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Nonlinear system analysis and control of electrical intelligent control platform based on automatic control principles

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ABSTRACT

In recent years, intelligent control has realized rapid development in the field of electrical engineering, the article initially studied the principle of electrical intelligent control, accordingly built the electrical intelligent control system, and designed the system hardware, the system module is divided into the main control module, the expansion module, the digital input and output module and the mounting rail. Based on the working principle of fuzzy control, design the software of the electrical intelligent control system, and optimize the traditional fuzzy controller by using fuzzy adaptive hybrid genetic algorithm, so as to improve the fuzzy control accuracy of the electrical intelligent control system in this paper. The electrical control system of this paper is applied to greenhouse greenhouse temperature and humidity control, substation air conditioning energy consumption control and subway station illumination control, and the control effect of the electrical intelligent control system of this paper is known through three experimental data. The system of this paper can effectively deal with the dissimilar data in the greenhouse temperature control experiment. Under the steady state environment, the temperature deviation of this paper's fuzzy control method and conventional single structure fuzzy control is within 0.1℃ and 1℃ respectively, and the humidity deviation is within 5%RH and 10%RH respectively. Obviously, the fuzzy control method in this paper has higher control accuracy. In the substation air conditioning energy consumption experiment, the annual power consumption of this paper's electrical intelligent control system and the traditional ventilation and air conditioning system are 32,660 degrees and 45,620 degrees, respectively. The electrical intelligent control system in this paper can save 22,000 yuan per year. The output illuminance of the subway station of the fuzzy control system in this paper increases with the comfort of the light environment and the density of the crowd, which achieves the expected effect.

Keywords: intelligent control; fuzzy control; fuzzy adaptive hybrid genetic; system analysis

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1. Introduction

As the pace of economic and technological progress is accelerating globally, various advanced control theories have been put forward and gradually applied to industrial production and people's daily life. The core idea of intelligent control lies in realizing self-adaptive, self-learning and self-optimizing control of complex systems. Traditional control methods often rely on precise mathematical models and fixed control strategies, which are difficult to cope with the nonlinearity, time-varying, uncertainty and other factors existing in the actual system [1-2]. Intelligent control, on the other hand, by simulating human thinking and behavioral processes, utilizes the powerful computing ability of computers to perform real-time perception, analysis, decision-making and control of the system. It can automatically adjust the control strategy according to the operational status of the system and changes in the external environment to achieve the optimal control effect [3-4]. As an important basic part of modern industrial production and urban construction, the control ability of electrical engineering has become an important factor in limiting and enhancing economic and social progress. At the same time, for the control in electrical engineering has become more and more complex, modern control theory and technology are gradually proposed and widely applied, and play a great advantage.

Linear control theory has been widely used in electrical engineering automation and has achieved certain results. However, in fact, the linear control technology is designed by model simplification through the stabilization of local linearity in the work of electrical products, and the inherent nonlinear characteristics of electrical products and equipment themselves are not taken into account, and there are always large control loopholes [5]. For example, linear control depends on the state variables fed back from product operation to realize control, and there are many variables in system operation that are not easy to measure [6]. Therefore, the development of electrical engineering in various fields, but also put forward higher requirements for its control technology, the practice needs to appear based on nonlinear control theory to make up for the shortcomings of linear control technology.

Electrical engineering automation is becoming the future direction of electrical systems, and intelligent control is the key node of electrical automation among them. Issaadi, S. et al. proposed a neural network based control strategy for photovoltaic (PV) power generation, which regulates the impedance of the electronic controller through an algorithm so that the PV generator can deliver the maximum output of power to the load in any condition. In addition, the neural network technology provides the ability to have the Lupin The neural structure of the neural network can be more accurate for optimal control regulation [7]. Yeganeh, M. S. O. et al. introduced Brain Emotional Learning Based Intelligent Controller (BELBIC) into the distributed intelligent control system of microgrids, which is capable of regulating the voltage amplitude and frequency deviation without adjusting the system model and parameters, and ensures that it carries out a low steady state variation at a higher bandwidth [8]. Lipu, M. H. et al. developed an advanced battery management system for electric vehicles based on highly efficient intelligent algorithms and controller methods to further improve the battery performance by exerting its precise detection, stable control, and safety protection functions [9].

Fuzzy control techniques applied in electrical engineering are able to reflect the nonlinear time-varying of the system and do not require mathematical model simplification and transformation of the controlled system, which makes it more flexible in the design of electrical products. Riahi, J. et al. designed a fuzzy controller capable of regulating the internal temperature and humidity of an agricultural greenhouse, and established a vector control model based on the optimization of fuzzy logic with the objective of reducing the cost of agricultural production. The optimal internal climate was achieved by driving a variable speed fan [10]. Arya, Y. pointed out that power systems with robust and intelligent automatic control strategies can effectively solve the performance degradation problem of large interconnected power systems, based on which a fuzzy classical controller based on the output scaling factor (SF) is proposed, and the results of the sensitivity analysis show that the proposed method is robust to a wide range of variations in the power system parameters, as well as in the magnitude and location of the step load disturbances [11]. Kryukov, O. V. et al. investigated the application of state-variable fuzzy logic control and artificial neural networks to redundant energy-efficient motor drives to achieve intelligent control and detection of the drive by formulating different control optimization strategies for stochastic and deterministic ingress states [12].

The existence of nonlinear dynamics in electrical systems cannot be ignored, so a large number of scholars have carried out research on the related problems. Hannan, M. A. et al. designed robust switches and controllers for the dynamic structure of three-phase induction motors as a nonlinear system, introduced intelligent controllers using different techniques in terms of scalar control and vector control, and made theoretical contribution to the development of induction motor drives [13]. Xu, B. et al. combined a strict feedback system with dynamic surface control and a controllable specification system with sliding mode control, and utilized the intelligent design and lupin technique to make the intelligent control have high tracking accuracy and strong robustness in nonlinear systems [14]. Chang, S. et al. showed that nonlinear control processes can have an impact on the stability of industrial control systems and proposed improvements to generalized auto-immunity control (GADRC) so that it can utilize the known information of the controlled object model to obtain reasonable controller and observer gains in order to improve the stability of the system [15]. Xu, B. et al. developed a class of uncertain strict feedback systems with robust design and learning, which utilizes a robust switching mechanism to pull back states beyond the adaptive control region, in addition to constructing an adaptive law based on the prediction error, which allows for more accurate state tracking performance [16]. Aourir, M. et al. described the process of designing a nonlinear controller for a single-stage PV grid-connected system, where power factor correction is achieved through a multi-loop controller and the DC link voltage-power balance is ensured through a filtered PI regulator, and simulation experimental results show that the designed nonlinear controller possesses a strong performance [17].

The article builds an electrical intelligent control system according to the principle of electrical intelligent control. The hardware design of the electrical control system and the software design of the electrical intelligent control system are based on the working principle of fuzzy control. The conventional fuzzy controller is optimized by fuzzy adaptive hybrid genetic algorithm to improve the fuzzy controller control accuracy of the electrical intelligent control system in this paper, and optimize the fuzzy controller factor and affiliation function. Then, the electrical intelligent control system constructed in this paper carries out multi-scenario experiments, respectively, in the greenhouse greenhouse, substation and subway station for temperature and humidity, air conditioning energy consumption and illumination control, according to the experimental results to explore the application effect of this paper's electrical intelligent control system.

2. Electrical intelligent control system construction

2.1. *Electrical Intelligent Control*

The core idea of intelligent control lies in realizing self-adaptive, self-learning and self-optimizing control of complex systems [18]. Traditional control methods often rely on precise mathematical models and fixed control strategies, which are difficult to cope with the nonlinearity, time-varying, uncertainty and other factors existing in the actual system. Intelligent control, on the other hand, carries out real-time perception, analysis, decision-making and control of the system by simulating the human thinking and behavioral process and using the powerful computing capability of computers. It can automatically adjust the control strategy according to the operational status of the system and changes in the external environment to achieve the optimal control effect. The technical basis of intelligent control mainly includes artificial neural network, fuzzy control, genetic algorithm and so on. By simulating the structure and function of neurons in the human brain, artificial neural network establishes a model with a high degree of nonlinear mapping ability, which is able to deal with complex control problems. Fuzzy control, on the other hand, makes use of fuzzy sets and fuzzy logic to model and control systems that are difficult to describe accurately, and is particularly suitable for dealing with uncertainty and ambiguity. Genetic algorithm, on the other hand, draws on the genetic mechanism in the process of biological evolution to search for optimal control parameters and strategies by simulating natural selection and genetic processes.

In the field of electrical engineering, the application of intelligent control technology has achieved remarkable results. Taking the electric power system as an example, intelligent control can help realize the functions of automatic scheduling, fault detection and recovery of the power grid, and improve the stability and reliability of the power system. In terms of motor control, intelligent control can adjust the control parameters in real time according to the operating status of the motor and load changes, realizing the efficient operation of the motor and energy saving. In addition, intelligent control plays an increasingly important role in industrial automated production lines, robot control and other fields.

2.2. Electrical control system control principle

The control principle of the electrical control system is to control the input of the PLC through the gear output of the cam controller, and then the PLC controls the frequency converter through the CAN bus utilizing through the PROFIBUS network, and the frequency converter controls the action of the main working mechanism such as ascending, descending, and speed change respectively. By changing the power supply frequency of the asynchronous motor, the purpose of speed regulation of the motor is achieved. At the same time, the motor shaft is equipped with a photoelectric encoder through the photoelectric encoder module, constituting a closed-loop speed regulation. The control principle structure is shown in Figure 1.

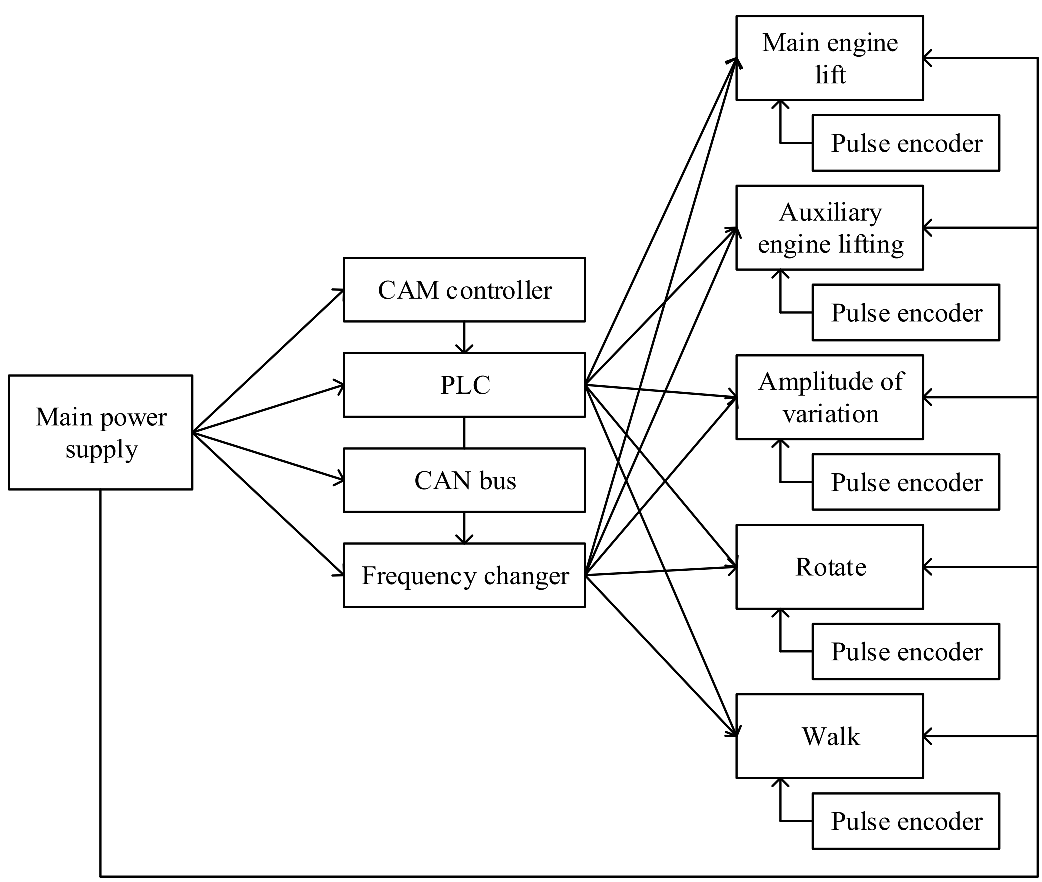

Fig. 1. The schematic diagram of control principle

2.3. Electrical control system hardware design

2.3.1. System master control. he main control of the electrical control system is controlled by SIMATIC S7-300 PLC, S7-300 is a modular PLC system, according to the need for a variety of functional modules can be combined and extended to control different requirements of the system and the control network, the instruction operation speed can be up to 0.6 ~ 0.1 μs. Floating-point numbering to achieve a more complex arithmetic operations, S7-300 operating system. The S7-300 operating system integrates the human-machine interface (HMI) service function, with powerful communication functions, which can be configured through the user interface of the engineering tool STEP7, and can be connected to the PROFIBUS-DP fieldbus and industrial Ethernet through a variety of communication processors.

The SIMATIC S7-300 PLC system consists of the central processing unit CPU, the signal module SM, the function module FM for performing special functions such as counting, positioning, closed-loop control, etc., the communication processor CP for connecting to the network and point-to-point connection, the power supply module PS for connecting the SIMATICS7-300 to a 120/230 V AC power supply, the interface module IM for connecting the mainframe CR and the expansion rack ER in a multiple rack configuration, and the placeholder module DM, the rail RACK, etc. The interface module IM for connecting the host rack CR to the expansion rack ER in a multi-rack configuration consists of the occupancy module DM and the rail RACK. The interface module IM can be used for multi-layer configuration to transfer the bus from one layer to another. The placeholder module DM is a slot reserved for unparameterized signaling modules or for later installation of interface modules.The S7-300 PLC can be connected directly to the program editor PG, the operator panel OP and other S7-PLCs via the MPI interface.

2.3.2. System Component Modules. This system PLC composition module mainly consists of the following parts: the main control module (the core of the brain), expansion module (remote IO site), digital input and output modules (acquisition and output of digital quantities) and mounting rails (the bridge between the modules connected to each other).

The structure of S7-300 PLC is 0, 1, 2, 3, ...8 slots from left to right. Slots 1 to 3 are fixedly assigned, where slot 1 inserts PS (power supply), slot 2 inserts CPU, slot 3 inserts IM, and slots 4 to 11 are assigned from the right.The S7-300 uses a backplane bus to physically and electrically connect the modules, which are fixed on DIN standard mounting rails. The system tasks require more than 8 signaling and communication processing modules, which can be expanded in multiple racks. Each rack has its own interface module inserted in a slot next to the CPU, which is responsible for communicating automatically with the other expansion racks.The slot-based addressing of the S7-300 PLC consists of the mounting rack number and the slot, rack number 0 to 3 and slot 4 to 11.All modules can be addressed by default, or you can assign your own address, which is carried out through the STEP7 software using a customized address assignment.

PLC control system hardware design selection:

1) CPU control module. The CPU module is CPU315-2DP, and the specific model is 6ES7 315-2EH14-0AB0.

CPU according to the system program in the PLC to control the entire PLC to run in an orderly manner, its main task is to accept and store the user program input from the programmer or interface, in the operation of the constant scanning of the I / O port input field status and data, and stored in the register, and then read the user instructions from the memory one by one, according to the user instructions for the transfer of data or arithmetic, to refresh the status of the relevant flag bits and the It refreshes the status of the relevant flag bits and the contents of the output image memory, and realizes output control, indicator printing or data communication functions through the output unit. It also has the function of diagnosing the internal circuit failure and syntax error of the instruction.

2) I/O signaling module. The DI module is SM321, specifically model 6ES7321-1BH02-4AA1, with transistorized inputs.

DI module includes 9 input points, each group of common endpoints number 16. The rated load voltage is 24V DC, the load voltage range is 20.4~28.8V, and the rated input voltage is 20V DC. Input voltage “1” range is 13~30V, input voltage “0” range is -3~+5V, typical power consumption is 3.5W. The input current “1” is 7mA and the maximum permissible quiescent current, e.g. for encoders, is 1.5mA. Typical input delays are 1.2 to 4.8ms, and the backplane bus consumes a maximum current of 35mA. The channels are electrically isolated from each other with an electrical test voltage of 500 V DC. Optical coupling is used between the channels and the backplane bus.

The DO module SM322, order number 6ES7322-1HH01-4AA1, is a relay output.The DO module consists of 4 inputs with 16 common endpoints per group. The rated voltage is 230V AC, the number of output groups is 8, the maximum output current is 2A, the maximum consumption current is 100mA, and the power loss is 4.5W. The capacity of the contact switch is 2A, the contact switching frequency is 2Hz for resistive loads and lamp loads, and 0.5Hz for inductive loads, and the service life is 106 times. The isolation method from the bus is photocoupling. Compared with other output methods, relay outputs offer the best safety isolation and flexibility.

3) Expansion module. ET200M is the communication module of Siemens remote workstation, which is the information exchange hub of the main control CPU and remote I/O site, and adopts the whole series of S7-300 modules.

4) Interface Module. The main function of the IM module is to provide different bus interfaces to realize the Siemens automation system and network communication, commonly used in the configuration when multiple sub-PLC control system racks connected to the host rack and expansion racks. Generally there are PROFIBUS, CAN, DeviceNet and other different interface forms.

2.4. Electrical control system software design

In the electrical equipment control system, PLC is the core control equipment, the main control functions of the system are realized by the PLC [19]. The design of the PLC control system includes the hardware configuration of the system, the production of the unit control flowchart, ladder programming, debugging, etc., to send some of the work is mainly through the CX-Programmer software to achieve. The software is Omron Group developed specifically for Omron PLC configuration and programming application software package PW. PLC control system design process in this paper is shown in Figure 2.

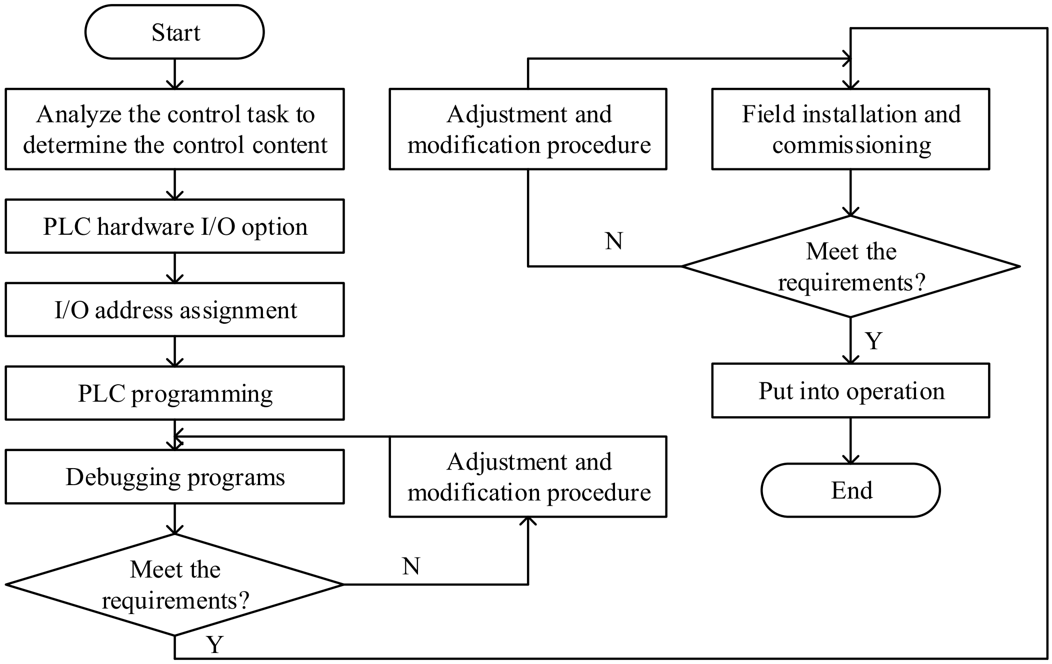

Fig. 2. The design steps of PLC control system

2.4.1. Working principle of fuzzy control:

1) The basic structure of fuzzy controller. Fuzzy control system is a kind of automatic control system, which is a digital control system constituted by computer technology with fuzzy language, fuzzy mathematics and other modern control theories as the theoretical basis [20]. It is summarized into a control language through people's experience, and then use fuzzy reasoning method to get the control quantity suitable for the control requirements. Fuzzy control system is usually composed of four components such as given input, fuzzy controller, controlled object and feedback signal. The structure of fuzzy control system is shown in Figure 3.

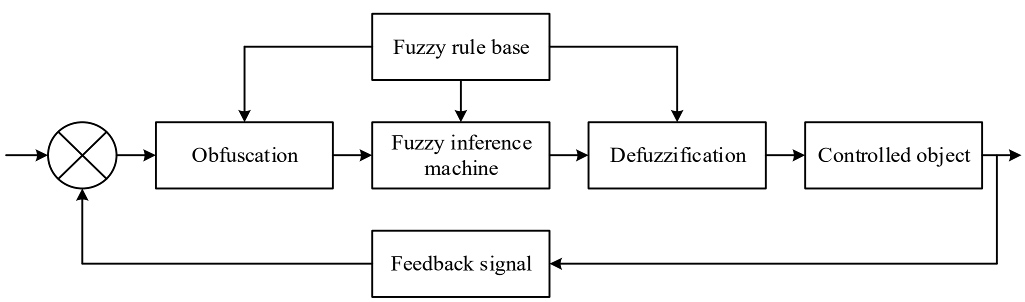

Fig. 3. Fuzzy control system structure

The fuzzy controller mainly consists of fuzzification, fuzzy rule base, fuzzy inference machine and inverse fuzzification and. Fuzzification is to transform the exact input of measurement into fuzzy variable language, fuzzy rule base stores all the rules in the fuzzy controller, which can be represented by several fuzzy pressure IF-THEN statements, and fuzzy inference machine deduces the fuzzy value of the output through fuzzy inference algorithm according to the rules in the fuzzy rule base, and then transforms it into the exact output variable through defuzzification.

2) Fuzzy inference algorithm. For fuzzy control the control algorithm is very important, the algorithm is good or bad directly determines the effect of system control. The realization of the fuzzy control function is realized by the computer through a certain algorithm. After the precise input quantity is

passed through the fuzzy algorithm, the corresponding precise output quantity is obtained, so as to control the controlled object. Commonly used control algorithms are inference method, table lookup method, self-correction method and analytic method. These algorithms mainly appear through the form of fuzzy reasoning [21]. The common inference methods are CRI method, Mamdani method and Tsukamoto method, among which Tsukamoto method, also called intensity transfer method, is intuitive and clear in its inference and simple in its computation, so Tsukamoto method is chosen in this project.

Let the input quantity be X_1, X_2 and the output quantity be Y and their linguistic variables are denoted by A_{i1}, B_{i2} and Y_i respectively. Then there are:

$$\begin{gathered} X_1 = \{A_{11}, A_{21}, \cdots, A_{j1}\} \\ X_{21} = \{B_{12}, B_{22}, \cdots, B_{k2}\} \\ Y = \{Y_1, Y_2, \cdots, Y_m\} \end{gathered} \tag{1}$$

And there is:

$$\begin{cases} \text{if } X_1 = A_{11}, \text{and } X_2 = B_{12}, \text{then } Y_1 = Y_1 \\ \text{if } X_1 = A_{21}, \text{and } X_2 = B_{22}, \text{then } Y_1 = Y_2 \\ \vdots \\ \text{if } X_1 = A_{j1}, \text{and } X_2 = B_{k2}, \text{then } Y_1 = Y_m \end{cases} \tag{2}$$

The detailed steps of the intensity transfer method are as follows:

Let input $X_1 = a_1, X_1 = a_2;\ a_1, a_2$ be the exact value.

(1) Strength of antecedent linguistic variables. For the first rule, then there are a_1, a_2 pairs of affiliations of linguistic variable values A_{j1} and B_{k2} in X_1, X_2:

$$u_{A \cap I}(a_1), u_{B12}(a_2) \tag{3}$$

Thus, the intensity generated in the first rule is:

$$w_1 = u_{A11}(a_1) \wedge u_{B12}(a_2) \tag{4}$$

Ditto there:

$$\begin{cases} w_2 = u_{A21}(a_1) \wedge u_{B22}(a_2) \\ w_3 = u_{A31}(a_1) \wedge u_{B32}(a_2) \\ \vdots \\ w_j = u_{Aj1}(a_1) \wedge u_{Bk2}(a_2) \end{cases} \tag{5}$$

(2) Finding the inference result. Since in the intensity transfer method, the intensity of the action of the exact value on the former piece is transferred to the latter piece and used as the fuzzy quantity affiliation of the latter piece, the inference result for the first conditional statement is:

$$Y_1^* = w_1 = Y_1(y_1) \tag{6}$$

Similarly, for the second through j th conditional statements, there are inference results:

$$\begin{cases} Y_2^* = w_2 = Y_2(y_2) \\ Y_3^* = w_3 = Y_3(y_3) \\ \vdots \\ Y_j^* = w_j = Y_j(y_j) \end{cases} \tag{7}$$

Then the final and total reasoning results in the elements corresponding to the posterior pieces as respectively:

$$y_1, y_2, y_3, \cdots, y_j \tag{8}$$

3) Defuzzification algorithm. In the control system for the object to be controlled need to input the precise quantity to control, but the fuzzy controller output is fuzzy quantity, so it is necessary to quantify the fuzzy quantity of the fuzzy controller output, called the defuzzification. There are three main methods for the exact quantification of the output: the center of gravity method, the subordinate degree method, and the weighted average method.

The center of gravity method is generally used in control systems to represent the exact value of the output u:

$$u = \int Y^*(y)dy / Y^*(y)dy \tag{9}$$

where Y_i^* is the affiliation value of Y_i, and so on Y_j^* is the affiliation value of Y_j, and we set $Y_1, Y_2, \cdots Y_j$, to be a monotonic function, and $y_1, y_2, \ldots, y_j$ to be the resultant element of the reasoning of $Y_1, Y_2, \cdots Y_j$ at affiliation $Y_1^*, Y_2^* \ldots, Y_j^*$, respectively. The following is the formula for finding u:

$$\begin{aligned} u &= (Y_1^* \times y_1 + Y_2^* \times y_2 + \cdots + Y_j^* \times y_j) / (Y_1^* + Y_2^* + \cdots + Y_j^*) \\ &= \sum_{i=1}^{j} (Y_i^* \times y_i) / \sum_{i=1}^{j} Y_i^* \end{aligned} \tag{10}$$

2.4.2. Fuzzy controller optimization:

1) Fuzzy control accuracy analysis. From the basic principle and design process of fuzzy controller, we know that the steady state process of fuzzy control can be described by the following fuzzy rules:

Let the error be ZE, the rate of change of error be ZE, and the control increment be ZE. The linguistic value corresponds to a certain range. The system enters the steady state when both the error and the error change enter the range of the steady state corresponding to the linguistic value.

Let the quantized values of the error, the error change rate and the control volume change rate at the moment of k be $E(k), EC(k)$ and $C(k)$ respectively, and their exact quantities be $e(k), ec(k)$ and $u(k)$ respectively, and the quantization factors of the error, the error change rate and the fuzzy output be K_1, K_2, K_3 respectively, then there are:

$$E(k) = INT[K_1 e(k) + 0.5] \tag{11}$$

$$EC(k) = INT[K_2 ec(k) + 0.5] \tag{12}$$

$$C(k) = f(E(k), EC(k)) \tag{13}$$

When $|K_1 e(k)| < 0.5$, $E(k) = 0$. When $|K_2 ec(k)| < 0.5$, $EC(k) = 0$.

When the system enters steady state, $ec(\infty) = 0$, but $ec(\infty)$ does not have to be 0, as long as $|K_r e(\infty)| < 0.5$ then $|E(\infty)| = 0$, thus the control increment is zero and the system is steady state.

It is obtained from $|K_1 e(\infty)| < 0.5$:

$$|e(\infty)| < \frac{1}{2K_1} \tag{14}$$

That is, when the fuzzy controller enters the stability, the actual control error is inside the neighborhood $(-\frac{1}{2K_1}, \frac{1}{2K_1})$. Where K_1 is the quantization factor of the fuzzy variable of the system error, it can be seen that the output error of the system at this moment is actually not zero, and at this time the fuzzy control has not been able to make the error further smaller.

There are many researches to solve this problem, and the most effective and direct method is to increase the integral term in the fuzzy control.

2) Fuzzy Adaptive Hybrid Genetic Algorithm (FAHGA) to optimize the factor of fuzzy controller. To improve the accuracy of the fuzzy controller, the integral term is added. The simulation object summation uses the identification results of HA1D type control valve. The principle of offline optimized fuzzy controller based on FAHGA algorithm is shown in Fig. 4.

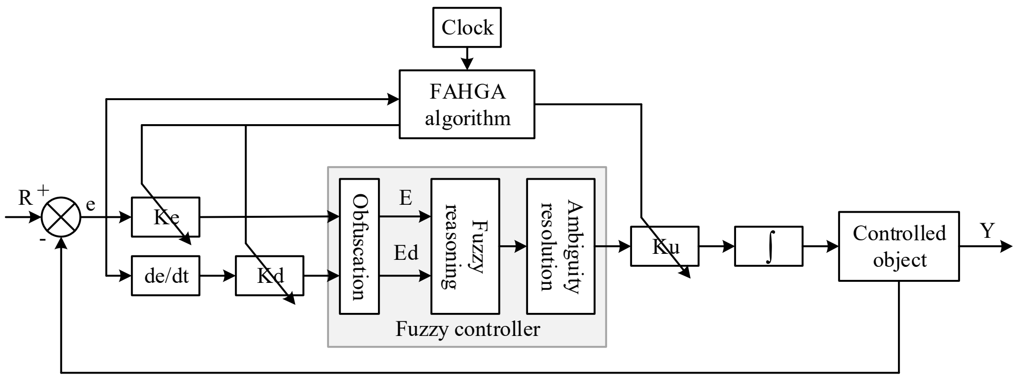

Fig. 4. Block diagram of off-line optimization of fuzzy controller

FAHGA algorithm design:

(1) Encoding. Encoding is a conversion method that transforms the feasible solution of a problem from its solution space to the search space that the genetic algorithm can handle. In this paper, we use binary encoding with a length of 20 bits. The search space for Ke, Kec, and Ku are chosen [0.01,5].

(2) Fitness function. The fitness in genetic algorithm refers to the degree of excellence of each individual in the population in the optimization calculation that is likely to reach or approach or contribute to finding the optimal solution. Population evolution is based on the fitness of each individual in the population, and the evaluation of the solution is performed based on the fitness value of each individual. The fitness function is the basis for selecting the operation, and the design of the fitness function directly affects the performance of the genetic algorithm, in order to obtain a satisfactory dynamic performance of the transition process, this paper chooses $ITAE$ indicators as the objective function:

$$J_{(IIAE)} = \int_0^\infty t\,|\,e\,|\,dt \tag{15}$$

In order not to have an overshooting amount, a penalty function is added and the objective function becomes:

$$J = \int_0^\infty (t\,|\,e\,| + t\,|\,w\,|)dt \quad e < 0 \tag{16}$$

where w is a constant when the system is overshooting c. The goal of the genetic algorithm is to find the parameter that minimizes the objective function and the fitness function is desirable:

$$f = 1/J \tag{17}$$

(3) Parameter setting. $f_{my} \in [0,1], E \in [-1,1], C_{optimal} \in [0,20], N \in [0,G], P_c \in [0.3,0.9], P_m \in [0,0.1], L \in [0,20]$, the controller saturated nonlinear link is taken as [-1, 1], the population size is 50, and the maximum number of evolutionary generations is 100.

3) Fuzzy adaptive hybrid genetic algorithm to optimize the fuzzy controller affiliation function. The schematic block diagram of optimizing the affiliation function of the fuzzy controller based on the FAHGA algorithm is shown in Fig. 5.

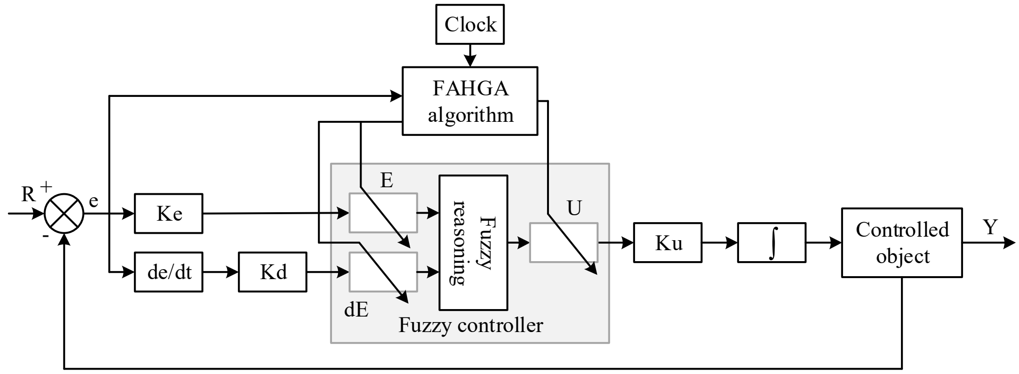

Fig. 5. FAHGA algorithm optimize the membership function of fuzzy controller block diagram

FAHGA algorithm design:

(1) Encoding. Encoding is a conversion method that transforms the feasible solution of a problem from its solution space to the search space that the genetic algorithm can handle. In this paper, we use binary coding with a coding length of 20 bits. Let the subordinate functions of e, ec, u are all symmetric about the y axis, using FAHGA to optimize the subordinate function in NM, NS or the vertices of PM, PS, $NM \in (-5,-3), NS \in (-3,-1)$, then a total of 6 parameters in the subordinate function need to be optimized.

(2) Adaptation function. Still choose $ITAE$ indicators as the objective function.

(3) Genetic operator. $E_1 \in [0,1], E_2 \in [-1,1], C_{optimal} \in [0,10], N \in [0,50], P_c \in [0.3,0.9], P_m \in [0,0.1]$, $L \in [0,5], Ke, Kec, Ku \in [0.01,5]$, before optimization $Ke = 0.7, Kec = 1, Ku = 1$, the controller saturation nonlinear link is taken as [-1, 1], the population size is 20, and the maximum number of evolutionary generations is 50.

3. Intelligent control analysis

The electrical intelligent control system designed and constructed in the previous section is used in three scenarios of greenhouse greenhouse, substation and subway station to test the control performance, environmental protection and energy saving effect and illumination control effect of this electrical intelligent control system.

3.1. Control performance analysis

1) Data pre-processing experiment. In order to verify the effectiveness of the data pre-processing method, in the greenhouse a heating process to carry out data pre-processing experiments, the initial temperature of 18.5 ℃, the target temperature of 23 ℃, the experiment lasted 20 min. due to the laboratory environment is more stable, the system is not easy to produce dissimilarity data in the process of operation, for this reason, this paper simulates the PLC in the external impact of the conditions of the sensor external power supply negative and CPU on the “sensor power” negative common ground contact failure, so that the temperature detection value deviates from the true value. “Sensor power” negative common ground contact failure, so that the temperature detection value deviates from the true value, to verify the effectiveness of data processing methods. Monitoring and management platform data sampling period of 1s, the collected 15 data preprocessing, initial data and processed data storage period of 1s, data preprocessing process of some of the original temperature data shown in Table 1, the processed temperature data shown in Table 2, the data processing results obtained as shown in Figure 6. According to the experimental results, the heating process, in the 6th to 8th min to produce three different data, the value of 20.8, 21.9, 20.7 ℃, respectively, the data

preprocessing method used in this paper effectively eliminates the generation of different data, and improves the reliability of the detection data.

Table 1. The table of original temperature data

Time/min	Temperature data/℃									
1~5	18.1	18.2	18.3	18.5	18.7	18.9	19.1	19.3	19.5	19.7
6~10	20.0	20.1	20.3	20.5	20.7	20.8	21.0	21.1	21.2	21.4
11~15	21.5	21.6	21.8	21.9	22.0	22.1	22.2	22.3	22.4	22.5
16~20	22.5	22.7	22.7	22.7	22.6	22.5	22.4	22.3	22.1	22.0

Table 2. The table of possessed original temperature data

Time/min	Temperature data/℃									
1~5	18.1	18.1	18.3	18.4	18.5	18.8	19.0	19.3	19.4	19.7
6~10	19.9	20.1	20.3	20.5	20.6	20.8	20.9	21.1	21.2	21.3
11~15	21.5	21.6	21.7	21.8	22.0	22.1	22.2	22.3	22.4	22.4
16~20	22.5	22.6	22.7	22.7	22.7	22.6	22.5	22.3	22.2	22.0

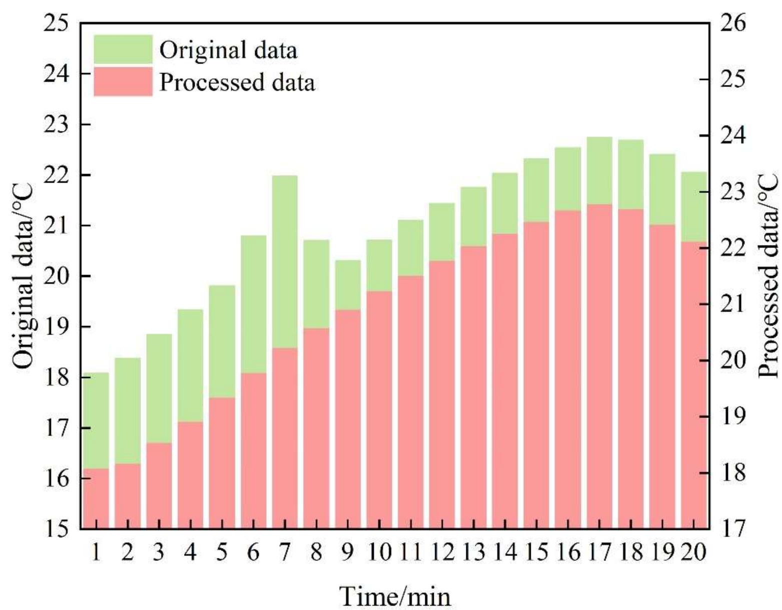

Fig. 6. The processing results of temperature

2) Fuzzy Adaptive Hybrid Genetic Algorithm Optimized Fuzzy Control Experiments. In order to verify the effectiveness of the fuzzy adaptive hybrid genetic algorithm optimized fuzzy control method (FAHGA), a comparison experiment using a single structure fuzzy control (conventional fuzzy control) and using the fuzzy adaptive hybrid genetic algorithm optimized fuzzy control method (FAHGA) was carried out, and the experiment consisted of a humidification and heating operation, with a target value of temperature of 24°C and a target value of humidity of 65% RH, in order to better Observe the temperature and humidity change process, the data storage period is 15s, and the control system carries out characteristic parameter identification once every 15s. Part of the experimental data of the conventional fuzzy control method is shown in Table 3, and the experimental data of the optimized fuzzy control method of the fuzzy adaptive hybrid genetic algorithm is shown in Table 4, and the curve is plotted according to the recorded data as shown in Figure 7.

From the analysis of the experimental results, it can be seen that the dynamic processes of the 2 control methods are comparable under similar initial environmental conditions. At steady state, the temperature deviation using conventional single structure fuzzy control is within 1°C and the humidity deviation is within 10% RH. When controlled by FAHGA method, the system is intelligently switched by the fuzzy controller at the moment of 18min, and enters into the fine regulation process from the fast control, and the temperature deviation is within 0.1℃ and the humidity deviation is within 5%RH after stabilization, and the temperature and humidity regulation accuracy is significantly improved compared with the conventional fuzzy control method, which meets the greenhouse crop growth requirements.

Table 3. The table of general structure fuzzy control data

Time/min	Experiment data									
	Temperature data/℃					Humidity data/RH%				
1~5	13.3	13.3	13.5	14.1	15.0	26.7	33.7	38.2	42.6	50.0
6~10	16.0	17.1	18.0	19.0	19.8	19.5	54.2	55.3	57.3	59.9
11~15	20.7	21.6	22.2	22.9	23.6	23.3	64.1	63.6	64.7	63.1
16~20	24.0	23.9	23.5	23.0	22.8	22.5	59.3	60.4	61.3	63.4
21~25	22.9	23.2	23.7	23.8	23.5	23.2	64.6	64.2	63.3	60.8
26~30	23.0	22.7	22.7	23.0	23.7	23.4	61.5	62.9	64.7	64.6
31~35	24.3	24.4	23.9	23.4	23.1	22.8	62.8	61.2	62.1	63.6
36~40	23.1	23.5	23.9	23.9	23.6	23.3	65.6	65.4	64.3	62.0

Table 4. The table of FAHGA structure fuzzy control data

Time/min	Experiment data									
	Temperature data/℃					Humidity data/RH%				
1~5	12.5	12.6	13.0	13.6	14.6	29.2	36.9	43.4	48.7	50.9
6~10	15.5	16.5	17.5	18.5	19.3	53.9	57.2	59.7	61.1	61.6
11~15	20.1	20.9	21.9	23.1	23.8	62.3	63.3	61.1	58.0	58.2
16~20	23.9	23.6	23.3	23.3	23.5	58.1	60.5	62.7	64.1	64.6
21~25	23.7	23.8	23.8	23.7	23.6	64.1	64.5	63.7	62.5	63.6
26~30	23.5	23.4	23.3	23.3	23.2	63.6	63.4	63.9	64.1	64.1
31~35	23.3	23.5	23.6	23.8	23.8	64.1	64.1	63.6	63.4	63.8
36~40	23.7	23.6	23.5	23.4	23.4	63.3	64.1	63.9	63.9	63.8

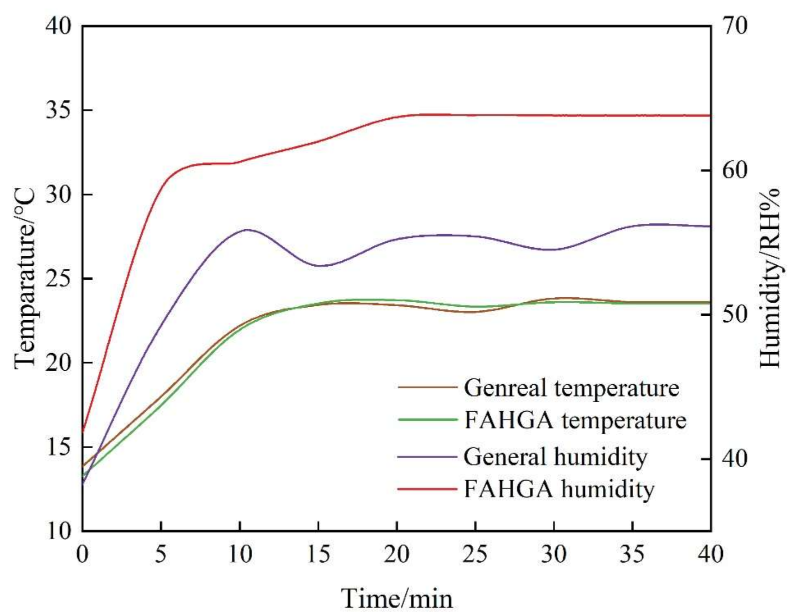

Fig. 7. The curve of general and FAHGA structure fuzzy control

3.2. Analysis of environmental protection and energy saving

Take the HVAC of a substation as an example to test the energy-saving effect of this paper's electrical intelligent control system. Using the intelligent control system of this paper, "controlled weak airflow" program, through the effective control of the indoor ambient temperature of the electrical equipment, to improve the safety and stability of the operation of the substation, and at the same time reduce the energy efficiency of the ventilation system. Controlled weak airflow ventilation with the help of intelligent control system, according to the indoor and outdoor ambient temperature changes, automatically adjust the air supply volume of the air supply device, to achieve energy-saving operation to meet the ambient temperature of the equipment operation.

The project's summer ventilation and air conditioning operating hours are based on 24 hours per day for 90 days, totaling 2,160 hours. In winter, the heating operation time is 24 hours per day for 90 days, totaling 2160 hours. The annual power consumption of the traditional ventilation and air conditioning system is shown in Table 5, and the power consumption of the electrical intelligent control system in this paper is shown in Table 6. The whole life cycle cost is shown in Table 7, in which the electricity cost is 0.635 Yuan/kWh.

From Table 5 and Table 6, the annual power consumption of the electrical intelligent control system of this paper is 32,660 degrees, and the annual power consumption of the traditional ventilation and air conditioning system is 45,620 degrees. From Table 7, it can be seen that the use of the electrical intelligent control system of this paper can save 22,000 yuan per year.

Table 5. Annual power consumption of traditional ventilation and air conditioning system

Season	Input power/kW	Load percentage	Time percentage	Time/h	Electricity consumption/kW
Winter	25	20%	10%	2160	1080
	25	40%	20%	2160	4320
	25	60%	40%	2160	12960
	25	80%	20%	2160	8640
	25	100%	10%	2160	5400
Summer	10.2	20%	10%	2160	441
	10.2	40%	20%	2160	1763
	10.2	60%	40%	2160	5288
	10.2	80%	20%	2160	3525
	10.2	100%	10%	2160	2203
Total					45620

Table 6. Energy consumption of our intelligent control system

Season	Input power/kW	Load percentage	Time percentage	Time/h	Electricity consumption/kW
Winter	20	20%	10%	2160	864
	20	40%	20%	2160	3456
	20	60%	40%	2160	10368
	20	80%	20%	2160	6912
	20	100%	10%	2160	4320
Summer	5.2	20%	10%	2160	225
	5.2	40%	20%	2160	899
	5.2	60%	40%	2160	2696
	5.2	80%	20%	2160	1797
	5.2	100%	10%	2160	1123
Total					32660

Table 7. Life cycle cost calculation

Item name	Our intelligent control system	Traditional system
Initial investment/104 yuan	50	40
Equipment total investment/104 yuan)	52	42

Electricity consumption/kWh per year	32660	45620
Operation cost/yuan per year	26488	45847
Maintenance cost/yuan per year	3000	11000
Life cycle n/year	15	15
Total life cycle cost/104 yuan	11.8	14.0

3.3. Illumination control analysis

According to the fuzzy controller designed in section 2.4, the fuzzy control rules can be obtained by quantifying the fuzzy rules in the argument domain after inverse fuzzification, and the output surface of the fuzzy inference system is shown in Fig. 8, in which Q is the comfort of the light environment, V is the density of the crowd, and ΔL is the amount of output illumination. From the output surface of Fig. 8, it can be seen that the fuzzy control system's output illuminance adjustment can better reflect the relationship between the crowd density and the comfort of the light environment in the subway station, and the output illuminance of the fuzzy control system increases when the comfort of the light environment and the density of the crowd are increased, which achieves the expected effect of the illumination control in this design.

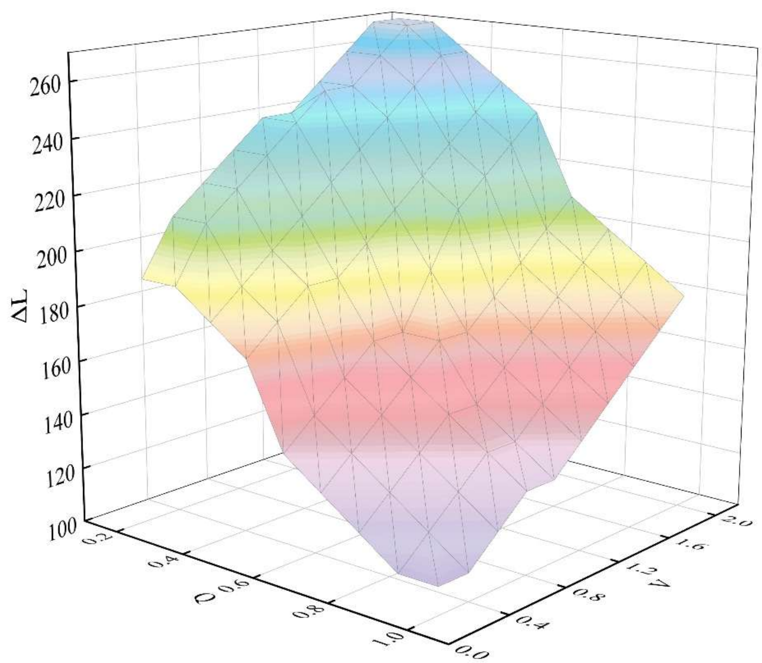

Fig. 8. Quantitative form of fuzzy control rules

4. Conclusion

The article builds an electrical intelligent control system, designs the system hardware and optimizes the fuzzy controller in the system software. The electrical intelligent control system of this paper will be used in a variety of scenarios to test the control performance and energy saving effect of the electrical intelligent control system of this paper.

In the greenhouse temperature control experiment, the original data produced three dissimilar data in the 6th~8th min, and the system in this paper effectively handled the dissimilar data. Under the steady state environment, the temperature deviation of the conventional single structure fuzzy control is within 1℃, and the humidity deviation is within 10% RH. When controlled by the FAHGA method, the temperature deviation is within 0.1°C and the humidity deviation is within 5% RH, and the control accuracy is significantly improved.

In the substation air conditioning energy consumption experiment, the annual power consumption of the electrical intelligent control system of this paper (32,660 degrees) is much lower than that of the traditional ventilation and air conditioning system (45,620 degrees). The annual cost of this paper's electrical intelligent control system is 22,000 yuan less than that of the traditional ventilation and air conditioning system.

In the subway station illumination experiment, the output illumination of the fuzzy control system of this paper increases with the comfort of the light environment and the crowd density, which achieves the expected effect.

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