Energy and Buildings 125 (2016) 66–74

Contents lists available at ScienceDirect

Energy and Buildings

journal homepage: www.elsevier.com/locate/enbuild

Application of multi-objective genetic algorithms to interior lighting optimization

Evangelos-Nikolaos D. Madias [a,*], Panagiotis A. Kontaxis [a,b], Frangiskos V. Topalis [a]

[a] Lighting Laboratory, School of Electrical and Computer Engineering, National Technical University of Athens, Heroon Polytechniou 9, 157 80 Zografou, Greece

[b] Department of Energy Technology Engineering, Technological Educational Institute of Athens, Agiou Spyridonos, 12243, Egaleo, Greece

ARTICLE INFO

Article history:
Received 23 February 2016
Received in revised form 16 April 2016
Accepted 30 April 2016
Available online 2 May 2016

Keywords:
Multi-objective optimization
Energy efficient lighting
Lighting control
NSGA

ABSTRACT

The energy consumed by artificial lighting represents a vast amount of total energy consumption of a building. LED luminaires combine many advantages and they are considered a prominent lighting technology. The utilization of miscellaneous optimization methods in lighting control has achieved a variety of benefits, such as energy savings while sustaining illuminance at the required levels. However, there is a lack of methods, which take into account the uniformity of lighting which is a significant factor that should be considered according to the EN 12464. This paper proposes a multi-objective optimization model for artificial lighting control so as to minimize energy consumption and the same time maximize uniformity of lighting while maintaining the illuminance at an appropriate level. Two objective functions have been used, the first is the summation of the dimming levels of the luminaires of an interior space and the second is the coefficient of variation of root mean square error of illuminance which is metric of the uniformity of artificial lighting. Both functions have been formulated as mathematical functions of the dimming levels of the luminaires. Constraints include the required level of illuminance and the luminaires' dimming capabilities. The Non-Dominated Sorting Genetic Algorithm II is used to carry out the optimization. The proposed model has been implemented in an office room and the results demonstrated significant energy savings up to 22%. The proposed approach is flexible and can be applied to all types of interior spaces and is independent of the geometry and configuration of the room.

1. Introduction

The decrease of energy consumption has been imperative in order to create sustainable buildings for the future. Lighting is energy intensive since the energy consumed for lighting represents a percentage of 25–35% of the total energy consumption of a building [1]. In the European Union the electricity consumed for lighting corresponds to the largest energy consumption percentage in the tertiary sector with 21.57%, namely 164 TWh in 2007 [2].

Several research papers have emphasized the advantages of solid state lighting. A life cycle assessment of two lighting technologies based on compact fluorescent and LED luminaires used for general office lighting has concluded that the LED luminaire has a lower environmental impact mainly due to high energy efficiency in its use [3]. Furthermore, the lifetime of LED luminaires has been highlighted as an indisputable advantage compared to traditional light sources [4,5]. In particular, LED luminaires have 9–10 times longer lives than fluorescent luminaires [6]. Moreover, LED luminaires provide more flexibility and versatility, regarding the control of their light output than other types of luminaires [7,8]. Thus, it is efficient to combine lighting controls with LED lighting. Conclusively, LED luminaires are considered as a prominent lighting technology for the future [6,9].

Several optimization techniques have been exploited in order to reduce the energy consumption of artificial lighting. Lighting control has been modelled as a linear programming problem so as to accomplish energy efficiency and satisfy occupants' lighting preferences [10]. The same authors used this formulation to integrate daylight exploitation, occupancy control and light level tuning strategies so as to achieve energy savings up to 60% [11]. Linear optimization has been utilized at another research so as to define the appropriate dimming levels of the luminaires and provide uniform lighting in occupied areas [12].

Multi-objective optimization methods have been widely used in lighting control. A multi-objective evolutionary algorithm was developed to design an exterior lighting system which reacts to dif-

* Corresponding author.
E-mail address: madiasevagelos@gmail.com (E.-N.D. Madias).

http://dx.doi.org/10.1016/j.enbuild.2016.04.078
0378-7788/

ferent user defined inputs, lighting pole positioning constraints and achieves low energy consumption as well optimum illuminance and uniformity according to standards [13]. A study has combined multi-objective optimization and subjective data obtained from psycho-visual tests to optimize lighting by considering not only energy saving but also visual preferences of the occupants of the room [14]. Some researchers used multi-objective optimization to maximize the accuracy of the illuminance on the work plane and at the same time minimize the power required by the luminaires with the aid of a generalized extremal optimization algorithm [15].

Genetic algorithms have been proven useful in lighting. A genetic algorithm has been employed in order to predict real-time daylight levels in an office, by using external measurements of illuminance [16]. A fitness function that considered light intensity, uniformity, shading effects and costs has been used as input for a genetic algorithm in order to optimize the design of lighting systems for greenhouse facilities [17]. The lighting system of a sports field, was designed through a genetic algorithm by maximizing the product of an illuminance and a uniformity function [18].

Plenty of other optimization methods have been applied in lighting control. Some researchers have utilized a neural network to describe the complex relationship between dimming level and measured illuminance on the task area and proposed an appropriate optimization algorithm for energy efficiency [19]. Moreover, an iterative optimization algorithm, which did not depend on the accurate knowledge of daylight distribution, was used to maximize spatial uniformity and minimize energy consumption in a lighting system that consisted of multiple luminaires, with integrated light and occupancy sensors and a central controller [20]. Another optimization algorithm, which took into account the relationship between the position of luminaires and the light sensors, was used for the design and implementation of an intelligent lighting system and achieved energy savings that ranged from 60 to 80% in an office room [8]. Particle Swarm Optimization has been also employed for energy saving control of luminaires in office lighting [21,22].

Reviewing the current literature it is noticeable that a lot of different methods exist to optimize lighting systems. However, there exist very few methods which take into account not only the level of illuminance but the uniformity of lighting as well. The uniformity of lighting is a significant factor which should be considered in the design of an indoor lighting system. Thus, EN 12464 establish particular standards not only for the levels of illuminance but for uniformity as well [23]. Furthermore, there exist no concrete methods to associate spatial uniformity with the dimming levels of the luminaires. Aim of this paper is to overcome the above mentioned obstacles and present a multi-objective optimization model for interior lighting that fully complies with the EN 12464. Special attention is being paid not only to the illuminance but to the uniformity of lighting as well. Both the illuminance as well as the uniformity have been formulated as mathematical functions of the dimming levels of the luminaires. A multi-objective genetic algorithm is used to calculate the optimum dimming level for each luminaire so as to fulfill the goals of the optimization, namely energy efficiency and at the same time sufficient illuminance and maximum uniformity. The rest of the paper is organized as described below. In Section 2 the formulation of the model is presented, which consists of the documentation of the theoretical background of multi-objective optimization and the mathematical representation of the proposed model. The operation of a multi-objective optimization genetic algorithm, namely the Non Dominated Sorting Genetic Algorithm, is explained in Section 3. In Section 4, a case study is shown, which concerns the application of the proposed optimization approach in an office lighting system. Finally, in Section 5 the results of the case study are documented and in Section 6 the conclusions of this research are presented.

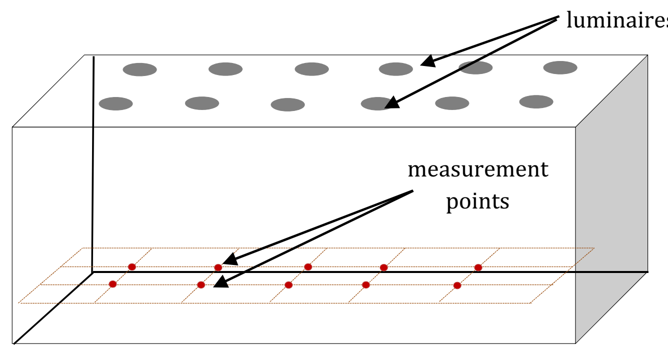

Fig. 1. Visual representation of the proposed approach.

2. Model formulation

2.1. Theoretical background

In real world applications, there exist a lot of problems where the decision maker must take a decision based on multiple and often conflicting criteria or objectives. In contrast to a single optimization problem, where the optimal solution is usually just one, a multi-objective optimization provides the decision maker with a set of solutions that fulfill all conflicting criteria. There exists rarely a single solution that satisfies all criteria or objectives concurrently [24].

The general form of a multi-objective minimization problem is the following one:

$$\begin{aligned} &\mathrm{Min}\,\mathbf{f}(\mathbf{x}) = \min\left\{f_1(x), f_2(x), \ldots, f_k(x)\right\} \\ &x = \{x_1, x_2, \ldots, x_z\} \end{aligned} \tag{1}$$

Subject to: $\mathbf{g}(\mathbf{x}) \geq 0$

$\mathbf{h}(\mathbf{x}) = 0$

$\mathbf{x}^l \leq \mathbf{x} \leq \mathbf{x}^u$ where $\mathbf{f}$ is a vector comprising of k objective functions, $\mathbf{x}$ is a vector comprising of z solutions, $\mathbf{g}$ and $\mathbf{h}$ are vectors corresponding to inequality and equality constraints respectively. Apart from the constraints, lower bounds ($\mathbf{x}^l$) and upper bounds ($\mathbf{x}^u$) can be applied to the solutions of the problem. The solutions of a multi-objective optimization problem are known as the Pareto optimal solutions [24,25].

2.2. Mathematical formulation of multi-objective optimization in interior lighting

The goal of the proposed model is to find the minimum dimming level of the luminaires so as to achieve energy saving as well as to comply with the specifications of EN 12464 regarding illuminance and uniformity in interior lighting. The model exploits the linear relationship which exists between the contribution of each luminaire and the illuminance on the task area. Particularly, an interior space area, which is illuminated by m luminaires, can be discretized into a grid of n measurement points, as shown in Fig. 1. The illuminance at a specific point of the workplane level (Ei), can then be represented as a linear combination of the contribution of each luminaire on that measurement point (c_{ij}) and the corresponding dimming level of that luminaire (dj) [10,11,22,26]. This model is based on the superposition theory, known from Physics. Representing the illuminance variable as a vector ($\mathbf{E}$) comprising of the values of illuminance on each measurement point, the dimming of the luminaires also as a vector ($\mathbf{d}$) and the contribution of each luminaire to each measurement point as a matrix (C), the model can be formulated as shown below:

$$E = \begin{bmatrix} E_1 \\ E_2 \\ \vdots \\ E_n \end{bmatrix} = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1m} \\ c_{21} & c_{22} & \cdots & c_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ c_{n1} & c_{n2} & \cdots & c_{nm} \end{bmatrix} \begin{bmatrix} d_1 \\ d_2 \\ \cdots \\ d_m \end{bmatrix} = C \times \mathbf{d} \tag{2}$$

The mean illuminance, can be modelled using the above mentioned formulation as a scalar function of the dimming levels of the luminaires, as shown in the following formula.

$$E_{av} = \frac{\Sigma_{i=1}^{n} E_i}{n} = \frac{\Sigma_{i=1}^{n}\Sigma_{j=1}^{m} c_{ij} d_j}{n} \tag{3}$$

There are two ways to find the contribution of a luminaire on a measurement point. The first method is through a light simulation software tool such as Relux [27]. The software can simulate the lighting system and calculate the illuminance at any surface of the room by applying a virtual measuring area which is defined by the user. The contribution of each luminaire is found by activating one luminaire at a time while deactivating the rest of the luminaires in the simulation model. The second method which is time-consuming, but can be carried out for evaluation purposes, is through actual measurement. Given an existing installation of luminaires, a set of measurements points onto the workplane area is selected. A luxmeter is placed on each one of them. In order to find the contribution of each luminaire to each measurement point the luminaire is switched on while the other luminaires are switched off. Then, the lux meter measures the illuminance on the measurement point.

The EN 12464 establishes specific requirements for interior lighting with regards to mean illuminance and uniformity, which is calculated by dividing the minimum value of illuminance by the mean illuminance, as shown below [23].

$$U_o = \frac{E_{min}}{E_{av}} \tag{4}$$

The above mentioned standard does not provide a direct mathematical function, which relates the uniformity with the dimming levels of the luminaires. After all, the minimum value of illuminance inside a room changes spatially depending on the dimming level of each luminaire. However, some optics-related studies have used the coefficient of variation of root mean square error as an evaluation criterion of the uniformity of irradiance and have produced various optimization algorithms to deduce the optimum location coordinates of LED arrays on the source plane (e.g. ceiling) while providing the highest uniformity of illumination on the target plane [28–30]. Minimization of the coefficient of the variation of the root mean square error leads to maximization of the uniformity. The coefficient of variation is given by the following expression:

$$CV = \frac{\sigma}{E_{av}} \tag{5}$$

where σ represents the standard error of illuminance, which is given by the following formula:

$$\sigma = \sqrt{\frac{\Sigma_{i=1}^{L}\Sigma_{j=1}^{W}(E_{ij} - E_{av})^2}{L \times W}} \tag{6}$$

where L and W are the measurement points along the two dimensions of the room.

In order to associate the standard error with the dimming levels of the luminaires, equation (6) must be formulated by integrating equations (2) and (3) as shown below:

$$\sigma = \sqrt{\frac{\Sigma_{i=1}^{L}\Sigma_{j=1}^{W}(E_{ij} - E_{av})^2}{L \times W}} = \frac{1}{\sqrt{L \times W}} \times \sqrt{\sum_{i=1}^{n}\left(\sum_{j=1}^{m} c_{ij} d_j - \frac{\Sigma_{i=1}^{n}\Sigma_{j=1}^{m} c_{ij} d_j}{n}\right)^2} \tag{7}$$

The coefficient of variation can now be rewritten as,

$$CV = \frac{n}{\sqrt{L \times W}} \times \frac{\sqrt{\Sigma_{i=1}^{n}\left(\Sigma_{j=1}^{m} c_{ij} d_j - \frac{\Sigma_{i=1}^{n}\Sigma_{j=1}^{m} c_{ij} d_j}{n}\right)^2}}{\Sigma_{i=1}^{n}\Sigma_{j=1}^{m} c_{ij} d_j} \tag{8}$$

Both the mean illuminance and the coefficient of variation of the root mean square error of the illuminance had been mathematically formulated as functions of the dimming levels of the luminaires. In order to quantify energy savings it is assumed that the dimming of the LED luminaires is controlled with pulse width modulation (PWM) and its dimming level (d_i) is approximately proportional to its power consumption (P_i) [12,31,32]. In order words, it is considered that an approximately linear relationship exists between the light output and power consumption. Thus, the minimization of dimming levels of all luminaires is identical to the minimization of power consumption of the artificial lighting system. However, even if the exact relationship between power consumption and light output is not linear, the minimization of dimming levels would still lead to energy consumption minimization. The assumption of linearity does not affect the core of the proposed multi-objective optimization approach. Taking into consideration the above mentioned information, the multi-objective optimization problem can be formed as below:

$$\begin{aligned} &\mathrm{Min}\,\mathbf{f}(\mathbf{d}) = \min\left\{f_1(\mathbf{d}), f_2(\mathbf{d})\right\} \\ &f_1(d) = \sum_{i=1}^{m} d_i \\ &f_2(d) = CV(d) = \frac{n}{\sqrt{L \times W}} \times \frac{\sqrt{\Sigma_{i=1}^{n}\left(\Sigma_{j=1}^{m} c_{ij} d_j - \frac{\Sigma_{i=1}^{n}\Sigma_{j=1}^{m} c_{ij} d_j}{n}\right)^2}}{\Sigma_{i=1}^{n}\Sigma_{j=1}^{m} c_{ij} d_j} \\ &\mathbf{d} = [d_1, d_2, ..., d_m] \end{aligned} \tag{9}$$

$$\text{Subject to: } E_{av} = \frac{\Sigma_{i=1}^{n}\Sigma_{j=1}^{m} c_{ij} d_j}{n} \geq E_{min}$$

$$D_{min} \leq \mathbf{d} \leq D_{max}$$

where:

d: is a vector comprising of the dimming levels of the luminaires

f1(d): is the first objective function, namely the summation of all the dimming levels

f2(d): is the second objective function namely the coefficient of variation of the root mean square error of illuminance

Emin: is the minimum value of the mean illuminance

Dmin, Dmax: are the lower and upper bounds which correspond to each luminaire's dimming capability.

3. Non dominated sorting genetic algorithm II

Genetic algorithms are a reliable method for solving many optimization problems either with continuous or discontinuous objective functions and do not depend on initial solution guesses [33]. The Non Dominated Sorting Genetic Algorithm II (NSGA II) is an evolutionary multi-objective optimization algorithm that was proposed by Deb et al. and performs well with real world problems [34]. The algorithm starts with the creation of an initial parent population of solutions, which fulfill both the objective functions. An

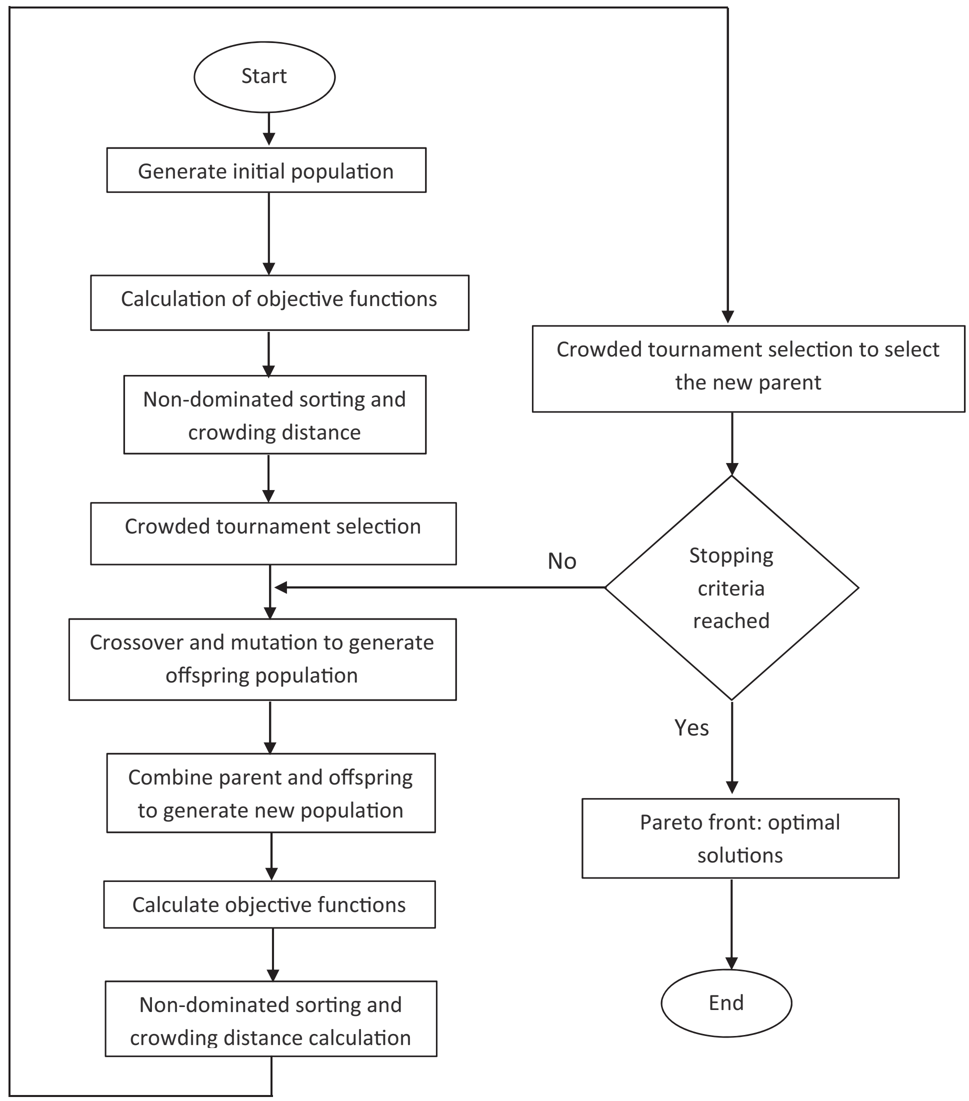

Fig. 2. Flowchart of NSGA.

evaluation procedure begins and the population is evaluated based on two criteria: domination and crowding distance. Regarding the criterion of domination, one individual (solution) is considered to dominate the other if two conditions hold true: first of all, it is no worse than the other in all objectives and second, it is strictly better in at least one objective. The criterion of domination ranks the entire population into different fronts. For example, the non-dominated solutions of the whole population are classified to front 1. The set of non-dominated solutions of the whole population apart from front 1 are classified to front 2, etc. The second criterion, namely the crowding distance is a metric of the space around a solution which is not occupied by another solution. A large crowding distance means that the solution is less crowded and should be preferred. Through the implementation of crowded tournament selection, the individuals which belong to a front with a higher rank and are characterized by a larger crowding distance are selected to produce offsprings, through the genetic operators of crossover and mutation. Crossover is able to create an offspring solution that preserves the same attributes with the parent solutions. Mutation is a genetic operator that can modify some gene values in order for the offsprings to have different characteristics than their parents. After the crowded tournament selection, the offspring and the parent population are combined to create a new population. The combination of individuals that belong to parent and offspring populations ensures elitism. The whole procedure is repeated until a certain condition is satisfied, e.g. a certain number of iterations is reached [35]. The result of the algorithm is a set of optimal solutions, namely the Pareto front of solutions. A flowchart of the NSGA II is shown below (Fig. 2).

4. Case study: office lighting

The proposed optimization model was tested in an actual office room which is located at the School of Electrical and Computer Engineering in the campus of the National Technical University of Athens, Zografou, Greece. The office dimensions are $8 \times 6 \times 2.8$ m. The office is illuminated by 15 recessed LED downlights. Each LED downlight has a total luminous flux of 2120 lm and its active power is 27W. The arrangement of the luminaires is depicted in Fig. 3. The light output of the luminaire can be controlled through the DALI protocol. The Digital Addressable Lighting Interface (DALI) is a communication protocol used for communication between lighting components [36]. A rectangular measurement grid with a length of 6.6 m and a width of 5 m was defined according to the EN 12464 and comprised of square cells. Totally, 54 measurement points were selected, namely 9 measurements points across the length of the

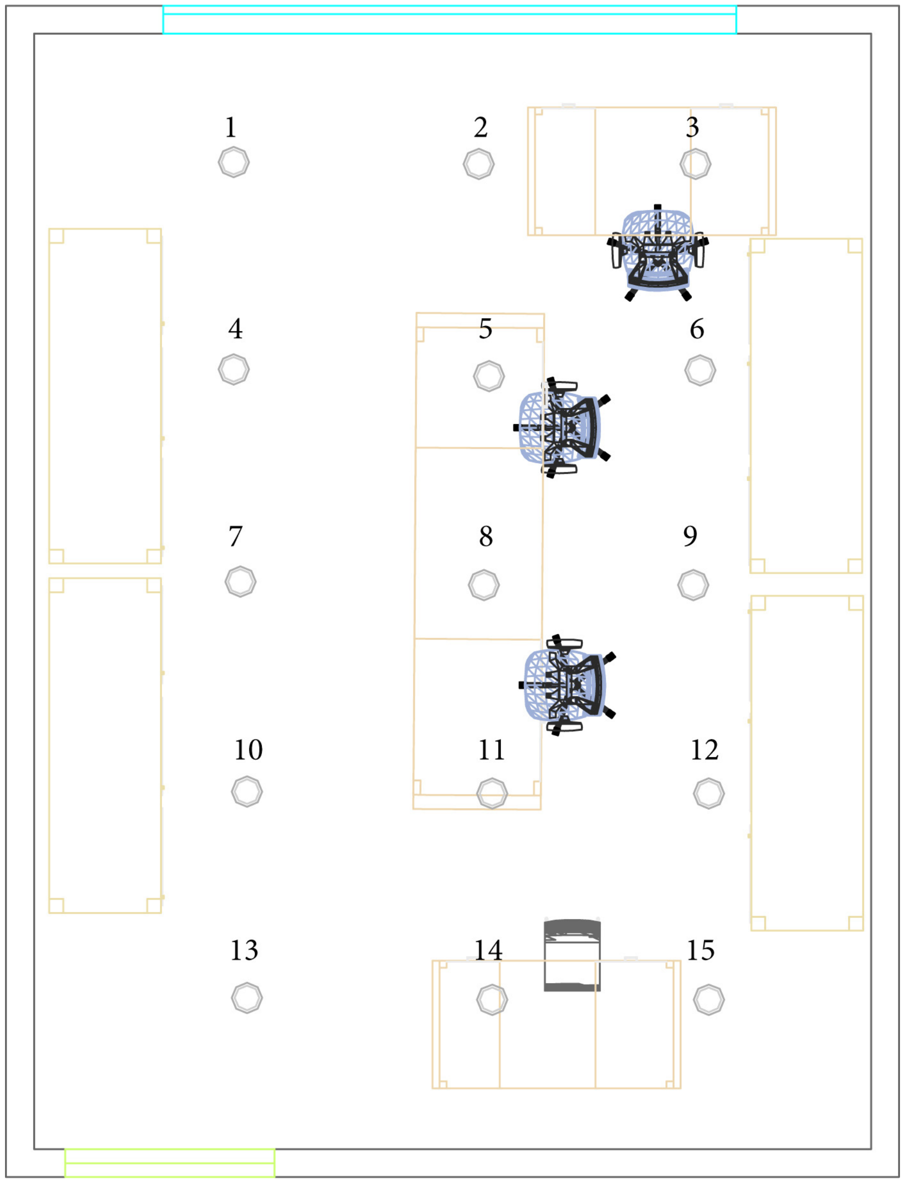

Fig. 3. Arrangement of the luminaires inside the room.

room and 6 measurement points across the width of the room. This measurement grid was used to calculate the average illuminance as well as the uniformity of lighting, as they are defined by the EN 12464, through the conduction of simulations in Relux, a lighting simulation tool [27]. The contribution of each one of the luminaires has also been calculated through the use of Relux. The average illuminance of the room, with all luminaires in their maximum light output, namely 100%, is 635 lx, the uniformity of lighting is 0.61 and the coefficient of variation of the mean square error of illuminance is 0.1721. A contour plot, which depicts the distribution of illuminance across the room, is shown in Fig. 4. Specific requirements regarding the lighting of office rooms, namely a threshold of 500 lx for the average illuminance and a threshold of 0.6 for the uniformity are established by the EN 12464 [23]. It is obvious that the lighting in the office room complies with the above mentioned requirements. However, through the application of the proposed multi-objective optimization, significant energy savings can be accomplished while enhancing uniformity and sustaining visual comfort. The mathematical formulation of the proposed multi-objective optimization, which is adapted to the arrangement of the above mentioned office room is presented below:

$$f_1(\mathbf{d}) = \sum_{i=1}^{15} d_i$$

$$f_2(d) = CV(d) = \frac{54}{\sqrt{9\times 6}} \times \frac{\sqrt{\Sigma_{i=1}^{54}\left(\Sigma_{j=1}^{15} c_{ij} d_j - \frac{\Sigma_{i=1}^{54}\Sigma_{j=1}^{15} c_{ij} d_j}{54}\right)^2}}{\Sigma_{i=1}^{54}\Sigma_{j=1}^{15} c_{ij} d_j}$$

$$\mathbf{d} = [d_1, d_2, \ldots, d_{15}] \tag{10}$$

$$\text{Subject to: } E_{av} = \frac{\Sigma_{i=1}^{54}\Sigma_{j=1}^{15} c_{ij} d_j}{n} \geq 500$$

$$0 \leq \mathbf{d} \leq 1$$

Aim of the optimization is to find the optimum dimming levels ($\mathbf{d}$=[d_1,d_2,. . ..,d_{15}]) that optimize both the objective functions ($f_1(\mathbf{d})$,$f_2(\mathbf{d})$) and comply with the constraint and the bounds. The constraint regards the average illuminance that should be above

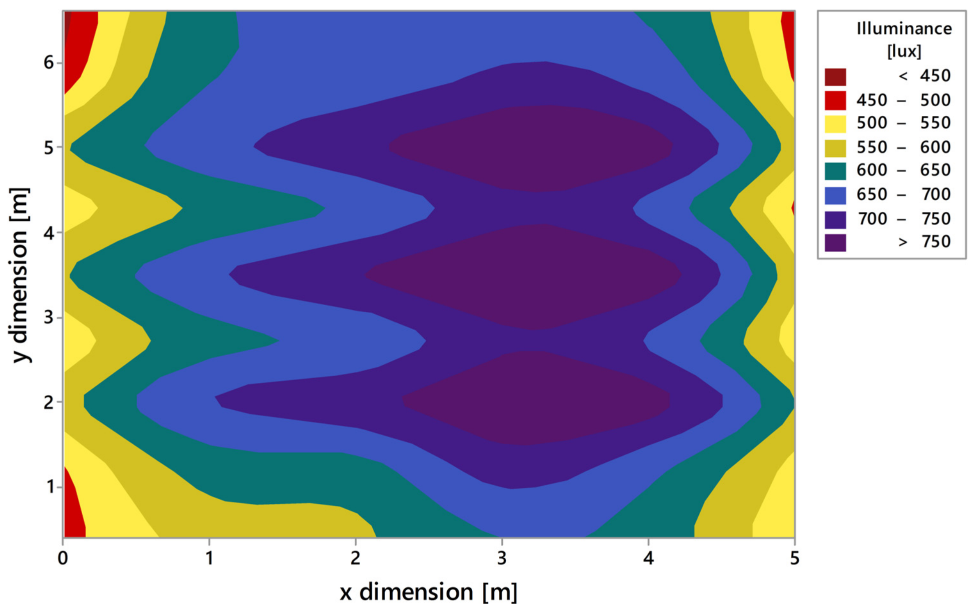

Fig. 4. Contour plot of the illuminance across the room.

500 lx, as it is mentioned before and the bounds correspond to each luminaire's dimming capability, namely from 0 to 1 (100%).

5. Results and discussion

A variant of NSGA-II was implemented in Matlab 2014a with the aid of the Global Optimization Toolbox [37]. The generated Pareto front that contains the set of 70 optimal solutions that optimize both the objective functions of the average illuminance and the coefficient of variation of the root mean square error of illuminance and satisfy the constraints and bounds, is shown in Fig. 5. The Pareto front also demonstrates the trade-off between the two objective functions.

Mathematically, all the solutions that belong to the Pareto front are equivalent. However, since only one solution is requested so as to be implemented, it is the decision maker's responsibility to evaluate the Pareto set of solutions according to his/her experience and the specific requirements of each optimization problem and select one as the solution to the problem [38]. In our case study, weights were attributed to each objective function so as to select the final solution as the weighted average of the results of both objective functions. A combination of equal weights (50%) to the performance of both objective functions gives the following dimming levels as the optimum solution:

$$(\mathbf{11})\mathbf{d} = [d_1, d_2, d_3, d_4, d_5, d_6, d_7, d_8, d_9, d_{10}, d_{11}, d_{12}, d_{13}, d_{14}, d_{15}] = 0.68, 0.86, 0.67, 0.93, 0.82, 0.67, 0.68, 0.70, 0.98, 0.99, 0.70, 0.99, 0.63, 0.68, 0.77]$$

The dimming of the luminaires at the above mentioned levels gives a total energy saving of 22%. This combination of dimming levels happens to be identical with the combination of dimming levels, which maximizes energy savings. The value of the average illuminance is 500 lx and the uniformity (U_o) is 0.64, higher than the initial uniformity which was 0.61. The value of the coefficient of variation of the mean square of illuminance is 0.1635. The dimming levels of luminaires are asymmetrical because this solution takes into account not only uniformity but energy saving as well. A contour plot that shows the distribution of illuminance across the room is presented in Fig. 6.

Furthermore, it should be noted for the sake of completeness, that the combination of dimming levels that maximizes uniformity (U_o), by minimizing the coefficient of variation of root mean square error of illuminance, is the following one:

$$(\mathbf{12})\mathbf{d} = [d_1, d_2, d_3, d_4, d_5, d_6, d_7, d_8, d_9, d_{10}, d_{11}, d_{12}, d_{13}, d_{14}, d_{15}] = [0.93, 0.74, 0.92, 0.94, 0.62, 0.83, 0.79, 0.69, 0.80, 0.96, 0.70, 0.83, 0.93, 0.78, 0.89]$$

The dimming of the luminaires at the above mentioned levels gives a total energy saving of 18%. It is self-evident that the dimming levels of the luminaires are almost symmetrical since this particular solution emphasizes uniformity rather than energy saving. The value of the average illuminance is 517 lx and the uniformity (U_o) is 0.77, much higher than the initial uniformity of 0.61. The value of the coefficient of variation of the mean square of illuminance is 0.1067. A contour plot that visualizes the results is presented below (Fig. 7).

Reviewing the results of the case study, the benefits of the proposed optimization approach should be highlighted. First of all, it is a fast and efficient optimization model since it requires low computational effort. Furthermore, it is an easily applicable method that requires zero interventions to a building, thus no additional cost and contributes to efficient energy management. This study documented significant energy savings, up to 22%. It is self-evident that the proposed optimization model could achieve even greater energy savings in spaces which are excessively illuminated. This model is also useful for the optimization of the initial lighting installation of an interior space, where the lighting design aims at an average illuminance which is higher than the maintained illuminance (and the required illuminance as well) because the maintenance factor is taken into account. In other words, the initial illuminance of an interior space is higher in order to compensate for the gradual loss of luminous flux due to lumen depreciation or dirt. This leads to energy waste. Furthermore, the proposed optimization model optimizes not only energy consumption but visual comfort as well, since it takes into account simultaneously both the illuminance and the uniformity of lighting inside the room. Thus, it enhances the quality of lighting so as to fully comply with the EN 12464. Moreover, it is an optimization model which is flexible, eas-

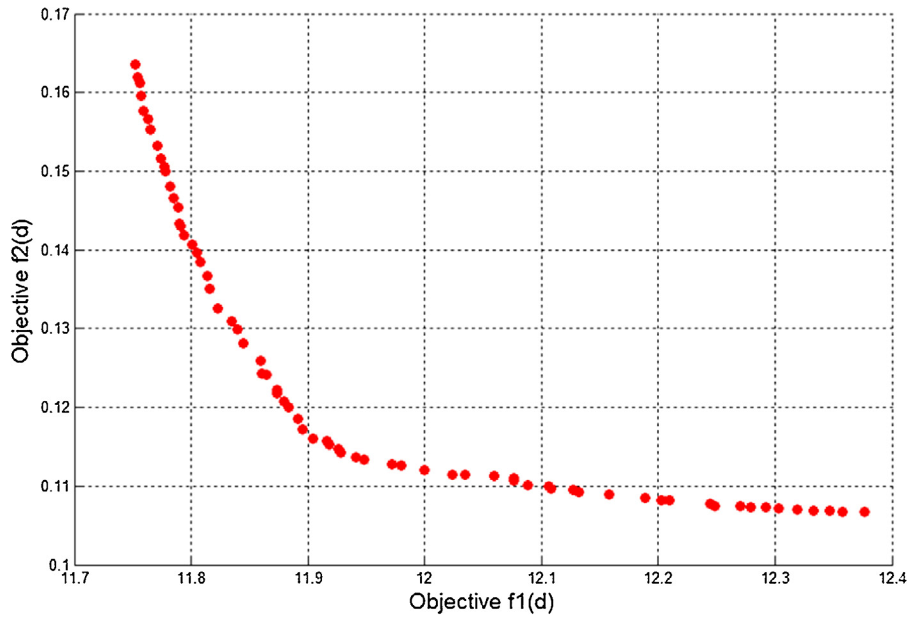

Fig. 5. Pareto front of optimal solutions.

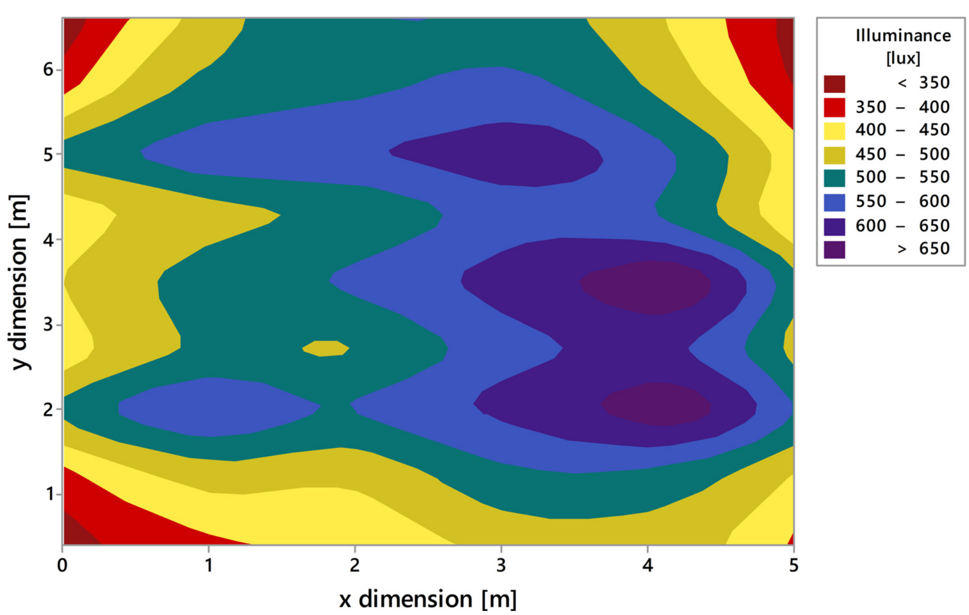

Fig. 6. Contour plot of the illuminance across the room (optimum solution).

ily customizable and can be applied to all types of interior spaces. The threshold of the required illuminance can easily be adjusted to meet the specific requirements, established by the standards for every type of interior space. Besides, the core of the optimization model, namely the function of the Non-Dominated Sorting Genetic Algorithm II remains the same and is independent of the configuration of the luminaires and the geometry of the room. Since the proposed optimization model provides specialized dimming levels for each luminaire it can be extremely useful in large spaces, where the optimization can be focused on particular areas which require a higher level of illuminance and uniformity than the ambient lighting. Although, the model was implemented in an office room which was illuminated by LED luminaires, it is obvious that it can also be applied to any type of dimmable light source. Combination of the proposed optimization method with daylight controls or occupancy sensors can further improve the energy efficiency of a lighting system. Future integration of this optimization model in a light simulation software would enhance the results of lighting calculations regarding energy savings, average illuminance and spatial uniformity and provide the lighting designer with the ability to optimize the lighting design of a room prior to the installation of luminaires.

6. Conclusions and future research

A significant amount of energy is used for lighting in buildings, thus making it imperative to implement energy efficient methods in lighting control systems. LED luminaires are considered a promising lighting solution since they are flexible to control, energy efficient and have a longer lifetime compared to traditional light sources. The application of optimization methods in lighting control has provided multiple benefits for energy savings and visual

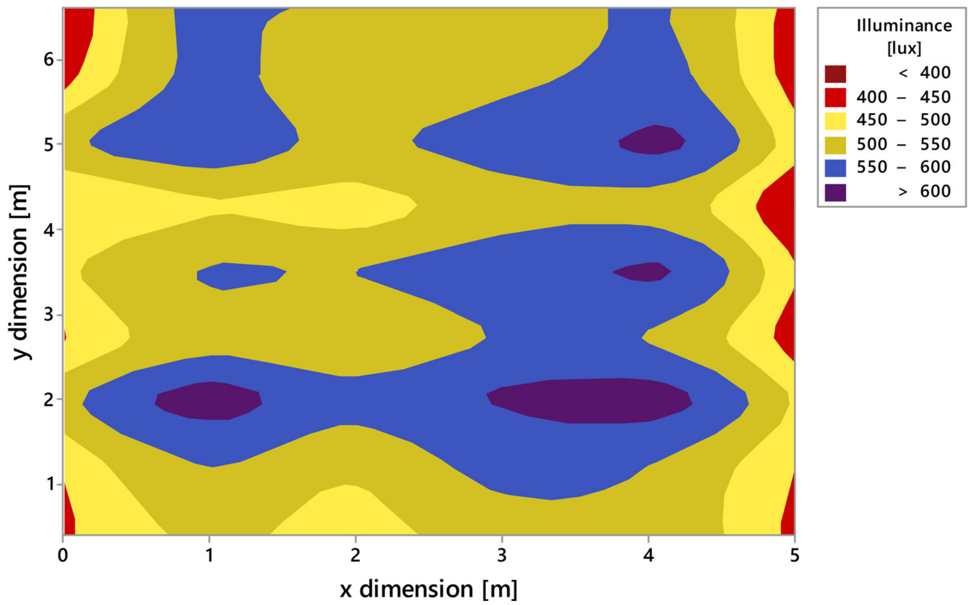

Fig. 7. Contour plot of the illuminance across the room (maximum uniformity).

comfort. In this paper, a new multi-objective optimization model has been proposed so as to satisfy two primary objectives, the minimization of the luminaires' dimming levels, which leads to energy saving and the maximization of uniformity by minimizing the coefficient of variation of root mean square error of illuminance. An evolutionary multi-objective genetic algorithm, namely the Non Dominated Sorting Genetic Algorithm II has been utilized to optimize the two objective functions while satisfying the constraints. A case study, which regards the application of the proposed optimization model in an office room that is illuminated by 15 LED luminaires, has led to significant energy savings, which ranged from 18% to 22%. The advantages of the optimization model for lighting engineers include its high flexibility, easy customization, zero intervention to the building, adaptability to all types of interior spaces and dimmable light sources, enhancement of lighting quality so as to fully comply with EN 12464 and of course the achievement of balance between energy efficiency and visual comfort. Future research concerns the cooperation of the proposed optimization model with daylight controls and occupancy sensors, the integration of this model to light simulation software as well as the application of other optimization methods to interior and exterior lighting.

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