

Article

Research on Energy Efficiency Optimization Control Strategy of Office Space Based on Genetic Simulated Annealing Strategy

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Abstract: Current energy-saving lighting control algorithms often face the dilemma of local optimality, which limits the energy-saving potential and comfort improvement of indoor lighting systems. The control parameters of the lighting system are optimized using a genetic simulated annealing algorithm to achieve the global optimal solution and enhance energy-saving efficacy in indoor lighting. The local search ability of the algorithm is enhanced by simulated annealing processing of excellent individuals after genetic operation. The genetic probability is adaptively adjusted according to the number of iterations and the fitness of the population, so that the algorithm enriches the population diversity in the early stage and avoids the “premature” convergence of the algorithm. A lamp illuminance model based on an artificial neural network and an indoor natural illuminance model based on a workbench are proposed to evaluate the lighting comfort, which provides a basis for constructing the fitness function of the optimization algorithm. Through the simulation experiment, the genetic simulated annealing algorithm is applied to the lighting scene introduced in this paper and compared with the traditional particle swarm optimization algorithm and genetic algorithm, the lighting energy saving performance is significantly improved.

Keywords: energy-efficient lighting control algorithm; genetic simulated annealing algorithm; illumination model



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1. Introduction

In recent years, with the rapid advancement of technologies such as the Internet of Things (IoT), big data, and artificial intelligence, intelligent lighting systems have become a research hotspot. These technologies provide robust support for the intelligent upgrading of lighting systems in open public areas, enabling automatic adjustments based on various factors, including ambient light, human activity, and time, to optimize lighting performance and achieve efficient energy use. As global energy shortages become increasingly widespread and living standards continue to improve, there is a growing demand for energy-efficient and comfortable lighting solutions [1]. Lighting is one of the building energy systems (BESs) that accounts for a large portion of energy consumption of commercial buildings, for example, in the United States with 17% of the total consumption [2]. In current research on lighting optimization control methods, linear programming is often used to calculate the appropriate lighting control outputs [3,4]. However, in real-world scenarios, the objective function that satisfies the lighting needs of occupants is nonlinear. This necessitates linearizing the objective function, which increases the complexity of the algorithm and the computational load. Reference [5] have employed particle swarm optimization (PSO) to address the problem of nonlinear objective functions. However, the traditional PSO algorithm tends to get trapped in local optima, making it difficult to achieve a global optimum. Furthermore, during the iterative process of the optimization algorithm,

it is necessary to obtain the indoor illuminance distribution under specific dimming parameters to evaluate lighting comfort and determine the algorithm's fitness. In practical lighting applications, sensors are typically installed on the ceiling to detect illuminance. This method only provides the average indoor illuminance, making it difficult to capture the illuminance distribution across different work surfaces. Consequently, achieving optimized lighting control becomes challenging. A robust state estimation algorithm based on sensitivity penalty is proposed in reference [6], which considers the explicit packet loss parameter. Reference [7] proposes an adaptive model update method to migrate the model from the previous running state to the current running state by identifying the fewest modifications to the model. It greatly reduces the amount of training data to meet the real-time requirements and improves the accuracy of model recognition. Reference [8] has employed a robust state estimator (RSE) based on sensitivity penalty used for local estimation; it can guarantee comparatively good estimation performance. Reference [9] has derived more computationally efficient conditions for the computationally difficult problem of dissipation analysis in large-scale network systems. The above research results provide the theoretical basis and technical support for the algorithm in this paper. In recent years, researchers propose a calculation model for the global horizontal irradiance and illuminance under a cloudless sky [10]. However, these methods require multiple physical parameters, such as the positions of calculation points and light sources, as well as the photometric curves of luminaires, making the calculation process complex. This paper presents a novel illuminance model based on a radial basis function (RBF) neural network, designed to streamline the process of illuminance distribution modeling for indoor lighting systems. By training the model with comprehensive data, it can accurately compute illuminance distributions for any configuration of luminaire brightness, thereby simplifying the traditionally complex illuminance modeling process. The estimated illuminance values are then incorporated into a penalty term within the fitness function of a genetic simulated annealing algorithm (GSAA), which optimizes luminaire control with energy efficiency as the primary objective while maintaining comfortable lighting conditions. The proposed GSAA framework leverages the strengths of both genetic algorithms (GAs) and simulated annealing (SA) to effectively avoid local optima, a common limitation in traditional optimization methods. By integrating these two optimization techniques, the GSAA not only addresses issues of high energy consumption but also introduces greater flexibility and adaptability in lighting control. This dual-method approach represents a significant advancement in the field of energy-efficient lighting, as it enables the system to intelligently balance user comfort with reduced energy usage. Ultimately, this work contributes to the development of smart, energy-efficient indoor lighting environments that offer enhanced comfort, safety, and sustainability, marking an improvement over conventional lighting control methods.

2. Luminaire Illuminance Model

2.1. Basic Principle

In general, indoor workers' visual attention is often focused on a specific horizontal work plane. Therefore, the illumination model under study pertains to the illuminance on a horizontal work plane at a determined height, excluding the influence of natural lighting. The luminaire illumination E_A at point $A(x, y)$ indoors is the sum of the illuminance produced by m light fixtures at point $A(x, y)$. Given the type of light fixtures and their installation positions, the illuminance at point A will be a function of the dimming ratio, where the dimming ratio $d_i (0 \leq d_i \leq 1, i = 1, 2, \dots, m)$ is defined as the ratio of the actual luminous flux to the maximum luminous flux. It can be expressed as

$$E_A = \sum_{i=1}^m f_i(x, y) \times d_i \quad (1)$$

In the formula, $f_i(x, y)$ represents the illumination produced by the first luminaire at the point when the dimming ratio is 1. Since $f_i(x, y)$ is a nonlinear function, there is a nonlinear relationship between the illuminance at point A and its position. Radial basis function neural networks have the advantages of a simple structure, straightforward training, and the ability to approximate any nonlinear function. In this paper, a radial basis function neural network is used to fit the illuminance distribution $f_i(x, y)$ of a single light fixture, and the illuminance E_A at point A is obtained by linearly summing the contributions from all the light fixtures.

2.2. Radial Basis Function Neural Network

The radial basis function neural network is a three-layer neural network consisting of an input layer, a hidden layer, and an output layer [11–13]. Its structure is illustrated in Figure 1.

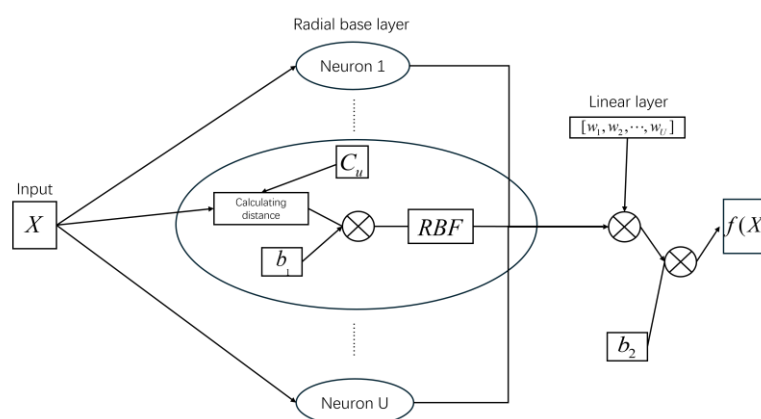


Figure 1. Structure of radial basis function neural network.

In Figure 1, C_u represents the center of the neuron u , which has the same dimensionality as the input X , and b_1 is a given constant bias that affects the shape of the radial basis function. Each neuron calculates the distance from the input vector to the neuron's center, and then multiplies this distance by the bias b_1 . The result is then passed to RBF ($rb(x) = e^{-x^2}$). The linear layer multiplies the output of the radial basis layer (a vector with U elements) by the weight vector $w = [w_1, w_2, \dots, w_U]^T$ and adds the constant bias b_2 . Therefore, RBFNN can generally be expressed as

$$f(X) = \sum_{u=1}^U w_u \times \exp(-(b_1 \times \|X - C_u\|_2)^2) + b_2 \quad (2)$$

The neural network is trained on data derived from measurements of luminaire illumination in a simulated office environment. High-precision illuminometers record illuminance values at different dimming ratios, including 100%, 75%, 50%, 25%, and off, by setting multiple measuring points at different locations. Environmental conditions (such as temperature and humidity) are also recorded during the measurement to facilitate data analysis. The collected data are systematically sorted into the training set, verification set, and test set, which provides a reliable basis for the illuminance distribution model and control 110 algorithm, and ensures the reliability and practicability of the research results.

The illuminance distribution x of a single luminaire is fitted with RBFNN, where the input X is the point coordinate (x, y) and the output is the point illuminance $f(x, y)$.

2.3. Establishment of the Illumination Model

The relationship between the illumination at any point indoors and the dimming ratio of the light fixtures can be derived from Equation (1). The overall network model is shown in Figure 2.

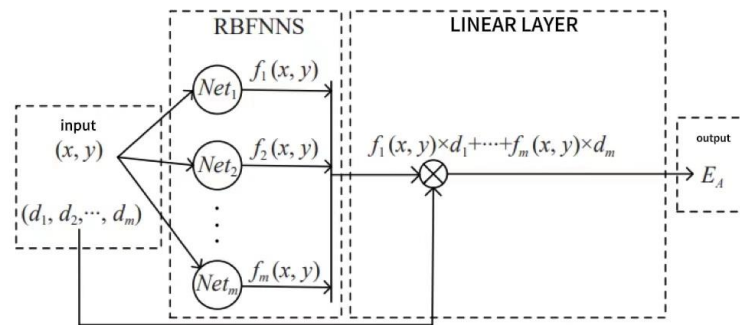


Figure 2. Schematic diagram of overall network model.

In Figure 2, each Net_i ($i = 1, 2, \dots, m$) in the RBFNNS represents the neural network structure shown in Figure 1. The illumination distribution function $f_i(x, y)$ for a single light fixture, obtained from the network, is multiplied by the corresponding dimming ratio d_i ($0 \leq d_i \leq 1, i = 1, 2, \dots, m$) and summed to obtain the illumination value at any point (x, y) . The input–output relationship is summarized as follows:

$$E_A = \sum_i^m \left(\sum_{u=1}^U w_u \times \exp(-(b1 \times \|X - C_u\|_2)^2) + b2 \right) \times d_i \quad (3)$$

3. Indoor Natural Illumination Model

We collected daylight data using the following approach: first, outdoor sky brightness was measured in typical seasons across different times of the day, including morning, noon, and evening, to capture daily and seasonal variations in light. These measurements were taken under various weather conditions, including sunny, cloudy, and overcast skies, to ensure coverage of diverse meteorological scenarios. A professional illuminance meter was used to measure sky brightness, with multiple sampling points to enhance data representativeness. We recorded the location and angle of each measurement point to ensure spatial consistency. The resulting data characteristics include the time-series distribution of sky brightness, mean and variance of brightness at specific times, brightness ranges under different weather conditions, and brightness trends. These characteristics provide a foundational dataset for simulating daylight's dynamic contributions to indoor lighting.

3.1. The Calculation of Indoor Direct Solar Illuminance

The calculation of the illumination generated by direct sunlight follows the characteristics of direct solar radiation. The illumination produced by unshaded direct sunlight entering indoors on the working surface should be equal to the outdoor direct sunlight illumination. However, the area affected by direct sunlight is limited to the solar patch within the room where the sunlight falls. Additionally, the direct sunlight passing through the window is influenced by the transmittance of the window glass.

The illumination of direct sunlight on the horizontal plane can be expressed as:

$$E_{dh} = E_{dn} \cdot \sin h_s \quad (4)$$

The direct sunlight illumination on a vertical plane can be calculated as:

$$E_{dv} = E_{dn} \cdot \cos \varepsilon \quad (5)$$

In the formula, h_s represents the solar altitude angle, measured in degrees, which is the angle between the sun and the horizontal plane. E_{dn} represents the normal illumination of direct sunlight. ε represents the wall solar azimuth angle. When the window sill is oriented north–south, $\varepsilon = A_s$. When the window sill is oriented east–west, $\varepsilon = A_s \pm 90$. A_s represents the angle between the projection of the direct sunlight on the horizontal plane

and the true south direction on the ground. It is typically measured with the south point (S) as 0° , with positive values toward the west and negative values toward the east.

Therefore, the illumination of direct sunlight in the indoor solar patch area can be expressed as: $E_d = E_{dh} \cdot K_\tau \cdot K_\tau$ is the total transmittance coefficient for side lighting.

3.2. The Calculation of Illumination Generated by the Indoor Sky Light

The illumination produced by the indoor sky light can be calculated using the solid angle projection law, as illustrated in Figure 3. Assuming A_1 is a uniformly luminous surface with constant brightness in all directions and A_2 is the illuminated surface, consider a differential area dA_1 on surface A_1 . The illumination it produces at point O on surface A_2 is given by: $dE = L_a d\Omega \cos i$.

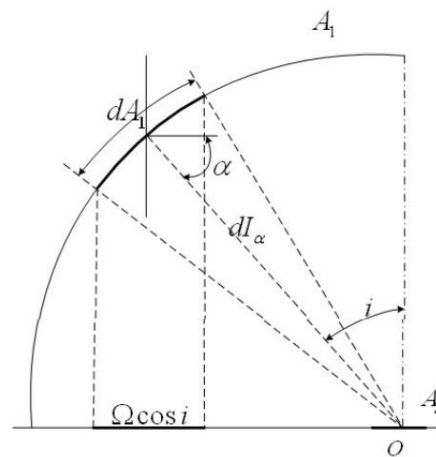


Figure 3. Solid angle projection law.

The total illumination at point O on surface A_1 from the entire luminous surface is given by: $E = \int_{\Omega} L_a \cos i d\Omega$.

When the luminous intensity of the light source is uniform in all directions, then $E = L_a \Omega \cos i$. In the formula, Ω represents the solid angle subtended by surface A_1 at point O .

Given a simple layout of an office environment as shown in Figure 4, with O as the origin point, and a specific point T in the room plane with coordinates (x, y) , the window sill on the left side has a width Y , height X , and the height difference between the bottom of the window sill and the working surface is h_t . The solid angle subtended by the window sill at point T can be calculated using the following formula:

$$\Omega = \frac{Y \cdot H \cos a}{(h_t + \frac{H}{2})^2 + x^2 + (Y_w + \frac{Y}{2} - y)^2} \quad (6)$$

In Equation (7),

$$\cos a = \cos \left\langle \vec{a}, \vec{b} \right\rangle = \frac{x}{\sqrt{(x^2 + (Y_w + \frac{Y}{2})^2 + (h_t + \frac{H}{2})^2)}} \quad (7)$$

$$\cos i = \cos \left\langle \vec{b}, \vec{c} \right\rangle = \frac{h_t + \frac{H}{2}}{\sqrt{(x^2 + (Y_w + \frac{Y}{2})^2 + (h_t + \frac{H}{2})^2)}} \quad (8)$$

In the previous calculation of outdoor sky light, the sky illuminance on the vertical plane can be obtained as:

$$E_{skyv} = \frac{(E_k - E_{dv}) \cdot \cos \varepsilon}{\sin h_s} \quad (9)$$

Therefore, the illumination of any point on the indoor working plane by the sky light can be obtained as follows:

$$E_s = \frac{E_{skyv} \cdot Y \cdot H \cdot x \cdot (h_t + \frac{H}{2})}{((h_t + \frac{H}{2})^2 + x^2 + (Y_w + \frac{Y}{2} - y)^2) \cdot 4\pi} \cdot K_\tau \quad (10)$$

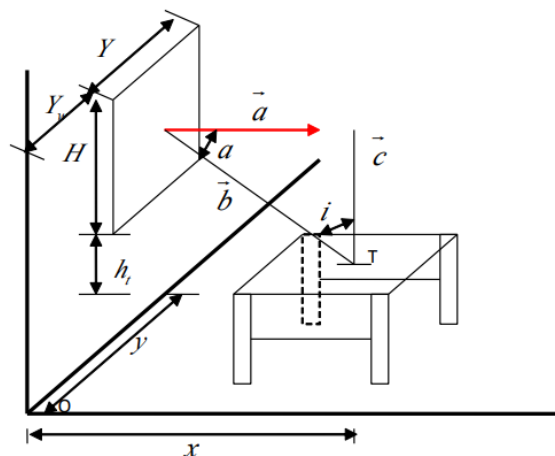


Figure 4. Simple layout of the office environment.

3.3. The Calculation of Illuminance Produced by Outdoor Reflected Light

The illuminance generated by outdoor reflected light, which enters the room after being reflected by outdoor shades, can be calculated in a similar manner to that of sky light illuminance on a specific point of the indoor working surface. The luminous brightness of the shade seen through the window at a certain point in the room should also be obtained first. Then the illumination generated at a certain point in the room is calculated by the law of solid angle projection. Because occlusions such as buildings, trees, etc., can be approximated as uniform diffuse reflective surfaces, the reflected illuminance can be calculated according to the following formula:

$$E_{ref0} = (E_{dv} + E_{skv}) \cdot \rho \quad (11)$$

ρ —the reflectivity of the occluded surface.

Similar to the calculation of illuminance produced by the sky light, the illuminance of outdoor reflected light at any point on the indoor working plane is:

$$E_s = \frac{E_{refo} \cdot Y \cdot H \cdot x \cdot (h_t + \frac{H}{2})}{((h_t + \frac{H}{2})^2 + x^2 + (Y_w + \frac{Y}{2} - y)^2) \cdot 4\pi} \cdot K_\tau \quad (12)$$

3.4. The Calculation of Illuminance Generated by Indoor Reflected Light

The indoor surface will reflect the natural light that shines into the room and reach a certain point after countless reflections to produce illumination at that point. According to the “decomposition flux rule” recommended by the British Institute of Building Science (BRS), the light flux entering the window is decomposed into three parts: the light flux entering the sky directly, the external reflected light flux entering the room through the lower part of the window, and the light flux generated by direct sunlight in the window. Indoor reflected light is affected by many factors, the most important is directly related to the outdoor light environment. If the illuminance generated at each point in the indoor area is basically a constant, then we can approximate by the following calculation:

$$E_{refi} = E_k \cdot C \quad (13)$$

C—constant, influence factor.

3.5. Integrated Indoor Brightness Calculation

The brightness of a certain point in the room, according to the above four factors, and the illuminance can be linearly superimposed, so it can be synthesized as follows:

$$E_{total} = E_d + E_s + E_{refo} + E_{refi} \quad (14)$$

4. Algorithm

4.1. Introduction of Simulated Genetic Annealing Algorithm

Genetic algorithm, as a global optimization search strategy inspired by the mechanisms of biological evolution in nature, was originally proposed by Professor John H. Holland in his pioneering work [14,15]. By simulating natural phenomena such as heredity, cross (hybridization), and variation in the biological population, the algorithm can effectively search for the optimal solution or approximate optimal solution in the solution space, showing strong adaptive and global search ability. The genetic algorithm (GA) is famous for its global optimization ability. However, it may be limited by the lack of local search ability in some cases, and it is easy to fall into the dilemma of premature convergence. In contrast, the simulated annealing algorithm (SAA), although inferior to GA in global breadth of exploring new solutions, has strong local searching ability, enabling it to dig deep into potential high-quality regions of solutions when optimizing complex problems [16–18].

In order to combine the advantages of the two, the genetic simulated annealing algorithm (GSAA) was developed. GSAA cleverly integrates the local search mechanism of SAA into the framework of GA and performs a simulated annealing process on elite individuals in the population after GA's genetic operations (such as selection, crossover, and mutation) are completed. This process not only retains the global exploration ability of GA, but also improves the ability of the algorithm to find the optimal solution in the search space through the local optimization characteristics of SAA [19].

With the continuous advancement of the iterative process, the GSAA algorithm can gradually reduce the search scope until it finally converges to the most competitive individual in the population, that is, the optimal solution of the problem. This algorithm design not only enhances the robustness and adaptability of the genetic algorithm, but also improves the solving efficiency, and provides a new perspective and powerful tool for solving complex optimization problems [20,21].

4.2. Design and Analysis of Algorithms

In the GA algorithm, the parameters of the optimization problem need to be genetically encoded first [22]. In the genetic simulated annealing algorithm (GSAA) developed here, the parameters for optimal dimming are encoded into genes. Each gene represents the dimming ratio for a light fixture, where the values range from 0 (off) to 1 (full brightness). The lighting arrangement ensures that each workstation receives adequate illumination according to specified comfort levels. For example, zones with personnel require an illumination level of approximately 300 lux, while zones without personnel are set to a minimum, conserving energy.

Assuming that there are n work stations in the room, in order to ensure the comfort of lighting, the illuminance on each work station should meet the following constraints:

$$E_j + E_{total,j} - T_j \geq 0 \quad (j = 1, 2, \dots, n) \quad (15)$$

where T_j is the expected illuminance value of the station; E_A is the estimated illuminance value of the station obtained by the illuminance model of the lamps; and $E_{total,j}$ obtains the illumination estimation value of the station for the natural illumination model. The value of T_j on the station with personnel can be in accordance with the relevant standards, and the value of T_j on the station without personnel should be as small as possible, so as to minimize the lighting energy consumption.

Under the above assumptions, the constrained optimization problem is transformed into an unconstrained optimization problem, and the fitness function is defined as

$$\cos t(\mathbf{d}) = \sum_i^m f(d_i) + \sum_j^n \theta(q_j(\mathbf{d}))q_j(\mathbf{d}) \quad (16)$$

where

$$q_j(d) = \max\{0, T_j - E_j - E_{total,j}\} \quad (17)$$

$$\theta(q_j(\mathbf{d})) = \begin{cases} 10, & \frac{q_j(\mathbf{d})}{T_j} \leq 0.1 \\ 100, & \frac{q_j(\mathbf{d})}{T_j} > 0.1 \end{cases} \quad (18)$$

In Equation (16), $\mathbf{d} = [d_1, d_2, \dots, d_m]$, and $\cos t(\mathbf{d})$ consists of two parts: The first part is the total lighting energy consumption, $f(d_i)$, which represents the energy consumption of the i th lamp and can be approximately reduced to a linear function of d_i . The second part is the penalty term transformed from the constraints. As can be seen from Equation (17), when the estimated illuminance value is greater than the expected value, it means that the demand for comfortable lighting has been achieved and the penalty term is 0 at this time. However, when the estimated illuminance value is less than the expected value, the comfort lighting demand is not satisfied, and the order of magnitude of the penalty term is defined by Equation (18). All in all, the practical significance of the fitness function is to require that the estimated illuminance is larger than the expected illuminance, and the closer the better. In the proposed GSAA algorithm, the optimization objective is the individual with the smallest fitness function value.

The genetic operations of GA include selection, crossover, and mutation.

1. Selection operator. The binary tournament method combined with the elite retention strategy is used to select individuals. That is, 20 individuals with the smallest fitness are selected from the population as elite individuals to be retained in the new offspring, and then two parents are randomly selected from the population with replacement, and their fitness functions are compared. The individual with the smaller fitness function is selected as the new offspring, and the process is repeated until the new population size reaches the original population size.
2. Crossover operator. The two-point crossover method is used to cross the partial genes of two parents to generate new individuals.

The crossover probability p_c and mutation probability p_m of GA greatly affect its performance. To avoid the “premature” convergence of the algorithm, large p_c and p_m are selected in the early stage of genetic evolution, which can enrich the diversity of the population. In the later stage of evolution, setting small p_c and p_m is beneficial to preserve the excellent individuals of the population and make the algorithm converge faster. At the same time, the individual with smaller fitness should select smaller p_c and p_m so that its excellent performance can be preserved, while the individual with larger fitness should increase p_c and p_m to generate a new individual structure with greater probability. Considering the above conditions, the designed adaptive crossover probability is as follows:

$$p_c = \begin{cases} g^{-0.5} \left(p_{c1} - (p_{c1} - p_{c2}) \frac{c_{avg} - c_c}{c_{avg} - c_{min}} \right), & c_c \leq c_{avg} \\ g^{-0.5} p_{c1}, & c_c > c_{avg} \end{cases} \quad (19)$$

where c_c is the smaller fitness value of the two individuals to be crossed; c_{min} and c_{avg} are the minimum and average fitness values of the population, respectively; g is the generation of population evolution; and p_{c1} and p_{c2} are the maximum and minimum crossing probabilities, respectively.

3. Mutation operator. Using basic bit mutation, a gene bit of an individual is randomly selected and replaced with a random number. Its mutation probability p_m is as follows:

$$p_m = \begin{cases} g^{-0.5} \left(p_{m1} - (p_{m1} - p_{m2}) \frac{c_{avg} - c_m}{c_{avg} - c} \right), & c_m \leq c_{avg} \\ g^{-0.5} p_{m1} & , \quad c_m < c_{avg} \end{cases} \quad (20)$$

where c_m is the fitness value of the individual to be mutated and p_{m1} and p_{m2} are the maximum and minimum mutation probabilities, respectively.

The idea of the SAA algorithm is to simulate the process of solid annealing and cooling, and to simulate the process of the optimization solution by gradually reducing the temperature [23,24]. In the lighting optimization in this paper, the combination of the simulated annealing operation and lighting control is mainly reflected in the random disturbance of the dimming ratio of the lamp and the gradual “cooling” process. First, after each genetic operation, a small dimming ratio adjustment is made for some excellent solutions (solutions that meet the illumination requirements and have low energy consumption) to simulate the fine tuning of the luminosity in the lighting system in order to distribute the local illumination more evenly and improve the overall comfort. Then, combined with the annealing acceptance criterion, an illumination state slightly lower than the current solution is tolerated by a decreasing probability (i.e., the temperature parameter), thus avoiding the algorithm falling into local optimality prematurely. In the later stage of optimization, the disturbance amplitude is gradually reduced, the probability of accepting the sub-optimal solution is reduced, and the “cooling” process is simulated, so that the lighting system tends to be stable, and finally the optimal lighting configuration is achieved taking into account comfort and energy saving. Such a simulated annealing operation enables the algorithm not only to quickly find feasible solutions but also to jump out of the local optimum, ensuring that the lighting optimization effect is more ideal globally.

In this paper, the exponential annealing method is used for cooling, namely:

$$T_i = T_{i-1}k \quad (21)$$

where T_i is the system temperature at iteration i ; T_{i-1} is the system temperature at iteration $i - 1$; and k is the cooling factor.

After the genetic operation, the top 20% of excellent individuals in the population are selected for the simulated annealing operation. First, these individuals are perturbed to generate new individuals. There are three ways of perturbation, which are exchange structure, reversal structure, and insertion structure. In each perturbation, one of the three types is selected according to a certain probability to be perturbed. Then, the Metropolis [25] criterion is adopted to judge whether to replace the current individual with a new individual. The Metropolis rule is as follows:

$$p = \begin{cases} 1 & , \text{cost}(\mathbf{d}') \leq \text{cost}(\mathbf{d}) \\ \exp\left\{ \frac{-(\text{cost}(\mathbf{d}') - \text{cost}(\mathbf{d}))}{T_i} \right\} & , \text{cost}(\mathbf{d}') > \text{cost}(\mathbf{d}) \end{cases} \quad (22)$$

where p is the probability that the new individual replaces the current individual; $\mathbf{d}$ represents the current dimming ratio combination; and $\mathbf{d}'$ represents the new dimming ratio combination generated after the perturbation.

Therefore, when $\text{cost}(\mathbf{d}') \leq \text{cost}(\mathbf{d})$, $\mathbf{d}'$ replaces $\mathbf{d}$ with probability p .

4.3. Implementation of the Algorithm

Firstly, the parameters are initialized, including population size N (the number of dimming schemes), maximum number of iterations M , crossover probability p_{c1} and p_{c2} , mutation probability p_{m1} and p_{m2} , gene dimension m (number of lamps), initial temperature T_0 , cooling factor k , etc. The algorithm then generates a random set of dimming ratio combinations as the initial population, with values ranging from 0 (off) to 1 (full light) in each combination to represent the brightness ratio of each fixture, ensuring that different areas can meet their illumination needs and achieve their energy savings goals. In each iteration, the algorithm first calculates the fitness value, estimates the regional

illumination and energy consumption under the current dimming combination through the lighting model, and determines the fitness function value according to the comfort level and energy consumption level. This results in the retention of high-performing individuals through selection operations to ensure that high-quality solutions are passed on to the next generation. The crossover operation exchanges the dimming ratio of some lamps and generates a new dimming scheme to improve the diversity of the solutions. The mutation operation introduces a small random change in the dimming ratio of the individual, which helps to jump out of the local optimum. Finally, the simulated annealing treatment further optimizes the optimal individual, fine-tuning the dimming ratio and allowing slightly inferior solutions to be accepted with decreasing probability to avoid premature convergence. As the cooling factor gradually decreases, the dimming combination gradually stabilizes, resulting in a globally optimal lighting configuration that takes into account comfort and energy saving.

5. Simulation Experiment

5.1. Illumination Model Testing

The simulation experiment in Figure 5 is conducted in a space measuring $4.5\text{ m} \times 7.0\text{ m} \times 3.2\text{ m}$, resulting in a total area of 31.5 square meters. Within this area, nine LED lamps are installed, each capable of achieving a maximum brightness of 1000 lux. The dimming ratio for these lamps ranges from 0 (off) to 1 (full brightness). And the office area is divided into six zones: zones 1 and 2 are by windows, zones 3 and 4 are close to zones 1 and 2, and zones 5 and 6 are close to zones 3 and 4 but far from zones 1 and 2. In the simulation scenario, zones 1 and 2 are positioned near the windows in the office, representing a typical office environment. Each zone measures 1.5 m by 0.8 m, with a height of 0.75 m. Zones 1 and 2 are placed 1 m away from the south-facing window, parallel to it, to examine the effects of direct natural light. Outdoor illuminance data are dynamically adjusted based on time and weather changes, simulating daylight conditions in the morning, noon, afternoon, and evening. Weather conditions include sunny and overcast scenarios, with corresponding outdoor illuminance values of approximately 8000 lx and 2000 lx, respectively. The window's light transmittance is assumed to be 90%. The illuminance value on the working surface and the position information of the measurement point are measured individually for each lamp. This yields a set of data consisting of position and illumination, with 30 sets obtained for each lamp as corresponding datasets. Subsequently, 18 groups of data are allocated to the training set, while 6 groups serve as the validation set and another 6 groups form the test set.

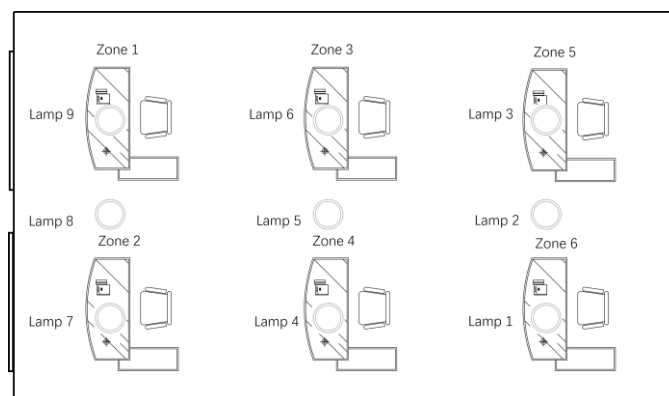


Figure 5. Schematic diagram of lighting scenes.

The lighting illumination model was trained using MATLAB R2023a, and the resulting illuminance model was evaluated on the test set. Taking lamp 1 as an example, its performance on the test set is presented in Table 1.

Table 1. Test result of lamp 1.

The Measured Illuminance Value/lx	Calculated Illuminance Value/lx	Relative Error/%
97	92	−5.20
144	139	−3.47
70	69	−1.43
136	135	−0.73
155	165	6.45
96	89	−7.29

Defining the average of the absolute values of the relative errors in Table 1 as e_1 , the formula $e_1 = 4.10\%$ can be obtained after calculating the statistics. Similarly, the $e_i (i = 2, 3, \dots, 9)$ of the illuminance model test results of other lamps and lanterns are obtained, the statistics of which are shown in Table 2.

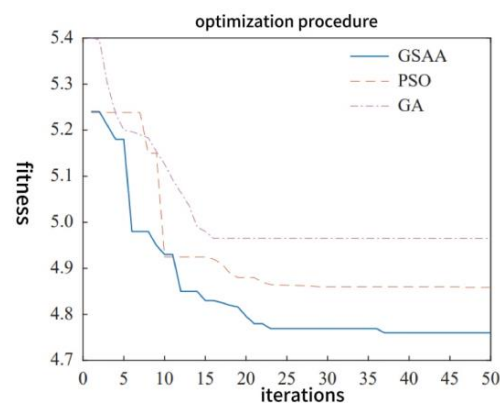
Table 2. Illumination model test results.

Lamp Number	$e_1/\%$
1	4.10
2	3.30
3	4.18
4	2.30
5	1.99
6	3.80
7	2.90
8	2.77
9	2.01

5.2. Comparison of Algorithms

In the lighting scenario described in the previous section, it is assumed that there are three people in the room. For the staffed zone, in order to meet the comfort of lighting d , the expected value of illumination T_j is set to 300 lx. For the unstaffed zone, the expected value of illumination T_j is set to 50 lx. The personnel state is 1 for staffed areas and 0 for unstaffed areas.

The GA algorithm, GSAA algorithm, and PSO (particle swarm optimization) algorithm are employed to optimize the dimming in the personnel distribution scenarios. The population size of each algorithm is set to 200, with a total of 50 iterations performed. Taking the indoor scenario with three individuals as an example, Figure 6 illustrates the optimization process of these algorithms. It can be observed that the GA algorithm exhibits premature convergence around the 16th iteration, resulting in a higher fitness value for its best individual found. Both the PSO and GSAA algorithms converge at approximately the 23rd iteration; however, GSAA achieves an optimal solution with a smaller fitness value, indicating its superior global search capability compared to the former.

**Figure 6.** Curves of optimization process.

As shown in Table 3, the dimming ratio combinations optimized by the three algorithms all achieve the target illuminance levels on the work surfaces in the occupied areas. From an energy consumption perspective, the dimming ratios can be approximately regarded as power ratios for the luminaires. Taking Table 4 as an example, the total dimming ratio for the nine luminaires optimized using PSO is 4.8. This represents a 46.78% energy savings compared to the scenario where all nine luminaires operate at full power with a total dimming ratio of 9. Similarly, the GA and GSAA algorithms yield energy savings of 42.89% and 49.33%, respectively.

Table 3. Lighting control results.

Station Number	1	2	3	4	5	6
Personnel presence	No	Yes	Yes	No	No	Yes
PSO optimizing illuminance/lx	271	324	303	269	180	293
GA optimizing illuminance/lx	289	321	291	271	178	294
GSAA optimizing illuminance/lx	217	309	299	285	196	297

Table 4. Optimized dimming ratios for individual luminaires.

Luminaire Number	1	2	3	4	5	6	7	8	9
PSO	0.05	0.98	1.00	0.84	0.20	0.01	0.01	0.75	0.96
GA	0.04	0.97	0.90	0.83	0.36	0.15	0.09	0.85	0.95
GSAA	0.04	0.46	0.95	0.69	0.62	0.07	0.10	0.72	0.91

6. Conclusions

In this paper, a new illumination model is proposed to provide the support of illumination calculation for the subsequent control algorithm. A genetic probability adaptive GSAA algorithm is designed, which integrates the local search ability of SAA and can converge to the global optimal solution better than the traditional algorithm.

The proposed algorithm has significant practical implications for enhancing energy efficiency and comfort in real-world applications. Its optimization capabilities allow for effective adjustments to lighting systems to meet varying environmental and usage requirements, leading to substantial energy savings in office buildings, commercial spaces, and other indoor settings.

However, there are potential challenges in the implementation process. Firstly, the success of the algorithm relies on accurate lighting models and the precise measurement of environmental parameters, necessitating the deployment of high-precision sensors and data acquisition devices in practical applications. Secondly, user behavior patterns and preferences may influence lighting needs, requiring the algorithm to possess sufficient flexibility to adapt to these variations. Additionally, existing lighting systems may need modifications or upgrades to effectively integrate with the intelligent control algorithm.

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