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Optimization of Indoor Luminaire Layout for General Lighting Scheme Using Improved Particle Swarm Optimization

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Abstract: An improved mathematical model and an improved particle swarm optimization (IPSO) are proposed for the complex design parameters and conflicting design goals of the indoor luminaire layout (ILL) problem. The ILL problem is formulated as a nonlinear constrained mixed-variable optimization problem that has four decision variables. For a general lighting scheme (GLS), the number and location of luminaires can be uniquely determined by optimizing four decision variables, which avoid using program loops to determine the number of luminaires. We improve the particle swarm optimization (PSO) in three aspects: (1) up-down probabilistic rounding (UDPR) method proposed to solve mixed integer, (2) improving the velocity of the best global particle, and (3) using nonlinear inertia weights with random items. The IPSO has better optimization results in an office study compared with the PSO and genetic algorithm (GA). The results are validated by DIALux simulation software, and a maximum deviation of 2.2% is found. The validated results show that the method using four decision variables increased the speed by 10.6% and the success rate by 23.33%. Furthermore, Indoor Luminaire Layout System APP is designed to provide guidelines visually for lighting designers and related researchers.

Keywords: luminaire layout; improved particle swarm algorithm; particle swarm optimization; genetic algorithm; optimization; general lighting scheme; APP

1. Introduction

In the trend of semiconductor illumination technology development and application, lighting plays a unique role in many aspects of sustainable development [1]. For indoor lighting design (ILD), the first thing to consider is the amount of luminaire. The main requirement for the amount of luminaire is the "right illuminance" (illuminance is an indirect indicator of the brightness of an object). An excessive number of luminaires will lead to energy waste and increase lighting power density (LPD) and luminaires' costs. LPD is an indicator to measure the energy efficiency of a lighting system [2]. Second, ILD could improve lighting quality, and that directly affects the efficiency of work, physical health, and psychological conditions and even affects the atmosphere and various effects in an indoor room [3–5]. However, the diversity of indoor environments and the mutual exclusion of lighting design parameters, including LDP, average illuminance (E_{mean}), overall uniformity (U_o), and maximum unified glare rating (UGR), pose difficulties for indoor luminaire layout (ILL). Carli et al. [6] and Beccali et al. [7] proposed a decision support system considering the quality of light, energy efficiency, and occupant comfort. The authors studied a street lighting system, integrating ergonomic and economic aspects, which is important and meaningful for large outdoor public lighting. The main emphasis of this paper is to design an energy-efficient luminaire layout method for a general lighting scheme (GLS), which maximizes or minimizes these design parameters within recommended limits.

To solve the ILL problem, current research works are divided into two categories: single-objective optimization and multiobjective optimization.

In 2013, Wang et al. [8] proposed an overall illumination control of a LED system based on a holistic and scalable neural network model to meet the table illumination preference of each office user and save energy consumption. However, when an ILL is changed, the network model trained can no longer be used. In 2017, Mendes et al. [9] developed a new bio-inspired optimization algorithm based on the competition over resources algorithm (COR) in order to reduce both the energy consumption of indoor illumination and the computational cost for the optimal lighting of a real-time system. Eventually, the feasibility of the algorithm was verified by theoretical proofs of classical benchmark functions and practical data in real-life optimal lighting. In 2017, Mattoni et al. [10] used a genetic algorithm (GA) to optimize indoor luminous systems by considering energy efficiency, U_o, and UGR. The number of luminaires is decided by the illuminance level in a satisfied range. Moreover, UGR and the distance of luminaires are controlled by two penalties. This method was limited to consider the same optimized mounting height for all the luminaires. In 2019, Mandal et al. [11] applied the particle swarm optimization (PSO) algorithm to ILD. They organized some conflicting objective parameters, such as average illuminance, overall uniformity, UGR, cost, and LPD, weighting them into a single-objective optimization model. This model consists of three decision variables (regular luminaire spacing along the length and width and luminaire mounting height). Thus, the number of luminaires is determined by a loop in the program, making the algorithm inefficient.

In 2016, Madias et al. [12] proposed an evolutionary multiobjective genetic algorithm (nondominated sorting genetic algorithm II, NSGA-II) to optimize the two objectives of reducing the energy consumption of buildings and improving the lighting uniformity of LEDs in buildings. The case shows that the optimization model has significant advantages, and significant energy savings in the range of 18% to 22% were reported. In 2017, Plebe et al. [13] provided a more flexible approach to the interior lighting design by considering E_{mean}, U_o, and energy consumption. The solution integrates the 3D graphics software Blender to reproduce architectural spaces and simulate lighting effects by using NSGA-II.

The ILL problem using single-objective optimization suffers from the difficulty of parameter weights in the process of designing. Although this problem can be solved by multiobjective optimization, it suffers from finding the Pareto optimal. In addition, determining the location of the luminaires efficiently while determining the number of luminaires is also a problem to be solved.

The PSO [14] is a kind of evolutionary algorithms that do not rely on the mathematical characteristic of the problems. It has been ubiquitous in daily life and industrial engineering, such as electricity [15], machine learning [16], and path planning [17]. To improve the PSO, research studies have been conducted on the improvement of inertia weights, which are mainly classified into linear adjusted inertia weight [18], fuzzy adjusted inertia weight [19], nonlinear adjusted inertia weight [20–22], and random adjusted inertia weight [23].

In this paper, we improve the mathematical model of the ILL problem, designing the weights among the parameters reasonably and formulating a mixed-integer single-objective optimization problem. The objective function has a penalty parameter to check compliance with minimum or maximum limits of design parameters and four decision variables (regular luminaire spacing along length L_t and width L_l, number of luminaires in a row N_a and column N_b). To solve the model efficiently, this paper presents the IPSO, using the up–down probabilistic rounding (UDPR) method to solve the mixed-integer optimization problem. Moreover, we improve the velocity of the best global particle, which is done by selecting two positions for updating randomly, increasing the probability of jumping out of the local optimum, and using nonlinear inertia weights with random items.

As a whole, the main contributions of this study are summarized as follows:

(1) An IPSO was proposed to solve the ILL problem. It was improved in three aspects: (1) Up–down probabilistic rounding (UDPR) method proposed to solve mixed integer,

(2) improving the velocity of the best global particle, and (3) using nonlinear inertia weights with random items.
(2) The ILL problem can use four mixed-variable decision variables to determine the number and address of the luminaires.
(3) The performance of the proposed method, including the algorithm and mathematical model, was improved in speed and success rate.
(4) The proposed method is expected to provide guidelines for lighting designers and related researchers.

Our method is validated with an office study in two aspects. In the first aspect, three algorithms are used in this study to investigate the effectiveness of the proposed algorithm, including proposed improved particle swarm optimization (IPSO), PSO, and GA [24]. In the second aspect, the optimal results obtained by the developed program are compared with the professional lighting simulation software DIALux V5.9 [25]. We further demonstrated that design parameters of the optimal luminaire layout are all improved when compared with lighting standards. Finally, Indoor Luminaire Layout System APP V1.0 [26] was designed by MATLAB App Designer V2019a [27] to provide guidelines visually for lighting designers and related researchers. The rest of the paper is organized as follows: Section 2 describes the scheme of the method and formulates the ILL problem. The proposed mathematical model of ILL is considered in Section 3. Section 4 presents our proposed IPSO. Section 5 shows case studies and their simulation results. Section 6 introduces our developed APP. Finally, conclusion is drawn in Section 7.

2. Problem Statement

This section is focused on the statement of the optimization problem in order to determine the ILL of an indoor lighting system for a general lighting scheme. The proposed method works on the design of large lighting locations for GLS whose N_a and N_b are greater than 2 (e.g., office, meeting room, sports hall). In the test study, we used an office using standard of GB 50034-2013 in China. However, for other international standards, we need to change the constraints of the ILL problem. The scheme of the method is presented in Figure 1. It can clearly be divided into three parts.

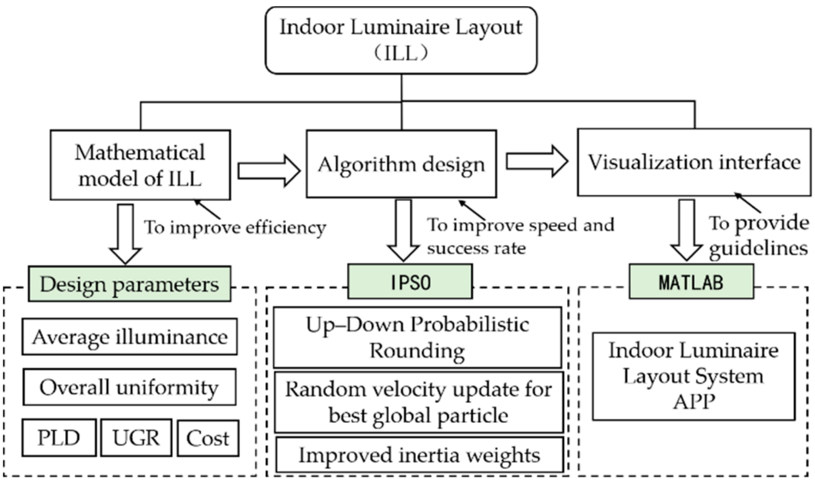


Figure 1. Structure graph of the method.

The first part (mathematical model of the ILL) aims to improve the efficiency through an improved mathematical model. At first, we select several design parameters from the collection of data. Those design parameters determine the constraints of ILL the problem. Then, the ILL problem is formulated as a nonlinear constrained mixed-variable optimization problem according to those design parameters. This model has two continuous (L_t and L_l) and two discrete (N_a and N_b) decision variables simultaneously with five inequality constraints.

The second part (algorithm design) aims to improve the speed and success rate in three aspects, as shown in the IPSO part of Figure 1. The third part (visualization interface) aims to provide guidelines for lighting designers and related researchers by designing Indoor Luminaire Layout System APP. It can be a decision-making support APP integrating professional lighting software (e.g., DIALux).

3. Mathematical Model of ILL

3.1. Selection of Design Parameters

To solve the ILL problem more reasonably and objectively, this paper uses NLPIR, a big data semantic intelligent analysis system, to process the data of indoor lighting design on web pages. NLPIR ICTCLAS (Institute of Computing Technology, Chinese Lexical Analysis System) is a Chinese lexical analysis system developed by the Institute of Computing Technology of the Chinese Academy of Sciences. The main functions of the software include "Label", "Word separation", "Classification", "Extracting high-frequency keyword", "Language statistics", and other functions. The main process is as follows: first, we crawled the web pages about "interior lighting design" and "interior lighting design requirements" using the precise collection to obtain data and then used the word separation function to separate the crawled data into words; finally, we used the wordclouds [28] to analyze the word frequency. After separating these words, the meaningless word was deleted and screened. The word frequency analysis results of the complete corpus are arranged in descending order of weight, as shown in Table 1. Therefore, it can be seen that designers and users are more concerned about average illuminance, overall uniformity, PLD, color temperature [29], UGR, and cost. The next part of this paper will also focus on these requirements for design.

Table 1. Word frequency.

Word	Frequency (%)	Rank
Lighting	7.65%	1
Average illuminance	4.97%	2
Environment	4.58%	3
Indoor	4.28%	4
Luminance	4.19%	5
Space	3.70%	6
Cost	3.51%	7
Uniformity	2.73%	8
Glare	2.63%	9
LPD	2.53%	10
Efficiency	2.14%	11
Color temperature	2.04%	12

3.2. The Quality of Lighting

$Q_{lighting}$ includes average illuminance, overall uniformity, and UGR.

(5) Average illuminance

The average illuminance can be calculated from the average of the grid points divided on the working plane, as shown in Equation (1):

$$E_{mean} = \frac{1}{G}\sum_{i=1}^{G} E_p^i \tag{1}$$

where G is the total number of grid points, and E_p^i is the total illuminance in the ith grid point, generated by all luminaires and lighting reflection, which is calculated by reference [30].

(6) Overall uniformity

Illuminance uniformity measures the distribution of illuminance in the horizontal plane of the room. If the brightness changes too much in the indoor environment, the eyes are forced to go through an adaptation process when human vision turns from one place to another. If this adaptation process repeats too many times, it will cause visual fatigue. The expression of uniformity is shown in Equation (2), which is the ratio of the minimum illuminance to the average illuminance on the working plane:

$$U_o = \frac{E_{\min}}{E_{mean}} \tag{2}$$

where $E_{\min}$ is the minimum illuminance value on the working plane (it is obtained by dividing the working plane into a grid and then comparing the illuminance values with that of each grid point).

(7) UGR

Glare is the high brightness formed in the field of view that interferes with vision or causes visual fatigue and discomfort. According to the CIE 117 (1955) publication "Discomfort Glare in Interior Lighting", we have Equation (3):

$$UGR = 8 \times \lg\left(\frac{0.25}{L_b}\sum \frac{{L^2}_s \cdot w}{p^2}\right) \tag{3}$$

where L_b is the background luminance, L_s is the luminance of the luminous part of each luminaire in the direction of the observer, and w is the solid angle formed by the luminous part of each luminaire at the eyes of the observer. P is the position index of each individual luminaire, which is determined by Guth's position index provided by CIE 117:1995.

3.3. Lighting Cost and Efficiency

(1) Lighting power density

Lighting power density is an indicator that must be considered in the lighting design. LPD is the power of the luminaire required per square meter, as shown in Equation (4), to promote the application of efficient luminaire. When achieving the same lighting effects, the number of luminaires is minimized, or the power is lower to achieve the aim of energy saving:

$$LPD = \frac{\sum_{i=1}^{N} P_i}{S} \tag{4}$$

where P_{i} is the power of each luminaire, and S is the surface area of the room.

(2) Cost

When more than two kinds of lighting designs achieve the same lighting effect, just the comparison of LPD to determine which one is better is far from enough. We also need economic comparison of each lighting design. The lighting costs per unit of illumination (cost) are used for lighting economic comparison because the illumination value of different lighting designs is various, as expressed by Equation (5):

$$C = \frac{N_a N_b C_l}{E_{mean}} \tag{5}$$

where C is the lighting cost per unit of illumination, and C_l is the cost of an individual luminaire. The lighting fee omits materials and labor costs, such as the cleaning agents used to clean the luminaires.

3.4. Single-Objective Optimization Model for Luminaire Layout

The evaluation of the indoor lighting environment depends on more than one aspect. Comfortable lighting must meet the requirements of E_{mean} ($E_{mean} \geq E_{mean\_\mathrm{limit}}$),

U_o ($U_o \geq U_{o\_limit}$), UGR ($UGR \leq UGR_{\text{limit}}$), LPD ($LPD \leq LPD_{\text{limit}}$), and cost ($C < C_{\text{limit}}$). Under the premise of meeting these requirements, increasing or decreasing these design parameters as much as possible can result in more comfortable lighting. Therefore, the objective function $F(X)$ designed by this paper is shown in Equation (6). Users can set the value of $\alpha (0 \leq \alpha \leq 10)$ (α represents the importance of $Q_{lighting}$). The larger the value of α, the higher $Q_{lighting}$ requires, and the power consumption and cost can be considered less. The setting of α could meet the requirements of ILD with different levels. In addition, the penalty function [31,32] is designed to penalize the solutions that do not meet the lighting design requirements:

$$\begin{aligned} &Max\ F(X) = (10-\alpha)\left(\frac{LPD_{\text{limit}}}{LPD} + \frac{C_{\text{limit}}}{C}\right) + \alpha\left(\frac{E_{mean}}{E_{mean\_\text{limit}}} + \frac{U_o}{U_{o\_\text{limit}}} + \frac{UGR_{\text{limit}}}{UGR}\right) - \lambda \sum_{i=1}^{5} Penalty_i \\ &s.t.\ X = (N_a, N_b, L_t, L_l) \\ &\quad 2 \leq N_a < \min\left(\frac{aLPD_{\text{limit}}S}{(a+b)P}, \frac{aC_{\text{limit}}}{(a+b)C_l}\right) \\ &\quad 2 \leq N_b < \min\left(\frac{bLPD_{\text{limit}}S}{(a+b)P}, \frac{bC_{\text{limit}}}{(a+b)C_l}\right) \\ &\quad a_l \leq L_t < \frac{a}{N_a - 1} \\ &\quad b_l \leq L_l < \frac{b}{N_b - 1} \end{aligned} \tag{6}$$

where λ is the penalty factor; a, b, and h are the length, width, and height of the room; and $Penalty_i$ is the penalty function. When the ith design parameter is satisfied, $Penalty_i$ equals 0. Otherwise, $Penalty_i$ is the distance between the design parameters and its corresponding limit value; $X = (N_a, N_b, L_t, L_l)$ is the independent variable, as shown in Figure 2. h_w, h_l, and h_c are the height of the working plane, the luminaire mounting height above the working plane, and the height of the luminaire below the ceiling, regular luminaire spacing along length L_t and width L_l.

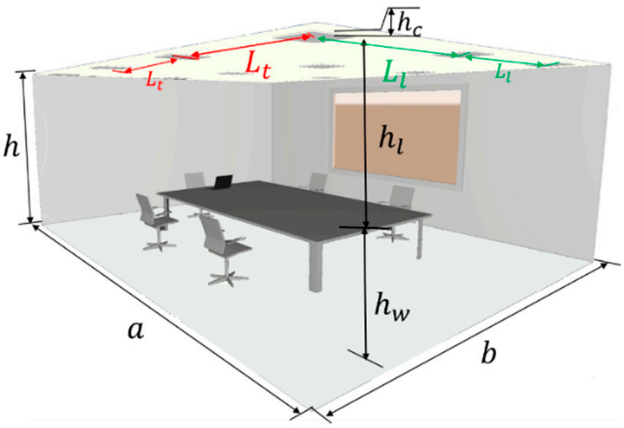


Figure 2. Room diagram. a, b and h are the length, width and height of the room; h_w, h_l, and h_c are the height of the working plane, the luminaire mounting height above the working plane, and the height of the luminaire below the ceiling, regular luminaire spacing along length L_t and width L_l.

Other limitations of design parameters can be determined in Table 1. However, the limitation of cost is described in Equation (7):

$$C_{\text{limit}} = \frac{N_{\max} C_l}{E_{mean\_\text{limit}}} \tag{7}$$

where $N_{\max}$ is the maximum number of luminaires, described by the utilization factor method [33], as shown in Equation (8):

$$N_{\max} = \frac{SE_{mean}}{\Phi \mu K} \tag{8}$$

where Φ is the luminous flux of each luminaire, μ is the utilization factor, and K is the maintenance factor or light loss factor.

The position of luminaires can be uniquely determined by these four decision variables (Equation (9)), and the coordinates of a luminaire refer to the coordinates of the center of the luminaire. Because we work on the design of large lighting locations for a general lighting scheme, N_a and N_b are set as greater than 2.

$$(x_i, y_j) = (\tfrac{b-(N_b-1)L_l}{2} + (i-1)L_l, \tfrac{a-(N_a-1)L_t}{2} + (j-1)L_t),\\ i = 1, 2, \cdots N_b, j = 1, 2, \cdots N_a \tag{9}$$

4. Algorithm Design

4.1. Basic Particle Swarm Algorithm

The PSO [14], also known as particle swarm algorithm, developed by Kennedy and Eberhart, is an optimization algorithm based on population intelligence theory. The velocity and position of the ith particle is manipulated according to Equations (10) and (11). Each particle is influenced by its previous velocity and the distances of its current position from its own best position and the group's best position, constantly converging to the optimal position:

$$v_i(t+1) = v_i(t) + c_1 rand_1(Pbest_i(t) - x_i(t)) + c_2 rand_2(Gbest(t) - x_i(t)) \tag{10}$$

$$x_i(t+1) = x_i(t) + v_i(t) \tag{11}$$

where $i = 1, 2, 3 \cdots N$ and N is the total number of particles of the population; $v_i(t)$ and $x_i(t)$ are the velocity and position of the ith particle at tth generation, $Pbest_i$ is the historical best position of the ith particle, $Gbest$ is the position of the best global particle, c_1 is the cognitive learning factor and c_2 is the social learning factor, and $rand_1$ and $rand_2$ are random numbers uniformly distributed within the range of $[0, 1]$.

Particles' movement depends mainly on the velocity at different moments (Equation (10)). However, when the velocity is too large, the capability of global search is stronger, and the local search is weaker, so the optimal solution is easily skipped; when the velocity is too small, it is easy to fall into the local optimum. In order to balance global search and local search, Shi and Eberhart [19] first proposed a particle swarm optimization algorithm with inertia weight, whose velocity update formula is shown in Equation (12):

$$v_i(t+1) = wv_i(t) + c_1 rand_1(Pbest_i(t) - x_i(t)) + c_2 rand_2(Gbest(t) - x_i(t)) \tag{12}$$

$$w = w_{\max} - \frac{T(w_{\max} - w_{\min})}{T_{\max}} \tag{13}$$

where $w_{\max}$ and $w_{\min}$ are the maximum and minimum of inertia weight, T is the current number of iterations, and $T_{\max}$ is the number of iterations.

4.2. Improved Particle Swarm Algorithm

Although the PSO has the advantages of rapid convergence speed, clear meaning, and simple operation, some shortcomings still exist, such as lacking dynamic regulation of speed, easy falling into local optima, and low convergence accuracy. To make the PSO suitable for solving the ILL problem, we improved the PSO from in aspects.

(1) Up–Down Probabilistic Rounding (UDPR)

After updating the position of the particle according to Equation (11), design variable x^* is obtained. To ensure that x^* is still an integer value, we need to perform an integer operation. First, the downward and upward rounding operations are performed on x^* to obtain $x^*{}_{down}$ and $x^*{}_{up}$. Then the probability of taking $x^*{}_{down}$ and $x^*{}_{up}$ depends on the distance from x^* to them, as shown in Equations (14) and (15). It maintains the diversity of populations better and enhances the global search capability.

$$P(x^*{}_{down}) = \frac{1/(x^* - x^*{}_{down})}{1/(x^* - x^*{}_{down}) + 1/(x^*{}_{up} - x^*)} \tag{14}$$

$$P(x^*{}_{up}) = \frac{1/(x^* - x^*{}_{up})}{1/(x^* - x^*{}_{down}) + 1/(x^*{}_{up} - x^*)} \tag{15}$$

(2) Random velocity update for best global particle

When a particle becomes the best global particle, its velocity update formula becomes Equation (16). The best global particle will keep moving at the velocity of the previous generation until it hits the boundary, limiting the "talent" of the best global particle. Inspired by Cai X et al. [34], we can use a random velocity update formula, as shown in Equation (17). From Figure 3, we know that this method can increase the probability of jumping out of the local optimum, thus increasing the capability of seeking global optimum:

$$v_i(t+1) = v_i(t) \tag{16}$$

$$v_i(t+1) = v_i(t) + c_2 rand_2(x_m(t) - x_u(t)) \tag{17}$$

where $x_m(t)$ and $x_u(t)$ are the random positions of two particles in the range of decision variables.

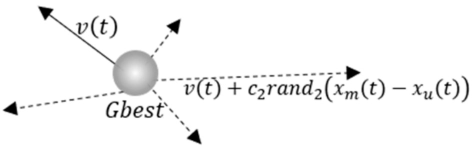


Figure 3. Diagram of the velocity of the best global particle.

(3) Improved inertia weights

Considerable searches have been performed on the improvement of inertia weights, which are mainly classified into linear adjusted inertia weight [18], fuzzy adjusted inertia weight [19], nonlinear adjusted inertia weight [20–22], and random adjusted inertia weight [23]. The purpose of adjusting inertia weight is to change the local and global search capability of the algorithm [15]. A smaller inertia weight improves the local search capability, and a larger inertia weight improves the global search capability. However, just decreasing or randomly selecting the inertia weight increases the possibility of falling into local optimum, and using a fuzzy adjusted inertia weight requires more parameters to be designed. This paper proposes a nonlinear random inertia weight based on nonlinear decreasing and adding of random numbers to make different inertia weights for different particles in the same generation, thus increasing particle diversity, as shown in Equation (18):

$$w = w_{\max} - (w_{\max} - w_{\min})\left(\frac{T}{T_{\max}}\right)^{\gamma} - \lambda * rand_3 \tag{18}$$

where γ is a constant, $1 < \gamma \le N$, and N is the number of populations. γ can control the ratio of global search and local search, and if γ is larger, the inertia weight decreases more slowly; otherwise, the inertia weights decrease more quickly. λ is the inertia deviation factor, $0 < \lambda < w_{\min}$, and $rand_3$ is a random number uniformly distributed within the range of $[0, 1]$.

The specific steps of the IPSO are as follows.

Step 1: Initialize the particle positions and velocities of the particle population randomly and uniformly in the search range; set $Pbest$ and $Gbest$ as zero matrices when $T = 0$.

Step 2: Calculate the fitness of each particle to get $Pbest$ and $Gbest$.

Step 3: Update velocity: the velocity is updated by Equation (17) for the best global particle and Equation (12) for the other particles. If the velocity is out of bounds, the velocity equals the boundary.

Step 4: Update position: for integer variables, the UDPR operation is performed on, and if the position is out of bounds, the position equals the boundary.

Step 5: Update *Pbest* and *Gbest*.

Step 6: Stop criterion: the maximum number of generations.

If not exceeded, set $T = T + 1$ and jump back to Step 3.

5. Experiments and Tests

5.1. Experiments

5.1.1. Lighting Standards

There are many ways of lighting, including general lighting, local lighting, mixed lighting, emergency lighting, and so on [35]. The method proposed in this paper is to design for general lighting places, such as conference rooms and offices, which bases on the lighting standard of GB 50034-2013 in China. Of course, other international standards just modify lighting design parameters, and our method still works. Table 2 shows the standard requirements for senior and general office lighting. Our design is based on the whole room, not the working area, which gives convenience when a desk is moved.

Table 2. Office lighting standards [1].

Codes	E_{mean} (lx)	U_o	UGR	LPD (W/m^2)	General Color Rendering Index (CRI)
Senior office	$\geq$500	$\geq$0.7	$\leq$19	$\leq$15	$\geq$80
General office	$\geq$300	$\geq$0.7	$\leq$19	$\leq$9	$\geq$80

[1] Based on GB 50034-2013 in China.

The E_{mean} and LPD requirements of senior and general offices are different, and the former is higher than the latter. Since senior offices need higher-quality lighting, LPD should be higher. According to different places, the requirements of UGR are also different; for example, offices and conference rooms have high requirements. The value of U_o is mainly determined by the location of the luminaire. If the uniformity is not high enough, it may cause visual fatigue and affect work efficiency. With the improvement of people's living standards, the CRI is no less than 80. What is more, in the indoor office, the luminaires need to be wiped at least two times a year, and K takes 0.80 according to GB 50034-2013. Finally, C_{limit} takes 3.26. Because the CRI is mainly determined by the type of luminaire selected, the color of indoor walls and homes, and so forth, it is not considered in the ILL.

5.1.2. Room Type

In order to test the mathematical model (Equation (6)) and algorithm proposed in this paper, we will design a luminaire layout for a hypothetical senior office. Assuming that the indoor surfaces are all diffuse surface, the average reflectance of each wall, floor, and ceiling is considered. The height of the working plane is 0.75 m above the floor (h_w), and the installation of luminaires occupies a height of 0.1 m (h_c), which means that the height of the luminaire above the working plane is 2.15 m (h_l) (Figure 2). The specific details of the room are shown in Table 3.

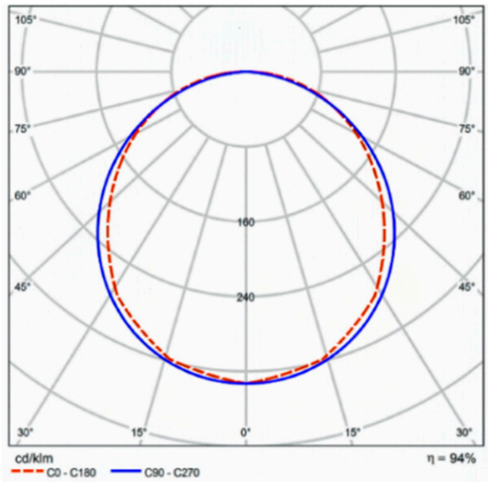
Table 3. Details of senior office room.

Item	Values
Dimension	$6 \times 8 \times 3$ m
Average reflectance	Ceiling: 0.8; wall: 0.8; floor: 0.2
Working plane height	0.75 m
Installation occupancy height	0.1 m

5.1.3. Luminaire Type

Here we choose a recessed luminaire, and the style of the luminaire is shown in Figure 4A. Figure 4B is the light intensity distribution curve of the luminaire, which is similar to the Lambert model. The cost per luminaire is RMB 78. The light intensity distribution information of the luminaire can be obtained by the IES file provided by the manufacturer. The details of the luminaire selected in this paper are shown in Table 4. The color temperature of the luminaire is 4000 K, which is an intermediate color and is suitable for an office and conference room.

(**A**)



(**B**)

Figure 4. Details of the luminaire. (**A**) is the outlook, and (**B**) is the polar intensity diagram of the luminaire.

Table 4. Details of the luminaire.

Item	Values
Dimension	500 × 500 × 100 mm
Power	29.3 W
Power factor (η)	0.94
Efficacy	97.9 lm/W
Color temperature	4000 K
Color rendering	RA > 80
Total luminous flux of luminaire	2868 lm

5.1.4. Experimental Process

The experiments of this paper were run on a laptop with i5-10210U CPU, 16G RAM, and MX250 GPU. All algorithms were run on a MATLAB 2019a platform and validated by DIALux V5.9 (DIALux evo 2021). Here, the IPSO was compared with the PSO and the GA. To ensure fairness, each algorithm was run 30 times independently, with a population size of 30 and an iteration number of 30, and all used UDPR. In order to test the mathematical model (Equation (6)) and algorithm proposed in this paper, many different room configurations and luminaire configurations were tested. We will only provide results for some representative room configurations and luminaire configurations. The optimization process of the IPSO is shown in Figure 5. Finally, we will get the optimal (N_a, N_b, L_t, L_l).

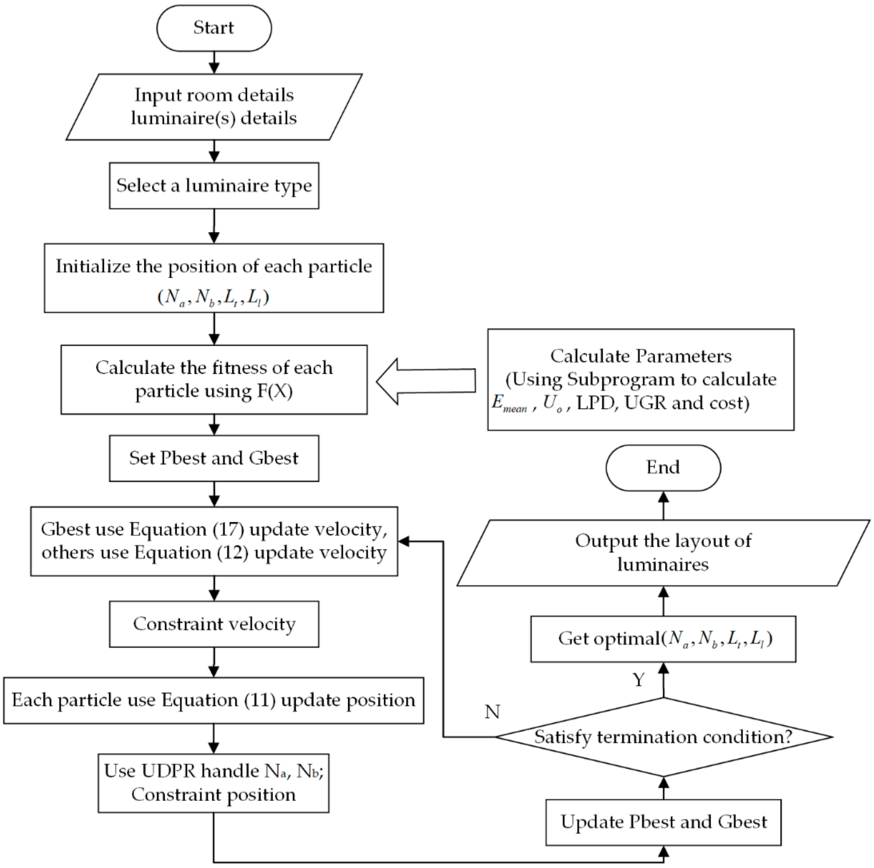


Figure 5. The flow diagram of the optimization process with an IPSO-based method.

5.2. Data Analyses and Results

5.2.1. ILL Problem Using IPSO-Based Method

The iterative motion of the particles is shown in Figure 6. Since the design variables are four-dimensional, different colors are used to represent different combinations of N_a and N_b for visualization purposes. After 30 iterations of the IPSO, the particles basically gather to a point, so this paper sets the algorithm to iterate 30 times.

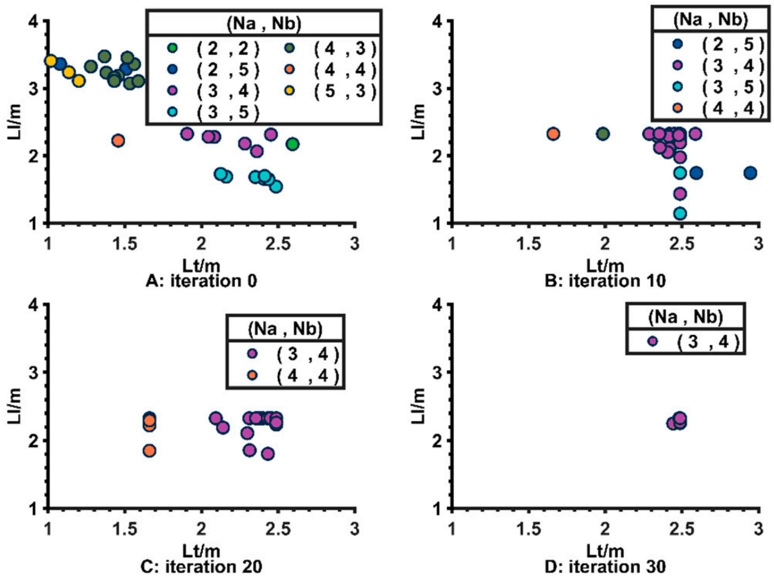


Figure 6. (**A**–**D**) Swarm (N_a, N_b, L_t, L_l) movement toward an optimal solution with iterations in the IPSO.

Furthermore, the optimal luminaire layout position obtained each time was recorded, as shown in Figure 7. The optimal luminaire layout position was almost unchanged.

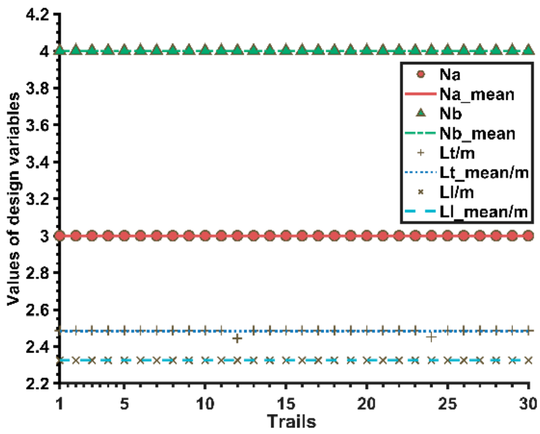


Figure 7. Variation of optimal decision variables and corresponding average values after running the program 30 times.

5.2.2. Comparison of the Proposed Method and Previous Methods

The performance of the proposed IPSO-based method was further compared with the PSO and GA. After each algorithm was run 30 times independently, changes in the average best fitness for each algorithm are shown in Figure 8. Average best fitness means the average of the best fitness values for each generation over 30 trials. The IPSO has a fast convergence speed and the best performance of finding the optimization. The GA has the slowest convergence speed and the worst performance of finding the optimization.

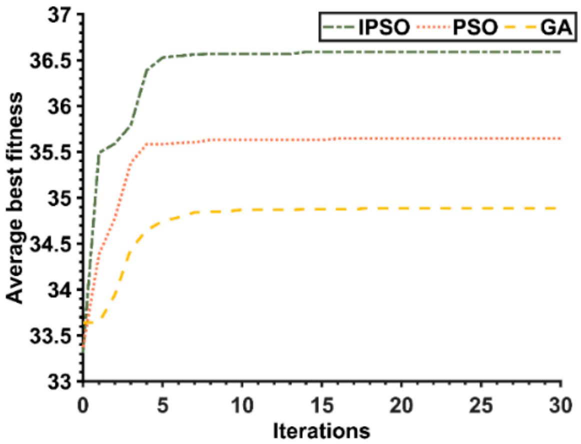


Figure 8. Average best fitness of the IPSO, PSO, and GA changed with iterations.

$Q_{lighting}$ as a performance indicator is used for comparison, as shown in Equation (19).

$$Q_{lighting} = \frac{E_{mean} - E_{mean\_\mathrm{limit}}}{E_{mean\_\mathrm{limit}}} + \frac{U_o - U_{o\_\mathrm{limit}}}{U_{o\_\mathrm{limit}}} + \frac{UGR_{\mathrm{limit}} - UGR}{UGR_{\mathrm{limit}}} \quad (19)$$

The best fitness value (BFV), the worst fitness value (WFV), the mean value (MV), and the standard deviation (STDEV) were selected to further evaluate the optimization ability. As shown in Table 5, both the IPSO and PSO can find the BFV after 30 trials, but the IPSO outperforms the PSO in all other respects. The optimal results of the GA get a worse layout of luminaires, which can be seen by the value of $Q_{lighting}$ in Table 6. To validate the advantage of four decision variables that this paper proposed, we compared the runtime and success rate with the method proposed in the paper [11]. The programs were run 30 times separately in the same environment. The proposed method was 10.6% faster than that in the paper [11] on average and had an additional 23.33% success rate. Finally, E_{mean} was 528 lx (recommended minimum is 500 lx), U_o was 0.89 (recommended minimum is 0.7), UGR was 17 (recommended maximum is 19), and LPD 7.325 was W/m^2 (recommended maximum is 15 W/m^2), as shown in Table 6. In other words, the proposed method can increase E_{mean} by 5.6% and U_o by 27.1% and decrease UGR by 10.5% and LPD by 51.2% compared with the lighting standard.

Table 5. Experimental results of each algorithm.

Algorithm	BFV	WFV	MV	STDEV
IPSO	36.677	35.351	36.589	0.331
PSO	36.677	33.541	35.645	1.150
GA	36.097	32.952	34.786	1.332

Table 6. Comparison of optimal results of different algorithms.

Type	N_a	N_b	L_t (m)	L_l (m)	E_{mean} (lx)	U_o	UGR	LPD (W/m^2)	$Q_{lighting}$	Success Rate
IPSO	3	4	2.488	2.326	528	0.89	17	7.325	0.43	93.33%
PSO	3	4	2.488	2.326	528	0.89	17	7.325	0.43	70.00%
GA	3	4	2.418	2.316	520	0.82	17	7.325	0.32	-

5.2.3. Validation

To validate the optimized layout from the IPSO, the same room parameters are used in the DIALux. Figure 9 shows a comparison of the illuminance distribution of the working plane, which sets a grid of 7 × 9 to show the point illuminance, and the contours only show the values of 460 lx, 475 lx, 500 lx, 525 lx and 550 lx, obtained by the developed program and DIALux. The maximum difference in illuminance is 50 lx, which is hardly perceptible by the human eye. Figure 10 is a pseudo-color graph of spatial illuminance. The black rectangle is a window, where no illuminance calculation was performed; therefore, it appears black. Figure 10 shows that the colors on the working plane are green, indicating a uniform distribution of illuminance on the working plane.

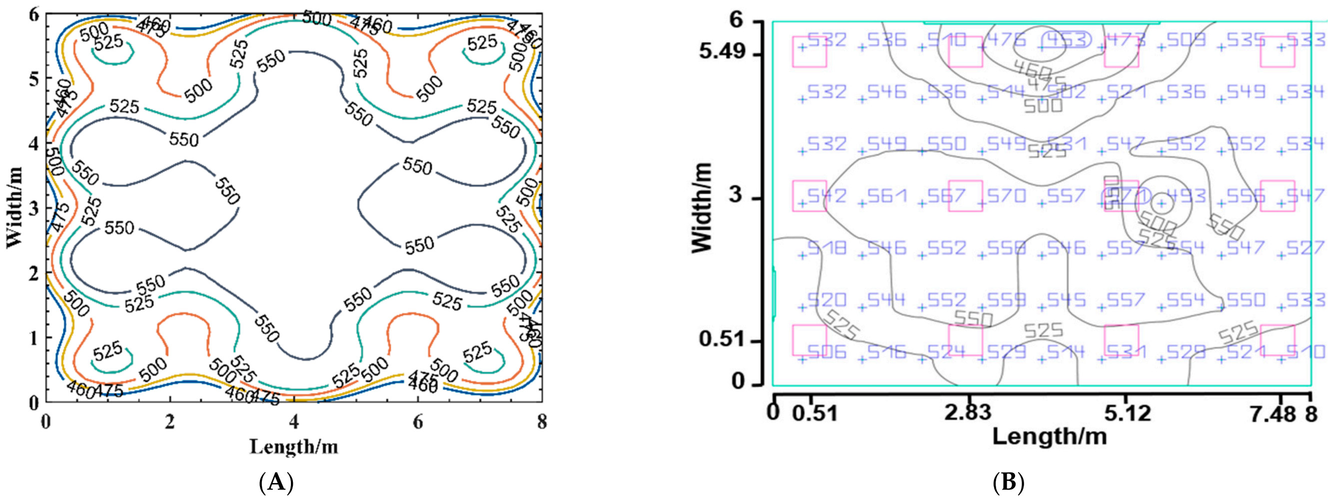


Figure 9. Contour map of illumination distribution on the working plane. (**A**) Results from the developed program and (**B**) results from DIALux.

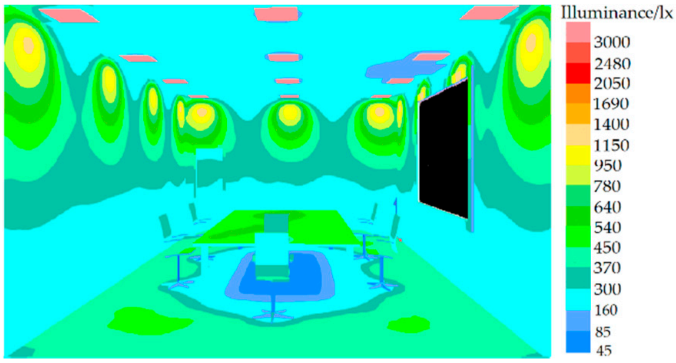


Figure 10. Pseudo-color graph of room space illuminance distribution.

UGR is computed with a grid of 7 × 9 on a horizontal plane of 1.2 m (the height of the human eyes when sitting down) from 0° to 360°, step 15°. First, we use DIALux to calculate the UGR. The results show that the maximum UGR value occurs in the direction of 30°. Therefore, a view angle of 30° is chosen to observe the results of the developed program and the DIALux simulation. As shown in Figure 11, both have the maximum UGR value of 17. UGR values are greater in the lower-left corner because the angle of observation is 30°.

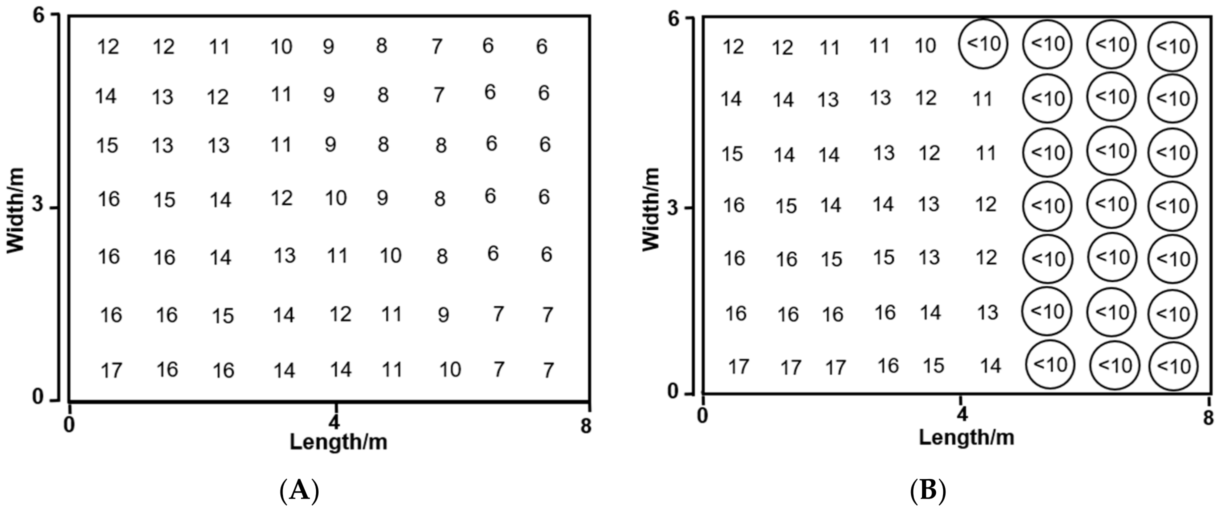


Figure 11. Grid-specific UGR values on a 1.2 m horizontal plane with a view angle of 30° calculated by the (**A**) developed program and (**B**) DIALux.

LPD has no variation since both use the same luminaires and number of luminaires. A detailed comparison of the design parameters is shown in Table 7. The deviation of E_{mean} and U_o is about 0.4% and 2.2%, which explains the difference of illuminance distribution in Figure 9 and proves the effectiveness of the algorithm and model proposed in this paper.

Table 7. Values of design parameters obtained from the developed program and DIALux.

Solution	E_{mean} (lx)	U_o	UGR	LPD (W/m^2)	CRI
Developed program	528	0.89	17	7.325	≥80
DIALux	530	0.91	17	7.325	≥80

6. Applications

In order to make it visual for lighting design engineers and related researchers to use the method proposed by this paper, we design an Indoor Luminaire Layout System APP using MATLAB APP Designer. As shown in Figure 12A, the beginning interface is divided into two parts: the left one is the input area, and the right one is the output area.

The input area includes room information and luminaire information. Clicking "Select" to select the IES file in the folder. After inputting the information, click "Begin" to get the optimization result, as shown in Figure 12B. The coordinates of the luminaires are displayed in the coordinate system, and the values of the optimal decision variables (N_a, N_b, L_t, L_l) are displayed simultaneously.

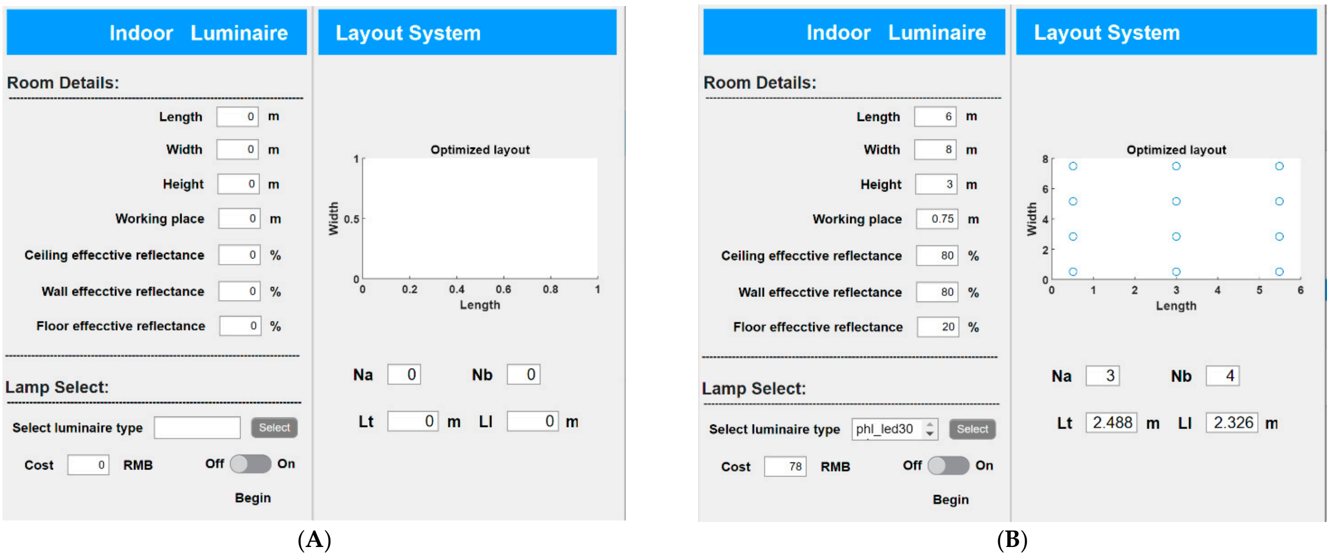


Figure 12. Interface of the Indoor Luminaire Layout System. (**A**) Beginning interface and (**B**) result interface of an example.

7. Conclusions

In order to address complex design parameters and conflicting design goals of the ILL problem, an improved mathematical model and an improved particle swarm algorithm are proposed. The proposed method works on the design of large lighting locations for GLS whose N_a and N_b are greater than 2 (e.g., office, meeting room, sports hall). In the aspect of the mathematical model, the ILL problem is formulated as a nonlinear constrained optimization problem, considering five mutually conflicting design parameters: E_{mean}, U, LPD, UGR, and cost. For GLS, the number and location of luminaires can be uniquely determined by optimizing four decision variables (N_a, N_b, L_t, L_l), which have been avoided using program loops to determine the number of luminaires. In the aspect of algorithm, since there exist integers and consecutive numbers of decision variables, UDPR is proposed, which improves the robustness compared with the traditional rounding method. The velocity of the best global particle is improved by randomly selecting two positions for updating, increasing the probability of jumping out of the local optimum. What is more, we use nonlinear inertia weights with random items to increase particle diversity.

In the case study, a typical senior office is taken to verify our method. Design parameters' limiting values are recommended by a Chinese lighting standard (GB 50034-2013). By comparing the IPSO with the PSO and GA, the results show that the IPSO has better convergence speed and optimization performance. Then we analyze the IPSO results, which show that the parameters that are optimized are improved compared with their limiting values. What is more, four decision variables this paper proposed in mathematical models contribute the speed of the program. E_{mean} is 528 lx (recommended minimum is 500 lx), U_o is 0.89 (recommended minimum is 0.7), UGR is 17 (recommended maximum is 19), and LPD is 7.325 W/m^2 (recommended maximum is 15 W/m^2). Further, our method was validated by DIALux. It shows that the deviation of E_{mean} and U is about 0.4% and 2.2%, and other parameters have no deviation, which shows the effectiveness of the algorithm and model proposed in this paper. Finally, we design an APP to facilitate the use of lighting design engineers and other related researchers, which is not considered an alternative to commercial lighting design. Lighting designers need to fill in the room details, select the illuminance IES file, and enter the price to get the recommended illuminance layout as a reference. Just by changing the illumination standards and luminaire information, it can be widely applied to GLS.

However, this study has some limitations and problems that need to be addressed and overcome in future research. On the one hand, lighting design parameters not only are those considered in this paper, but also include the contribution of daylight into the room, human preferences, and the spatial distribution of colors in the environment. On the other hand, the minimum illuminance values tend to occur in the corners of the room, which are generally not working areas. However, in order to improve U_o, it is necessary to increase the brightness in this area. Further, it will affect the distribution of luminaires and waste energy.

Under this research, it is efficient to study daylight-responsive indoor smart lighting control systems in future research, because our research promises a high quality of lighting when there is no daylight. Altogether, the method proposed in this paper provides some new facets to the ILL that deserve more research and investigation in the future.

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Nomenclature

APP	application
cost	lighting costs per unit of illumination
CRI	general color rendering index
E_{mean}	average illuminance
GA	genetic algorithm
GLS	general lighting scheme
ILD	indoor lighting design
ILL	indoor luminaire layout
IPSO	improved particle swarm optimization
LED	light-emitting diode
N_a	number of luminaires in a row
N_b	number of luminaires in a column
L_t	regular luminaire spacing along length
L_l	regular luminaire spacing along width
PSO	particle swarm optimization
$Q_{lighting}$	quality of lighting
U_o	overall uniformity
UDPR	up–down probabilistic rounding
UGR	unified glare rating
lm/W	lumen per watt

Lm	lumen
m	meter
W	watt
W/m^2	watt per square meter

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