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# Tunnel Lighting Control Strategy Based on Fuzzy Control Rules

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Abstract. *The tunnel lighting control strategy based on fuzzy control rules can not only reduce the waste of tunnel lighting power, but also improve the service life of LED lamps and ensure the driving safety of drivers. According to the three real-time changing parameters, namely the brightness outside the tunnel, the traffic flow and the vehicle speed, the fuzzy rules of the required brightness inside the tunnel are established, and the safety and energy saving are verified by comparing with the lighting specifications at home and abroad. In order to reduce the dimming frequency and improve the dimming stability, the brightness ladder is divided according to the required brightness curve in the hole under fuzzy rules, and the classification prediction model of brightness ladder is designed by using BP neural network. Aiming at the problem that BP neural network is sensitive to initial weights and easily falls into local minimum, an improved particle swarm optimization algorithm is used to optimize the weights and thresholds of the model to improve the accuracy of classification prediction. The simulation results show that the classification prediction accuracy of the model can reach 96%, and the energy saving effect is over 30%.*
**Keywords:** tunnel lighting, operation life, fuzzy control, neural network, Intelligence Algorithms

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1. **Introduction.** According to the data of Statistical Bulletin on the Development of Transportation Industry issued by the Ministry of Transport in 2021, by the end of 2021, there were 23,268 highway tunnels with 24,698,900 linear meters in China, including 1,599 extra-long tunnels with 7,170,800 linear meters, 6,211 long tunnels with 10,844,300 linear meters, making it the country with the longest tunnel length in the world [1]. Due to the special semi-closed structure of the tunnel, the tunnel must provide artificial lighting. However, in the lighting control of a large number of long-distance tunnels, unreasonable lighting control strategies will not only lead to a lot of waste, but also fail to ensure the driver's driving safety. At the same time, with the green energy-saving concepts such as "peak carbon dioxide emissions" and "carbon neutrality" put forward, how to save energy and reduce consumption of tunnel lighting under the premise of ensuring safety has become one of the main research directions.

In the research on energy-saving control of tunnel lighting abroad, literature [2] puts forward two different dimming strategies based on traffic flow during the day and at night. During the daytime, PID performs closed-loop dimming. The control method at night is to detect whether there is any vehicle driving, and turn on the lighting when there is a vehicle driving, otherwise turn off the lighting lamps. However, in the case of small traffic, especially at night, it is necessary to switch lamps frequently. Literature [3] obtains the required brightness value of tunnel lighting through fuzzy neural network algorithm and multivariate data fusion. This method is based on the control method of estimating LED luminous flux, which effectively verifies the conclusion that there is a relationship between LED dimming and luminous flux.

In the research on energy-saving control of tunnel lighting in China, literature [4] takes Huangyan Expressway in Shaanxi Province as an example, establishes a structural equivalent fuzzy neural network combining fuzzy control and neural network, studies the real-time changing tunnel traffic information, analyzes the lighting control problem in the middle section, and draws the conclusion that the quality of tunnel lighting is closely related to the control mode. Literature [5] uses mathematical methods, based on the length of lighting segments specified in Lighting Rules, divides each lighting segment into smaller segments to ensure that the designed brightness of each lighting segment is closer to the brightness adaptability curve, and establishes a control model with three inputs and one output by using neural network, which has obvious energy-saving effect. Literature [6] proposed using fuzzy mathematics to improve the traditional PID control. The simulation results show that compared with the traditional PID, the improved fuzzy PID takes shorter time to adjust the brightness to the expected value and the system tends to be stable, and draws the conclusion that fuzzy mathematics can effectively improve the tunnel lighting control.

To sum up, intelligent control combined with multivariate data can effectively save electricity. Therefore, at present, the research on energy-saving control of tunnel lighting is mostly the transformation from traditional logic control to intelligent control, but less research involves the safety of lighting control strategy and the decline of lamp life. Aiming at this problem, this paper studies the safety of tunnel lighting and the improvement of the service life of lamps on the basis of energy-saving control of tunnel lighting.

In this paper, the detailed rules for lighting design of highway tunnels (JTG/TD70/2-01-2014) is taken as the safety standard [7], and the fuzzy control rules of the required brightness in the tunnel are formulated according to the brightness outside the tunnel, the traffic flow and the vehicle speed, and a step dimming strategy of subdivision brightness is proposed. Using BP neural network to complete the design of brightness classification prediction model, improve the inertia factor of updating formula of particle swarm location and speed, optimize the weight and threshold of the model with improved particle swarm algorithm, improve the prediction accuracy, qualitatively analyze the feasibility of the strategy, and quantitatively analyze the energy saving of the strategy.

## 2. Establish fuzzy control rules.

### 2.1. Principles of Fuzzy Control.

When using traditional control methods to solve specific engineering problems, it is necessary to establish a mathematical model that describes the relationship between internal variables, such as the order and parameters of the mathematical model [8]. However, many unresolved problems in engineering practice have the characteristics of nonlinearity and strong coupling, making it difficult to establish mathematical models, and even unable to provide specific mathematical models due to the inability to describe their laws in mathematical language.

Since 1965, the fuzzy control theory was founded, and the fuzzy control system has strong robustness, which provides a new mathematical tool for describing ambiguous and complicated practical engineering problems [9]. The related theory of fuzzy control is based on the development of fuzzy mathematics. The characteristic of fuzzy mathematics is fuzzy set. The difference between fuzzy set and classical set is that classical set can get the result of yes or no, but fuzzy set can get the degree of yes or no [10,11].

A fuzzy system generally consists of an input part, a fuzzy controller, and an output part. The specific composition of a general fuzzy control system is shown in Figure 1. The input part is dynamically obtained from the tunnel environment by the wireless sensor network [12]. The main part of a fuzzy system is a fuzzy controller, which functions to complete input to output and provide precise control quantities. The fuzzy controller also includes fuzzification, knowledge base establishment, fuzzy reasoning, and clarity.

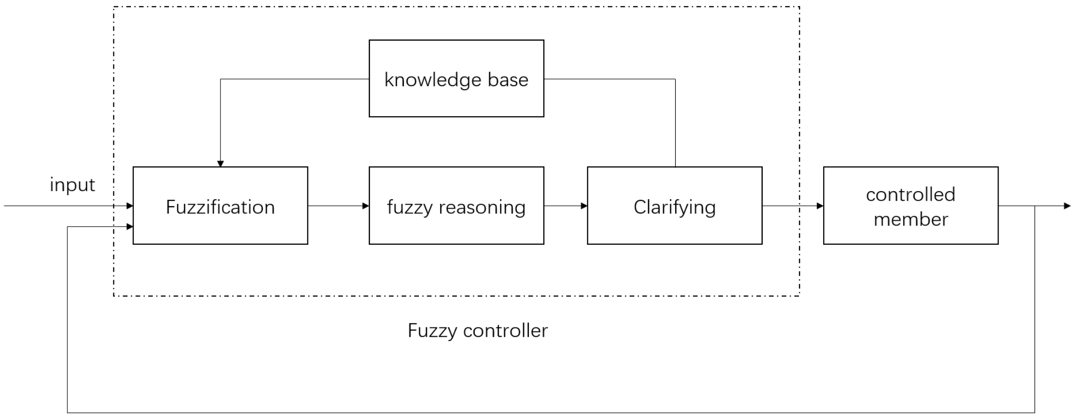



Figure 1. Fuzzy control system

2.2. **Parameter fuzzification.** The required brightness in the tunnel needs to be calculated by analyzing the real-time dynamic data of relevant parameters, and the real-time traffic data is uploaded wirelessly through the Internet of Things [13,14].

The brightness L outside the tunnel is blurred into five categories: very bright, relatively bright, average, relatively dark, and very dark. The traffic flow N is blurred into five categories: large, large, average, small, and very small. The speed V is blurred into three categories: fast, average, and slow. The fuzzy set in the universe is represented by the marks of NB, NS, ZO, PS and PB.

The parameter range for brightness outside the tunnel is set to [0,3800], the range for vehicle speed is [0,60], and the range for vehicle flow is [0,2000]. The fuzzy rule division of brightness outside the tunnel, traffic flow, and vehicle speed is shown in Tables 1, 2, and 3.

Table 1. Fuzzy Rule Division of Brightness Outside the Cave

| Fuzzy set | NB | NS | ZO | PS | PB |
|---|---|---|---|---|---|
| Brightness outside the cave | 760 | 1520 | 2280 | 3040 | 3800 |

Table 2. Fuzzy Rule Division of Vehicle Flow

| Fuzzy set | NB | NS | ZO | PS | PB |
|---|---|---|---|---|---|
| Traffic volume | 400 | 800 | 1200 | 1600 | 2000 |

Table 3. Fuzzy Rule Division of Vehicle Speed

| Fuzzy set | NB | ZO | PB |
|---|---|---|---|
| speed of a motor vehicle | 20 | 40 | 60 |

2.3. **Selection of membership function.** In the fuzzy inference process, in order to achieve the expected effect of fuzzy control rules, it is necessary to select appropriate membership functions [15]. There is no unified method for determining the membership function, and people usually determine the membership function based on accumulated experience and relevant knowledge [16]. Below is a summary and comparison of five commonly used membership functions.

(1) Triangle

$$f(x,a,b,c)=\begin{cases}0 & x<a\\ \frac{x-a}{b-a} & a\le x<b\\ \frac{c-x}{c-b} & b\le x<c\\ 0 & c\le x\end{cases} \tag{1}$$

In the equation, $a \le b \le c$.

(2) Bell shaped

$$f(x,a,b,c)=\frac{1}{1+\left|\frac{x-c}{a}\right|^{2b}} \tag{2}$$

In the equation, c determines the center position of the function, and a and b determine the shape of the membership function.

(3) Gaussian type

$$f(x,a,b,c)=e^{-\frac{(x-c)^2}{2\sigma^2}} \tag{3}$$

In the equation, c determines the center position of the function, $\sigma$ Determine the width of the function curve.

(4) Sigmoid shape

$$f(x,a,c)=\frac{1}{1+e^{-a(x-c)}} \tag{4}$$

The function graph in the equation is symmetrical about the center of the point, and a and c determine the shape of the function.

(5) Trapezoid

$$f(x,a,b,c,d)=\begin{cases}\frac{x-a}{b-a} & x\le x<b\\ 1 & b\le x<c\\ \frac{d-x}{d-c} & c\le x<d\\ 0 & d\le x\end{cases} \tag{5}$$

The curve graphs of these five membership functions are shown in Figures 2. Generally speaking, the sharper the curve shape of the membership function, the higher its resolution and control sensitivity, such as the relatively high control sensitivity of the triangular membership function; On the contrary, if the curve shape is relatively flat, the control characteristics are also relatively flat, and the stability performance is also good, such as the bell function, which is relatively flat and stable [17]. The criterion for selecting the membership function is to use a high-resolution fuzzy set in areas with larger errors, a slightly higher resolution fuzzy set in areas with smaller errors, and a high-resolution fuzzy set when the error approaches zero.

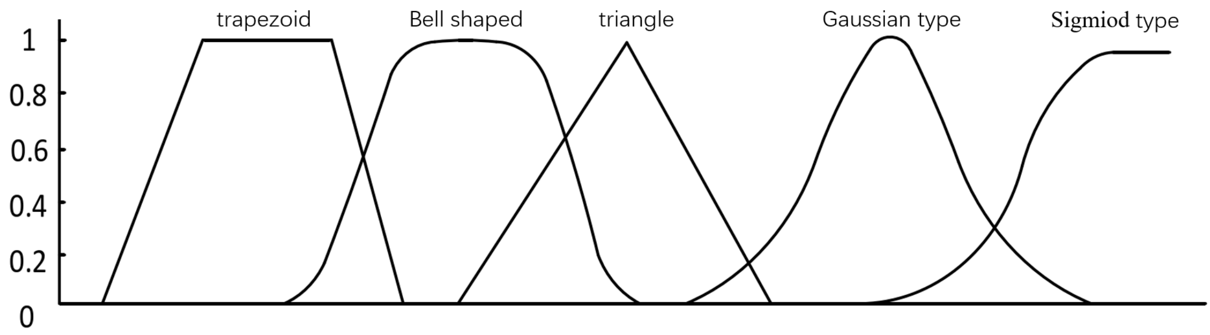
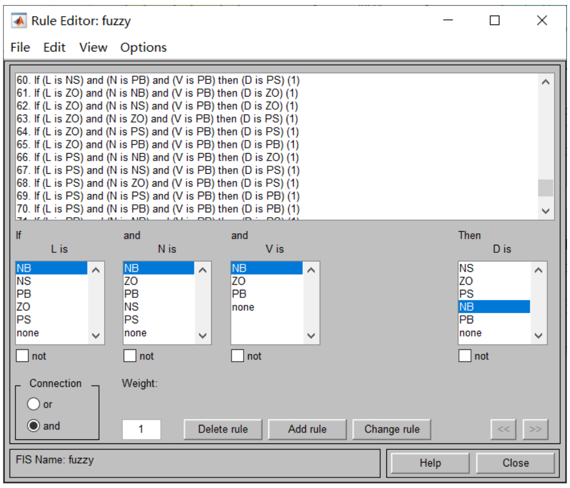
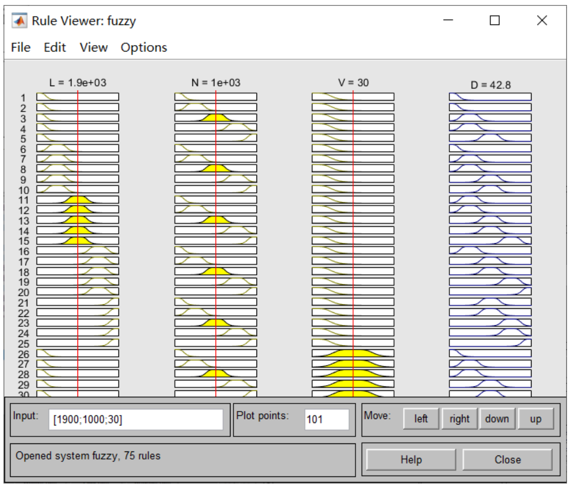



FIGURE 2. Five common membership function graphs

The tunnel lighting control system requires high stability in dimming, so the edges of the triangular and trapezoidal membership functions are not smooth enough to achieve smooth dimming, and the stability is not as good as the bell membership functions [18]. Therefore, the triangular and trapezoidal membership functions are not considered. The advantage of the Gaussian membership function is that its control sensitivity is higher than that of the bell membership function. However, compared to the stability of the peak of the membership function, the bell membership function is superior to the Gaussian membership function. Therefore, in order to maintain smooth dimming, this article chooses the bell membership function. The fuzzy rules and simulation environment are shown in Figures 3(A) and 3(B).




(A) Fuzzy Rule Interface

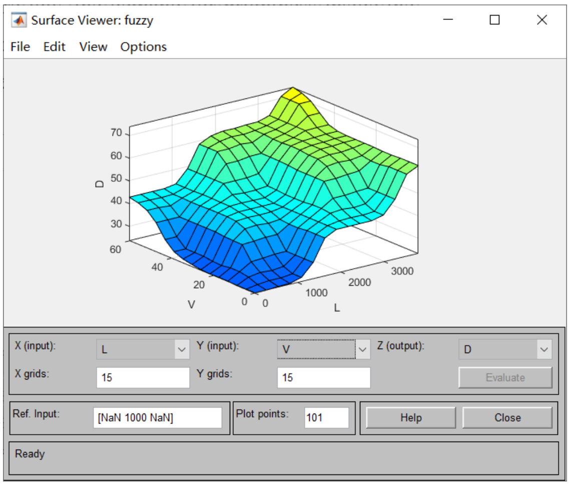



(B) Simulation environment

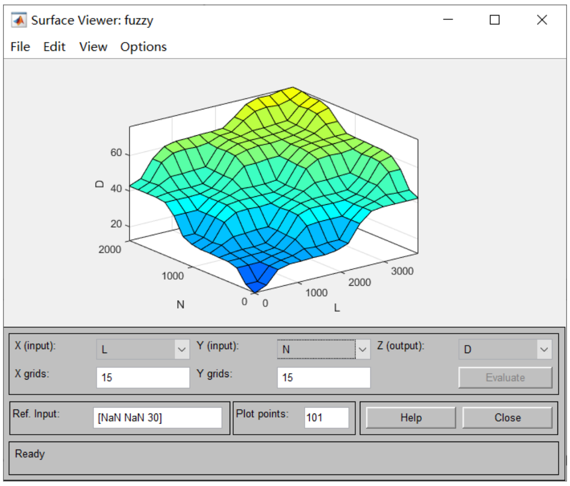
FIGURE 3. Simulation result

## 3. Simulation and analysis.

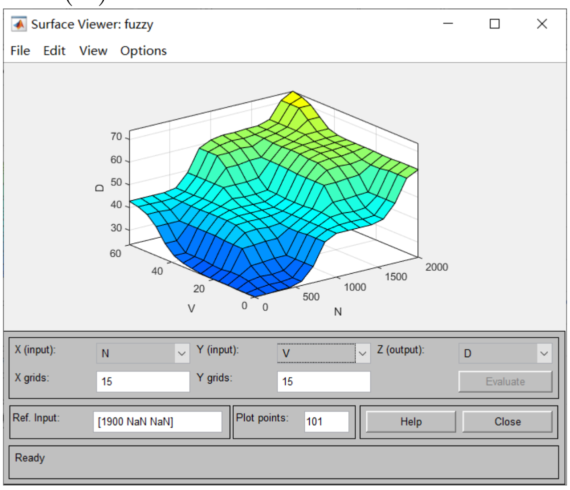
**3.1. Reasonability Analysis of Fuzzy Control Rules.** Analyze the rationality of fuzzy control rules, take fixed values for the brightness outside the tunnel, traffic flow, and vehicle speed, and output the required brightness inside the tunnel. Figures 4(A) show the output surface graph of the constant value of traffic flow, brightness outside the tunnel, and vehicle speed, with a traffic flow rate of 1000 veh/(h · ln); Figures 4(B) show the output curve of the vehicle speed with a fixed value, brightness outside the tunnel, and traffic flow. The vehicle speed is set at a fixed value of 30km/h; Figures 4(C) show the output surface graph of the brightness outside the tunnel, which is related to vehicle flow and speed, with a constant value taken. The brightness outside the tunnel is taken as 1900cd/m$^2$. Use the readfis function to call the fuzzy controller, input the brightness outside the tunnel, traffic flow, and vehicle speed data, and obtain the required brightness output curve inside the tunnel within a day as shown in Figure 4(D).




(A) Determination of traffic flow




(B) Vehicle speed determination




(C) Brightness determination


(D) Brightness output curve

Figure 4. Analysis of fuzzy control rules

From Figures 4(A), it can be seen that the traffic flow is constant. When the brightness outside the tunnel and the speed are high, the demand for brightness inside the tunnel is higher; When the brightness outside the tunnel and the vehicle speed are low, the required brightness inside the tunnel is very low. From Figures 4(B), it can be seen that at a certain speed, when the brightness outside the tunnel and the traffic flow are high, the demand for brightness inside the tunnel is higher; When the brightness outside the tunnel and the traffic flow are low, the demand for brightness inside the tunnel is very low. From Figures 4(C), it can be seen that the brightness outside the tunnel is constant. When the traffic flow and speed are high, the demand for brightness inside the tunnel is higher;

According to the brightness output curve in Figure 8, the range of required brightness in the tunnel needs to be adjusted within a day is very wide. If the required brightness in the tunnel is always set to the highest design brightness for tunnel lighting, it will inevitably cause energy waste; If you choose to operate with a low demand for brightness inside the tunnel, the driver's driving safety cannot be guaranteed during the time period when the demand for brightness inside the tunnel is high. The brightness output curve shows an increase in the demand for brightness in the tunnel during the morning and evening peak periods, with the highest demand for brightness in the tunnel at noon, which is in line with the characteristics of tunnel lighting. Fuzzy control rules are more reasonable.

3.2. **Subdivision brightness step dimming strategy.** (1) Principle of Subdivision Brightness Step Dimming Strategy LED lamps determine the output brightness by changing the amount of forward current flowing through them, but frequent changes in current can affect the lifespan of LEDs. Based on this characteristic of LED, it is best to provide a constant working current to the LED during use to ensure the stability of its various parameters [19].

In the intelligent dimming control system, the sampling time interval of the sensor determines how often the LED light is adjusted. If the sampling time is too short, it will cause frequent changes in the forward current of the LED, causing unstable dimming. If the sampling time is too long, it will cause insufficient dimming. Therefore, the design of this paper is based on fuzzy rules to analyze and classify real-time parameters, so the mapping ability of neural networks to complex nonlinear systems is needed. Belonging to the same brightness step does not require dimming. Lighting according to the maximum brightness of this brightness step not only ensures real-time dimming of tunnel lighting, but also avoids frequent dimming of LED lamps.

In summary, the segmented brightness step dimming strategy is different from the traditional control mode of graded dimming. It is based on real-time changes in brightness outside the tunnel, traffic flow, and vehicle speed data to grade the required brightness inside the tunnel. Real time dimming can be performed, rather than simply based on time or a single factor. At the same time, the division of the required brightness in the tunnel by the brightness ladder is much smaller than the span of traditional brightness grading. Therefore, the dimming strategy of subdividing the brightness ladder can effectively solve the problem of excessive dimming amplitude in traditional lighting control, which is prone to glare.

(2) Division of brightness steps

The implementation premise of the subdivided brightness step dimming strategy is to complete the division of the brightness step. The division of the brightness step needs to be determined based on the specific brightness characteristics required in the tunnel. Figures 2-10 show the variation curve of the required brightness in the tunnel over time within a day output by the fuzzy controller.

In the figure, it can be seen that the range of changes in the required brightness inside the tunnel within a day is relatively large, almost spanning the entire design brightness range. However, the distribution of the maximum and minimum values of the required brightness inside the tunnel is relatively concentrated. Dividing the brightness ladder based on the characteristic that the maximum and minimum values are concentrated in a fixed time interval can help reduce the dimming frequency of LED lamps.

The situation where the required brightness in the tunnel is less than $20\text{cd/m}^2$ is concentrated from 1pm to 5am, so the lowest brightness ladder can be set to $20\text{cd/m}^2$. During this time period, LED lighting fixtures maintain a brightness of $20\text{cd/m}^2$, which can ensure the required brightness in the tunnel is achieved and the stability of LED lighting current during this time period can be maximized. Similarly, $70\text{cd/m}^2$ is set as the highest brightness step. The remaining required brightness in the tunnel is evenly distributed, and the brightness ladder is divided by the method of average distribution. The specific brightness ladder division is shown in Table 4.

Table 4. Brightness step division table

| Brightness ladder | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| Demand brightness | (0,20] | (20,30] | (30,40] | (40,50] | (50,60] | (60,70] | (70,83.6] |
| Output brightness | 20 | 30 | 40 | 50 | 60 | 70 | 83.6 |

## 4. Design and optimization of classification prediction models.

**4.1. BP neural network.** BP neural networks generally have a structure of three or more layers. As shown in Figure 5, the structure of a three-layer BP neural network is shown. The input signal passes through the input layer, hidden layer, and output layer in sequence, and the output result is not fixed. The number of hidden layers is not fixed and can be increased according to actual needs. The BP neural network has no connections to the neurons within the same layer and can achieve full connectivity between each layer. It is a feedback free network and is trained using a guided learning method [20].

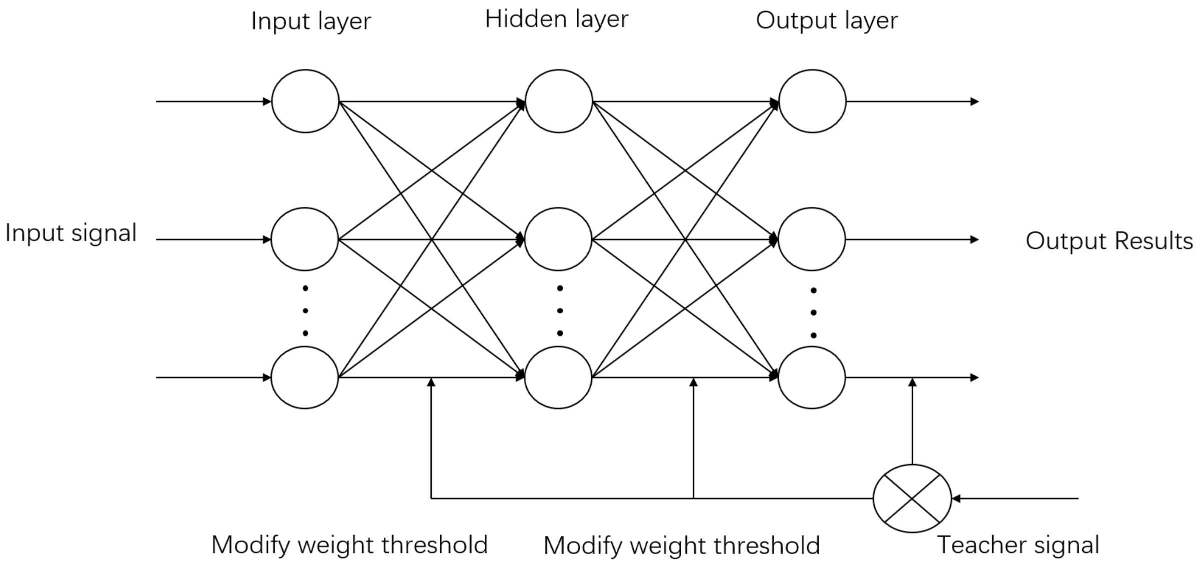



Figure 5. Three layer BP neural network structure

The forward propagation process of input samples, the backward propagation process of output errors, and the cyclic memory training process constitute the implementation process of the BP neural network learning algorithm [21].

BP neural network has strong generalization ability and can complete any complex nonlinear mapping problem according to mathematical logic analysis. At the same time, the BP network is easy to expand, and once its standards change, only the training method of the network needs to be modified to complete the creation of new input output maps [22,23]. So BP neural network has been widely studied and promoted by many scholars, and at the same time, BP neural network also has some shortcomings:

(1) The BP neural network adopts a gradient descent learning method, so it is easy to fall into local extreme points during the learning convergence process, resulting in training failure.

(2) The selection of the number of hidden layers and nodes is generally based on experience or repeated experiments, lacking theoretical guidance.

4.2. **Particle Swarm Optimization.** Suppose a group of particles are randomly initialized in a solvable space. Each particle represents a potential solution to the actual problem. The position, speed and fitness values of each particle represent its characteristics. Particles move in solvable space, and the best position experienced by each particle itself is the individual extremum *pbest*, while the optimal solution found by the entire population is the global extremum *gbest*. When particles move in space, it is necessary to judge whether the individual extreme value needs to be updated by comparing the individual extreme value with the current fitness value, and whether the global extreme value needs to be updated by comparing the individual extreme value with the global extreme value [24]. When finding individual and global extremum values, particles can update their speed and position according to the following formula:

$$v_{i+1} = \omega * v_i + c_1 r_1 (p_{bi} - x_i) + c_2 r_2 (g_{bi} - x_i) \tag{6}$$

$$x_{i+1} = x_i + v_{i+1} \tag{7}$$

Among them, $c_1$ and $c_2$ are learning factors, taking the random number between $(0, 2)$; $\omega$ is the inertia weight factor; $r_1$ and $r_2$ is a uniform random number within the range of (0,1); $v_i$ is the velocity vector of the particle, $v_i \in [-v_{\max}, v_{\max}]$, $v_{\max}$ is a constant; $p_{bi}$ is the current optimal position of the particle, which is the individual extreme value, $g_{bi}$ is the global extremum of the current particle swarm. The process of particle swarm optimization algorithm is shown in Figure 6.

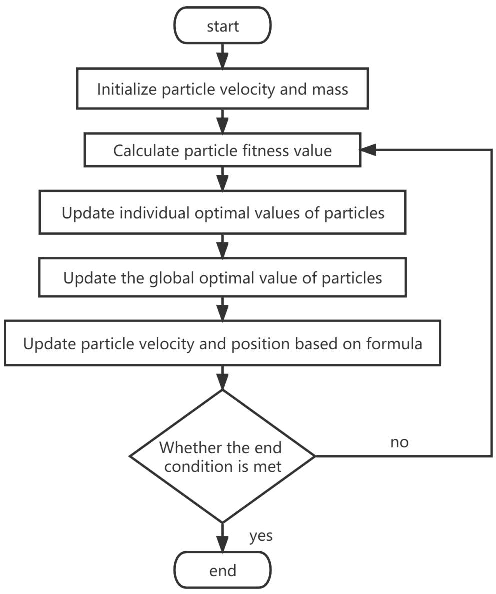



Figure 6. Particle Swarm Optimization Algorithm Flowchart

4.3. **Optimization of classification prediction model.** (1) Design of BP neural network classification and prediction model

1. Selection of hidden layers

BP neural networks can contain different numbers of hidden layers, but Hecht has proven that a hidden layer can complete any mapping from multi-dimensional to multi-dimensional. So, although there is no limit to the number of hidden layer nodes, usually only one hidden layer is selected. The two hidden layers can not significantly improve the performance, but increase the complexity of the network, reduce the efficiency of the optimization algorithm, and may also cause overfitting. Therefore, this article adopts an implicit layer.

2. Node design of each layer

The classification prediction model in this article has three input parameters, namely brightness outside the tunnel, traffic flow, and vehicle speed. The output brightness ladder is divided into seven categories. From this, it can be concluded that the prediction model designed in this article should have 3 nodes in the input layer and 7 nodes in the output layer. The number of hidden layer nodes can usually be calculated based on the following experience:

$$p = \sqrt{n+q} + b \tag{8}$$

In the formula, n represents the number of input layer neuron nodes, q represents the number of output layer neuron nodes, b is an integer between 1 and 10, and p represents the number of hidden layer neuron nodes. According to this empirical formula, the number of neuron nodes in the hidden layer is 5∼14. In this paper, the Control variates is used. With the same data set and the same training times and other conditions, after many experiments, by comparing the size of the experimental mean square error, the number of neuron nodes in the hidden layer is finally determined to be 12.

(2) Particle Swarm Optimization of BP Neural Network In this paper, the particle swarm optimization algorithm is mainly used to optimize the weights and thresholds of the BP neural network, and optimize some parameters of the particle swarm optimization algorithm.[25,26,27] The optimization process is shown in Figure 7, and the steps shown in the flow chart are as follows:

1. Determine the topology structure of the BP neural network, initialize the weights and thresholds of the network. The weights and thresholds of BP network are regarded as the particles of particle swarm optimization algorithm.

2. Initialize the population by randomly generating the initial position and velocity of particles. Set learning factors $c_1$ and $c_2$, convergence accuracy $\delta$,Inertia factor $\omega$ The values of parameters such as maximum number of iterations.

This article adopts adaptive adjustment $\omega$ The method of taking values. This adaptive adjustment $\omega$ The method of taking values can make $\omega$ The value of decreases gradually as the number of iterations increases, $\omega$ The adaptive value taking function is as follows:

$$\omega = \omega_{max} - \mathrm{a}\frac{(\omega_{max} - \omega_{min})}{b} \tag{9}$$

In the formula, a represents the current number of iterations, and $b$ represents the total number of iterations, $\omega_{max}$ and $\omega_{min}$ is the maximum value of the inertia factor and the minimum value of the inertia factor, respectively.

3. Particle fitness value calculation: complete the fitness value calculation of each particle in the population according to the fitness function.

4. First, judge the individual optimal value of the particle. By comparing the fitness value of the current particle with the fitness value of the historical optimal position of the particle, if the current position is better, update the individual extreme value, otherwise maintain the historical optimal position. Similarly, by comparing the fitness value of the historical optimal position of particles with the fitness value of the global optimal position, if the global extreme value is inferior to the particle extreme value, the global optimal position will be updated, otherwise, the historical optimal position of the current global extreme value will be maintained [28].

5. Update the velocity and position of particles according to Formulas (6) and (7).
6. Before reaching the set maximum number of iterations or failing to meet convergence accuracy $\delta$, Repeat Steps (3) to (5).
7. After the particle swarm optimization algorithm is completed, the optimal weights and thresholds of the BP neural network are obtained, and the obtained weights and thresholds are substituted into the BP neural network for re learning and training to obtain the final prediction result.

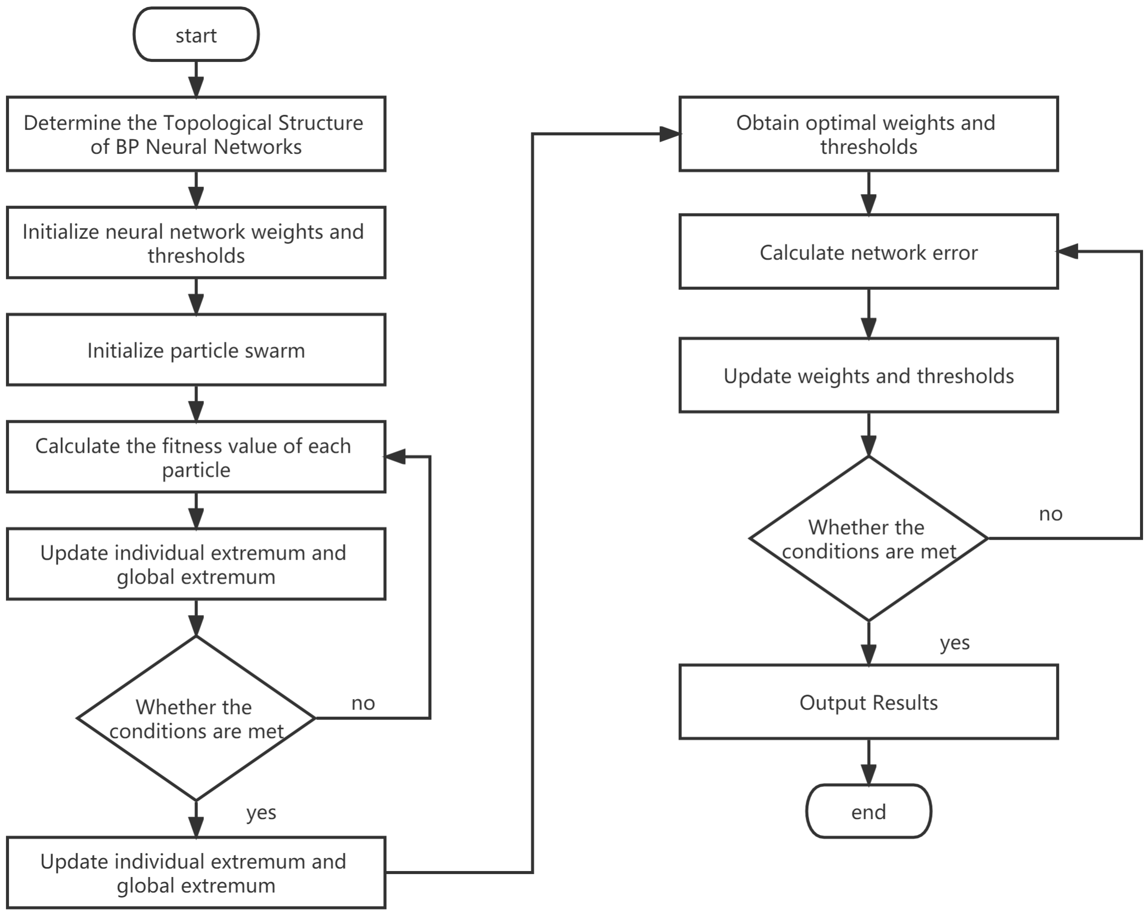



FIGURE 7. Particle Swarm Optimization BP Neural Network Flowchart

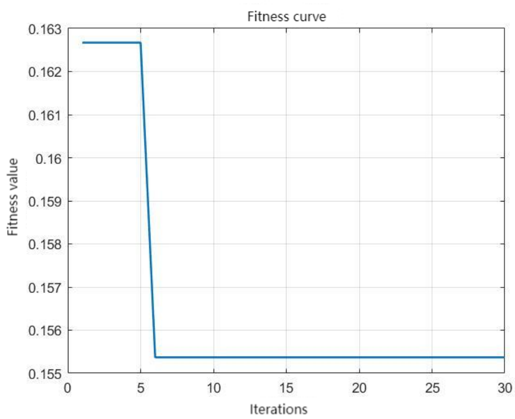
## 5. **Simulation and analysis.**

5.1. **Data processing.** In order to train the model's ability to classify and predict various traffic situations, mathematical methods were used to expand the data samples to 1000 sets. The readfis function was used to call the fuzzy controller to batch process the samples and obtain the corresponding results of the required brightness in the tunnel. 800 sets of data were selected for training, and the remaining 200 sets of data were tested. Table 5 shows some data processed by some fuzzy control rules. Due to the different dimensions of the values of various factors that affect the required brightness in the tunnel, if there is a significant difference in the order of magnitude between the input and output, the classification prediction error will be large. Therefore, in order to accelerate the training speed of the neural network, the data samples are normalized. After completing the BP neural network learning and training, the results are subjected to reverse normalization processing to restore the final output results to normal values.

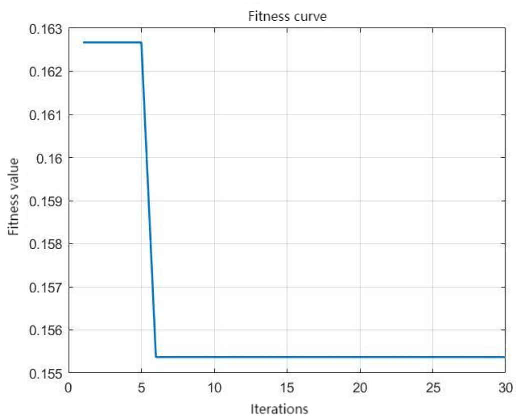
TABLE 5. Data processed by fuzzy rules

| Serial Number | brightness | Traffic volume | speed | Demand brightness | Brightness ladder |
|---|---|---|---|---|---|
| 1 | 14 | 110 | 34 | 13.9 | 1 |
| 2 | 199 | 289 | 55 | 25.4 | 2 |
| 3 | 55 | 1025 | 44 | 32.5 | 3 |
| 4 | 1814 | 947 | 40 | 45.8 | 4 |
| 5 | 2544 | 836 | 49 | 58.5 | 5 |
| 6 | 3703 | 1024 | 33 | 62.3 | 6 |
| 7 | 3658 | 1364 | 29 | 70.8 | 7 |

5.2. **Brightness step classification prediction results.** In this chapter, the root mean square error of training is taken as the fitness function of PSO-BP and the improved PSO-BP. The smaller the fitness value of the model, the smaller the classification prediction error, and the higher the classification prediction accuracy of BP neural network. After the simulation through MATLAB software, the change curve of the fitness value of the PSO-BP prediction model and the improved PSO-BP prediction model is shown in Figure 8. The PSO algorithm has a strong ability to search for the optimal weights and thresholds of the BP neural network, and a better fitness value can be obtained when the number of iterations is less than 10. The improved PSO algorithm also improves the ability to ensure local convergence on the premise of ensuring the global search ability, Under the condition that the number of iterations is almost constant, a better fitness value is obtained.




(A) PSO-BP fitness curve




(B) Improved PSO-BP fitness curve

FIGURE 8. Fitness curve

The classification results of BP model, PSO-BP model and improved PSO-BP model are shown in Table 6. The accuracy of the BP prediction model for brightness step classification prediction is 78%, and the accuracy of PSO-BP is 86.5%. The improved PSO-BP prediction accuracy can reach 90.5%.

The accuracy of the BP prediction model is relatively low, which verifies the shortcomings of BP neural networks such as being prone to falling into local extremes. It is necessary to optimize the weights and thresholds to improve performance. The PSO-BP model has improved prediction accuracy compared to the BP model, indicating that the particle swarm optimization algorithm can optimize the weights and thresholds of the BP neural network. The optimized weights and thresholds improve the prediction accuracy of the BP neural network. The improved PSO-BP model has the highest prediction accuracy, which can verify the inertia factor $\omega$ The size of the value does have an impact on the performance of particle swarm optimization algorithms. This article adopts adaptive adjustment $\omega$ The method of taking values enables particle swarm optimization algorithm to achieve significant performance in the early stages $\omega$ Value, thus ensuring the global search ability of particle swarm optimization algorithm in the early stage, and inertia weight as the number of iterations increases $\omega$ The value of gradually decreases, so it can easily jump out of the local minimum, making the improved PSO-BP prediction model search for the best value among these models.

Table 6. Classification prediction accuracy

| Type | BP | PSO-BP | Improved PSO-BP |
|---|---|---|---|
| Accuracy rate | 78% | 86.5% | 90.5% |

The improved PSO-BP model has a high accuracy in classifying brightness steps. In order to test the model's ability to classify brightness steps in actual tunnel lighting situations, the model was used to test some measured data. Figure 9 shows the accuracy of classification prediction. The normal traffic data input parameters have fewer outlier, and the accuracy of classification prediction has been improved. The accuracy of classification prediction for 50 groups of data is 96%, which can better complete the classification prediction task of the brightness ladder, and provide a new method for the division of the required brightness in the tunnel.

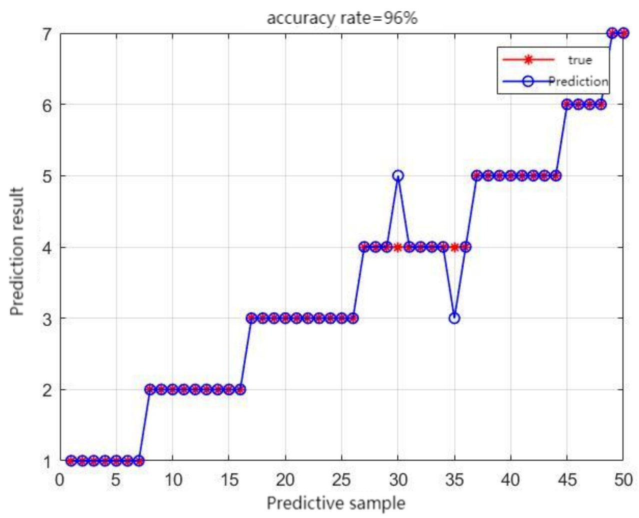



Figure 9. Accuracy of brightness step classification prediction

5.3. **Energy saving performance analysis.** After completing the design and simulation of the control strategy, energy-saving analysis will be conducted by comparing the widely used time control mode, outdoor brightness adaptive mode, and fuzzy control method. Figure 10 shows the required brightness curve inside the tunnel under four lighting modes.

From the figure, it can be seen that the demand for brightness in the hole of the segmented brightness step dimming strategy is significantly lower than that of the time control mode, therefore, the energy-saving performance is much higher than that of the time control mode.

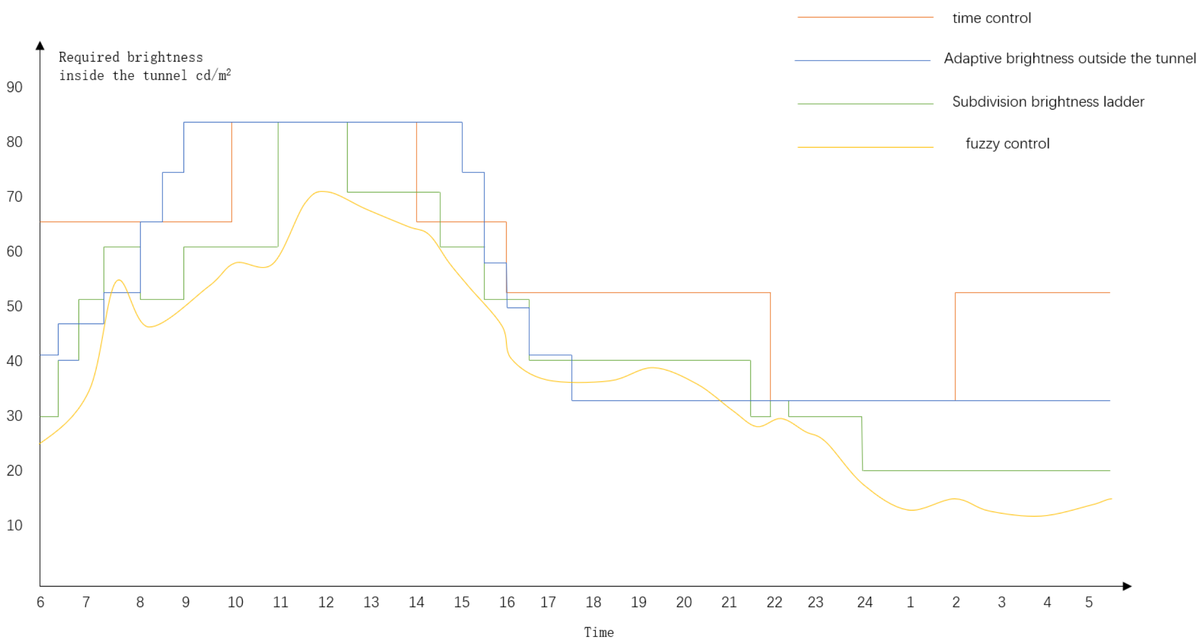



FIGURE 10. Luminance demand curve inside the tunnel

Compared with the adaptive mode of brightness outside the tunnel, the overall demand for brightness inside the tunnel is also significantly reduced, and the output brightness is greater than the adaptive mode of brightness outside the tunnel during the morning and evening peak periods. Whether in the morning or evening, the brightness outside the cave is relatively low, so it is difficult to meet the actual situation and provide safe and reasonable lighting control solely by adjusting the brightness outside the cave. The subdivided brightness step dimming strategy can adjust the required brightness inside the tunnel in real-time based on multiple parameters.

Compared with fuzzy control, the dimming frequency of LED lamps under the segmented brightness step dimming strategy is significantly reduced, which is conducive to ensuring the stable dimming and long-term service life of LED lamps. On the basis of energy-saving lighting, it ensures energy-saving in tunnel lighting construction and maintenance costs, ensures the stability of dimming, and also ensures the safety of drivers.

The curves and the area enclosed by the horizontal axis in Figures 4-7 represent the electrical energy consumption of each lighting mode [29]. By calculation, compared to the time control method, the control method of subdividing the brightness step can save 31.1% of electricity. Although the energy-saving rate of the fuzzy control method has slightly decreased, it can still reduce significant electricity waste and greatly improve the stability and safety of dimming. Therefore, this dimming strategy is superior to other control modes.

6. **Conclusion and outlook.** Based on the verified fuzzy control rules, the BP neural network in neural network control is selected to design the brightness step classification prediction model, and an improved particle swarm optimization algorithm is used to optimize the weights and thresholds of the BP neural network, further improving the

prediction accuracy, with a prediction accuracy of 96%. Compared to the widely used time control modes, it has been calculated and analyzed that the segmented brightness ladder strategy can save 31.3% of electricity while also reducing the frequency of dimming, effectively extending the service life of the lamp. There are still some shortcomings in this study.When studying the fuzzy control rules of urban tunnel lighting, only the brightness outside the tunnel and the vehicle are considered.In the actual urban tunnel environment, there are several influencing factors, such as flow and speed, as well as visibility and automobile exhaust.Concentration and other influencing factors, more parameters should be selected for further study and analysis. As well as using a single algorithm to optimize the BP neural network classification prediction model, the shortcomings of the algorithm itself cannot be avoided. The accuracy of classification prediction can be further improved by using fusion algorithm and adding chaotic mapping.

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## REFERENCES

[1] Ministry of Transport of the People's Republic of China Statistical Bulletin on the Development of the Transportation Industry in 2021, 2022.

[2] L. Qin, L. Dong, W. Xu, "An intelligent luminance control method for tunnel lighting based on traffic volume," *Sustainability*, vol. 9, no. 12, pp. 2208, 2017.

[3] L. Wang, "Complex systems modeling via fuzzy logic," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 26, no. 1, pp. 100-106, 1996.

[4] X. Sha, "Research on Energy Saving Technology of LED Light Source in Huangyan ExpresswayTunnel Lighting," *Highway Engineering*, vol. 43, no. 6, pp. 299–303, 2018.

[5] H. Don, "Design of LED Tunnel Lighting Intelligent Control System," Ph.D.dissertation, South China University of Technology, 2016.

[6] W. He, H.-B. Qin, G.-F. Du, "Design of Tunnel Lighting Control System Based on Fuzzy PID Algorithm," *Measurement and Control Technology*, vol. 39, no. 7, pp. 113–116+121, 2020.

[7] Industry Recommended Standards of the People's Republic of China, "Detailed Rules for Lighting Design of Highway Tunnels," Ministry of Transport of the People's Republic of China, 2014.

[8] W. Wang, "Research on Navigation Control System of Wheeled Robot Based on ARM," Ph.D.dissertation, Beijing University Of Posts and Telecommunications, 2011.

[9] C.-M. Li, "Design of Intelligent Tunnel Lighting Control System," Ph.D.dissertation, Hunan University, 2018.

[10] K. Wang, P. Xu, C.-M. Chen, K. Saru, S. Mohammad, A.Mamoun, "Neural architecture search for robust networks in 6G-enabled massive IoT domain," *IEEE Internet of Things Journal*, vol. 8, no. 7, pp. 5332-5339, 2020.

[11] P. Xu, K. Wang, M.H. Mohammad, C.-M. Chen, W.-G. Lin, R.H. Md, F. Giancarlo, "Adversarial Robustness in Graph-Based Neural Architecture Search for Edge AI Transportation Systems," *IEEE Transactions on Intelligent Transportation Systems*, vol. 24, no. 8, pp. 8465-8474, 2023.

[12] J.-N. Chen,Y.-P. Zhou, Z.-J. Huang, "An Efficient Aggregate Signature Schemefor Healthcare Wireless Sensor Networks," *Journal of Netuwork Intelligence*, vol. 6, no. 1, pp. 1-15, 2021.

[13] H. Xiong, Z. Qu, X. Huang, K.-H. Ye, "Revocable and Unbounded Attribute-based Encryption Scheme with Adaptive Security for Integrating Digital Twins in Internet of Things," *IEEE Journal on Selected Areas in Communications*, 2023. [Online]. Available: https://doi.org/10.1109

[14] H. Xiong, H.-X. Wang, W.-Z. Meng, K.-H. Ye, "Attribute-based Data Sharing Scheme with Flexible Search Functionality for Cloud Assisted Autonomous Transportation System," *IEEE Transactions on Industrial Informatics*, 2023. [Online]. Available: https://doi.org/10.1109

[15] G.-B. Sun, S. Zhou, Y.-J. Chiu, "Motor Torque Compensation Control Strategy of PureElectric Bus Based on Fuzzy Reasoning," *Journal of Network Intelligence*, vol. 8, no. 1, pp. 237-258, 2023.

[16] J. Wang, "Research on Fuzzy Control of Urban Intelligent Lighting System Based on Illumination and Traffic Flow," Ph.D.dissertation, University of Electronic Science and technology, 2017.

[17] J.-L. Liu, "Research on short-term photovoltaic power generation power prediction based on similar day theory and PCA-IPSO-Elman model," Ph.D.dissertation, Lanzhou Jiaotong University, 2019.
[18] G.-F. Du, "Design of Tunnel Lighting Control System Based on Fuzzy PID," Ph.D.dissertation, HangZhou DianZi University, 2019.
[19] L.-N. Zhao, "Research and Design of a Three Channel Wide Voltage Switching High Power LED Driver Circuit," Ph.D.dissertation, Xi'an University of Electronic Science and Technology, 2012.
[20] Y.-M. Gao, "Short term power load forecasting based on GA-PSO algorithm optimized BP network," Ph.D.dissertation, Guizhou Normal University, 2014.
[21] Y.-Y. Chenxie, "Research on the Application of GA-PSO-BP Neural Network in the Prediction of Copper and Zinc Content in EDXRF," Ph.D.dissertation, East China Institute Of Technology, 2022.
[22] X.-M. You, "Experimental Study on the Explosion Characteristics of the Interaction between Liquid Lithium and Coolant," Ph.D.dissertation, Shanghai Jiaotong University, 2017.
[23] K.-Y. Liu, "Development of a water quality detection platform for fish pond aquaculture based on BP neural network," Ph.D.dissertation, chongqing university of technology, 2022.
[24] D.-Y. Cui, "Research on the Turbine Digital Electric Hydraulic Control System Modeling Simulation and Parameter Optimization Based on the Method of Modified Particle Swarm Optimization," Ph.D.dissertation, North China Electric Power University, 2016.
[25] F.-Q. Zhang, S.-Y. Wu, Y. Wang, R. Xiong, G.-Y. Ding, P. Mei, L.-Y. Liu, "Application of quantum genetic optimization of LVQ neural network in smart city traffic network prediction," *IEEE Access*, vol. 8, pp. 104555-104564, 2020.
[26] T.-Y. Wu, A.-K. Shao, J.-S. Pan, "Toward a Chaotic-Based Tumbleweed Optimization Algorithm," *Mathematics*, vol. 11, no. 10, 2339, 2023.
[27] T.-Y. Wu, H.-N. Li, S.-C. Chu, "An Improved Phasmatodea Population Evolution Algorithm with Chaotic Maps," *Mathematics*, vol. 11, no. 9, 1977, 2023.
[28] Y.-F. Ren, S. Tian, X.-Y. Shao, "NRDBA-BP reference crop evapotranspiration prediction based on MIV," *Journal of Shaanxi University of Technology*, vol. 37, no. 2, pp. 48–56, 2021.
[29] X.-H. Li, "Research on energy-saving control of highway tunnel lighting," Ph.D.dissertation, Shijiazhuang Tiedao University, 2020.