrary, using the smallest values of the previous variables lead to achieving minimum sDA, and ASE, and maximum LE. On the other hand, maximum CE resulted at the smallest WWR, U-value, and SHGC alongside the largest buildings’ reflectance. In order to validate the previous results and construct a dataset to act as a benchmark for metaheuristics optimization, 594 simulations were conducted, 297 for daylighting and 297 for energy, covering all possible combinations of design variables. (Figure 3) represents the annual simulation results considering only external painting of 79% for both buildings only, due to limited paper space, where the x-axis represents the WWRs, and the y-axis plots of sDA, ASE, CE, and LE for different Tvis, which act as an identity to certain glazing.

| Objective | Maximum | Minimum |
|-----------|---------|---------|
| sDA (%)   | 83.3    | 7.6     |
| ASE (%)   | 20.8    | 9       |
| CE (kWh/m²)| 110.6  | 54.6    |
| LE (kWh/m²)| 23.7   | 6.2     |

As obtaining the weight of each objective is out of this study’s scope, all objectives are assumed to hold equal weights. WSO is calculated using equation (3), at 79 % WWR, 70 % Tvis and 79% both buildings reflectance, the maximum WSO was observed 2.85, its corresponding values for sDA, ASE, CE, and LE were 66 %, 17.6 %, 58 kWh/m² and 9.95 kWh/m² respectively, shown as black dots in (Figure 3). Because of the stochastic nature of metaheuristics algorithms, each set of settings were tested several times [12] until achieving the most frequent behavior, to be used for comparison. The attained WSO values of GA and PSO for different settings configurations are shown in (Figure 4) and (Figure 5) as a function of the required generations to achieve the global optimum.

Regarding GA performance, it was observed that doubling the initial boost, leads to reduce the convergence time, at small population sizes only. On the other hand, inbreeding mate selection outperforms outbreeding one at population sizes 5 and 10. However, at 20 and 40 population size, outbreeding mate selection shows great potential for decreasing the convergence time. Also, GA’s settings have no effect in convergence time at 50 population size. Overall, population size is the most influential setting for GA performance. So, the most performing settings for each population size are...
extracted and explained separately as shown in (Figure 6). On the other hand, at 0.2 particle’s velocity, PSO shows great potential in decreasing the convergence time nearly for all swarm sizes. However, more than 0.4 particle’s velocity, the possibility of getting stuck in local optimum solution “local optima” increased. Also, several times PSO shows a tendency to provide an insufficient exploration of the solution space, due to the increased probability of distributing swarms around concentrated regions in the solution space. This is evident for swarm size of 10, where swarms were trapped around local optima, nearly for all velocities. In general, swarm size is influencing the convergence time more than the particle’s velocity, so the most performing velocity for each swarm size is extracted and explained separately as shown in (Figure 7).

Figure 3. Annual simulation results showing sDA, ASE, LE, and CE for different WWRs, glazing materials, and external painting of 79% reflectance.

Figure 4. Convergence based on the number of generations for possible combinations of GA settings.

Overall, (Figure 6) and (Figure 7) verified that larger population or swarm sizes required fewer generations to achieve optimum designs than smaller sizes. Also, PSO outperforms GA for all population sizes. Yet, for façade design problems that rely on performing computationally demanding sets of simulations, the number of generations is insufficient to assess the convergence time and doesn’t provide a full overview of the performance of the optimization algorithms. Hence, the effect of population and swarm sizes on the convergence time considers the WSO values of GA and PSO.
algorithms as a function of the number of evaluations, or in this case, the number of simulations, as illustrated in (Figure 8) and (Figure 9).

**Figure 6.** Convergence based on the number of generations for the best performing settings at each population size for GA algorithm.

**Figure 7.** Convergence based on the number of generations for the best performing settings at each swarm size for PSO algorithm.

**Figure 8.** Convergence based on the number of simulations for the best performing settings at each population size for GA algorithm.

**Figure 9.** Convergence based on the number of simulations for the best performing settings at each swarm size for PSO algorithm.

PSO was able to converge to optimum solutions due to its faster convergence speed than GA, for all population sizes. GA required additional computational effort to converge, where the needed numbers of simulations were 180, 165, 160, 240, and 255 runs for population sizes of 5, 10, 20, 40, and 50, respectively. This conclusion doesn’t concur with the previous result that is shown in (Figure 6), proving that GA isn’t sensitive to population sizes for such type of problems. While PSO required less effort to converge, where the required numbers of simulations were 85, 70, 65, 45, and 60 runs for the corresponding swarm sizes. PSO managed to converge in less than 85 simulation runs for all swarm sizes, confirming that larger swarm sizes required fewer simulation runs to converge than smaller swarm sizes. PSO results also showed the best optimization performance can be obtained when the swarm size equals 10 times the number of design variables, and this rule-of-thumb is considered as an adequate population size for such type of problems. For the study problem in hand of 4 design variables, the optimum solution was achieved only after 45 simulations, and a swarm size of 40. The reason behind this improved performance with larger swarm sizes is because of the increased
probability to distribute swarms at various positions in such larger swarm sizes within the solution space, where swarms move toward global and local best solutions from their current positions, and the optimum solutions can be obtained much faster.

4. Conclusions

This paper presented reviews, methodological tools and measures to help designers evaluating the potential contribution of simulation-based metaheuristics to optimize the design of façades. It verified the promising potentials of the tested metaheuristic optimization algorithms to acquire optimum solutions, regarding daylighting and energy demand performances.

Compared to traditional holistic methods, such as brute force or exhaustive search, the optimization algorithms demonstrated much faster performance to converge to optimum design solutions after conducting only 15% of the required simulation runs. Still, given a rather new application of metaheuristics in the design of façades, coupled with the lack of agreement about the most adequate algorithm, the paper also explored the effect of optimization algorithms’ settings on the convergence time for GA and PSO algorithms to obtain optimum solutions. PSO shows great performance at 0.2 particle’s velocity. However, population and swarm sizes are the most influential factors for the convergence time of GA and PSO respectively, however, by considering the number of simulations GA becomes insensitive to population size. Interestingly, the results verified that PSO, in general, was much faster than GA to converge. Yet, PSO can get trapped in local optima, while its swarm size indeed had a great impact on the convergence time. Therefore, to cut the required processing and simulation times, it is recommended that the designer should get involved in adjusting the settings of the used algorithms rather than simply using a tool’s default parameters. In this, the results concluded a rule-of-thumb: a better PSO performance can be achieved if the swarm size equals 10 times the number of search variables. This suggestion also implies that metaheuristics optimization algorithms can be utilized in conjunction with performance simulations as an accelerated pre-diagnostic tool during the early stages of design to predict the amount of daylighting and energy consumption of spaces overlooking obstructed environments. Besides, this can be used to identify the development strategies for dense contexts, providing the means for setting regulations of newly built spaces. It is recommended for future research to study the optimization algorithms’ settings for different problems by varying room geometry, surrounding context and simulation metrics. Such future explorations can provide more suggestions to provide more comprehensive settings for lessening the convergence time.

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