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RESEARCH ARTICLE

A Control Method for Improved Fuzzy PID of GSOM for Fish Scale Evolution

ZUOXUN WANG, CHUANYU CUI, JINXUE SUI, YONG ZHANG, AND CHANGKUN GUO

College of Information and Electronics Engineering, Shandong Technology and Business University, Yantai 264005, China

Corresponding author: Zuoxun Wang (wangzuoxun@126.com)

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ABSTRACT Fuzzy PID control is a control method with good adaptability and stability in complex environments. It is used to achieve precise regulation and stable control of the system. In this paper, a fish scale evolution GSOM is proposed to improve the control method of fuzzy PID. Firstly, the fish scale regulation system is established and the differential evolution theory is introduced to realize the evolutionary upgrading of the system. Secondly, the GSOM module is introduced. The system is optimized by self-organized mapping neural network to achieve dynamic regulation of polymorphic inputs. Meanwhile, the fuzzy rule base and parameter regulation mechanism in fuzzy PID control are dynamically optimized. Improve the performance of the control system. Finally, the control method of improved fuzzy PID for fish scale evolution GSOM is simulated using MATLAB. The simulation experiments also compare several traditional PID control methods. The comparison indexes include stability, robustness, control accuracy and feedback output effect. The results show that the method in this paper is more stable and has fewer iterations when facing the dynamic input environment. The tracking error and control output of the controller system are significantly improved. It has good feedback output effect, solves the saturation problem and has higher control accuracy.

INDEX TERMS Fish scale regulation system, differential evolution, GSOM, dynamic regulation, fuzzy rule base, parameter regulation mechanism.

I. INTRODUCTION

In the field of control engineering, PID (Proportional-Integral-Derivative) controller is a classical feedback control algorithm. It is widely used in industrial control systems [1], [2], [3], [4], [5], [6], [7]. The PID controller regulates the output of the system by means of three components: proportional, integral and differential to achieve precise control of the target value. However, the traditional PID controller performs poorly when facing complex and nonlinear systems. For example, the field of multi-machine cooperative control in industrial robotics [8]. In order to overcome the limitations of traditional PID controllers, fuzzy PID control has emerged.

The basic form of fuzzy PID control is based on the introduction of fuzzy logic theory to traditional PID control [9]. It enables the controller to handle fuzzy and uncertain inputs, thus improving the robustness and adaptability of the system. Today's fuzzy PID controllers are composed of three main components: fuzzification, fuzzy inference and defuzzification. The fuzzification stage converts the input and output quantities into fuzzy sets. The fuzzy inference stage generates fuzzy outputs by reasoning based on a set of fuzzy rules. And the defuzzification stage converts the fuzzy output into actual control quantities. In recent years, domestic and foreign scholars have proposed many innovative methods and models for the field of fuzzy PID control [10], [11], [12], [13], [14], [15], [16], [17].

Literature [10] proposed a fuzzy adaptive PID control method for a multi-mechanism wheeled mobile robot. The method adjusts the parameters of the PID controller in real time through a fuzzy logic system. Thus, smooth and efficient movement of the robot is realized. However, the design

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and parameter adjustment of the fuzzy logic system is more complicated. It requires a large amount of experimental data and experience to determine the fuzzy rules and parameters. This increases the difficulty of designing and debugging the system. A fractional order general type 2 fuzzy PID controller design algorithm is given in literature [11]. The method utilizes the NT-type approximation algorithm to obtain the defuzzification results directly, avoiding the traditional iterative approximation process. Simulation results show that the controller optimizes the system response speed and stabilization time compared to other controllers under perturbation and parameter uncertainty. However, the algorithm is limited by the scope of application of the approximation algorithm. Therefore the dynamic adaptation performance of the controller still needs further improvement. Literature [12] proposed a single axis rotary inertial guidance system with fuzzy PID control based on tracking differentiator. This single axis rotary inertial guidance system utilizes a dual closed loop controller. Where the position loop uses a conventional PID algorithm and the velocity loop uses a tracking differentiator based fuzzy PID algorithm. This ensures stable velocity control of the system. However, when the system is faced with rapidly changing external disturbances, the fuzzy PID controller is unable to adjust the parameters in a timely and effective manner, resulting in the stability of the system being compromised. Literature [13] proposed a multi-loop decentralized control method for discrete fuzzy systems under dynamic triggering. The study designed a multi-loop decentralized H∞ class PID control. Resource saving and decentralized design of controllers are achieved through the idea of dynamic event triggering mechanism and node distribution. In terms of control accuracy, there exists a large delay to the system state change. It leads to a reduction in control accuracy.

Literature [14] proposed a fuzzy predictive PID based DC motor speed control. The study formed a predictive PID controller by combining a fuzzy PID controller and a backward level controller. The mean absolute error and mean square error were significantly reduced. However, the method is more sensitive to the selection of fuzzy rules and parameters in practical applications. Literature [15] investigated an online PID parameter optimization control method for wind power generation system based on genetic algorithm. The method proposes an anti-saturation PID control strategy using genetic algorithm. It can effectively solve the integral saturation problem and suppress the harmonics in the output waveform to improve the power factor of the system. However, in practical applications, the control method exists sensitivity to the parameter settings of the genetic algorithm. The controller output curve is not satisfactory enough under dynamic changes. Further optimization of the algorithm is needed to improve the stability and consistency of the control effect.

A PID controller tuning method based on chaotic atom search optimization algorithm is given in literature [16]. The study effectively improves the convergence speed and accuracy of the algorithm by introducing a chaotic version of the atomic search optimization algorithm. It shows superior performance in DC motor speed control. However the effect of the controller output curve needs to be further optimized and improved. Literature [17] proposes a multi-objective simulated annealing algorithm to rectify the PID controller. In the paper, the method is compared with single objective simulated annealing algorithm and constant gauge tuning PID controller. The flexibility of this paper's method in PID tuning is demonstrated. However, the PID controller underperforms in terms of tracking error and stability to dynamic changes. The simulated annealing algorithm needs further optimization and upgrading.

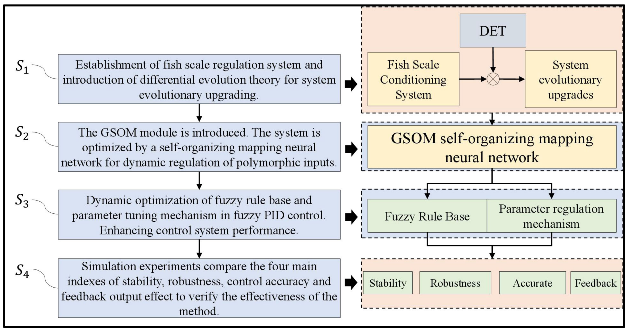

FIGURE 1. Overall program flow design diagram.

In this paper, a fish-scale evolution GSOM improved fuzzy PID control method is proposed. It introduces the fish scale regulation system, differential evolution theory [18] and dynamic regulation of GSOM module [19]. It effectively improves the stability, control accuracy and feedback output effect of traditional fuzzy PID control. The method provides a new research scheme for the control optimization of fuzzy PID. The flow design diagram of this paper is shown in Fig. 1. The terminology about this paper is shown in Table 1.

This paper is experimentally compared with the traditional method. The specific performance is as follows:

(1) Stability. The improved fuzzy PID controller can reach a steady state faster compared to the traditional PID.The optimization rules of the FSEG PID controller enable the system to respond quickly to changes in the target setting. The vibration amplitude is smaller in the face of disturbance signals, showing higher stability and anti-interference ability.

(2) Robustness. Under the changing input environment, the FSEG PID controller has fewer iterations and is easy to enter a stable state. Compared with the traditional PID controller, the FSEG PID controller has faster response speed and control capability.

(3) Control accuracy. Through the error tracking effect and output disturbance analysis, the optimized FSEG PID controller exhibits a small range of error tracking. It has efficient control accuracy. It can effectively control the output disturbance and realize the accurate tracking of the target value.

TABLE 1. Interpretation of nouns.

Name	Meaning
DET	Differential evolution theory
GSOM	Growing self-organizing network
SA PID	Simulated annealing algorithm to improve PID
GA PID	Genetic algorithm to improve PID
FSEG PID	Fish scale evolution GSOM improved fuzzy PID
FSEGA PID	Improved fuzzy PID after one optimization
FSEGA2 PID	Improved fuzzy PID after secondary optimization
Round(x)	Round up for x

(4) Feedback output effect. Among the fuzzy PID controls, FSEG PID has the shortest feedback output time. It shows faster response speed and more accurate control ability.

II. RELATED WORK

A. FISH SCALE CONDITIONING SYSTEM

Fish scale regulation system is a regulation system based on the arrangement of fish scales. It aims to optimize the performance of a fuzzy PID controller. The design of the system is inspired by the behavioral characteristics of fish in different water temperature environments. In particular, fish scales aggregate at lower water temperatures to reduce the surface area for heat dissipation in order to maintain body temperature. At higher water temperatures, fish scales are dispersed to increase the surface area for heat dissipation. The role of the fish scale regulation system is to simulate this behavioral feature to cope with different working environments and task demands. The introduction of differential evolution theory further optimizes and upgrades this system. The process of the fish scale regulation system is mainly divided into initializing the population, calculating the differences of scene parameters, and updating the population state.

Initializing the population is one of the key steps in building a fish scale regulation system. Define the parameter space of the control system, which includes proportional coefficients (K_p), integral coefficients (K_i) and differential coefficients (K_d). The parameter space needs to set the range and accuracy of the parameters according to its specific application scenario. Set the range of K_p, K_i and K_d all to $[a, b]$ and the precision all to p. Set up initialized individuals to be represented with the help of a collection of individuals. That is, $\mathcal{F} = \{f_1, f_2, \cdots\cdots, f_m\}$. The set of individuals $\mathcal{F}$ is the initial starting point of the population. For each individual in $\mathcal{F}$, generate its own corresponding K_p, K_d and K_i respectively which can be denoted as $\mathcal{H} = \{f_1 \rightarrow (K_{p1}, K_{i1}, K_{d1}), f_2 \rightarrow (K_{p2}, K_{i2}, K_{d2}), \cdots\cdots, f_m \rightarrow (K_{pm}, K_{im}, K_{dm})\}$. K_p, K_i and K_d corresponding to each individual satisfy the range requirement $[a, b]$ between, which meets the set accuracy requirement. For each individual, its fitness is calculated using differential evolution theory. That is, the performance of the system at the moment based on the current parameter settings is evaluated to assess the control effect. It is known that the common way of calculating the fitness in differential evolutionary algorithms is based on the error function. Therefore, in the scenario of fuzzy PID control, the error function is used to evaluate the control effect. The metrics for calculating the fitness are as follows

$$Fit = \sum_{i=1}^{m} (out_{target\_i} - out_{actual\_i})^2 \tag{1}$$

where, Fit is the total fitness function of the initialized population of fish scales. m is the total number of individuals. out_{target_k} and out_{actual_k} are the target and actual outputs of each individual system in the scenario of fuzzy PID control. Thus, the error function here is constant based on the error between the actual output of the system and the target output. The fitness of a single individual is calculated as the absolute value of the difference between the actual output of the system and the target output for that individual. i.e. $Fit(k) = |out_{target\_k} - out_{actual\_k}|$. The smaller the value of the fitness thus calculated, the better the control of the system. The higher the fitness of an individual, thus the more likely it is to be the parent of the next generation.

The initial individuals generated are formed into an initial population, which serves as the starting point for the differential evolution algorithm. Each individual in the population represents a PID control strategy. It is known that $\mathcal{H} = \{f_1 \rightarrow (K_{p1}, K_{i1}, K_{d1}),\quad f_2 \rightarrow (K_{p2}, K_{i2}, K_{d2}), \cdots\cdots, f_m \rightarrow (K_{pm}, K_{im}, K_{dm})\}$. An individual parameter vector can be used to represent $X_k = (K_{pk}, K_{ik}, K_{dk})$. K_{pk}, K_{ik} and K_{dk} are the proportionality coefficients, integral coefficients and differential coefficients of the k-th individual, respectively. The process of initializing the population can be denoted as $X_k = (rand(a, b), rand(a, b), rand(a, b))$.

Scene parameters are the important parameter factors in the actual application scenarios of this paper. The process of calculating the differences of scene parameters is a very critical step in the fish scale regulation system. It is used to evaluate the current working state of the system to decide whether the population is clustered or dispersed. The actual scene parameter is denoted by Φ and its reference value is represented as a vector form. $\Phi_{ref} = [\phi_1, \phi_2, \cdots\cdots, \phi_m]$. The difference between the current scene parameter Φ_{ref} and the reference scene parameter $\Phi_{current}$ is calculated using the reference scene parameter Φ_{ref}. i.e., $\Delta\Phi = |\Phi_{current} - \Phi_{ref}|$. This difference determines the aggregation or dispersion state of the population in the fish scale regulation system for dynamic regulation of scene changes. In the model, the influence of the scene parameters on the parameters of the fuzzy PID controller and the response of the controller to changes in the

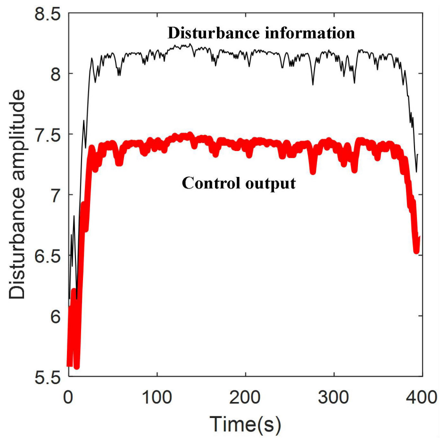

FIGURE 2. Perturbation of the control output.

scene parameters are set. The controller output is expressed as

$$u(t) = (K_p + \Delta\Phi_k) \cdot e(t\_k) + (K_i + \Delta\Phi_k) \cdot \int_0^t e(\tau)d\tau + (K_d + \Delta\Phi_k) \cdot (de(t\_k)/dt) \quad (2)$$

where, $u(t)$ is the output of the fuzzy PID controller at the moment t. $e(t\_k)$ denotes the deviation of the k-th individual at the current moment. That is, the error between the desired value and the actual value. $e(t\_k)$ corresponds to the fitness function, i.e., $e(t\_k) \leftrightarrow Fit(k)$. $\int_0^t e(\tau)d\tau$ represents the integral term of the deviation. It represents the accumulation of the deviation over time. $de(t)/dt$ denotes the differential term of the deviation. It represents the rate of change of the deviation over time. $\Delta\Phi_k$ is the difference between the current scene parameter $\Phi_{current\_k}$ and the reference scene parameter Φ_{ref_k} for the k-th individual. The main purpose of the difference of the scene parameters in the fish scale regulation system is to regulate the system output in the fuzzy PID control. It fine-tunes the system control effect through the fitness function of each individual.

When perturbation information is present in the controller, the system control output changes non-directionally. As shown in Fig. 2. Therefore, the fish scale regulation control characteristic theorem is established in the updating group state. The theorem can effectively inhibit this phenomenon. The theorem contains the following parameters. The important current parameter of fuzzy PID is $\Gamma_{current}$. The ideal regulation parameter is Γ_{goal}. The parameter threshold is Γ_{threv}. The total fitness function of the fish scale initialized population is Fit. The fish scale aggregation coefficient is σ_{gather} and the fish scale dispersion coefficient is $\sigma_{disperse}$. The details of the theorem are shown as follows.

(1) If $\Gamma_{current} < (\Gamma_{goal} - \Gamma_{threv}) \cdot Fit$, then the fish scales are aggregated. The fisheye regulation system will reduce the magnitude of variation of the fuzzy PID parameters to maintain the stability of the controller. Update the parameter: $\Gamma_{current} = Fit \cdot \Gamma_{current} + \sigma_{gather} \cdot (\Gamma_{goal} - \Gamma_{current})$.

(2) If $\Gamma_{current} \geq (\Gamma_{goal} - \Gamma_{threv}) \cdot Fit$, the fish are scattered. The fish scale regulation system will increase the magnitude of change of the fuzzy PID parameter to speed up the adaptation to the changing environment. Update parameter: $\Gamma_{current} = Fit \cdot \Gamma_{current} - \sigma_{disperse} \cdot (\Gamma_{current} - \Gamma_{goal})$.

(3) If $|\Gamma_{current} - \Gamma_{goal}| \leq \Gamma_{threv}$, the fish population remains in a stable state. The fish scale regulation system uses the general fuzzy PID parameter regulation strategy. Continue to keep the controller in equilibrium.

The parameter $\Gamma_{current}$ in the Fish Scale Regulation Control Characterization Theorem is specified as the fuzzy set center position parameter and the gain parameter. The fuzzy set center position parameter and the gain parameter affect the affiliation function characteristics and the dynamic stability of the fuzzy PID system. They determine the degree of output saturation of the system. Therefore the application of the fish scale regulation control characteristic theorem is the key to adjust the controller output saturation degree of the fish scale regulation system. It can effectively prevent the occurrence of oversaturation and undersaturation phenomena of the system and maintain the stable operation of the system. Here σ_{gather} and $\sigma_{disperse}$ are the feedback results of the differential evolutionary algorithm to dynamically adjust the fishscale system.σ_{gather} and $\sigma_{disperse}$ are adjusted as

$$\sigma_{gather} = \sigma_{gold} + p_1 \cdot (\Gamma_{goal} - \Gamma_{current}) \quad (3)$$

$$\sigma_{disperse} = \sigma_{dold} + p_2 \cdot (\Gamma_{current} - \Gamma_{goal}) \quad (4)$$

where, σ_{gold} and σ_{dold} are the fish scale aggregation coefficient and fish scale dispersion coefficient before adjustment. p_1 is the scaling factor in the differential evolution algorithm. It is used to control the step size of the adjustment. p_2 is the convergence factor in the differential evolutionary algorithm. It is used to control the step size of the adjustment. In the differential evolutionary algorithm, both p_1 and p_2 are constants and take values in the range of [0, 1]. It is mainly used to control the magnitude of adjustment. When Γ_{goal} deviates far from $\Gamma_{current}$, the magnitude of adjustment of σ_{gold} and σ_{dold} will become larger to speed up the convergence of the system. When Γ_{goal} is close to $\Gamma_{current}$, the adjustment amplitude will decrease to keep the stability of the system. In this way, differential evolution can dynamically adjust the aggregation and dispersion coefficients in the fish scale adjustment system. This enables the system to better adapt to different working environments and task requirements. Thus, the effect of fuzzy PID control is improved. Among them, the control diagram of the differential evolution feedback fish scale system is shown in Fig. 3. After the initialization of the group, the calculation of the difference of the scene parameters and the update of the group state, the establishment of the fish scale regulation system after differential evolution is completed. For different individual $\mathcal{F} = \{f_1, f_2, \cdots\cdots, f_m\}$ and initialized $\mathcal{H} = \{f_1 \rightarrow (K_{p1}, K_{i1}, K_{d1}), f_2 \rightarrow (K_{p2}, K_{i2}, K_{d2}), \cdots\cdots, f_m \rightarrow (K_{pm}, K_{im}, K_{dm})\}$. We can complete the tasks of adaptation iteration, controller output response, parameter optimization and saturation regulation through the fish scale

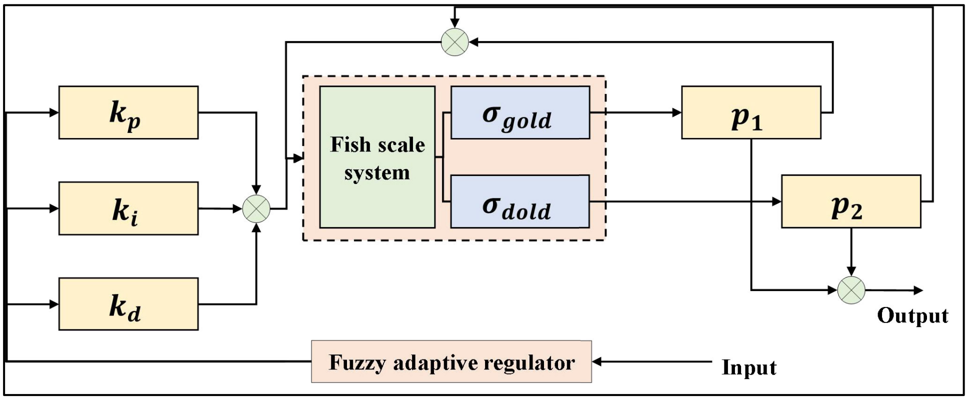

FIGURE 3. Control diagram of a differential evolutionary feedback fish scale system.

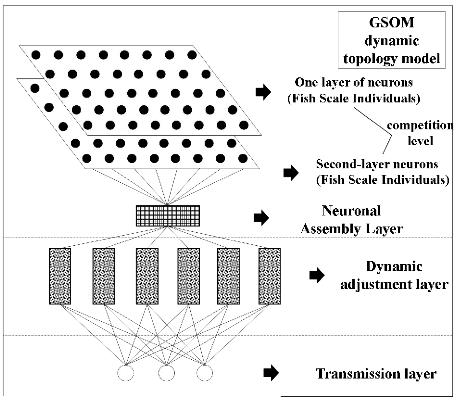

FIGURE 4. Structural modeling of GSOM in individuals with fish scales.

regulation behavior. Reliable guarantee is provided for system stability and regulation performance.

B. DYNAMIC ADJUSTMENT OF GSOM

The established fish scale regulation system needs further optimization to adapt to the steady state operation under the complex changing environment and improve the system robustness.The GSOM module is a self-organized neural network structure. It has the characteristics of dynamic growth and polymorphic input dynamic regulation. The introduction of GSOM module in the fish scale regulation system can make the system better adapt to the constantly changing complex input environment and realize stable operation. The GSOM structure of the fish scale individual is shown in Fig. 4.

Each neuron in a self-organizing neural network structure can be considered as the root node of the network. And the connection weights between neurons are expressed as the strength of the branches. The weight relationship of neurons determines the flexibility of fish scale regulation. It can be expressed as follows

$$W = \sum_{d=1}^{m} (\Phi_{current\_d} - \Phi_{ref\_d})(\Phi_{current\_d} - \eta \cdot (\partial\Phi / \Phi_{current\_d})) \qquad (5)$$

where W is the total weight. Here the neuron equivalent is the fish scale individual $\mathcal{F} = \{f_1, f_2, \cdots\cdots, f_m\}$. $\Phi_{current\_d}$ is the current scene parameter of the dth neuron individual. Φ_{ref_d} is the reference scene parameter of the dth neuron individual. η is the learning rate. It is used to control the step size of weight update. Due to the dynamic adjustability of GSOM itself, the neurons are replaced with actual fish scale individuals to form fish scale individual neurons. This way the weights can determine the information transfer of the fish scale individual neurons. It is the key to dynamic parameter tuning. A self-organizing mapping neural network is a network structure that contains multiple layers of such fish-scale individual neurons. This self-organizing mapping neural network becomes even more complex when multiple complex inputs are involved in the practical application of fuzzy PID control. Therefore, the main goal of GSOM is to map the input space into a low-dimensional topology while maintaining the topological relationships between the input data. This accomplishes steady-state operation in complex changing environments and also reduces the complexity of the data. For each fish scale individual f_d in the fuzzy PID, it is first mapped into a neural network by competitive learning. Each GSOM fish scale neuron individual corresponds to a $\Phi_{current\_d}$ and a weight $W(d)$ which indicates the position of that neuron in the input space. By constantly adjusting $W(d)$ dynamically, the individual fish scale neuron can gradually adapt to the distribution characteristics of the input space. The input variables in the fuzzy PID control are set to be N, which are denoted as $Input = \{input_1, input_2, \cdots\cdots, input_N\}$. The fuzzy rules are M denoted as $NL = \{nl_1, nl_2, \cdots\cdots, nl_M\}$. The weight of each fuzzy rule is denoted as $W(d)$ of the individual fish scale. Then the weight parameter in the fuzzy PID can be dynamically updated by GSOM as

$$W_{input_i}(d\_(t+1)) = W_{input_i}(d\_t) + \eta(t) \cdot \Gamma_{threv}(t) \cdot (W_{nl_j}(d\_t) - W_{input_i}(d\_t)) \qquad (6)$$

where, $W_{input_i}(d\_(t+1))$ denotes the weight of the ith input variable at moment $t+1$. $W_{input_i}(d\_t)$ denotes the weight of the ith input variable at moment t. $\eta(t)$ is the learning rate

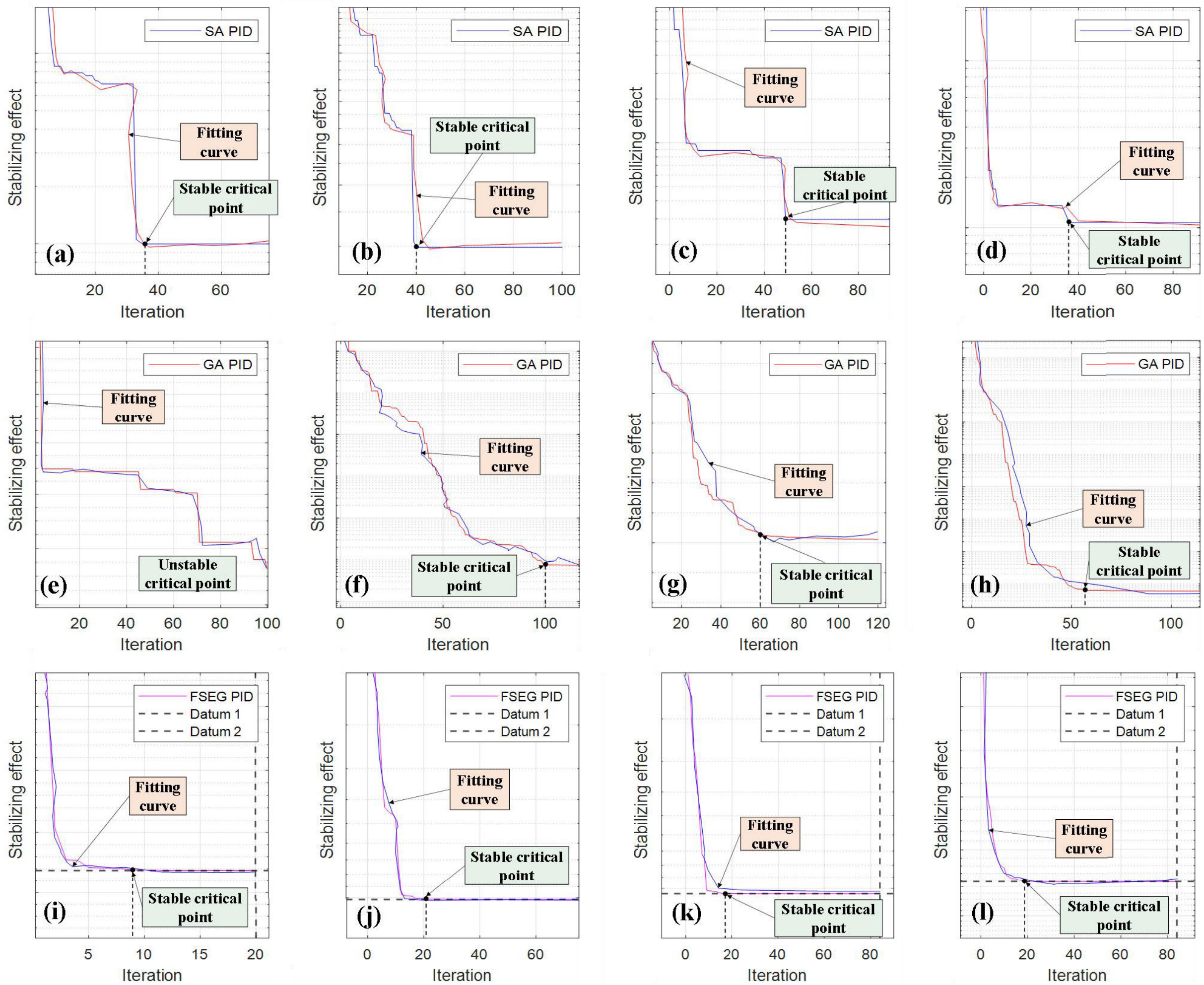

FIGURE 5. **Comparative experiments on fitting effects.**

at moment t. $\Gamma_{threv}(t)$ is the parameter threshold at moment t. $W_{nl_j}(d\_t)$ denotes the weight of the jth fuzzy rule at moment t.

The following explanation is given for the working principle of Eq. (6). In the process of weight updating, the learning rate $\eta(t)$ controls the step size of weight updating so that it decreases gradually during the training process to ensure stability. The difference weight $W_{nl_j}(d\_t) - W_{input_i}(d\_t)$ represents the topological relationship between the jth fuzzy rule and the ith input variable. This means that only the neurons of the input variables associated with the weights of the current fuzzy rule are updated. $\Gamma_{threv}(t)$ denotes the threshold limit for the desired weight change. When the weights of the fuzzy rule gradually converge to the weights of the input variables. Then dynamic regulation and optimization of weights is achieved.

Based on the above information, the fuzzy PID controller can adaptively optimize the weights according to the changing control environment. So that the fish scale regulation system is optimized by self-organized mapping neural network. It can improve the fitting effect of the output curve of the PID controller. So that the fuzzy PID controller regulates the output more accurately and achieves more stable operation. About the fitting effect of PID controller output curve. The method of this paper compares SA PID and GA PID. the fitting effect comparison experiment is shown in Fig. 5.

Figures (a-d) show the fitting effect of SA PID. The fitting curve is basically able to fulfill the fitting task. The number of iterations at the stabilization threshold is basically between 30-50 times. Figures (e-h) show the fitting effect of GA PID. When the controller output curve changes greatly, the fitting curve error is large. The number of iterations at the stabilization threshold is basically between 50-100 times. In the range of 50-100 iterations interval, the phenomenon of not being able to reach the stabilization state occurs. Therefore the stabilization effect is poor. Figure (i-l) shows the fitting effect of FSEG PID.FSEG PID has a better fitting curve compared to SA PID and GA PID. The number of iterations is basically stable between 0-20. The validity of the established method is verified.

C. DYNAMIC OPTIMIZATION OF FUZZY PID CONTROL

1) FUZZY RULE BASE

Now, based on the above information, the fuzzy rule base [20] and parameter adjustment mechanism in fuzzy PID control are dynamically optimized. Set up the fuzzy rule base in fuzzy PID control. The fuzzy rule base is initialized as R_{ij}^k. The general rule is defined as if $e = e_i$, and $ec = ec_j$, then $u = u_k$. The general rule can be based on the empirical information in the actual application scenario. The evaluation function $T = \sum_{d=1}^{m}(e_t)^2$is set. The affiliation function is parameterized and this parameter is updated by the Fish Scale Adjustment Control Characteristic Theorem. The parameterized affiliation function is denoted as $\mathcal{P}(f_k; c, \sigma) = e^{-(f_k-c)^2/2\sigma^2}$. f_k denotes the random variable of the affiliation function. If $\mathcal{P}(f_k; c, \sigma) < (\mathcal{P}_{goal}(f_k; c, \sigma) - \mathcal{P}_{threv}) \cdot Fit(k)$ and $T = \sum_{d=1}^{m}(e_t)^2 \leq Fit(k)$, the update rule of the affiliation function becomes $\mathcal{P}(f_k; c, \sigma) = T \cdot \mathcal{P}(f_k; c, \sigma) + \sigma_{gather} \cdot ((\mathcal{P}_{goal}(f_k; c, \sigma) - \mathcal{P}(f_k; c, \sigma))$. Otherwise, the update rule is $\mathcal{P}(f_k; c, \sigma) = Fit(k) \cdot \mathcal{P}(f_k; c, \sigma) + \sigma_{gather} \cdot ((\mathcal{P}_{goal}(f_k; c, \sigma) - P(f_k; c, \sigma))$. Such an update rule in the fuzzy rule base will make it possible to better regulate its own response attributes when faced with control inputs under different conditions. Improving the feedback output effect of fuzzification and fuzzy inference. There is also a need to improve the fuzzy rule base by the differential evolution idea in it to select and retain the rules with higher adaptation in the fish scale evolution GSOM. It is known that $X_k = (K_{pk}, K_{ik}, K_{dk})$ take the fish scale regulation mutation operation as $K_{pk}^{new} = K_{pk}^{old} + \mathcal{P}(\{_{\|}; \rfloor, \sigma) \cdot (\mathcal{R}_{\nabla\dashv\backslash\lceil\infty} - \mathcal{R}_{\nabla\dashv\backslash\lceil\in})$. Where R_{rand1} and R_{rand2} are randomly selected rule bases. $P(f_k; c, \sigma)$ is the mutation factor. K_{pk}^{old} and K_{pk}^{new} are the scale parameters of the kth fish scale individual before and after the update, respectively.K_{ik} and K_{dk} mutation operations are carried out with the same operation. The cross mutation operation in the rule base is denoted as

$$K_{child1} = \begin{cases} K_{pk}^{new} & if\ R_{rand1}/R_{rand2} \leq rand(a, b)\ or\ CR \\ K_{pk}^{old} & otherwise \end{cases} \tag{7}$$

where, K_{child1} is the crossover parameter of K_{pk}. CR is the probability of cross-mutation. K_{child2} and K_{child3} are both cross-mutated in the same way. The principle of cross-mutation of the rule base is to keep the rules with higher fitness and discard the rules with lower fitness.

2) PARAMETER REGULATION MECHANISM

The parameter tuning mechanism in fuzzy PID is the key to improve the performance of the control system. However, since fuzzy PID requires the determination of fuzzy sets, affiliation functions, and fuzzy rules, this increases the complexity of system modeling and regulation. Therefore, the parameter tuning of the fuzzy PID controller is more complex compared to the traditional PID control. There is performance instability in parameter tuning. Especially, the problem is more prominent when dealing with complex dynamic systems and rapidly changing environments. In order to overcome the above shortcomings, this paper optimizes the parameter regulation mechanism from the established fish scale evolution GSOM to complete the further upgrading of fuzzy PID. Define the multi-objective function in fuzzy PID, which includes output error and rate of change, etc.

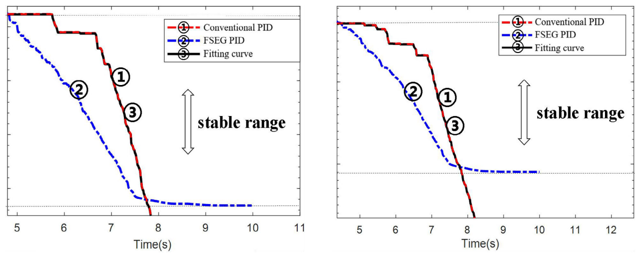

FIGURE 6. Stability effects of conventional PID and FSEG PID output curves.

$$\mathcal{J}(\Phi_{current}, \Gamma_{current}) = \sum_{d=1}^{m}(\Phi_{current} \cdot \sigma_{gather}^2 + \Gamma_{current} \cdot \sigma_{disperse}^2)/(\mu_1 \cdot e_d^2 + \mu_2 \cdot \dot{e}_d^2) \tag{8}$$

where $\mathcal{J}(\Phi_{current}, \Gamma_{current})$ is the parameter objective function with respect to $\Phi_{current}$ and $\Gamma_{current}$. μ_1 and μ_2 are both weighting coefficients. e_d is the error at the current moment.$\dot{e}_d$is the rate of change of the error at the current moment. The parameters $\Phi_{current}$ and $\Gamma_{current}$ are iteratively updated according to the fish scale evolution GSOM. The set values of the parameter initialization are $\Phi_{current} = r_1$ and $\Gamma_{current} = r_2$. If the operations taken satisfy conditions 1 and 2 respectively. i.e., $V_d > Xn_d + (W_{input_i}(d\_(t+1)) \cdot r_1 - W_{input_i}(d\_(t+1)) \cdot r_2)$ or $V_d \leq Xn_d + (W_{input_i}(d\_(t+1)) \cdot r_1 - W_{input_i}(d\_(t+1)) \cdot r_2) \cdot Fit(d)$. Then the parameter optimization rule taken is

$$Para = \begin{cases} V_d \cdot Para, W_{input_i}(d\_(t+1)) = W_{input_i}(d\_t) \\ \qquad Condition1 \\ \\ W_{input_i}(d\_(t+1)) \cdot Para, W_{input_i}(d\_(t+1))_* \\ \qquad Condition2 \end{cases} \tag{9}$$

where V_d is the parameter update factor of the dth individual. $Para$ is the general parameter collectively. $W_{input_i}(d\_(t+1)) = W_{input_i}(d\_t)$ denotes the weights after updating. $W_{input_i}(d\_(t+1))_*$ denotes that the weights remain unchanged after updating. For the convenience of representation, *Condition* 1 and *Condition* 2 denote the conditions 1 and 2 satisfied by the parameter optimization rule, respectively. The parameters of the new iteration select the fish scales with higher fitness as the next generation population.

Based on the above information, the fuzzy rule base and parameter regulation mechanism are dynamically optimized. It combines with the fish scale regulation control characteristic theorem, which can help the controller to make a fast

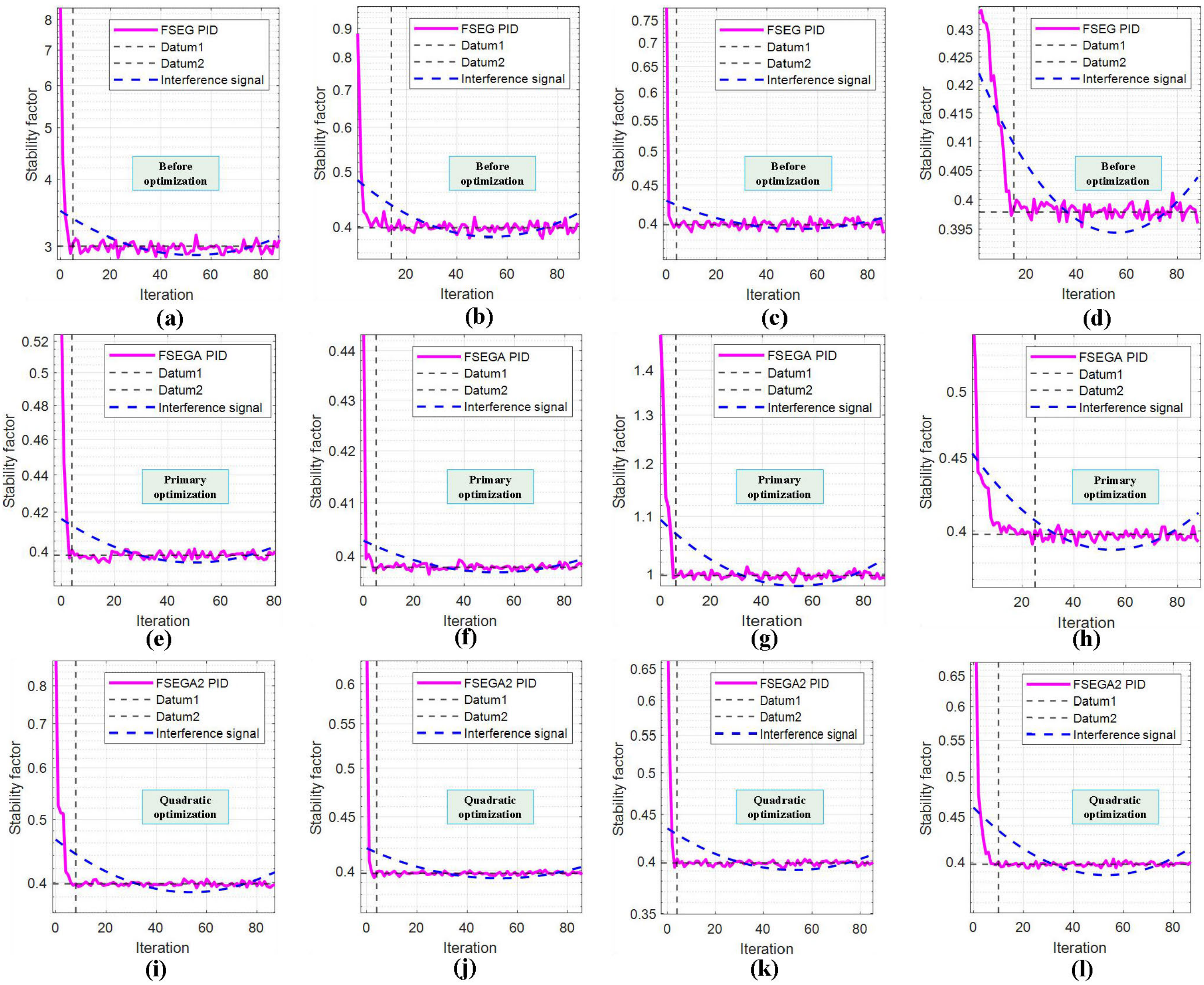

FIGURE 7. Stabilization effect of interfering signals encountered before and after FSEG PID optimization.

response to the disturbance signal. Thus, the vibration amplitude of the controller output curve is reduced after reaching the steady state and basically remains stable. This process can improve the robustness and stability of the control system and realize more reliable control effect.

D. EXPERIMENTAL ANALYSIS

In this part, the effectiveness of this paper will be verified by experimental simulation. The comparison indexes are stability, robustness, control accuracy and feedback output effect. The simulation experiments are now analyzed.

1) STABILITY

The stability of fuzzy PID control is reflected in the smoothness of the controller output curve and the ability to resist interference. Specifically manifested in the controller's resistance to system perturbations and parameter changes. So that the system can operate stably near the target value. A stable fuzzy PID controller output curve has a small amount of overshoot and oscillation, and can respond quickly to changes in the target setting. Fig. 6 demonstrates the stabilization effect of the conventional PID and FSEG PID output curves. In Fig. 6, the conventional PID output curve does not reach a good stabilization state in the setup time. While the FSEG output curve is close to the steady state after 8 seconds. The stabilization effect becomes more significant with the increase of time.

Fig. 7 demonstrates the stabilization effect of the controller output curve before and after the FSEG PID optimization after reaching the steady state and encountering the disturbance signal. In which the primary and secondary optimization are carried out through the parameter optimization rules, respectively. Figs. (a-d) show the FSEG PID before optimization. figs. (e-h) show the FSEGA PID. figs. (i-l)

TABLE 2. Comparison of FSEG, FSEGA and FSEGA2 metrics.

method	Iterations	Stabilizing factor	Stabilization time
FSEG PID	Round(6.4248)=7	0.39789	5.618747s
	Round(7.2749)=8	0.40267	5.612717s
	Round(6.0618)=7	0.39721	5.709507s
	Round(17.1120)=18	0.39700	5.767400s
FSEGA PID	Round(6.7412)=7	0.39847	5.577246s
	Round(4.7028)=5	0.36545	5.602410s
	Round(6.2914)=7	0.99106	5.419827s
	Round(9.2409)=10	0.40278	5.552409s
FSEGA 2 PID	Round(5.1042)=6	0.39994	5.587163s
	Round(4.7016)=5	0.39260	5.545791s
	Round(3.7798)=4	0.39353	5.402744s
	Round(6.5417)=7	0.39882	5.514613s

show the FSEGA2 PID. table 2 demonstrates the number of iterations (rounded upwards), the stabilization factor, and the stabilization time corresponding to the three approaches, respectively.

From Fig. 7, it can be seen that in the four experiments of FSEGA2 PID, the stabilization curves after encountering disturbance signals have smaller vibration amplitude compared to FSEG PID and FSEGA PID. It is verified that the optimized FSEG PID has a better stabilization effect. Based on the above analysis, the simulation process verifies that the optimized FSEG possesses higher stability when facing interference signals.

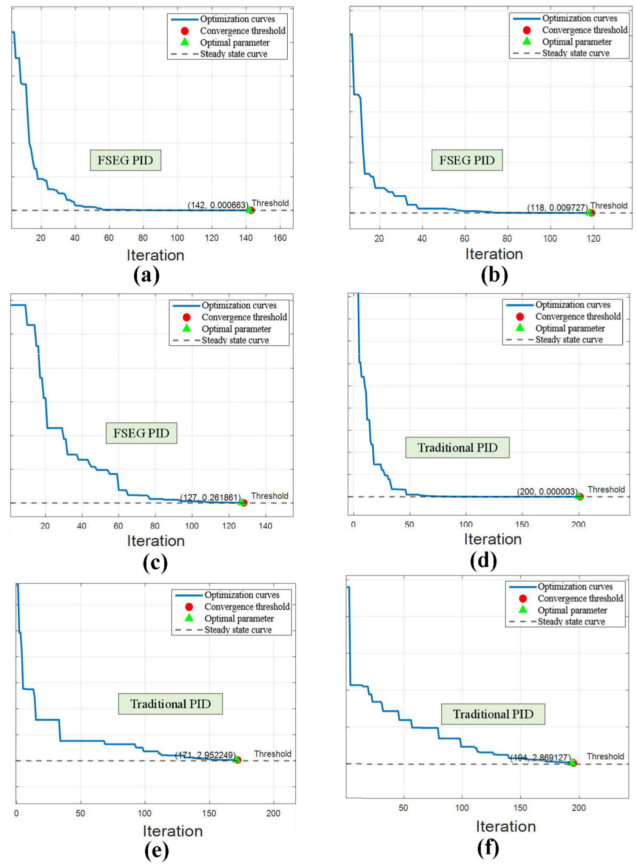

FIGURE 8. Stabilization effects of FSEG PID and conventional PID in changing input environments.

2) ROBUSTNESS

The robustness of fuzzy PID control is expressed as the ability to maintain stability and control performance under different varying input environments. In this experiment, we compare the stabilization effect of FSEG PID and conventional PID under varying input environments. As shown in Fig. 8. Figures (a-c) show the robustness effect of FSEG PID. Figs. (d-f) show the robustness effect of the conventional PID. the iteration numbers of the FSEG PID are 143, 119, and 128, respectively. the iteration numbers of the conventional PID are 201, 172, and 195, respectively. the convergence thresholds and the optimal parameters of the two methods are relatively close to each other. This experiment verifies that the FSEG PID has fewer iterations in case of input environment changes. It is easier to enter the steady state and more robust.

3) CONTROL ACCURACY

The control accuracy of fuzzy PID is reflected in the ability to handle system tracking errors. In this experiment, we compare and analyze the application of different methods in fuzzy PID controllers to evaluate their impact on system tracking error. Finally judge the control accuracy of different methods. Figure 9 shows the error tracking effect and output interference of the general PID controller and the constant PID controller. Figure 10 shows the error tracking effect and output interference of FSEGA PID and FSEGA2 PID.

The output interference in Figure 9(a) and (c) both has a maximum drop, a minimum drop and an extreme drop. The larger the limit difference, the more confusing the output interference will be, and the worse the error tracking effect will be. There are interference-free signal parts in both the outputs of Figure 9(b) and (d). Then the smallest drop at this time is scattered on the yellow plane. They have countless extreme drops, and the extreme drops are unstable. Therefore, the error tracking effect at this time is the worst. The output interference in Figure 10(a-c) has a maximum drop, a minimum drop and an extreme drop. The range of the interference-free signal part in Figure 10(d) is larger. It means there are fewer interfering signals in the output interference. Although there are countless extreme gaps, within the range, interference information appears less frequently. A wide range of interference-free signals makes the output interference more stable.

Since the control accuracy of fuzzy PID is reflected in the ability to process system tracking errors, the error tracking effects in Figures 9 and 10 can intuitively reflect the control accuracy. The error curve can be regarded as an ideal error curve. The higher the consistency between the output

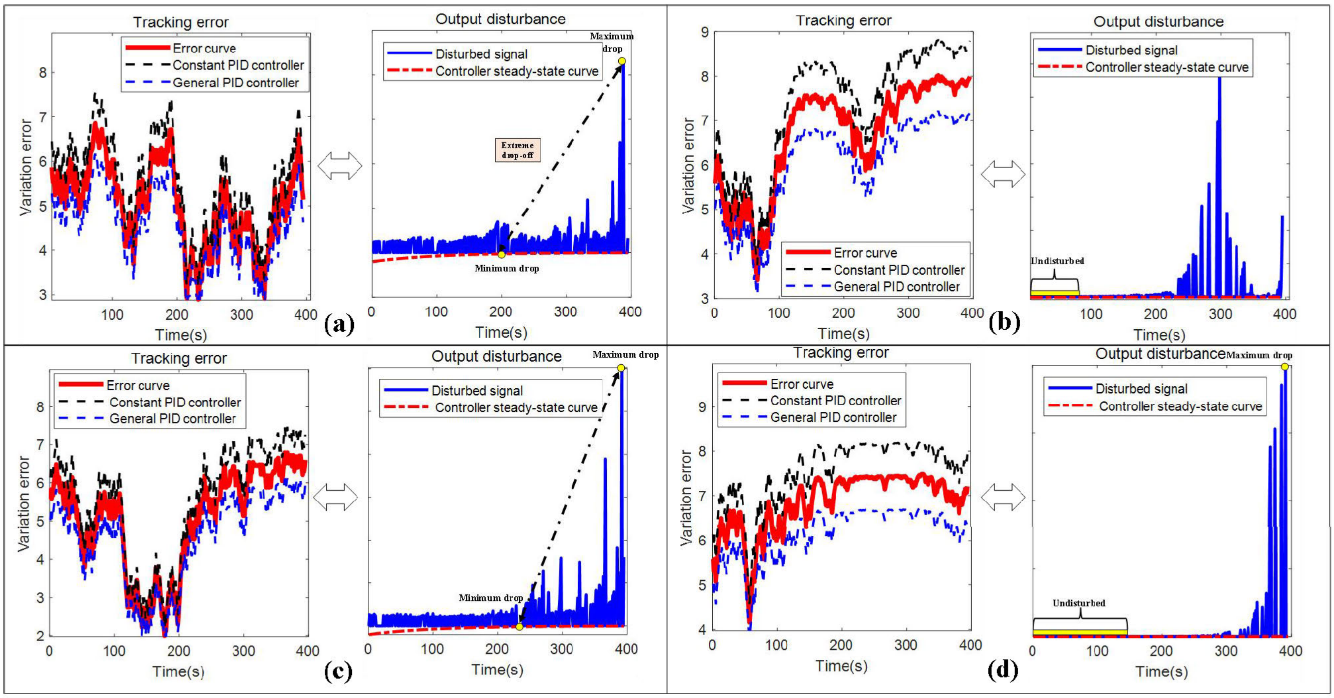

FIGURE 9. Error tracking and output disturbances in general PID controllers and constant PID controllers.

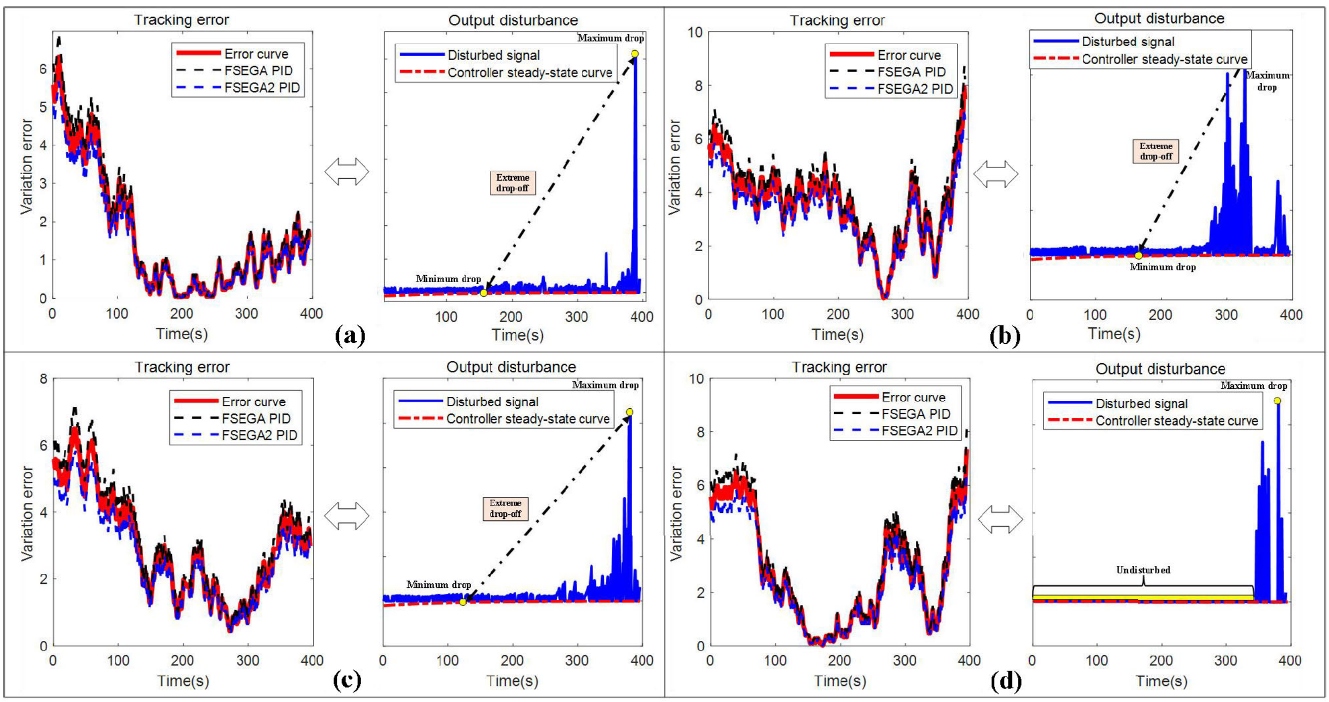

FIGURE 10. Error tracking effects and output disturbances of FSEGA PID and FSEGA2 PID.

errors of different methods over time and the Error curve, the higher the control accuracy. Therefore, according to the error tracking effect in Figure 9, it can be seen that the control accuracy of the general PID controller is better than that of the constant PID controller. The control accuracy shown in Figure 9(a) and (c) is better than Figure 9(b) and (d). In Figure 10, the control accuracy of FSEGA2 PID is better than that of FSEGA PID. The above analysis verifies the

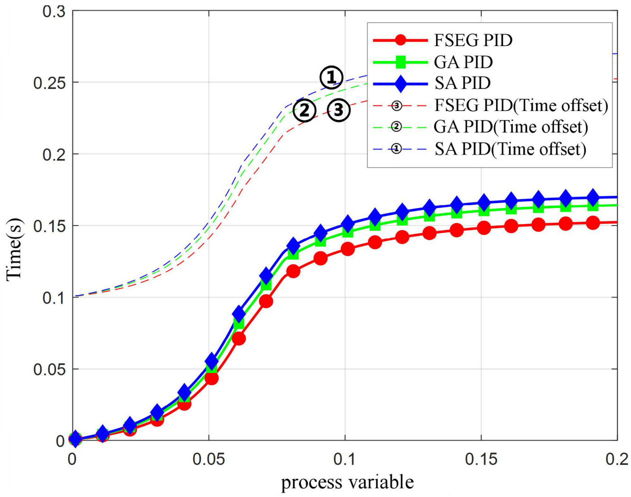

FIGURE 11. **Feedback output effect.**

effectiveness of the method in this paper in terms of control accuracy.

4) FEEDBACK OUTPUT EFFECT

In fuzzy PID control, the feedback output is one of the important indicators to evaluate the performance of the controller. This part compares the effect of different methods before and after time offset. These methods include FSEG PID, GA PID and SA PID. simulation results are shown in Fig. 11.

After experimental observation, it is found that FSEG PID has a better feedback output effect compared to other methods with the shortest feedback output time. It shows faster response speed and more accurate control capability. This means that in the control process, FSEG PID can sense and respond to the system state faster. Thus, the tracking and control of the target value can be realized.

III. CONCLUSION

In order to improve the control effect of fuzzy PID, this paper proposes a fish scale evolution GSOM to improve the control method of fuzzy PID. The method mainly consists of fishscale affine optimization algorithm, differential evolution algorithm and GSOM module. Among them, the fish scale affine optimization algorithm is a heuristic algorithm. It solves the problem of changing controller input environment by simulating the synergy between fish scales. Differential evolutionary algorithm is an optimization algorithm based on inter-individual differences and variation operations. It is used to find the global optimal solution.GSOM dynamic regulation is a self-organizing mapping neural network. It enables dynamic regulation of polymorphic inputs and optimizes the system control parameters.GSOM improves the fuzzy rule base and parameter regulation mechanism in fuzzy PID. It enhances the flexibility and robustness of the controller and makes it more suitable for control tasks in complex environments. Simulation experiments verify that the method proposed in this paper possesses better results in terms of stability, robustness, control accuracy and feedback output effect. Therefore, the method in this paper has important practical significance and application value for improving the performance of control systems and solving control problems in real engineering.

IV. LIMITATIONS AND FUTURE WORK

In this paper, there is a problem of computational complexity in optimizing the fuzzy rule base and parameter regulation mechanism with the help of GSOM. As the optimization of fuzzy rule base and parameters requires a large number of iterative computations and searches. Especially in high dimensional spaces. This can lead to high computational cost and affect the real-time and efficiency of the algorithm. To solve this problem, we consider introducing more efficient optimization algorithms or improving the existing algorithms in the future. In addition, the use of model simplification and dimensionality reduction techniques to reduce the computational complexity is also one of the scopes we consider. Examples include feature selection, dimensionality reduction algorithms, etc. In addition, fuzzy PID control will become more complicated when a multi-order control system is involved in practical application scenarios. For example, the multi-machine cooperative task in the multi-intelligent body cooperative intelligent loading robot. Therefore, about the fuzzy PID in the multi-order control system environment is also the aspect we want to focus on in the future.

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ZUOXUN WANG received the B.E. degree in motor and control from Shandong University of Technology, in 1997, the M.E. degree in computer application technology from Northeast Electric Power University, in 2005, and the Ph.D. degree in control theory and control engineering from the Institute of Automation, Chinese Academy of Sciences, in 2015. He is currently a Professor with the School of Information and Electronic Engineering, Shandong Technology and Business University. He is the author/coauthor of over 40 journal papers and conference paper. His research interests include intelligent robot and control.

CHUANYU CUI was born in 1999. He is currently pursuing the master's in electronic information degree with Shandong Institute of Commerce and Industry. His research interests include robot behavior planning and automated loading and unloading truck robots. He is also interested in the direction of image recognition, machine learning, and microcontroller technology. He has participated in mathematical modeling, physics competitions, mathematics competitions and other competitions and won relevant awards, and also published some patents.

JINXUE SUI received the B.E. degree in automation from Shandong University of Technology, in 2001, the M.E. degree in control theory and control engineering from Northeast Electric Power University, in 2005, and the Ph.D. degree in navigation, directing and control from Naval Aviation University, in 2009. He is currently a Professor with the School of Information and Electronic Engineering, Shandong Technology and Business University. He is the author/coauthor of over 30 journal articles and conference papers. His research interests include intelligent robot and control.

YONG ZHANG was born in June 1979. He received the Ph.D. degree in engineering from the School of Information and Electronic Engineering, Shandong University of Business and Economics. He is currently a Lecturer and a Teacher with the School of Information and Electronic Engineering, Shandong University of Business and Economics. He led or participated in the development and application of "A Leakage Monitoring System for Rigid Landfills in Qinghai," A GPRS Based Environmental Monitoring System for Coastal Wetlands in the Yellow River Delta," "An Intelligent Fully Automatic Vegetable Transplanting Machine," "A Tea Withering and Drying System," and "A Fully Automatic Tea Processing and Production Line." He has published more than ten SCI, EI, and other articles, authorized two utility model patents, and one software copyright, and accepted one invention patent.

CHANGKUN GUO received the B.Eng. degree in computer science and technology from Ludong University, Yantai, China, in 2021. He is currently pursuing the master's degree in electronic and information engineering with the School of Information and Electronic Engineering, Shandong Technology and Business University, Yantai. His research interests include robots, robot control, and multiagent systems.