layers of exploration to unfold. "Although the elegant go-fast boats are designed using digital tools and CFD (Computational Fluid Dynamics), their forms are not 'found' in the computer" (Lynn 2010).

In our inquiry, one thing remains a constant: the student participation and their perception of their own learning, as well as the introduction of specialists, e.g., neuropsychologists, who may clarify parameters that remain undiscussed. According to the suggestion of a neurosurgeon, one issue that is worth examining is whether the students were right- or left-handed. As the hand preference cross-references to the opposite hemisphere, the presence of left-handed students may change the accuracy of the results. In our case, the sample was fairly small (11 students), and so this factor is negligible but should be considered with larger sample pools in the future.

ACKNOWLEDGMENTS

The author would like to thank all the students in his Bio-prototypes course for their participation in the project and their valuable feedback for the process, particularly Richard Brewer, Jammy Chong, Carlos Echeverria, Scott Hill, Dimelsa Medina, Ana Ros, and Sitki Sipahi. Special thanks to Professor John Sandell for proofreading the manuscript and Dr. Nikos Haliasos of the National Hospital of Neurology and Neurosurgery (London) for his suggestions in matters of a cognitive nature.

Additional information on differences between left and right hemisphere:
http://frank.mtsu.edu/~studskl/hd/hemis.html

and on convergent and divergent thinking:
http://www.problem-solving-techniques.com/Convergent-Thinking.html
http://www.learningandteaching.info/learning/converge.htm

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PERFORMATIVE TOPOLOGIES:

AN EVOLUTIONARY SHAPE OPTIMIZATION FRAMEWORK FOR DAYLIGHTING PERFORMANCE COUPLING A PARTICLE-SPRING SYSTEM WITH AN ENERGY SIMULATION TOOL

ABSTRACT

This paper develops a methodological approach for use in design practice that combines an external simulation tool (EnergyPlus™) with an evolutionary optimization strategy for the form finding of complex fenestration systems. On the one hand, based on previous research, it presents a novel approach for the shape morphogenesis that exploits a genetic algorithm technique to control a limited set of parameters; on the other hand, it facilitates the integration of a simulation tool capable of handling increasing levels of complexity with greater data interoperability. In doing so, the paper will argue the heuristic potential of the proposed method in aiding the designers' decision making while increasing the formal possibilities of their final design solutions.

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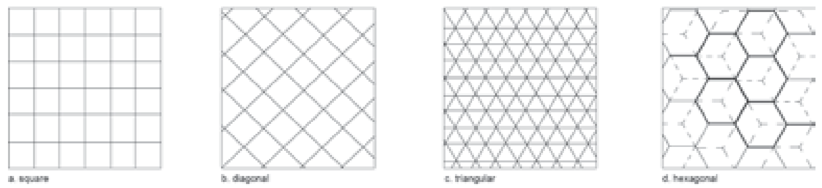


figure 1

1 INTRODUCTION

1.1 Daylight and Architecture

Building envelopes represent only 10–20 percent of the initial building costs (Rivard et al. 1998); despite this, they play an important role in the regulation of the indoor environment in response to climatic conditions, enabling filtration and protection from heat, light, and noise. The majority of energy loss in buildings is through the exterior glazed envelope. According to the US Department of Energy (2010), in commercial buildings the largest electricity expenditure figure is due to artificial lighting, which accounts for an overall 17 percent of the total amount and so exceeds other services such as heating and cooling consumption. From this perspective, daylight regulation is probably the most crucial issue not only as an energy-efficiency strategy but also for its relevance to architectural design and the resulting effects on the occupants' comfort. This is corroborated by extensive research that has identified that daylight has an impact on how space is perceived. This is particularly true for workplace buildings (Galasiu and Veitch 2006; Webb 2006), and it can contribute to well-being and productivity (Cuttle 2002)(.

Improving energy efficiency and reducing consumptions by the use of daylighting can prove to be troublesome due to the many and often contrasting performance parameters a designer faces. An example of this difficulty is that despite increased daylight being beneficial in reducing the need for artificial lighting and subsequently increasing electricity savings, it may also increase the indoor temperature when trapped inside a space. This effect may be desired during the winter season but is likely to be undesirable during the summer when cooling loads need to be limited. Moreover, glare caused by excessive illuminance levels can be detrimental for visual comfort and inhibit the correct performance of various tasks undertaken within the space. Since the actual performance of daylighting depends on how daylight is effectively delivered, designers have the challenge of not only meeting quantitative requirements but also, and more importantly, solving them spatially, i.e., designing those elements and devices that allow the control of light penetration. It is this delicate balance between quantitative performance and geometric variables that calls for an integrated optimization strategy that aims to widen the range of possible solutions and subsequently provide a valuable design decision support system.

1.2 Objectives and Structure

The main purpose of this research is to explore how a generative algorithm technique can be integrated within a building simulation tool for the daylighting and thermal comfort optimization of building envelopes. Specifically, it will identify how the use of a particle spring system, when coupled with an evolutionary optimization strategy, could lead to a novel approach for the design of complex shading devices and fenestration systems. There are two main objectives in undertaking this research. Based on previous work, it outlines a methodological framework for a form-finding tool based on daylighting optimization that uses a limited number of parameters to control the heuristic search of the solution space. The potential of an integrated building simulation tool such as EnergyPlus™—which is normally used for engineering design and compliance checking—will be investigated in relation to the analysis of complex geometries and subsequent identification and extraction of useful performance indicators relating to the specific optimization problem.

figure 1

The four regular planar tessellations (from left: QUAD, DIA, TRI, HEX).

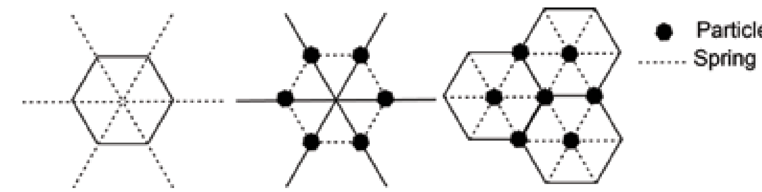


figure 2

Finally, it is believed that optimization applied to architectural design is useful only when it can be open to new alternative solutions rather than just seeking the best possible solution; hence the approach presented here attempts to provide designers with a decision support tool that could broaden the range of possibilities they consider and could thus be useful for design exploration, particularly during the early stages.

The remainder of this paper is structured as follows: Section 2 describes the implemented algorithms and the overall optimization methodological framework. Section 3 illustrates the results. Section 4 discusses the implications of the findings and highlights the potential for further research work. Section 5 concludes this work, outlining the main ideas, methods, and findings discovered throughout the research.

2 METHODOLOGY

2.1 Particle Spring System for Shape Generation

The approach taken here to account for the generation of shapes employs a particle spring system. Such systems have been widely exploited within the gaming industry to simulate physics and give a realistic feedback about an object's collision and cloth simulation. A particle spring system relies on simple Newtonian physics to calculate forces applied to a given system, and in so doing it models complex behavior in different contexts. The basic elements of a particle spring system, as the name suggests, is a particle and its properties such as its position in space (x, y, and z coordinates), velocity and mass, and a spring which connects two or more particles. The system can comprise as many particles and springs as the nature of the problem requires; in addition, they can be arranged to simulate the behavior of virtually any object.

Not surprisingly, due to their versatility, simplicity, and limited computational effort to simulate physics, particle spring systems have been successfully employed to model building structures, especially for form-finding purposes (Kilian and Ochsendorf 2005). In particular, funicular and grid shell structures have been widely studied with the use of particle spring systems, and different algorithms have been developed. For instance, among these, the implementation called dynamic relaxation algorithm—developed by Chris Williams to model the courtyard roof structure of the British Museum by Norman Foster—is well known. Nonetheless, despite being able to calculate forces accurately, a particle spring system is often exploited for its form-finding capabilities to evaluate how forms adapt under certain forces.

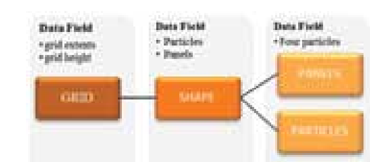


figure 3

Hence, the morphogenetic potential of such systems can be inherently applied to larger scopes than building structures. In fact, the capacity of a mass and spring system to generate complex shapes extends far beyond building structures, as research in the biomedical field has shown (Pierre-Frederic Villard et al. 2008). While still retaining all the physics parameters, in the context of this research, a particle spring system is specifically and purely used as a form-generation algorithm. In particular, as informed by previous research (Rakha and Nassar 2011; Yi and Malkawi 2009), the mass spring system behavior and the resulting generated form are controlled by a predefined set of particles. The scope of this application therefore aims to outline an algorithm that can generate form using a limited number of variables, and as a result achieve complexity while reducing computational resources.

figure 2

A shape made up of particles and springs.

figure 3

Grid and shapes hierarchy.

2.2 Planar Tessellations

In order to be able to generate shapes and exploit the algorithm morphogenetic potential at full, four different grid topologies have been implemented. The methodological approach here has been to test and evaluate the performance of typical tilings used in complex building fenestration systems, which are usually based on rectangular, diamond, triangular, or hexagonal grids.

Figure 3 shows the general hierarchy used to store and organize data in order to generate these topologies. Each of the elements of the grid is structured as a shape with particles in place of its vertices and springs along its edges (Figure 2). This representation of shape allows it to be dynamic and to obtain different geometrical configurations according to the physics parameters fed into the system.

2.3 The Building Scenario

The baseline model used to run the simulation and optimize the facade shading system is a typical office block readapted from the standard EnergyPlus™ benchmark library, whose parameters and limitations to real-world application are fully discussed in Kämpf, Wetter et al. (2010). The main geometrical parameters and site conditions are listed in Table 1. This configuration is indifferent to a particular orientation with respect to the north, as all exterior surfaces have the same solar exposure. The optimization study is undertaken for the south-facing facade, which is typically the most demanding in terms of solar gains and shading requirements. The terrain characteristics are input to approximate exterior reflections due to the ground, and the radiant gains are those of a typical city environment. The primary scope is the geometric optimization of the external shading of the building. In order to accomplish a full energy simulation, the material characteristics of the main building components have to be defined. Each grid topology as illustrated in the previous section is then initialized on a sample facade, and it is allowed to evolve its geometry while keeping the border at a fixed location. The scope of this limitation would be to ensure that a reference baseline scenario could be compared to other evolved topologies.

Table 1: Main building parameters.

Dimensions LxWxH	10m x 10m x 30 m
Location	London
Terrain condition	City
Fenestration shading orientation	South
Simulation period 1	Winter Typical (December & February)
Simulation period 2	Summer Typical (June & July)
Solution Algorithm	Conduction Transfer Algorithm With Shadowing Calculation
Internal Gains	
People	20 people per square meter (mq/person)
Lighting & Equipment	16 W per square meter (W/mq)
Required target illuminance level	550 lux

The roof, floors, exterior walls, and glazing properties are all set to standard values according to commonly used construction materials. The scope of these material input values is to correctly calculate heat gains and losses, and to have some metrics performing the optimization task. It is noted that the material selection and component construction to achieve energy efficiency is beyond the scope of the work presented here.

In order to correctly evaluate the building performance in terms of energy consumption and daylighting levels, the overall building volume has to be associated with one or more thermal zones. Ideally a thermal zone would be required for each space where temperature changes significantly,

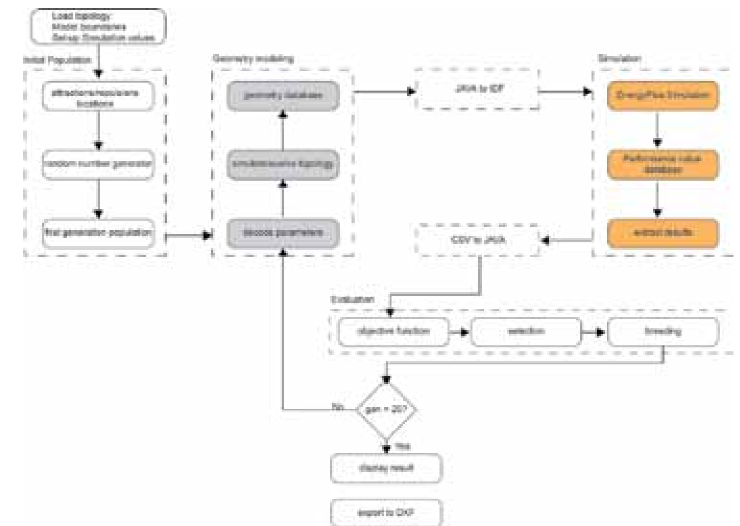


figure 4

figure 4

The optimization framework.

thus assigning each floor to a distinct zone; however, a model comprising only three thermal zones is implemented. Although this is not accurate for a proper energy analysis, it is still a valid approximation for the design optimization task that is considered here. This simple thermodynamic model comprising a few thermal zones is indeed sufficient to evaluate and compare design outputs where geometry is the only variable. In addition to determining daylighting illuminance levels and related electric lighting consumption, a reference point has been set at half the height of a particular zone. The reference point takes some input values such as location and desired lux value at that point. This value is the lighting level that would be produced if overhead electric lighting were operating at full power; hence when the set value is not reached, lights are turned on at that point. Finally, each grid topology is initialized.

2.4 Genetic Algorithm Implementation – Genetic Operators and Optimization Framework

The outlined design optimization task has been implemented with a genetic algorithm (GA), following the successful results obtained in prior research that similarly explored the potential of this algorithm to facilitate performance-based facade design (Caldas and Norford 2002; Gagne and Andersen 2010)(. In addition to this, among the advantages of using an evolutionary algorithm over other nonadaptive and deterministic strategies are 1) the blindness of GAs to auxiliary information (indeed, GAs require only payoff values associated with some strings) and 2) the smaller time to compute a solution resulting from the parallel processing of bits of strings (Goldberg 1989). The genetic algorithm selects geometric configurations in accordance to how well they respond to a solution (fitness) and then recombines them to produce new ones (offspring). In the proposed implementation, two nonoverlapping micropopulations (less than 30 samples) are sampled at each iteration. This means that new offspring (children) will replace the ones in the old population (parents) with the aim of increasing the overall fitness of the population. The population also stores information about best and worst chromosomes, together with other statistical data useful to progress and eventually stop the search. The roulette wheel selection method (RWS) is used here, though, to avoid overdominated population due to the small number of samples the RWS has been augmented with an elitist model. At every generation selection, crossover and mutation are applied to an entire population. Once the selection is completed and new offspring have been generated from the old population, the genetic operators of crossover and mutation are applied before exchanging the parents of the old population with the newly generated children again. As outlined in Figure 4, an initial baseline population is generated and used to start up the optimization framework. This first population enters the geometry-modeling loop that generates the geometry to be evaluated later by the simulation loop. This procedure is repeated for all populations until the convergence criterion (here the maximum number of generations) has been met.

2.5 Objective Function Formulation

The whole optimization task is performed against a reference case being a flat undeformed squared grid. The objective function for the optimization routine combines three parameters. The first takes into account the illuminance ratio expressed as.

$$IR = \max\left(\frac{Calc\ Avg\ Lux}{Ref\ Avg\ Lux}\right)$$

However, the illuminance ratio alone does not take into account the energy consumptions due to electricity demands required to maintain artificial lighting to ensure visual comfort targets. The objective function for this case would be the minimization of the total electricity energy required against the reference building during the simulated period, and it is expressed as in equation 1.

$$F(x) = \min\left(\frac{Calc\ E_{lighting}}{Ref\ E_{lighting}}\right) \tag{1}$$

Finally, the increased daylighting levels might produce unwanted overheating, especially during summer, leading to higher indoor temperatures which in turn would require more energy to cool the environment. The solar gains of the facade are thus also evaluated; in particular, the strategy is to allow increased solar gains during winter while reducing them during the summer. This is accomplished by defining the solar gain optimization factor (SGO) as in the following equation:

$$SGO = \max\left(\frac{Winter\ Solar\ Gains}{Summer\ Solar\ Gains}\right) \tag{2}$$

Hence the final objective function aggregates both the energy consumption and the lighting levels with respect to a standard typical solution used for the same design scenario. The result of this leads to a multi-objective function whose terms are maximized and weighted as expressed in equation 3:

$$F(x) = \max\left(\frac{Calc\ SGO}{Ref\ SGO}\right)w_1 + \max\left(\frac{Ref\ E_{lighting}}{Calc\ E_{lighting}}\right)w_2 + \max\left(\frac{Calc\ IR}{Ref\ IT}\right)w_3 \tag{3}$$

where w_1, w_2, and w_3 are weighting factors set to .35, .45, and .20 respectively.

3 RESULTS

The optimization routine has been tested to evaluate the performance of different topologies against the same reference case (a typical flat-shading system); thus all solutions with a fitness value greater than one are considered as optimal. The simulation period considered is two typical months during either the winter or the summer season, as described above. At this stage the simulation does not take into account any external obstructions other than those provided by the shading system—hence, other buildings and structures are omitted in order to save time. Reflections due to the ground are nevertheless computed. In this model the objective function evaluates the stored values from the reference points in each of the three zones. This might be a strong limitation during the design of a real building, although in this context it is a reasonable approximation since the only variable being compared among different solutions is the shape.

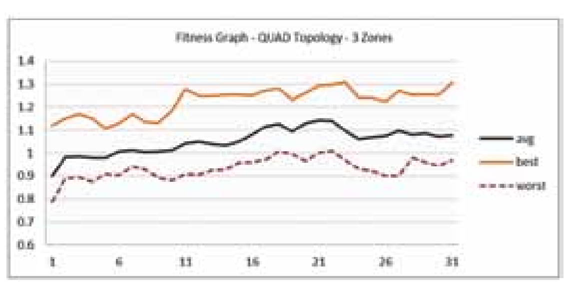


figure 5

figure 5

Average, best, and worst over 30 generations.

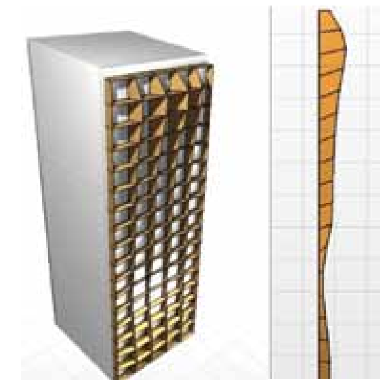


figure 6

figure 7

figure 8

The optimization routine carried out for the QUAD topology found optimal solutions from the first generation, although the average fitness of the population reaches values greater than one only after the fifth generation. The maximum fitness value is obtained after the 21st generation, where, again, a solution with a score of about 1.30 is found (Figure 5). The best solution found for the QUAD topology is shown in Figure 6. The optimized shading system presents a curvilinear cross-section profile with panels inclined at various angles from bottom to top.

The overall depth in the bottom section of the facade is smaller compared to the upper section. The panels' inclination varies from -10° to 40° according to the panel depth, which changes from as little as 30 cm up to 210 cm. The resulting performance of the gain coefficient has increased by nearly 50 percent compared to the reference scenario. The average illuminance value similarly has increased by 55 percent, while the electricity consumption shows an overall reduction of 5 percent compared to the reference flat-shading system. It is also worth mentioning that among the found solutions are some that—while having performance values pretty similar to the reference case—still offer alternative shapes that a designer can consider. Table 2 identifies two such alternative solutions whose performance is identical but that differ in their cross-section profile, which shows a waving and a mild parabolic pattern as illustrated in Figure 7 and Figure 8 respectively.

In order to compute a whole optimization routine within a reasonable amount of time (between two and three hours for 30 generations), the total number of panels has to be less than 250 units. A compromise has been introduced in order to keep the number of panels at a minimum while having shapes of comparable size that would virtually cover the same area. As a result of this compromise, different, slightly irregular grids are used as input for the optimization. From the results of the optimization comparing different topologies, it can be clearly seen that the hexagonal (HEX) grid topology far outweighs all the others, whereas the diamond grid (DIA) is the one with lowest performance. The rectangular (QUAD) and triangular (TRI) grids attain overall similar performance values, although the former has a larger count of optimal solutions compared to the latter.

figure 9

figure 6

Best solution for a three-zone building with QUAD topology.

figure 7

Average solution 1.

figure 8

Average solution 2.

figure 9

Fitness comparison between different topologies.

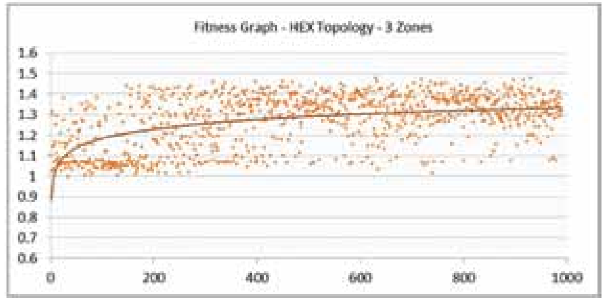


figure 10

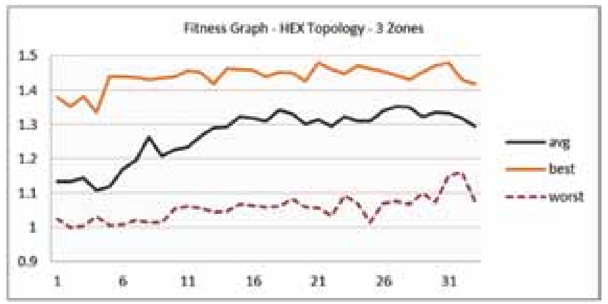


figure 11

Table 2: Cross-sectional profile comparison for three best solutions.

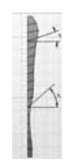
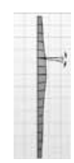
	Ref System	Best solution 1	Avg solution 1	Avg solution 2
				
Depth	80 cm	Min 30 cm Max 210 cm	Min 80 cm Min 60 cm	Max 180 Max 210 cm
Angle	0°	Min-10° Max 40°	Min 0 Max 8.5°	Min 0 Max 8°
Gain OptFactor	0.12	0.18	0.11	0.11
Total Electricity Consumption [MJ]	694	668	698	694
Mean Lux	403	650	450	500
TOT VAR %		25%	1%	1%

Figure 10 shows overall fitness trends and best solutions found for the HEX topology alone. The average fitness for this topology records very high performance values from the beginning of the optimization procedure. The maximum performance figure for this topology is around 1.5. This is similar to what has been observed from previous results, i.e., the optimized configuration presents a curvilinear cross-section profile that approximately increases in depth from the bottom to the top of the facade.

This cross-sectional recurring pattern highlights a convergence toward a self-shading structure that is capable of balancing between direct sunlight, required illuminance levels, and solar gains between summer and winter. A deeper analysis of the optimized configuration reveals that the particular angles at which panels are placed changes so that they act either as reflectors or as proper shading devices during the different seasons. This can be observed in all final optimized topologies, which as illustrated in Table 3 and Figure 12 present a curvilinear cross-section that tends to be prominently concave for the DIA grid and convex for all others.

figure 10

Fitness trend for hexagonal topology.

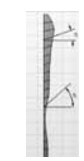
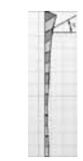
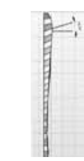
figure 11

Average, best, and worst over 30 generations.

As reported in Table 3, the HEX topology is the one with smaller differences in the inclination of panels, which span a range between -15° and 17°. Compared to other topologies, the depth of the panel changes also varies little, from 60 cm to 180 cm only. The topology with greatest variation in the inclination angle of the panels is the QUAD, where panels span over a magnitude of 50°. The panels of the TRI topology are those with largest depth figure, comprising a maximum of 280 cm. The DIA topology has dimensional properties that fall between those of the other topologies. This analysis suggests that topologies that have fewer edges (TRI) seek to adapt to geometric configurations that exhibit great dimensional variations, while those that have more edges (HEX) can easily adapt to better performing configurations with smaller dimensional changes.

After the optimization of all the best-found configurations for each of the topologies, an increased performance is presented with respect to the reference case. Indeed, except for the TRI grid all final solutions have an increased solar gain optimization factor, which leads to better control of solar gains throughout the year. Figure 13 emphasizes how the HEX grid mean solar gains are always lower than those of the reference case, except during winter months, which is when the former configuration allows more solar energy to enter though the facade. As a result, the HEX grid optimized configuration is able to reduce electricity consumption due to artificial lighting by nearly 5 percent on a yearly average and up to 9 percent during winter (Figure 14).

Table 3: Cross-sectional profile comparison of different topologies—best solutions.

	Best QUAD solution	Best DIA solution	Best TRI solution	Best HEX solution
				
Depth	Min 30 cm Max 210 cm	Min 50 cm Max 220 cm	Min 50 cm Max 280 cm	Min 60 cm Max 180 cm
Angle	Min-18° Max 40°	-5° 24°	0° 29°	-15° 17°
Gain OptFactor	0.18	0.15	0.12	0.22
Total Electricity Consumption [MJ]	668	693	663	653
Mean Lux	650	500	650	800
TOT VAR %	25%	13%	13%	45%

4 DISCUSSION

The implemented evolutionary optimization framework, which combined a generative form-finding algorithm with an external simulation tool in order to evaluate different geometric configurations of a shading system, was able to find solutions with varying degrees of increased performance with respect to a reference design scenario. In particular, following the findings observed in the previous section the developed optimization routine produced solutions that show a recurring pattern across the different studied topologies. The cross-section profiles of the optimized configuration notably showed that panels were arranged and dimensioned in such a way that the goals of the optimization were maximized with respect to a standardized design condition. The genetic algorithm—supported by a form-finding strategy that employed a limited set of parameters (8 control points) to evolve the shape of the shading system—fine-tuned a much higher set of data comprising up to 720 different parameters for the most demanding case of the HEX topology. This figure results from the combination of the 240 panels comprising a HEX grid with the three parameters that were changed during the optimization, i.e., the length, depth, and angle of each panel. In addition, the

figure 12

figure 12

Best solution for HEX, TRI, and DIA topologies.

integration of a powerful external simulation tool such as EnergyPlus™ allowed the extraction of meaningful performance indicators that proved useful in evaluating the different configurations and subsequently comparing their energy efficiency.

It is also worth considering some aspects related to the capabilities of the developed optimization task to generate forms, which is ultimately the subject of this research. A particle-spring system with a set of control points was used to generate form variations within some predefined grid topologies. The results showed that the algorithm successfully morphed the geometry to accomplish self-shading structures according to the goals of the optimization. Some constraints nevertheless reduced the range of formal possibilities that one could obtain. This was mainly in order to save computational time for the simulation; in fact, one of these limitations was the total number of panels. In addition, the form generation through the particle-spring system relied upon a number of parameters that were kept constant during the whole length of the simulation. The values assigned to these parameters have been gathered by trial and error during previous experiments and fine-tuned in such a way that some conditions were satisfied. One of these conditions was to constrain the panels to stay planar, thus reducing the number of those that would not. Although planarity itself was not a mandatory requirement for the success of the optimization outlined in this study, it is still a critical issue if fabrication feasibility has to be taken into account. Another condition along with planarity was to ensure that the particle-spring system would not generate self-intersecting shapes. A collision detection algorithm has not been implemented for this purpose, as some parameters—i.e., the spring drag coefficient and the force intensity—allowed easy control of this condition. On the one hand, these limitations ensured the feasibility of the generated forms; on the other hand, they effectively reduced the range of formal possibilities one could achieve. With respect to this, a different approach would be to incorporate a control system that operates over the phenotype of a particular solution rather than on the genotype. The optimization would thus be run without constraining the range of possibilities too much, and only those shapes that violate the feasibility constraints would be set with a null fitness. As an example, Figure 15 shows two grids obtained with the same parameters setting; the grid on the left shows areas of either highly nonplanar facets or self-intersecting panels, while the one on the right deforms correctly. Further enhancements of the proposed optimization could fully take into account these feasibility and fabrication issues and introduce some other optimization subroutines.

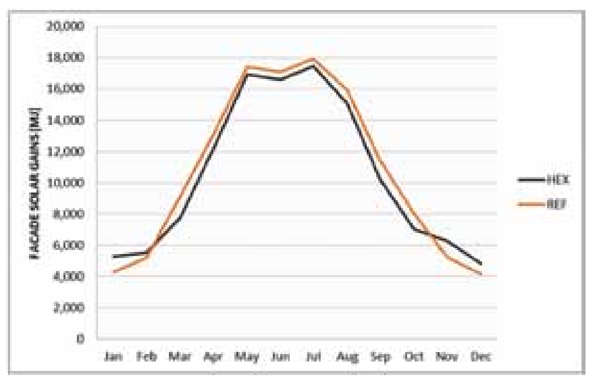


figure 13

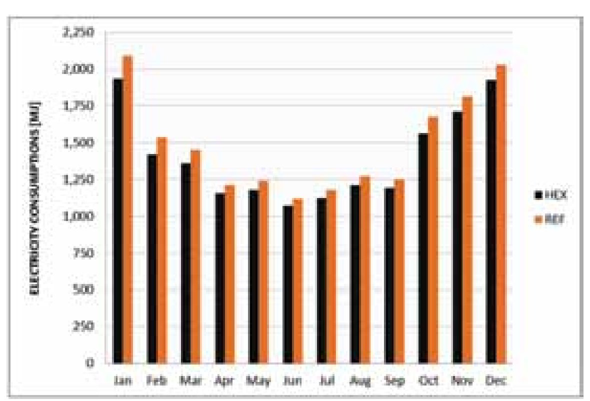


figure 14

figure 13

Solar gains comparison between best HEX solution and reference design scenario.

figure 14

Electricity consumption comparison between best HEX solution and reference facade.

An alternative approach to widen the formal range of the solutions evaluated during the optimization would be to start without a predefined set of topologies. Instead, the topological order would result from the optimization algorithm. This would include an inverse ray-tracing algorithm in the optimization, similarly to the recently developed SHADERADE (Sargent et al. 2011) method where solar rays are traced back from a window along different solar angles in order to compute a shading volume.

From this perspective an interesting approach would be the coupling of the GA with a supervised machine-learning algorithm such as the artificial neural network (ANN) or the support vector machine (SVM). In this case the GA would be used to evolve either shading volumes or alternative topologies, while the SVM, once trained with a dataset gathered from the simulation tool, would output the optimized solutions (Hanna and Mahdavi 2006). Similarly, other studies have proved the efficacy of combining a GA with an ANN in order to improve the processing time of the optimization (Wong et al. 2010).

5 CONCLUSIONS

Although an increasing amount of resources and tools are now available, a performance-based approach in design practice still poses great challenges, due not only to the computational power required to perform accurate calculations, but also to the difficulty in identifying the most relevant parameters that are useful to drive the generation of form. This is particularly true when it comes to evaluating a final design scheme and how it responds to the environment in order to achieve user comfort. Designers face an intricate task in disentangling that which unravels from the complex thermodynamic behavior of buildings. Most often, they adopt simulation models that are based on two mutually exclusive conditions that seek to balance computational resources versus the time available. Complex shapes are allowed through adoption of simplified calculation methods only; conversely, highly constrained geometrical inputs are employed when more robust and accurate solutions are required for compliance with regulatory frameworks. As a result, the former approach misses the opportunity to build flexible simulation models that could lead to a potential miscommunication between the various parties involved in the design process, while the latter simply disregards designers' expectations in achieving increasingly novel solutions. The research presented in this paper has attempted to reconcile this apparent conflict and outlined a possible evolutionary optimization strategy for daylighting performance of complex fenestration systems. This strategy combines an external simulation tool with a generative form-finding algorithm technique. The main goals addressed were the reduction of the number of parameters required to manipulate the geometrical input while still allowing the possibility of undertaking an accurate simulation of the resulting complex shapes. The formulated methodological framework thus sets out the basis for a possible environmental decision support system to employ during the conceptual stages of design, which could broaden the range of formal possibilities a designer can pursue.

Initially, different shapes were generated using a particle spring-system and a set of control points, and then their performance was independently evaluated against a reference model. In fact, regardless of the GA limitations to find global optimum solutions and in order to augment the formal exploration,

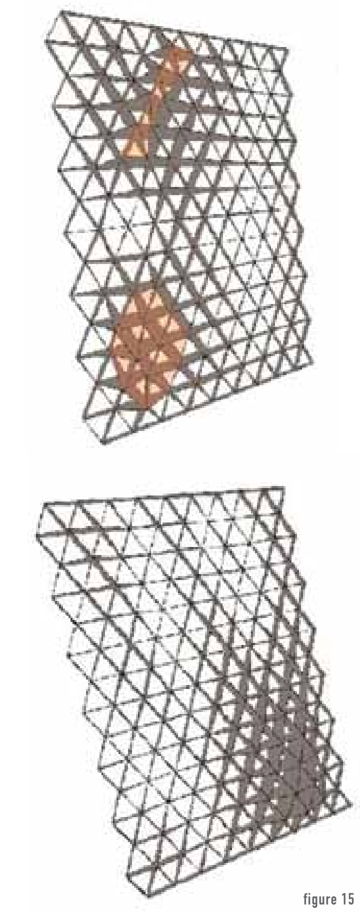


figure 15

figure 15

A feasible grid compared to a nonfeasible one.

the performance evaluation was carried out against a standardized design option. Thereafter, different shapes have also been compared to each other to further understand the responsiveness of daylighting for four different grid topologies. Results have shown that the rich correlation of the different simulation parameters employed in the optimization framework was also portrayed in the complex geometrical arrangements of the optimized solutions. Even though limitations and improvements have also been discussed to further enhance the form-finding capabilities of the implemented algorithm, the implemented routine still successfully discovered enhanced and novel configurations that offered alternative solutions to a reference design scenario.

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WORK IN PROGRESS

AN INTEGRAL APPROACH TO STRUCTURAL OPTIMIZATION AND FABRICATION

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ABSTRACT

Integral structural optimization and fabrication seeks the synthesis of two original approaches: that of topological optimization (TO) and robotic hotwire cutting (HWC) (McGee 2011; Feringa 2011). TO allows for the reduction of up to 70 percent of the volume of concrete to support a given structure (Dombernowsky and Sondergaard 2011). A strength of the method is that it allows one to come up with structural designs that lie beyond the grasp of traditional means of design. A design space is a discretized volume, delimiting where the optimization will take place. The number of cells used to discretize the design space thus sets the resolution of the TO. While the approach of the application of TO as a constitutive design tool centers on structural aspects in the design phase (Xie 2010), this process yields structures that cannot be realized within a conventional budget. As such, the ensuing design is optimal in a narrow sense; while optimal structurally, construction can prove to be prohibitively expensive. This paper reports ongoing research efforts on the development of a cost-effective methodology for the realization of TO concrete structures using HWC.