Multi-objective Genetic Algorithm for Interior Lighting Design

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Abstract. This paper proposes a novel system to help in the design of interior lighting. It is based on multi-objective optimization of the key criteria involved in lighting design: the respect of a given target level of illuminance, uniformity of lighting, and electrical energy saving. The proposed solution integrates the 3D graphic software Blender, used to reproduce the architectural space and to simulate the effect of illumination, and the genetic algorithm NSGA-II. This solution offers advantages in design flexibility over previous related works.

Keywords: Lighting design · Genetic algorithm · Blender

1 Introduction

The design of interior lighting is the crucial and complex process of integrating luminaries into the fabric of architecture [11,17]. The goal is to select the lighting equipment and their placement in the interior environment, that result in a comfortable and pleasant visual experience. The design process should take into account several aspects, such as the type of occupants and the type of activities in the given space, or the interior surface finishes and furnishings.

In addition, in the last decades increasing attention has been paid to the issue of energy savings. In U.S. the energy consumed for lighting accounts for about 30% of the total energy consumed by commercial buildings, and in the European Union the yearly consumption is over 170 TWh. Therefore, the concept of *sustainable* lighting design has become central in architectural strategies [23].

A well established aids offered by computational tools to the designer is by photorealistic architectural rendering, simulating in computer graphics the effect of a lighting solution on a model of the interior environment [15]. Mathematically, this is the solution of the *direct lighting problem*. The drawback of direct lighting tools is that, if the achieved illumination is not satisfactory, it is not easy to infer which modifications to the current solution may lead to improvements. Very likely, the final solution chosen by the designer over a collection of trials, will be far from optimal.

As discussed in Sect. 2, a more effective assistance would be given by computational tools implementing the *inverse lighting problem*: the determination

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of the lighting equipment and their placement from specifications on the illuminance. This is the line of research undertaken by this paper. The inverse lighting problem lacks reliable analytic solutions, therefore it is often formulated as an optimization problem. The proposed methodology aims to optimize the main common requirements of interior lighting design, chiefly the desired level of average luminous intensity, the uniformity of light in the interior space, taking into account energy consumption. Due to the clashing of these multiple factors, the resulting problem is multi-objective in nature, as discusses in Sect. 3, where previous proposals for interior lighting design are compared and contrasted with the present one.

Our methodology, detailed in Sect. 4, is based on the combination of a 3D graphic software providing a rendering engine for direct illumination, and genetic algorithms for solving the multi-objective inverse illumination optimization. Results on a variety of interior environments are shown in Sect. 5.

2 The Inverse Lighting Problem

In a nutshell, lighting design for interior spaces is the process of integration of artificial light sources in architectural complexes – be it industrial, public or private [11]. Since the discovery of the electric light system by Thomas Edison in 1879, lighting design has experienced several significant revolutions, such as fluorescent lamps in 1938 and, more recently, solid-state lighting.

Traditionally, illumination design has been seen as a blend of art and practice, where all the challenges are left to the creativity and the experience of the design architect. Given the aesthetic nature of the task, lighting design may seems difficult to formally model. Nevertheless, the design process has been lately considered as a mathematical and physical problem to be solved with optimization techniques.

The *inverse lighting problem* [2,14,20,24] is the problem of determining potential light sources satisfying a set of given illumination requirements, for a pre-defined interior space. Conversely, the *direct lighting problem* refers to the computation of radiance distribution in an environment that is completely known a priori, including its lighting parameters. In the inverse problem, lighting configurations are inferred from the desired illumination requirements, taking into account positions, kinds of luminaries, intensities and number of light sources. Energy efficiency is often considered as well.

Given the many feasible solutions possible, the application of optimization methods still allows the designer to have a degree of freedom and creativity in the final choice of the lighting configuration, from one of the optimal solutions obtained.

2.1 Blender as Direct Engine

A system facing the inverse lighting problem must provide two fundamental components:

- a three-dimensional environment able to accurately reproduce the architectural space and its spectral reflectometric properties;
- a physical simulation platform for illumination calculation in sample points of the architectural space.

Several approaches were considered in order to satisfy these requirements. Lightsolve [1] is an interactive dedicated environment for daylight design, with a performance-driven decision support system. The system lacks a detailed architectural reproduction, and the inclusion of interior furniture is difficult to manage. In [10] the 3d models of building facades are obtained with the simple modeling tool Google SketchUp, which offers a quick and easy way to outline an architectural space, but resulting in a low level of realism. Conversely, the popular software Radiance, widely used in the field of optimal lighting design [9,15,19], consists of a sophisticated physically-correct rendering engine for illumination calculation, and it allows architectural spaces reproduction at arbitrary levels of detail. Nevertheless, it is a non-interactive system composed by a collection of command-line programs, and all architectural specifications have to be coded into configuration files. Attempts have been made to unify those extremes, for example Painting With Light is an integration environment for Rhinoceros, a commercial CAD software, and Radiance [4].

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 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, and is known for its remarkable software integrity [12]. Thanks to its intrinsic versatility, Blender has already been applied to a number of different problems, including industrial applications [21].

3 Multi-objective Optimization

Interior illumination design involves multiple and often conflicting factors, therefore the resulting problem is multi-objective in nature. In contrast to a single-optimization problem, where there is usually a single optimal solution, a multi-objective optimization finds a set of solutions that satisfies all conflicting criteria.

Multi-objective optimization methods have been widely used in architectural and lighting design, and plenty of them are nature-inspired. A particle swarm optimization algorithm was developed to design curtain wall facades for office buildings and to achieves low energy consumption [22]. A study has adopted multicriteria ant colony optimization to design paneled building envelopes, optimizing lighting performance and cost criteria [25]. Harmony search algorithms have been applied in the field of civil engineering several times, such as structural design optimization [16], and residential buildings design with low-emission and energy-efficient requirements [7].

But most of all, genetic algorithms have been proven to be successfully useful in a variety of architectural tasks, including lighting. The *GENE_ARCH* tool [3,4] is a popular generative design system for energy-efficient and sustainable architectural solutions, based on a Pareto genetic algorithm. In [26] genetic algorithms and parametric modeling are combined to explore the morphology of a dome, taking into account structural performance and daylight transmittance. A micro-genetic algorithm is used in [10] to explore facade designs based on illuminance and glare criteria. A study has applied genetic programming to design decorative wall of lights, and to create stained-glass window for large public spaces [19].

For the problem in hand, we used two objectives treated as multi-objective, and we deem this is the appropriate value for real cases. In fact we might have more requirements for illumination design, for example in our experiments we used as illumination quality both the deviation from a target value, and the overall uniformity. However, it seems that requirements can always be unified in two combined fitness only, which are significantly conflicting: one the sum up to lighting quality, and a contrasting one that expresses the cost for achieving quality.

3.1 Previous Related Works

There is a number of multi-objective genetic formulations of the inverse lighting problem that shares similarities with the one here proposed. A variant of genetic algorithm called *generalized extremal optimization* is used in [5] to minimize the deviation of lighting to a desired target, and the energy consumption. Our algorithm takes into account also the uniformity of lighting, but the main difference is that the methodology proposed by Cassol et al. is customized to a rectangular enclosure formed by surfaces that are perfectly diffuse, while our system is fully flexible in the geometry of the interior space, and the properties of the surfaces.

In [27] one of the criteria to satisfy, named *suitable office lighting*, is derived by interpolating subjective data obtained from psycho-visual tests, while the other criteria is energy savings. The optimization is solved using genetic algorithm, but it affects only the relative dimming of two fixed light sources.

In [18] a genetic algorithm was employed for simultaneously minimizing the power consumption and the uniformity of the illuminance. Our algorithm takes into account, in addition to the uniformity, the adherence of the average illumination to a given target. But the most important difference is that in Madias et al. the location of the light sources is assumed constant, and only their dimming is variable, while in our strategy there is full flexibility in light selection, placement, and dimming.

3.2 NSGA-II

The Non-dominated Sorting Genetic Algorithm II (NSGA-II), introduced by Deb et al. [6], is an elitist multi-objective genetic algorithm that performs well with real world problems, producing Pareto-optimal solutions to the optimization problem. The evaluation of the population of solutions takes into account the dominance and the crowding distance of the individuals. The first criterion is used to sort the population into different fronts of non-dominated individuals, while the second criterion gives preference to solutions that are less crowded. Non-dominated individuals belonging to a high-rank front with a larger crowding distance are selected to reproduce more than others. The offspring are generated through the genetic operators of crossover and mutation. The next-generation population is then selected among the best individuals from both the offspring and the parent population, ensuring elitism. The result of the algorithm is the set of non-dominated solutions of the whole final population, namely the Pareto front.

One of the key working principles of the genetic algorithm is the chromosomal representation of a solution. The algorithm works with a coding of decision variables, instead of the variable themselves, and choosing the right representation scheme is crucial to its performance [13]. The most traditional approach is to code the decision variables in a binary string of fixed length, which is a natural translation of real-life genetic chromosomes. Such strings are directly manipulated by the genetic operators, crossover and mutation, to obtain a new (and hopefully better) set of individuals. Another well established method is the floating point representation of chromosomes, where each solution is coded as a vector of floating point numbers, and crossover and mutation operators are adapted to handle real parameter values.

For the algorithm presented in this paper, 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. A lamp specification 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 are implemented 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.

3.3 Fitness Evaluation and Constraint Handling

The goal of the proposed model is to find the lighting configuration that best satisfies the most common and compelling requirements faced by the lighting designer. In accordance to what stated in the Introduction, there are goals directly related with the quality of the lighting, and an additional goal of energy saving. We adopt as goal for the light quality the combination of two objectives: achieving an illuminance level closest as possible to the given target, and obtaining light distribution uniform enough in the given space. The evaluation of light quality is performed on samplers S, horizontal surfaces distributed in the interior space, captured by virtual cameras placed in Blender over each sampler. The system allows two placement methods: one automatic that locate as much as evenly as possible the sample in the space, or a manual placing, more convenient in the case of complex spaces, or when key portions of the space, that require the best quality, are known in advance. 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:

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

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

$$f_1\left(I\right)=wt(I)+(1-w)u(I) \tag{3}$$

where S_i is the illumination measured on the i-th sampler 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 they 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 Eqs. (1) and (2) 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:

$$f_2\left(I\right)=\frac{\sum_{i=0}^{N}C_i}{V} \tag{4}$$

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:

- a lamp must be placed inside the room and in contact with the room surface;
- two lamps can not be placed in the same location;
- a lamp should be mounted on the walls or on the ceiling in accordance with its model of light fixture;

- 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 method based on preserving feasibility of solutions. In this approach, two feasible solutions, after crossover and mutation operation, will create two feasible offspring. Nevertheless, it can happen that crossover produces an individual composed of exactly the same lamps of another solution. In that case, the duplicated solution is discarded.

4 The Proposed Strategy

The algorithm presented in this paper has been implemented in the form of a Blender script, composed by 9 main Python modules. The simulation environment set-up is performed by the first group of modules, which rely on Blender's modeling features. 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 obtained rendered images are processed by the second group of python modules to extract light intensity values and their distribution across the interior space.

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 Sect. 3.2, with the support of an evolutionary computation python framework named DEAP [8], 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

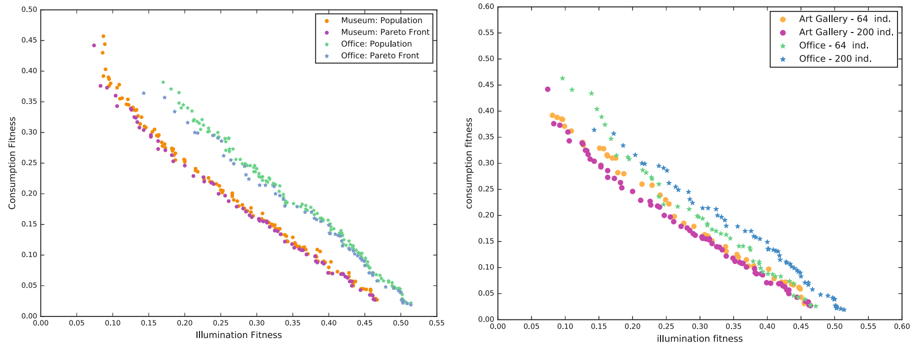

Fig. 1. On the left the final populations and the Pareto fronts in the two case studies. On the right the comparison of Pareto fronts for executions with 64 and 200 individuals.

environment. Optionally, a photorealistic rendering of the illuminated scene can be generated.

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.

5.1 Art Gallery

The first case study is an art gallery environment hosting temporary exhibitions, its dimensions are $24 \times 12 \times 4.5$ m. The architecture of this room is characterized by a wide open space with high ceilings, a supporting beam, and two load-bearing columns placed in the middle of the room. A temporary wallboard is also placed as support for hanging canvas painting, and other ground stands are used for various sculpture exhibitions.

A total of 16 samplers have been used to evaluate illumination levels, placed in key areas where light should create visual interest. An illumination target of 0.95 has been selected, since the overall lighting level needed for art exhibitions is slightly lower than typical. The genetic algorithm has been run with a population of 200 individuals, the final population after 30 generations is shown on the left in

Fig. 2. Two renderings, a plan view and an interior view, of two different optimal light configurations in the art gallery environment.

Fig. 1, where it is possible to appreciate how the solutions smoothly span a large Pareto front of the two fitness. The right plot in Fig. 1 shows that the algorithm with an initial population of 64 individuals and 20 generations only already provides an acceptable approximation of the best Pareto front, obtained with 200 individuals. The Fig. 2 shows photorealistic renderings of two of the solutions belonging to the Pareto front, the first gives more importance to the quality of illumination, while the second privileges optimal energy consumption. A more qualitative evaluation of the quality of light is given by the isophotes plotted at 1 m level in the room, in Fig. 4 on the left. This case study demonstrates how the presented algorithm can be a suitable tool to effectively design light configuration for a frequently changing environment, a temporary art gallery, with minimum effort from the user.

5.2 Office

The second case study is a typical open-space office, with dimensions of $29 \times 13 \times 3$ m, composed by a reception area connected to an hallway leading to the main office area. The space is suitable for 20 work stations, and it also includes a separated private area serving as meeting room or as lounge room. The architecture is even more complicated by the presence of a curved wall in the reception, a supporting column and a full window wall in the office area. A total of 12 samples have been used, evenly spaced in the working area, and an illumination target of 1.0 has been specified, since office work requires standard lighting level. Apart from number of samples and illumination target, all parameters of the algorithm are the same as in the Art Gallery case. As in the previous

Fig. 3. Two renderings, a plan view and an interior view, of two different optimal light configurations in the open-space office.

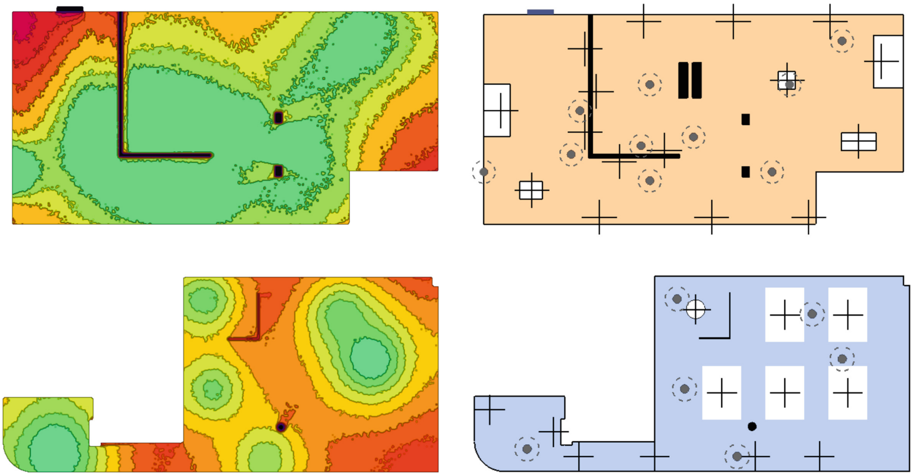

Fig. 4. On the left plots of isophotes. On the right configurations of the solutions, dots and a dashed circles represent lamps, crosses represent samplers.

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 did not reach the same optimal level in the illumination fitness as the previous one. This result can be explained by the greater complexity of the planimetry of the office, a narrow and long hallway near to a large spacious room appears to be more challenging to illuminate uniformly. Nonetheless, the visual results are rather satisfying, as shown in the photorealistic renderings of two optimal solutions in Fig. 3, the first one preferring light quality and uniformity, the second one considering higher level of energy saving.

The final results of both cases are single executions, it is not practical to perform several runs with different seeds. The timing, on a iMac Intel Core i7 4 GHz, is of 377 min for the Art Gallery with 200 individuals and 30 generations, and 305 min for the Office, in both cases 97% of the time is spent in the rendering of light.

6 Conclusions

This paper proposed a system for inverse design of interior lighting based on the integration between the 3D graphic software Blender and a multi-objective genetic algorithm. The system takes as input an arbitrary interior environment, including realistic furniture and materials, with the description of the lighting requirements in terms of desired average illumination. It produces a Pareto front of solutions minimizing the compliance with the target illumination level, the uniformity of light distribution in the interior space, and the consumption of electric power. The cases presented demonstrate the effectiveness of the system in helping the process of lighting design in complex architectural interiors.

References

1. Andersen, M., Gagne, J.M., Kleindienst, S.: Interactive expert support for early stage full-year daylighting design: a user's perspective on Lightsolve. Autom. Constr. **35**, 338–352 (2013)
2. Baltes, H. (ed.): Inverse Source Problems in Optics. Princeton University Press, Princeton (1978)
3. Caldas, L.: Generation of energy-efficient architecture solutions applying GENE_ARCH: an evolution-based generative design system. Adv. Eng. Inform. **22**, 59–70 (2008)
4. Caldas, L.: Painting with light: an interactive evolutionary system for daylighting design. Building and Environment (2016). https://doi.org/10.1016/j.buildenv.2016.07.023
5. Cassol, F., Schneider, P.S., França, F.H., Neto, A.J.S.: Multi-objective optimization as a new approach to illumination design of interior spaces. Build. Environ. **46**, 331–338 (2011)
6. Deb, K., Agrawal, S., Pratap, A., Meyarivan, T.: A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II. In: International Conference on Parallel Problem Solving From Nature, pp. 849–858 (2000)
7. Fesanghary, M., Asadi, S., Geem, Z.W.: Design of low-emission and energy-efficient residential buildings using a multi-objective optimization algorithm. Build. Environ. **49**, 245–250 (2012)
8. Fortin, F.A., De Rainville, F.M., Gardner, M.A., Parizeau, M., Gagné, C.: DEAP: evolutionary algorithms made easy. J. Mach. Learn. Res. **13**, 2171–2175 (2012)
9. Futrell, B., Ozelkan, E.C., Brentrup, D.: Optimizing complex building design for annual daylighting performance and evaluation of optimization algorithms. Energy Build. **92**, 234–245 (2014)

10. Gagne, J., Andersen, M.: A generative facade design method based on daylighting performance goals. J. Build. Performance Simul. **5**, 141–154 (2012)
11. Gordon, G.: Interior Lighting for Designers. Wiley, New York (2014)
12. Grasso, G., Plebe, A.: Conceptual integrity without concepts. In: International Conference on Software Engineering and Knowledge Engineering, pp. 422–427. KSI Research Inc. and Knowledge Systems Institute, Pittsburgh (PA) (2016)
13. Janikow, C.Z., Michalewicz, Z.: An experimental comparison of binary and floating point representations in genetic algorithms. In: Proceedings of the 4th International Conference on Genetic Algorithms, pp. 31–36 (1991)
14. Kawai, J., Painter, J.S., Cohen, M.F.: Radioptimization: goal based rendering. In: Proceedings of the 20th Annual Conference on Computer Graphics and Interactive Techniques, pp. 147–154 (1993)
15. Larson, G.W., Shakespeare, R.: Rendering with Radiance: The Art and Science of Lighting Visualization. Morgan Kaufmann, San Francisco (1997)
16. Lee, K.S., Geem, Z.W.: A new structural optimization method based on the harmony search algorithm. Comput. Struct. **82**, 781–798 (2004)
17. Livingston, J.: Designing with Light: The Art, Science, and Practice of Architectural Lighting Design. John Wiley, New York (2015)
18. Madias, E.N.D., Kontaxis, P.A., Topalis, F.V.: Application of multi-objective genetic algorithms to interior lighting optimization. Energy Build. **125**, 66–74 (2016)
19. Moylan, K., Ross, B.J.: Interior illumination design using genetic programming. In: Johnson, C., Carballal, A., Correia, J. (eds.) EvoMUSART 2015. LNCS, vol. 9027, pp. 148–160. Springer, Cham (2015). https://doi.org/10.1007/978-3-319-16498-4_14
20. Patow, G., Pueyo, X.: A survey of inverse rendering problems. Comput. Graphics Forum **22**, 663–687 (2003)
21. Plebe, A., Grasso, G.: Particle physics and polyedra proximity calculation for hazard simulations in large-scale industrial plants. In: American Institute of Physics Conference Proceedings, pp. 090003-1–090003-4 (2016)
22. Rapone, G., Saro, O.: Optimisation of curtain wall facades for office buildings by means of PSO algorithm. Energy Build. **45**, 189–196 (2012)
23. Sansoni, P., Farini, A., Mercatelli, L. (eds.): Sustainable Indoor Lighting. Springer, Berlin (2015). https://doi.org/10.1007/978-1-4471-6633-7
24. Schoeneman, C., Dorsey, J., Smits, B., Arvo, J., Greenberg, D.: Painting with light. In: Proceedings of the 20th Annual Conference on Computer Graphics and Interactive Techniques, pp. 143–146 (1993)
25. Shea, K., Sedgwick, A., Antonuntto, G.: Multicriteria optimization of paneled building envelopes using ant colony optimization. In: Smith, I.F.C. (ed.) EG-ICE 2006. LNCS (LNAI), vol. 4200, pp. 627–636. Springer, Heidelberg (2006). https://doi.org/10.1007/11888598_56
26. Turrin, M., von Buelow, P., Stouffs, R.: Design explorations of performance driven geometry in architectural design using parametric modeling and genetic algorithms. Adv. Eng. Inform. **25**, 656–675 (2011)
27. Villa, C., Labayrade, R.: Multi-objective optimisation of lighting installations taking into account user preferences - a pilot study. Lighting Res. Technol. **45**, 176–196 (2013)