Evolving Illumination Design Following Genetic Strategies

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Abstract: Interior lighting design is a challenging task where are involved multiple constraints that need to be optimized for producing an accurate illumination avoiding possible glare. This paper, then, takes up the issue of providing a computational tool able to produce a proper lighting plan in interior spaces for a comfortable and optimal vision in all environments, taking also into account the energy consumption as little as possible. For finding acceptable solutions we have used the metaphor of the genetic evolution in a multi-objective model, where individuals are lists of possible light sources, their positions and lighting levels. For finding acceptable solutions we have used the metaphor of the genetic evolution in a multi-objective model, where every individual is a list of light sources; their positions; and lighting levels. Further, for properly evaluating each individual, we have developed two conflicting objective functions, one for optimizing the level of brightness, and the second one for maximising the energy saving, satisfying, obviously, the additional constraints to respect the architectural structure to be lighted. From the randomly initial population of individuals generations are constructed using crossover and mutation operators, whilst the fittest offspring is preserved via an elitist Pareto-dominance selection approach. In addition to the multi-objective genetic algorithm, the 3D graphic software Blender has been used in order to reproduce the architectural space to be lighted, with the aim to evaluate then, the accuracy and uniformity of the produced lighting through a physical simulation of its brightness. The main goal of the developed tool is to provide to the designer (i.e. the decision maker) a set of interiors illumination design options, for the given environment to be lit, ensuring (i) uniform illumination distribution; (ii) accuracy of the illumination produced; (iii) avoiding harsh brightness, and glare; and (iv) low energy consumptions. Two case studies have been considered in our evaluation experiments, and for each of these the algorithm was performed on two different instances and with different types of complexity respectively.

1 INTRODUCTION

Forms of artificial lighting have been introduced since antiquity to make visual perception possible when, and where sunlight is lacking (Wunderlich, 2003). In most of the contemporary world a considerable amount of time is spent indoor, and often with insufficient daylight illumination. The human vision system, like in most primates and several mammals, is able to adapt itself to very low light levels so that we may properly move inside interior environments, orient ourselves, and carry out actions. Unfortunately, this adaptation occurs through the rod photoreceptor-based *scotopic* vision, deprived from color and detailed local feature analysis. The vision with full color perception, and object recognition based on local features, is produced via cone photoreceptor-based *photopic* vision, that becomes active with adequate light levels only (Palmer, 1999). In view of this, the lighting equipment selection and its placement becomes crucial, in order to offer comfortable living environments, and improve the quality of life. Thus, integrating luminaries into the buildings aims to assign a visual perception to a sufficient level for reliable recognition, and cope with the environment, and, sometimes, elevate the vision to higher levels of appreciation, as for instance in interior spaces hosting artworks (Cuttle, 2015). However, providing comfortable and pleasant visual experiences is not an easy task, because to determine the proper lighting equipment selection, and their correct placements require the designer to satisfy several constraints, such as the type of occupants and the type of activities in the given space, or the interior surface finishes, and furnishings (Gordon, 2014; Livingston, 2015). Quite often, the aim to provide enough indoor light for a comfortable photopic vision, must take into account also the demand in terms of energy to be spent for lighting

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(Sansoni et al., 2015). In U.S. the energy consumed for lighting accounts for about 30% of the total energy consumed by commercial buildings, whilst in the European Union the yearly consumption is over 170 TWh (Bertoldi et al., 2012).

The problem of the interior lighting design is then a challenging task due to its complex and hard properties, and the many constraints to be satisfied. Indeed, to perform a proper and accurate illumination, the designer must not only take care about a right combination between daylight and artificial illumination, but primarily must take into account: (1) the light reflection (specular, diffuse, or directional-diffuse), which strongly depend on the materials composition used; (2) degree of reflection; (3) shading; (4) uniform distribution of luminaries; (5) energy consumption, with the purpose to avoid harsh brightness, and glare. The disadvantage of using the traditional methodologies is that the designer must specify the location, and power of the luminaries; run a computational tool for achieving an illuminance proposal, and check if it is satisfactory. If however it isn't the required one, then the computational tool must be run again.

It is clear that the interior lighting design involves multiple factors, often conflicting, proving, thus, the multi–objective properties of the problem. This paper proposes a method for searching lighting solutions for interior environment, based on the use of a multi-objective genetic algorithm optimization technique, and followed by a clustering of the solutions on the Pareto front. Typically multi-objective optimization methods generates too many solutions in the final Pareto set, and selecting a single one that best reflects the preferences of the architect requires a drastic reduction of the search space of solutions, here implemented with clustering. The computation of the direct illumination, necessary to compute the fitness of the population of solutions during the genetic algorithm, is performed using the 3D graphic software Blender, which allows to physically evaluating the lighting produced. Finally, results on a variety of interior environments, with different architectural complexities, will be shown in order to evaluate the accuracy and efficiency of the presented method.

The paper is structured as follow: in Sect. 2 we describe the evolutionary multi-objective approach, focusing on the description and details of the algorithm developed; in Sect. 3 we introduce the 3D graphic software Blender, used as simulation environment, whilst in Sect. 4 is described the clustering of the solutions approach, which was designed for restrict search space of solutions, facilitating, then, the decision maker in choosing of the best illumination option produced; Sect. 5 contains the experimental results performed; and, finally, Sect. 6 contains the concluding remarks.

2 THE *NSGA-II* FOR INTERIOR ILLUMINATION DESIGN

Solve the interior illumination design problem means satisfying multiple constraints involved but often in conflict, showing a natural multi-objective approach. Multi-objective optimization problems are characterized by having two or more objective functions to be optimized; therefore, in contrast to single-objective ones, the goal becomes to determine the set of best tradeoffs between all the conflicting criteria, whose set is called *Pareto optimal set*.

In this work, for solving the described problem, we propose the well-known NSGA-II algorithm, in which we developed a novel chromosomal representation of solutions, specifically tailored for lighting design optimization. Each individual represents a possible illumination configuration, and it is coded as a vector of variable length, containing a set of lamp specifications, that is the set of features describing the luminaries in the 3D environment, including position and orientation, intensity, color temperature of light, and model of light fixture (wall or ceiling mount). Special operators of crossover and mutation have been designed to handle this peculiar chromosomal representation. The design of such operators is, however, facilitated by the transparency of the representation itself. Therefore, our approach is introduced especially to deal with representation of complex structured individuals, and it ensures more flexibility with respect to previous proposals.

The Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Deb et al., 2000), is an elitist multi-objective genetic algorithm that performs well with real world problems, producing Pareto-optimal solutions to the optimization problem. The elitist approach favours the best solutions of a population by giving them an opportunity to be directly carried over to the next generation. This strategy makes sure that the best fitness values do not deteriorate during the evolution, and it enhances the probability of creating better offspring. The elitism is integrated in the algorithm by selecting the next-generation population of size N among the best individuals from the offspring and the parent population combined together (size $2N$). This selection strategy, named *crowded tournament selection*, takes into account two criteria: the non-domination and the crowding distance of the individuals. The first is the non-domination rank of the solution in the population, and it is used to classify the entire $2N$ population into non-dominated fronts. The second criterion is a measure of the search space around the solution, which is not occupied by any other solution in the population. Giving preference to solutions that are less crowded (with larger crowding distances) ensures a better spread among the solutions during the evolution. These conditions make sure that non-dominated individuals belonging to a high-rank front and residing in a less crowded area, are selected to reproduce more than others. The result of the algorithm is the set of non-dominated solutions of the whole final population, namely the Pareto front.

In the implementation of the NSGA-II algorithm proposed in this paper, at each step t of evolution, there is a population $\mathcal{P}^{(t)} = \{I_i\}$, which elements are individuals, coding a lighting solution: $I = \langle \mathcal{L}_1, \mathcal{L}_2, \cdots, \mathcal{L}_L \rangle$, and $\mathcal{L} = \langle d, \{C, W\}, \mathbf{p}, l, w, k \rangle$. The genetic code of an individual I is a ordered set of lamp descriptions $\mathcal{L}$, in which d is a code identifying the type of commercial lamp, the second parameter specifies the type of placement: C for ceiling or W for wall. The vector $\mathbf{p}$ specifies the 3D coordinates of the lamp placement, l is the intensity of the lamp in lumen, w its electrical consumption in watt, and k the color temperature in Kelvin degrees. Note that the number of lamp description L in a single individual is not fixed, but constrained: $L_{\text{MIN}} \leq L \leq L_{\text{MAX}}$. The initial population $\mathcal{P}^{(0)}$ is generated randomly, using a set of predefined real lamps, each with a set of feasible combinations of intensity l and color temperature k. The type of lamp d specifies if the lamp can be mounted on the ceiling or on walls. The variation of the population is based on two fundamental operations: crossover and mutation. Given two individuals, $I_1 = \left\langle \mathcal{L}_1^{(1)}, \cdots, \mathcal{L}_{L^{(1)}}^{(1)} \right\rangle$, and $I_2 = \left\langle \mathcal{L}_1^{(2)}, \cdots, \mathcal{L}_{L^{(2)}}^{(2)} \right\rangle$, we define as two-points crossover the following function:

$$\chi(\langle I_1, I_2 \rangle) = \Big\langle \left\langle \mathcal{L}_1^{(1)}, \cdots, \mathcal{L}_i^{(1)}, \mathcal{L}_{i+1}^{(2)}, \cdots, \mathcal{L}_j^{(2)}, \cdots, \mathcal{L}_{j+1}^{(1)}, \cdots, \mathcal{L}_{L^{(1)}}^{(1)} \right\rangle, \left\langle \mathcal{L}_1^{(2)}, \cdots, \mathcal{L}_i^{(2)}, \mathcal{L}_{i+1}^{(1)}, \cdots, \mathcal{L}_j^{(1)}, \cdots, \mathcal{L}_{j+1}^{(2)}, \cdots, \mathcal{L}_{L^{(2)}}^{(2)} \right\rangle \Big\rangle \quad (1)$$

where i and j are two random integers such that $1 < i < j < \min\{L^{(1)}, L^{(2)}\}$. Note that $\chi(\cdot)$ takes two individuals as input and returns two modified individuals. The mutation function $\omega(\cdot)$ operates on a single individual, and it is the composition of two different levels of mutation. The upper level is that of the ordered set of lamp descriptions, and it is mutated as following:

$$\omega_U(I) = \begin{cases} I \setminus \mathcal{L}_i & \text{if } r < 0.5 \\ I \bigcup \{\mathcal{L}_{L+1}\} & \text{if } r > 0.5 \end{cases} \quad (2)$$

where r, here and in all the following equations, is a random number in range $0 \cdots 1$, i is a random integer in range $1 \cdots L$. The lamp description $\mathcal{L}_{L+1}$ is a new lamp taken randomly from the set of possible lamps. Mutation at the lower level, that of single lamp description, is given by:

$$\omega_L(\mathcal{L}) = \begin{cases} \langle d', \{C, W\}, \mathbf{p}, l, w, k \rangle & \text{if } r > \pi_d \\ \langle d, \{C, W\}, \mathbf{p} + \Delta\mathbf{p}, l, w, k \rangle & \text{if } r > \pi_p \\ \langle d, \{C, W\}, \mathbf{p}, l', w, k \rangle & \text{if } r > \pi_l \\ \langle d, \{C, W\}, \mathbf{p}, l, w, k' \rangle & \text{if } r > \pi_k \end{cases} \quad (3)$$

where d' is a new lamp code, extracted randomly from the set of available types of lamps, l' is a new level of illumination, selected randomly from the set of possible light intensities for the lamp of type d, similarly for k'. The displacement $\Delta\mathbf{p}$ of lamp positioning is computed in a random direction from the center $\mathbf{p}$, and with random offset within a neighbourhood, decreased in the course of the evolution. The parameters $\pi_{\{d,p,l,k\}}$ are the mutation probabilities for, respectively, lamp code, lamp position, lighting level, and color temperature.

During the evolution the entire population is replaced, $\mathcal{P}^{(t+1)} \leftarrow \mathcal{P}^{(t)}$, using the crowded tournament selection strategy described above. The size of the population remains constant during evolution. In this last equation the tournament dominance criterion is based on two contrasting objectives: the quality of the light, and the saving of energy. In turn, the light quality is computed as the combination of two objectives: achieving an illuminance level closest as possible to the given target, an obtaining light distribution uniform enough in the given space. The evaluation of light quality is preformed on samples S, surfaces distributed in the interior space, that can be placed in ways convenient to ensure best lighting quality in key portions of the space. Compliance with the target level of light, and degree of uniformity, are combined in a single fitness f_1 of the individual I, with the following computations:

$$t(I) = \frac{1}{M} \sum_{i=0}^{M} |S_i - T\| \quad (4)$$

$$u(I) = \sqrt{\frac{1}{M} \sum_{i=0}^{M} \left(S_i - \overline{S}\right)^2} \quad (5)$$

$$f_1(I) = wt(I) + (1 - w)u(I) \quad (6)$$

where S_i is the illumination measured on the sample S_i produced by the lighting configuration of individual

I, and M is the number of samplers S. Note that treating $t(I)$ and $u(i)$ as separate fitness in multi-objective optimization would be incorrect, because are not conflicting. It can be easily verified in the limit case of an individual $\hat{I}$ that illuminates all samplers exactly at target level T, from equations (4) and (5) we obtain $t(\hat{I}) = u(\hat{I}) = 0$. The weight w control the balance between the desired compliance with the target level of light and uniformity, the default value used in all reported results is 0.5. Energy consumption represents the second fitness and it is quantified as the overall power consumption of the lamps (measured in Watt) divided by the volume of the room:

$$f_2(I) = \frac{1}{V}\sum_{i=0}^{N} C_i \tag{7}$$

where C_i is the amount of Watts consumed by the i-th lamp of the individual I, V the volume of the interior environment in m^3, and N the number of lamps composing the solution.

In the presented problem of lighting optimization there are some conditions on the design process to be satisfied, therefore a constraint handling method has to be considered as well. The constrains in question concern positioning the lamps inside the interior environment, where a lamp should be mounted on the walls or on the ceiling in accordance with its model of light fixture and in contact with the room surface, and two lamps cannot be placed in the same location. Furthermore, depending on the room design, there might be some areas where the lamp placement is not allowed, for example in presence of windows, pillars, or supporting beams. The constraint specifications are provided to the system within the 3D model of the environment itself. The walls and ceiling are structured as a discrete grid of vertices, each representing a feasible position for a lamp. With this approach, the set of constraints can be effortlessly reformulated for different experiments, ensuring absolute flexibility in the design process. Since the satisfaction of the above constraints is mandatory for the problem, they can be referred as *hard constraints*. To handle them, we adopted a strategy based on preserving feasibility of solutions, where crossover and mutation operations are specifically designed to always produce feasible offspring from feasible solutions.

3 BLENDER AS SIMULATION ENVIRONMENT

For the purpose of evaluating a lighting configuration, a virtual environment able to accurately reproduce the architectural space and its spectral reflectometric properties is needed. Moreover, a physical simulation platform must be considered as well for correct illumination calculation in sample points of the architectural space.

This paper investigates the adoption of the 3D graphic software *Blender* as a unified solution to the two requirements stated above. Firstly, Blender is the most comprehensive open-source 3D computer graphic tool available. It is particularly suitable for modeling architectural interiors, with the possibility of importing components from CAD files. Secondly, Blender provides a physically based rendering engine, named Cycles, able to exhaustively evaluate lighting configurations needed for solving the inverse lighting problem. Moreover, Blender embeds a Python interpreter, which can run scripts supplied by the user, in order to extend its functionalities. Thanks to its intrinsic versatility, Blender has already been applied to a number of different problems, from the medical field (Daenzer et al., 2007) to industrial applications (Plebe and Grasso, 2016).

The algorithm here presented has been implemented in the form of a Blender script, composed of 9 main Python modules. The first group of modules, which rely on Blenders modeling features, performs the simulation environment set-up. The architectural interior scene of interest is represented inside the computer graphics software by means of geometric meshes and material shaders. The room structure (walls, floors, ceiling) and its furnishings are defined by the meshes, while colors, textures and reflectivity properties of the objects are specified through the shaders. When evaluating the fitness of a solution, the 3D scene is enriched with further supporting elements: the proposed lamps illuminating the environment, and basic 3D structures employed to perform individual lighting measurements at locations of interest. Using a sophisticated ray-tracing render engine, Blender executes an accurate simulation of illumination, taking into account a variety of environmental factors. The second group of python modules to extract light intensity values and their distribution across the interior space processes the obtained rendered images.

These outputs are used, in the third group of modules, by the genetic algorithm to compute the actual fitness values of a solution. After evaluating the entire current population and selecting the mating pool, the genetic operators of crossover and mutation are applied to generate the offspring. The operators are specifically implemented for the presented case problem, as mentioned in in the previous sections, with the support of an evolutionary computation python

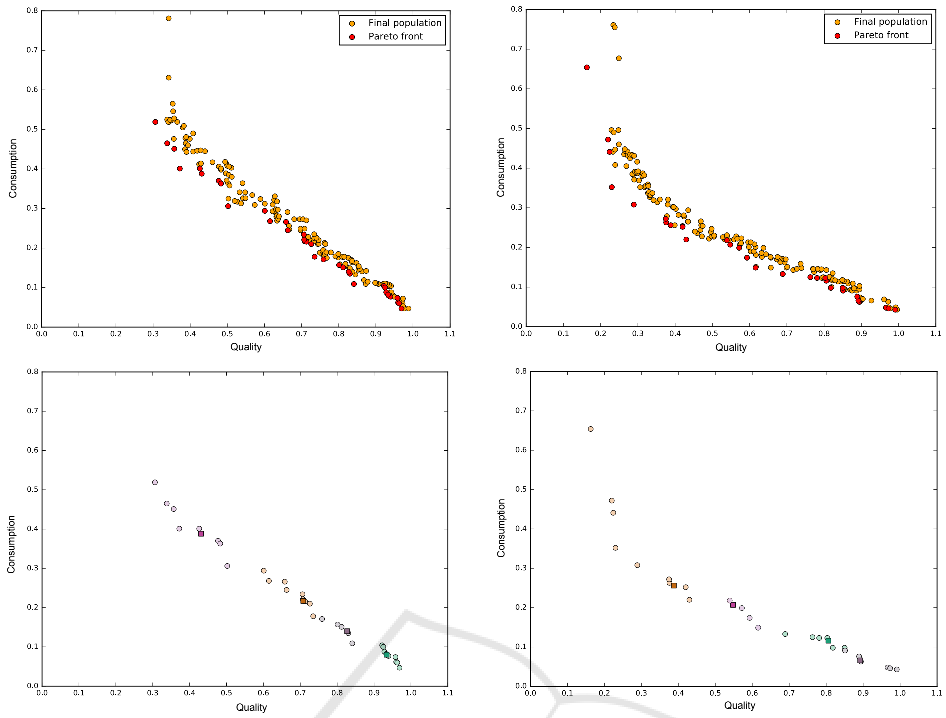

Figure 1: Final populations of the optimization in the two case studies: the coffee shop on the left, and the shopping mall on the right. The plots in the upper row are the complete populations at the end of the optimization, and the Pareto fronts, in the lower row there are the results of the clustering, solutions with the star mark are the representative solutions of the four clusters.

framework named DEAP (Fortin et al., 2012), which allows to freely customize any component of the genetic algorithm workflow. At the end of the execution of the algorithm, the obtained result is the Pareto front of the final population, namely the set of non-dominated solutions, each one of them representing an optimal lighting configuration for the given interior environment. Optionally, a photorealistic rendering of the illuminated scene can be generated.

4 CLUSTERING THE FINAL POPULATION

As in most multi-objective optimization problems, our lighting design system typically generates too many solutions in the final Pareto set, and selecting a single one that best reflects the preferences of the architect can be a daunting task. A considerable amount of research effort has been devoted to alleviate this inconvenience in the general multi-objective case, with several proposed methods that reduce the Pareto optimal set to a set of solutions that is attractive to the decision maker. A large part of the proposed methods assumes that the preferences of the decision maker are well known in advance, and can be expressed in mathematical terms and incorporated in the optimization algorithm (Jaimes and Coello, 2013; Bechikh et al., 2015). The situation of the architectural lighting design is different. Although the objectives defined in our optimization problem capture important requirements of the design process, there are aesthetic and stylistic components of the design process that elude mathematical formulations. The great advantage of a tool like the one here proposed is for the architect to drastically restrict the search space of solutions, and to concentrate his or her creativity on a small number of simulated solutions. It is difficult to prescribe in advance any preferred part of the Pareto front, in principle the entire front can offer attractive solutions to the lighting designers, the choice is up to their expertise and aesthetic disposition. For this reason we focused on methods commonly classified as *a posteriori* (Zio and Bazzo, 2010), where the selection of a small subset of solutions is made on the entire final approximate Pareto front, computed without the incorporation of preferences from the the decision maker.

First, we partitioned the set of solutions into a predefined number of clusters N_c, using the subtractive clustering algorithm (Chiu, 1994; Zio and Bazzo, 2012). Let us define O the set of vectors in the fitness space of the final solutions $\mathcal{F}$: $O = \{\mathbf{f}(\mathcal{S}) \,|\, \mathcal{S} \in \mathcal{F}\}$. The vectors are normalized with all dimensions in range $[0,1]$, we call $\bar{O}$ the set of normalized vectors. For each solution a "potential" function ψ is introduced, that captures the neighborhood size of the solutions: $\psi^{(0)}(o_i) = \sum_{o \in \bar{O}} \mathrm{e}^{\frac{4}{r_I{}^2}\|o_i - o\|}, \quad o_i \in \bar{O}$. The superscript (0) is meant because the previous equation provides the initial values of the potentials, which are updated recursively, each time identifying as a cluster center the solution with the largest potential:

$$
\begin{aligned}
c_k &= \arg\max_{o \in \bar{O}} \left\{ \psi^{(k)}(o) \right\}, && (8)\\
\Delta\psi^{(k)}(o_i) &= \mathrm{e}^{\frac{4}{r_O{}^2}\beta\|o_i - c_k\|}\, \psi^{(k)}(c_k),\ o_i \in \bar{O}, && (9)\\
\psi^{(k+1)}(o_i) &= \psi^{(k)}(o_i) - \Delta\psi^{(k)}(o_i),\ o_i \in \bar{O}. && (10)
\end{aligned}
$$

Equation (8) computes the center of the k-th cluster, the recursive loop is terminated when $k = N_c$, the predefined number of clusters. The parameters r_I and r_O act effectively as radii, influencing, respectively, the range of neighborhood of a solution and the closeness of distinct cluster. Their values are computed as a function of the number of desired clusters N_c: $r_I = \frac{2}{N_c}$, $r_O = \frac{2.5}{N_c}$.

All solutions $\mathcal{S}$ in $\mathcal{F}$ are partitioned in the clusters according to the distance of the vectors in fitness space to the cluster centers. Calling $\bar{\mathcal{S}}^{(k)}$ the solution in $\mathcal{F}$ that is center of cluster k, corresponding to the normalized vector c_k, the partitioning is done as following:

$$
\begin{aligned}
&Q = \Big\langle \\
&\left\{ \mathcal{S} \,:\, \arg\max_{k \in [1..N_c]} \left\{ \left\| \mathbf{f}(\mathcal{S}) - \mathbf{f}(\bar{\mathcal{S}}^{(k)}) \right\| \right\} = 1 \right\}, \\
&\ldots, \\
&\left\{ \mathcal{S} \,:\, \arg\max_{k \in [1..N_c]} \left\{ \left\| \mathbf{f}(\mathcal{S}) - \mathbf{f}(\bar{\mathcal{S}}^{(k)}) \right\| \right\} = N_c \right\} \Big\rangle.
\end{aligned} \qquad (11)
$$

The solutions offered to the architect for her subjective evaluation and final decision are the centers of the clusters.

5 RESULTS

We evaluated empirically our lighting optimization algorithm on two case studies. As discussed in the Introduction, a satisfactory lighting quality is highly dependent on the visual tasks that are to be performed in the interior space, and on specific requirements of visual interest within the space. These specifications are passed to the model with the placement of the samplers and fixing the target illumination level. All genetic parameters of the model have been tuned in a preliminary phase on simpler and smaller rooms, and these settings did not required further tweaking in the two case studies. The chosen case environments are both complex architectural interiors, with irregular and non-convex planimetries, demonstrating that there are no limitations in the flexibility of application of the presented system. The first case study environment is the interior of a coffee shop. The architecture of this room has size of $14 \times 10 \times 2.8$ meter, and it is characterized by a long and narrow dining area leading to a wider space with a lounge room and a bar counter. A total of 13 samplers have been used to evaluate illumination levels, placed in key areas where light should create visual interest. The genetic algorithm has been run with a population of 200 individuals, the final population is shown in Fig. 1, where it is possible to appreciate how the solutions smoothly span a large Pareto front of the two fitness. The final solutions are clustered in order to provide a small and manageable subset of solutions, we used four clusters in both the cases here experimented. It is then a designer choice to pick a desired solution among the four proposed, as a tradeoff between lighting quality and energy consumption. The Fig. 2 shows photorealistic renderings of two solutions belonging to the Pareto front. The second case study is the hall of a shopping mall, of size $12 \times 11 \times 4.0$ meter. It is composed of a central area connected to secondary small shop. The main space contains a column with display stands and an area serving as lounge room, while the secondary area for the small shop has a lower ceiling level and contains several product racks and a counter with the cash register. A total of 14 samples have been used, with a genetic population of 200 individuals. The Fig. 3 shows two optimal solutions of lighting configurations. As in the previous case study, there is a wide and smooth coverage of the Pareto front. However, as can be seen in Fig. 1, the Pareto front of this case study reached even better levels of consumption fitness than the previous one. This result can be explained by the brighter shading of walls and floors in the mall environment (pale yellow and white) reflecting more light than the deep red and beige color tones of the coffee shop, which requires more intense light sources in order to reach the same perceived illumination level. Nonetheless, the visual results are rather satisfying in both case studies, demonstrating how the presented algorithm can be a suitable tool to effectively design light configuration for a variety of different environments, with minimum effort from the user.

Figure 2: Two interior views of two different optimal lighting configurations in the coffee shop environment.

Figure 3: Two interior views of two different optimal lighting configurations in the shopping mall case study.

6 CONCLUSIONS

Most part of life in industrial contemporary society is spent indoor, with activities going on even when daylight is over. Therefore there is a demand for artificial lighting, which is often a critical compromise between the achievement of light level allowing full photopic vision everywhere in the interior space, and energy consumption. The strategy here proposed takes as input an arbitrary layout of interior space, including realistic furniture and materials, and a list of possible realistic light sources, generating as output solutions, optimal under the compliance with the target illumination level, and the consumption of electric power. However, for designing an accurate interior illumination and able to not be glare nor inadequate, it is needed to optimize multiple constraints, often conflicting, which make hard the use of classical computational methods. Thus, a multi-objective genetic algorithm has been developed for interior lighting design, with the main aim to (1) optimize the level of luminous intensity, and (2) maximizing the energy saving. Moreover, a clustering of solutions approach has been also developed, in order to reduce the search space and the Pareto front, helping, then, the decision maker in the choice and selection of the more appropriate illumination. In combination to NSGA-II, the proposed computational tool is based also on a 3D graphic software, that is Blender, for providing a rendering engine for direct illumination and reproduce the architectural space to be lighted. Two different case studies have been considered in order to evaluate the accuracy, and efficiency of the illumination produced, based on different complex shapes of the architectural interiors (irregular and non-convex), which make harder the design of an uniform illumination distribution. Finally, from the analysis of the several experiments performed, the presented algorithm has showed to be a suitable and effective tool for interior lighting design in a variety of different environments.

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