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Intelligent Control of Solar LED Streetlamp Based on Adaptive Fuzzy PI Control

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Abstract

INTRODUCTION: As road traffic develops, energy-saving and efficient street lights have become a key research field for relevant professionals.

OBJECTIVES: To reduce streetlights energy consumption, a fireworks algorithm is used to optimize the membership function parameters of fuzzy control and the initial parameters of PI control.

METHODS: A fireworks algorithm improved adaptive fuzzy PI solar LED street light control system is designed.

RESULTS: The results showed that in the calculation of Root-mean-square deviation and mean absolute error, the Root-mean-square deviation of the adaptive fuzzy PI control system improved by the fireworks algorithm was 0.213, 0.258, 0.243, 0.220, and the Mean absolute error was 0.143, 0.152, 0.154, 0.139, respectively, which proved that the prediction accuracy was high, and the stability was good. In the calculation of the 1-day power consumption of the solar LED intelligent control system, the average power consumption of the designed solar LED intelligent control system was about 2000W, which was 25.9%, 47.4%, and 42.9% lower than the other three control methods, respectively.

CONCLUSION: This proves that its energy consumption is low, and its heat generation is low, and the battery service life is long. The research and design of an adaptive fuzzy PI control solar LED street light intelligent control system has good performance, which can effectively achieve intelligent management and energy conservation and emission reduction in smart cities.

Keywords: Fireworks algorithm; fuzzy control; PI control; adaptive; intelligent control of streetlights

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1. Introduction

As social economy develops, energy conservation, environmental protection, and low-carbon emission reduction have become the main directions for development in various countries [1]. Streetlights, as the infrastructure for urban road lighting, consume a large amount of energy and cause a lot of pollution during nighttime lighting. Therefore, exploring the intelligent lighting technology of urban streetlights is extremely important for building a smart city. The most important components of streetlights are light sources and street light controllers. In terms of light sources, LED, as a new type of green and environmentally friendly light source, is currently widely used in urban streetlights. In terms of street light controllers, traditional control methods have low maintenance feedback efficiency and are difficult to manage when streetlights malfunction. The main development trend at this stage is towards intelligence [2]. Intelligent street lighting refers to the use of computer network technology to implement unmanned supervision, while improving the safety of street lighting and reducing costs, achieving green and environmentally friendly intelligent management [3]. In this context, the study first utilizes Maximum Power Point Tracking (MPPT) to obtain maximum output power, and then uses Fireworks Algorithm (FWA) to optimize the membership function parameters of fuzzy control and the initial parameters of PI control. A FWA improved adaptive fuzzy PI control system is designed, and finally applied to the solar LED street lighting system. The research content mainly includes five parts, with the first part being the background introduction. The second part is a review of the current research status of intelligence and digitization of street lighting systems both domestically and internationally. The third part proposes the design of an intelligent street lighting system. The first section constructs a solar LED street lighting system. The second section introduces the specific process and function design of the FWA algorithm. The third section designs an improved adaptive fuzzy PI control system for FWA. The fourth part is the system performance analysis. The first section is the effect analysis of FWA parameter optimization, and the second section is the actual effect analysis of FWA improved adaptive fuzzy PI control system. The fifth part is a summary of the previous text and proposes the shortcomings of the research.

2. Related Works

With the continuous promotion of smart city construction, the intelligence and digitization of street lighting systems have become the current development trend. Domestic and foreign scholars have made much progress in the design of street lighting intelligent systems. Chen X designed a highway anti fog intelligent street light control system based on Purple Bee technology to meet the lighting requirements of highways in foggy environments. The system used a system on chip solution as the core device, and automatically controlled the LED street lights on and off for lighting based on real-time temperature and humidity data collected. The results showed that the system had high practicality [4]. Researchers such as Smys D S designed an intelligent streetlight power management system based on artificial networks to reduce the energy consumption of street lighting systems. The system controlled the power of the lighting system through light intensity and weather conditions. The results showed that the system reduced the power consumption of streetlights [5]. Carli R and others designed a Dynamic programming algorithm based on decentralized control of large-scale lighting system energy transformation to artificially improve the energy utilization rate. It integrated discrete Dynamic programming with additive decomposition and value function, and the results showed an improved energy efficiency of street lighting system [6]. Khandagale H P et al. designed a street light controller technology based on the global mobile communication system to make the control of streetlights simpler. It utilized users' mobile devices to send commands to the street light application system through SMS. The results showed that this technology provided reliable remote access for people [7]. Ahmad S and other researchers designed an IoT based street light automation model to meet the power demand of solar streetlights. The model used pressure sensors to generate electricity through pressure or load, reducing the power generation load of solar streetlights [8]. Kumar N et al. designed a traffic light control system based on fuzzy reasoning to improve the control efficiency. The duration of the traffic light was dynamically adjusted by taking real-time traffic information as input. The results show that the system has good performance [9].

Kornaga V I and other scholars designed an LED driver intelligent lighting system with a flyback topology structure to improve street light systems performance. It utilized the drive topology to reduce costs, and the results showed that the system had high efficiency [10]. Researchers such as de Oliveira Reis OA designed an intelligent lighting system based on the Android platform and the Internet of Things to achieve remote control of streetlights. The model was built through the Internet of Things, automation, microcontroller, and Android platform, and the results showed that the system had multifunctionality [11]. JIA R et al. designed an intelligent street lighting system based on motion sensors to reduce the energy consumption of streetlights at night. After users entered the street and were detected by motion sensors, they transmited messages through wireless networks to improve lighting intensity. The results showed that the system can effectively achieve energy conservation [12]. Scholars such as Gong S designed an intelligent lighting control system based on OpenCV image processing technology to improve the control efficiency. The system captured the driving route and pedestrian vehicle density through a camera, and compared them through image processing, effectively obtaining traffic density [13]. To reduce street lighting power consumption, Abdullah A and other researchers designed an intelligent energy-saving system based on infrared sensors and controllers, which was composed of Photoresistor, infrared sensors, batteries and LEDs. The light and darkness of the lights depended on the speed of the detected object movement. The results showed that the system had a good energy-saving effect [14].

In summary, many scholars have achieved a series of achievements in the field of intelligent street lighting, but there is relatively little research on solar LED street light control. In view of this, a FWA improved adaptive fuzzy PI control system is designed using FWA to optimize the membership function parameters of fuzzy control and the initial parameters of PI control, to improve solar LED streetlights performance.

3. Adaptive Fuzzy PI Control for Solar LED Street Lamp Intelligent Control

The first section of this chapter mainly introduces the construction of the solar LED street lighting system, the second section introduces the FWA algorithm, and the third section mainly focuses on FWA improved adaptive fuzzy PI control system construction and related function design.

3.1 Solar LED Street Lighting System

Solar LED streetlights are a new type of energy-saving and environmentally friendly streetlight powered by solar energy, and they support remote control and can use control systems to achieve intelligent management. The solar LED streetlight used in the study consists of a solar battery pack, power controller, battery, control system, wireless communication module, and LED light. The basic system structure is shown below.

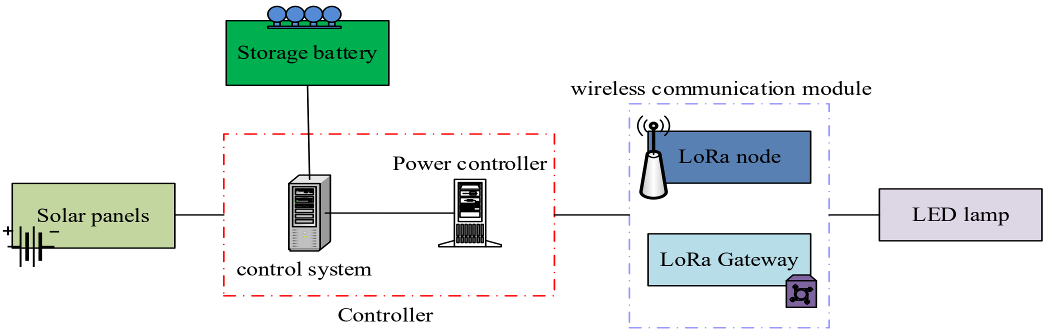

Figure 1. Structure of solar LED streetlamp system

In Figure 1, after energy conversion, due to the unstable voltage of the electricity generated by solar energy, directly charging the battery will cause damage to the battery. Therefore, it is first transmitted to the controller to stabilize the voltage, and then stored in the battery. To maximize the energy conversion and achieve maximum power output, MPPT algorithm can increase the output power. Then, centralized control and remote monitoring of streetlights are achieved through wireless communication modules. Currently, commonly used IoT communication technologies include narrowband IoT, LoRa gateway, and Purple Bee gateway. Among them, the narrowband IoT has a transmission distance of over 10km, a node capacity of about 200000 bytes for single network access, a theoretical battery life of 10 years, a module cost of about 5-10 US dollars, a paid frequency band, and a transmission speed of 160-250 kbps. The transmission distance of LoRa gateway in cities is 1-2km, and it is 20km in suburbs. The capacity of the access node is about 60000 bytes, the theoretical battery life is 10 years, the module cost is about $5, the frequency band used is free, and the transmission speed is 0.3-50kbps. The transmission distance of the Purple Bee Gateway is 10m~100m, the capacity of a single network node is about 60000 bytes, the theoretical battery life is 2 years, the module cost is about 1-2 US dollars, the frequency band used is free, and the transmission speed is 250kbps. Comparing the three gateway technologies comprehensively, LoRa technology has the characteristics of long communication transmission distance, long battery life, use of free frequency bands, and low cost. Therefore, the LoRa gateway is studied as a wireless communication module for street light systems. The network of streetlights is connected in parallel, and the current finally reaches the LED lights to provide lighting. The structure of charging solar LED lights is shown in Figure 2.

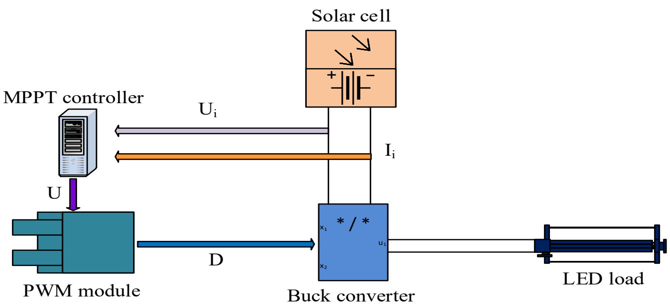

Figure 2. Specific structure of solar LED lamp charging

In Figure 2, the maximum output power is obtained by passing the voltage through the MPPT. Due to the rapid opening and closing action of the circuit's switch valve, a pulse width modulation power drive module is used to adjust the driving current according to changes in load to obtain an appropriate duty cycle, in order to achieve the purpose of switching voltage stabilization. The current is input to the step-down converter for step-down transformation and load charging [15]. MPPT can simulate the output power curve of solar panels based on the current environment, continuously adjust the output power of streetlights, detect the number of parallel interleaving modules, read the sampling voltage and current values, and obtain the maximum output power. The relationship between voltage, current, and impedance after buck conversion is shown in equation (1).

$$\begin{cases} D = \dfrac{U_0}{U_i} \\ R_i = \dfrac{U_i}{I_i} = \dfrac{R_L}{D^2} \end{cases} \tag{1}$$

In equation (1), D represents the duty cycle, U_0

represents load voltage, U_i and I_i represent the output voltage and current of the solar cell, R_i represents the equivalent input impedance of the step-down converter, and R_L represents load resistance. The relationship between input voltage and output voltage during circuit operation is shown in equation (2).

$$D' = \frac{U_{D'} + U_b}{U_{D'} + U_s} \tag{2}$$

In equation (2), D' represents the duty cycle of the circuit switch, U_b represents battery voltage, U_s represents solar panel output voltage, and $U_{D'}$ represents the turn-on voltage drop of the LED.

3.2 FWA Algorithm and Function Design

As a non-biomimetic swarm intelligence algorithm, FWA improves the population adaptability to the environment through interactive transmission of information, thereby obtaining the global optimal solution [16]. The basic framework of FWA is shown in Figure 3.

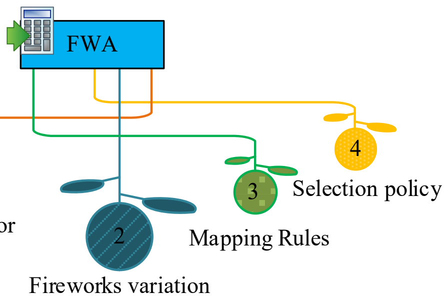

Figure 3. Basic framework diagram of FWA

In Figure 3, FWA includes four steps: fireworks explosion, fireworks mutation, mapping rules, and selection strategies [17]. Firstly, the fireworks population is initialized, and individual fireworks' fitness value is calculated. The fitness function is shown in equation (3).

$$f(\zeta_i) = \omega_1 \times (\sum_{i=1}^{N} \eta)^{-1} + \omega_2 \times acc \tag{3}$$

In equation (3), $f(\zeta_i)$ represents i's fitness value, N represents the total number of features, ω_1 represents the weight of features, acc represents classification accuracy, ω_2 represents classification accuracy weight, η represents whether the feature is selected, the selected value is 1, and the unselected value is 0. Then carried out the fireworks explosion operation. If the fireworks explosion generates sparks, the explosion intensity and amplitude, and displacement need to be calculated. The explosion intensity refers to the number of sparks and individual fireworks explosion radius. The calculation formula for the explosion radius is shown in equation (4).

$$r_i = r' \times \frac{f(\zeta_i) - Y_{\min} + \lambda}{\sum_{i=1}^{N} [f(\zeta_i) - Y_{\min}] + \lambda} \tag{4}$$

In equation (4), r_i represents the explosion radius, r' represents the explosion radius adjustment constant, $Y_{\min}$ represents the optimal fitness value, and λ represents the parameter that prevents the denominator from being 0 [18]. The number of sparks is calculated in equation (5).

$$s_i = s' \times \frac{Y_{\max} - f(\zeta_i) + \lambda}{\sum_{i=1}^{N} [Y_{\max} - f(\zeta_i)] + \lambda} \tag{5}$$

In equation (5), s_i represents the number of sparks, $Y_{\max}$ represents the worst fitness value, and s' represents the constant number of sparks. In the calculation, the number of sparks is limited, as shown in equation (6).

$$s_i = \begin{cases} round(a \times s'), s_i < a \times s' \\ round(b \times s'), s_i > b \times s' \\ round(s'), a \times s' \le s_i \le b \times s' \end{cases} \tag{6}$$

In equation (6), a and b represent constants, $a < b < 1$, and $round$ represent rounding functions. The calculation formula for explosion amplitude is shown in (7).

$$A_i = A' \times \frac{f(\zeta_i) - Y_{\min} + \lambda}{\sum_{i=1}^{N} [f(\zeta_i) - Y_{\min}] + \lambda} \tag{7}$$

In equation (7), A_i represents the explosion amplitude, and A' represents the amplitude adjustment constant. The calculation method for displacement operation is shown in equation (8).

$$x_i^k = x_i^k + u(-A_i, A_i) \tag{8}$$

In equation (8), x_i^k represents i's position in k dimension, and $u(-A_i, A_i)$ is a random number within $(-A_i, A_i)$ range. The calculation formula for explosive sparks obtained from explosive operations is shown in equation (9).

$$e(x_i^k) = x_i^k + r_i \times rand(-1,1) \tag{10}$$

In equation (9), represents the explosive spark generated by the explosion, and $rand(-1,1)$ represents a random number located within the range of [-1,1]. The next step is to perform the fireworks mutation operation, and the specific calculation method is shown in equation (10).

$$\hat{x}_i = x_{best} + c \times (x_{best} - x_i) \tag{10}$$

In equation (10), $\hat{x}_i$ represents the mutation spark, x_{best} represents the fireworks at the current optimal position, and c represents the learning factor. The next step is to process sparks beyond the boundary through mapping rules, and the calculation formula is shown in equation (11).

$$x_i^k = x_l^k + rand(0,1) \times (x_u^k - x_l^k) \tag{11}$$

In equation (11), x_l^k represents k -th dimensional position lower boundary of the fireworks, x_u^k represents the upper boundary of the k-th dimensional fireworks position, and $rand(0,1)$ represents the random number within the [0,1] interval. Finally, the next generation of fireworks individuals is selected through a selection strategy, and the calculation formula is shown in equation (12).

$$p(x_i)=\frac{\sum_{j=1}^{K}\left\|x_i-x_j\right\|}{\sum_{i=1}^{K}\sum_{j=1}^{K}\left\|x_i-x_j\right\|} \tag{12}$$

In equation (13), $p(x_i)$ represents probability, K represents all individual fireworks, and $\left\|x_i-x_j\right\|$ represents the Euclidean distance between fireworks. The FWA process is shown in Figure 3.

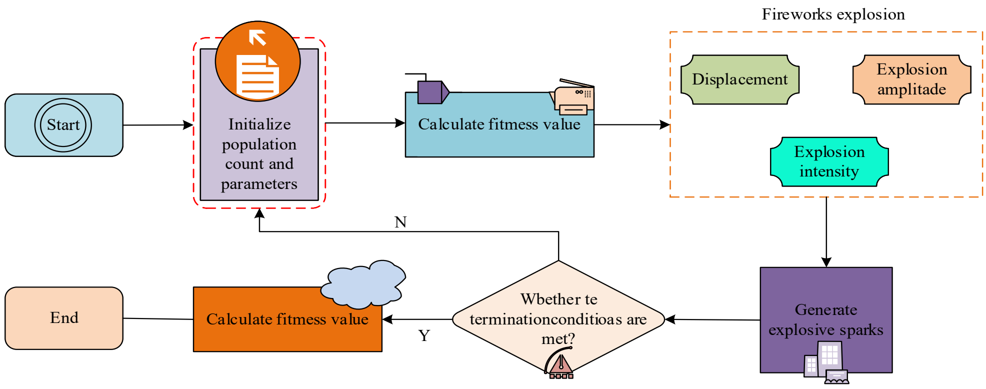

Figure 4. FWA algorithm flowchart

In Figure 4, after inputting data, the population number and parameters of the fireworks are first initialized, and fitness values are calculated. Then, fireworks explosion operations are carried out based on fitness, and explosion intensity, amplitude, and displacement are calculated respectively to generate explosion sparks. Fireworks quantity is limited through restriction methods, and fireworks are mutated to ensure population diversity. Finally, the optimal solution of the population is calculated to determine whether the conditions are met, If satisfied, terminate; otherwise, return to continue iteration. The parameters of the FWA algorithm include the number of fireworks set off, explosion radius, mutation probability, and maximum iteration number. When selecting FWA parameters, factors such as population size, explosion coefficient, attenuation factor, number of iterations, probability of crossover and mutation should be considered. Therefore, the study selects and adjusts parameters based on the complexity of the problem, the complexity of computational resources, and experience.

3.3 Adaptive Fuzzy PI Control System Based on FWA Improvement

Due to the inconsistent parameters of various modules in the staggered parallel power supply system used for solar LED streetlights, the current shared by each module will be uneven, which can cause some problems in the circuit. At times, it can cause modules to be lightly loaded, unloaded, overloaded, or overloaded, thereby affecting the normal operation of the entire electrical circuit. At times, it can cause module damage and create safety hazards. The current sharing control method is currently the mainstream method for average current. Traditional current sharing control techniques mainly include model prediction, fuzzy control, automatic average current sharing method, master-slave control current sharing method, and output impedance method. However, these methods all have some drawbacks. PI control is a control method with a simple structure and high stability, which has been widely used in control circuits. However, due to its linear control and the fact that the power system is usually nonlinear, it is difficult to obtain accurate PI parameters, resulting in poor control performance [19-20]. To solve these problems, a current sharing control technology combining fuzzy and PI control is studied for system stability. Fuzzy PI control parameters are optimized through FWA, and the FWA adaptive fuzzy PI control structure is shown below.

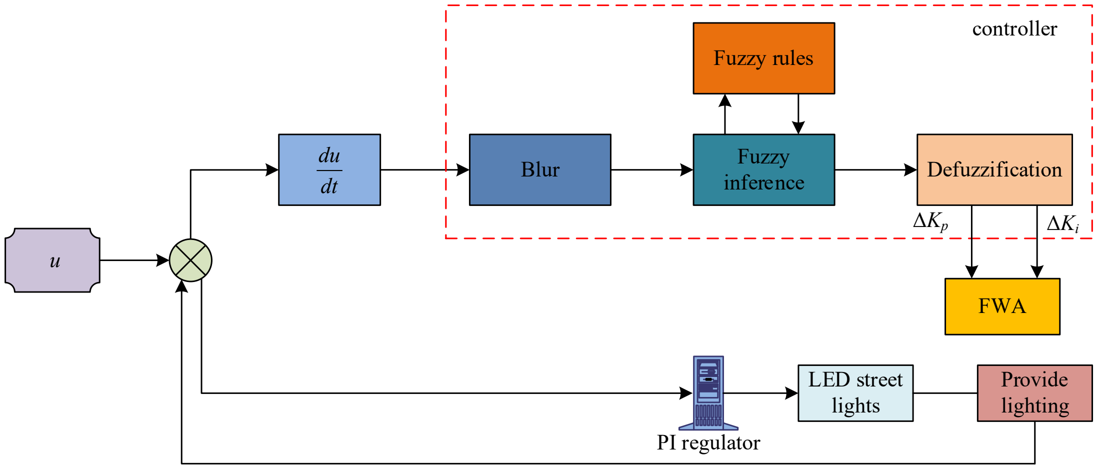

Figure 5. Adaptive fuzzy PI control structure diagram

In Figure 5, using FWA to optimize the membership function parameters of fuzzy control and the initial parameters of PI controller, among which the membership function parameters of fuzzy control include shape, size, position, etc. Function of. The initial parameters of PI control include proportional gain and integral gain. The calculated controller deviation and deviation change rate after optimization are input into the fuzzy controller for fuzzy processing. The input is reasonably inferred through fuzzy rules, and the PI parameters are adjusted in real-time using the inferred results in the PI controller to achieve adaptive control [21]. The objective function of the FWA optimized adaptive fuzzy PI control applied to the streetlamp power supply system is shown in equation (13).

$$F(T)=\int_0^T\left[\frac{e(T)}{EI(T)}\right]^2 dt \tag{13}$$

In equation (13), $F(T)$ represents the objective function, T represents the iterations, $e(T)$ represents the error, $EI(T)$ represents the expected value of street light illumination, and dt represents differentiation. After optimizing parameters through FWA, the fitness function transformation form is shown in equation (14).

$$f(\zeta_i')=\frac{1}{N}\sum_{i=1}^{N}\left[\frac{EI(T)}{e(T)}\right]^2 \tag{14}$$

In equation (14), $f(\zeta_i')$ represents the optimized fitness value. The specific expression form of PI control is shown in equation (15).

$$y(k)=e(k)\times K_p+K_i\times\sum_0^k[e(k)] \tag{15}$$

In equation (15), $y(k)$ represents the output, $e(k)$ represents the error, and K_p and K_i represent the PI coefficients. The flow chart of FWA optimized adaptive fuzzy PI control current sharing technology is shown in Figure 6.

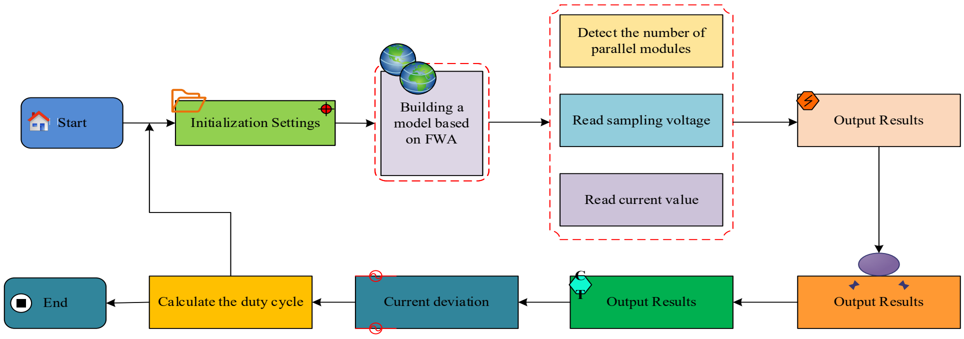

Figure 6. Adaptive fuzzy PI control structure diagram

In Figure 6, the settings are first initialized, a fuzzy PI controller is constructed based on the fireworks position, the output power of the streetlights is adjusted, the number of parallel interleaving modules is detected, and the sampling voltage and current values are read. Then the voltage deviation is calculated and input into the fuzzy PI voltage loop controller, the total current reference value is calculated, the current is evenly distributed to each module, and the deviation of each current path is calculated. Finally, each deviation is input to the PI Current loop controller, and the duty cycle of each output is calculated to achieve current sharing. The designed adaptive fuzzy PI control system uses the maximum output power and other environmental parameters to adjust and optimize the output power of the streetlamps in real time, so as to maximize the power of the solar panels.

4. Intelligent Control Results Analysis for Solar LED Street Lights Based on FWA Improved Adaptive Fuzzy PI Control

The first section of this chapter mainly analyzes the performance of the MPPT algorithm and the effect of FWA parameter optimization. The second section mainly analyzes the actual effect of FWA improved adaptive fuzzy PI control system.

4.1 MPPT Algorithm and FWA Parameter Optimization Performance Analysis

The study first verifies the performance of the MPPT algorithm in the street lighting system. The parameters of the solar cell pack used are as follows: E has a rated power of 15W, a rated voltage of 18.05W, a rated current of 0.83A, an open circuit voltage of 21.6V, and a short circuit current of 0.9A. The battery parameters are as follows: the rated voltage is 12V, the Nameplate capacity is 120AH, and the temperature compensation coefficient is -3.3Mv/℃/CELL. Using the measured output voltage and current values of solar cells collected from 8 am to 6 pm during the day, the power changes of solar cells with and without the MPPT algorithm are shown in Figure 7.

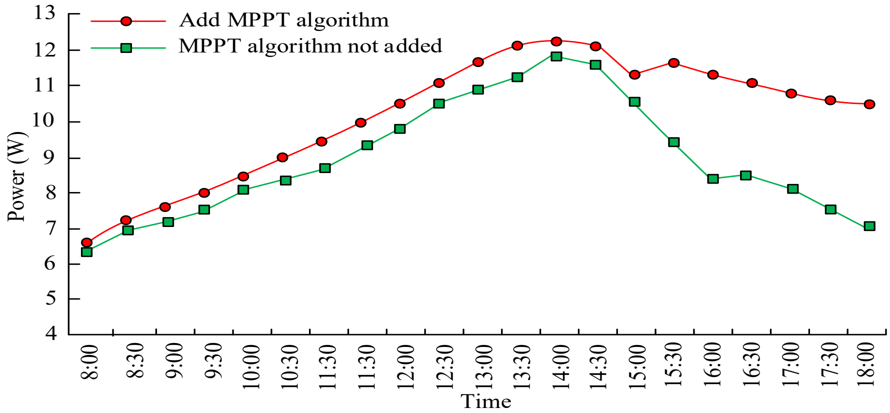

Figure 7. Power changes of solar cells with and without MPPT algorithm

From Figure 7, it can be seen that from 8:00 in the morning to 2:00 in the afternoon, the light intensity gradually increases with time. The power of both MPPT algorithm and non MPPT algorithm gradually increases, reaching its maximum power at 2:00. The maximum power with MPPT is 12.4W, and that without MPPT is 11.3W. From 2:00 pm to 6:00 pm, the power of both MPPT algorithm and non MPPT algorithm decreased, but the power of MPPT algorithm decreased slower. Overall, the power curve with MPPT has been consistently above power curve without MPPT. The MPPT algorithm can improve the utilization rate of solar panel power generation. Then, parameter optimization was performed using FWA in four datasets: Ionosphere, Wine, Sonar, and German, and compared with GA and PSO. The results are shown in Table 1.

From Table 1, it can be seen that in the Ionosphere dataset, the number of features selected by FWA is 13.8 ± 3.47, with a classification accuracy of 95.87 ± 1.58, the number of features selected by genetic algorithm is 12.9 ± 3.26, with a classification accuracy of 92.62 ± 1.97, and the number of features selected by particle swarm optimization algorithm is 11.7 ± 2.93, with a classification accuracy of 94.86 ± 1.95. In the Wine dataset, the number of features selected by the three algorithms is 4.9 ± 0.53, 4.7 ± 0.62, 3.51 ± 1.75, and the classification accuracy is 97.24 ± 1.15, 93.89 ± 2.01, and 96.85 ± 1.87, respectively. In the Sonar dataset, the number of features selected by the three algorithms is 23.7 ± 3.40, 23.2 ± 3.53, and 21.5 ± 3.04, respectively, with classification accuracy of 97.01 ± 1.98, 92.77 ± 2.43, and 93.86 ± 5.04. In the German dataset, the number of features selected by the three algorithms is 13.1 ± 1.98, 11.7 ± 3.01, 12.3 ± 3.30, and the classification accuracy is 86.90 ± 2.03, 81.01 ± 1.88, and 81.95 ± 1.82, respectively. In the three datasets, the number of features selected by FWA is smaller than that of other algorithms, and the classification accuracy is higher than other algorithms, indicating that the optimization effect of FWA parameters is good. Finally, the performance of the FWA adaptive fuzzy PI controller is tested and compared with the fuzzy PI controller, and considering the changes in parameters, temperature, and voltage fluctuations of the control system. The step curve can evaluate the stability and response speed of the control system. Their step curves are shown below.

Table 1. Four Algorithms for Predicting Results on A Dataset

Data set	FWA		GA		PSO	
	Number of features	ACC (%)	Number of features	ACC (%)	Number of features	ACC (%)
Ionosphere	13.8±3.47	95.87±1.58	12.9±3.26	92.62±1.97	11.7±2.93	94.86±1.95
Wine	4.9±0.53	97.24±1.15	4.7±0.62	93.89±2.01	3.51±1.75	96.85±1.87
Sonar	23.7±3.40	97.01±1.98	23.2±3.53	92.77±2.43	21.5±3.04	93.86±5.04
German	13.1±1.98	86.90±2.03	11.7±3.01	81.01±1.88	12.3±3.30	81.95±1.82

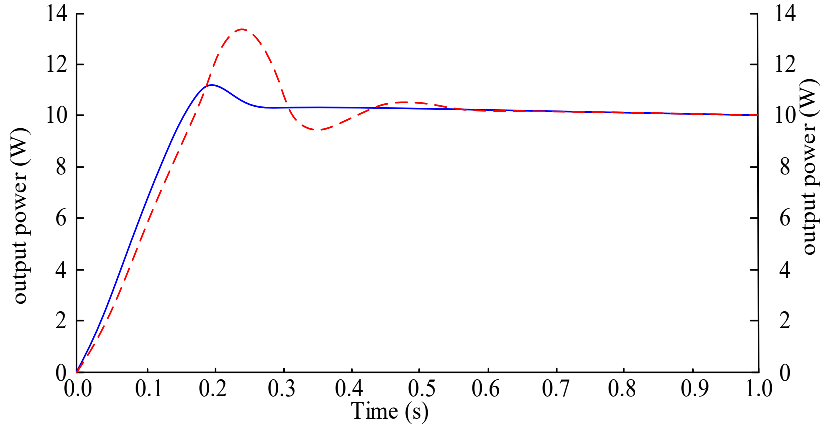

Figure 8. Step curves of two controllers

From Figure 8, output response of FWA improved adaptive fuzzy PI controller and fuzzy PI controller both rapidly increases between 0 and 0.1 seconds. From 0.1s to 0.15s, the step curve of FWA improved adaptive fuzzy PI control decreases slightly and gradually flattenes, while the step curve of the other is still in the upward stage. From 0.15s to 0.4s, the step curve of the adaptive fuzzy PI controller gradually decreases, then rises, and then gradually stabilizes, but there are still small fluctuations afterwards. The step curve of the FWA improved system has reached a horizontal state. The FWA improved system has fast response speed and high stability.

4.2 Solar LED Intelligent Control System Effect Analysis

To test the performance of FWA improved control system, FWA improved control system is evaluated by Root-mean-square deviation and mean absolute error and compared with the fuzzy PI control system in Table 2.

Table 2. Root-mean-square deviation and mean absolute error

Model	Index	First month	The second month	The third month	The fourth month
FPI	RMSE	0.237	0.266	0.274	0.245
	MAE	0.148	0.162	0.167	0.154
FWA-FPI	RMSE	0.213	0.258	0.243	0.220
	MAE	0.143	0.152	0.154	0.139

It can be seen from Table 2 that in four months, the Root-mean-square deviation of the fuzzy PI control system is 0.23, 0.266, 0.274, 0.245, the Mean absolute error is 0.148, 0.162, 0.167, 0.154, the Root-mean-square deviation of fuzzy PI control system improved by FWA is 0.213, 0.258, 0.243, 0.220, and the Mean absolute error is 0.143, 0.152, 0.154, 0.139, respectively. The two index values of the FWA improved adaptive fuzzy PI control system are higher, indicating high prediction accuracy and good stability. Then data are collected from 50 sampling points for two months and the solar panel power generation in two systems is calculated in Figure 9.

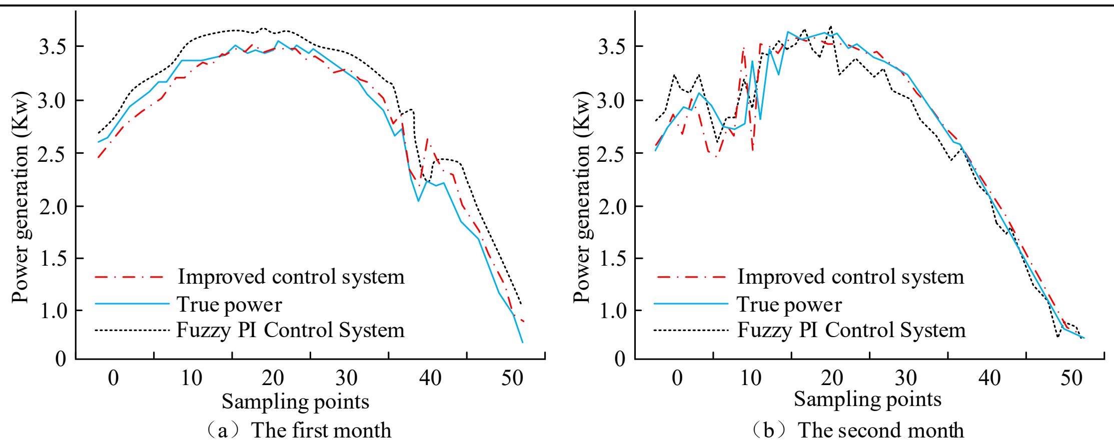

Figure 9. Step curves of two controllers

It can be seen from Figure 9 (a) that when the sampling point is between 0 and 20, the power and real power obtained by two systems are both increasing; when the sampling point is between 20 and 50, the power and real power obtained by two systems are both decreasing. From Figure 9 (b), it can be seen that the trend between the power obtained by two systems and the actual power is consistent with Figure 9 (a). The FWA improved system has a higher fit with the real power curve, indicating a higher accuracy of the system. Finally, the power consumption of the solar LED intelligent control system designed during the day is tested and compared with the fuzzy PI control system, fuzzy control, and PI control in Figure 10.

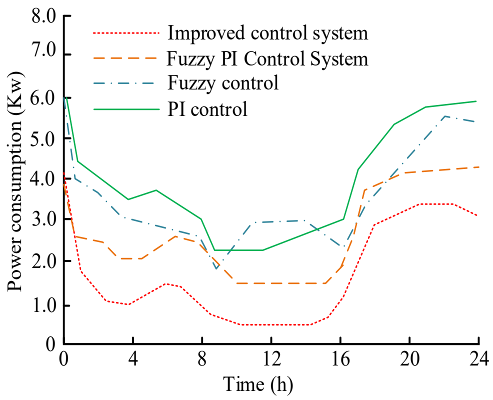

Figure 10. Power consumption of solar LED intelligent control system

From Figure 10, it can be seen that the lighting consumption power curve of the designed solar LED intelligent control system is below other curves, with an average consumption power of about 2000W for 24 hours, 2700W for fuzzy PI control, 3800W for fuzzy control, and 3500W for PI control. The designed solar LED intelligent control system reduces power consumption by 25.9%, 47.4%, and 42.9% compared to the other three control methods, respectively, indicating that the system consumes less power and reduces heat generation, extending the service life of the battery.

However, when applying the system to actual urban lighting infrastructure, there may be technical implementation, compatibility issues, sensor accuracy, power supply, maintenance and management, as well as security and privacy issues and challenges. Although the designed intelligent lighting system is based on theoretical design and simulation optimization, technical implementation issues may be encountered in practical applications, such as the distribution and layout of streetlights, which may affect the overall performance of the system. And the system may need to be compatible with existing urban infrastructure and control systems, which may require additional technology conversion or interface development to ensure smooth integration into the existing system. In addition, sensor accuracy may affect the performance of the system. If the sensor accuracy is insufficient, it may lead to system misjudgment, thereby affecting the correct operation of streetlights. The intelligent street light system requires power supply. If the power supply is unstable or interrupted, it may affect the normal operation of the streetlight, so it is necessary to ensure a stable power supply. Compared to traditional streetlight control systems, intelligent streetlight control systems require more maintenance and management, such as regular inspections and maintenance of sensors, electronic devices, and communication systems. Therefore, more resources and manpower are needed to maintain and manage this system. Finally, an intelligent street light system may include a large number of sensors and cameras, which may collect a large amount of personal information and sensitive data. Therefore, additional measures need to be taken to ensure the security and privacy protection of this data. In addition to the above factors, there may also be some external factors that may affect the performance of the system, such as weather conditions, urban environment and layout, traffic safety, energy supply, etc. When implementing intelligent lighting systems, it is necessary to fully consider these factors and take corresponding measures to solve these problems to ensure the normal operation and performance of the system.

5. Conclusion

With the acceleration of urbanization, how to make street lighting systems more environmentally friendly has become a focus of concern for relevant personnel. Under the condition of meeting the maximum output power of the solar cell pack, to reduce its energy consumption and extend its usage time, the MPPT is studied to obtain the maximum output power. The parameters of the membership function of the fuzzy control and the initial parameters of the PI control are optimized using FWA, and an FWA modified adaptive fuzzy PI control system is designed. The results showed that in the output power of solar cells, the maximum power with the addition of MPPT algorithm was 12.4W, and the maximum power without the addition of MPPT algorithm was 11.3W, indicating that MPPT algorithm can improve the utilization efficiency of solar panel power generation. During parameter optimization, the number of features selected by FWA in the Ionosphere dataset was 13.8 ± 3.47, with a classification accuracy of 95.87 ± 1.58. The number of features selected by FWA in the Wine dataset was 4.9 ± 0.53, with a classification accuracy of 97.24 ± 1.15. The number of features selected by FWA in the Sonar dataset was 23.7 ± 3.40, with a classification accuracy of 97.01 ± 1.98. The number of features selected by FWA in the German dataset was 13.1 ± 1.98, with a classification accuracy of 86.90 ± 2.03. This indicates that the optimization effect of FWA parameters is good. In the comparison of step curves, the FWA improved adaptive fuzzy PI control system reaches its maximum value faster and reaches a stable state quickly, indicating its fast response speed and high stability. In the calculation of solar panel power generation, the FWA improved adaptive fuzzy PI control system has a higher fitting degree with the real power curve, indicating its high accuracy. The above results indicate that the FWA improved adaptive fuzzy PI control system has the characteristics of fast response speed, high stability, accurate prediction, and high accuracy. At the same time, the system exhibits better performance in terms of energy consumption and heat generation, while extending the service life of the battery. However, without considering the complexity of algorithms and models, it may affect the performance and feasibility of practical applications and will continue in this area in the future. For example, the neural network architecture can be optimized to reduce the number of hidden layers and reduce the complexity of the model.

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