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Building Intelligent Lighting Energy Saving System Based on Particle Swarm Optimization Algorithm Optimized by Penalty Function

Zhiwei Zhang[1,*]
[1] Henan Polytechnic Institute, Nanyang, Henan, 473000, China
Corresponding authors: (e-mail: zhiwei_zhang23@outlook.com).

Abstract With the implementation of energy-saving and emission reduction policies, intelligent lighting systems in buildings are facing higher energy-saving requirements. However, general particle optimization algorithms have some limitations when dealing with multi-objective optimization problems. Therefore, this study improves the particle swarm optimization algorithm using penalty functions and optimizes the vector machine model to form a particle swarm-support vector machine model for energy consumption optimization control of building intelligent lighting systems. In comparison with the baseline model, the improved model reduced the average lighting energy consumption by about 5.7%, and the actual lighting power fluctuated between 4150W and 4400W. After 24 training iterations, the prediction accuracy of the model reached 90%. In addition, the importance of factors such as building orientation and lighting intensity decreased from 0.07 and 0.06 to 0.06 and 0.05, respectively, demonstrating a more balanced impact on the lighting system. Therefore, the model not only maintains comfortable lighting conditions while effectively optimizing the lighting energy use of buildings, but also improves energy efficiency.

Index Terms Penalty function; POS algorithm; SVM; Intelligent lighting; PSO-SVM model

I. Introduction

On a global scale, the construction industry is one of the main areas of energy consumption, and its energy conservation and emission reduction are of great significance for achieving sustainable development. With the increasing awareness of environmental protection and the popularization of green building concepts, intelligent lighting systems in buildings have received widespread attention as an effective means of energy conservation and emission reduction [1], [2]. Intelligent lighting systems can significantly reduce energy consumption and improve lighting quality by automatically adjusting lighting intensity and distribution, meeting needs for a comfortable and healthy lighting environment. According to the International Energy Agency, the energy use of the construction sector accounts for about 30% of the global total energy consumption, while contributing about 40% of direct and indirect carbon dioxide emissions worldwide. With the increasingly severe global climate change problem, reducing energy consumption in the construction industry has become a key link in achieving sustainable development goals [3]. Especially in China, with the acceleration of urbanization, the energy consumption and carbon emissions of the construction industry are also increasing year by year, which has brought enormous pressure to China's energy supply and environmental protection. How to balance lighting quality and energy efficiency while considering the activity patterns of personnel inside the building and natural lighting conditions has become a technical challenge [4], [5]. To overcome these limitations, an improved Particle Swarm Optimization (PSO) algorithm on the basis of penalty function is proposed. Then, it is combined with support vector machine (SVM) to form the optimized method (PSO-SVM) model, aiming to optimize the energy consumption control of building intelligent lighting systems. The innovation of the research lies in the fact that the algorithm utilizes the characteristics of penalty functions to transform constrained optimization problems into unconstrained problems. Meanwhile, the SVM model is optimized through the improved PSO algorithm to construct a composite model. It is expected to provide new solutions for the field of building energy efficiency and promote the development and application of intelligent lighting technology.

The research contains four parts. The first part introduces the research and analysis of building intelligent control lighting systems by domestic and foreign researchers. The second part introduces the optimization process of PSO based on penalty function and the constructed control model. The third part is the performance testing and application effect analysis. The fourth part summarizes the effectiveness of the PSO-SVM model in reducing energy consumption and improving energy efficiency, and points out that the adaptability and stability of the model in practical applications need further verification. Finally, directions for further optimization are proposed.

II. Related works

Various researchers have conducted research on lighting control algorithms. Yan H et al. proposed an intelligent lighting automation control system based on Zigbee and RFID technology to address the unified management of hospital lighting equipment. A new PSO method was proposed to overcome the local optima and premature convergence in PSO. The new algorithm could quickly find the optimal combination of lighting equipment, improve computational efficiency by 6.208%, demonstrating its advantages [6]. Kar Pushpendu et al. proposed an intelligent lighting system to address the office buildings, especially workplaces, being unable to meet personal indoor comfort requirements. Compared with traditional fluorescent lighting systems, the proposed lighting system improved energy efficiency by approximately 72% [7]. Swathika G V O et al. proposed a daylight harvesting technology to address the daily lighting needs and sustainable development goals. The results showed that architectural design had a significant impact on sunlight harvesting [8]. E Belloni et al. proposed a new street lighting control algorithm to reduce energy consumption in urban buildings, urban transportation, and public lighting systems. The method could be further improved on the basis of other boundary conditions like sunlight and weather data [9]. Areen A proposed a novel framework to improve building performance while preserving its architectural concept. The framework used Grasshopper plugin to develop a parametric model to adjust the opening ratio of facade panels and verified it through simulation software. The results showed that the optimized dynamic system achieved 20% energy savings and 31% reduction in daylight intensity levels [10].

Tzu Chia Chen et al. proposed a system for managing and monitoring lighting indices in smart cities, addressing the energy management and lighting index monitoring. The system was divided into two stages: data collection and monitoring system activation, followed by analysis of the operation of the control system and its impact on the performance of the numerical model. The results showed that the intelligent implementation system generated an average of 1.75 times the satisfactory results [11]. Alina B proposed a deep spatiotemporal feature extraction method on the basis of PSO for optimizing the video frame selection and 3D feature extraction stages in content-based video retrieval. It solved the information redundancy that may arise from fixed key frame sampling methods. The results showed that this method outperformed multiple benchmark sampling methods in terms of efficiency [12]. Bhardwaj A proposed an augmented Lagrangian dual method using sharp enhancement functions for the exact penalty representation problem of mixed integer convex optimization problems. The results showed that this method provided alternative proof and quantification of finite penalty parameters for the above situation [13]. Ali Aamir et al. proposed a constrained composite differential evolution optimization algorithm to find the optimal solution for the complex nonlinearity and new constraints in the optimal power flow problem. This algorithm combined two effective constraint processing techniques, feasibility rules and ε constraint method, to search within the feasible space. The results demonstrated the effectiveness and performance [14]. Baidya Kayal Esh et al. proposed an analysis method using a double exponential model that included total changes and penalty functions to improve the diagnostic accuracy of imaging in patients with osteosarcoma. Compared with the traditional dual index model, these two methods significantly improved the accuracy and repeatability of image quality scoring, especially in terms of diffusion coefficient and parameter estimation [15].

At present, most of the solutions for building lighting control are based on local optimization using PSO, and some use control frameworks for energy consumption control. The particle swarm optimization is mostly based on feature extraction and constraint composite difference problems. The penalty function is used to solve the precise punishment, or to use the penalty function to solve the low image quality. However, PSO algorithms for lighting have limitations due to constraints, and simply using penalty functions cannot solve the building energy efficiency. Therefore, the penalty function is used to optimize PSO and combined with SVM to construct a model. The fusion model proposed is expected to provide new ideas for energy-saving control of intelligent lighting in buildings.

III. Improved algorithm for building intelligent lighting energy saving system

III. A. Lighting control based on improved PSO

With the introduction of emission reduction policies, intelligent lighting systems in buildings are required to achieve more efficient energy-saving effects. Although traditional particle swarm optimization algorithms can transform dimming problems into particle optimization problems to solve, they cannot effectively handle multi-objective optimization tasks with constraints. This study addresses this issue by introducing a penalty function. The algorithm for introducing a penalty function is shown in Figure 1.

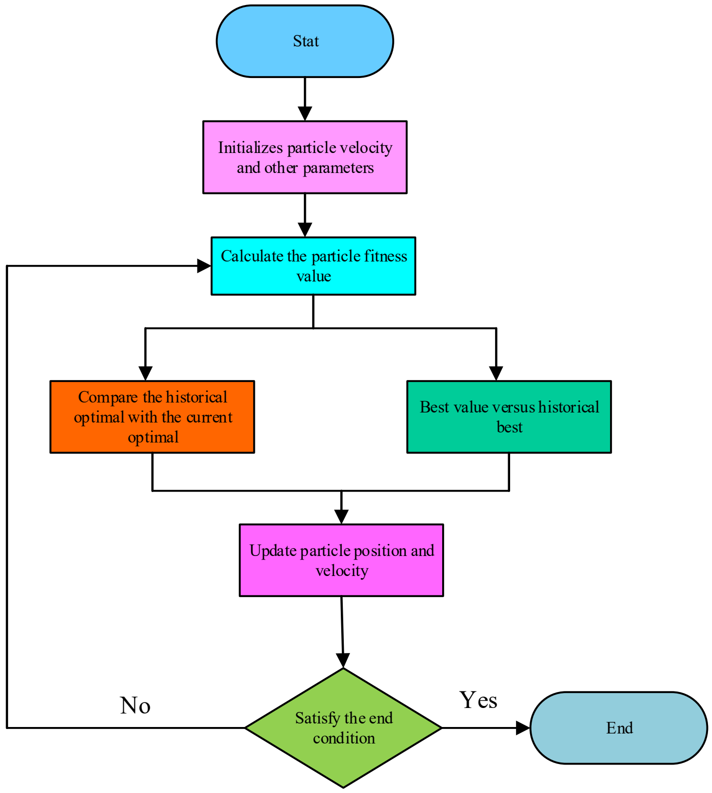

Figure1: The algorithm process for introducing the penalty function

The process of the improved algorithm in Figure 1 is divided into six main steps. The first step is to treat each method in the building energy-saving control system as a particle of an algorithm, and then randomly initialize independent particles, that is, the position and velocity of independent schemes. At the same time, the basic parameters of the algorithm are set, such asiterations, penalty factor, population size, etc. The second step is to define a penalty function based on the lighting control model and use it to assess the fitness value of each particle [16]. The third step is to compare the fitness values of particles calculated by the algorithm with the optimal values of particles in historical algorithms. If the current fitness value is better, the best position record of the particle and its corresponding fitness value are updated. The fourth step is to compare the individual optimal fitness value of particles with the global optimal fitness value of the entire population. Finally, if the predetermined maximum number of iterations has been reached is determined. If reached, the algorithm stops running. The specific form of the penalty function can be expressed as equation (1).

$$F(x,M)=f(x)+Mp(x)=f(x)+M\sum_{i=1}^{m}\left[\min\left(0,g_i(x)\right)\right]^2 \tag{1}$$

In equation (1), m represents the number of unknowns. M represents the penalty factor, which is a constant. $Mp(x)$ represents the penalty function for punishing the lighting system. The fitness function of the improved particle swarm algorithm can be represented by equation (2).

$$F=W+M\left(\max\left(E-E_r^T\right)\right) \tag{2}$$

In equation (2), W represents the desired illuminance in the building. E represents the actual power consumption of building lighting. E_r^T represents the predicted power generated by the building. The fitness function can not only solve the illumination value of the building, but also calculate the illumination parameter values of the lighting fixtures in the space at the lowest energy consumption of the building. The framework of the improved algorithm is shown in Figure 2.

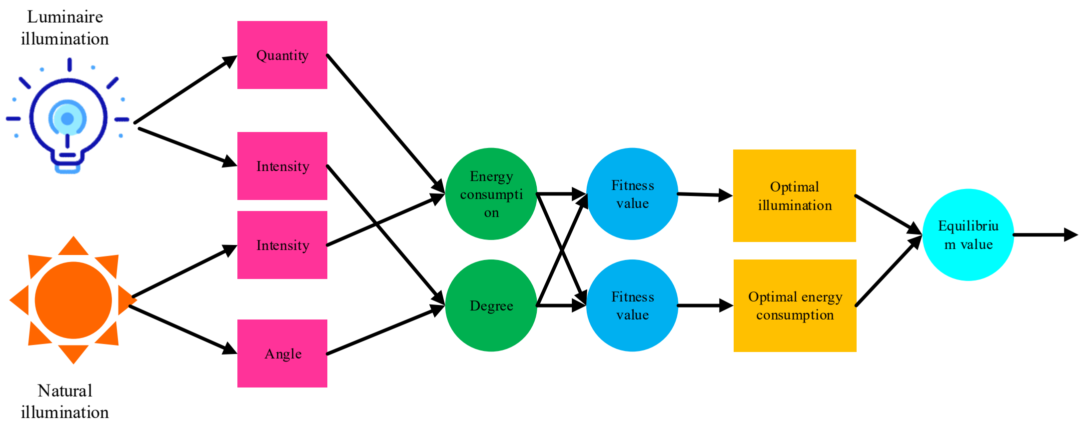

Figure 2: Framework diagram of the improved algorithm

In the framework diagram of the improved algorithm in Figure 2, the light flux from the lamps in the building determines the brightness of the building lighting. The sunlight in a building is determined by the opening of the curtains in the building. By optimizing and calculating the particles in the penalty function population, the fitness function of the particles is obtained. The fitness function is used to optimize and solve factors such as lighting fixtures and lighting positions [17], [18]. The optimal lighting position in the building and the optimal number of lighting fixtures are obtained. The total energy consumption value generated by the lighting system in the space is finally output. The relationship between the output of the lighting fixtures in the space and the illuminance of the supplementary light can be represented by equation (3).

$$E_a = G_a \bullet \Phi \tag{3}$$

In equation (3), E_a signifies the intensity of supplementary lighting required after illumination by the lamp. G_a represents the light intensity provided by the lamp. Φ represents the adjustable luminous flux of the lamp. The improved fitness function can be adjust, as shown in equation (4).

$$f = \sum_{i=1}^{D} \frac{\Phi_i}{\mu_i} + \sum_{j=1}^{n} \left(\frac{E_{raj} + E_{saj} + E_{naj}}{E_{naj}} \right)^2 \times 1000 \tag{4}$$

In equation (4), D signifies the number of lamps. $\sum_{i=1}^{D} \frac{\Phi_i}{\mu_i}$ signifies the total power consumption of the lighting fixture. j represents the working face coefficient. E_{raj} represents supplementary illumination. E_{saj} represents the light intensity after adjusting the curtain illumination. E_{naj} represents the minimum illuminance value required for the working face. The energy consumption of the lighting system can be expressed as equation (5).

$$W = R \times 1 \times \Phi \times u^T \tag{5}$$

In equation (5), R represents the proportionality coefficient. u represents the vector of light flux. T represents the number of iterations. The inverse square law of distance calculated from point illuminance can obtain the illumination intensity of the light source on the plane, as displayed in equation (6).

$$E_n = \frac{d\Phi}{dA_n} = \frac{I_\theta d\omega}{dA_n} = I_\theta \frac{dA_n / L^2}{dA_n} = \frac{I_\theta}{L^2} \tag{6}$$

In equation (6), E_n represents directional illumination. A_n represents the area element. L signifies the distance between the light source and the calculation point. θ signifies the angle of incidence of light. ω represents the angle at which the light rays are directed towards the plane. I represents the illumination intensity of the light source. The illuminance in the horizontal direction can be represented as equation (7).

$$E_h = E_n \cos\theta \tag{7}$$

In equation (7), $E_n \cos\theta$ represents the cosine value of directional illumination. E_h represents its illuminance value in horizontal illumination. In the three-dimensional space of a building, the cosine value of the incident angle and the distance between the light source and the calculation point can be expressed as equation (8).

$$\begin{cases} \cos\theta = \dfrac{|z_i - z_j|}{\sqrt{\left[(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2\right]}} \\ L = \sqrt{\left[(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2\right]} \end{cases} \tag{8}$$

In equation (8), x, y, and z represent the horizontal, vertical, and spatial coordinates in three-dimensional space. i represents the initial coordinates of the light ray. j represents the calculated coordinates of the light ray. The light distribution of various types of lamps is determined based on the luminous flux standards of the lamps, so the actual illuminance calculation needs to consider the actual luminous flux and maintenance factor of the lamps. Therefore, the horizontal illuminance can be transformed into equation (9).

$$E_h = \frac{\Phi K E_n \cos\theta}{1000} = \frac{|z_i - z_j| \Phi K I_\theta}{1000\left[(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2\right]^{3/2}} \tag{9}$$

According to equations (6) - (9), the independent illuminance between the lighting fixtures inside the building can be calculated. The true illuminance at the unknown point is the sum of the illuminance of the independent lighting fixtures at the unknown point in the building. Therefore, when there are j lighting fixtures indoors, the illuminance at point P is expressed as equation (10).

$$E = E_{1h} + E_{2h} + \ldots E_{ih} \ldots + E_{jh} = \sum_{i=1}^{j} E_{ih} \tag{10}$$

The improved algorithm can regulate construction energy consumption and calculate natural light sources through fitness functions and penalty functions, ultimately controlling the intelligent lighting system of buildings and achieving a balance between illumination and energy consumption. The intelligent control structure of buildings on the basis of the improved algorithm is displayed in Figure 3.

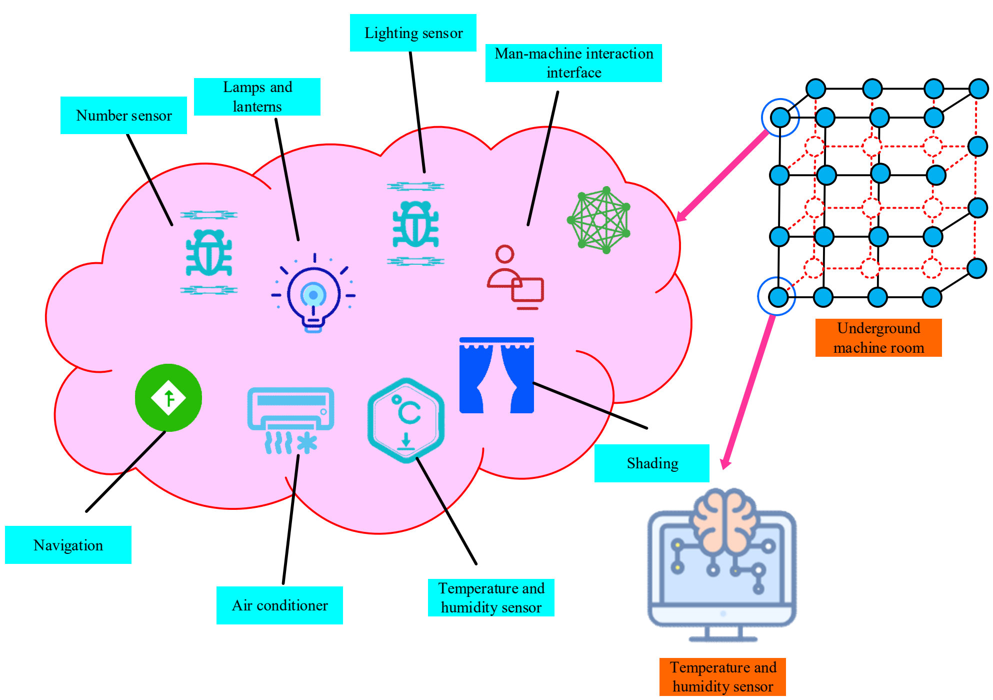

Figure 3: The intelligent control structure of buildings based on the improved algorithm

In the internal structure of the building intelligent control system shown in Figure 3, the building intelligent system in the structure generally uses a hierarchical architecture. The system is controlled and managed by central monitoring equipment. However, the architecture of the system lacks some built-in devices that support communication between building lighting and electromechanical equipment, and there are no standardized regulations to calculate these connections [19]. Due to the rapid development of the Internet of Things, general network technologies have been unable to meet the requirements of new and green buildings. A computing process node (CPN) is introduced into the lighting control system. The node controls the switches and other lighting equipment and electromechanical devices in the lighting building, and is interconnected with CPN nodes in other spaces, forming a CPN network.

III. B. Lighting energy consumption control model based on PSO-SVM

The study optimizes the PSO algorithm that can solve the global optimal problem and addresses its existing constraint issues, but its application in building lighting energy consumption is somewhat insufficient. In order to better predict and control the lighting energy consumption of buildings, based on the global optimization characteristics of the improved PSO, the SVM is optimized to find the optimal parameters within the local area. Then, a PSO-SVM lighting energy consumption control model is constructed. The control process is displayed in Figure 4.

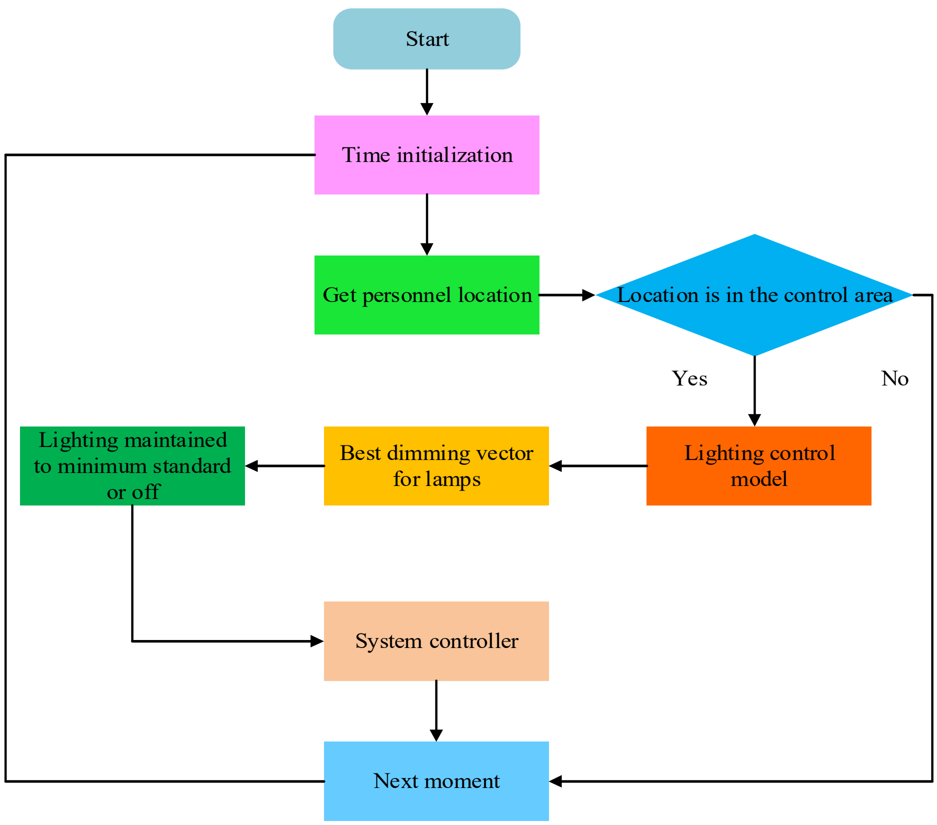

Figure 4: The control flow of the model

In the model control process shown in Figure 4, the system adjusts the brightness output of the lighting fixtures to ensure that a specific area achieves the required illumination while reducing the illumination value of other areas, thereby improving the accuracy of illumination control. The process is divided into several steps. The first step is data collection and initialization processing. The second step is to initialize the SVM model parameters and obtain the initial positions of particles in the model. The third step is to calculate the fitness value of the particles, and then update the other parameter values of the particles based on the fitness value. The fourth step is to start model training and search for the optimal solution. After the iteration is completed, whether the conditions for the final process to end are met is determined. Finally, the optimal parameters of the obtained model are applied to test and train the SVM model, and the energy consumption prediction model is obtained in this way. In this process, the

PSO is used to globally optimize the parameters of SVM, and its fitness function can be represented by equation (11).

$$F=\frac{\sum_{j=1}^{n}\left[\sum_{j=1}^{m}\left(y_{jt}^{*}-y_{ji}\right)^{2}\right]}{n} \tag{11}$$

In equation (11), n represents the total collected building energy consumption. m represents the node steps through which energy consumption occurs. y_{ji} represents the actual consumption of building energy. y_{jt}^{*} represents the energy consumption calculated by the prediction model, that is, the predicted energy consumption. System energy consumption is generally regarded as a nonlinear problem, so radial basis functions are chosen as the kernel function, as displayed in equation (12).

$$k\left(x_i,x_j\right)=\exp\left(-\frac{\left\|x_i-x_j\right\|^{2}}{2\sigma^{2}}\right) \tag{12}$$

In equation (12), x_i signifies the vector of the factor to be predicted. x_j signifies the sample vector of the support vector. σ represents the kernel function parameter. Usually, the prediction performance is analyzed using the average relative error and Root Mean Square Error (RMSE). It can be expressed as equation (13).

$$MAPE=\frac{1}{n}\sum_{i=1}^{n}\frac{\left|y_i-\hat{y}_i\right|}{y_i}\times 100\% \tag{13}$$

Relative mean variance can be explained as the absolute value of relative error, which is generally applied to assess the performance of predictive models. The RMSE is represented by equation (14).

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i-\hat{y}_i\right)}^{2} \tag{14}$$

In equation (14), y_i signifies the actual energy consumption value. $\hat{y}_i$ represents the predicted energy consumption value. Based on the context, the regression function of the improved model can be derived, as shown in equation (15).

$$f\left(x\right)=\sum_{i=1}^{n}\left(\alpha_i^{*}-\alpha_i\right)k\left(x_i,x_j\right)+b \tag{15}$$

In equation (15), α_i^{*} and α_i represent Lagrangian factors. k represents the coefficient of the function. b represents the bias term. The control process of the improved model for building lighting is shown in Figure 5.

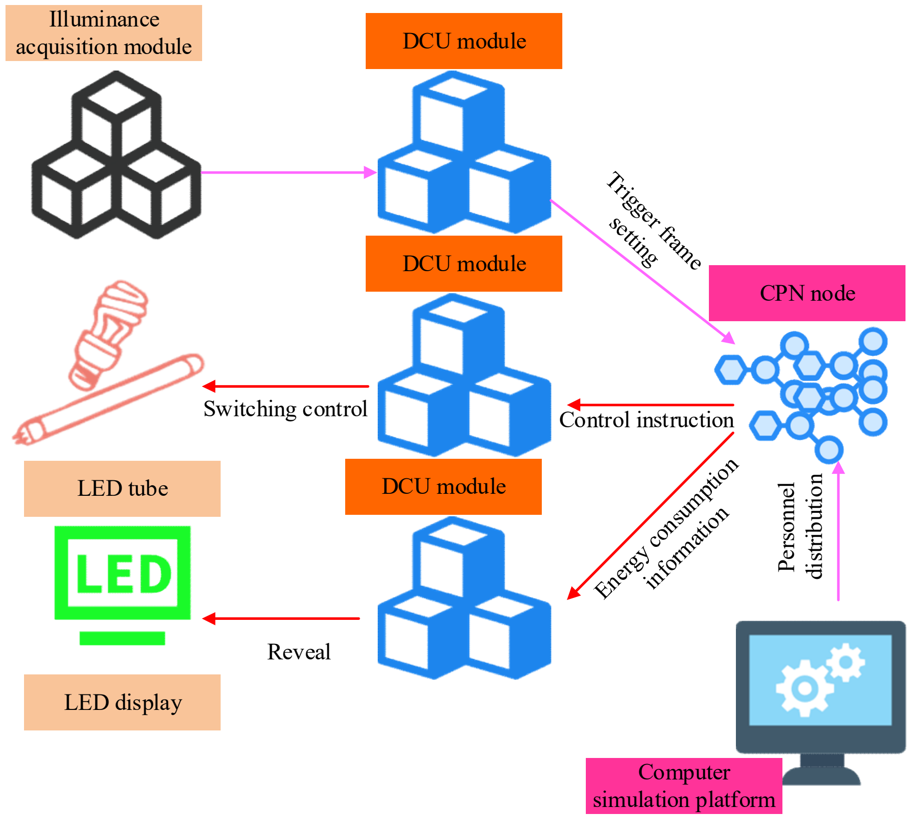

Figure 5: Improve the control process of the model on the building lighting

In the model control system shown in Figure 5, the illuminance sensor is responsible for collecting indoor light intensity data and transmitting these data to the CPN in each space through a distributed control unit (DCU). These data interact and influence each other, forming a distribution model of indoor lighting in buildings. In addition, the cloud platform can construct a personnel movement model inside the building based on the actual situation, and then transmit the information in the model to the designated CPN node. The CPN nodes in each space utilize scene patterns, changes in lighting fields, and data on personnel movement to achieve intelligent lighting control through DCU and control modules, in order to meet the needs of indoor lighting environments [20]. After DCU converts the data format and communication protocol, the display screen can show these data. CPN control will issue specific instructions, and the intelligent controller will adjust the switches and lighting systems inside the building according to the content of its instructions. The connection between the control modules is shown in Figure 6.

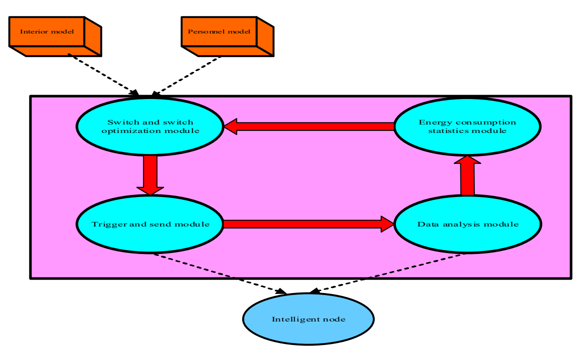

Figure 6: The connection between the modules of control

In the control module described in Figure 6, the intelligent lighting system control software consists of four main functional modules. The switch and dimming optimization module is responsible for collecting input indoor lighting intensity and specific personnel location distribution inside the building, while controlling the lighting on in the office area inside the building. In order to achieve optimal lighting effects, this module can also regulate the lighting equipment that is already in operation. The module for triggering and sending frames completes data exchange by transmitting information through the number of triggered frames. It can also serve as a bridge for information exchange between software and intelligent nodes. The analysis module is responsible for parsing the data returned by nodes, extracting variables from hexadecimal data frames, and decoding the data. The statistical module mainly records and stores data for users to access data information for energy consumption analysis, calculation, and statistics, providing new technical means for users to manage energy consumption.

IV. Performance testing and application effect analysis of PSO-SVM lighting control model

IV. A. Performance testing of PSO-SVM lighting control model

PSO has good performance in dealing with global optimization problems, but it has some constraints and linear limitations. Therefore, this study uses penalty functions to optimize it. A PSO-SVM model is proposed to predict intelligent lighting energy-saving systems in buildings, improving the energy-saving effect of the system. The model parameter requirements are displayed in Table 1.Table 1: Parameter settings for the improved algorithm

Serial number	Item	Demand
1	Software platform	NS-3 (Network simulation), OMNeT++ (discrete event simulation), MATLAB (Mathematical computation and simulation)
2	Learning framework	TensorFlow, PyTorch
3	Programming suNSOrt	NumPy Python Scientific, SciPy
4	GPU	NVIDIA Tesla V100, NVIDIA Quadro RTX 8000
5	CPU	Intel Xeon Platinum 8280
6	Number of iterations	10000 times (range to ensure the model is fully trained)
7	Hardware configuration	4 NVIDIA Tesla V100 Gpus, 256GB RAM, NVMe SSD (high-speed storage system)
8	Network architecture	Multiple convolution layers, fully connected layers, and LSTM layers (determined by problem complexity)

From Table 1, suitable parameter settings for the improved model include software platforms such as NS-3 for network simulation, OMNeT++for discrete event simulation, and MATLAB for mathematical calculations and simulations. These tools provide powerful simulation and computational capabilities for experiments. In terms of the deep learning framework, TensorFlow and PyTorch, two popular frameworks, are used to build and train neural networks, demonstrating advanced machine learning techniques in experiments. In terms of hardware configuration, high-performance NVIDIA Tesla V100 GPU and NVIDIA Quadro RTX 8000 are used, which provide necessary computing resources for training deep learning models. The server equipped with Intel Xeon Platinum 8280 CPU provides stable processing power for the entire system. In terms of hardware configuration, the server is equipped with 4 NVIDIA Tesla V100 GPUs and 256GB of RAM, as well as NVMe SSD high-speed storage system, ensuring high efficiency in data processing and model training. The energy consumption of buildings under different model controls is shown in Figure 7.

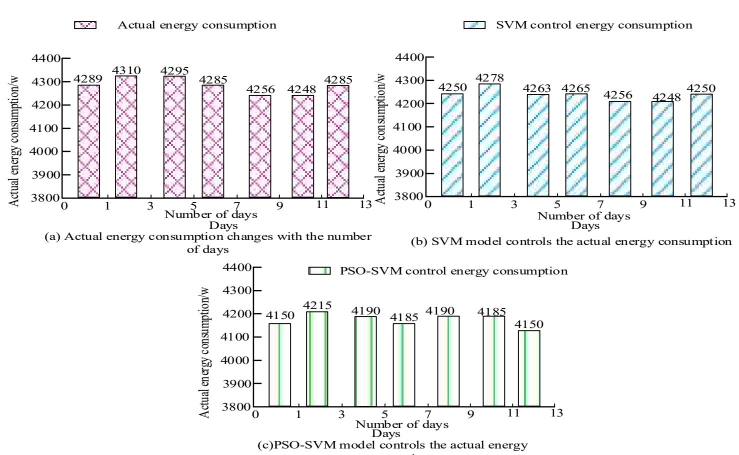

Figure 7: Different types of village landscape structure

Figure 7 shows the changes in actual energy consumption, energy consumption under SVM model control, and energy consumption under PSO-SVM model control. In Figure 7 (a), the actual energy consumption showed a fluctuating trend, starting from 4400W, gradually decreasing to 3800W, and then rising again to around 4200 watts. This fluctuation may be related to personnel activities inside the building, changes in the external environment, or equipment usage. Figure 7 (b) shows the energy consumption under SVM control. The energy consumption started from 4400W and gradually stabilized at around 4200W, indicating that the SVM model achieved optimization and stability of energy consumption to a certain extent. Figure 7 (c) shows the energy consumption under PSO-SVM control. The energy consumption started at 4400W and eventually stabilized at around 4150 watts, which was lower than the energy consumption under SVM control. This indicates that the PSO-SVM model has further optimized the parameters of the SVM model through PSO, thereby achieving more accurate energy consumption control. The difference between the model error and the actual value is predicted, as shown in Figure 8.

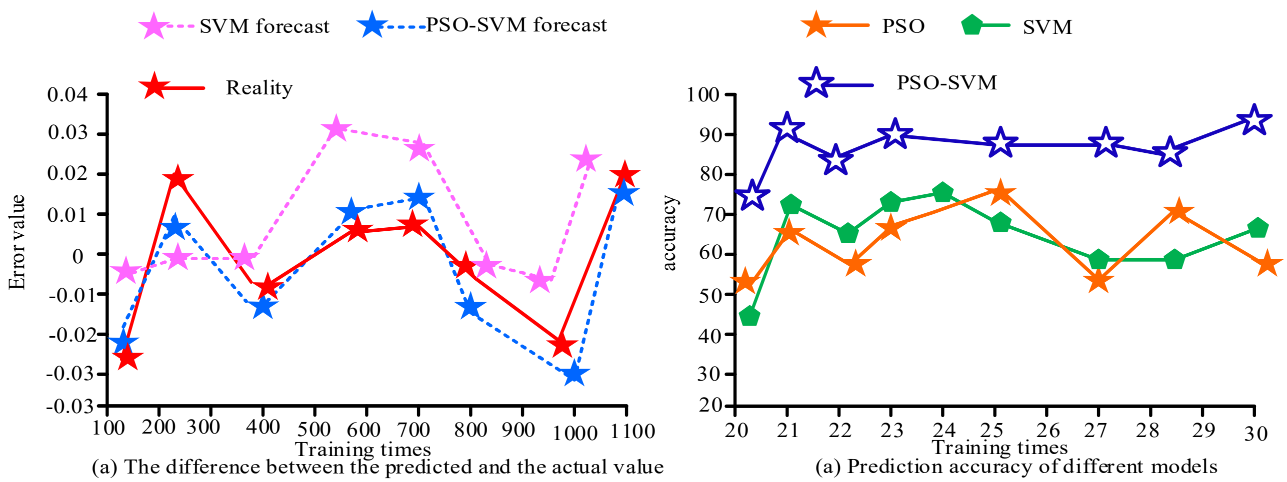

Figure 8: Different types of village landscape structure

Figure 8 illustrates the prediction error and the accuracy of different prediction models. In Figure 8 (a), as the iterations increased, the prediction error gradually decreased. At first, the error was relatively large, at -0.03. When the number of iterations reached 1100, the error was almost zero. Figure 8 (b) shows the accuracy changes of different models. The PSO-SVM model had the lowest accuracy at only 30% after 21 iterations. Then, it steadily increased with the increase of iterations, reaching a peak of 90% at 24 iterations. This improvement is attributed to the PSO-SVM integrating PSO, which optimizes the parameters of SVM, thereby enhancing its predictive ability. As the iteration progresses, the model's ability to learn and adapt to data features increases, resulting in a corresponding improvement in prediction accuracy.

IV. B. Application effect analysis of PSO-SVM lighting control model

The significant improvement in energy consumption control effectiveness and model prediction accuracy demonstrated by performance testing fully demonstrates the efficiency and practicality of the improved model. Then, the study further explores the performance of the PSO-SVM lighting control model in practical applications, and how to further improve building energy efficiency and environmental comfort through these technologies. The impact of different landscape structures on intelligent lighting is shown in Figure 9.

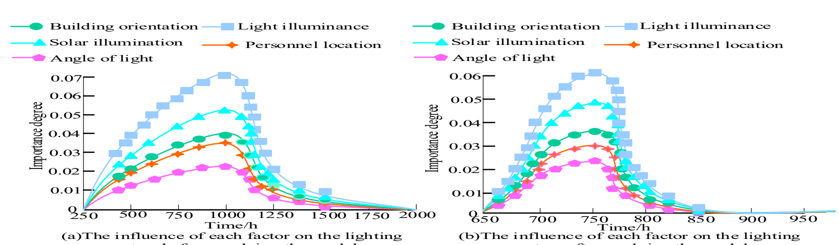

Figure 9: Different types of village landscape structure

Figure 9 shows the changes in the impact of various factors on the lighting system before and after applying the model. In Figure 9 (a), before applying the model, the impact of building orientation on the lighting system was the highest, reaching an importance level of 0.07, followed by light intensity at 0.06, and the impact of personnel position and light angle at 0.05 and 0.04, respectively. This indicates that without model regulation, building orientation is the most significant factor affecting lighting systems. In Figure 9 (b), after applying the model, the importance of building orientation decreased to 0.06, the lighting intensity also decreased to 0.05, while the personnel position decreased to 0.04, and the light angle decreased to 0.03. This may be due to the model adjusting the lighting control strategy through optimization algorithms, enabling the system to respond more intelligently to environmental changes and personnel needs, rather than relying solely on building orientation or lighting intensity. The model reduces sensitivity to personnel location factors by adjusting lighting to accommodate personnel positions. The correlation of different factors under control conditions is shown in Figure 10.

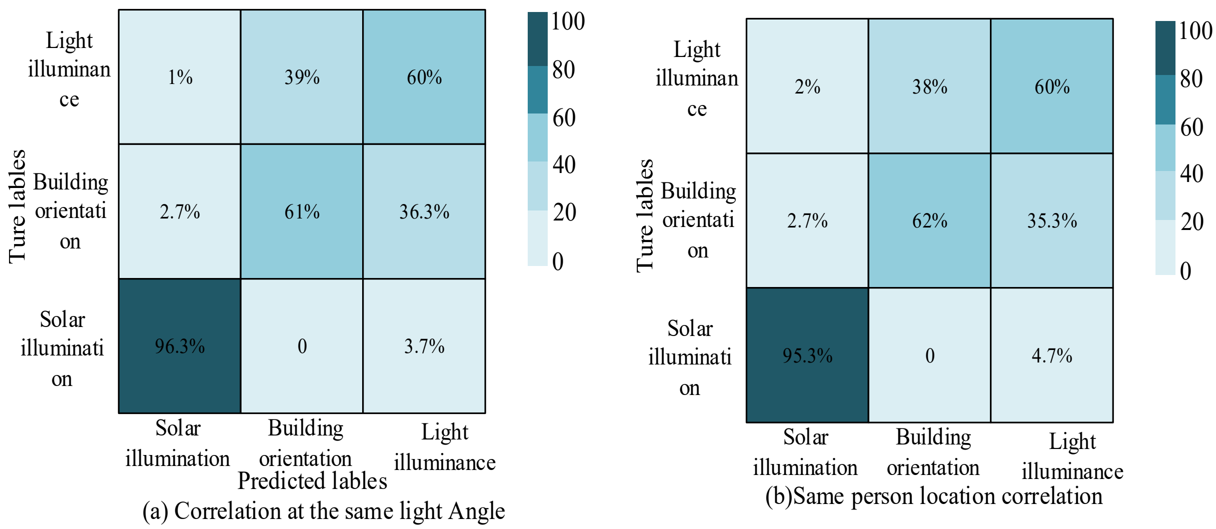

Figure 10: Correlation of the different factors under the control conditions

Figure 10 shows the correlation between light intensity and building orientation, as well as sunlight, under the same lighting angle and consistent distribution of building personnel. In Figure 10 (a), at the same lighting angle, the correlation of building orientation was 2.7% at a lighting angle of 1%, while the correlation of solar lighting was as high as 96.3%. When the lighting angle increased to 39%, the correlation of building orientation significantly increased to 61%, while the correlation of solar lighting decreased to 3.7%. When the predicted label was solar illumination, the probability of the actual label being solar illumination was 96.3%. In Figure 10 (b), the situation where the distribution of building personnel was consistent was similar to that under the same lighting conditions. The reasons for these changes may be related to the capture and distribution of natural light by the illumination angle. When the lighting angle is low, the position of the sun has a direct impact on the illumination. Therefore, the correlation of solar illumination is high. The energy consumption changes of different buildings before and after applying the model are shown in Figure 11.

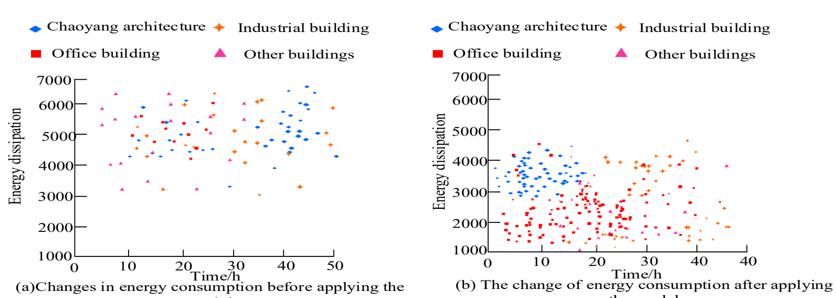

Figure 11: Energy consumption changes of different buildings before and after the application model

Figure 11 shows the energy consumption changes of different types of buildings (Chaoyang buildings, industrial buildings, office buildings, and other buildings) from 0 to 50 hours before and after applying the model. In Figure 11 (a), before applying the model, there were significant differences and large fluctuations in energy consumption among different types of buildings. The energy consumption of Chaoyang buildings fluctuated between 3000 and 6000, while the energy consumption of other buildings fluctuated between 3000 and 6000. After applying the model, the fluctuation range of energy consumption in Figure 11 (b) significantly decreased. The energy consumption differences among different types of buildings also decreased. The energy consumption of Chaoyang buildings fluctuated between 3000 and 4000, while the energy consumption of other buildings fluctuated between 2000 and 4000. It may be that the model adjusts energy consumption based on the orientation, usage, and external environmental conditions of the building through intelligent control strategies, such as optimizing the use of lighting, air conditioning, and other energy consumption systems.

V. Conclusion

The increasing demand for energy-efficient building design has prompted the development of advanced control systems that can optimize lighting energy consumption while maintaining sufficient lighting levels. To address the limitations of traditional PSO algorithms in handling constrained optimization problems in building intelligent lighting systems, a PSO algorithm based on penalty function was proposed. Then, it was combined with SVM to create a PSO-SVM for precise lighting control. Compared with the baseline SVM, the PSO-SVM reduced the average lighting energy consumption by about 5.7%, and the actual lighting power fluctuated between 4150W and 4400W. After 24 training iterations, the prediction accuracy reached 90%. In addition, the importance of factors such as building orientation and lighting intensity decreased from 0.07 and 0.06 to 0.06 and 0.05, respectively, demonstrating a more balanced impact on the lighting system. In summary, the PSO-SVM model effectively reduces energy consumption, improves energy efficiency, and optimizes the lighting energy use of buildings while maintaining comfortable lighting conditions. However, the adaptability and stability of the algorithm in practical applications need further verification. Its universality under different building types and environmental conditions needs to be examined. This is a direction that can be optimized in future research.

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