Use of Monte Carlo Methods to Optimize Office Lighting Appearance Under Consideration of Various Visual Attributes

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ABSTRACT
In this paper, we introduce a multi-objective optimization methodology under uncertainty to design office lighting. It is aimed at identifying the value ranges of decision variables (i.e. physical properties) that realize the best possible trade-offs between various preferences on visual attributes.

1. INTRODUCTION
The appearance of an object depends on the values of its physical properties (e.g. reflectance, specularity, texture, etc.). Optimization of appearance with respect to various visual attributes considered at the same time is an issue that has applications in different areas (e.g. aesthetic design in marketing, visual performance based-design for road material, street and architecture lighting). However, preferences with respect to visual attributes are inherently uncertain, since they are collected from psychovisual tests conducted with a panel of observers. The aim of this study is to introduce a multi-objective optimization methodology under uncertainty, in order to identify the value ranges of decision variables (i.e. physical properties) featuring the best possible trade-offs between various preferences on visual attributes.

After presenting the case study and the psychovisual data acquisition, the optimization method will be detailed. It relies on the use of an Evolutionary Algorithm along with a Monte Carlo (MC) process. Then, to overcome the limitations of this initial method in terms of computational cost, a Metropolis-Hastings (MH) algorithm[1] is implemented. The results of the latter highlight the usefulness of the proposed methodology.

2. CASE STUDY AND PSYCHOVISUAL DATA ACQUISITION
The case study is a single person-office, lit by two light sources: a ceiling luminary and an angle-arm desk lamp. 16 stimuli were assessed during the subjective experiment (corresponding to 0, 33, 66 and 100 % of the maximum flux for each lamp). Figures 1 show two examples of assessed luminous environment. A panel of 36 observers was asked to evaluate all the 16 stimuli in terms of "suitability to work" and "cosiness". Two protocols were investigated; rating (resp. paired-comparison) protocol was used to collect the judgment of preferences about "cosiness" (resp. "suitability"). Mean values and 95% confidence interval (assuming normal distribution from Central limit theorem) were computed for each of the 16 stimuli. Figures 2 present uncertain psychovisual functions "suitability" and "cosiness" estimated from these statistical data. This experiment is described with additional details in [1].

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[1] *MH is based on constructing a Markov Chain.*

3. MULTIOBJECTIVE OPTIMIZATION
The genetic algorithm NSGA-II (Non-dominated Sorting Genetic Algorithm [2]) was employed with: Two decision variables:

- x_1: percentage of ceiling luminous flux;
- x_2 : percentage of desk lamp luminous flux.
- Two objective functions:
- $f_1(x_1,x_2)$: the opposite of the psychovisual function "suitability";
- $f_2(x_1,x_2)$: the opposite of the psychovisual function "cosiness".

Running the algorithm with the mean psychovisual functions leads to a Pareto front (see Figure 3: all non-dominated solutions i.e. better than others on at least one objective) which identifies all the best possible tradeoffs between "suitability" and "cosiness" (see Figures 4(a&b)). Nevertheless, this optimization process does not take into account the uncertainties inherent to psychovisual functions.

4. MONTE CARLO METHOD (MC)
Uncertainties of psychovisual functions are handled through a Monte Carlo process. For each draw, a probable "suitable" function and a probable "cosy" function are randomly chosen: for each of the 16 sampled stimuli, the values of observer preferences are randomly drawn according to their Probability Density Functions (PDF). The corresponding Pareto front is then obtained using NSGA-II. After a large number of draws (e.g. 10000 draws), the set of all Pareto fronts outlines the "uncertain Pareto front" (see Figures 5(a&b)).

5. OPTIMIZATION UNDER CONSTRAINTS
Usually, most of the identified tradeoffs are not of interest. For instance, only those that guarantee that the "suitability" and the "cosiness" are above two thresholds should be identified, i.e. $f_1 < f_{1max}$ and $f_2 < f_{2max}$. Figure 6(a) presents an example of such constraints, and the corresponding range values of the decision variables x_1 and x_2. These range values are actually the applicative results of the method, since they indicate the possible values of the decision variables that match the requirements, taking into account the uncertainties of both psychovisual functions. For example, in order to obtain $f_1 < -0.75$ and $f_2 < -12.5$, x_1 should be between 45% and 60% and x_2 should be between 40% and 80% (in fact in this example there are two areas in the decision space and Figures 6(b) give more accurate information).

6. METROPOLIS-HASTINGS METHOD
Monte Carlo method is time consuming. 10 000 draws were performed but only 3.4% of them were of interest, i.e. led to a Pareto front intersecting the constraint area. In order to decrease the computing time while obtaining the same results, we propose to implement a Metropolis-Hastings method [3]: it allows to

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sample the uncertain psychovisual functions in a way that the corresponding Pareto fronts do intersect the constraint area. This algorithm begins with a period of "burn in" corresponding to the search of a first solution for which the Pareto front intercepts the constraint area. Then, two kinds of mutations are performed, depending on the relevance of the sampled psychovisual functions (i.e. does the corresponding Pareto front intersect the constraint area?):

- in this event, a local mutation occurs: a slight variation around the previous psychovisual functions is performed;
- else, a global mutation is performed: two new random psychovisual functions are drawn.

The detailed behavior of this algorithm is described in Figure 7.

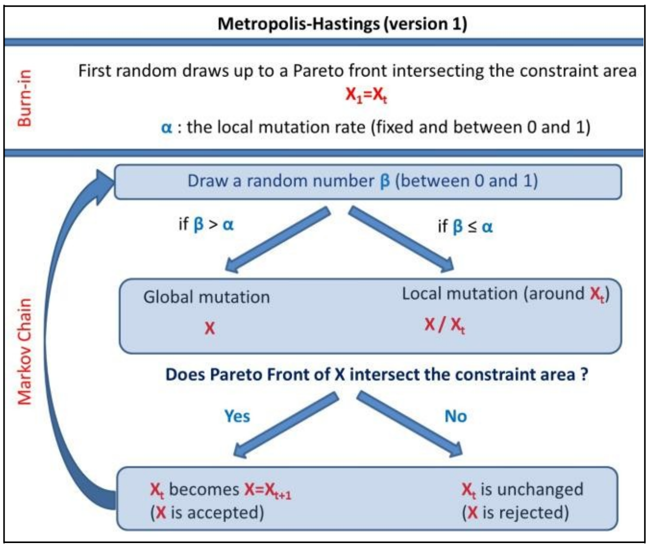

Figure 7: The MH algorithm (version 1)

7. RESULTS AND CONCLUSIONS

Relevance of MH is directly related to the difficulty of finding a solution, i.e. to the size of the constraint area. The same result reached with MC can be obtained using MH with 29 times fewer computation efforts, i.e. 350 draws. The proposed method allows to identify the range of the physical properties of an object, so as to optimize its appearance against various visual attributes at the same time, taking into account the uncertainties of the psychovisual functions. Moreover, the MH method can be orders of magnitude more efficient than the MC method, depending on the constraints of the visual attributes.

This framework has many advantages;
1) other optimization algorithms (different than NSGA-II) can be used;
2) it can be applied to other areas, not only lighting design;
3) it presents good properties of scalability with respect to the number of objective functions and decision variables;
4) the risk that each solution does not respect the constraints can be obtained;
5) it can be extended to identify robust solutions.

In future work, the probability of each tradeoff will be assessed. Figure 8 presents the obtained result with MC, in order to identify the most reliable object parameter values. MH algorithm will be modified to obtain the same result: the Markov Chain will take into account the probability distribution (PDF) of the uncertain objective functions in the acceptance ratio. The principle of this algorithm is described in Figure 9.

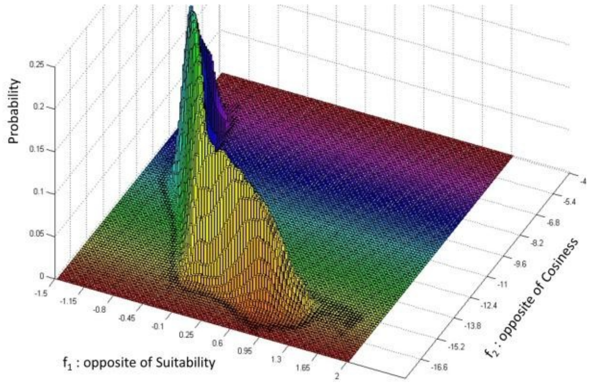

Figure 8: Probability of tradeoffs (MC method)

8. ACKNOWLEGMENTS

The authors thank Celine Villa for the materials and the case study that she has developed.

9. REFERENCES

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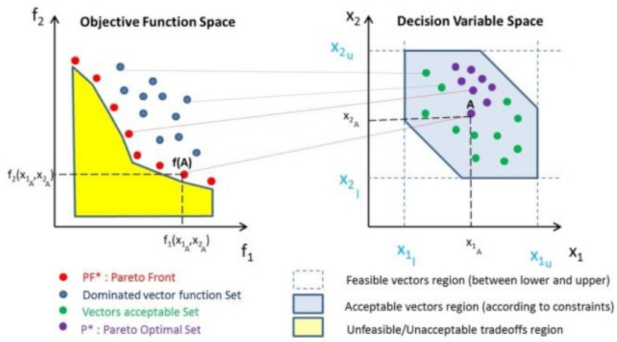
[2] Deb K, Agrawal S, Pratap A, Meyarivan T. A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation 2002 6(2): 182-197.
[3] Hastings WK. Monte Carlo sampling methods using Markov chains and their applications. Biometrika 1970 57(1) 97-109.



Figures 3: Illustration of Pareto front concept

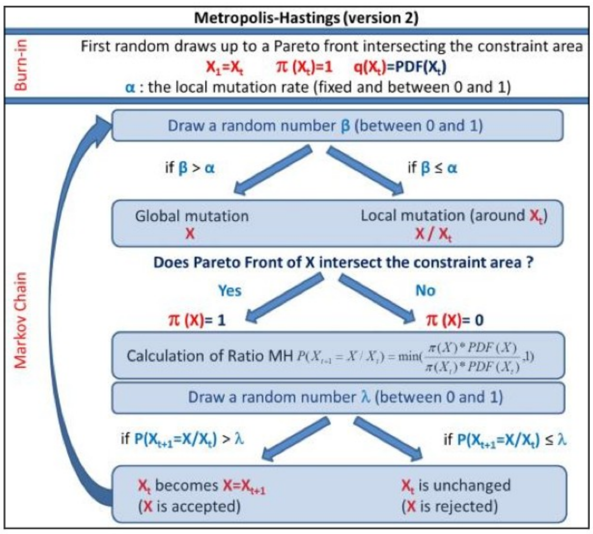
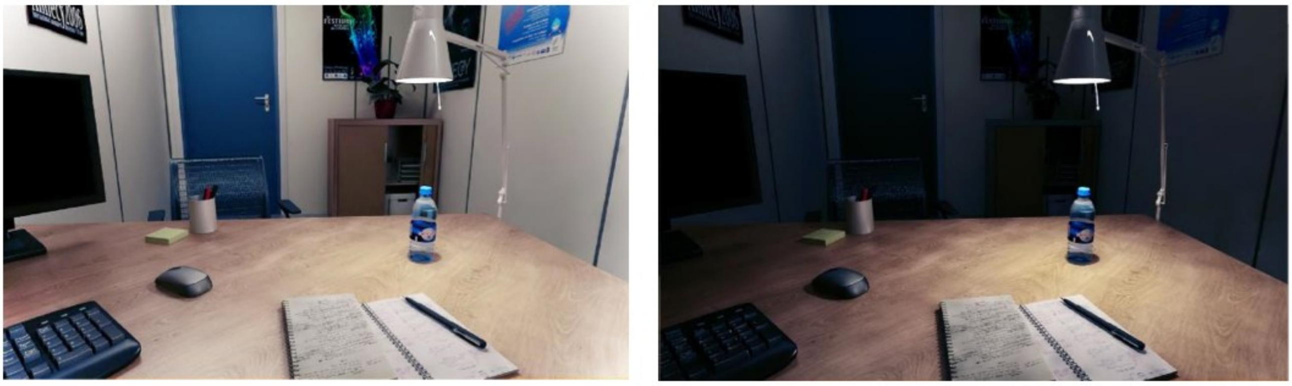
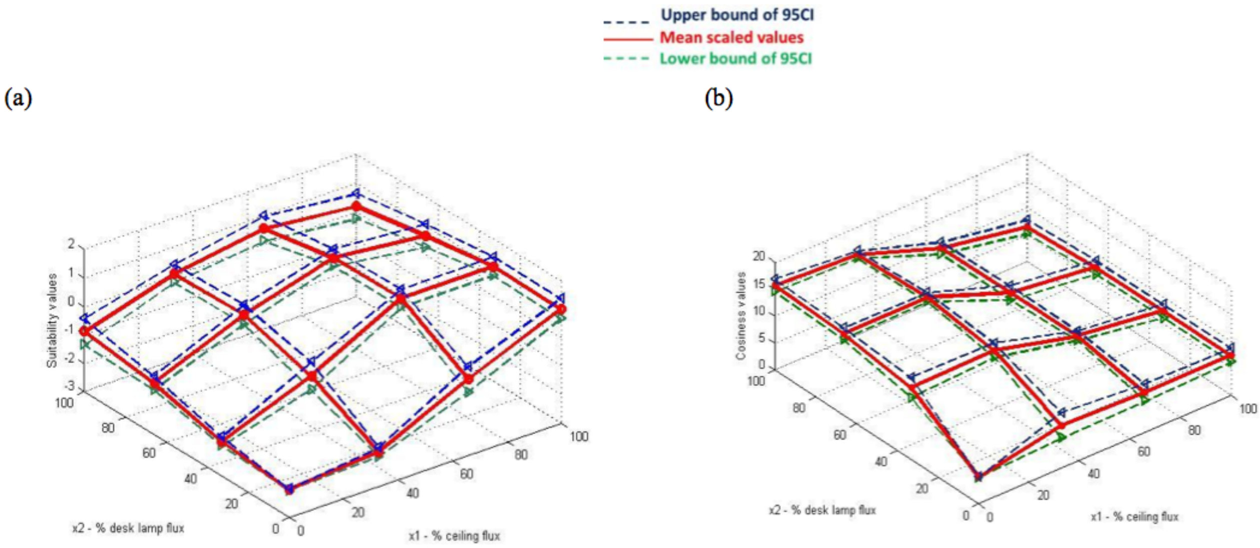


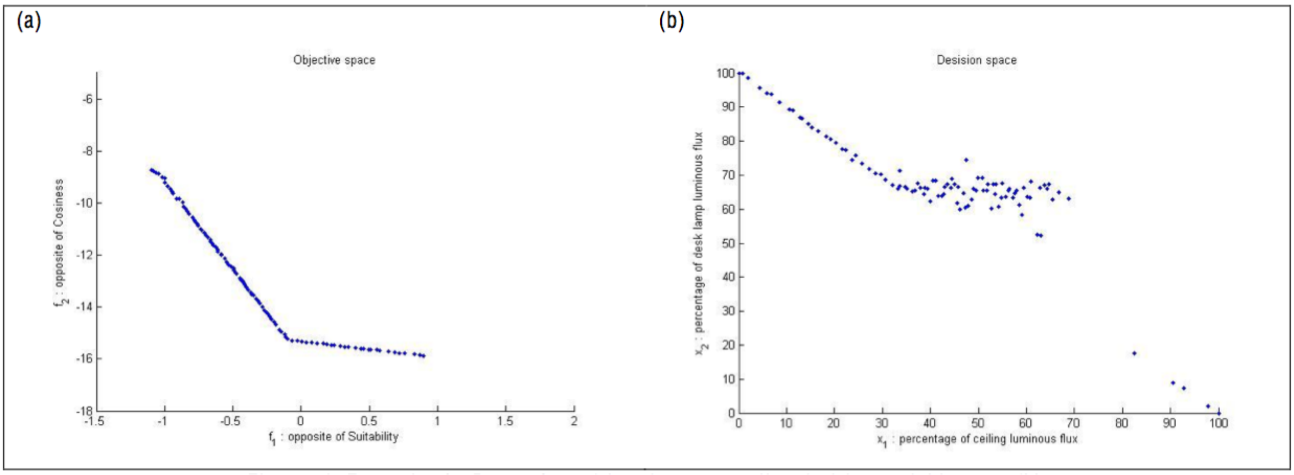
Figure 9: The MH algorithm (version 2)



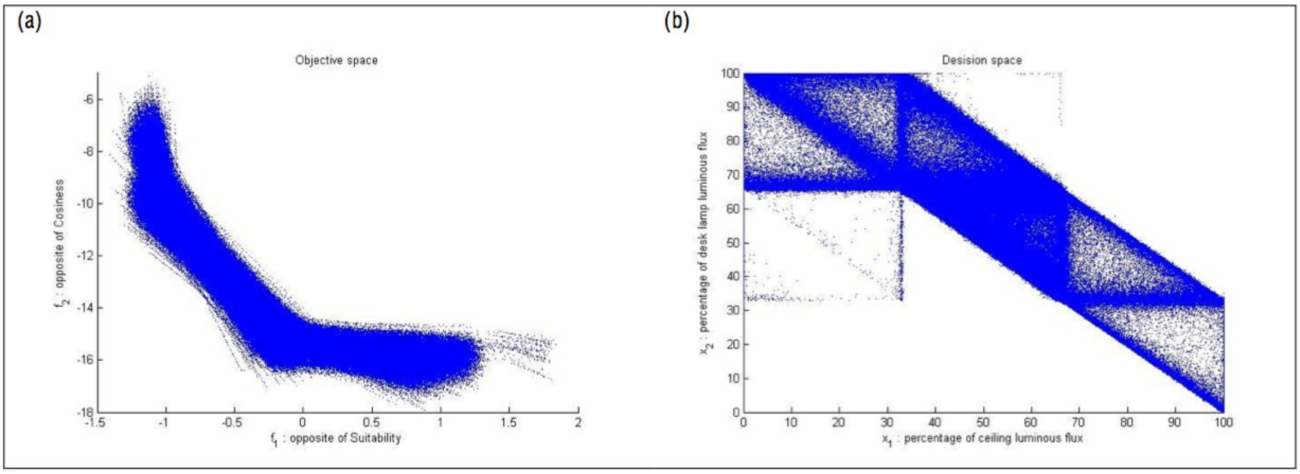
Figures 1: Two examples of lighting solutions assessed during the psychovisual experiment



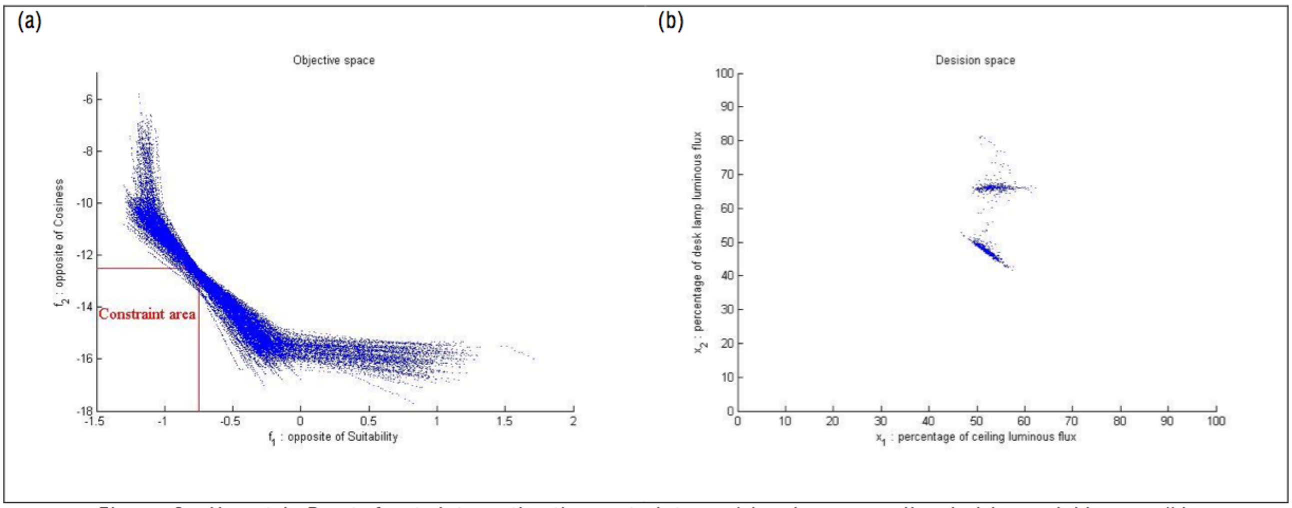
Figures 2: "Suitable" (a) and "cosiness" (b) uncertain psychovisual functions



Figures 4: Example of a Pareto front (a) and corresponding decision variable space (b).



Figures 5: "Uncertain Pareto front" (a) and corresponding Decision Variable space (b). Results with 10.000 MC draws.



Figures 6: "Uncertain Pareto front" intersecting the constraint area (a) and corresponding decision variable space (b).