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A GA-based Self-tuning PID Temperature Controller for Environmental Simulation Tests

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Abstract. With the rapid development of computer technology and the integration of artificial intelligence technology, numerous advanced parameter tuning methods for PID controllers have emerged, driving extensive research into self-tuning PID control systems. To address challenges such as time delays, model uncertainties, and time-domain variability in temperature control during environmental simulation experiments, this paper proposes a self-tuning PID controller tailored for such scenarios. Leveraging genetic algorithms (GA), a dynamic PID parameter optimization framework is developed to achieve precise temperature regulation. The proposed method enhances the genetic algorithm by incorporating real-time adjustments to PID parameters based on both the deviation from the target temperature and its rate of change. By exploiting the adaptability of GA and introducing variable-length chromosome encoding inspired by DNA mechanisms, the optimized controller enables robust self-tuning of PID parameters. This approach effectively resolves the challenges of maintaining temperature accuracy in complex vacuum environments during simulation tests.

Keywords: environmental simulation test, GA, self tuning, PID temperature controller

1 Introduction

Spacecraft environmental simulation tests are ground-based pre-launch procedures designed to replicate outer space conditions, Temperature control accuracy directly impacts component reliability assessments. Traditional PID controllers face limitations in nonlinear and time-varying environments, necessitating adaptive strategies. While fuzzy logic offers robustness for uncertain systems, its reliance on heuristic rules limits global optimization capabilities.

Spacecraft environmental simulation test is a work project, which carried out on the ground before the launch of a spacecraft, mainly simulated the environmental conditions of outer space and verified the various performance and functions of spacecraft machine components under vacuum and temperature fusion conditions. In the environmental simulation tests of spacecraft components and the entire satellite, temperature is a key parameter for measurement and control. Dynamic indicators such as slope control and stability have been proposed in temperature control [1]. During the ground environment simulation test of spacecraft, temperature control is related to the accuracy of verification. In the temperature control process of thermal testing, each test product is different, and the thermal characteristics of the product are also different. It is not allowed to conduct debugging and testing before the temperature index is reached. The requirements for temperature rise and fall slope and overshoot index are more stringent. The temperature control of simulating outer space radiation heat transfer on the ground is inevitably not linear, therefore, different PID temperature controllers need to be found, which is based on the

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current temperature value to achieve the target temperature value.

In the current commonly used temperature control methods, it is generally used for industrial temperature control processes where the object remains unchanged for a long time [2] or for research on adaptive controllers that can adjust control parameters online [3]. The temperature control in simulation experiments is an independent digital closed-loop measurement and control system. After the system is started, the temperature signal is transmitted to the collector by the temperature sensor, and the collector completes the analog-to-digital conversion. After digital filtering the collected digital signal, the measured value is compared with the target temperature value, and then enters the control program. The temperature control quantity is calculated, which is based on the sampled data through the control algorithm. The digital signal is input to the excitation power supply according to the digital control quantity, and the excitation power supply drives the heating unit to achieve continuous adjustment of the test product. Environmental simulation tests (such as vacuum thermal tests) require rapid temperature stabilization under complex operating conditions, and traditional PID relies on manual parameter tuning, making it difficult to cope with time-varying loads and multiple interference sources.

Genetic algorithms have strong optimization capabilities and can solve various complex optimization problems. They have broad adaptability and excellent robustness, and have broad application prospects [4, 5]. According to the characteristics of genetic algorithm, as long as the parameters of the controller are genotyped and the performance indicators are composed of corresponding fitness, genetic algorithm can be used to optimize the controller parameters and achieve continuous adjustability of the entire system.

PID controllers are widely used in industrial control due to their simple structure and high reliability, but their parameter tuning relies on empirical formulas and is difficult to adapt to nonlinear and time-varying systems. Self tuning PID technology enhances adaptability by adjusting parameters online, but traditional self-tuning methods such as Ziegler Nichols are susceptible to model errors. The combination of fuzzy PID and genetic algorithm provides a new approach for self-tuning PID: the former achieves dynamic parameter adjustment, while the latter solves the global optimization problem of fuzzy rules and membership functions.

In the process of conducting environmental simulation experiments for spacecraft, achieving high-precision temperature control often requires non-linear automatic adjustment based on the target temperature value. The parameters of the controller need to be self-tuning to the PID temperature controller according to the approaching temperature value in order to achieve this. Key contributions of this paper include:

(1) Optimization of PID temperature controller for temperature control system used in spacecraft environment simulation test.

(2) Genetic algorithm applied for optimization, improvement and expansion in vacuum low-temperature environment.

(3) We have built a distributed temperature control system based on WLAN to achieve synchronous temperature acquisition and control.

The paper is structured as follows: section 2 introduces related work. Section 3 presents principle of PID algorithm. Section 4 conducts the main content of the proposed method. Section 5 provides the simulation analysis of the proposed method. In section 6, experiments are carried out to test the performance of the PID Controller. Section 7 concludes the paper.

2 Related Work

During spacecraft environmental simulation experiments, it is necessary to establish a simulated "vacuum cold black" environment in outer space using liquid nitrogen refrigeration and vacuum containers, and conduct various performance tests in this background environment. When conducting spacecraft system testing in an environmental simulation test system, its temperature index is an important assessment parameter in the simulation test. In order to accurately assess the various performance indicators of spacecraft, it is necessary to accurately achieve the target temperature of each cabin, component, boundary, etc. during simulation experiments, so temperature control is particularly important.

At present, PID control is already the most basic and commonly used control method in the field of temperature control. PID control is one of the classic control methods in industrial control, which has the advantages of strong robustness, simple structure, and reliability. Due to the advantages and wide applicability of PID control, researchers have developed various improvement methods for PID control design. With the rapid development of control theory, the combination of PID control method with various advanced control methods has given birth to various composite control methods, which have achieved good results in large time-delay systems. However, how to tune PID parameters is a complex optimization process, and conventional PID control parameter tuning has become a major bottleneck affecting the application of PID control. Moreover, due to inappropriate parameters, the system performance is poor, which seriously hinders the application and development of PID control [6-9].

When PID control is applied to temperature control, the parameters need to be manually adjusted, which requires rich experience accumulation. However, the controlled object is different each time, and the PID controller which has been manually adjusted cannot achieve the best control effect on the target temperature. Therefore, it is difficult to achieve the desired effect through manual adjustment. Therefore, it is necessary to achieve self-tuning of PID parameters, when the target temperature changes. This involves testing, monitoring, and providing feedback on the actual system operation to obtain the main system parameters and performance parameters. Then, the parameters of the PID temperature controller which is based on the feedback results are reset, and the tuned parameters are set as the control parameters of the PID controller for actual control, in order to achieve better performance.

With the deepening of PID control research, fuzzy control has also emerged and developed in the field of control [10]. Fuzzy control is a control algorithm which is based on fuzzy rules, whose fuzzy rules are often composed of knowledge accumulated and summarized based on the actual experience of personnel, and are more suitable for objects without precise mathematical models and objects that change frequently. Although PID method is convenient and simple to control, it cannot solve parameter changes and nonlinear problems. Fuzzy control does not require precise models and relies solely on the intuitive judgment and experience of personnel, making it easier to apply. Fuzzy PID control has been successfully applied in industrial control [11].

In recent years, the use of genetic algorithms for optimization in fuzzy control has become a hot research topic [12, 13], mainly used for optimizing proportional factors, membership functions, and control rules in fuzzy controllers. However, the optimization process is offline and cannot achieve online optimization. Because completing the entire algorithm in general genetic algorithms requires a certain amount of time, has a slow convergence speed, and cannot achieve online optimization, it will greatly limit the improvement of controller accuracy. Genetic algorithms are widely used in industrial control and have achieved expected results [14-17].

The development of computer technology has promoted the continuous updating and iteration of PID control algorithms, providing great selectivity and renewability for the self-tuning of PID parameters, making parameter self-tuning and parameter setting more feasible [18]. In recent years, researchers have proposed various improvement methods, such as adaptive PID control and adaptive fuzzy PID control [19, 20].

Although PID temperature controllers have achieved some results in spacecraft environmental simulation experiments, there is still significant room for improvement in terms of convergence, stability, and accuracy [21, 22]. In the process of spacecraft simulation experiments, the requirements for temperature control accuracy are gradually increasing, and the demand for intelligent temperature control has become very urgent. This study is based on the strong optimization ability of genetic algorithm and fuzzy PID control [23, 24], and proposes a self-tuning PID temperature controller that can be used for environmental simulation experiments to solve the problem of slow convergence speed and improve the performance of the control system. Aim to achieve precise control of temperature rise, fall, and temperature maintenance, and meet the control requirements of the target temperature.

3 Principle of PID Algorithm

3.1 Basic Principles of PID Control

The control law of a PID controller consists of three stages: proportional (P), integral (I), and derivative (D). The expression for its control output u (t) is:

$$\upsilon(t) = K_p\,(e(t)+\frac{1}{T_i}\int_0^t e(\tau)\,d\tau + T_d\,\frac{de(t)}{dt}) \tag{1}$$

Among them, K_p is the proportionality coefficient, T_i is the integral time constant, T_i is the differential time constant, and e (t) is the system error, which is the difference between the given value r (t) and the actual output value y (t): e(t)=r(t)-y(t). The proportional component can quickly respond to deviations, the integral component is used to eliminate steady-state errors, and the derivative component can predict the trend of deviation changes and improve the dynamic performance of the system.

3.2 Self Tuning Principle

The core of a self-tuning PID controller is the ability to automatically adjust PID parameters based on the characteristics of the controlled object K_p, T_i, T_d . The commonly used Ziegler Nichols tuning formula is as follows:

$$G_{obj}(\mathrm{s})=\frac{K_0}{\left(T_0 s+1\right)}e^{-\tau s} \tag{2}$$

According to the object model, the PID parameter tuning formula is:

$$K_p=\frac{1.2T_0}{K_0\tau} \tag{3}$$

$$T_i = 2\tau \tag{4}$$

$$T_d = 0.5\tau \tag{5}$$

By deduction, it can be concluded that:
Proportional control (P):=0.5Ku;
Proportional integral control (PI):=$0.45K_u$,=$0.83T_u$;
Proportional integral derivative control (PID):=$0.6K_u$,=$0.5T_u$,=$0.125T_u$.
Through this method, the self-tuning PID controller can automatically determine appropriate PID parameters which is based on the actual dynamic characteristics of the controlled object, improve control performance at last.

4 Proposed Method

In this section, the composition of the environmental simulation test system, fuzzy PID design, system transfer function based on infrared heater, and PID temperature control parameter self-tuning are mainly introduced. Design concept: In order to achieve the target temperature quickly and stably, a “dual-mode optimization” structure is proposed for temperature control, which combines offline optimization and online self-tuning. Genetic algorithm optimizes the fuzzy rule base, which includes membership functions (encoding parameters such as triangle vertices, rule weights, etc.), and fitness functions that integrate overshoot, adjustment time, and energy consumption. a self-tuning PID controller intervenes to automatically adjust the PID controller parameters (ΔK_p, ΔK_i, ΔK_d), Trigger GA fine-tuning rule library every 5 minutes to cope with environmental disturbances, thus achieving online self-tuning.

4.1 Composition of the Experimental System

The entire experimental system consists of an infrared heater (cage), test products, environmental simulator, temperature sensor, measurement and control host, temperature monitoring equipment, and programmable power control circuit, as shown in Fig. 1. Among them, the environmental simulator is a simulation device for establishing vacuum cooling, the infrared heater is used to apply temperature to the test product, the temperature sensor is used to monitor the temperature of the test product, the temperature monitoring device converts the obtained temperature into analog to digital, so that the measured temperature can be displayed in the measurement and control software, and the measurement and control host applies corresponding power values and temperature feedback to each temperature zone based on the target temperature. The measurement and control host and temperature monitoring equipment are connected in the form of a local area network (LAN) through a switch. The measurement and control software (host) runs periodically to monitor and apply power values to each partition to ensure real-time control of all temperature monitoring devices.

The entire experimental system is an independent digital closed-loop measurement and control system. After the system is started, the temperature signal collected by the temperature sensor is converted from analog to digital by the temperature monitoring device. After smoothing and digital filtering the collected analog signals, the measured values and set values are sent to the control program of the measurement and control host. The control program calculates the control quantity from the collected digital data and sends the calculated digital control signal to the programmable power supply. The programmable power supply applies power to the infrared heater (cage), causing it to heat up and achieve continuous automatic temperature adjustment of the test product. When the temperature exceeds the deviation, the control program automatically adjusts to increase, decrease, or maintain the power applied to the infrared heater (cage) through the programmable power supply.

The measurement and control host is the core component of the entire experimental system. It mainly compares and judges the actual temperature value with the target temperature value based on the sampled temperature signal, and selects the control algorithm to execute. According to the input data of the measurement and control host, it calculates the output control quantity to achieve the control power output. The control program is developed by computer software and embedded with a self-tuning PID temperature controller. The infrared heater (cage) used in the experimental system is a heating strip made of alloy, which is distributed according to rules to achieve uniform temperature application. Experimental products refer to various types of products that participate in experiments. Using a T-shaped thermocouple as the temperature sensor, the temperature sensor is composed of a copper constantan thermocouple as the commonly used temperature measuring element. It has a wide temperature measurement range (-200~+200°C) and good linearity throughout the entire measurement range, which can effectively complete temperature measurement.

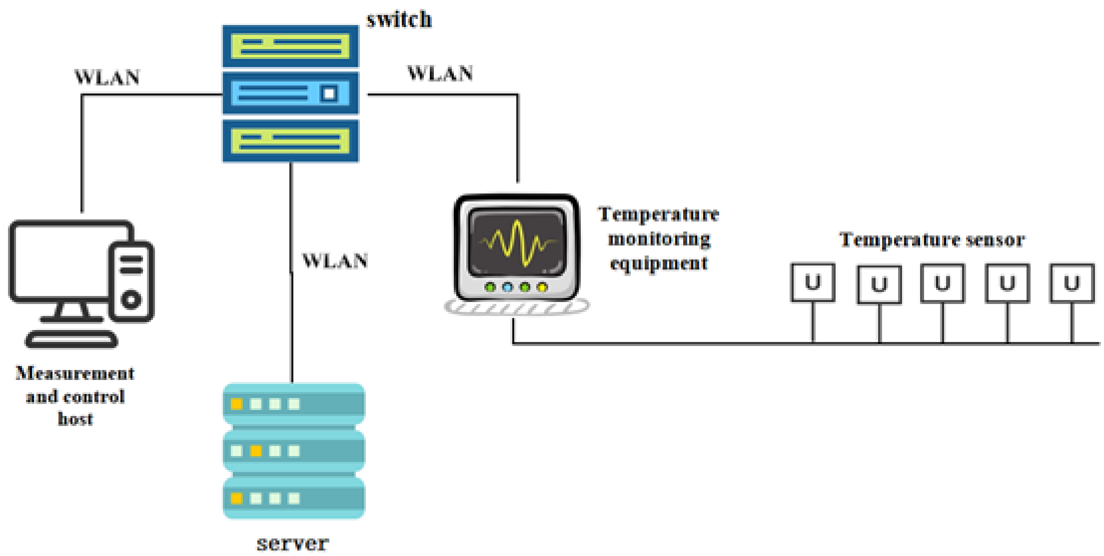

Fig. 1. Hardware connection architecture for temperature measurement and control in the experimental system

4.2 System Transfer Function

The mathematical model of the digital closed-loop measurement and control system for the entire experiment can accurately reflect the actual characteristics of temperature control and temperature changes. The system has temperature-control pure hysteresis characteristics and temperature self-control balance ability. At the beginning of the experiment, its mathematical model can be described using a first-order system with a pure hysteresis link, and the transfer function is:

$$G(s) = \frac{Ke^{-\tau s}}{Ts+1} \tag{6}$$

In the formula, K represents static gain, T represents time constant, τ represents pure lag time, and s represents complex variable. In steady state, the input and output of the controlled object exhibit a linear relationship. As the self balancing ability of the controlled object increases, the static gain K will decrease, and vice versa. When the system has a first-order input, the time it takes for the output to reach another steady state is a time constant T. The larger the value of T, the longer it takes for the system's state to change, and vice versa. When the output changes, the time required for the output to follow the change is the lag time, which represents the time for the output response to lag behind the excitation input. The lag time is mainly due to the temperature not reaching the target temperature immediately.

The commonly used method in engineering is to apply a step input signal to the process object, measure the step response of the process object, and then use the step response curve to determine the approximate transfer function of the process. Specifically, the Cohen Cohen formula is used to determine the approximate transfer function [20].

The formula is as follows:

$$K = \Delta C / \Delta M \tag{7}$$

$$T = 1.5\left(t_{0.632} - t_{0.28}\right) \tag{8}$$

$$\tau = 1.5(t_{0.28} - t_{0.632}/3) \tag{9}$$

In the formula:

K represents the gain coefficient, T represents time constant, ΔC represents the output response of the system, ΔM represents system step inputs, $t_{0.28}$ represents the time (s) when the object's ascent curve is 0.28, $t_{0.632}$ represents the time (s) when the object's ascent curve is 0.632.

The temperature measurement range of the experimental system depends on the temperature measurement range of the temperature sensor. The T-type thermocouple which is used in the system is calibrated for a temperature range of -150℃ to+200℃. By analyzing a large amount of experimental data, in order to determine whether it is suitable for practical applications, and given an input step signal of +150 ℃, we can obtain:

$\Delta M = 150$,
$\Delta C = 150-10 = 140$,
$t_{0.28} = 0.28\Delta C = 0.28*140 = 39.2s$,
$t_{0.632} = 0.632\Delta C = 0.632*140 = 88.48s$.
Thus, it can be concluded that:
$K = \Delta C/\Delta M = 140/150 = 0.93$,
$T = 1.5(t_{0.632}, t_{0.28}) = 1.5*(88.48-39.2) = 73.92s$,
$\tau = 1.5(t_{0.28} - t_{0.632}/3) = 1.5*(39.2-88.48/3) = 14.565s$.

The transfer function of the digital closed-loop measurement and control system for the entire experiment can be obtained as follows:

$$G(s) = \frac{0.93}{73.92s+1} e^{-14.565s} \tag{10}$$

4.3 Fuzzy PID Design

Fuzzy control is an automatic control theory, which is based on fuzzy mathematics and develope. Since the research on using fuzzy logic to construct fuzzy controllers, significant progress has been made in the study of fuzzy control theory and its applications. Fuzzy control methods have been increasingly applied in various fields [23].

The basic principle diagram of fuzzy control is shown in Fig. 2.

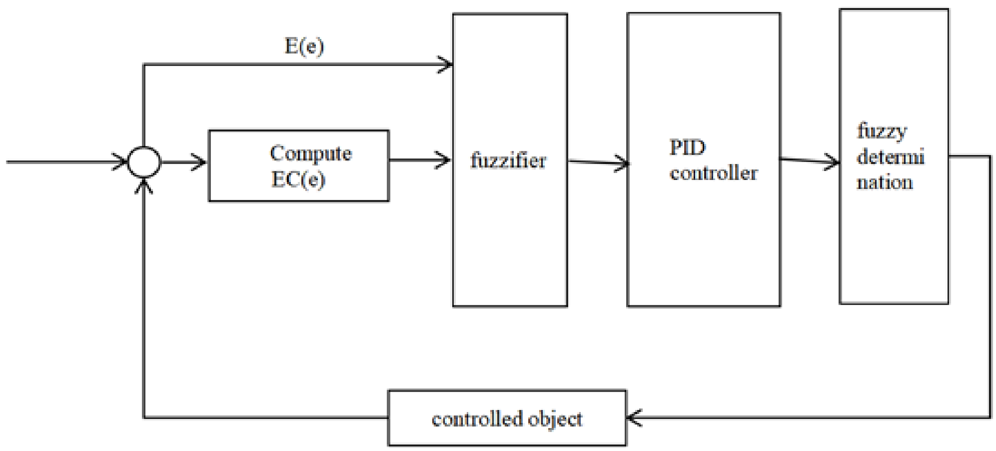

Fig. 2. Fuzzy control structure diagram

In a fuzzy control system, it is known to be a small hysteresis and uncertain system, which may be greatly affected by environmental disturbances. At the same time, the temperature control system is used in spacecraft environmental simulation experiments, it requires high system stability, temperature control accuracy, and good robustness. During the temperature control process, continuously monitor the temperature error e and error rate ec, and then uses these two parameters as inputs for the PID controller. Using a temperature control scheme which is based on fuzzy PID control, adjust the PID proportional, integral, and derivative control parameters in real time to ensure that the temperature reaches the target temperature. Fig. 3 shows the structure diagram of temperature control. The relationship between error and error variation is expressed as:

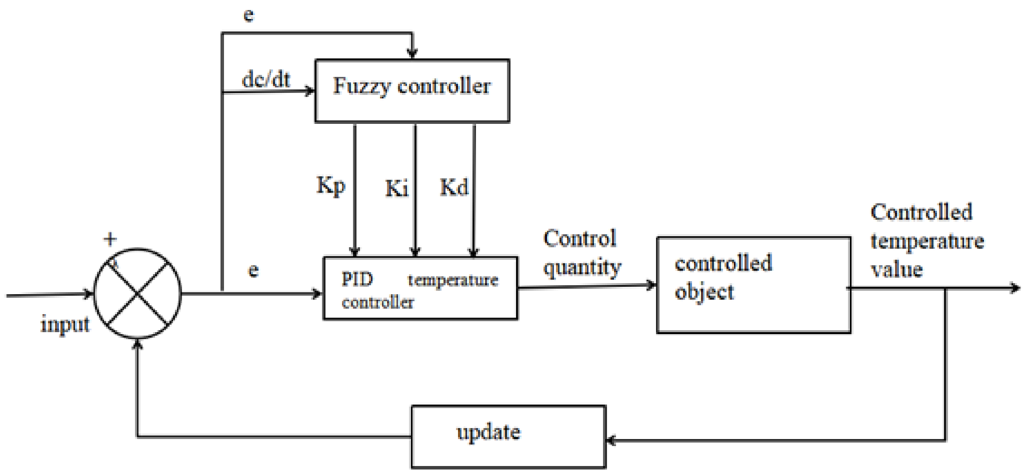

Fig. 3. Temperature control structure diagram

$$e(k)=input(k)-out(k) \tag{11}$$

$$ec(k) = \left(e(k) - e(k-1)\right) / T \quad \mathbf{(12)}$$

Among them, T is the sampling interval, input is the reference input, and out is the output of the object.

In the temperature control system, a triangular membership function is used to define temperature error, error change rate, and control quantity, making the complexity of the function form smaller, as shown in Fig. 4.

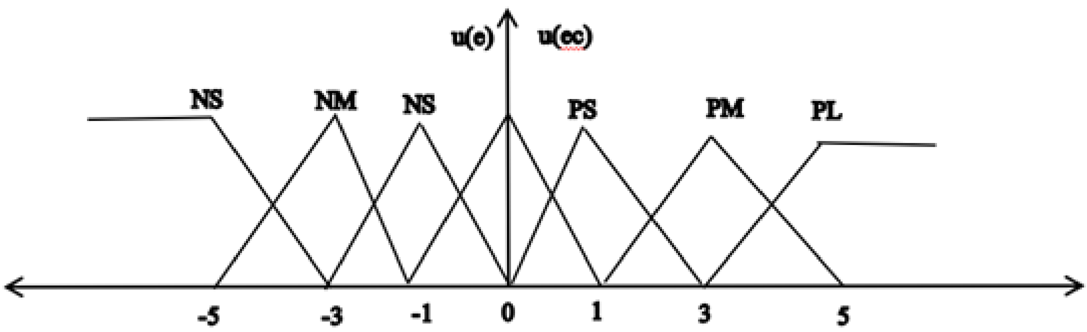

Fig. 4. Schematic diagram of membership function curve

Define the value of error as:

{negative large, negative medium, negative small, negative zero, positive zero, positive small, center, positive large}

Recorded as:

{PL, PM, PS, P0, N0, NS, NM, NL}

PL represents "negative large", PM represents "negative medium", PS represents "negative small", P0 represents "negative zero", N0 represents "positive zero", NS represents "positive small", NM represents "center", NL represents "positive large".

The fuzzy control rules for setting temperature control parameters K_p, K_i and K_d are defined in Table 1.

Table 1. Parameter K_p, K_i, K_d setting state control table

u / E / Ec	NL	NM	NS	NO	PO	PS	PM	PL
NL	NL	NM	MN	NS	NS	PS	PS	PM
NM	NL	NM	NM	NS	NS	PS	PM	PL
NS	NL	NM	NS	NS	NS	PS	PM	PL
NO	NL	NS	NS	NO	NO	PM	PM	PL
PS	NM	NM	PS	PS	PS	PM	PM	PL
PM	NM	NM	PS	PS	PS	PM	PM	PL
PL	NM	NM	PM	PM	PM	PM	PL	PL

The output of temperature control can only accurately control the temperature of each circuit after fine processing, combined with the three correction parameters K_p, K_i, K_d, As a control variable of PID controller. Using the center of gravity method to calculate the precise control parameters of temperature control output, this method defuzzifies the fuzzy quantity of temperature control to obtain the precise control parameters $\upsilon(k)$:

$$\upsilon(k)=\frac{\sum_{i}(\eta(i)\times v(i))}{\sum_{i}\eta(i)} \tag{13}$$

In the formula: υ(k) is a fuzzy set element, $\eta(i)$ is a membership function.

The values of temperature control parameters K_p, K_i, and K_d can be obtained in real time from equation (13), and then multiplied by their respective scaling factors to determine the tuning values of the parameters, thereby achieving self-tuning of the PID controller.

4.4 Optimization Rule Base Based on Genetic Algorithm

(1) Genetic algorithm

Genetic algorithm is a parallel random search optimization algorithm proposed by Professor Holland in 1962, which simulates biological genetics and evolution. This algorithm encodes the problem to be optimized into individuals, and the encoding of individuals is their ‘genes’. A certain population is composed of several individuals, and then the principle of biological evolution of “survival of the fittest” is applied. Based on a certain objective function, the population evolves towards the direction of better performance of the objective function, thereby optimizing the parameters. Its algorithm is simple, can be processed in parallel, and can obtain the global optimal solution.

The main characteristics of genetic algorithm are: firstly, genetic algorithm operates on the encoding of parameters, rather than on the parameters themselves; Secondly, genetic algorithms operate in parallel from many points, rather than being limited to one point; Thirdly, genetic algorithms calculate the fitness value through the objective function without the need for other derivations, resulting in less dependence on the problem; Fourthly, the optimization rules of genetic algorithms are determined by probability rather than determinacy; Fifth, genetic algorithms perform humorous heuristic searches in the solution space, rather than blindly exhaustive or completely random searches; Sixth, genetic algorithms have almost no restrictions on the function to be optimized. They do not require the function to be continuous or differentiable, and can be either an explicit function represented by mathematical analytical expressions, a mapping matrix, or even an implicit function of neural networks; Seventh, genetic algorithms have parallel computing characteristics, so they can improve computing speed through large-scale parallel computing; Eighth, genetic algorithms are more suitable for optimizing large-scale complex problems; Ninth, genetic algorithms are computationally simple and highly functional. Fig. 5 shows the schematic diagram of the algorithm iteration process.

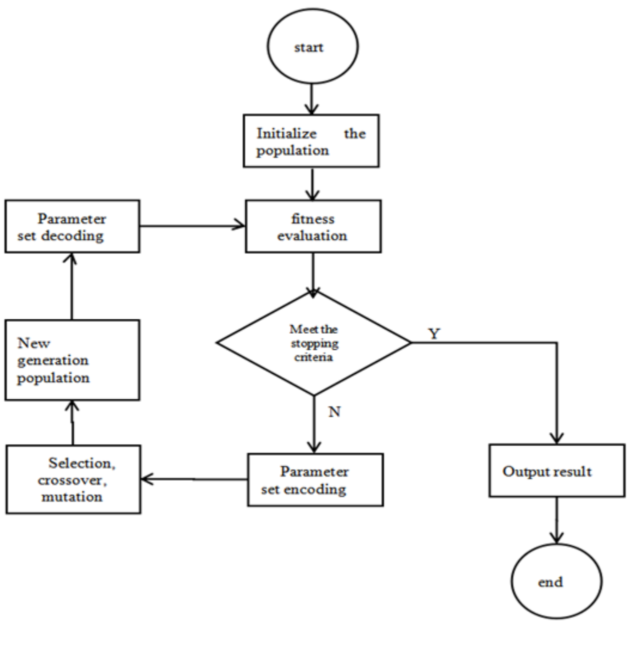

Fig. 5. Algorithm iteration process

The basic operations of genetic algorithm include selection, replication, crossover, and mutation. The premise of evolution when choosing replication, that is, the process of selecting individuals with strong vitality from an old population to generate a new population, reflects the principle of "survival of the fittest". The replication operation is performed based on the individual's fitness value and is achieved through probabilistic random selection method. If implemented using a computer program, a uniformly distributed random number between 0 and 1 can be generated. If the replication probability of a gene string is $1 \geq x \geq 0$, then when the generated random number is between 0 and x, the individual is replicated and responsible for elimination. And it can be achieved through the expected value method, fitness ratio method, and ranking method of lamp calculation. Copy operations can select excellent individuals from old populations for reproduction, while crossover operations generate new individual gene combinations. Cross simulation of biological reproduction phenomenon, through the exchange and combination of two chromosomes, generates new excellent genes. The process of crossover: Choose two individuals and randomly select one or more swapping points in their encoding. Swap the parts to the right of the swapping points of the two individuals to obtain two new encodings. The sweat wiping strategy includes point crossing, multi-point crossing, consistent crossing, sequential crossing, and periodic crossing. One of the most basic methods of point crossing is that there is a chromosome breakpoint, for example, two individuals with a 15 digit code intersect. If the intersection point is the 11th digit, then:

Individual 1:11011 01011 **01101** → 11011 01011 **10110**

Individual 2:01010 10110 **10110** → 01010 10110 **01101**

Cross operation can generate new code segments, simulating genetic mutations in organisms and randomly changing individual coding values with a small probability. When an individual is encoded in binary, a certain encoding bit is randomly reversed, that is, 1 becomes 0, or 0 becomes 1. If there is only selection and crossover without mutation, it is impossible to search for elements outside the initial gene combination space, and the evolution process is trapped in local solutions, and the final result is not globally optimal. Mutation precisely compensates for this deficiency, expands the understanding space, and makes it possible to obtain better optimization results on a larger scale.

(2) Genetic Algorithm Optimization of Fuzzy Rules

Due to the fact that the fuzzy rules of fuzzy controllers are mainly formulated based on accumulated experience in previous research and production processes, the rule library designed based on experience may have redundant rules, which increases the computational burden. When dealing with temperature coupling interference, rules formulated solely based on experience are difficult to ensure good consistency control performance. And fixed rule libraries are difficult to adapt to complex and changing working conditions, requiring dynamic adjustments.

Genetic algorithms have inherent hidden parallelism and better global optimization capabilities, which can eliminate redundant rules, resolve rule conflicts, and enhance the system's adaptability to complex operating conditions. Therefore, using genetic algorithm to optimize the fuzzy rule library makes the rules in the rule library more accurate, thereby improving the temperature control accuracy. The schematic diagram of GFPC (genetic algorithm based fuzzy PID controller), an improved fuzzy PID controller based on GA, which is shown in Fig. 6.

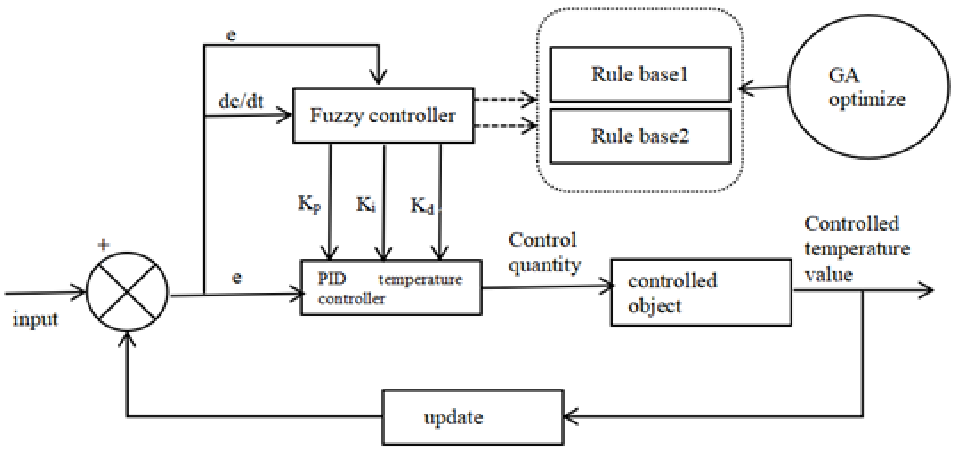

Fig. 6. GFPC temperature control structure diagram

Genetic algorithm optimizes the rule base by simulating the process of biological evolution (selection, crossover, mutation). The specific process is as follows:

Firstly, coding design. Each chromosome represents a rule library, and the chromosome length is: rule number x3 (K_p, K_i, K_d). Gene encoding adopts real number encoding or integer encoding, and each gene represents a regular output value (K_p, K_i, K_d).

Secondly, initial population generation. Randomly generate several chromosomes, each corresponding to an initial rule library. The initial rule library is designed based on experience.

Thirdly, the design of the fitness function is used to evaluate the performance of the rule library. Taking into account indicators such as control accuracy, response speed, and time efficiency, the fitness function is designed as follows:

$$\text{Fitness} = 0.2\sigma\% + 0.3t_s + 0.4\int \left|e(t)\right| dt + 0.1\gamma_t \tag{14}$$

Among them:

$\sigma\%$ represents overshoot, t_s represents the adjustment of time, $\int |e(t)|\, dt$ represents error integral, γ_t represents time efficiency.

Fourth, choose the operation. Using roulette wheel selection, prioritize selecting chromosomes with high fitness to enter the next generation.

Fifth, cross operation. Using single point crossing to generate new chromosomes.

Sixth, mutation operation. Choose a higher initial value (such as 0.1) and gradually decrease it with iterations to avoid premature convergence.

Seventh, generation selection. Repeated selection, crossover, and mutation operations will retain chromosomes with high fitness values in the next generation, while chromosomes with the lowest fitness will be eliminated.

(3) Fuzzy rule initialization

The initialization of fuzzy rules is the process of generating an initial population. Common methods include:

Random initialization: Randomly generate a set of fuzzy rules as the initial population. Each rule consists of a premise part (fuzzy set of input variables) and a conclusion part (fuzzy set of output variables).

Initialization based on expert knowledge: If domain experts provide some fuzzy rules, these rules can be used as part of the initial population, and other rules can be randomly generated to supplement the population.

Data driven initialization: Extracting fuzzy rules from data through clustering, classification, and other data mining methods as the initial population.

This paper chooses to use random initialization.

(4) Fuzzy rule encoding

Encoding is the process of representing fuzzy rules as chromosomes in genetic algorithms. Common encoding methods include:

Binary encoding: Encode the premises and conclusions of fuzzy rules into binary strings. For example, each fuzzy set can be represented by a Binary string representation, rules are composed of multiple such strings connected together.

Real number encoding: Directly using real numbers to represent the parameters of fuzzy rules, such as the center and width of membership functions. This method is more suitable for continuous use Optimization problem.

Mixed encoding: Combining binary and real encoding, some parameters are represented in binary and some in real.

This paper chooses to use binary encoding.

(5) Genetic manipulation

After encoding, genetic algorithms optimize fuzzy rules through operations such as selection, crossover, and mutation.

Selection: Select outstanding individuals to enter the next generation based on the fitness function.

Crossing: Generate new individuals through crossing operations, such as single point crossing, multi-point crossing, etc.

Mutation: Introducing new genes through mutation operations, such as randomly changing the encoding of a fuzzy set.

(6) Fitness function

The fitness function is used to evaluate the performance of fuzzy rules, usually based on the performance of the rule system on training data, such as classification accuracy, error, etc.

4.5 Key Issues of GA Optimization Rule Library

When using genetic algorithm (GA) to optimize the rule base of a fuzzy system, the following key points should be noted to ensure efficient optimization process and reliable results:

(1) Representation and Encoding of Rule Library

Rule representation: Each rule typically consists of a premise part (fuzzy set of input variables) and a conclusion part (fuzzy set of output variables) form. The logical structure of the rules needs to be clearly defined. The encoding methods include binary encoding, real encoding, mixed encoding, and encoding length.

(2) Design of fitness function

The fitness function is used to evaluate the performance of the rule library, and attention should be paid to the following during design:

Clear objective: The fitness function should directly reflect the optimization objective, such as minimizing error, maximizing classification accuracy, etc.

Multi objective optimization: If the rule base needs to optimize multiple objectives (such as accuracy and complexity) simultaneously, multi-objective optimization methods (such as NSGA-II) can be used.

Avoid overfitting: Add a penalty term for rule complexity in the fitness function to prevent the rule library from becoming too complex.

Computational efficiency: The calculation of the fitness function should be as efficient as possible to avoid excessive computational costs.

(3) Constraint handling of rule library

Rule consistency: Ensure that the rules in the rule library are logically consistent and avoid conflicts.

Rule integrity: Ensure that the rule base covers all possible input scenarios to avoid omissions.

Parameter range constraint: The parameters of the membership function (such as center and width) should be within a reasonable range, and constraints can be handled through penalty function or correction methods.

5 Simulation Analysis

In order to ensure the consistency of simulation results, the simulated sheet-like infrared heater is divided into four zones, with one heat flow meter corresponding to a distance of 2cm vertically from each zone for temperature measurement. The temperature control target temperature is +120°C, and a comparative analysis is conducted using non tuned PID control and self-tuning PID control. Fig. 7 shows Schematic diagram of the sub bureau of the sheet-like infrared heater, Table 2 shows Corresponding heat flow meter numbers for partition.

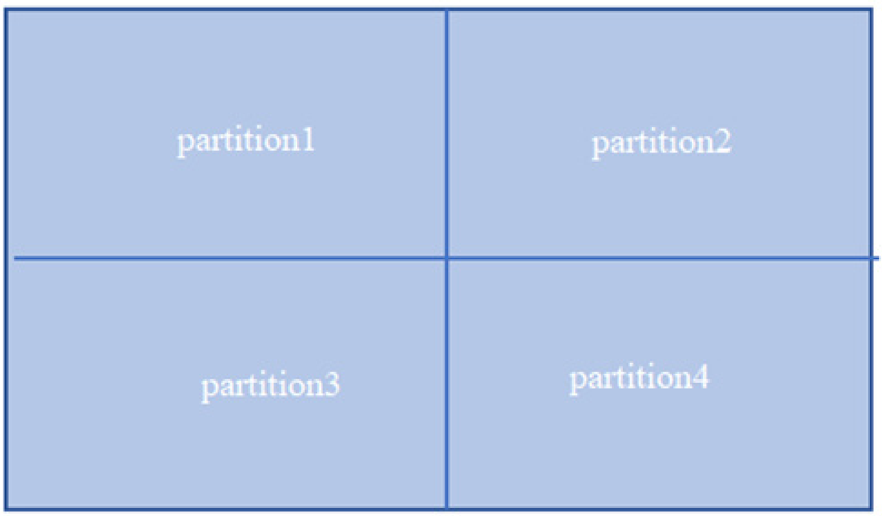

Fig. 7. Schematic diagram of the sub bureau of the sheet-like infrared heater

Table 2. Corresponding heat flow meter numbers for partition

Serial number	Partition	Temperature sensor
1	Partition1	RLJ01
2	Partition2	RLJ02
3	Partition3	RLJ03
4	Partition4	RLJ04

(1) Simulation of Traditional PID Temperature Control

Infrared heating device is an object with self balancing ability, which can be described by a second-order system with pure hysteresis link [24]. For second-order non oscillatory systems, parameter identification can reduce them to first-order models. Using the temperature output as the control object, according to the temperature mathematical model established in section 4.2, it is determined that the temperature control system can be equivalently described as a first-order inertial hysteresis system, Fig. 8 shows Simulation structure diagram of PID control system, and the transfer function of the system is:

$$\mathrm{G}(\mathrm{s})=\frac{0.93}{73.92\mathrm{s}+1}e^{-14.565s} \tag{15}$$

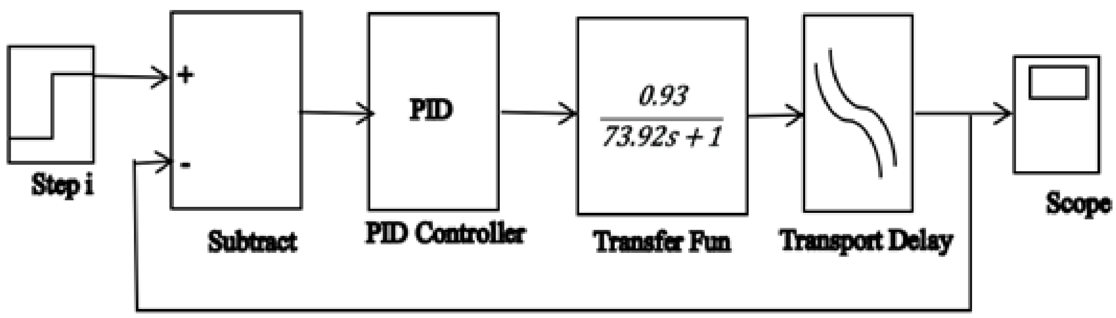

Fig. 8. Simulation structure diagram of PID control system

Firstly, in order to verify the PID control of a single partition, three parameters are set for PID control: K_p=2.1, K_i=0.05, K_d=0.02. At this point, perform a single zone control simulation as shown in Fig. 9.

In Fig. 9, it can be seen that the PID control of a single zone exhibits overshoot during the temperature rise period, with overshoot greater than 10°C. After overshoot, it begins to approach the target temperature, and this process requires a period of time to reach the target temperature from the overshoot, and the duration is slightly longer.

Secondly, in order to verify the simultaneous PID control of four partitions, the three parameter settings for PID control remain unchanged: K_p=2.1, K_i=0.05, K_d=0.02. At this point, perform a 4-partition control simulation as shown in Fig. 10.

In Fig. 10, it can be seen that the PID control of zone 4 still exhibits overshoot during the temperature rise stage. The overshoot is affected by the coupling of each circuit and varies, with the maximum overshoot reaching+15 °C The overshoot of all circuits is also affected by coupling effects when approaching the target temperature, and cannot reach the target temperature at the same time. When all zone temperatures reach the target temperature, the duration increases, but ultimately it can reach the target temperature.

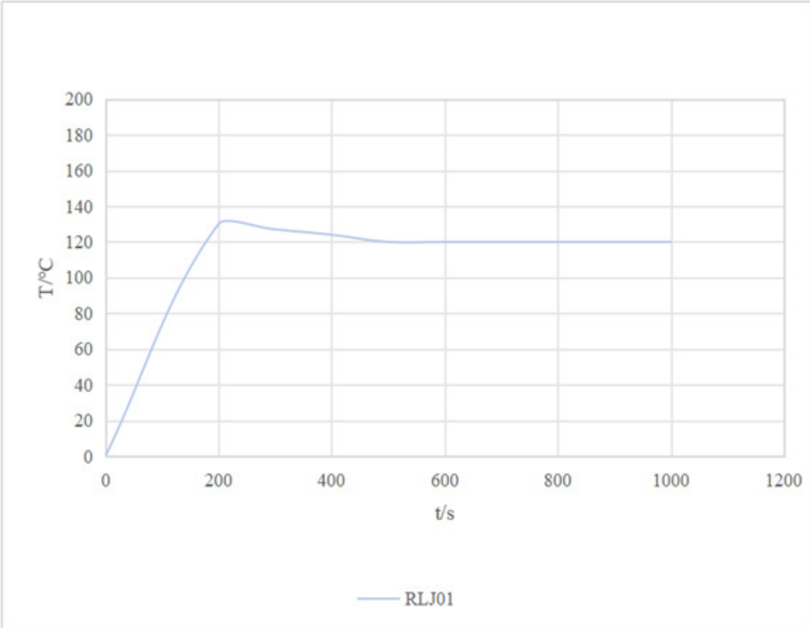

Fig. 9. PID control single partition response curve

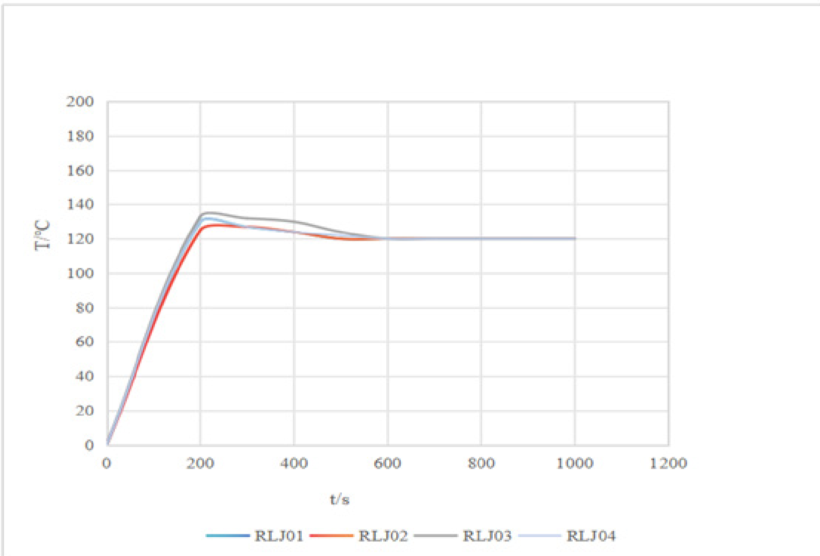

Fig. 10. PID Control 4-zone response curve

(2) Simulation of Self-tuning PID Temperature Control

In order to introduce self-tuning PID control in the later stage of fuzzy PID control, where the intervention timing rule of self-tuning PID control is: distance from the target temperature error and real-time temperature T_t<T (T_t represents the measured temperature, T represents the target temperature). Simulate according to both single zone and 4-zone.

Firstly, in order to compare the effect of self-tuning PID intervention, the initial PID control parameters were still set to: K_p=2.1, K_i=0.05, K_d=0.02. At this point, perform a single zone control simulation as shown in Fig. 11.

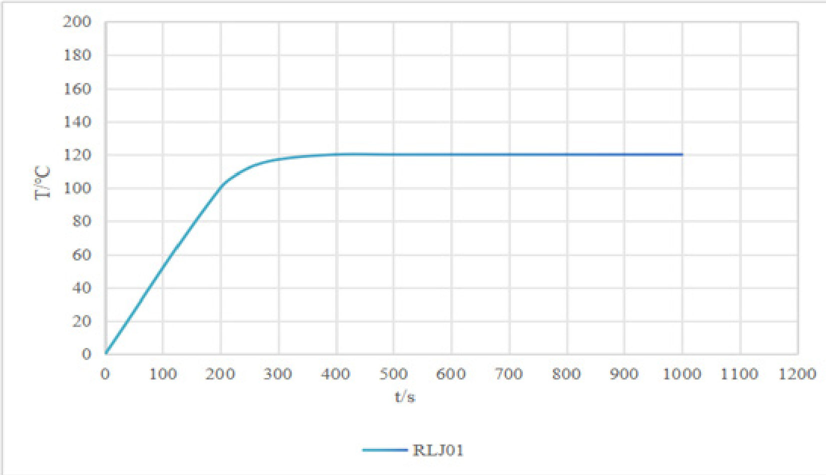

Fig. 11. Response curve of control single partition after self-tuning PID intervention

In Fig. 11, it can be seen that the self-tuning PID control of a single zone did not exhibit overshoot during the temperature rise stage. As it approached the target temperature, the heating rate decreased, gradually approaching the target temperature, and finally stabilizing in the target temperature range.

Secondly, in order to compare the effectiveness of self-tuning PID intervention, it was verified that four partitions were controlled simultaneously, with the initial PID control parameters still set to: K_p=2.1, K_i=0.05, K_d=0.02. At this point, perform a 4-partition control simulation as shown in Fig. 12.

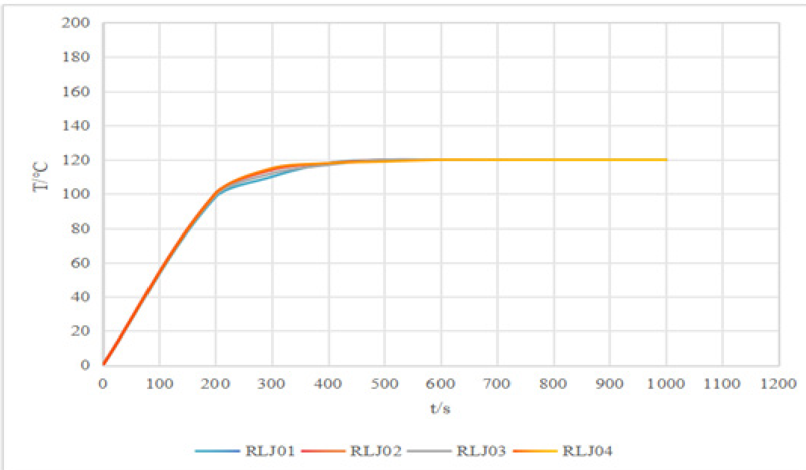

Fig. 12. Response curve of control 4 zones after self-tuning PID intervention

In Fig. 12, it can be seen that the self-tuning PID control of Zone 4 did not exhibit overshoot during the temperature rise period. As the temperature of all circuits approached the target temperature, the heating rate decreased, and the heating rate trend of Zone 4 was consistent. With coupling effects, there were some heating rate errors when approaching the target temperature, but it was ultimately able to reach the target temperature.

(3) Simulation result analysis

Comparing the two control methods that only use fuzzy PID and self-tuning PID for later intervention, it can be seen that PID control has a large overshoot in the response curve and a long time period to return to the target;

The control that intervenes in the later stage of self-tuning PID has no overshoot and converges quickly.
Based on the above simulation and analysis, the results shown in Table 3 can be obtained.

Table 3. Comparative analysis results

Serial number	Compare projects	PID control	Self tuning PID control	Result
1	Control accuracy (°C)	±2	±2	consistent
2	Rising time period (s)	200	200	consistent
3	Overshoot comparison	Over tuning occurs	No overshoot	Self tuning PID control with no overshoot
4	Approaching the target temperature in seconds	400	300	Self tuning PID takes short time
5	Reaching the target temperature	reach	reach	consistent

6 Experimental Validations

In this section, self-tuning PID controller will undergo physical verification experiments, comparing it with traditional PID control to confirm its consistency and superiority with simulation results.

6.1 Experimental System Construction

Steps for building the experimental system:

Firstly, lift a sheet-like infrared heater (cage) and place it flat inside the environmental simulator, with the black paint emitting surface facing the product.

Secondly, align the temperature sensors of the four heat flow meters with the four zones of the infrared heater and paste them together, with a distance of 2cm from the infrared heater (cage).

Thirdly, connect the heat flow meter temperature sensor to the temperature monitoring device (temperature collector circuit).

Fourthly, connect each infrared heater (cage) to its own independent programmable power control circuit.

Fifth, temperature monitoring equipment, program-controlled power control circuits, and measurement and control hosts are connected through a local area network (LAN).

Sixth, the measurement and control software (host) runs periodically to monitor and apply power values to each partition to ensure real-time control of all temperature monitoring devices.

During the experimental verification, the sheet-like infrared heater is still divided into four zones, and the temperature control target temperature is still +120°C. Non tuning PID control and self-tuning PID control are used for comparative analysis and comparison. The three parameter settings of PID control are consistent with those during simulation: K_p=2.1, K_i=0.05, K_d=0.02. Fig. 13 shows Physical Sheet Infrared Heater.

Fig. 13. Physical sheet infrared heater

In order to verify the actual usage, the background temperature of the environmental simulator is monitored and controlled at T=100k.

6.2 Test Results

Firstly, verify the PID control and self-tuning PID temperature control during single loop heating and temperature maintenance, and organize the experimental data analysis results as shown in Fig. 14 and Fig. 15.

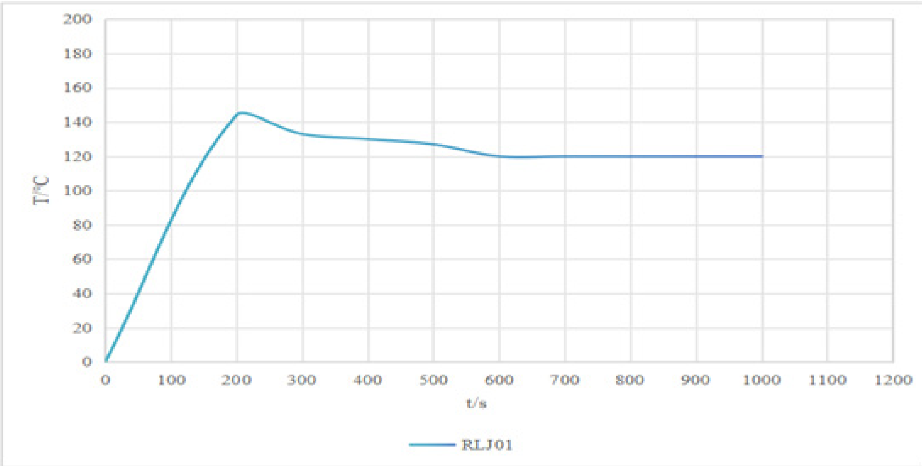

Fig. 14. PID control single partition response measured curve

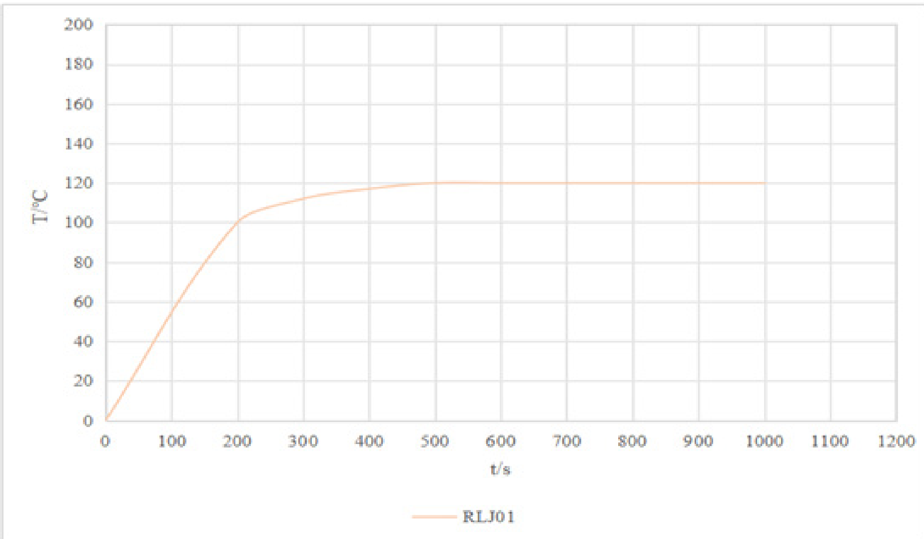

Fig. 15. Control single zone measured curve after self-tuning PID intervention

Secondly, verify the PID control and self-tuning PID temperature control during the four loop heating and temperature maintenance, and organize the experimental data analysis results as shown in Fig. 16 and Fig. 17.

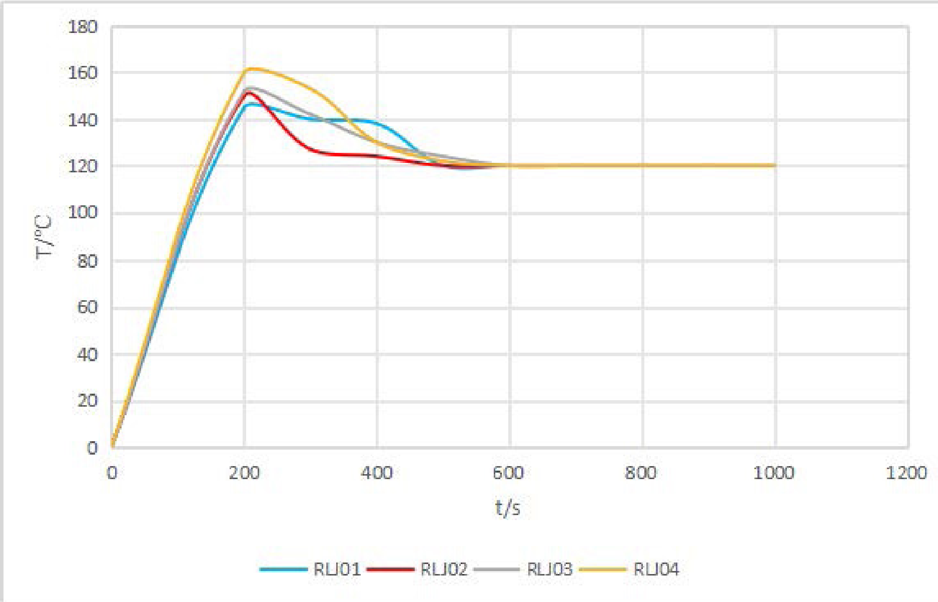

Fig. 16. PID Control 4-zone response measurement curve

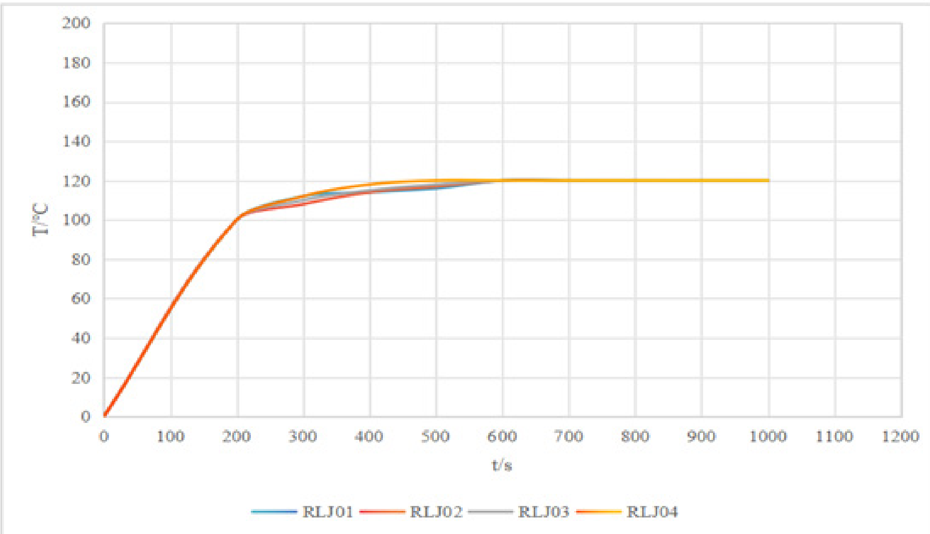

Fig. 17. Actual response curve of control 4 zones after self-tuning PID intervention

Fig. 14 and Fig. 15 respectively demonstrate the temperature control effects of traditional PID control and self-tuning PID control on the experimental product. From the graph analysis, it can be seen that self-tuning PID can avoid overshoot in the actual heating control process. Fig. 16 and Fig. 17 respectively record the experimental data analysis results under traditional PID control and self-tuning PID control for multi-channel (4-channel control during the experiment) control. It can be seen from the figures that under multi-channel control, the temperature difference range of traditional PID control decreased from a maximum overshoot of 20°C to an overshoot of 0°C under self-tuning PID control, and the temperature consistency of the multi-channel control loop under self-tuning PID control was better than that of the traditional PID control loop.

Through simulation and practical experiments, it has been verified that PID control without PID parameter tuning is greatly affected by external environmental factors. When reaching the target temperature, overshoot increases and the stabilization time becomes longer. Compared with self-tuning PID control, the stabilization time increases by 100 seconds. The use of a self-tuning PID controller that intervenes later in the temperature control process has shown significant improvement in temperature control using infrared heaters (cages), effectively controlling temperature deviations without exceeding the tolerance, ensuring the consistency of the target temperature for temperature control.

7 Conclusion

This paper proposes a real-time self-tuning PID controller based on a genetic algorithm, which can effectively control the temperature of an infrared simulator and keep the temperature error within the required range. Through simulation and experimental validations, this paper proposes that fuzzy PID controller is used in the early stage to rapidly approach the target temperature in environmental testing, and the PID controller which is based on genetic algorithm with self-tuning parameters is used in the later stage to reduce the error between the target temperature and the actual controlled temperature value, effectively control the overshoot. The controller which uses self-tuning PID parameters can control the temperature to approach the target temperature, significantly improves the consistency between the target temperature and the actual controlled temperature.

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