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Research Article

Design of the Urban Lighting Control System Based on Optical Multisensor Technology and the GM Model

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Lighting has emerged as a central concern in the domain of city planning and design in recent decades. Better lighting does more than just make cities safer and more secure; it also makes them more aesthetically pleasing and easier to live in. A single type of optical sensor is no longer sufficient to meet the needs of intelligent lighting for urban roads, and as such, there is a growing demand for cutting-edge control systems that can adapt to the dynamic lighting needs in urban environments. This paper's goal is to create an intelligent urban lighting control system by integrating optical multisensor technology and the gray model (GM model). Programmable logic controller (PLC) serves as the system's central processing unit, with light intensity sensors and color sensor-detecting devices placed strategically throughout each city and linked directly to the controller. Each road streetlight is equipped with a motion sensor detection device that is tasked with identifying the presence of vehicles and pedestrians within its field of view. Data fusion technology is utilized to process the environmental data gathered by optical multisensors, the collected data are then used to control and predict outcomes using the robust prediction capability of the GM model, and the result is a lighting control strategy that is both efficient and intelligent. In the end, the strategy presented in this paper is applied to improving the management of an industrial park lighting system's energy consumption. The results of the evaluations show that the fresh method is successful in dimming, prediction, and control. This conclusively demonstrates the efficacy of the paper's proposed design solution, which integrates optical multisensor technology with sophisticated control algorithms and data analysis to improve the quality of life in urban areas by boosting the efficiency and sustainability of the urban lighting system.

1. Introduction

Since urban lighting is such an integral part of smart cities, it is experiencing rapid, intelligent, and environmentally friendly growth. Cities are also looking for strategies to optimize energy consumption in light of rising concerns about sustainability and the need to reduce energy use. As a result, it is important for communities to work towards creating a more sophisticated method of controlling their streetlights. There is a growing recognition of the importance of urban lighting control systems to the health, safety, and attractiveness of metropolitan areas [1]. Public, street, park, and building lighting can all benefit from these systems, which regulate and manage lighting settings to maximize efficiency while maintaining enough illumination. Although urban lighting control systems help improve city life, they are still constrained in their effectiveness. Traditional urban lighting control systems, for instance, frequently rely on predetermined schedules or manual adjustments that ignore dynamic factors such as pedestrian traffic, weather conditions, and natural light, leading to systems that lack flexibility and adaptability to meet the changing lighting needs of a city. Therefore, it is crucial to create a smart and logical lighting control system as cities grow and their lighting requirements alter.

Technology advancements have allowed for the creation of better and more efficient lighting control systems, which is particularly significant given the significance of urban lighting. The urban lighting industry is currently on board with the idea that digital and intelligent technologies can be used to better utilize lighting facilities and energy usage, all while satisfying public traffic and avoiding excessive energy consumption and simple and brutal control means [2]. Researchers are, therefore, focusing more of their efforts on street lighting control systems, with the goal of creating more practical intelligent lighting management systems. Literature [3] relies on natural-light-sensing sensors to measure illumination levels. The streetlight comes on when there is not enough daylight, combining the benefits of both artificial and natural illumination while reducing power use. Infrared sensors are used to track passing vehicles and people in the published works [4]. These experts devised and constructed a smart lighting system that can swiftly detect pedestrian and vehicle movements and activate street lighting fixtures to improve safety and convenience. Intelligent control algorithms for intelligent lighting systems were proposed in literature [5], with researchers studying and analyzing the microcontroller system's algorithm in order to determine the best way to process wireless control signals for use in regulating the functioning of intersection traffic lights. They demonstrated that the algorithm was able to fairly disperse traffic and significantly cut down on the waiting time.

Previous research has shown that sensor technology is essential in creating and deploying urban lighting management systems. However, it has proven challenging for a single type of sensor to meet the needs of intelligent lighting for urban roads due to the variability of external natural light (sunny, cloudy, etc.). New opportunities for investigating better and more efficient urban lighting control systems have emerged with the rapid growth of sensor technology, notably optical sensor technology [6]. Furthermore, this paper also focuses on the reasonable and intelligent control strategy needed for the intelligent lighting management system for urban highways, in addition to the assistance of sensor technology. In light of these needs, the purpose of this paper is to investigate the design of optical multisensor technology and the GM model-based urban lighting control system, with the goal of making urban lighting systems more energy efficient and environmentally friendly in the aim to better the quality of life in urban areas. The novel components of this paper's research are, first, the integration of various optical sensors to collect data of the road lighting environment in real time (light intensity sensor, color sensor, and motion sensor). Intelligent and responsive control of the lighting system is possible with the help of data collection on aspects such as light level, pedestrian flow, traffic flow, and weather conditions. Second, this paper uses an enhanced version of the GM (1,1) model for lighting prediction control, namely, the polynomial discrete gray model GM (1,1,K), to solve the inadequacies of the traditional model. The GM (1,1,K) model predicts future lighting demand and aids the system in making educated lighting control decisions by assessing environmental data acquired by optical multisensors. In the end, the strategy presented in this paper is applied to improving the management of an industrial park lighting system's energy consumption. The results of the trials show that the precision and consistency of system lighting measurements are enhanced by the use of optical multisensor technology, while the GM (1,1,K) model offers useful insights for lighting prediction and optimization. In this way, the new technology succeeds in three respects at once: dimming effect, prediction performance, and control performance.

2. Related Theory and Technology

2.1. Optical Sensors. Urban lighting control systems rely heavily on optical sensors, which are devices that can detect and quantify light or electromagnetic waves [7]. Figure 1 depicts the primary uses for four different types of optical sensors that are frequently employed: light intensity sensors, color sensors, motion sensors, and occupancy sensors. Roadway illumination factors including brightness, color temperature, occupancy levels, and ambient light may be tracked in real time thanks to the strategic placement of these sensors in metropolitan highways. Lighting control techniques, energy optimization, and user happiness can all benefit from this information gathered by the system. For instance, the system can reduce the brightness of artificial lighting or turn it off altogether if a light intensity sensor detects a drop in ambient light owing to daylight saving time [8]. When a motion detector senses movement, the system can brighten the lights in that area for further security and visibility [9]. In parks, the system can light specific paths based on detected occupancy, while dimming other areas to save energy [10].

2.2. Multisensor Data Fusion Technology. In the 1980s, advancements in data processing led to the creation of data fusion technology. With the purpose to improve the accuracy of the data gathered by sensors, this technology performs operations such as analysis, filtering, and synthesis [11]. Data fusion technology has become increasingly popular as a result of the growing sophistication of computing and communication systems. There are now three distinct forms of data fusion architecture in use today: centralized, distributed, and hybrid [12]. The sensor of the centralized kind, shown in Figure 2(a), cannot perform any analysis or make any decisions on its own and must instead transmit the raw data it has collected to a central processor for processing. Figure 2(b) depicts a distributed architecture in which the sensor transfers the raw data it has collected to the fusion node for preprocessing and then transfers the results of that preprocessing to the processor for analysis and decision-making. The hybrid structure combines elements of both the centralized and decentralized models. It combines their benefits but at the expense of a high computational and communication cost.

Because lamps are spread out along different routes, and the terminal sensors in this system will detect the values of many environmental parameters, including light intensity, color, and motion, a great deal of data will be generated on the system. This system uses a distributed data fusion architecture to improve analysis and judgment.

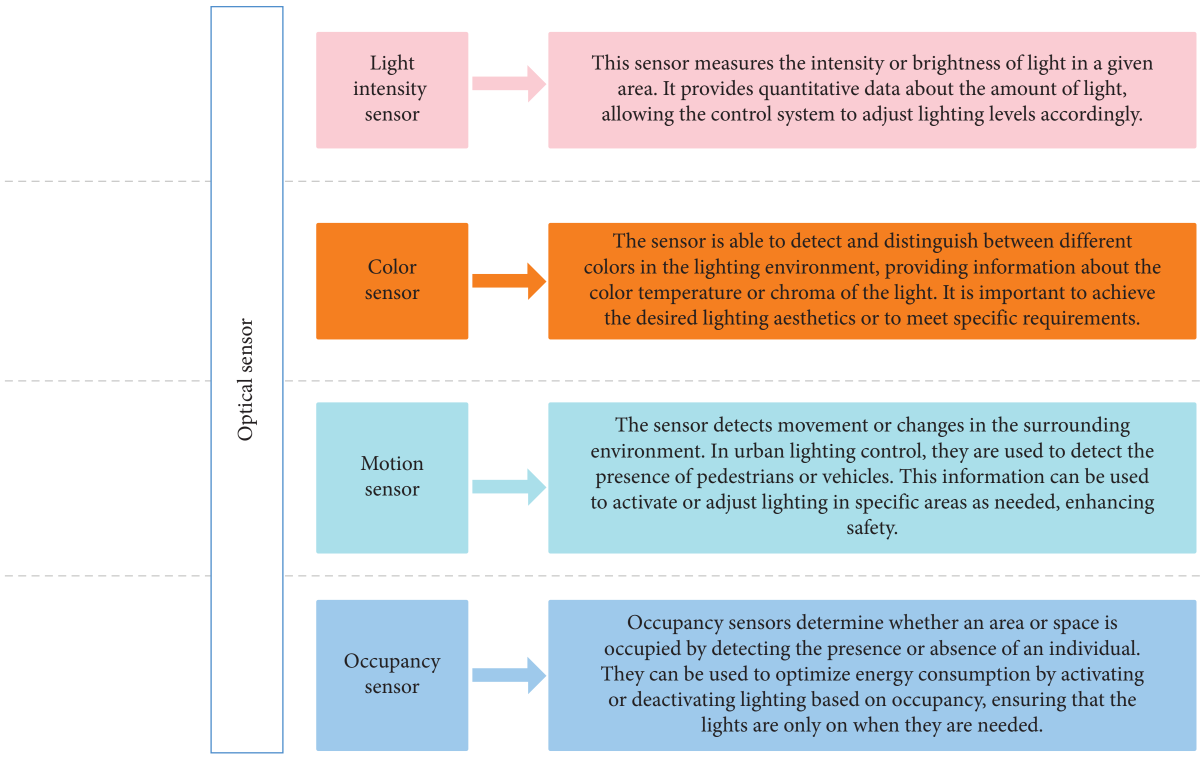
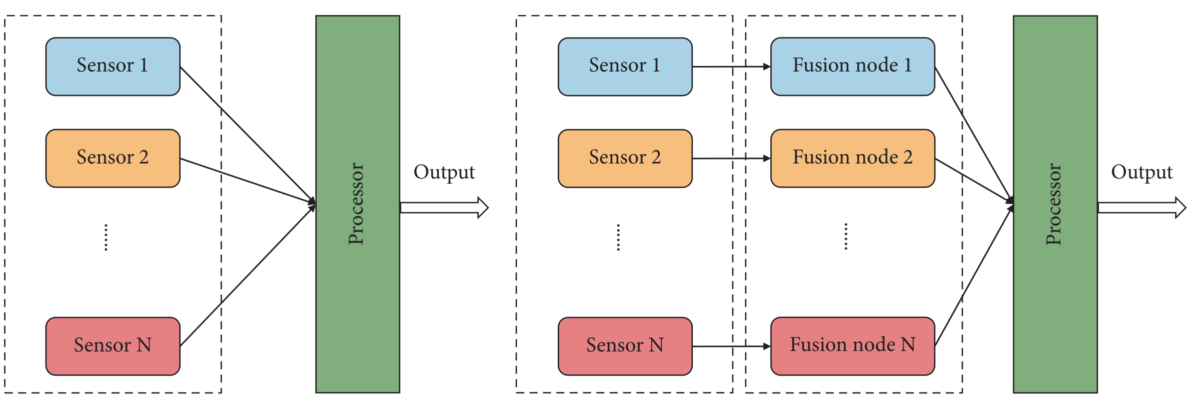


Figure 1: Classification of optical sensors.



(a) (b)

Figure 2: Overall structure of data fusion technology. (a) Centralized processing method. (b) Distributed processing method.

2.3. GM Model. Invented by the Chinese mathematician and economist Deng Julong in the 1980s [13], the gray model (GM) is a form of mathematical modeling. To put it another way, the model lowers the randomness and uncertainty in data series by forming correlations between known data points and unknown future values, allowing it to make predictions based on limited or incomplete data. As a result, GM models are widely employed in many different sectors, including business, agriculture, and economics [14], thanks to their many benefits when working with data series. The GM (1,1) model is used to evaluate and predict linear data series, whereas the GM (2,1) model is used to handle nonlinear data series, and these are currently the most popular GM models. The GM (1,1) model is the simplest and most extensively employed model for predicting the gray system. A first-order differential equation is constructed from a sequence of observed data in this model. The model obtains these estimates for the series' starting points and growth rates by solving the differential equation. It is possible to make forecasts about future values using these parameters. When the data series is nonlinear, the GM (2,1) model is an extension of the GM (1,1) model. For better prediction results, it adds a new cumulative generation operation.

The GM model is crucial in the development of lighting management programs. The dynamic aspects of lighting demand in urban areas, such as time of day, weather, and consumption, can be captured by this method, making it an effective tool for lighting demand analysis and forecasting based on limited data.

3. System Design

Management agencies have spent a lot of time and money on fixing various issues plaguing the current urban lighting system, such as the unreasonableness of its control methods and accompanying massive energy waste. The system's main goal is to design a scientific, reasonable, and environmentally friendly urban intelligent lighting control system, and it does so by adhering to the principles of safety and reliability, high applicability, and scalability. In order to increase energy efficiency, decrease operating costs, and boost user satisfaction in urban lighting environments, the system collects and processes data of environmental factors surrounding streetlights through optical multisensors and also uses the GM model to control and predict the collected data to achieve a more efficient and intelligent lighting control strategy.

3.1. General Architecture of the Control System. This paper proposes a "sensing-processing-decision-control" lighting system for roads that relies on optical multisensors to detect environmental changes, process data in real time, and generate control strategies. There are two main components to the system: software and hardware. The bulk of the hardware system consists of terminal devices, controllers, and a server platform, with sensors detecting the intensity and color of natural light strategically positioned across the city and communicating with a central hub controller. Every streetlight has motion detectors built in to check if there are any passing vehicles or pedestrians. The controller for the road's lights can be found in the streetlight distribution box. The streetlight monitoring system may be remotely monitored in real time thanks to Ethernet-based connection between the primary controller and the database management center. Figure 3 depicts the system's general design, which is primarily mirrored in the software platform system of the control room. This system includes the communication interface software, data processing software, and operation management software.

The control system is the brains of the operation, processing data from optical multisensors in the field to determine the optimal brightness level for streetlights and assigning different lighting strategies based on the state of the road. Because of this, the upper and lower networks make up the lighting control system architecture presented in this paper. Ethernet ties the city's central controller to regional monitoring stations across the metropolis. Each district's central light intensity and color sensor wirelessly transmit data about the district's natural illumination to the district's main controller, which then activates or deactivates the district's streetlights and sends data about the district's portion of the city's roads to the monitoring center, where it is displayed. Each road in the city is equipped with a controller for the city's streetlights, and the streetlights on both sides of the road are wired together. Each motorway streetlight or sidewalk street light is equipped with a motion sensor, and the information detected is sent to the road light controller, which then activates appropriate streetlights based on the information sent by the motion sensor. Through the streetlight controller, data from the lower network are relayed to the higher network's master controller. This allows the entire lighting control system to communicate across a network. Figure 4 depicts the overall system network architecture.

3.2. Selection and Design of Optical Multisensor

3.2.1. Light Intensity Sensor Module. By measuring exterior ambient brightness, the light intensity sensor module may determine if the streetlight has to be activated [15]. The light intensity sensor is built as an analog-to-digital converter so that the collected amplified signal can be converted into a digital signal that can be read using a computer. LM393 is useful for a wide variety of tasks, including switch control, alarms, and temperature monitoring, thanks to its ability to compare and output high- and low-level signals based on a variety of input signals. It is well suited for both long-term operation and quick response thanks to its low power consumption, high-speed response, and other qualities. As a result, the light intensity sensor module in this research was developed using the LM393 chip. Figure 5 depicts the light intensity sensor's internal workings.

In this research, a light intensity sensor measures the level of illumination from streetlights and sends that information through an analog-to-digital converter for use by the system. When conditions on the road alter, the streetlight must adapt its settings accordingly. When the streetlight is too bright, the system adjusts the driver circuit's output current to lower the intensity of the light. However, when ambient light levels are low, the system takes action to modify the driving circuit's output current, keeping the streetlight illuminated.

3.2.2. Color Sensor. The results from a color sensor can be utilized to change the streetlight's intensity or hue to match the ambient light level or desired effect [16]. In order to determine the color of the observed light, the system works by detecting the intensity of the light across a spectrum of wavelengths. If the sensor senses that it is getting dark, for instance, it can instruct the streetlight to shine brighter. On the other hand, the streetlight can be dimmed or turned off if the sensor determines that there is already enough light outside. In sum, color sensors play a crucial role in street lighting management systems by providing real-time feedback on the illumination conditions to allow for efficient and adaptive regulation of streetlights. In this study, an RGB color sensor is utilized to accomplish intelligent lighting system control by detecting and analyzing the color of light in the surrounding environment through the measurement of light intensity across three color channels: red, green, and blue. Figure 6 depicts the inner workings of an RGB color sensor.

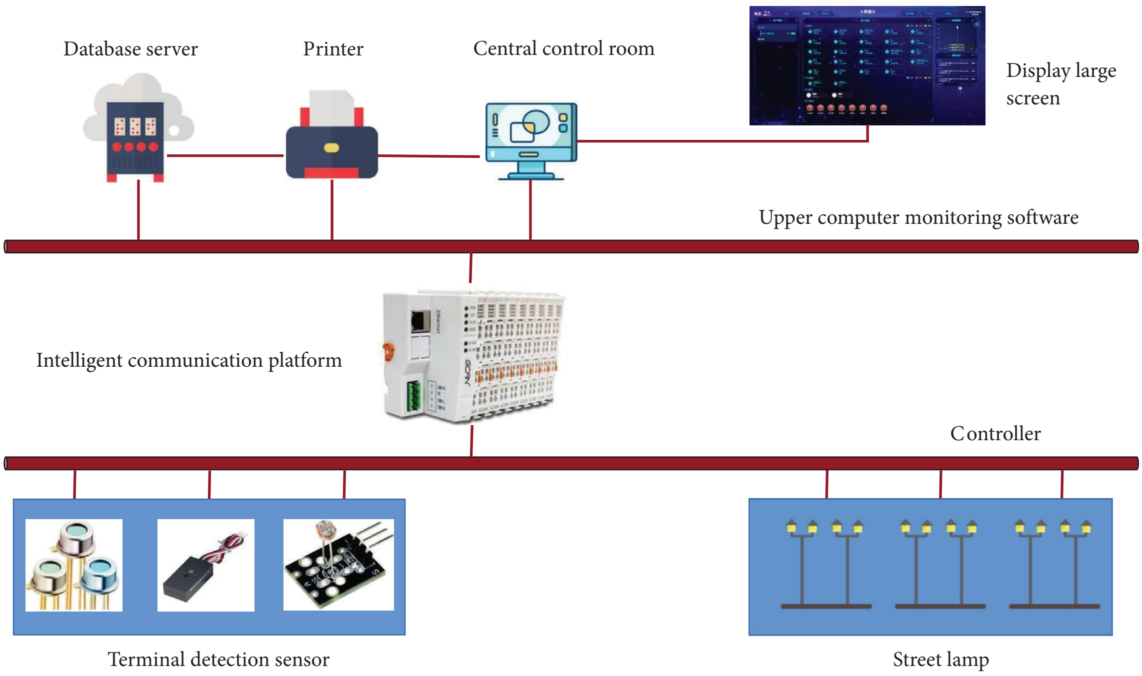


FIGURE 3: System architecture diagram.

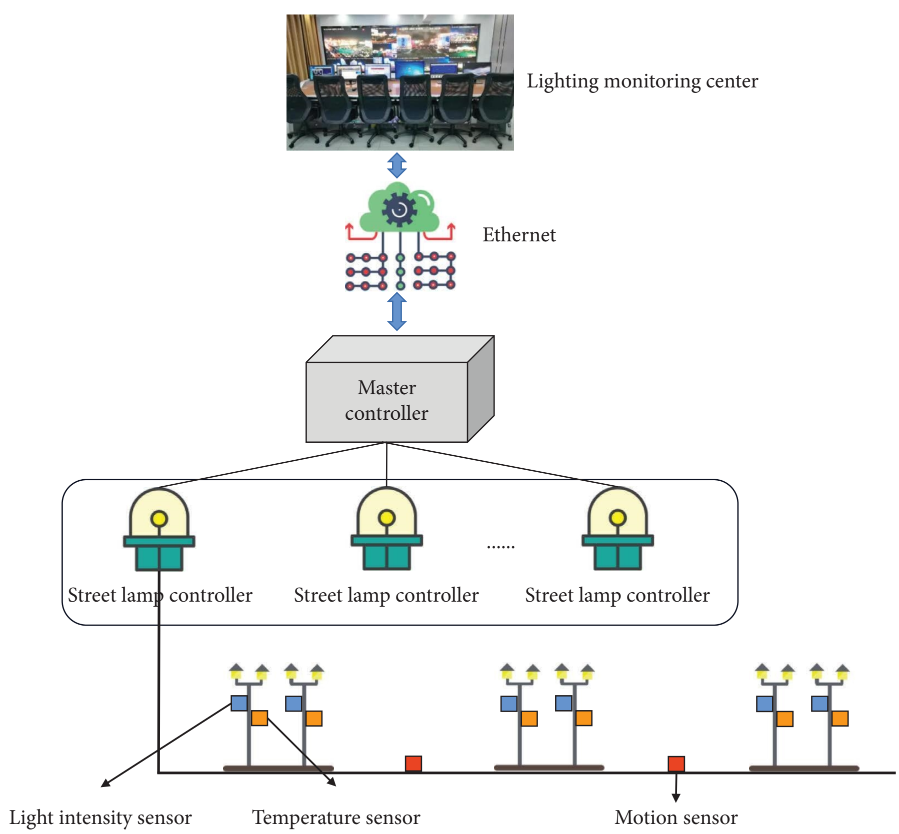


FIGURE 4: System network architecture.

3.2.3. Motion Sensor Module. The motion sensor module in this system uses an infrared pyroelectric module to detect oncoming pedestrians and vehicles [17]. After a short period, the streetlight installed on the terminal module returns to its dim setting after being activated by a high-level signal if a person or vehicle is spotted passing by. The circuit layout of the infrared sensor is depicted in Figure 7.

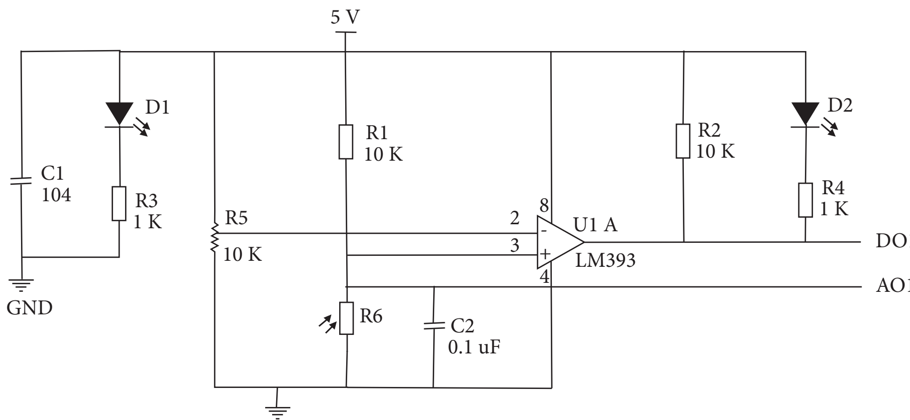


Figure 5: Working principle diagram of the light intensity sensor.

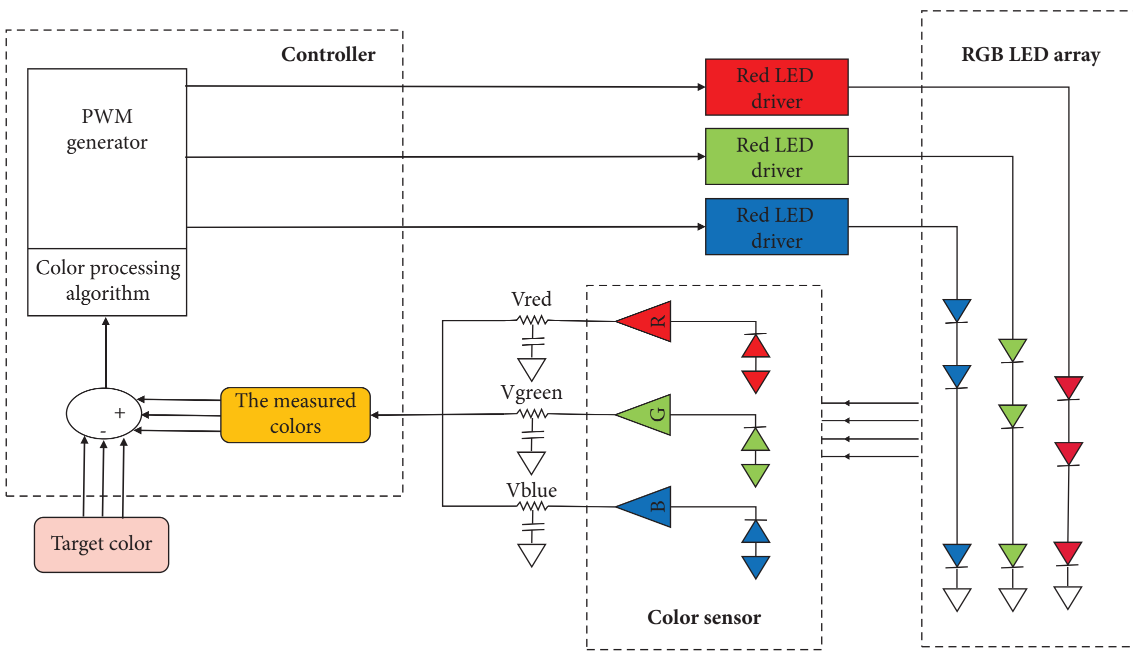


Figure 6: Working principle diagram of the RGB color sensor.

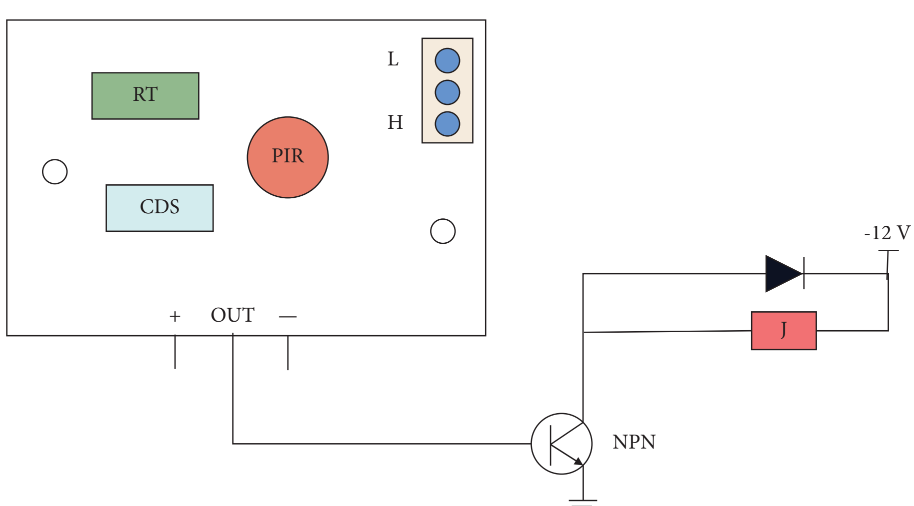


Figure 7: Working principle diagram of the infrared sensor.

Pyroelectric element PIR is shown in Figure 7. Changes in road temperature cause an increase in charge density at the pyroelectric exterior's electrodes, which causes a discharge of static electricity in all directions. Light density resistor (LDR) and temperature correction resistor (TCR) interfaces make it simple to add new capabilities to the sensor. The connector for the jumper cap is labeled "LH." We would not be able to keep setting it off while it is in *L*. Contrarily, when set to *H*, it might be activated multiple times while waiting.

3.2.4. Data Processing Module Design. Once data have been acquired from the aforementioned optical sensors, it will be processed using data fusion-based algorithms to improve the accuracy of the data and streamline the system's operation. Optical multisensor data fusion can be thought of as a four-step process: In the first step, sensors are used to collect data on the lighting conditions near the streetlight, including the intensity and color of the light, as well as the traffic flow in and out of the area. The second step involves removing potential sources of error from the raw data that were obtained. In the final phase, all of the data that passed the first two filters are combined. The ideal fusion results are achieved in the fourth stage by fusing the findings from the fusion at the data level with the information at the decision level. The whole fusion process is depicted in Figure 8.

One of the features that the lighting control system must have is data processing, as the controller is more interested in summary statistics than in the raw readings from each sensor's terminal. An adaptive weighted fusion algorithm is used in the system's processing link for data-level fusion, allowing for the fusion of data from several sensors [18]. The system will next employ the polynomial discrete gray model G (1,1,K) for lighting prediction control in the decision-level fusion phase.

3.3. Predictive Control Model

3.3.1. GM (1,1) Prediction Model. The gray GM (1,1) model is the GM model's simplest and most common variant. Its underlying premise is that for a given data series, a new set of data series with a discernible trend can be formed through cumulative addition, and a model can then be constructed to forecast based on the growing trend of the new data series. The cumulative reduction approach is then used to do an inverse reduction, recovering the predicted values of the original dataset [19].

Assume that the original data series $a^{(0)}$ has C observations, i.e., $a^{(0)} = \{a^{(0)}(1), a^{(0)}(2) \ldots a^{(0)}(C)\}$. The original data series $a^{(0)}$ is cumulated to generate a new series $a^{(1)}$, which weakens the irregularity and randomness of the data series and the effect of random perturbation on the data. The cumulative generation reveals the development of the gray volume accumulation process and brings out the patterns contained in the cluttered raw data.

Let the resulting new array be $A^{(1)}(C) = \{A^{(1)}(1), A^{(1)}(2) \ldots A^{(1)}(C)\}$, where $A^{(1)}(C)$ is defined as shown in the following formula:

$$A^{(1)}(C) = \sum_{i=1}^{C} a^{(0)}(i), i = 2, 3, \cdots, C. \quad (1)$$

Then, we calculate its immediate mean equal brand new series $Z^{(1)}$ from $A^{(1)}$, as shown in the following formula:

$$\begin{cases} Z^{(1)} = \left\{Z^{(1)}(2), Z^{(1)}(3), \cdots, Z^{(1)}(C)\right\}, \\ Z^{(1)}(i) = 0.5a^{(1)}(i) + 0.5a^{(1)}(i-1). \end{cases} \quad (2)$$

For the series $A^{(1)}$, $Z^{(1)}$ establishes the whitening differential formula and constructs the GM (1,1) model as shown in the following formula:

$$\frac{\mathrm{d}a^{(1)}}{\mathrm{d}t} + ka^{(1)} = b. \quad (3)$$

Its whitening formula is as follows:

$$a^{(0)}(i) + k * Z^{(1)}(i) = b, \quad (4)$$

where k and b denote the system development coefficient and the driving term coefficient, respectively, which are the parameters to be determined for the model. The traditional GM models are based on data using the least squares method to solve for the parameters as shown in the following formula:

$$\begin{aligned} a^* &= [k, b]^T \\ &= \left(M^T \bullet M\right)^T M \bullet N, \end{aligned} \quad (5)$$

where M and N are parameters whose definitions are given in the following formulas:

$$M = \begin{bmatrix} a^{(0)}(2) \\ a^{(0)}(3) \\ \vdots \\ a^{(0)}(C) \end{bmatrix}, \quad (6)$$

$$N = \begin{bmatrix} -z^{(0)}(2)1 \\ -z^{(0)}(3)1 \\ \vdots \\ -z^{(0)}(C)1 \end{bmatrix}. \quad (7)$$

The two formula parameters are derived from this. Formula (8) shows the solution of formula (3):

$$a^{(1)}(t) = \left(a^{(1)}(1) - \frac{b}{k}\right) \bullet e^{-kt} + \frac{b}{k}. \quad (8)$$

Formula (9) shows the temporal response series of the GM (1,1) model:

$$\hat{a}^{(1)}(i+1) = \left(a^{(1)}(1) - \frac{b}{k}\right) \bullet e^{-ki} + \frac{b}{k}, i = 1, 2, \cdots, C. \quad (9)$$

Predicted values are calculated by reducing the aforementioned results cumulatively, as indicated in the following formula:

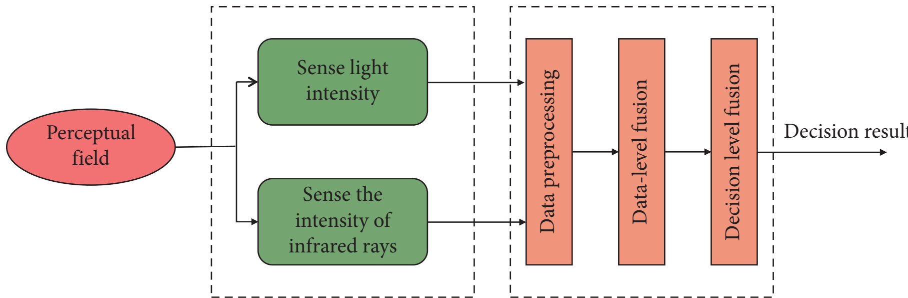


Figure 8: Optical multisensor data fusion process.

$$\hat{a}^{(0)}(i+1) = \hat{a}^{(1)}(i+1) - \hat{a}^{(1)}(i) = \left(1-e^{k}\right)\left(x^{(0)}(1) - \frac{b}{k}\right)\bullet e^{-ki}, i = 1, 2, \cdots, C. \tag{10}$$

The prediction accuracy of the GM (1,1) model is highly dependent on the model parameters k and b. The optimality of the solution of the sought parameters directly affects the prediction accuracy of the model. It is shown that when the data series changes smoothly (i.e., $|k| < 0.5$), the error of the GM (1,1) model is small and the prediction effect is very satisfactory. However, for high growth data series (i.e., $|k| > 0.5$), the error is large and the prediction results are not satisfactory [20].

3.3.2. Polynomial Discrete Gray Model. The conventional GM (1,1) model solely employs the sequence of system behavior without the external action sequence because it is a single series prediction model. Because of this, issues such as high data distribution performance needs, weak anti-interference ability, and limited application arise [21]. An improved solution is provided by the proposed polynomial discrete gray model (GM (1,1,K) model) [22]. The model is commonly used to fit data series with high unpredictability and uncertainty because it incorporates the best features of the nonflush gray model, the power exponential gray model, and the discrete gray model. In light of this, the predictive control model for the urban lighting system in this paper is the GM (1,1,K) model.

With a nonnegative original series $A^{(0)}(i) = \{a^{(0)}(1), a^{(0)}(2), \cdots, a^{(0)}(C)\}, i = 1, 2, \cdots, C,$ the first-order cumulative sequence of $a^{(0)}(i)$ is shown in the following formula:

$$a^{(1)}(i) = \left\{a^{(1)}(1), a^{(1)}(2), \cdots, a^{(1)}(C)\right\} = \sum_{j=1}^{i} a^{(0)}(j), i = 1, 2, \cdots, C. \tag{11}$$

Let us assume that the discrete polynomial model is GM (1,1,K), defined as follows:

$$a^{(1)}(i) = \lambda a^{(1)}(i-1) + \delta_0 + \delta_1 i^{r} + \cdots + \delta_K i^{Kr}. \tag{12}$$

Let the parameters of the GM (1,1,K) model be $P = [\lambda, \delta_0, \delta_1, \cdots, \delta_K]^T$; then, the least squares estimate of P is shown in the following formula:

$$\hat{P} = \left(N^T N\right)^{-1} M, \tag{13}$$

where M and N are parameters whose definitions are given in the following formulas:

$$N = \begin{bmatrix} a^{(1)}(1) & 1 & 2^{r} & \cdots & 2^{Kr} \\ a^{(1)}(1) & 1 & 3^{r} & \cdots & 3^{Kr} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ a^{(1)}(C-1) & 1 & C^{r} & \cdots & C^{Kr} \end{bmatrix}, \tag{14}$$

$$M = \begin{bmatrix} a^{(1)}(2) \\ a^{(1)}(3) \\ \vdots \\ a^{(1)}(C) \end{bmatrix}, \tag{15}$$

where r is the conditioning operator and K is the number of polynomials.

If the initial condition $\hat{a}^{(1)}(1) = a^{(1)}(1)$ is given, the estimate of GM (1,1,K) is obtained as shown in the following formula:

$$\hat{a}^{(1)}(i) = \hat{\lambda}\hat{a}^{(1)}(i-1) + \hat{\delta}_0 + \hat{\delta}_1 i^{r} + \cdots + \hat{\delta}_K i^{Kr}. \tag{16}$$

If the initial condition $\hat{a}^{(0)}(1) = \hat{a}^{(0)}(1)$ is given, the predicted value of the original series is obtained as shown in the following formula:

$$\hat{a}^{(0)}(i) = \hat{a}^{(1)}(i) - \hat{a}^{(1)}(i-1), i = 2, 3, \cdots, C. \tag{17}$$

New GM (1,1,K) incorporates the best features of multiple gray models into a single framework, and its two independently adjustable parameters, r and K, allow for greater flexibility in dealing with real-world issues. This makes the model more useful as a predictive control model for the urban lighting system under investigation in this paper.

4. System Performance Testing

4.1. Experimental Design. Experiments are conducted from three perspectives (dimming effect, prediction performance, and control performance) to evaluate the practicability and efficacy of the lighting control system described in the present paper. First, the house model, PLC controller, PC upper computer (Simulink module), LED driver, light intensity sensor, color sensor, and infrared sensor make up the major components of the intelligent lighting experiment platform upon which the first and second sets of experiments are based. A municipal W industrial park was chosen as the experimental object for the third round of experiments. The park spans 3,000 square meters across two stories above ground. In 2021, the industrial park will need a total of 117,356.48 Kw·h of electricity. The paper presents a method for regulating the park's lighting system's energy use in such a way as to achieve maximum efficiency.

4.2. Experimental Results and Analysis

4.2.1. Experiment 1: Dimming Effect Analysis. A fixed illuminance tracking experiment was first developed to test the control system's dimming effect after the optical multisensor and the GM model had been validated. In Figure 9(a), we see the dimming effect achieved by operating the lighting control system with illuminance set to $R = 100\mathrm{l}x$. We also ran tests comparing the enhanced GM model to the VAE model and the GAN model to prove that it is superior to these other methods when it comes to the dimming impact. To test the anti-interference capabilities of various models, a $20\mathrm{l}x$-strong disturbance is superimposed on the measured light level for 60 seconds. Figures 9(b)–9(d) depict the outcomes of the tests.

Figure 9(a) demonstrates how well the system follows the desired brightness level without straying too far from the target. As can be seen from Figures 9(b)–9(d), when the system was disturbed in 60 s, the control system using the GM model can swiftly recover from disturbances and resume following the programmed illuminance value. The response time of the systems using the VAE and GAN models is longer. This demonstrates that the GM-based lighting control system can generate reliable predictions by analyzing data from optical multisensors about the lighting environment in relation to variables such as time of day, weather conditions, and pedestrian flow. As a result, the urban lighting system is better able to adapt to shifting environmental circumstances and user preferences with this method's adaptive lighting management, which features a good dimming effect and excellent interference immunity.

4.2.2. Experiment 2: Predictive Performance Analysis. On a typical workday in the park, we conducted studies to predict future performance. The energy consumption of the industrial park was predicted using the lighting control technology described in this paper. In the experiment, the optical multisensor developed in this paper is used to collect data on parameters such as light intensity, temperature, and pedestrian traffic flow, and the data from these sensors are then combined to gain a more holistic understanding of the lighting environment, which in turn increases the precision and reliability of the lighting measurements. The predicted and actual energy consumption of the new lighting system is shown as a function of time in Figure 10.

Figure 10 shows that when the method presented in this paper was applied to the park lighting management system, the projected energy consumption figures were quite close to the actual values. This demonstrates the high prediction performance of the optical multisensor and the GM model-based lighting control system and the extremely satisfactory prediction accuracy of campus lighting energy usage. This is because the optical multisensor improves the accuracy and reliability of lighting measurements by combining data from several sensors to provide a more thorough picture of the lighting environment. The GM model can make reliable forecasts because it considers a wide range of variables, including time of day, weather, and foot traffic. Therefore, combining these two technologies not only helps reduce energy waste but also boosts the reliability of lighting control systems' forecasts.

4.2.3. Experiment 3: Optimal Control Performance Analysis. There is a clearer distinction between slow and busy times at the city's W industrial park. Therefore, the power consumption of the park's lighting system may be predicted using the street lighting management system proposed in this paper, which can then be utilized to give data standards for subsequent energy consumption control and aid firms in saving energy and reducing emissions. The experiment involved creating a column chart from the monitored lighting system's monthly energy consumption data. The approach of entering a single number is used to make calculations easier, and the outcomes of efforts to optimize energy use are shown in Figure 11.

Figure 11 illustrates that after implementing the energy consumption optimization control strategy proposed in this research, the lighting system at this industrial park uses an estimated annual total of 40,099 Kw·h of power. This industrial park's lighting system has reduced its electricity use by approximately two thirds compared to what it was in 2021. This is due to the fact that optical multisensors are used to collect data about the lighting environment, and the GM model is then used to analyze and forecast the lighting demand based on these limited data, analyze the pattern and trend of lighting consumption, and come up with a reliable prediction of the lighting demand in the future. We can deduce that the industrial park's lighting system has a lower annual average power consumption during the months of 1 and 3, when business volume is greatly reduced and working hours are correspondingly shorter. In addition, the lighting system uses less energy at this time of day. Power usage increases and decreases in tandem with fluctuating order volumes in other months. The paper's approach has been shown to greatly boost the park's lighting system's energy

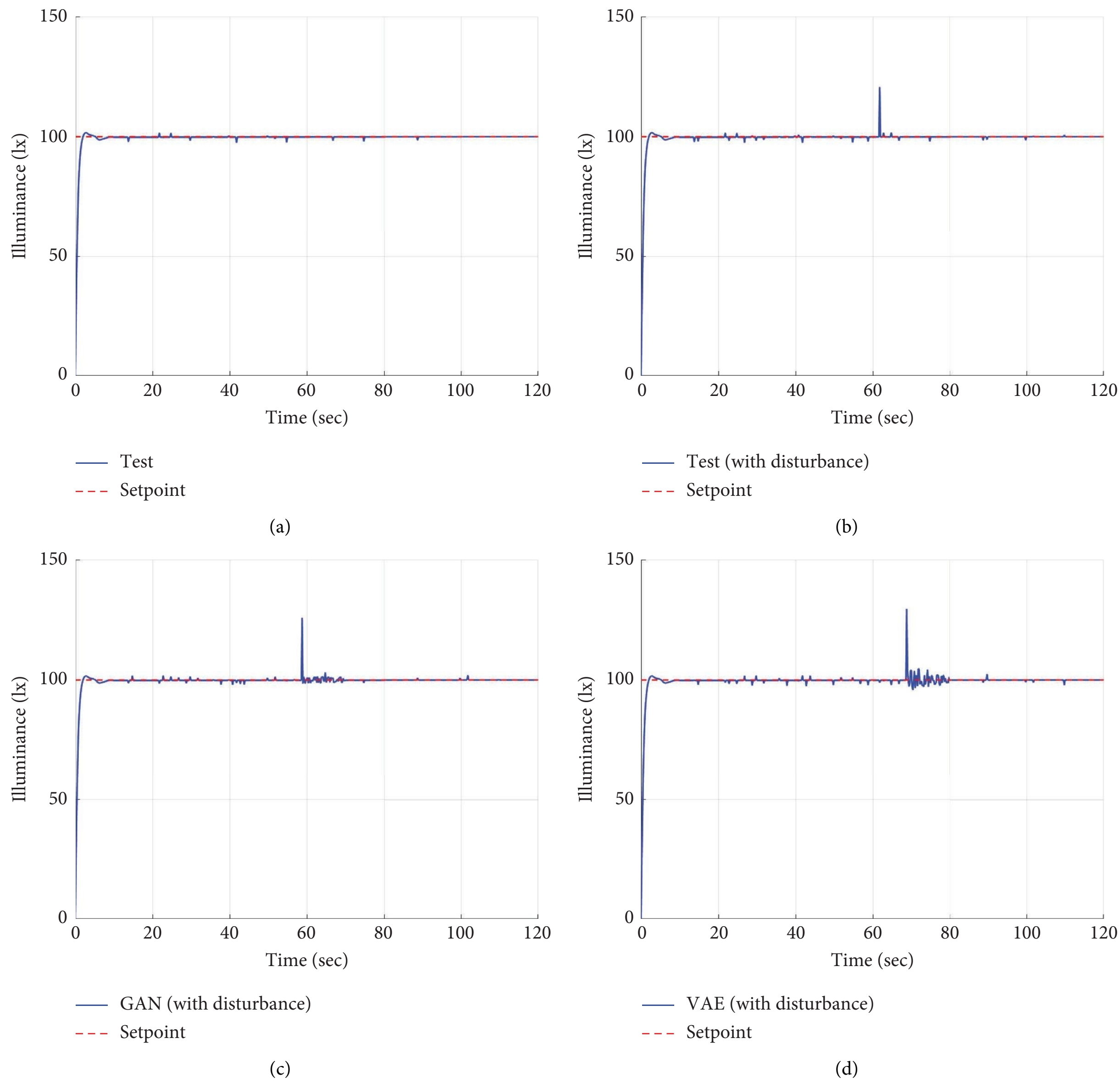


Figure 9: Dimming effect of the system controller. (a) Actual illuminance L-time curve. (b) Actual illuminance L-time curve when disturbed. (c) Actual illuminance L-time curve of GAN when disturbed. (d) Actual illuminance L-time curve of VAE when disturbed.

consumption optimization control performance; therefore, it is worth spreading the word about and putting into practice.

In conclusion, the aforementioned tests proved the usefulness of combining optical multisensor technologies and GM models in municipal lighting management systems. Therefore, it is worthwhile to promote and apply the lighting control system developed in this study since it helps improve energy efficiency, reduce operating costs, and boost user happiness in urban lighting environments.

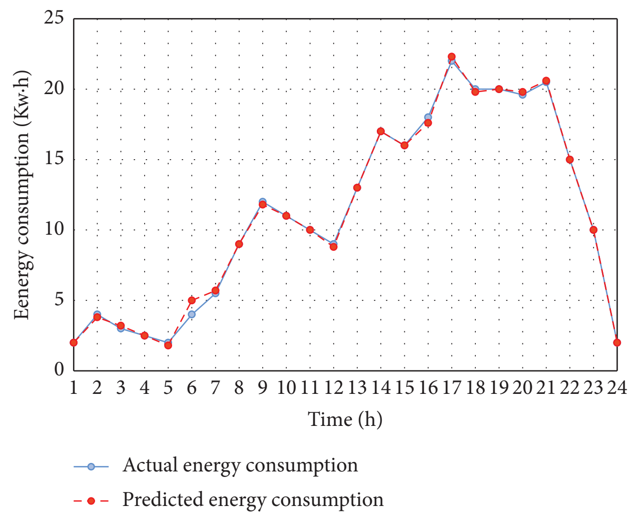


Figure 10: Relationship between predicted and actual energy consumption of the system.

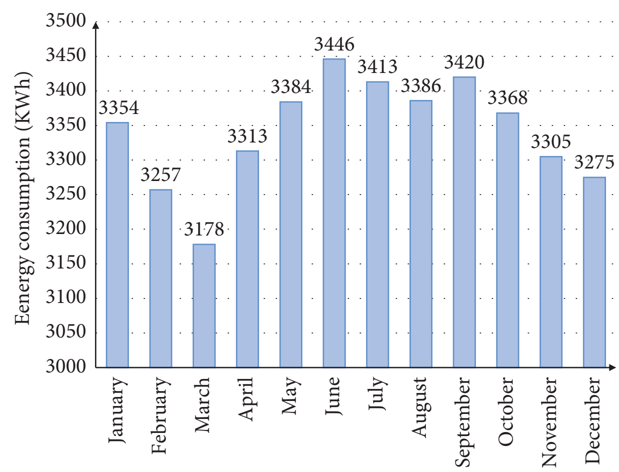


Figure 11: Energy consumption optimization control results.

5. Conclusion

The smart city's urban lighting sector is growing rapidly, intelligently, and sustainably, and urban lighting management systems are becoming increasingly important to urban functionality, safety, and aesthetics. City planners and administrators in urban lighting today prioritize centralized control, uniform administration, and energy conservation and environmental protection. In this study, we investigate real-world urban lighting requirements and propose a management system using optical multisensors and the GM model to achieve them. The system continuously monitors and records lighting conditions using optical sensors such as light intensity, motion, and color sensors. This information lets lights be controlled and altered in real time for various situations. However, adding GM models to urban lighting control systems improves their functionality. The GM model analyzes past data and forecasts future lighting needs to optimize energy usage and meet lighting needs in various urban environments. Simulation tests confirmed the system's dimming effect, prediction performance, and control performance, demonstrating that this paper's lighting control system can optimize energy consumption and implement precise lighting controls.

In conclusion, this paper's investigation into optical multisensor techniques and GM models for urban lighting control has shown their potential to enhance the performance and utility of urban lighting systems, and it has provided new avenues for the development of such systems. However, the urban lighting control system described in this work still confronts significant constraints due to the enormous quantity of information involved and the wide coverage of the street lighting system, and more research is needed to solve these issues and limits. First, additional optimization of the optimal parameters of the GM model is required. The prediction accuracy of the model is adversely affected because the parameters derived in this approach are not optimal, especially when forecasting nonstationary data series, for which the parameter model calculated using conventional mathematical methods will generate substantial mistakes. The artificial intelligence algorithms built by humans in recent years have perfectly solved several highly complicated optimization issues and presented a fresh notion for the solution of this problem by emulating the evolutionary mechanism of real creatures. The gray model accuracy will be improved by exploring the use of an ant colony algorithm to solve the GM model parameters. Second, the Internet of things, big data, and cloud computing have all found widespread use in a variety of industries; furthermore, the integration of these new technologies can be investigated in the future to further improve the effectiveness of urban lighting control systems. Third, given the urban nature of streetlights, the collected data can be supplemented with information about ambient noise, exhaust levels, and particulate matter 2.5 (PM2.5) levels to inform not only lighting strategy but also air pollution prevention and control initiatives.

Data Availability

The datasets used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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