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Application of a Differential Evolution Algorithm in the Design of Public Lighting Installations Maximizing Energy Efficiency

Ovidio Rabaza [a], Daniel Gómez-Lorente [a], Antonio M. Pozo [b], and Francisco Pérez-Ocón [b]

[a]Department of Civil Engineering, University of Granada, Granada, Spain; [b]Department of Optics, University of Granada, Granada, Spain

ABSTRACT
This article presents a differential evolution (DE) algorithm that can be used to plan public lighting for streets, roadways, and freeways and maximize the energy efficiency of the installation. The algorithm was applied to a model based on new relationships between the energy efficiency of street lighting systems and geometric parameters such as street width, luminaire height, and distance between poles. These relationships were derived from the regression analysis of a large sample of outputs. The results of this algorithm consisted of the luminaire arrangement (one-sided, two-sided staggered, and two-sided coupled), luminaire height, luminaire type, and pole spacing for the most energy-efficient installation. The input of the algorithm was the lighting class or illuminance level, street width, as well as various other luminaire parameters. When these results were compared with those of DIALux, the performance of this new method was found to be extremely satisfactory. Furthermore, the constraints applied guaranteed compliance with the recommendations of the International Commission on Illumination.

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Differential evolution algorithm; energy efficiency; optimization; public lighting

1. Introduction

Currently, the design of public lighting is an optimization problem solved with techniques based on evolutionary algorithms (Eiben and Smith 2003; Fernandez et al. 2010; Garcia and Herrera 2009), which guarantee that the installation will meet all requirements. Previous studies using multi-objective optimization algorithms (Deb 1999; Fonseca and Fleming 1993) provided design solutions that optimize certain lighting parameters. For example, in Gómez-Lorente et al. (2013) and Rabaza et al. (2013), where multi-objective algorithms were applied, the two parameters optimized were energy efficiency and uniformity of illuminance where the illumination level corresponded to the recommended values for the road type.

This research presents an even simpler and more accurate procedure to rapidly plan energy-efficient solutions for road lighting design. For this purpose, we applied a differential evolution (DE) algorithm (Storn and Price 1997). This evolutionary technique has been successfully used in various continuous optimization problems (Gómez-Lorente et al. 2012) where it has performed well and provided solutions for complex problems with linear or nonlinear functions.

The parameters in the DE algorithm are luminaire arrangement (one-sided, two-sided coupled, and two-sided staggered), luminaire height (*H*), luminaire type (e.g., metal halide [MH], light emitting diode [LED], high-pressure sodium [HPS], high-pressure mercury [HPM] lamps, etc.), and the average lighting magnitude (illuminance E_{av} or luminance L_{av}). Finally, for a given road width and type, the DE algorithm provides the optimal spacing between luminaires for the most energy-efficient solution. The level of illumination and uniformity act in this case as decision makers because they must comply with the recommendations of the CIE (2010).

Road lighting designers generally use certain software packages to quickly obtain a lighting configuration for a given straight road segment with a uniform width. The input data are only the width of the road to be illuminated as well as the illumination level and uniformity. At the end of the optimization process, these software packages generate various sets of (theoretical) results with

CONTACT Ovidio Rabaza ovidio@ugr.es University of Granada, Campus de Fuentenueva, 18071 Granada, Spain.
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the distribution, height, and spacing of luminaires that meet the lighting requirements recommended in the standards (European Committee for Standardization 2015). The designer then selects the most suitable option and, when necessary, redistributes the luminaires so that they are better adjusted to the road layout.

This research followed this same procedure and obtained a quick plan based on the input data. However, the difference was that our objective was to maximize the energy efficiency of an installation that complied with the UNE EN 13201 standard (European Committee for Standardization 2015). Instead of generating a large number of possible solutions, our method generated the one that was the most energy efficient.

Although in any quick plan, the results obtained are for an ideal scenario, in many cases they are applicable to real contexts. This is the case for freeways or motorways, where power consumption is considerably higher than on city streets. In addition, the route is mostly uniform.

In a second stage, it is necessary to adjust this initial solution to the specific characteristics of the road layout or the surrounding environment, such as trees, garage entrances, etc. However, what is important here is that our starting point is the most efficient energy solution.

When road width is not uniform, it may be necessary to adopt solutions in which luminaire spacing is not necessarily constant (Sędziwy 2015). Moreover, other things to be considered are elements such as intersections, small-radius curves ($R < 300$ m), and roundabouts, which must be studied separately with other methods that spatially optimize the lighting design (Feng and Murray 2017). In any case, the method presented in this article is applicable to many real contexts and is compatible with the previously mentioned methods.

The rest of this article is organized as follows. Section 2 briefly describes the model or equations on which the algorithm is based. Section 3 explains how to apply the differential evolution algorithm to obtain optimal public lighting design solutions. Section 4 shows how the algorithm was applied to three streets with different widths and lighting levels. Finally, the conclusions derived from this research are given in Section 5.

2. Background theory

The lighting system for a street or road should consider the parameters defined by the technical committees of the CIE (2010), the world's leading authority on light, lighting, and color. In street lighting design, the most important parameters are illuminance (E) or luminance (L) levels of the roadway, overall uniformity (U_0), and energy consumption. In other words, the installation should be as energy efficient as possible because this is quite a large expenditure for city councils and public administration (Kostic and Djokic 2009; Radulovic et al. 2011). However, at the same time, savings must be achieved without any loss of visibility, security, etc. (Tetri et al. 2017).

Illuminance E can be defined as the received luminous flux per unit of surface ($E = d\phi/ds$); luminance L is the emitted luminous flux within a given solid angle per unit of surface in a given direction; and the overall uniformity U_0 is the ratio between the minimum and average illuminance ($E_{\min}/E_{\mathrm{av}}$) or luminance ($L_{\min}/L_{\mathrm{av}}$). The overall uniformity measures lighting homogeneity and thus the quality of the installation.

The energy efficiency of lighting installations is calculated according to the power density indicator (European Standard EN 13201-5; European Committee for Standardization 2015), which is defined as

$$D_P = \frac{P_T}{A_T \times X_{av}} \tag{1}$$

where A_T is the total illuminated surface of the street; P_T is the total electrical power installed, including the light sources and electrical auxiliary devices; and X_{av} is the average value (illuminance or luminance) on the ground. As shown in Table 1, this parameter is the basis for establishing a set of energy efficiency classes for lighting installations based on European standard EN 13201-5 (European Commission 2017; European Committee for Standardization 2015; Ministry of Industry, Tourism and Trade 2008).

(Rabaza et al. 2016) showed that the power density indicator of a lighting installation could be calculated based on road width and luminaire height, along with three parameters that characterize the

Table 1. Energy label for street lighting installations and energy consumption in terms of the power density indicator.

Energy class	D_p [W/(lux·m²)]
A	0.000–0.014
B	0.015–0.024
C	0.025–0.034
D	0.035–0.044
E	0.045–0.054
F	0.055–0.064
G	0.065–0.074

luminaire by means of the following second-degree polynomial:

$$\varepsilon = a_0 + a_1 r + a_2 r^2 \tag{2}$$

where r is the width/height ratio (ω/H); a_j denotes the specific coefficients that characterize the luminaire; and ε is the inverse of the power density indicator ($1/D_P$).

Figure 1 shows that as the width-to-height ratio (r) increases, the efficiency of the installation also increases. In other words, the power density indicator decreases in accordance with Table 1.

2.1. Model

The functions of the evolutionary algorithm that give the most efficient energy solution are two expressions of a model (Rabaza et al. 2016) that can be used to design street lighting with ease and precision. The first expression of the model is the equation that calculates the optimal spacing between luminaires for maximum energy efficiency:

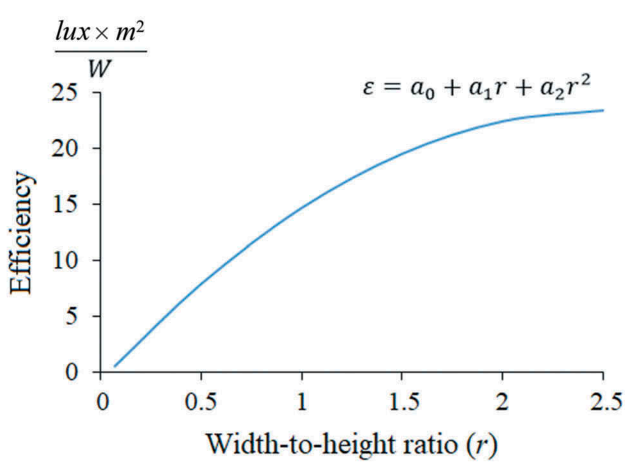

Fig. 1. Example of a polynomial plot that shows energy efficiency as a function of street width and luminaire height of a certain lighting system.

$$S = \frac{k \times P}{\omega \times E_{av}} \times \left(a_0 + a_1 \times \frac{\omega}{H} + a_2 \times \left(\frac{\omega}{H}\right)^2 \right) \tag{3}$$

where S is the distance between luminaires; P is the electrical power consumed by the luminaire; E_{av} is the average illuminance required for the road type; H is luminaire height; ω is the road width; and k is a coefficient with two possible values: $k = 1$ (if the arrangement of luminaires is one-sided) or $k = 2$ (if the arrangement is two-sided or staggered). The a_j values are parameters provided by the manufacturer that characterize the luminaire (Rabaza et al. 2016).

As shown in Table 2, k is determined by the width/height ratio (ω/H) that indicates the configuration or distribution of the luminaires. Figure 2 depicts the three types of street lighting arrangement.

According to lighting designers (Boyce 2009; Bureau of Indian Standards 2003; Peña-García et al. 2015; Van Bommel 2015), the one-sided configuration is advisable when the width of the road is equal to or less than the mounting height. The staggered arrangement is the best choice when the road width is one to one-and-a-half times that of the mounting height. The two-sided coupled arrangement should be selected when road widths are more than one-and-a-half times that of the mounting height.

Obviously, ω and E_{av} are fixed parameters determined by the characteristics of the road, as well as by the lighting levels recommended by the CIE. The other parameters (H, k, and luminaire data such as P and a_j) are the variables used by the algorithm to find the optimal solution.

The second expression of the model or decision maker (4) indicates the threshold value for the overall uniformity of the installation. The algorithm uses this expression to discard solutions that do not comply with the recommended uniformity value and implements it after the luminaire height (H) and the distance between luminaires (S) are known.

Table 2. Luminaire configuration as a function of street width and mounting height (Rabaza et al. 2016).

Configuration	r (ω/H)
One-sided	$r \leq 1$
Two-sided staggered	$1 < r < 1.5$
Two-sided coupled	$1.5 \leq r$

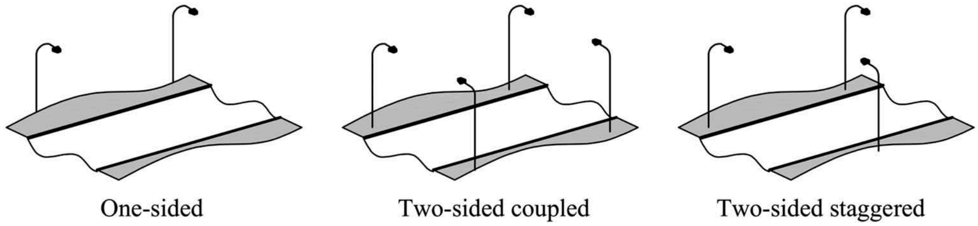

Fig. 2. One-sided, two-sided coupled, and two-sided staggered configurations for typical street lighting installations.

$$U_0 \leq \beta_0 + \beta_1 \times S + \beta_2 \times H + \beta_3 \times \omega + \beta_4 \times E_{av} \quad (4)$$

where the β_j values are luminaire parameters provided by the manufacturer (Rabaza et al. 2016). The overall uniformity U_0 quantifies the homogeneity of the lighting and thus the quality of the installation. Table 3 shows the values recommended by the CIE with respect to road type.

3. Differential evolution algorithm

The evolutionary algorithm class known as differential evolution consists of an optimization technique that, in combination with the previously described model (Rabaza et al. 2016), can be used to obtain the most energy-efficient solution for road lighting design.

The algorithm code was written in Matlab, where a population of N individuals was chosen to explore the search space for n generations. At the end of the process, the most energy-efficient solution is obtained. The method was applied to various case studies, which were later compared with DIALux (DIAL GmbH 2018) to demonstrate their robustness.

The DE algorithm (Storn and Price 1997) follows the general procedure of an evolutionary algorithm (Eiben and Smith 2003; Fernandez et al. 2010; Garcia and Herrera 2009). It is a stochastic optimization technique based on the evolution of a population of solutions. The DE usually begins with a uniform random population to cover the entire search space to the extent possible.

Table 3. Lighting series classes and their corresponding uniformity values.

Lighting class	U_0
Low-speed areas (P series)	≥0.2
Conflict areas (CE series)	≥0.4
High-speed areas (ME series)	≥0.4

3.1. Parameter encoding and individual structure

First, it is necessary to define the solution codification. In this DE algorithm, each individual in the population encodes a complete solution. In other words, all of the variables participating in the design of the public lighting are sequentially encoded in each individual. In fact, one individual is composed of three different variables (see Fig. 3), where K is the distribution of the luminaires on the street (1 for one-sided or 2 for two-sided coupled and two-sided staggered); H is the luminaire height; Ψ is the luminaire type identified by a number (e.g., 1 for the 171 W MH luminaire; 2 for the 131 W LED luminaire; 3 for the 150 W HPS luminaire; 4 for the 250 W HPM luminaire, etc.); and E_{av} indicates the average illuminance.

The second and fourth parameters have specific ranges of values. When the values for a certain individual are outside of these ranges, the algorithm will discard the individual. More specifically, the second parameter, luminaire height (H), ranges from 6 m to 12 m. In the case of the fourth parameter, average illuminance (E_{av}) depends on the street designation and has the limit values, shown in Table 4.

3.2. Mutation operation

After initialization, the DE algorithm applies the mutation operator to generate a mutant vector $V_{i,G}$ with respect to each individual $X_{i,G}$ in the current population (see Fig. 4). For each target $X_{i,G}$ at

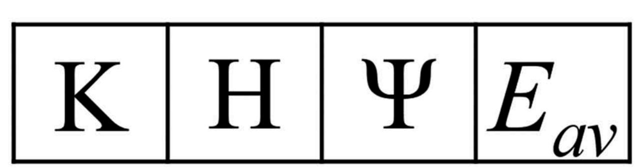

Fig. 3. Individual.

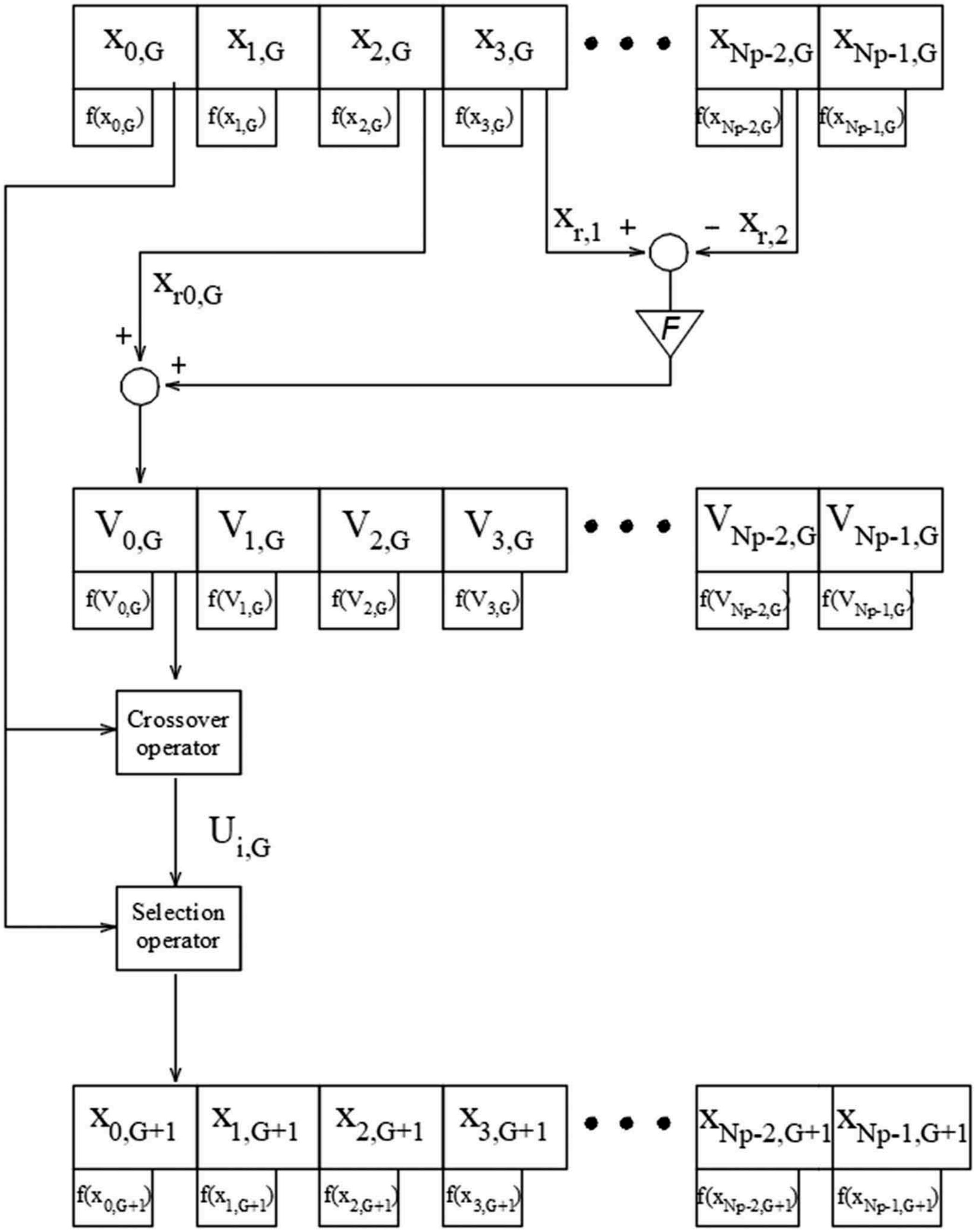

Fig. 4. Diagram of the DE algorithm.

Table 4. Lighting series classes and their corresponding illuminance and luminance values (CIE 2010; Rabaza et al. 2016).

	Illuminance (lux)								
Lighting class	2	3	5	7.5	10	15	20	30	50
Low-speed areas	P6	P5	P4	P3	P2	P1			
Conflict areas				CE5	CE4	CE3	CE2	CE1	CE0
High-speed areas			ME6	ME5	ME4	ME3	ME2	ME1	
Luminance (cd/m^2)			0.3	0.5	0.75	1	1.5	2	

generation G, its associated mutant vector $V_{i,G} = \{V^1_{i,G}, \ldots, V^D_{i,G}\}$. The method of creating this mutant vector is what differentiates one DE scheme from another. Six of the most frequently referenced strategies are listed below:

- "DE/Rand/1":

$$V_{i,G} = X^i_{r_1,G} + F \times \left(X^i_{r_2,G} - X^i_{r_3,G}\right) \tag{5}$$

- "DE/Best/1":

$$V_{i,G} = X_{best,G} + F \times \left(X^i_{r_1,G} - X^i_{r_2,G}\right) \tag{6}$$

- "DE/RandToBest/1":

$$V_{i,G} = X_{i,G} + F \times \left(X_{best,G} - X_{i,G}\right) + F \times \left(X^i_{r_1,G} - X^i_{r_2,G}\right) \tag{7}$$

- "DE/Best/2":

$$V_{i,G} = X_{best,G} + F \times \left(X^i_{r_1,G} - X^i_{r_2,G}\right) + F \times \left(X^i_{r_3,G} - X^i_{r_4,G}\right) \tag{8}$$

- "DE/rand/2":

$$V_{i,G} = X^i_{r_1,G} + F \times \left(X^i_{r_2,G} - X^i_{r_3,G}\right) + F \times \left(X^i_{r_4,G} - X^i_{r_5,G}\right) \tag{9}$$

- "DE/RandToBest/2":

$$V_{i,G} = X_{i,G} + F \times \left(X_{best,G} - X_{i,G}\right) + F \times \left(X^i_{r_1,G} - X^i_{r_2,G}\right) + F \times \left(X^i_{r_3,G} - X^i_{r_4,G}\right) \tag{10}$$

The indices r^i_1, r^i_2, r^i_3, r^i_4, r^i_5 are mutually exclusive integers, randomly generated within the range [1, NP], which are also different from the base index i. These indices are randomly generated, once for each mutation. The scaling factor F is a positive control parameter for scaling the difference vectors. $X_{best,G}$ is the best individual of the population in terms of fitness.

3.3. Crossover operator

After the mutation phase, a crossover operation is applied to increase the potential diversity of the population. The DE algorithm can use three kinds of crossover schemes, known as binomial, exponential, and arithmetic crossovers. This operator is applied to each pair of the target vector $X_{i,G}$ and its corresponding mutant vector $V_{i,G}$ to generate a new trial vector denoted as $U_{i,G}$. The mutant vector exchanges its components with the target vector $X_{i,G}$.

Our focus is on the binomial crossover scheme, which is performed on each component whenever a randomly selected number between 0 and 1 is less than or equal to the crossover rate (CR). The CR is a user-specified constant within the range [0, 1] that controls the fraction of parameter values copied from the mutant vector. This scheme may be outlined as shown in (11).

$$U^j_{i,G} = \begin{cases} V^j_{i,G} \; if \; rand(0,1) \le CR \; or \; j = j_{rand} \\ X^j_{i,G} \; Otherwise \end{cases} \tag{11}$$

where rand (0, 1) [0, 1] is a uniformly distributed random number; j ranges in {1, 2, …, D}; and j_{rand} ϵ {1, 2, …, D}is a randomly chosen index, which ensures that $U_{i,G}$ gets at least one component from $V_{i,G}$. Finally, we describe the arithmetic crossover, which generates the trial vector $U_{i,G}$ as shown in (12).

$$U_{i,G} = X_{i,G} + K \times \left(V_{i,G} - X_{i,G}\right) \tag{12}$$

where K is the combination coefficient used in the interval [0, 1]. This strategy is known as "DE/CurrentToRand/1."

In this research, the mutation strategy that produced the best results was the DE/Rand/2. This strategy worked best when the crossing operator had values of 0.7. This meant that there was a 70% chance that each gene of the individual would cross with the previously mutated individual.

3.4. Selection operator

When the trial vector is generated, it is necessary to decide which individual between X_{iG} and $U_{i,G}$ should survive in the population of the next generation G + 1. The selection operator is described as follows:

$$X_{i,G+1} = \begin{cases} U_{i,G} \; if \; f\left(U_{i,G}\right) is \; better \; than \; f\left(X_{i,G}\right) \\ X_{i,G} \; Otherwise \end{cases} \tag{13}$$

where f() is the fitness function to be minimized. If the new trial vector yields a solution equal to or better than the target vector, it replaces the corresponding target vector in the next generation. Otherwise, the target is retained in the population. Therefore, the population always improves or retains the same fitness values but never deteriorates. This one-to-one selection procedure generally remains fixed in most of the DE algorithms.

3.5. Fitness function

In order to evaluate the generated configuration, a fitness value must be defined for each individual. In our case, the fitness values were measured as the power density indicator (objective function), which classifies the energy efficiency of the street lighting installation. From (2) it follows that

$$D_P = \frac{1}{a_0 + a_1 \frac{\omega}{H} + a_2 \left(\frac{\omega}{H}\right)^2} \tag{14}$$

and, replacing the previous expression in (3) of the model, our objective function is obtained:

$$f(S,k) = \frac{P \times k}{E_{av} \times \omega \times S} \equiv D_P \tag{15}$$

In addition, it is necessary to use (4) to verify that each solution meets the desired uniformity. Otherwise, the algorithm will discard that solution.

Therefore, the algorithm will only provide those solutions whose luminaire height is 6–12 m and the spacing between them is within a range of 10–50 m. As for the input parameters, only road widths of 6–12 m are considered and lighting levels of 2–50 lux in the case of illuminance and 0.3–3.5 cd/m^2 in the case of luminance.

4. Simulation results and discussion

The algorithm was validated with examples. The selected cases were those with illumination levels of 10, 20, and 30 lux. According to the CIE, these intervals correspond to the CE4, CE2, and CE1 lighting classes, respectively (equivalent to ME4, ME2 and ME1, based on the luminance criteria in Table 4).

We used three street widths of 7, 8, and 10 m. The mounting heights for each specific case were those obtained with the DE algorithm to maximize energy efficiency.

Only four common types of luminaires were considered (Campisi et al. 2018). They were chosen at random from different manufacturers and had different characteristics and power levels (see Fig. 5).

Tables 5 and 6 show the a_j and β_j parameters that specifically define them in the model (Rabaza et al. 2016).

4.1. Example 1: CE4 lighting class (E_{av} = 10 lux)

In our first example, a road with a width of 7 m was illuminated with the CE4 lighting class (illumination level = 10 lux). The evolution of the solution group with the best individuals is reflected in the convergent energy efficiency (D_P) curve (see Fig. 6).

Fig. 5. Randomly selected luminaires: 171 W MH, 131 W LED, 150 W HPS, and 250 W HPM.

Table 5. Luminaire coefficients.

Luminaire with	a_0	a_1	a_2
171 W metal halide lamp	−0.839	19.381	−3.874
131 W LED lamp	0.599	54.254	−17.035
150 W high-pressure sodium lamp	12.336	18.829	−5.352
250 W high-pressure mercury lamp	3.8644	15.653	−4.284

Table 6. Coefficients of the inequality equation that solves the minimum uniformity of the lighting installation.

Luminaire	β_0	β_1	β_2	β_3	β_4
MH	−0.22	−0.0082	0.0685	−0.0049	0.0092
LED	−0.21	−0.0011	0.0656	−0.0211	0.0084
HPS	−0.21	0.0003	0.0358	0.0063	0.0075
HPM	−0.20	−0.0004	0.0465	−0.0101	0.0102

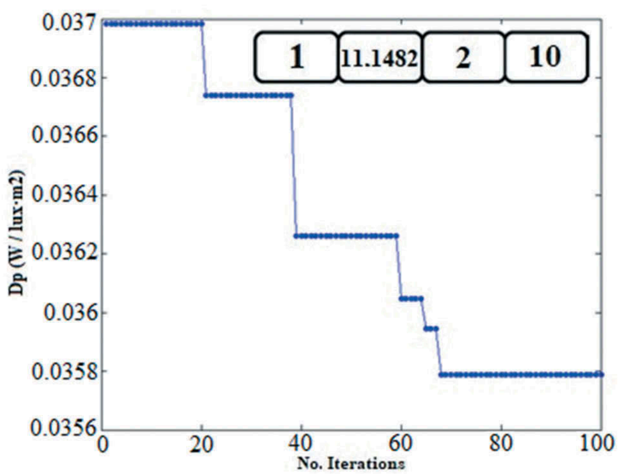

Fig. 6. DE map of convergence for a road width of 7 m and E_{av} = 10 lux.

The output of the DE algorithm shows that the most efficient installation is a unilateral pole distribution or a one-sided arrangement (1), LED luminaires (2) situated at a height of 11.1482 m, and an average illuminance of 10 lux. The spacing between poles and uniformity were automatically calculated with (3) and (4). Equation (1) was used to obtain the energy class. Table 7 shows the results of the model optimized with the DE algorithm.

Table 8. Comparison between solutions obtained with the model. The third column is the optimized solution with the DE algorithm, and the last column is the proposed solution.

Data	Magnitude	DE algorithm	Dialux
Inputs	Height	11.14 m	10 m
	E_{av}	10 lux	10 lux
	ω	7 m	7 m
	r	0.63	0.70
	Arrangement	One-sided	One-sided
Outputs	D_P ($1/\varepsilon_E$)	0.0358 W/lux/m^2	0.0331 W/lux/m^2
	Energy class	D	C
	Spacing	53.31 m	56.57 m
	Uniformity	≥0.4	≥0.32

If we enter the parameters obtained with our optimized model (one-sided, S = 52.31 m and H = 11.14 m) into DIALux, we obtain the simulation result in Table 7, where the illuminance is 9.65 lux and the uniformity is 0.44, which is higher than 0.4 as predicted by the model.

The DIALux simulation coincided with our results, where the illuminance was an input for the model (E_{av} = 9.65 lux) and luminaire spacing and uniformity was an output (S = 52.31 m, $U_0 \geq 0.4$). Furthermore, the solution in Table 7 is the most energy-efficient because the DE algorithm uses 171 W MH, 131 W LED, 150 W HPS, and 250 W HPM lamps as the luminaires.

In any case, the energy efficiency of the installation could be further enhanced by expanding the database of luminaires and then reiterating the procedure until a better configuration is found. If instead we decided to lower the height of the luminaire in order to increase the ω/h ratio (Fig. 1 indicates that this would increase the energy efficiency), the uniformity would sharply decline. This is confirmed in Table 8, which shows the result of applying the model when luminaire height is reduced to 10 m. This result was then compared to the result for the previous height of 11.14 m.

As can be observed in Table 8, the new luminaire height improved the energy class and thus

Table 7. Optimal solution of the model plus DE algorithm for a street with a width of 7 m and a CE5 lighting class compared to the DIALux simulation.

Lighting class	Lamp	Arrangement	S (m)	H (m)	E_{av} (lux)	Uniformity	Energy class (W/lux/m^2)
Model+DE	131 W LED	One-sided	52.31	11.14	10	$0.4 \leq U_0$	D (0.0358)
DIALux					9.65	0.44	NaN

Note. NaN = Not a Number.

energy efficiency. Nevertheless, the same was not true for the uniformity value, which was lower than the one recommended by the CIE.

To further demonstrate the consistency of the model, the spacing, height, and arrangement values of the luminaires were entered into DIALux (H = 10 m, S = 56.57 m). The results of the simulation were identical to those provided by the model with E_{av} = 9.83 lux and U_0 = 0.34.

4.2. Example 2: CE2 lighting class (E_{av} = 20 lux)

In our second validation example, a road with a width of 8 m was illuminated with a CE2 lighting class (illumination level = 20 lux). The evolution of the solution group with the best individuals is reflected in the convergent energy efficiency curve (see Fig. 7).

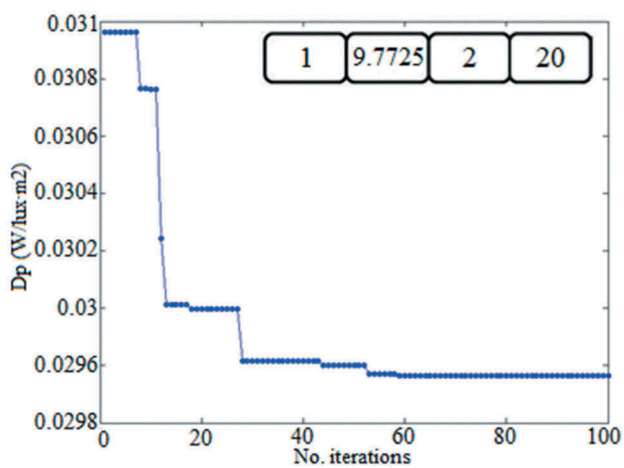

Fig. 7. DE map of convergence for a road width of 8 m and E_{av} = 20 lux.

The output of the DE algorithm provided the most energy-efficient installation, which was the unilateral distribution or one-sided arrangement of LED luminaires at a height of 9.7725 m with an average illuminance of 20 lux. The spacing between poles, uniformity, and energy class were obtained by applying (3), (4), and (1) of the model, respectively. The results are shown in Table 9.

When the parameters obtained with the optimization in our model (LED lamp, one-sided, S = 27.51 m and H = 9.77 m) were entered into DIALux, the resulting levels of lighting and uniformity were the same (E_{av} = 20.08 lux and U_0 = 0.74; see Table 9). Consequently, the results of the model plus optimization and the simulation coincided.

4.3. Example 3: CE1 lighting class (E_{av} = 30 lux)

In our third validation example, a road with a width of 10 m was illuminated with a CE1 lighting class (illumination level = 30 lux). The evolution of the solution group with the best individuals is reflected in the convergent energy efficiency curve (see Fig. 8).

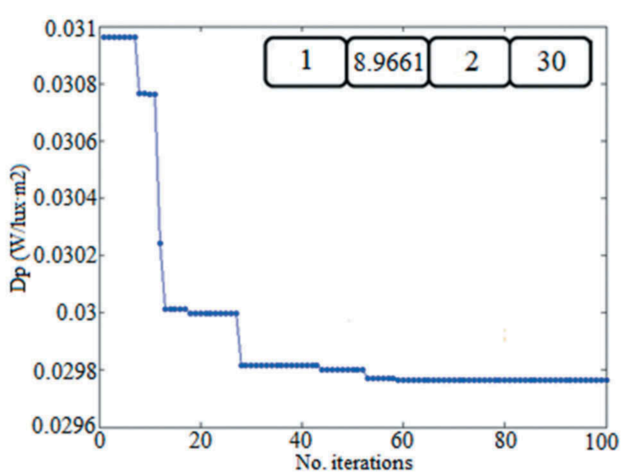

Fig. 8. DE map of convergence for a road width of 10 m and E_{av} = 30 lux.

According to the output of the DE algorithm, the most efficient installation is a unilateral distribution or a one-sided arrangement of LED luminaires situated at a height of 8.9661 m with an average illuminance of 30 lux. The spacing between poles, uniformity, and energy class were obtained by applying (3), (4), and (1) of the model. The results are shown in Table 10.

When the parameters obtained with the optimization in our model (LED lamp, one-sided, S = 17.43 m and H = 8.97 m) were entered into DIALux, the levels of lighting and uniformity (E_{av} = 30.21 lux and U_0 = 0.45) were the same (see Table 10). The results of the model plus optimization and the simulation thus coincided.

Obviously, if the installation required an even higher level of energy efficiency, this method could be used with another luminaire to obtain a new design without the use of simulation software programs. All that is necessary are the eight parameters (a_0, a_1, a_2, β_0, β_1, β_2, β_3, β_4) of the new luminaire, provided by the manufacturer, to find

Table 9. Optimal solution of the model plus DE algorithm for a street with a width of 8 m and a CE3 lighting class compared to the DIALux simulation.

Source	Lamp	Arrangement	*S* (m)	*H* (m)	E_{av} (lux)	Uniformity	Energy class (W/lux/m^2)
Model+DE	131 W LED	One-sided	27.51	9.77	20	$0.49 \leq U_0$	C (0.0298)
DIALux					20.08	0.74	NaN

Note. NaN = Not a Number.

Table 10. Optimal solution of the model plus DE algorithm for a street with a width of 10 m and a CE2 lighting class compared to the DIALux simulation.

Source	Lamp	Arrangement	*S* (m)	*H* (m)	E_{av} (lux)	Uniformity	Energy class (W/lux/m^2)
Model+DE	131 W LED	One-sided	17.43	8.97	30	$0.40 \leq U_0$	C (0.0251)
DIALux					30.21	0.45	NaN

Note. NaN = Not a Number.

the most energy-efficient design for the new installation.

5. Conclusions

This article describes a method to simplify the design of street lighting systems by using a DE algorithm. This algorithm is able to design the most energy-efficient installation, while at the same time satisfying CIE specifications. The following conclusions can be derived from the results of our study:

(1) The DE algorithm provides the luminaire arrangement, height, types, and spacing for a given street in order to maximize energy efficiency. The lighting level and uniformity are decision makers used to rule out solutions that do not comply with CIE recommendations.
(2) The algorithm uses the model expressed by (3) and (4) to calculate the most energy-efficient solution for luminaire spacing in addition to meeting the uniformity criterion.
(3) To verify the applicability of the algorithm and model, we studied three types of streets, each with a different width and traffic density.
(4) Finally, the results of the DE algorithm were compared to those of DIALux. In each of the examples, the algorithm provided design solutions (luminaire height, arrangement, spacing, and type) that were subsequently compared to the simulations with DIALux. The DIALux illuminance and uniformity values exactly coincided with those of the algorithm.

The results of our research thus confirmed the usefulness of this tool based on an evolutionary algorithm. Because of its accuracy and simplicity, it could easily be implemented in software or specialized codes to facilitate the calculation of lighting design in urban planning, architecture and engineering projects.

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ORCID

Ovidio Rabaza http://orcid.org/0000-0003-2766-2103
Daniel Gómez-Lorente http://orcid.org/0000-0001-6728-0041

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Appendix. Differential evolution algorithm basic structure

```
Begin differential evolution algorithm
Set street parameters
Initialize the population
Evaluate initial population
if iluminance criterion is satisfied do
    take the individual as a member of the population
end if
while number of iterations
    Mutate each individual with the height and interdistance bounded limits
    for each mutated individual
        Evaluate individual
        if a random number is < than CR parameter do
            replace the original individual with the mutated individual
        else do
            discard the mutated individual
        end if
    end for
Evaluate new population
for each individual of the new population
    if is better than the individual of the same position in the original population
        if satisfies iluminance limits do
            replace the individual of the new population by the individual of the original population
        end if
    end if
end for
display the best individual of the last population.
```