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Optimization of real-time adaptive regulation in human specimen fluid exchange process based on fuzzy control theory

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Abstract There are strong coupling relationships among temperature, pressure, flow rate and other parameters in the process of human specimen fluid exchange, which are easily affected by external disturbances, leading to the decrease of control accuracy and response lag. In this paper, a real-time adaptive regulation method based on fuzzy control theory for human specimen liquid exchange process is proposed to solve the problems of poor stability and weak anti-interference ability of traditional PID control when facing a nonlinear, multivariable coupled system. The study designed a two-input and three-output fuzzy adaptive PID controller to adjust the PID parameters in real time with the error and its derivatives as the control inputs, at the same time, the hybrid adaptive particle swarm algorithm (HAPSO) was proposed to optimize the parameters of the fuzzy controller through the introduction of the relative evolution factor and the particle diversity factor, and combined with the optimization strategy of the small living environment. Simulation results show that the HAPSO-optimized fuzzy adaptive PID control system reduces the overshooting amount from 10% to 3.5%, the stabilization time from 21 s to 17 s, and the liquid level fluctuation range from 18 cm to 6 cm compared with the traditional PID control system. In addition, the optimized system can be quickly stabilized at 16 °C and keep smaller fluctuation when the external environment changes in the temperature control test, which showing excellent robustness. The study proves that the adaptive regulation method based on fuzzy control theory and HAPSO optimization can effectively improve the control accuracy and stability of the human specimen liquid exchange process, which provides a new technical solution for the automation control in related fields.

Index Terms Fuzzy control theory, adaptive regulation, human specimen fluid exchange, hybrid adaptive particle swarm algorithm, parameter optimization, PID control

I. Introduction

Human anatomy is one of the most basic morphological subjects in medical schools, which is highly intuitive and its practical teaching is very important. In the era of rapid development of science and technology, the teaching and learning resources of human anatomy have been greatly enriched, such as resin models, plasticized specimens, multimedia teaching resources have basically been popularized in medical schools, and some medical schools have even introduced more advanced digital human system and virtual anatomy system [1]-[4]. However, in the teaching of human anatomy, no type of teaching resources can replace the position of human specimens in anatomy teaching [5]. Human specimens are more capable of attracting students' attention and arousing their interest in teaching, and human specimens are more capable of reflecting the real structure of the human body in a more graphic way [6], [7]. Therefore, in the actual teaching of human anatomy, teachers mainly teach through human specimens, and students mainly learn through the observation of human specimens.

In the long run, human specimens are scarce resources, in order to better and many times repeated use of human specimens, it is necessary to solve the problem of preservation of human specimens [8]. In the history of the development of human anatomy, 5% formaldehyde aqueous solution has long played an important role in the preservation of human specimens [9]. Formaldehyde, chemical formula HCHO, also known as anthranilic aldehyde, is soluble in water and ethanol. The concentration of formaldehyde aqueous solution can be up to 55%, usually used 35%~40% formaldehyde aqueous solution, called formalin, is a colorless liquid with a strong irritating odor [10]-[13]. A large number of studies have confirmed that formaldehyde is a highly toxic substance, which has a huge harmful effect on the human body [14]. Although formaldehyde has a great harm to the human body, but formaldehyde is very easy to combine with protein amino group to make it denatured, and can fix the lipid material, strong penetration, sterilization, antiseptic effect is good, but also has the preparation of convenient, cheap and many other advantages [15]-[17]. Therefore, 5% formaldehyde aqueous solution, is still the most commonly used preservation fluid for human specimens [18]. In view of the almost irreplaceable nature of formaldehyde in the preservation of human specimens, as well as the serious hazardous effects on human health, scholars in recent years have studied the optimization of the process of changing the fluid of human specimens, aiming to reduce the impact of formaldehyde on human health [19]-[21].

Liquid exchange of human specimens is an essential process for preserving human tissues or organs, and its quality directly affects the preservation effect of specimens and the value of subsequent research. In the process of fluid exchange, temperature, pressure, flow rate and other parameters need to be precisely controlled, but there are complex nonlinear relationships and strong coupling characteristics between these parameters, and the traditional control methods are difficult to meet the requirements of high precision and high stability. PID control is widely used in industrial process control because of its simplicity and ease of use, but in the face of the human specimen fluid exchange of this kind of nonlinear, time-varying, multivariable system, fixed-parameter PID controller shows obvious limitations, such as response lag, large overshooting, and interference. However, in the face of such nonlinear, time-varying, multivariable systems as human specimen fluid exchange, fixed-parameter PID controllers show obvious limitations, such as response lag, overshooting, and poor interference resistance. In recent years, the development of intelligent control theory provides a new method for solving the control problems of complex systems. Fuzzy control, as a control strategy based on human empirical knowledge, can deal with the uncertainty and nonlinear characteristics of the system and realize effective control without the need of an accurate mathematical model. However, the design of traditional fuzzy controllers relies on expert experience and lacks a systematic approach to parameter adjustment, making it difficult to obtain optimal control. Particle swarm optimization (PSO) algorithm, as an efficient population intelligence optimization algorithm, shows advantages in solving high-dimensional nonlinear optimization problems, but the standard PSO algorithm is prone to converge prematurely and fall into local optimal solutions. Therefore, combining fuzzy control theory and improved optimization algorithms to design an efficient adaptive control system applicable to the fluid exchange process of human specimens has become an important topic of current research. At present, domestic and international research on such systems mainly focuses on the industrial process control field, and relatively little research has been conducted for the special biomedical application of human specimen fluid exchange.Wu et al. (2025) proposed a bi-asynchronous fuzzy control method based on the triggering of memory events, which effectively improves the control performance of the semi-Markovian jump system.Abdellatif et al. (2025) combined the hybrid machine learning and multi-objective particle swarm optimization algorithms to structural seismic design and achieved good results.Ezlin et al.(2024) proposed an improved inverse analytic logic mining model in discrete Hopfield neural networks to optimize the training of small habitat genetic algorithms. These studies provide important theoretical and methodological references for this paper.

In this study, a real-time adaptive regulation method based on fuzzy control theory to optimize the fluid exchange process of human specimen is proposed. Firstly, a two-input and three-output fuzzy adaptive PID controller is designed to realize the dynamic adjustment of the control parameters, secondly, a hybrid adaptive particle swarm algorithm (HAPSO) is proposed to solve the problem that the standard PSO algorithm is easy to fall into the local optimum through the introduction of relative evolutionary factor and particle diversity factor and the combination of the small habitat optimization strategy, finally, the HAPSO algorithm is applied to optimize the parameters of the fuzzy PID controller, and the effectiveness of the proposed method is verified by simulation experiments. The innovation of this study lies in the organic combination of fuzzy control theory and improved optimization algorithm, which provides a high-precision and high-stability adaptive control scheme for the human specimen liquid exchange process. By improving the inertia weight adjustment strategy in the particle swarm algorithm, the algorithm's global searching ability and local refinement searching ability are enhanced, so as to obtain better control parameters.

II. Fuzzy control-based real-time regulation method for human specimen fluid exchange process

In this chapter, fuzzy adaptive PID controller design is based on fuzzy PID control theory, and the standard particle swarm algorithm is improved to propose a hybrid adaptive particle swarm algorithm (HAPSO), which is applied to optimize the fuzzy adaptive PID controller, so as to realize real-time adaptive regulation of the human specimen liquid exchange process.

II. A.Fuzzy PID control theory

Fuzzy control [22] takes fuzzy mathematics as the theoretical basis and automatic control principle and computer control as the technical support. Fuzzy mathematics mainly includes fuzzy set theory, fuzzy language knowledge expression and fuzzy rule reasoning.

II. A. 1) Fuzzy control fundamentals

The fuzzy control algorithm first needs to convert the clear rules in the fuzzy direction. The error E is obtained by differing the process value obtained by sampling from the set value and is used as an input value for the fuzzy controller. The input error E is fuzzified and calculated by fuzzy control rule R. A fuzzy vector e can be obtained for error E. In fuzzy control, the fuzzy control quantity u is the product of fuzzy vector e and fuzzy control rule R, Eq:

$$u = e * R \tag{1}$$

The overall structure of the fuzzy control system is shown in Fig. 1, the sensor collects the value of the controlled object and the value obtained by making difference with the reference value, and then enters into the fuzzy control inference part through A/D converter, and then goes through the fuzzy quantization, fuzzy control rule inference, fuzzy decision-making to calculate the fuzzy quantity, and then finally obtains the digital control quantity through the non-fuzzy processing. This closed-loop control realizes the whole fuzzy control.

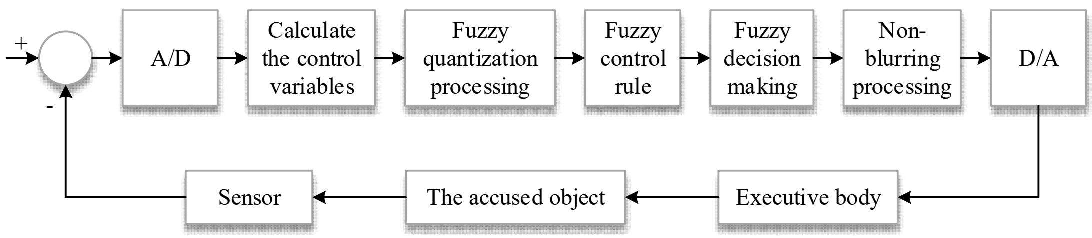

Figure 1: Structure of the fuzzy control system

II. A. 2) Basic structure of a fuzzy controller

Fuzzy control generally consists of four parts: fuzzy controller, input/output interface device, generalized object, and sensor. Compared to the traditional control system, fuzzy control system is the replacement of the traditional controller with a fuzzy controller. Therefore, fuzzy controller (FC) is the most important part of fuzzy control system. Fuzzy inference controllers are a class of linguistic algorithmic controllers, which control based on established linguistic rules and later output the corresponding control quantities.

(1) Input interface

The main role of input interface is fuzzification. Fuzzification mainly refers to the process of transforming the clear values of the input into fuzzy subsets and affiliation functions by appropriate changes. Fuzzification is indispensable because in order to adapt these clear values to the inference rules constructed by the linguistic expressions in subsequent calculations, they need to be converted into fuzzy quantities, i.e. fuzzy subsets. For the number of fuzzy subsets, the control accuracy can be improved when the number is high, but when the number is high, the number of fuzzy rules will correspondingly grow more rapidly, thus increasing the amount of computation substantially, and the number of fuzzy subsets is generally chosen according to the arithmetic power of the computer and the complexity of the algorithms, and the larger the number of fuzzy subsets, the greater the control accuracy, and, at the same time, it will be accompanied by the enhancement of the demand of the arithmetic power of the computer and the program's computation With the time increase.

(2) Knowledge base

A knowledge base generally consists of a database and a rule base. The database holds the set of affiliation functions for input-output calculations. It can provide data support to the reasoning machine in the process of causing reasoning, and generally converts digital quantities into fuzzy quantities. The rule base provides a series of control rules in the reasoning machine reasoning, stored in the approximate reasoning in some of the conditional choice statements and some algorithms in the approximate reasoning.

(3) Fuzzy Reasoning and Clarification

According to the input fuzzy quantities, according to the fuzzy inference rules in the knowledge base, fuzzy inference in the form of linguistic inference so as to solve the relationship, this process is fuzzy inference. The fuzzy reasoning obtained is still a fuzzy set, which is often the output of an irregular multi-segment set due to the computation of the affiliation function. Clarification, i.e., defuzzification interface needs to map these multi-segmented, irregular fuzzy sets into a representative value, and finally output an exact output as the output of the controller.

II. A. 3) Fuzzy adaptive PID controller design

In this paper, the controlled object is the process of human specimen liquid exchange, and the adopted controller selects the program of two inputs and three outputs, the fuzzy controller takes the deviation e and its derivative ec as the control inputs, and the outputs are the three parameters of the PID controller, and the PID controller is updated directly. For different controlled object deviation and deviation derivatives, the fuzzy controller will input different proportional, integral and differential parameters to the PID controller, which can be used for different processes, the fuzzy PID controller is able to adaptively find the optimal control parameters of the PID, so as to have better stability and dynamic characteristics. The principle of fuzzy adaptive PID controller is shown in Figure 2.

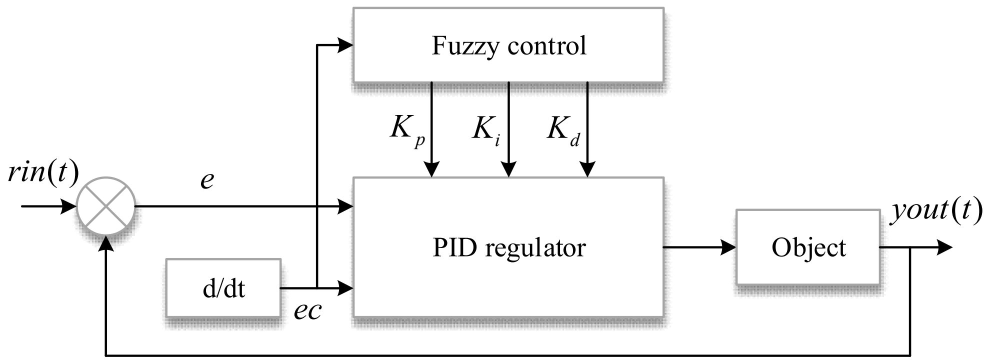

Figure 2: Principle of fuzzy adaptive PID controller

II. B.Particle Swarm Algorithm Improvement

II. B. 1) Standard Particle Swarm Algorithm

The particle swarm algorithm [23] first initializes a group of random particles (random solutions), the goodness of the solutions is determined by a fitness function, then the particles update themselves by following the current 2 optimal solutions, the first one is the particle itself and the second one is the optimal solution currently found by the whole population. Finally, the search is carried out by the particles continuously following the 2 optimal solutions until a specified number of iterations is reached or a preset arithmetic accuracy is satisfied. In this case, the particle velocity and position update iteration formula is shown in equation (2):

$$\begin{cases} v_i^{k+1} = \omega v_i^k + c_1 \times r_1 \times (pbest_i - x_i^k) + c_2 \times r_2 \times (gbest - x_i^k) \\ x_i^{k+1} = x_i^k + v_i^{k+1} \end{cases} \tag{2}$$

where x_i^k, v_i^k denotes the speed and position of the i nd particle in the k rd iteration, respectively, c_1 denotes the degree of self-cognition, which is used to track the current individual optimal position of the i th particle $pbest_i$, c_2 denotes the degree of cognition of the group, which is used to track the current global optimal position of the whole population $gbest$, r_1, r_2 is a random number in the interval [0,1], and ω refers to the inertia weights.

The standard particle swarm algorithm adjusts ω linearly and is calculated as in equation (3):

$$\omega = \omega_{\max} - \frac{(\omega_{\max} - \omega_{\min}) \times k}{k_{\max}} \tag{3}$$

The particle swarm algorithm is usually defaulted to the standard particle swarm algorithm, and the flow of the algorithm is shown in Figure 3.

II. B. 2) Improved methods for dynamic adaptive weighting

In the standard particle swarm algorithm, ω varies linearly with the number of iterations, and for some nonlinear complex function optimization problems, the use of linear decreasing weight adjustment formula often makes the population fall into the local optimal solution due to the lack of improvement in the enlightenment of the particles. Moreover, ω is not linked to the actual algorithm execution state, and is only related to the number of selected generations, which lacks certain rationality. Based on this, this paper proposes an adaptive weight adjustment strategy that is nonlinear and combines the state of the algorithm's generation selection process.

In the iterative process of the algorithm, the distance between the individual optimal value of different particles and the optimal value of the group of this iteration is different, if the same weight is set, the particles that are farther away from the optimal value of the group position close to the group are obviously slower, which affects the efficiency of the search, so in order to make these particles close to them faster, their inertia weights can be increased so that they have a faster flight speed. In addition, in the late stage of generation selection, in order to enable the algorithm to search the nearby neighborhood more finely, the inertia weights of the particles at this time should be set to be smaller.

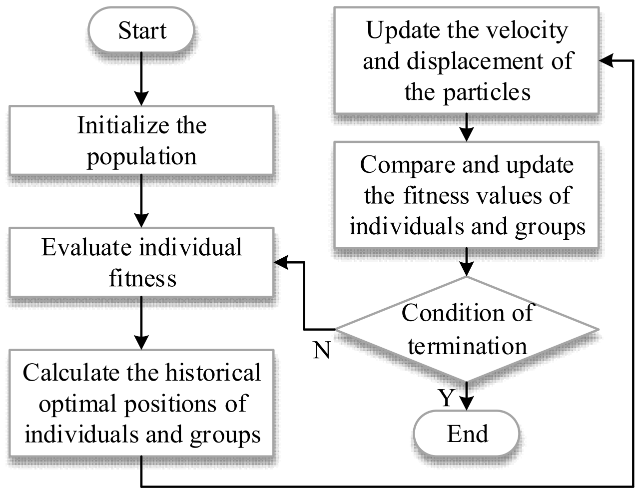

Figure 3: Flowchart of the standard PSO algorithm

For this reason, this paper introduces 2 indicators for the improvement of the weight adjustment strategy: relative evolution factor l_i and particle diversity factor tg.

Among them, the relative evolution factor l_i, which associates the state information of each particle with the inertia weights to determine the distance between the individual optimal values of different particles and the group optimal values, thus adjusting the inertia weights, can be expressed as:

$$l_i = \frac{\min(F_{i,k}, F_{gbest.k})}{\max(F_{i,k}, F_{gbest.k})} \tag{4}$$

where, $F_{gbest,k}$ is the global optimal fitness value of the k nd iteration, $F_{i,k}$ is the i th particle fitness value of the k th iteration.

It can be seen that in each iteration, the closer the individual optimal value of particle i is to the global optimal value of this iteration, l_i the closer it is to 1.

The particle diversity factor tg, on the other hand, is to determine whether the algorithm has reached the late iteration, because the later the iteration, the lower the particle diversity, which can be indirectly represented by the standard deviation σ of the different particle fitness values $F_{i,k}$ to calculate the degree of its dispersion:

$$\overline{F_k} = \frac{1}{N}\sum_{i=1}^{N} F_{i,k} \tag{5}$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(F_{i,k} - \overline{F}_k)^2} \tag{6}$$

$$tg = \frac{1}{1+\sigma} \tag{7}$$

where, N is the total number of particles.

For the particle swarm algorithm, let ω_i be the weight of the i rd particle, the smaller the relative evolution factor is, indicating that the further away from the population optimum, then the larger it should be, thus enabling the particle to fly faster to the neighborhood of the optimal solution. The lower the particle diversity is, the later the iteration is, the smaller it should be, enabling the algorithm to perform a finer search, and thus can be expressed in equation (8):

$$\omega_i = 1 - l_i \times \omega_i + tg \times \omega_{ig} \tag{8}$$

where ω_1, ω_{tg} is a constant, ω_1 takes the value of [0.4,0.6] and ω_{tg} takes the value of [0.05,0.20].

However, due to the particle "close" phenomenon, the algorithm will fall into a local optimum when the diversity of particles is poor. In order to set up a diversity critical index tg_{ref}, when $tg \geq tg_{ref}$, when the particle diversity is poor, can be introduced into the small habitat optimization population strategy to optimize, improve the diversity, jump out of the local optimum.

II. B. 3) Strategies for optimizing populations in microhabitats

The small habitat optimization population strategy [24] is to first merge the offspring population after crossover and mutation with the parent population to form a new population, and then use pre-selection and crowding to select the better adapted part from it to continue the next iteration, which better maintains the diversity of the population, and can well jump out of the locally optimal solution, the steps are as follows:

(1) Perform selection, crossover, and mutation operations on the population.

(2) Combine the M genetically produced offspring individuals with the N parent individuals and calculate the Hemming distance between every 2 individuals in the new population using the following formula:

$$\| x_i - x_j \| = \sqrt{\sum_{t=1}^{d} (x_{it} - x_{jt})^2}, \begin{cases} i = 1, 2, \cdots, M+N-1 \\ j = i+1, \cdots, M+N \end{cases} \tag{9}$$

where d is the dimension of x_i and x_j.

Denote the small habitat radius by S. When $\| x_i - x_j \| < S$, penalize the less adapted of the two using Eq. (10):

$$F_{\min}(x_i, x_j) = Peanlty \tag{10}$$

(3) Rank the fitness of individuals in the new population and select the N individuals with the best fitness as the parent population for the next iteration of the particle swarm algorithm.

II. B. 4) HAPSO algorithm flow

The specific flow of HAPSO algorithm is as follows:

Step1: Initialize the initial position and velocity of the particle.

Step2: Calculate the individual optimal fitness value and global optimal fitness value to obtain the particle's individual optimal position $pbest_i$, this iteration global optimal position $gbest$.

Step3: Calculate the relative evolution factor and diversity factor of the population according to Eqs. (4)~(7), and get the inertia weight ω_i of each particle, when $tg < tg_{ref}$, execute Step5, otherwise execute in order.

Step4: Execute the small habitat optimization population strategy to select the N individuals with the best fitness as the parent population for the next iteration of the particle swarm algorithm.

Step5: Judge whether the termination condition is reached, if not, update the particle velocity and position according to equation (2) and return to Step2. otherwise, the algorithm ends the run.

II. C.Parameter optimization of HAPSO-based fuzzy PID controller

In adaptive fuzzy PID control system, in addition to the fuzzy rules having an effect on the system performance, the quantization factor and the initial PID parameters also affect the control effect. The HAPSO algorithm is used to optimize the five parameters, the quantization factor of the error and the rate of change of the error as well as the initial parameter values of the PID K_{p0}, K_{i0}, K_{d0} in the adaptive fuzzy PID controller, to obtain the optimal values so as to obtain a good control effect.

The schematic diagram of HAPSO optimized fuzzy PID is shown in Fig. 4.

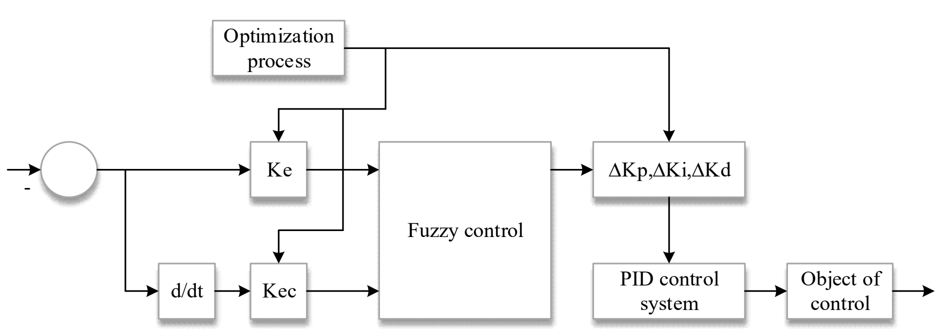

Figure 4: The principle of HAPSO optimizing fuzzy PID

The fitness function uses the ITAE metric, i.e:

$$J = \int_0^{\infty} t \,|\, e(t) \,|\, d_t \tag{11}$$

The HAPSO optimized fuzzy PID flowchart is shown in Fig. 5.

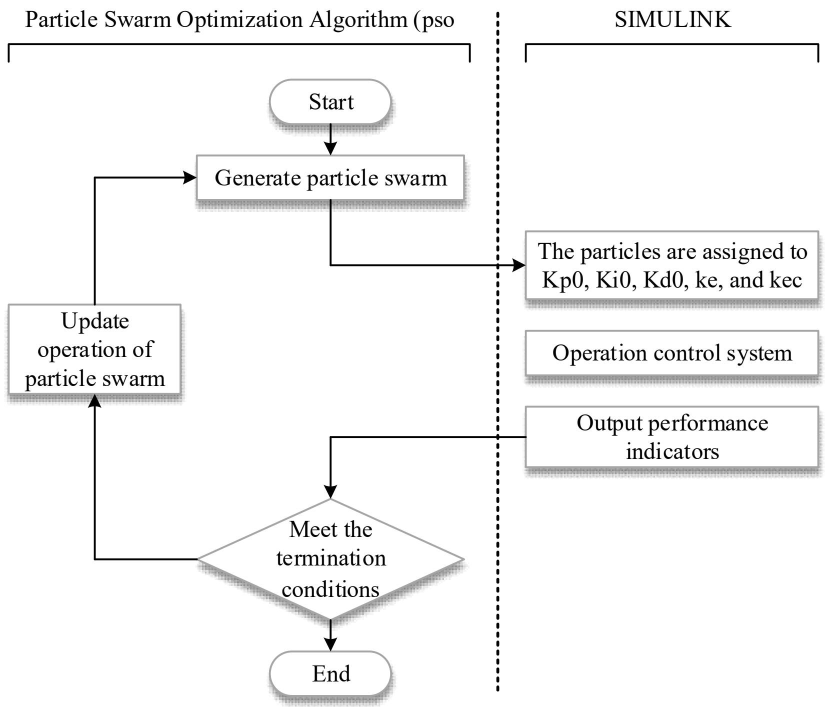

Figure 5: Flowchart of HAPSO optimizing fuzzy PID

The HAPSO algorithm optimizes the fuzzy PID parameters through a three part program. The first part of the HAPSO optimization program written by MATALB, the second part is the SIMULINK simulation model, and the third part is the linking program between the HAPSO optimization program and the SIMULINK simulation model.

(1) HAPSO optimization program

In order to send the optimization parameters of the adaptive fuzzy PID controller to the connection program pso_fuzzypid.m, it is implemented by calling the function handle through the feval function.

(2) SIMULINK simulation modeling

SIMULINK system simulation model for HAPSO optimization is established on the basis of adaptive fuzzy PID controller. Add the indicator part of human specimen liquid exchange process in the model. It is obtained by integrating the product of time and absolute value of error, and setting the output value of output port 1 will be used as the adaptation value of HAPSO algorithm.

(3) Connection program

In the connection procedure, firstly, the parameters optimized by the particle swarm algorithm are assigned to the SIMULINK model by using the assignin function, then the SIMULINK model is run by using the sim function, and finally, the simulation results, i.e., the value of the fitness function, are returned to the HAPSO optimization procedure, and the cycle of operation continues until the iteration condition is reached.

III. Simulation analysis of adaptive fuzzy PID controller optimization

In order to verify the practical effect of the proposed HAPSO-based adaptive fuzzy PID controller in regulating the human specimen liquid exchange process, simulation experiments are conducted in this chapter to compare the performance of the HAPSO algorithm and evaluate the control effect of the adaptive fuzzy PID controller, respectively.

III. A. Simulation of HAPSO-based PID controller parameter optimization

The conventional step signal is used as input, and the PID parameters are tuned using the HAPSO and Z-N methods, and simulation experiments are carried out to obtain the comparison curves of the PID parameters tuned by the

HAPSO and Z-N methods as shown in Fig. 6. When the liquid level in the human specimen container is initially set to 260 cm, the rise time of the PID controller tuned by the ordinary Z-N method and the PID controller optimized by HAPSO are 5.8 s and 6.2 s, the overshooting amount is 23% and 13%, and the steady state time is 30 s and 24 s. It can be seen that, with the optimization of the PID parameters by HAPSO, the overshooting amount and the steady state time are significantly reduced and the control effect is improved. are significantly reduced and the control effect is improved.

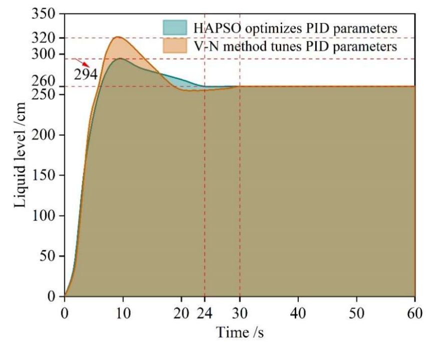

Figure 6: Comparison of PID parameters tuned by HAPSO and Z-N methods

Based on the premise of good calibration effect of HAPSO algorithm, the initial liquid level is set to 170cm, simulation experiment is carried out, and the set liquid level is changed to 260cm at 40 s. Ordinary PID and fuzzy adaptive PID are respectively used to control the liquid exchange process of human specimen, tracking the control effect, and obtain the comparison of the response curve between the PID and the fuzzy adaptive PID, such as shown in Fig. 7.

It can be seen that the fuzzy adaptive PID optimized by HAPSO improves the overshooting amount and steady state time indexes compared with the ordinary PID optimized by HAPSO, which can better satisfy the response requirements of the system, and the tracking and stabilizing effect is better than that of the ordinary PID.

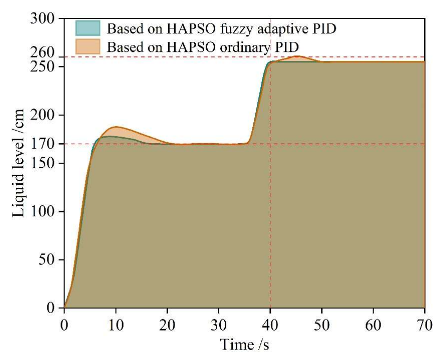

Figure 7: Comparison of PID and fuzzy adaptive PID response curves

A comparison of the performance of the system when reaching the first steady state is shown in Table 1. The results show that the fuzzy adaptive PID control overshoots and the time to reach steady state are significantly reduced.

Table 1: Comparison of Simulation Results

Algorithm	Overadjustment /%	Stabilization time /s	Liquid level /cm
PID	10	21	169~187
Fuzzy Adaptive PID	3.5	17	170~176

III. B. Simulation of control effect of adaptive fuzzy PID controller

III. B. 1) Comparison of Adaptive Fuzzy Control and PID Control Results

Comparison of the results of the step response using adaptive fuzzy PID control and PID control system is shown in Fig. 8. From the comparison results, it can be seen that the stability and anti-interference ability of adaptive fuzzy

PID control is better than conventional PID control. In the process of responding to the step temperature control command, the temperature overshoot caused by adaptive fuzzy PID control and only PID control algorithm is small and can be stabilized quickly. Temperature stabilization control, the external ambient temperature and thermal load sent to change, adaptive fuzzy PID control can make the control temperature quickly stabilized, volatility is small, anti-interference ability, while only using PID control algorithms of the controller by the outside world is more likely to destabilize and easy. As a result, the adaptive fuzzy PID control has fast response, short stabilization time, and better adaptability to the load changes, and the control system has good followability, stability and robustness.

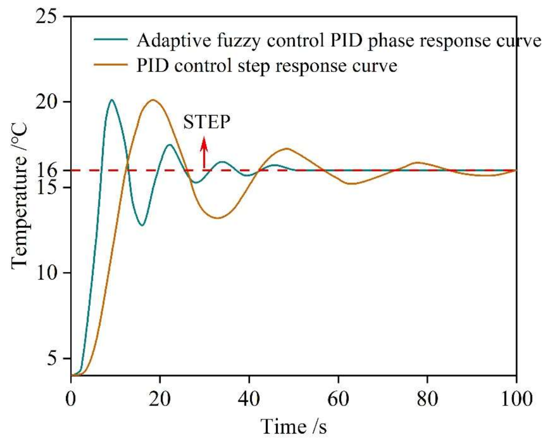

Figure 8: The step response results of adaptive fuzzy PID control and PIDD control systems

III. B. 2) Comparison of adaptive fuzzy control results before and after optimization

The variation curve of the cost function adaptation value with the number of optimization iterations for the optimization of the human specimen fluid exchange process using the HAPSO algorithm is shown in Fig. 9. It can be seen that after 50 optimization iterations, the cost function adaptation value is stable at around 525.

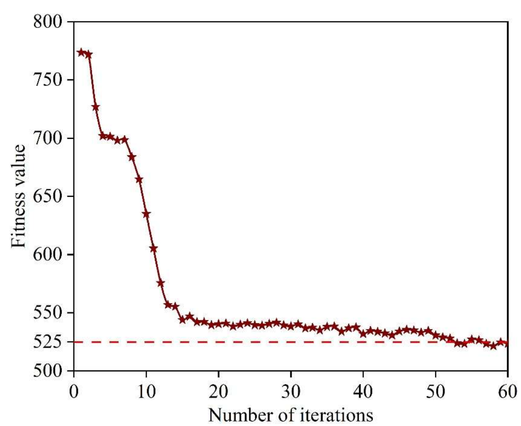

Figure 9: The curve of the cost function varying with the number of optimization iterations

The simulation results of the fuzzy adaptive PID controller after optimization with HAPSO are compared with the simulation results when the parameters are not optimized in the same graph, and the corresponding system response curves of the optimal control parameters during the optimization iteration process are shown in Fig. 10, and the optimized controller has a faster transient response speed and smaller steady-state error, which demonstrates the effectiveness of the HAPSO optimization algorithm.

The temperature of both control schemes was finally stabilized at 16°C within the normal range of 4~25°C. However, it is obvious from the curve that the temperature output curve of the human specimen liquid exchange process optimized by the HAPSO algorithm has the characteristics of small overshooting amount, short rise time, short regulation time and small stabilization error, and the control system has a more excellent control performance.

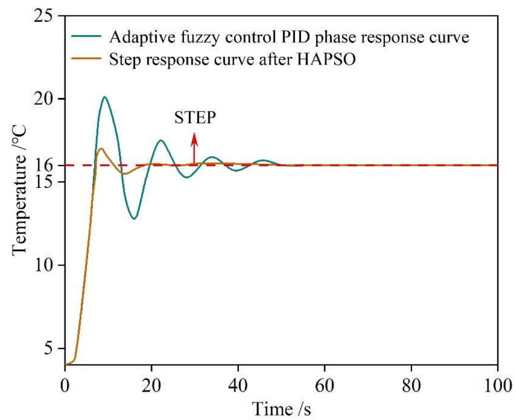

Figure 10: The output of the fuzzy adaptive PID controller before and after optimization

IV. Conclusion

In this paper, through the combination of improved particle swarm algorithm and fuzzy control theory, a real-time adaptive regulation method for human specimen liquid exchange process is constructed. The experimental data show that, compared with the PID controller tuned by ordinary Z-N method and the PID controller optimized by HAPSO, when the initial liquid level is set to 260 cm, the former has a rise time of 5.8 s, an overshooting amount of 23%, and a steady state time of 30 s, while the latter has a rise time of 6.2 s, an overshooting amount of only 13%, and the steady state time is shortened to 24 s. Based on the good HAPSO rectification effect, the fuzzy adaptive PID control was further optimized. The adaptive value of the cost function is stabilized at about 525 after 50 optimization iterations, which verifies the convergence of the algorithm. In the tracking control test when the initial liquid level is set to 170 cm and the set level is changed to 260 cm at 40 s, the fuzzy adaptive PID controller shows less volatility and stronger anti-interference ability in the temperature stabilization control, which enables the control temperature to quickly reach and stabilize at 16 °C, which is located within the normal temperature range of 4 °C to 25 °C for the preservation of human specimens. The hybrid adaptive particle swarm algorithm proposed in this study effectively overcomes the problem that the standard PSO algorithm is prone to fall into local optimum by introducing the relative evolution factor and particle diversity factor and combining the small habitat optimization population strategy. The experimental results prove that the real-time adaptive regulation method based on fuzzy control theory has obvious advantages in the control of human specimen liquid exchange process, which provides a new technical idea for similar control systems with high precision and strong robustness requirements.

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