Physicochem. Probl. Miner. Process., 59(3), 2023, 169942

http://www.journalssystem.com/ppmp

Physicochemical Problems of Mineral Processing

ISSN 1643-1049

Research on the mill feeding system of an elastic variable universe fuzzy control based on particle swarm optimization algorithm

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Abstract: The grinding process in the concentrator is a part of the largest energy consumption, but also the most likely to cause a waste of resources, so the optimization of the grinding process is a very important link. The traditional fuzzy controller relies solely on the expert knowledge summary to construct control rules, which can cause significant steady-state errors in the model. In order to solve the above problem, this paper proposes an elastic variable universe fuzzy control based on Particle Swarm Optimization (PSO) algorithm. The elastic universe fuzzy control model does not need precise fuzzy rules, but only needs to input the general trend of the rules, and the division of the universe is performed by the contraction-expansion factor. The control performance is directly related to the contraction-expansion factor, so this article also proposes using particle swarm optimization to optimize the scaling factor to achieve the optimal value. Finally, simulation models of traditional fuzzy control and elastic universe fuzzy control of feeding system of mill were built using Python to verify the control effect. Its simulation results show that the time of the reaction of the fuzzy control system in the elastic variable theory universe based on particle swarm optimization was shorter by 34.48% comparing to the traditional one. Elastic variable universe fuzzy control based on particle swarm optimization (PSO) effectively improved the control accuracy of the mill feeding system and improved the response speed of the system to a certain extent.

Keywords: fuzzy control, contraction-expansion factor, particle swarm optimization

1. Introduction

Mineral resources are extremely important for the development of human society, security and economic guarantee for the country, and food and blood for industry. In the process of mineral processing, grinding (Yuan et al., 2007; Wang et al., 2021) is a crucial process in the process of mineral processing. The qualified rate of its products and the continuous stability of production are important factors that greatly affect the product quality and metal recovery in the subsequent process of mineral processing. The feed link of the mill is a very important part, and its accuracy will directly affect the production index of the grinding products and subsequent operations.

Early mainly used manual control that the operator according to the ore quantity of real-time measurement manually adjust the number of the feeder switch and the feeding amount of each feeder, the control mode requires the operator to always pay attention to the ore fluctuation, labor intensity and adjust the speed is slow, poor stability. With the continuous development of automatic control technology, in order to solve the problems existing in manual control, control algorithms (Alexandrov and Palenov, 2022; Zhou et al., 2022) such as single loop closed-loop control, PID control, deformation control, large interval sampling integral control method, fuzzy control (Wang et al., 2022) are widely used in the feeding control of the concentrator feeder. With the increase of the scale and complexity of

DOI: 10.37190/ppmp/169942

modern industrial production, the demand for control system is higher and higher. Fuzzy controller is widely used because it is independent of the controlled object and strong robustness. However, with the increasing application of fuzzy control, some shortcomings of fuzzy controller have been exposed. For example, the control precision is not high due to the limited range and low accuracy. As the grinding process itself belongs to the time-varying multi-input and output nonlinear control system, there are many influencing factors, such as site environment, ore properties, personnel operation level, mill running state, etc. (Zhao et al., 2022; Lv et al., 2021) These factors have a great interference to the fuzzy control system, so that the control parameters of the fuzzy control system cannot be adjusted in time, which will lead to a larger the control error, it is difficult to obtain satisfactory control effect and affect the production quality. After the preliminary study of the mill feeding process, it is found that the error in the feeding process is the most direct factor leading to the poor feeding control effect. Therefore, the research on the control of the mill feed quantity in concentrator should be carried out in the direction of better control strategy, so as to achieve the purpose of keeping the mill feed relatively stable.

In the recent years, researchers have investigated an interdisciplinary approach to designing machines for additive manufacturing based on the powder bed fusion process and analyzed the AM process involves several design technological issues (Righettini and Strada, 2021). A four-wheel robot omnidirectional trajectory tracking control method based on PID and odometer was proposed for the treatment of lung diseases by the proposed Covid-19 aromatherapy robot (Iswanto et al., 2021). The particle swarm optimization algorithm is used to optimize the control parameters of the hybrid control system which combines PID controller and fuzzy controller (Duong et al., 2022). PSO algorithm is one of the most representative algorithms, which is widely used in various optimization problems due to its easy implementation of models, strong global search ability, and good parallelism (Najim e al., 1995). PSO algorithm is used to solve the function optimization problem (Uguz et al., 2015; Chang, 2017). PSO algorithm is not only a new multilevel image threshold segmentation method, but also can maintain image quality in medical imaging (Muruganandham and Wahida Banu, 2010). Moreover, PSO algorithm has substantially improved the accuracy of feature classification and gene clustering of DNA microarray data sets (Prasad et al., 2018) . However, PSO algorithm is rarely used in mining field.

Since the rule selection of fuzzy control is not specific, and heavily depends on the expert knowledge of the designer. To solve this difficulty, it combines fuzzy control with PSO algorithm and proposes an elastic variable theory universe fuzzy control algorithm based on the PSO algorithm in this paper. Firstly, the fuzzy control algorithm of elastic variable universe is proposed on the basis of traditional fuzzy control algorithm. The elastic domain can be divided by contraction-expansion factor, and the control can be realized by elastic universe without precise control rules. In the whole control process, the value of the contraction-expansion factor is very important. Therefore, based on the fuzzy control algorithm of the elastic variable universe, PSO algorithm is proposed to optimize and adjust the contraction-expansion factor (Chen et al., 2008), so that the stretching factor changes with the change of system state and reaches the optimal value, so as to improve the performance of the mill feed control system. Finally, Python was used to model and simulate the mill feeding process and the simulation results were analyzed. The results show that the proposed algorithm is superior to fuzzy control and can improve the overall robustness and accuracy of the mill feeding system.

2. Fuzzy control

2.1. Development and application of fuzzy control

Fuzzy control is a mathematical model with simple structure, strong robustness and independent of the precision of the controlled object. Its goal, like other practical theories, is to solve various practical problems (Euzebio et al., 2015). The basic idea of fuzzy control is to apply fuzzy set theory in the control method, transform the natural language of human control strategy into the control algorithm described by the algorithm language acceptable to the computer. Through simulating the way of thinking of human to effectively control some of the controlled objects that cannot be constructed mathematical models, such as mineral processing float grinding process, industrial boiler combustion process, etc.

With the emergence of a fuzzy concept, people began to study fuzzy control theory and applied the relevant results to the practical production and life. Fuzzy control has only experienced several decades from its birth to now, but it has already achieved good research results in many fields. In particular, the mutual integration of fuzzy control with neural networks, genetic algorithms, chaos theory and other new disciplines is showing its huge application and development potential, and has been well used in systems engineering, automation control, network technology, etc. (Reznik et al., 2000).

2.2. Fuzzy controller

The fuzzy controller is the core of the fuzzy control system and the main guarantee of the control quality of the fuzzy control system (Blanchett et al., 2000). Its basic structure is shown in Fig. 1. The fuzzy controller consists of four parts: fuzzification, knowledge base, fuzzy reasoning, and defuzzification.

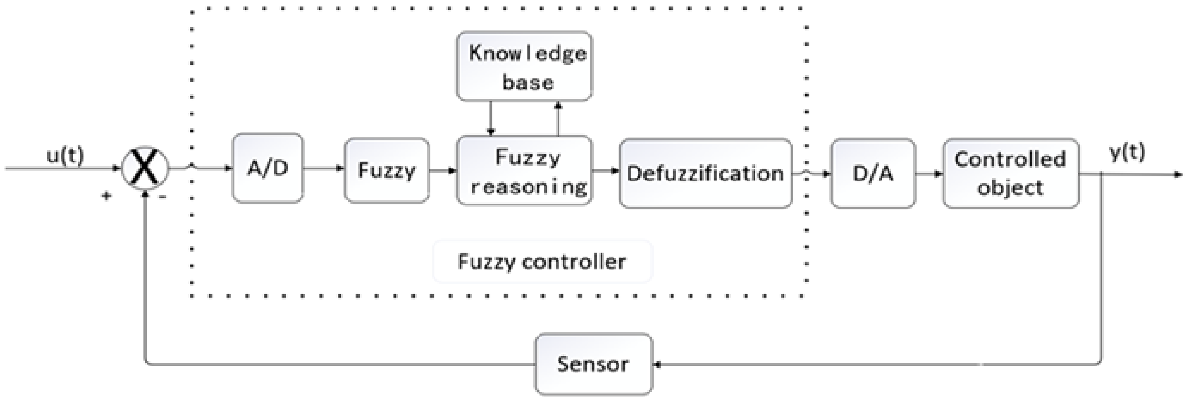

Fig. 1. Structure diagram of the fuzzy control system

The fuzzy controller (Juang et al., 2008) plays an important role in the fuzzy automatic control system. Hence, it is very important to design and adjust the work of the fuzzy controller in the fuzzy control system. In fuzzy control applications, the observed quantity is usually a definite quantity or a precise numerical quantity within a certain range. Because fuzzy control operations are based on fuzzy set theory, fuzzification is very necessary. The basic idea of fuzzification is to define a fuzzy map (Elith et al., 2002), as a fuzzy relation from the numeric domain to the linguistic domain, to map the numerical signal to the linguistic domain. Its essence is to obtain the membership function of the fuzzy set in the numerical field that corresponds to the corresponding concept (Euzebio et al., 2015). This process specifically includes quantification and fuzzy division of the universe of discourse.

The design of control rules is the key to designing the fuzzy controller, which generally includes three parts: selecting the word set that describes the input and output variables, establishing the control rules of the fuzzy controller, and select of the universe, quantization factor, and scale factor.

(1) Select the word set that describes the input and output variables

The control rules of the fuzzy controller are expressed as a group of fuzzy conditional statements in which a set of words, namely:

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

which is usually abbreviated as {NB, NM, NS, 0, PS, PM, PB}.

When words are selected to describe the state of the input variable of the error change, "zero" is often divided into "positive zero" and "negative zero;" thus, the corresponding word set becomes:

{negative big, negative medium, negative small, negative zero, positive zero, positive small, positive medium, positive big},

{NB, NM, NS, NO, PO, PS, PM, PB}.

The words that describe the input and output variables have fuzzy characteristics and can be represented by fuzzy sets.

(2) Establish the control rules of the fuzzy controller

The control rules of the fuzzy controller are based on manual control strategies. Based on existing experience and technical knowledge, the operator performs comprehensive analysis to make control decisions and adjust the control function of the controlled object so that the system can achieve the expected goal. The fuzzy control rule table is shown in Table 1.

Table 1. Fuzzy control rule table

c \ ce	NB	NM	NS	O	PS	PM	PB
NB	PB	PB	PB	PB	PM	O	O
NM	PB	PB	PB	PB	PM	O	O
NS	PM	PM	PM	PM	O	NS	NS
NO	PM	PM	PS	O	NS	NM	NM
PO	PM	PM	PS	O	NS	NM	NM
PS	PS	PS	O	NM	NM	NM	NM
PM	O	O	NM	NB	NB	NB	NB
PB	O	O	NM	NB	NB	NB	NB

(3) Select of the universe, quantization factor, and scale factor

Let the basic universe of error be $\left[-x_e, x_e\right]$ and the basic domain of error change was $[-xec, xec]$. The variation range of the control quantity actually required by the controlled object is called the basic universe of the output variable (control quantity) of the fuzzy controller, which is set to $[-yu, yu]$. The quantities within the basic universe of control quantities are exact and their fuzzy domains are as follows:

- fuzzy subset universe of error variables is

$$\{-n, -n+1, \dots, 0, \dots, n-1, n\}$$

- fuzzy subset universe of error variation is

$$\{-m, -m+1, \dots, 0, \dots, m-1, m\}$$

- fuzzy subset universe of control quantity is

$$\{-l, -l+1, \dots, 0, \dots, l-1, l\}.$$

The parameters that define the controller are as follows:

$$Ke = n/xe \tag{1}$$

$$Kec = m/xce \tag{2}$$

$$Ku = yu/l \tag{3}$$

Since the basic universe of control quantities is a continuous real number domain, the transformation from the fuzzy set universe of control quantities to the basic universe can be calculated using the following formula:

$$y_{uj} = Ku/lj \tag{4}$$

Comparing the quantization factor and the scale factor (Blanchett et al., 2000), it is easy to see that both are derived by considering the transformation of two universes; however, the quantization factor has a quantization effect on the input variable, whereas the scale factor only plays a proportional role for the output.

3. Elastic variable universe fuzzy control strategy based on particle swarm optimization

3.1. Principle and implementation of elastic variable universe fuzzy control

After the preliminary design of fuzzy controller, it is usually necessary to constantly adjust the rules to obtain satisfactory control results. The traditional fuzzy controller is essentially an interpolator, and the whole control process of fuzzification, fuzzy reasoning, fuzzy decision and defuzzification can be equivalent to an interpolation function, that is, the whole algorithm is the approximation to the corresponding function and is the fitting of the corresponding function, but because of its limited grade, lack of integral adjustment and poor adaptive ability, there are problems of low control accuracy.

In order to solve the problems existing in traditional fuzzy control, this paper proposes an elastic variable universe fuzzy control strategy. The strategy processes the variable universe (Liu et al., 2020) by dividing the quantization factor Ke and Kec, and the scaling factor Ku by the corresponding input scaling factor and multiplying them by the corresponding output scaling factor. The variable universe fuzzy controller is designed by dividing the input variable by the corresponding scaling factor and multiplying the output variable by the corresponding scaling factor. The scaling factor is not a fixed value and will dynamically change with changes in system state to dynamically adjust the size of the universe and ultimately improve the control accuracy of the system.

Assume that the initial universe of discourse range of the error universe (Li et al., 2002) is [-E,E] and the universe of discourse range after the transformation of the universe of discourse is [-α(x)E,α(x)E]. The universe transformation diagram is shown in Fig. 2.

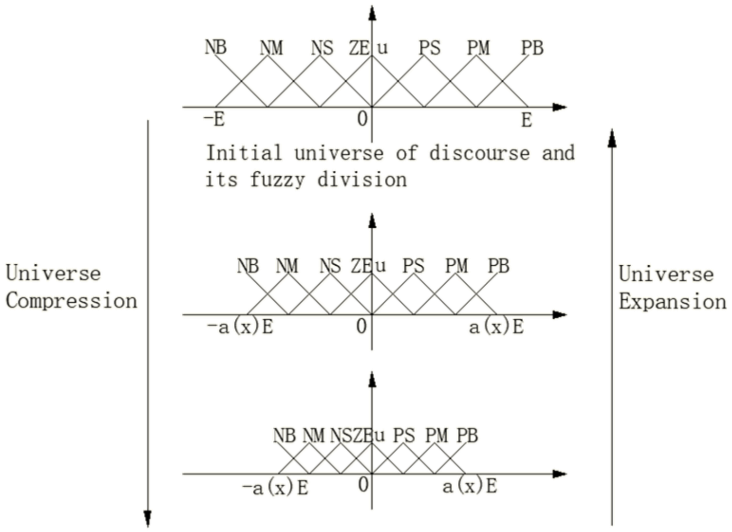

Fig. 2. Universe transformation diagram

The contraction-expansion factor has the following properties:
(1) duality:$\forall x \in X,\alpha\ (x)=\alpha\ (-x)$
(2) zero tendency: $\alpha(0)=0$
(3) monotonicity: $\alpha$is strictly monotonically increasing over the universe $[-E, E]$
(4) coordination: $\forall\ x \in X,|x| \leq \alpha\ (x)E$
(5) formality: $\alpha(\pm E)=1$.

The form of the input scope contraction-expansion factor is shown below:

$$\alpha(x) = 1 - ce^{-kx^2},\ c \in (0,1), k > 0 \tag{5}$$

$$\alpha(x) = \left(\frac{|x|}{E}\right)^{\tau},\ \tau \in (0,1). \tag{6}$$

In the dual-input single-output system, x in equations (2-1) and (2-2) is the error e and the error rate of change ec. c, k, and τ are all adjustable parameters.

The form of the output scope contraction-expansion factor is shown below:

$$\beta(t) = k\sum_{i=1}^{n} pi \int_0^1 ei\,(\tau)d\tau + \beta(0) \tag{7}$$

$$\beta(x,y) = \left(\frac{|x|}{E}\right)^{T1}\left(\frac{|y|}{EC}\right)^{T2} \tag{8}$$

$$\beta(x,y) = \frac{1}{2}\left[\left(\frac{|x|}{E}\right)^{T1} + \left(\frac{|y|}{EC}\right)^{T2}\right] \tag{9}$$

where k and pi are both adjustable parameters, and n is the number of input variables of the system. $\beta(0)$ needs to be set according to the actual scenario; generally, $\beta(0)$ =1. Additionally, $T_1 > 0$ and $T_2 < 1$.

3.2. Elastic variable universe fuzzy control system based on particle swarm optimization

3.2.1. Particle swarm optimization

PSO was proposed by Dr. Kennedy and Professor Eberhart in 1995 (Zadeh, 1965). The basic concept of PSO originated from research on predicting the behavior of birds. The following scenario exists: a group of birds is randomly searching for food and there is only a piece of food in the area. The simplest and most effective approach is to search the surrounding area of the bird that is currently closest to the food. PSO was inspired by this model and uses it to solve the optimization problem (Yu et al., 2008). Since PSO algorithm has fast convergence speed, fewer parameters and better performance, many researchers have tried to apply it in various fields, such as engineering problem optimization, neural network integration (Mao et al., 2022), TSP problem (Elloumi et al., 2014), multi-objective problem solving (Dhal and Azad, 2021) and in face recognition (Krisshna et al., 2014), automatic generation of software structure test data (Prajapati, 2021), feature selection of classifier, optimization of wind power plant (WPP) grid fault LVRT capability (Muisyo et al., 2022), tram energy saving performance (Xing et al., 2022), etc., and achieve good results.

In an n -dimensional search space, particle swarm X is composed of m particles, and the population is represented as $X = \{X1, X2, \cdots, Xn\}$. Where the position of each particle is expressed as$xi = (xi1, xi2, \cdots, xin)^T (i = 1,2, \cdots, m)$. The velocity is expressed as $v_i = (v_{i1}, v_{i2}, \cdots, v_{in})^T$ $(i = 1,2, \cdots, m)$. The extreme value of an individual is expressed as $pi = (pi1, pi2, \cdots, pin)^T (i = 1,2, \cdots, m)$. The population extreme value of the population is expressed as$pg = (pg1, pg2, \cdots, pgn)^T (g = 1,2, \cdots, m)$. According to PSO algorithm, when finding the optimal values of Pbest and Gbest, each particle can update its speed and new position according to the following formula (Kumar and Kumar, 2022):

$$V_{id}^{k} = \omega\, V_{id}^{k-1} + C1rand\left(Pbestid - X_{id}^{k-1}\right) + C2rand(Gbestid - X_{id}^{k-1}) \tag{10}$$

$$X_{id}^{k} = X_{id}^{k-1} + V_{id}^{k} \tag{11}$$

where V_{id}: current velocity of the $i-th$ in $d-dimensional$ space; X_{id}: current position of the $i-th$ particle in $d-dimensional$ space; ω: inertia weight; $Pbestid$: $d-th$ dimension of the individual extreme value of the $i-th$ variable; $Gbestid$: $d-th$ dimension of the global optimal solution; $C1$ and $C2$: acceleration constants; $rand$: random number in [0,1].

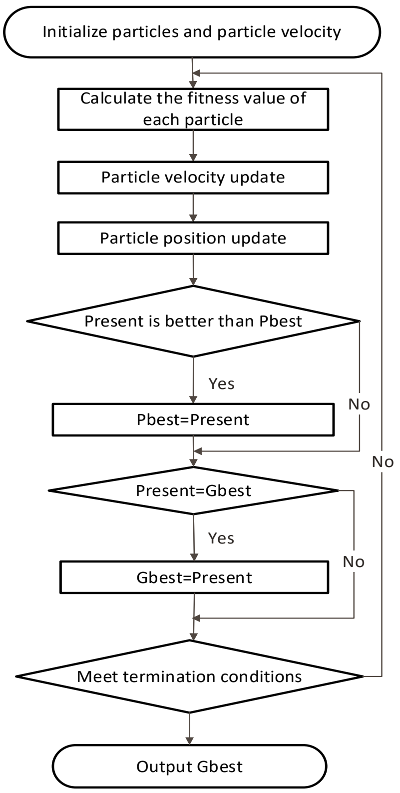

Fig. 3. is a flow chart of the PSO algorithm

3.2.2. Design concept for elastic variable universe fuzzy control based on particle swarm optimization

According to the fuzzy control theory, the quality of fuzzy control largely depends on the value of variable language of input and output of fuzzy controller. In other words, a fuzzy controller can approximate any ideal control function if there are enough language variables and are sufficiently refined in their domains of discussion. But adding enough language variables means a rapid increase in control rules. If the number of control rules is not changed, the problem can be solved by changing the theory universe fuzzy control. In general, the law of domain change will shrink the domain as the input becomes smaller, and expand the universe as the input becomes larger depending on the size of the input and output. In the process of universe shrinking, fuzzy control rules are actually added, thus improving the precision fuzzy control system.

The design concept of the elastic variable universe fuzzy control system (Pang et al., 2018) based on PSO is shown in Fig. 4. First, the PSO algorithm is used to optimize the scaling factor α in each sampling period, and Contraction-expansion factor β is used as the Contraction-expansion factor of variable universe fuzzy control systems in the next sampling period. Since fuzzy control is already capable of rough control of the system (Camacho et al., 2020), PSO for scaling factor optimization only requires a small population size and number of iterations to achieve a high precision optimization solution. Because of this, the implementation and real-time performance of the algorithm can be well guaranteed.

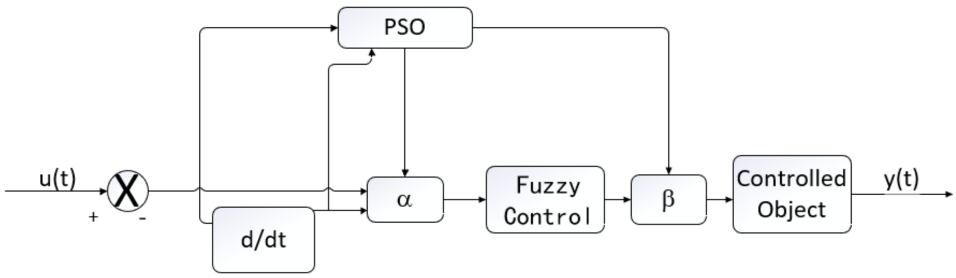

Fig. 4. Design idea of the elastic variable universe fuzzy control system based on PSO

Fig. 4 shows that the universe of discourse changes with the contraction-expansion factor, the fuzzy rules of the fuzzy controller will become more accurate, while the fuzzy control rules of the traditional fuzzy controller are single and unchangeable.

In this paper, the study of elastic variable theory universe fuzzy control based on the PSO algorithm is applied to the mill feeding system to solve the slow speed problem of the mill feeding system.

4. Simulation experiment and analysis of the elastic variable universe fuzzy control mill feeding system based on particle swarm optimization

The purpose of the crushing grinding process is to achieve preliminary monomer dissociation of gangue minerals and useful minerals, so as to facilitate the subsequent sorting operation, so the crushing grinding operation is a very important part of the mineral processing process. Flow chart of mill feeding process equipment in concentrator is shown in Fig. 5.

4.1. The data acquisition method and establishment of the simulation model for the feeding system of a mill with an elastic variable universe of fuzzy control based on particle swarm optimization

This experiment was conducted in 2022 at a beneficiation plant in Yunnan Province of China, where two sampling machines were used to sample the ore. After sampling, the on-site operators sent the ore samples to the beneficiation laboratory, and based on the experience of the on-site operators, the ore particle size and the weight displayed on the electronic belt scale were selected as influencing factors for analysis. The ore particle size of each batch of ore samples is analyzed in the beneficiation laboratory.

The weight of the electronic belt scale refers to the weight of the ore on the transportation belt measured by the electronic belt scale. The dataset for the weight of the electronic belt scale is sampled for one adjustment cycle of the feeder, that is, one cycle from the actual value to the set value, with a

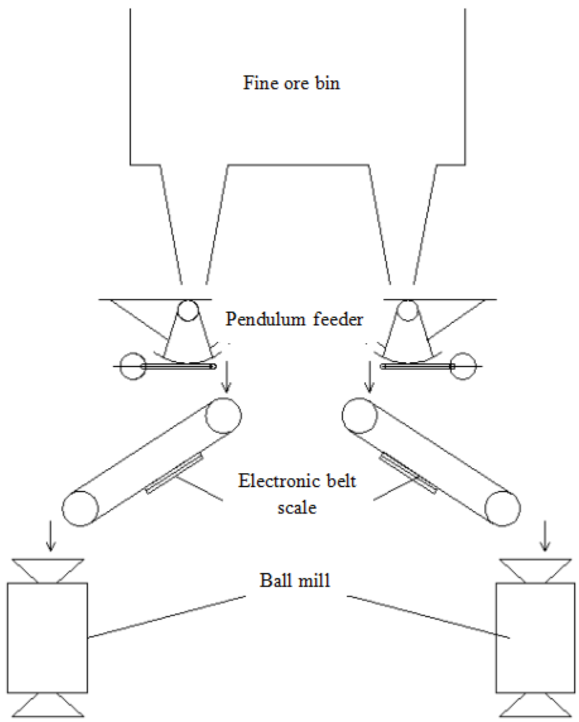

Fig. 5. Flow chart of mill feeding process equipment in concentrator

sampling period set at 10 minutes. The sampling cycle of the sampling machine is half an hour. When the sampling machine is working, the motor frequency of the current two feeders is recorded for 5 hours.

After the performance of the elastic variable universe fuzzy control based on the PSO algorithm proposed in this paper is tested, and then it is applied to the feed of the mill. In addition, the traditional fuzzy controller with double input and single output is selected as the comparison object of the fuzzy controller in the elastic variable theory universe for comparative analysis of the algorithms. In the early stage of the PSO algorithm, there are some extraordinary individuals with outstanding competitiveness who affect the global optimum performance of the algorithm (Gu et al., 2022), and in the later stage, the local optimal solution is determined instead of the global optimal solution because of the reduction of individual differences in the population. Therefore, the fitness function of the PSO algorithm must be constructed based on relevant performance indicators for the system, and then the contraction-expansion factor can be optimized through the PSO algorithm.

So in all the experiments, the population size of PSO algorithm was set to be 100,the maximum number of iteration is 300, the inertia weight ω was set to 0.8, C_1 was set to 2 and C_2 was set to 2.Limit position to interval [0,1] and speed to interval [-1,1].To eliminate stochastic discrepancy, each experiment is independently run with 30 times for comparisons. The experiments are developed using Python 3.8. To eliminate stochastic discrepancy, each experiment is independently run with 30 times for comparisons, and limit the position and speed to the ranges of [0,1] and [-1,1] respectively.

To verify the performance of the elastic variable universe fuzzy control system based on the PSO algorithm applied to the feed control of the mill, In this paper, the pure hysteresis problem of the motor transmission part in the feeding process of a mill in a concentrator is transformed into a mathematical optimization problem, and its transfer function (Chen et al., 2008) is as follows :

$$G_0(s) = \frac{K_0 e^{-ts}}{T_0 s+1}, \tag{12}$$

where K_0: magnification factor; t: pure lag time; T_0: inertia time constant.

The transfer function was used as a fitness function for modeling through Python, in which $T_0 = 0.85$, $K_0 = [0,1]$, and the optimal individual fitness test was conducted through the fitness function to find the optimal value of the fitness function and the position of the optimal particle, in which the position of the optimal particle corresponds to the value of the stretching factor α and β.The model diagram of the transfer function is shown in Fig. 6, and the test results are shown in Fig. 7.

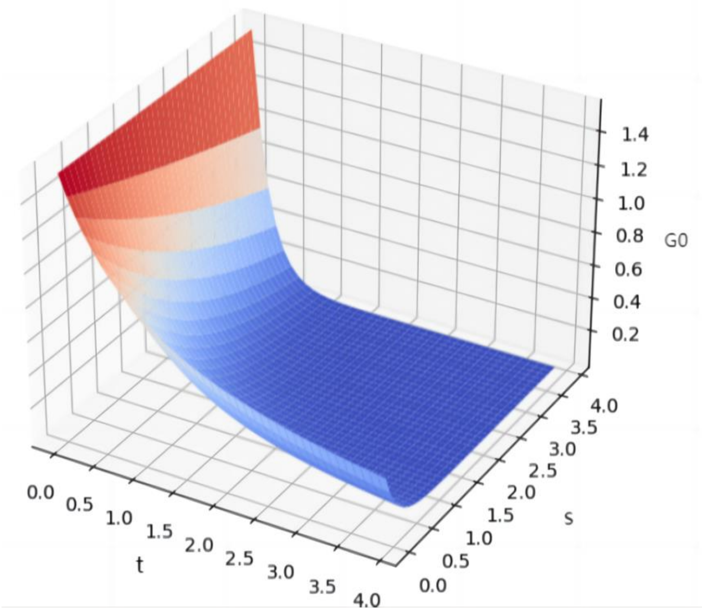

Fig. 6. The model diagram of the transfer function

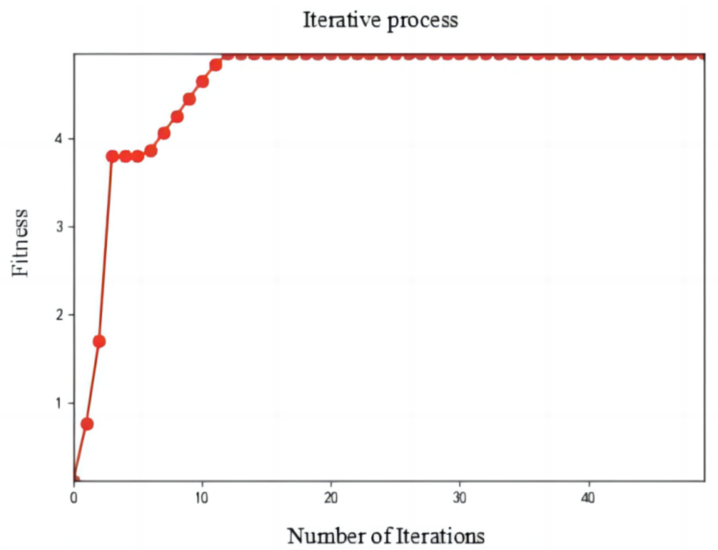

Fig. 7. Test results for the fitness function

As can be seen from Fig. 6, the algorithm can make the lag time of the motor drive part in the feeding process of the mill approach to the optimal value through only 12 iterations, which is 4.97, and the corresponding particle position is [0.826973069,1.284119983], and the expansion factor $\alpha = 0.826973069$ and $\beta = 1.284119983$. By comparing the optimal value obtained by the PSO algorithm with the set value, the experimental results show that the optimal value matching the set value can be quickly searched and has a strong function extremum optimization ability. Then the algorithm can improve the overall robustness and accuracy of the mill feeding system greatly.

4.2. Simulation experiment and comparative analysis of the elastic variable universe fuzzy control mill feeding system based on particle swarm optimization

Based on the experimental results in Section 3.1, this section uses the fuzzy control system of elastic variable theory universe based on the PSO algorithm to control the feed amount of the mill, and compares the feed amount with that of the traditional fuzzy control system. The feed amount of the mill is set at 210Kg. The simulation results are shown in Fig. 8, where Figs. (a) and (b) are the simulation results of the traditional fuzzy controller, Fig. (c) and (d) show the simulation results of fuzzy control system with elastic variable theory universe based on PSO.

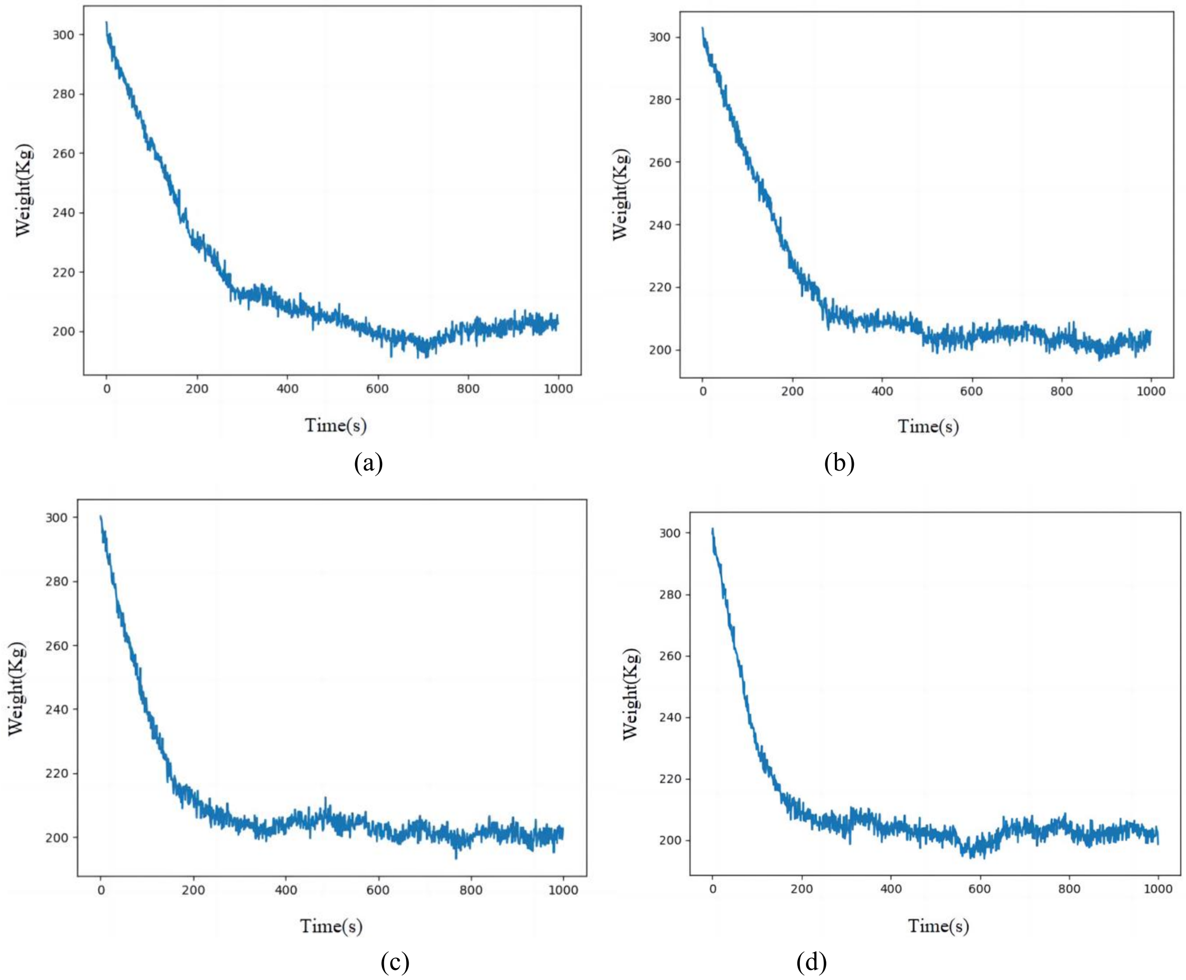

Fig. 8. (a), (b) simulation diagram of traditional fuzzy controller, (c), (d) Simulation diagram of PSO-based fuzzy control system with elastic variable theory universe

From (a) and (b) in Fig. 8, it can be seen that the simulation results under the fuzzy control system gradually approach to the set value of 210Kg for the mill feed from 290S, which fluctuates sharply around 210Kg. As can be seen from (c) and (d), the simulation results of PSO under the elastic variable theory universe fuzzy control system steadily approach the set value of 210Kg from 190S, and the fluctuation range is small. Good control effect is achieved, the time to steady state is shorter, and the dynamic characteristics of the system are improved. In order to further analyze the performance of the fuzzy control system in the elastic variable theory universe based on the PSO algorithm, the feeding reaction time characteristics of the mill in different control systems are given in Table 2 when the feed quantity is 210kg. It can be seen from the table that the reaction schedule of the fuzzy control system in the elastic variable theory universe based on the PSO algorithm is shorter than that of the traditional fuzzy control system, shortened by 34.48%. It can be seen that the fuzzy control of the elastic variable theory universe based on the PSO algorithm is superior to the traditional fuzzy control in response speed and control precision. Therefore, the fuzzy control of the elastic variable theory universe based on the PSO algorithm is superior to the traditional fuzzy control for the control of mill feed quantity, and the control algorithm proposed in this paper is suitable for the control object which requires high control precision and reaction speed.

Table 2. Feed reaction time evaluation table of the mill with different control systems when the feed volume is 210kg

control system	response time（s）	The response time of the two control systems is shortened（%）
Traditional fuzzy control system	290	34.48
Elastic variable theory universe fuzzy control system based on the PSO algorithm	190	

5. Conclusions

In this paper, to overcome the drawbacks of conventional Fuzzy controller feed control system in the mill, a novel fuzzy control system of elastic variable theory universe based on the PSO algorithm is proposed. Firstly, the control system proposed in this paper is applied to the pure hysterical link in the motor drive part of the mill feeding process in a concentrator. The experimental results show that the fuzzy controller with PSO has a better performance of the problem of pure delay in the motor drive part in the mill feeding process, which can reach the optimal value in a very short time and is consistent with the set value. Finally, the fuzzy control system of elastic variable theory universe based on the PSO algorithm is applied to the control of the feed amount of the fuzzy control system, and compared with the traditional fuzzy control algorithm, the reaction speed and control accuracy of the optimized mill feeding system are better than the traditional fuzzy controller. The simulation results of the mill feeding system based on the fuzzy control modeling in Python can be displayed in 3D view. The results are more concise, convenient for operators to observe and record, improve production efficiency to a greater extent, achieve energy saving and consumption reduction, which is of great significance for the mineral processing industry.

In the future, we will further study the following issues: (1) Although the results in the study passed the test of a Python simulation, because of time constraints and limited experimental equipment, they were not tested using engineering practice in an actual production site. Therefore, this also needs to be tested and continuously improved in actual field operation. (2) Although elastic variable universe fuzzy control based on PSO is achieved powerful optimization, it is difficult to implement online optimization control because of its slow optimization speed. How to solve the problem of online optimization control will be further explored. (3) The improvement of PSO algorithm is a research hotspot. How to improve the performance of PSO algorithm globally, and improve the local optimization ability of the algorithm while still maintaining the global search ability will have great significance.

Acknowledgements

This work was supported by the National Engineering and Technology Research Center for Development & Utilization of Phosphate Resources Open Fund (No. NECP2022-11), and Yunnan Province Young Talents Project Fund (No. CG22166F219A) , Funded by the Yunnan Provincial Department of Science and Technology(No. 202101AT070277).

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